Bringing predictability into a geometallurgical program

An iron ore case study

Viktor Lishchuk

Mineral processing
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ABSTRACT

The risks of starting, operating and closing mining projects have become higher than ever. In order to stay ahead of the competition, mining companies have to manage various risks: technical, environmental, legal, regulatory, political, cyber, financial and social. Some of these can be mitigated with the help of geometallurgy. Geometallurgy aims to link geological variability with responses in the beneficiation process by a wide usage of automated mineralogy, proxy metallurgical tests, and process simulation. However, traditional geometallurgy has neglected the non-technical aspects of mining. This has caused wide-spread discussion among researchers on the benefits of geometallurgy and its place in industry.

In order to improve predictability in geometallurgy, such programs should cover planning, and the testing of hypotheses, and only then should there be an attempt to develop suitable technical tools. Such approach would ensure that those tools would be useful and are needed, not only from the technical point of view, but also from the users’ perspective. Therefore, this thesis introduces methodology on how to decrease uncertainty in the production planning and thus determine how much effort to put into decreasing uncertainty in geometallurgical programs.

The predictability improvement of a geometallurgical program starts at the planning stage. The classification system developed here, through the survey (interviews) and literature review, indicates different ways to link geological information with metallurgical responses, and suggests areas where technical development is called for. The proposed developments can be tested before the start of the geometallurgical program with synthetic data. For the iron ore reference study (Malmberget), it was shown that implementation of geometallurgy is beneficial in terms of net present value (NPV) and internal rate of return (IRR), and building geometallurgical spatial model for the process properties (recovery and total concentrate tonnages), and that it requires fewer samples for making a reliable process prediction than concentrate quality. The new process and proxy for mineralogical characterisation models were developed as part of the geometallurgical program for the iron ore case study (Leveäniemi): an estimator of ore quality ($X_{LTU}$), a model for iron recovery in WLIMS, a model for iron-oxides liberation prediction. Additionally, it was found that DT may be applied only for studying marginal ores. The evaluation of different spatial process modelling methods showed that tree methods can be successfully employed in predicting non-additive variables (recoveries).
KEY WORDS

Additivity
Apatite iron ore (AIO)
Block model
Change of support
Classification
Data integration
DT
Feed quality
Geometallurgical program
Geometallurgy
Iron ore
Iron recovery
Leveäniemi
Liberation
Machine learning
Magnetic separation
Malmberget
Mineralogical approach
Mineralogy
Prediction
Proxies
Proxies approach
Sampling
Simulation
Synthetic ore body
Traditional approach
WLIMS
My journey towards this dissertation started four years ago, on 26 November 2014. The dissertation was a sweet dream and the voyage towards this dream was full of excitement, adventures, and discoveries. Although disappointments, sadness, and boredom tried to set up in front of me, a positive attitude, hard work, determination, and love for the journey itself stirred my spirit and mind.

After finishing courses at Aalto University, I started a Master thesis internship for Outotec in Russia as a process engineer. This was my first experience of being exposed to the mining industry and mineral processing. While finalizing my Master thesis, I discovered for myself a new and rapidly developing field called geometallurgy. Geometallurgy gave me answers to most of the questions needed for wrapping up the Master thesis. After that I knew that I want to contribute more to the body of knowledge in the field of geometallurgy, and opportunity to do so presented itself just few months after I have graduated from Aalto University. A fully funded PhD position in geometallurgy was opened at Luleå University of Technology. It is needless to say, how glad I was to start working in one of Europe’s largest and most dedicated geometallurgical teams.

The project was challenging and exciting in the same time. Communication and collaboration between five partners (LKAB, Boliden, Lundin, Outotec, Chalmers University, and Luleå University of Technology) had to be established and maintained, regardless of any changes. This was a great experience for me, and I have improved both my technical and soft skills, which are required for large projects.

Through the years, I have dedicated a great deal of my life into this work. A lot of research and education yielded large pile of documentation, including scientific and conference papers, technical reports, student reports, master theses, and presentations. As is often the case in such projects, less than half of the work done over the course of it actually found its way into this thesis. Now it is time to share the final outcome of my work with everyone and get ready for setting new goals and dream new dreams.

Viktor Lisichuk
November, 2018
Luleå, Sweden
ACKNOWLEDGEMENTS

A PhD is a lonely endeavour; however it would not be possible without others, especially my supervisors. My PhD work was supervised by a prominent professor, Pertti Lamberg, whose positive attitude, excellent strategic vision and great inspirational skills helped me to shape the red line of the research. Nevertheless, strategy without action is not more than just a wish list. And I am grateful to Cecilia Lund for supporting me in everyday scientific activities and steering the research process when it was entering mysterious and obscure areas. At some points there were bad times that no-one could help. But without bad times, good times cannot be appreciated. I highly appreciate the great support received from Bertil Pålsson who helped to finalize my PhD trip and tempered my knowledge and skills in scientific research. In addition, I am glad I could discuss my work with Simon Michaux, Maria Pettersson and Yousef Ghorbani. This work would be much poorer without your complementary expertise and positive attitude, which was much needed towards the end of this project.

The thesis was part of the PREP research project supported by VINNOVA SIO STRIM project nr. 2014-01933. The project involved several industrial and research partners, whose support and trust is greatly acknowledged: Lewis Wild, Therese Lindberg, Kari Niiranen, Mattias Gustafsson, Monika Sammelin from LKAB; Sofia Hoglund from Boliden; and Anders Gustafsson from Zinkgruven Mine of Lundin Mining. I warmly thank Outotec for providing with software and Chalmers university team for being part of the project.

I am also grateful to those who have made technical contributions to the thesis and assisted with experiments: Ulf Nordstrom, Kartikay Singh, Efraín Cárdenas, and EMERALD students from cohorts 2016-2018.

I would like to thank Mehdi Parian, Tommy Karlkvist, and Pierre-Henri Koch for their comments and suggestions regarding the text. It would be impossible to fit this thesis into a geometallurgical framework without work done by Abdul Mwanga, Christina Wanhainen, Mehdi Parian, and Pierre-Henri Koch. My friends, whom I met in Luleå, but who will forever remain in my heart, deserve a particular note of thanks: Anders Sand, Erdogan Kol, Mehdi Parian, Pierre-Henri Koch and his wife Coralie, Tommy & Lindsay Karlkvist. My warm thanks are to the Nordic Barbara Club and its members: Emilia Nordstrom, Tobias & Nathalie Kampmann, Elena Miroshnikova, and many others. You have always been near when friends were needed. Riia Chmielowski, thank you a lot for proofreading my manuscripts and your valuable comments. Very warm thanks to Anneli Engstrom for being an administrative angel during all these years. It was a pleasure to work, discuss, cooperate and have many great moments with colleagues from the Division of Minerals and Metallurgical Engineering, and the Division of Architecture and Water.

Finally, this thesis would not be possible without support and encouragements from my family and those whose love was motivating and inspiring.

In memory of Dee Bradshaw, a great inspiration to me and many others.
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This thesis is based on following papers:


Paper E  Lishchuk V., Lamberg P., Lund C., Miroshnikova E., 2018. Simulation of a mining value chain with a synthetic ore body model: Iron ore example. Minerals, 8 (11), 536 (Published)

Author's contribution to the papers included in the thesis:

**Paper A**
The author collected data through the thorough literature review, design and distribution of the online survey and design of the interview questions. The author presented Mikheevskoye case study. P.-H.K. and C.L. presented Malmberget reference case. P.L. contributed in supervisory capacity.

**Paper B**
The author took part in sampling, did sample preparation and supervision of the laboratory tests, which included grinding and magnetic separation with DT and WLIMS. The author organised and supervised sample preparation for analytical work (QEMSCAN, XRF), and did interpretation of the results. Modelling was done by author as well as most of the writing was done by author. G.M. contributed with analytical work (QEMSCAN, Chemical assays, SATMAGAN). P.-H.K. assisted with sampling and laboratory tests. B.P. and C.L. contributed in supervisory capacity.

**Paper C**
The author designed the model and computational framework and carried out the implementation. Simulations, interpretation of the results and work on manuscript was mainly done by the author. C.L. provided case study data. P.L. contributed in supervisory capacity.

**Paper D**
The author designed the model and computational framework and carried out the implementation. The author also took lead in writing the manuscript. C.L. provided case study data. P.L. contributed in supervisory capacity.

**Paper E**
The author designed the model and computational framework and carried out the implementation. The author also took lead in writing the manuscript. C.L. provided case study data. E.M. assisted with mathematical interpretation of the data. P.L. supervised the project.

**Paper F**
The author analysed the data, derived the models, worked out the technical details, and performed the numerical calculations. Interpretation of results and writing was done by the author. The other co-author contributed in a supervisory capacity.
Other work not included in the thesis:

Articles in conference proceedings:

**Conference paper 1**


**Conference paper 2**


**Conference paper 3**


**Conference paper 4**


**Tools developed:**

1. Virtual environment in MATLAB for generating synthetic deposit and integrate synthetic spatial and process data
2. Interactive tutorials for using laboratory equipment and following safety procedures in mineral processing laboratory.
ABBREVIATIONS

General:

1D  One dimensional
2D  Two dimensional
3D  Three dimensional
AG  Autogenous mill
AI  Association Index
AIO  Apatite iron ore
ANC  Acid neutralised capacity
Auto-SEM  Automated particle analysis by Scanning Electron Microscopy
Auto-SEM-EDS  Automated particle analysis by Scanning Electron Microscopy / Energy Dispersive X-Ray Spectroscopy
AVE  Classifier is an arithmetic average from EN, LR, SMO, IBk, K*, M5, RF and M5P
BM  Block model
BWI  Bond work index
CEET  Comminution Economic Evaluation Tool
cf.  Confer/Conferatur (“compare”)
DI  Difference Index
DT  Davis tube
DWi  Drop weight index
e.g.  Exempli Gratia (“for example”, “for instance”)
EDS  Energy Dispersive X-Ray Spectroscopy
EMC  Element-to-mineral conversion
EN  Elastic Net
FLEET  Flotation Economic Evaluation Tool
FV  Future value
GAM  Generalized additive model
GCT  Geometallurgical comminution test
GeM  Geometallurgical Mapping and Mine Modelling (project)
GeMCi  GeM Comminution index
GRG  Gravity Recoverable Gold
HIMS  High-intensity magnetic separator
HRC  Henry-Reinhardt charts
HSC  H [enthalpy], S [entropy] and C [heat capacity]
i.e.  Id Est (“that is”, “namely”, “in other words”)
IBk  Instance-bases learning with parameter k
ICP  Inductively Coupled Plasma
ID  Identification number
IGS  Integrated Geometallurgical Simulator
IOCG  Iron Oxide Copper Gold
JKMSI  Julius Krutschnitt Mineral Separability Indicator
K*  K* instance-based classifier
LIMS  Low intensity magnetic separator
LKAB  Luossavaara-Kiirunavaara AB
LOI  Loss on ignition
LR  Linear regression
LR  Linear regression
LTU  Luleå University of Technology
M  M5Rules
M5P  Machine learning algorithm - model trees
M5Rules  Machine learning algorithm - rules from model trees
MAGNASAT  Magnetic Susceptibility Meter
MATLAB  Matrix laboratory
MED  Classifier is a median estimated from EN, LR, SMO, IBk, K*, M5, RF and M5P.
MLA  Mineral liberation analyser
MODSIM  Modular simulator for mineral processing plants
MP  Mass pull
N/A  Not available
NPV  Net present value
P80  Size passing fraction = 80%
PC  Principal component
PCA  Principal component analysis
PLS  Partial least square regression = projection to latent structures
ppm  Parts per million
PREP  Primary resource efficiency for enhanced prediction
PSD  Particle size distribution
PV  Present value
QEHS  Quality, Environmental, Health and Safety
QEMSCAN  Quantitative Evaluation of Minerals by Scanning electron microscopy
QXRD  Quantitative XRD
R&D  Research and development
RF  Random forest
RF  Random forest
ROM  Run of mine
RSD  Relative standard deviation
SAG  Semi-autogenous mill
SATMAGA  Saturation Magnetization Analyser
SEM  Scanning electron microscope
SG  Specific gravity
SMC  SAG Mill Comminution
SMO  Sequential minimal optimization for support vector regression
SPI  MinnovEX SAG power index test
WEKA  Waikato Environment for Knowledge Analysis developed at the University of Waikato, New Zealand.
WLIMS  Wet low-intensity magnetic separation
XRD  X-ray diffraction
XRF  X-ray fluorescence
XRT  X-ray tomography
T    Tesla
A    Ampere

Minerals:

Ab    Albite
Act   Actinolite
Amph  Amphibole
Ap    Apatite
Bt    Biotite
Cal   Calcite
FeTi-oxides Oxide minerals containing iron and titanium
Fsp   Feldspar
Grt   Garnet
Hem   Hematite
Ilm   Ilmenite
K-Fsp K-Feldspar
Mgt   Magnetite
Px    Pyroxene
Py    Pyrite
Qtz   Quartz
Sulp. Sulphides
(l, m, n) Non-zero numbers where l is an x-intercept, m is an y-intercept, and n is an z-intercept.

\( \hat{p}_j \) Iteratively adjusted mass proportion of the mineral grades

\((x_0, y_0, z_0)\) Coordinates of the centre of the geological domain

\(C_m\) Mining cost

\(C_p\) Processing cost

\(C_s\) Sales cost

\(D_{I_{\text{Otr}}}\) Difference index, %

\(G_{\text{XRF}}\) Component’s grade analysed by synthetic XRF

\(G_{\text{true}}\) Synthetic value of the component grade of the sample

\(L_{Fe-ax}\) Liberation of iron oxides

\(M(i)\) Mineral grade in the sample

\(M^{DT}\) Mass pull in Davis tube

\(M^{WLIMS}\) Mass pull in WLIMS

\(P_{80}\) Size passing fraction = 80%

\(Q_p\) Processed amount of material, units per period

\(Q_m\) Mined amount of material, units per period

\(Q_r\) Material recovered in mining and process, units per period

\(R^{DT}_{Fe}\) Recovery in Davis tube

\(R^{WLIMS}_{Fe}\) Recovery in WLIMS

\(RSD_{EI}\) Relative standard deviation

\(R_{\text{cum}}\) Cumulative recovery, %

\((T, S, N)\) Functions of coordinates \((x, y, z)\) of the voxel

\(X_{DHD}\) Input variables to the spatial process model

\(X_{LTU}\) \(X_{LTU}, \%\)

\(X_{PS}\) Input variables to the non-spatial process model

\(Y_{DHD}\) Process model (spatial)

\(Y_{PS}\) Process model (non-spatial)

\((a, b, c)\) Semi-axes of the ellipsoid

\(n_r\) Random noise

\(p_j\) Mass proportion of the mineral grades before adjustment

\((x, y, z)\) Coordinates of the voxel’s locations

\(\kappa\) Correction factor

\(\rho\) Density of the mineral

24.3 [%] \(Fe^{2+}\) content in pure magnetite sample

\(max\) Sample maximum

\(mean\) The "average" number calculated by adding all data points and dividing by the number of data points
**median**

The middle number found by ordering all data points and selecting the one in the middle

**min**

Sample minimum

**std**

Standard deviation

**A**

Matrix of chemical composition of minerals

**L**

Total number of minerals

**M**

Mineral grade in a given voxel scaled to the interval of minimum and maximum values defined for the mineral

**N**

Number of particles

**p**

The metal price

**R**

Recovery, %

**d**

Discounting rate

**n**

Any real number

\[ \sigma = (x_o, y_o, z_o) \]

Centre of the ellipsoid

**p**

Mass proportion of particle in a size class

**r**

Distance (e.g., euclidian or manhattan) in 1-, 2- or 3-dimensional space between the voxel of interest and the centre of the geological domain (ellipsoid)

**s**

Systematic error

**t**

A systematic component which considers non-magnetic forces involved in separation performance in WLIMS

**x**

Vector of mass proportions of minerals in a voxel

**ε**

Measurement error which can be described by a normal distribution with standard deviation \( \sigma \) and expected value 0

**μ**

Mean of population

**σ**

Standard deviation

\( \chi(i) \)

Mass proportion of mineral in a particle
CHAPTER 1  INTRODUCTION

“Never pray to be a better slave when God is trying to get you out of your situation.”

Shannon L. Alder

1.1. Background and motivation

The modern mining industry is exposed to serious risks, including complex geology (e.g., geometric shapes of deposits, deep seated deposits); lower ore grades; variability in ore quality (e.g., textural complexities); large production volumes, and as a result increased waste quantities; demands from metal producers; metal prices fluctuations; and stricter environmental regulations (Bridge et al., 2013; Curry et al., 2013; Dominy and O’Connor, 2016; Kojovic et al., 2010; Lund and Lamberg, 2014; Williams, 2013). Many of those risks could be mitigated or eliminated by applying geometallurgy. Geometallurgy is a team-based and multidisciplinary approach (Bayraktar, 2014; Parian, 2017) that aims at linking geological (i.e., the source of variability in the feed) and mineral processing parts (i.e., variability of the ore performance in the process) of the mining value chain, to build a model for production management – a geometallurgical model (Dunham and Vann, 2007; Kittler et al., 2011; Lamberg, 2011; Lund and Lamberg, 2014; McQuiston and Bechaud, 1968; Navarra et al., 2018; Vann et al., 2011). While the approach is not new, recent advances in automated mineralogy, data processing and metallurgical testing have made it more feasible in practice (Lamberg and Lund, 2012; Schouwstra et al., 2013). A geometallurgical model aims to provide a quantitative prediction of metallurgical performance, i.e., quality of concentrates and tailings, recoveries, throughput; environmental impact (such as fresh water consumption for a treated ton of ore); and overall economical fluctuations of the project. It can also be oriented at solving problems as a black box (the entire processing plant in a single model), by processing sections (e.g., comminution, concentration, leaching, dewatering, etc.), or with only one processing unit (e.g., crusher, mill, flotation cell etc.). The ultimate goal of geometallurgy is a spatial predictive model (Dunham and Vann, 2007; Lund and Lamberg, 2014; Vann et al. 2011). The process of creating, maintaining and utilising a geometallurgical model is called a geometallurgical program. Within a geometallurgical program the geometallurgical models define the use of geological data, sampling strategy, testing methods and simulation outcome.

Geometallurgy is said to help in optimisation of mineral resource utilisation (Philander and Rozendaal, 2013). According to Dunham and Vann, (2007) geometallurgy can give increased total metal recovery and improved asset utilisation. In addition, Lamberg, (2011) listed in his review that geometallurgy has potential to bring benefits, such as better controlled ore deposit utilization, higher flexibility in introduction of new technological solutions, lower operational risks, and wider access to economical optimisation of the full operation. Introduction of geometallurgy at early
stages of the project can decrease the level of uncertainty in future project stages and consequently in production (Baumgartner et al., 2011).

Actively used geometallurgical models can be applied to identify, correct, or prevent current processing issues, preventing future problems, or in a more holistic approach to optimize the full production chain based on ore variability. While correcting can be contained within a single processing unit, e.g., mine, comminution, concentration or dewatering, preventing must always involve several processing units or processing unit parts. In this, the geometallurgical program offers invaluable benefits by providing relevant information and connecting the terminology for all relevant parties. The applications of geometallurgy are not limited to process problems but may include mine stability and blasting (Bridge et al., 2013; Hunt and Berry, 2017). Additional benefits from applying geometallurgy are widely discussed in literature and include: reduced energy consumption, optimised water consumption and process control, ensuring products quality (Beniscelli, 2011; Bridge et al., 2013; Coward et al., 2009).

Establishing geometallurgy in a mine and developing a geometallurgical program is associated with risks of getting either low or no benefits due to low predictability. Predictability issues may be caused by the complexity of the process, low agility of the geometallurgical program, lack of collaboration between stakeholders or even insufficient automation. Predictability, as a term, occurs often in the literature when discussing the quality of the geometallurgical models, although it lacks its own definition in a geometallurgical context. The nearest definition of predictability was found in Mckee, (2013), stating that correctly implemented geometallurgy (aka, Mine-to-Mill) will provide “Improved predictability and hence consistency of both mining and processing performance by providing performance benchmarks for the range of ore types present in every mining operation. Such predictability allows operations to identify when performance slips below benchmarks and promptly initiate corrective action”. Predictability is believed to be in balance with available data and business’ tolerance for complex models (Everett and Howard, 2011). The need for improvement in predictability of metal grades for maximising the throughput and recovery was emphasized by Esper et al., (2013). Moreover, the predictability improvement from the perspective of product grade and yields in iron ore by applying multivariate statistics was discussed by Vatandoost et al., (2013). Many other scholars use the term predictability in their research in connection with geometallurgy, e.g., Minz et al., (2015); Chetty and Deshenthree, (2018); Seaman et al., (2016); Vatandoost, (2010). In this thesis, it is asserted that predictability in geometallurgy is more than just semantics, and the concept of predictability can be precisely described.

The thesis is based on the following geometallurgical concepts developed at Luleå University of Technology (LTU):

- Development of geometallurgical program starts from the proper mineralogical characterisation (Lund, 2013);
- Ore behaviour in the process can be linked to the mineralogical properties by properly designed geometallurgical tests (Mwanga, 2016); followed by
- Mineralogy based process modelling (Minz, 2016; Parian, 2017); and
The hypothesis of this thesis is formulated as following:

The efficiency of a geometallurgical program can be improved by enhancing the predictability of the process parameters throughout the mining value chain: a more advanced level of geometallurgical application would correspond to a more advanced level of predictability.

Verifying the hypothesis leads to the aim of the thesis, which is to:

Increase the predictability of the geometallurgical programs by identifying areas where developments (i.e., geometallurgical and spatial process models) are needed, testing the potential benefits of these developments, and making the developments (process and spatial predictive models).

The proof of concept will be done for the iron ore case study. First, the ideas and concepts developing in the thesis will be tested by using historical data from the reference case with well-developed geometallurgical program – Malmberget (Lund, 2013). Then a geometallurgical program and geometallurgical models will be developed for the Leveäniemi apatite iron ore, using Davis tube (DT) as a geometallurgical proxy tool for predicting process performance parameters. Both Malmberget and Leveäniemi deposits are apatite iron ores located close to each other and share mineralogical and genetic similarities.

1.3. Objectives

Predictability of the process parameters requires a well-defined geometallurgical program; available tools for measuring variability in process response; understanding of the data flows in the geometallurgical program; and available routines for the spatial modelling. There are no universal solutions to these tasks, and they will vary from case to case. Therefore, fulfilling the aim of the thesis covers four objectives:

Objective 1: Identifying gaps in the methods applied in geometallurgy and thus show areas where development to improve predictability is needed. More detailed geometallurgical data and more advanced usage of the data may lead to increased predictability after answering the following questions:

- What type of geometallurgical data is used for the modelling and how can this data be generated (approach)?
- How is geometallurgical data used in production (application)?
- Who are the stakeholders and what is their role in geometallurgy?
Objective 2: Development of a framework for testing ideas about data integration and decision making in geometallurgical programs before starting and implementing geometallurgical program. The framework should be implemented as a synthetic testing environment and allow to:

- Simulate the parts of the mining value chain which represent the highest interest for geometallurgy, i.e., geology, mining, process, economy, and sampling.
- Support spatially cohesive data with high spatial resolution.
- Predict sampling outcome and economic benefits from the geometallurgical program.

Objective 3: Filling in gaps in the methods applied in geometallurgy by developing geometallurgical testworks and geometallurgical models for evaluating and predicting process performance. The gaps are in:

- **Ore classification**: DT test results may be used in iron ore classification.
- **Geometallurgical testwork**: There are similarities between the DT and wet low-intensity magnetic separation (WLIMS) in how the material is separated into concentrate and tailings. Thus, the DT might be used as a geometallurgical tool to model WLIMS results.
- **Mineralogical characterisation**: Liberation of the feed might be predicted based on the DT test results.

Objective 4: Development of a spatial predictive models which could be used for populating a geological database and block model with process parameters which will improve predictability of the plant feed and thus allow more controlled production.

Each objective has a subject and is based on the case(s). It includes experimental work and follows methodological procedures, as well as aims at the expected outcome (Table 1).

1.4. **Structure of the thesis**

The thesis is divided into two main parts. The first part (Part I) consists of seven chapters. Part I summarises the most relevant work and clarifies some aspects that were not fully explained in the published papers. The second part (Part II) consists of six appended papers where different aspects of the thesis are highlighted. Part I is organised as follows.

- **CHAPTER 1 “Introduction”** provides background information about the project and introduces the theoretical framework on which current study is based in terms of hypothesis, aim and objectives.
- **CHAPTER 2 “Literature review”** surveys the extensive literature on geometallurgy with emphasize on iron ore. Particular attention is paid to the structure and implementation of geometallurgical programs.
- **In CHAPTER 3 “Materials and Experimental”**, the data retrieval is described and covers the geological background of the selected case study, and methodology employed for the metallurgical testwork and mineralogical characterisation.
• CHAPTER 4 “Methodology” focuses on how data were treated and how modelling was executed.
• In CHAPTER 5 “Results”, the most significant results are presented from the social study of the geometallurgical programs, using synthetic data for assessing geometallurgical programs and both process and spatial modelling in geometallurgy.
• CHAPTER 6 “Discussions” discusses the implications caused by the key findings.
• CHAPTER 7 “Conclusions” summarises the key findings of the thesis and concludes the research work.
• Finally, CHAPTER 8 “Future research and recommendations” provides recommendations for the future work based on the key findings of the thesis.

Table 1 The outline of the doctoral thesis.

<table>
<thead>
<tr>
<th>Objectives</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Question</td>
<td>How much geometallurgy is needed?*</td>
<td>How to build and are there benefits of using a geometallurgical program?</td>
<td>Which tools should be employed?</td>
<td>How can the process parameters of the ore from the deposit be predicted?</td>
</tr>
<tr>
<td>Subject</td>
<td>Geometallurgical program</td>
<td>Data integration</td>
<td>DT</td>
<td>Spatial process modelling</td>
</tr>
<tr>
<td>Cases</td>
<td>52 cases</td>
<td>Malmberget iron ore reference case</td>
<td>Leveäniemi apatite iron ore case study</td>
<td></td>
</tr>
<tr>
<td>Materials and experimental</td>
<td>Survey (interviews), Literature review</td>
<td>Historical case study</td>
<td>Sampling, sample preparation, WLIMS, DT, Geometallurgical comminution test (GCT), QEMSCAN, Chemical assays</td>
<td></td>
</tr>
<tr>
<td>Method</td>
<td>Synthesis of the classification system</td>
<td>Virtual environment in MATLAB code, HSC SIM</td>
<td>Principal component analysis (PCA)/projection to latent structures (PLS)</td>
<td>Machine learning (WEKA), PCA/PLS, Leapfrog</td>
</tr>
<tr>
<td>Expected outcome</td>
<td>Structure of the geometallurgical programs</td>
<td>Virtual environment for testing production scenarios</td>
<td>Prediction tool (patterns)</td>
<td>Spatial model</td>
</tr>
<tr>
<td>Contribution to increase predictability</td>
<td>Defines the framework to be established in order to increase predictability</td>
<td>Testing hypotheses on sampling, data integration, modelling</td>
<td>Development a novel testwork and modelling process parameters</td>
<td>Deploying process parameters in a spatial model</td>
</tr>
</tbody>
</table>

* The cases were selected on the basis of the alleged existence of geometallurgical activities, therefore it was assumed that geometallurgy is used in all the cases reviewed.
“With a library it is easier to hope for serendipity than to look for a precise answer.”

Lemony Snicket,
When Did You See Her Last?

2.1. Geometallurgical programs

The process of creating, maintaining and utilising a geometallurgical model is called a geometallurgical program (Figure 1). A geometallurgical program at a mine can include several sub-models to account for the complexity of the mining value chain and process. Within a geometallurgical program, geometallurgical models define the use of geological data, sampling strategy, testing methods and simulation outcome. The geometallurgical program consists of actions to increase the knowledge on the ore body variation (geological and processing properties), its effects on ore processing, and its use in production planning and management. The utilization of the ore body remains suboptimal if the variation for parameters having effect in processing of the ore is not considered. Properly applied geometallurgy improves overall ore utilization and lowers operational risks (Lishchuk et al., 2015b, 2015a).

Establishment of the geometallurgical program requires involvement of various professionals from different disciplines (Beniscelli, 2011) and availability of harmonised modelling and simulation tools. The high-fidelity orebody model (Powell, 2013) with a high resolution and utility of the information. Geometallurgical programs can be one-off or continuous. An one-off program aims at building a geometallurgical model once and a continuous program aims at building and improving the model iteratively over the lifetime of a mine.
2.1.1. Geological data

Variability in geological and mineralogical parameters has an impact on the metallurgical response in the beneficiation process. Sciortino et al., (2013) showed a correlation between the metallurgical recovery of nickel and degree of ore serpentinisation. Stradling (2011) reported on effects of correlation between alteration intensity and hardness in size reduction. Williams and Richardson (2004) introduced an idea of a geometallurgical matrix of crucial parameters that facilitates assessment of the geological variability.

2.1.2. Sampling

One challenge that a geometallurgical program needs to solve initially is defining how many samples are needed for different assays and techniques involved in development of a reliable geometallurgical model. If the number of samples are too small, the model can be inaccurate or even defective. Larger number of samples gives higher prediction accuracy, but costs and time spent on additional sampling and their assays have to be justified. Good sampling strategy must consider geological and metallurgical variability along with errors in sampling (Gy, 1976; Minnitt et al., 2007) and errors in analysis and modelling (Bulled and McInnes, 2005). Adequate geometallurgical sampling requires good knowledge of the ore body. A geological database and block model accompanied by internal company expertise on ore body and beneficiation process often provide a solid basis for planning and conducting sampling campaigns. Yet, a challenge exists in the fact that geological information is mostly qualitative, and its quality is difficult to estimate. Therefore, primary sampling, mainly by drilling, secondary sampling from drill cores for assaying and tertiary sampling for geometallurgical testing is often an iterative process. In the present geometallurgical approach, geological information is used as initial information in classification and domaining and is then critically evaluated against the results of the geometallurgical tests. The number of required samples for different characterisation methods in geometallurgical programs is a widely discussed topic. David, (2014) recommended up to 30 variability samples for metallurgical testing at different mine design stages. Williams and Richardson, (2004) assumed several hundreds of samples for metallurgical and geometallurgical testing, >1 000 samples for a mineralogical study and >10 000 of samples for traditional chemical assays. Dominy et al., (2018) suggests the number of metallurgical samples for metallurgical testwork based on the project stage, i.e., scoping, pre-feasibility, feasibility; heterogeneity, i.e., high, low; and type of metallurgical testwork, i.e., composite, variability, pilot. Sufficient amount of material has to be provided for geometallurgical testing. A geometallurgical sampling program must consider implications from the minimum mass of samples required for metallurgical tests (Coward et al., 2009). Examples of sampling strategy include:

- A geometallurgical matrix which is aimed to facilitate domaining by classifying samples by rock type, mineralisation and alteration (Baumgartner et al., 2011);
- The primary response framework linking directly measurable, e.g., mass, density, grain size; and rock attributes that describe the rock's responses in the process (e.g., throughput, recovery) (Coward et al., 2009); and
• The geomeallurgical domaining used in selecting composite samples based on the process performance of the domains (Keeney and Walters, 2011).

2.1.3. Testing

The development of a geomeallurgical model requires access to a large number of samples that define the ore processing properties. The basic knowledge and sample material collected by drilling, drill core logging and chemical assays is not sufficient. Additional characterisation techniques are needed. Geomeallurgical tests - small tests that characterise the metallurgical properties and give quantitative information on the variability - are commonly used. Geomeallurgical tests need to be fast and inexpensive, they should use only small amount of sample but still reliably characterise processability. Quite a few geomeallurgical tests are available for different areas of beneficiation and the most commonly used are listed in Table 2.

Table 2 List of available geometallurgical tests.

<table>
<thead>
<tr>
<th>Process</th>
<th>Geometallurgical tests</th>
<th>Metallurgical tests</th>
<th>Corresponding production scale equipment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grinding</td>
<td>GCT (Mwanga et al., 2017, 2015, 2014), GeM Comminution index (GeMCi) (Kojovic et al., 2010), MinnovEX SAG Power Index Test (SPI) (Kosick et al., 2002), SMC Test© (Morrell, 2004), (Heiskari et al., 2019)</td>
<td>Grindability test</td>
<td>AG, SAG, ball mill, crushers, Isa mill, Vertimill etc.</td>
</tr>
<tr>
<td>Ore sorting</td>
<td>N/A</td>
<td>Sorting test</td>
<td>Ore sorter (XRT, hyperspectral, laser, etc)</td>
</tr>
<tr>
<td>Flotation</td>
<td>Microflotation (Larsen et al., 2013), JKMSI (Hunt et al., 2011), “Shaker test” (Vos et al., 2014)</td>
<td>Conventional flotation test</td>
<td>Conventional self-aspirating and forced air flotation cells, pneumatic flotation cells etc.</td>
</tr>
<tr>
<td>Magnetic / electrical separation</td>
<td>DT (Davis, 1918; Finch and Leroux, 1982; Murariu and Svoboda, 2003), Frantz separator (Oberteuffer, 1974)</td>
<td>Laboratory high-tension separator, dry and wet LIMS separator, laboratory dry and wet HIMS drum separator</td>
<td>Dry and wet low and high intensity magnetic and electrical separators</td>
</tr>
<tr>
<td>Gravity separation</td>
<td>Mozley laboratory separator (Cordingley et al., 1994), GRG test (Dominy, 2013; Zhou and Cabri, 2004)</td>
<td>Shaking table, jig, spiral concentrators</td>
<td>Triple-deck table, Knelson separator, spiral concentrating, Reichert cone concentrator, jig, etc.</td>
</tr>
<tr>
<td>Leaching</td>
<td>Small-scale hydrometallurgical tests (Kuhar et al., 2011; Turner et al., 2013)</td>
<td>Column leaching test, tank leach test, compacted granular leach test, pH-dependence leaching test</td>
<td>Heap leaching, bioleaching etc.</td>
</tr>
</tbody>
</table>

Methods and parameters for testing have to be selected carefully since a geomeallurgical test has to correlate with selected processing technologies and be comparable with conventional metallurgical tests. Despite the great number of available geomeallurgical tests, there are still areas (e.g., flotation) where available geomeallurgical methods do not provide acceptable repeatability or decent correlation with the real process.
2.1.4. Mineralogical characterisation

Mineralogical information about the feed is required for building predictive models in the next step. Mineralogical information about the process streams allows for mass balancing in the process simulation and understanding the process behaviour. The most common methods for mineralogical characterisation are listed in Table 3.

It is worth mentioning that element-to-mineral conversion is a technique for converting the bulk chemical composition of a sample to mineral grades by applying a set of linear algebraic equations (Braun, 1986; Lamberg et al., 1997; Paktunc, 1998; Parian, 2015; Whiten, 2008) and examples of its recent use can be found in Lund, (2013), Parian et al., (2015), Gustafsson, (2016), and Mena Silva et al., (2018).

Mineral liberation properties, as a part of mineralogical information, can provide an estimation of the efficiency of the separation processes. Liberation based models are also common in mineral processing simulation (Ersayin, 2007; King and Schneider, 1995; Lamberg, 2011).

Table 3 Some mineralogical characterisation techniques.

<table>
<thead>
<tr>
<th>Information type</th>
<th>Characterisation technique</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chemical information (chemical composition)</td>
<td>X-ray fluorescence spectroscopy (XRF)</td>
</tr>
<tr>
<td></td>
<td>Dissolution + atomic absorption spectroscopy (AAS)</td>
</tr>
<tr>
<td></td>
<td>Inductively coupled plasma optical emission spectrometry (ICP-OES)</td>
</tr>
<tr>
<td></td>
<td>Inductively coupled plasma mass spectrometry (ICP-MS)</td>
</tr>
<tr>
<td></td>
<td>Electron probe micro-analysis (EPMA) with energy-dispersive spectrometer (EDS)</td>
</tr>
<tr>
<td></td>
<td>EPMA with wavelength-dispersive spectrometer (WDS)</td>
</tr>
<tr>
<td>Qualitative mineralogical (list of minerals) information</td>
<td>Optical microscopy</td>
</tr>
<tr>
<td></td>
<td>X-ray diffraction (XRD)</td>
</tr>
<tr>
<td>Quantitative mineralogical (modal mineralogy) information</td>
<td>Automated mineralogy, e.g., MLA, QEMSCAN (Gu et al., 2014), MinScan (ZEISS, 2018), INCAMineral (Oxford Instruments, 2018)</td>
</tr>
<tr>
<td></td>
<td>Quantitative X-ray diffraction (QXRD) with Rietveld refinement (Mandile and Johnson, 1998)</td>
</tr>
<tr>
<td></td>
<td>Element-to-mineral conversion (EMC) (Braun, 1986; Lamberg et al., 1997; Paktunc, 1998; Parian, 2015; Whiten, 2008)</td>
</tr>
<tr>
<td></td>
<td>Combined element-to-mineral conversion and QXRD (Parian et al., 2015)</td>
</tr>
<tr>
<td></td>
<td>hyperspectral imaging (e.g., Linton et al., 2013)</td>
</tr>
<tr>
<td></td>
<td>Semi- (Delbem et al., 2015) or automated optical microscopy (Donskoi et al., 2013)</td>
</tr>
<tr>
<td></td>
<td>Raman spectroscopy (Kauppinen, 2017; Wells and Ramanaidou, 2015)</td>
</tr>
<tr>
<td>Other methods</td>
<td>X-ray computed tomography (XRT) e.g., (Dominy et al., 2011; Howard et al., 2011; Jardine et al., 2018; Reyes et al., 2017)</td>
</tr>
</tbody>
</table>

2.1.5. Process

2.1.5.1 Modelling

Based on the test results a predictive model may be created within a geometallurgical program. The input parameters of the models come from the properties provided by a geological model. Commonly used parameters are elemental grades, e.g., Cu wt%, Au ppm; mineralisation type, e.g,
massive ore, breccia, disseminated; and hosting lithology. Model output represents production forecast: throughput, concentrate tons produced, metal recoveries, concentrate quality parameters, tailing properties, and economic key figures.

Depending on whether the model input comes from elemental grades, mineralogical properties or some other properties (such as geometallurgical testing), a modelling approach can be classified as traditional, mineralogical or proxy. For example, quantitative results obtained by chemical assays such as XRF or ICP will primarily be used for traditional models; results from Auto-SEM, XRD, QXRD and EMC conversion can be used for mineralogical models; and combination of analysis methods for chemical assays coupled with geometallurgical tests - in proxy models.

2.1.5.2 Simulation

Simulation of geological feed composition or metallurgical responses is a common practice for investigating alternative production scenarios and estimating production risks in the mining industry. Different process simulators are common in mineral processing in general and in geometallurgy particularly (Table 4). Separate simulators are often used for comminution and beneficiation. Only a few simulators are commercially available for simulating the full mineral processing chain in one platform.

2.1.6. Geometallurgical mapping

Geometallurgical mapping (i.e., geometallurgical spatial modelling or geometallurgical block modelling) is the ultimate product of geometallurgy and stands for estimation of geological inputs and/or metallurgical response in a spatial model; commonly the spatial presentation and result saved in separate blocks is called block model. Each block may store geological, chemical compositional, geotechnical, geomechanical, geophysical, metallurgical and other relevant information. This allows making managerial decisions about the best outcome of plant response and plant sustainability under geological uncertainty and different concentrator operational modes (Bridge et al., 2013; Keeney et al., 2011; Lamberg, 2011; Navarra et al., 2017; Walker, 2014; Williams and Richardson, 2004).

Software packages that may be applied to geometallurgical mapping are Vulcan (Maptek), Surpac (Geovia), Leapfrog® (ARANZ Geo Limited), Micromine (MICROMINE). Mapping can be done by geometallurgical spatial units: classes and domains. A geometallurgical class is characterised by homogeneity in the mineral processing responses. Homogeneity here means that metallurgical response varies only little or variability can be expressed in acceptable manner with simple equations. Geometallurgical classes, which show spatial continuity, are called domains.

There is a large body of knowledge on spatial modelling of geometallurgical parameters, such as hardness (Musafer et al., 2013; Preece, 2006), metal grades (Hosseini and Asghari, 2014), grindability (work index), throughput and metal recovery (David, 2007; Deutsch, 2013; Keeney, 2010; Keeney and Walters, 2009). Earlier research has focussed on the development of different methods and mathematical apparatus for connecting metallurgical parameters (geometallurgical
indices) and spatially distributed geological information. Obtaining non-biased modelling results requires use of an appropriate geostatistical tool, e.g., kriging, nearest neighbour method, inverse distance method, and other. Linear geostatistical methods perform poorly on nonlinear parameters typical to geological data. Nonlinearity is also known as non-additivity and is widely discussed, e.g., by Dunham and Vann, (2007), Coward et al., (2009), Walters, (2011).

Table 4 Examples of simulators used in mineral processing.

<table>
<thead>
<tr>
<th>Simulator</th>
<th>Main functions</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bruno</td>
<td>Crushing and screening simulation software tool.</td>
<td>(Kaja, 2002; Metso Minerals, 2007)</td>
</tr>
<tr>
<td>Cycad Process</td>
<td>Hydrometallurgy, pyrometallurgy, minerals processing, mass and energy balance.</td>
<td>(Cycad Process - official website, 2016)</td>
</tr>
<tr>
<td>ECS/CEMulator</td>
<td>Cement process simulators.</td>
<td>(FLSmidth - official website, 2015)</td>
</tr>
<tr>
<td>HSC Chemistry</td>
<td>Flowsheet simulation, mineral processing simulation (crushing, grinding, classification, flotation), mineralogical calculations, numerical data fitting, mass balancing, heat and material balances, etc.</td>
<td>Outotec, (Outotec 2012)</td>
</tr>
<tr>
<td>IDEAS</td>
<td>Flowsheet simulation, mineral processing simulation (crushing, grinding, classification, flotation, gravity separation, magnetic separation, solid liquid separation), automation.</td>
<td>Andritz, (ANDRITZ - official website, 2016)</td>
</tr>
<tr>
<td>Integrated Geometallurgical Simulator (IGS)</td>
<td>Flowsheet simulation, mineral processing simulation (grinding and flotation).</td>
<td>SGS, (SGS, 2016)</td>
</tr>
<tr>
<td>JKTech's JKSimBlast, JKSimMet and JKSimFloat</td>
<td>Geology and mining (block modelling, mining production, drilling and blasting, loading and hauling, stockpiling management), mineral processing (crushing, grinding and milling, flotation).</td>
<td>Anglo Platinum W. H. Bryan Mining and Geology research centre and JKTech, (Ziemski et al., 2010)</td>
</tr>
<tr>
<td>LIMN</td>
<td>An Excel based flowsheet solution package.</td>
<td>(Leroux, D., Hardie, 2003)</td>
</tr>
<tr>
<td>METSIM</td>
<td>General-purpose process simulation system which covers following processes: SAG/ball milling, flotation, leaching, cyanidation, roasting, smelting.</td>
<td>(METSIM®, 2018)</td>
</tr>
<tr>
<td>Metsmart</td>
<td>Flowsheet simulation, mineral processing simulation (crushing, grinding, flotation, classification, solid liquid separation).</td>
<td>Minerality, (Minerality - official website, 2016)</td>
</tr>
<tr>
<td>Microsoft Excel based simulator</td>
<td>Flowsheet simulation, mineral processing simulation (classification, magnetic separation, flotation).</td>
<td>(Suthers et al., 2004)</td>
</tr>
<tr>
<td>MinOOcad</td>
<td>Flowsheet simulation, mineral processing simulation (crushing, grinding, classification, ore transportation).</td>
<td>Metso, (Herbst and Pate, 1998)</td>
</tr>
<tr>
<td>MODSIM</td>
<td>Flowsheet simulation, mineral processing simulation (crushing, grinding, classification, flotation, gravity separation, magnetic separation, solid liquid separation).</td>
<td>Mineral Technologies, Inc., MTI, (King, 2001; Schneider, 1995)</td>
</tr>
<tr>
<td>SimSci DYNSIM</td>
<td>Platform that mimics or emulates the real mineral processing plant.</td>
<td>Schneider electrics, (Mielli, 2014; Schneider Electric, 2016)</td>
</tr>
<tr>
<td>USIM-PAC</td>
<td>Process simulator for mineral processing, food processing, bio refining, waste and wastewater treatment.</td>
<td>(Caspeo, 2018)</td>
</tr>
</tbody>
</table>

Other relevant studies link geology with downstream processes. Journel, (1974) linked geostatistical simulation of the ore bodies with characteristics of the ore recovered by mining. Although the problems addressed by Journel, (1974) cannot be considered purely geometallurgical,
the study describes the implications on the plant feed from variability in metal grades and overburden thickness, which both create an important link for connecting the entire mine-to-metal value chain and thus are also of interest to geometallurgy. Connecting grade variability with production planning was further considered by (Jupp et al., 2013). Short-term grade variability was the main concern of his study. Additionally, problem of non-linearity or non-additivity was raised in connection with block modelling. Everett, (2011) contributed to the determination of the mining sequence through the sequence simulation by analysis of marginal value of the ore block which covered production-related costs. Iron grade was used as an input for defining block’s value. Higher iron content corresponded to a higher block value. Contaminants or penalty materials would reduce block value (i.e., an opportunity cost).

The importance of geometallurgical mapping in the mining value chain by reconciliation between geological, mining, process and economic data was shown by many scholars (Appendix II). Most of them either use or emphasise on a future application of geometallurgical block model as a platform for the integration between geological and process data.

2.1.6.1 Challenges in geometallurgical mapping

Most of the problems in geometallurgical mapping belong either to the geostatistical problems (Appendix IV) or to the process data modelling problems (Appendix V). Geostatistical problems account for the spatial solutions required for deploying any ore property inside block model. Process modelling problems consider issues specific for deploying process performance parameters into the block model. The key issues in geometallurgical block modelling are additivity and change of support.

Additivity. Additivity is a mathematical property that allows to calculate the mean of the variables by linear averaging (Carrasco et al., 2008 and Coward et al., 2009). For instance, mineral and elemental grades are additive parameters and the mean value can easily be calculated. (Dunham and Vann, 2007). However, process (response) variables, such as reagent consumption, throughput and recovery and some rock properties such as rate constants and geomechanical measurements (Deutsch, 2013), may behave in a non-additive way (Riquelme et al., 2009; Walker, 2014). For instance: Bond work index (BWi) might tend to be biased towards the harder material in a blend (Deutsch et al., 2016); recoveries in flotation behave non-linearly when multiple ores are blended (Deutsch et al., 2016); or for a single ore type, as it was shown in (Richmond and Shaw, 2009) with a Kubelka-Munk function example for kaolin reflectivity. Non additivity can be of a two types: mathematical and machine based. (Newton and Graham, 2011; Walters, 2011). Therefore, this thesis mainly focuses on the mathematical definition of additivity. Linear geostatistics methods (e.g., kriging) are not suitable for non-additive variables (Deutsch, 2015; Dunham and Vann, 2007). However, response variables estimated with kriging still can be used for visualising trends and understanding spatial features (Deutsch, 2013).

Support. Process properties are often measured on much larger average volumes than assay data. The averaging volume over which the data are measured or defined is also known as the support (Chilès and Delfiner, 2012). Increase of support (e.g., increase of a composite size, increase of a
block size in a block model) causes lower variance and induces spatial smoothing effect (Chilès and Delfiner, 2012; Mery et al., 2017). So, even though the average values of the process properties of drill core samples and mining blocks will be similar, the variability will be smaller for larger supports (Dunham and Vann, 2007). Solving these challenges would allow to propagate process parameters data into a geological database and/or block model and further used for managerial decisions in mining production.

**New methods - Machine learning.** Machine-learning is a part of computer science that focuses on studying mathematical models and algorithms to make predictions. Predictions are developed through the interpretation of data and patterns by connecting the data with the knowledge set and developing the learning algorithms (Oliver and Willingham, 2016; Suthaharan, 2016). Machine-learning methods have multiple advantages over other approaches (Table 5) particularly in geosciences, where it challenges geostatistical and Bayesian approaches (Daya et al., 2018). Machine-learning algorithms are widely used in applications such as predicting acid rock drainage chemistry (Betrie et al., 2014), resource model development (Oliver and Willingham, 2016), classification of drill core textures for process simulation (Tiu, 2017), and predictive modelling for spatial variables (Hengl et al., 2018). One of the main advantages of machine-learning methods is their capacity to deal with the additivity issue.

Table 5 Some classification methods for populating the block model with process properties.

<table>
<thead>
<tr>
<th>Approaches</th>
<th>Spatial method</th>
<th>Additivity assumption</th>
<th>Number of samples</th>
<th>Missing values and zeros have impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Block calculation with regression model (multi-linear)</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Low</td>
</tr>
<tr>
<td>Geostatistical (kriging)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>High</td>
</tr>
<tr>
<td>Geostatistical simulation</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>High</td>
</tr>
<tr>
<td>Machine-learning</td>
<td>Depends on method</td>
<td>No</td>
<td>N/A</td>
<td>Medium</td>
</tr>
<tr>
<td>Neural networks</td>
<td>Depends on method</td>
<td>No</td>
<td>N/A</td>
<td>Medium</td>
</tr>
<tr>
<td>Multivariate statistics</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>High</td>
</tr>
<tr>
<td>Process simulation (e.g., HSC SIM, MODSIM)</td>
<td>No</td>
<td>No</td>
<td>N/A</td>
<td>Low</td>
</tr>
</tbody>
</table>

* Function additivity - the mean of the variables may be calculated by a simple linear average (Dunham and Vann, 2007).
** Machine additivity - if the value represents a measure of property A which has a deleterious effect on mill performance then it is possible that when two samples I and II are combined, the higher value will have a disproportionate effect with the composite sample having a value different than the arithmetic mean of the individual samples. This type of additivity is referred to as machine additivity and represents blending. (Bye, 2011; Newton and Graham, 2011).

Building reasonable predictive model using machine-learning methods requires a trial and error approach using either supervised or unsupervised learning algorithms. Supervised learning assigns points to the classes based on class labels (pre-defined) classes. Unsupervised learning deals with segmenting feature space into classes without any previous training (Aggarwal, 2014; Suthaharan, 2016).
2.1.6.2 Traditional block modelling

The geological block model is built by propagating desired properties from the drill core samples (usually described in a geological database of drill cores) into the blocks. The blocks dimensions may be constant or vary depending on the structure of the ore body. These samples are usually obtained by characterisation of drill core segments. Knowing the spatial locations of each drill cores’ collars and in situ orientation allows to calculate the spatial location for each sample. Qualitative and quantitative information about the drill core samples is structured into a geological database. Samples, drill cores and the block model represent three main units in geometallurgical block modelling (Table 6).

Table 6 Samples, drill cores and block model.

<table>
<thead>
<tr>
<th>Properties</th>
<th>Samples</th>
<th>Drill core</th>
<th>Block model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimensions</td>
<td>1D</td>
<td>2D</td>
<td>3D</td>
</tr>
<tr>
<td>Typical sizes</td>
<td>~several grams to several kilograms</td>
<td>~ several meters to several hundred meters</td>
<td>~ hundreds of thousands to millions of blocks 10-125000 m3</td>
</tr>
<tr>
<td>Typical units to describe size</td>
<td>kg (weight)</td>
<td>m (length)</td>
<td>m3, (volume)</td>
</tr>
<tr>
<td>Spatial location</td>
<td>May not be known</td>
<td>Known for each sample (composite) with certain level of precision</td>
<td>Known for each block</td>
</tr>
<tr>
<td>Chemical assays</td>
<td>Measured</td>
<td>Measured</td>
<td>Estimated (modelled)</td>
</tr>
<tr>
<td>Geological description</td>
<td>May not be known</td>
<td>Logged</td>
<td>Estimated (modelled)</td>
</tr>
<tr>
<td>Process properties</td>
<td>Measured</td>
<td>Measured or Estimated</td>
<td>May not be known</td>
</tr>
<tr>
<td>Uncertainty level of the properties</td>
<td>Low</td>
<td>Moderate to low</td>
<td>Moderate to high</td>
</tr>
<tr>
<td>Complexity of structure</td>
<td>Simple (list of properties)</td>
<td>Moderate (form of database)</td>
<td>Complex (complex database of a large size database)</td>
</tr>
</tbody>
</table>

2.1.6.3 Geometallurgical block modelling

Modelling variability of the process parameters in a highly heterogeneous ore body is usually very complicated but can be simplified by domaining (Figure 2). Domaining is a delineating of the continuous areas with homogeneous processing (or geological) properties (David, 2007; Sanchidrián et al., 2012). Description of the variability of process parameters within an ore body or within a domain is done by classification of the ore samples, drill core samples or blocks in a block model. The classification procedure assigns process properties to the block based on the geological properties of the block, e.g., elemental grade, mineral grade, grain size, lithological type, colour, specific gravity etc.
Regression (e.g., tailing leach acid consumption at Olympic dam mine presented by Macmillan et al., (2011)), multivariate statistics (e.g., BWI and Drop weight index (DWi) at Cadia East mine developed by Keeney et al., (2011); Keeney and Walters, (2011); Newton and Graham, (2011)), and geostatistics (e.g., BWI and SPI for Escondida mine described by Preece, (2006)) are common methods for classification of the process parameters (Table 5). The major difference between these methods are whether they can account for the spatial correlation and can manage the issue of additivity.

The selection of the process modelling method depends on the information available for classification as a primary input, variable $X$. For instance, spatial location information allows using geostatistical methods while process simulation can only be used if chemical or mineralogical information is available. Five different scenarios are listed in Figure 3.

Integration of process data into a spatial deposit model yields geometallurgical block model (Figure 4). Geological database (Figure 4 step A) and traditional block model (Figure 4 step B) with iron grades estimated in blocks, are usually available as input data.

### 2.2. Geometallurgy of iron ores

Iron oxides are the only class of iron bearing minerals having commercial interest in iron production. Magnetite (72.36% Fe), hematite (69.94% Fe), ilmenite (36.80% Fe) and limonite (62.85% Fe) form the oxide class. Siderite (48.20% Fe) is the only mineral in the carbonate class. Based on location, rock mechanical conditions, commodity grade, hydrogeology, available technologies of iron ore, the extraction method could be either open pit or underground mining. Iron ore processing prepares ore to be fed to the furnace and includes several steps: size reduction (i.e., blasting, crushing, grinding), screening, blending, concentrating (mainly includes magnetic separation, but may also involve flotation, jiggng, spirals etc.) and agglomerating (i.e., sinter, pellets, briquettes, and nodules).
<table>
<thead>
<tr>
<th>SCENARIO</th>
<th>PROCESS SAMPLES</th>
<th>GEOLOGICAL DATABASE</th>
<th>BLOCK MODEL</th>
<th>METHOD &amp; LIMITATIONS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$X = {C_{x,y,z}, P}$</td>
<td>NA</td>
<td>$X = {C_{x,y,z}}$</td>
<td>Spatial methods. Requires high number of process samples.</td>
</tr>
<tr>
<td>2</td>
<td>NA</td>
<td>$X = {C_{x,y,z}, P}$</td>
<td>$X = {C_{x,y,z}}$</td>
<td>Spatial methods. Limited number of process parameters can be measured for drill cores.</td>
</tr>
<tr>
<td>3</td>
<td>$X = {G, P}$</td>
<td>NA</td>
<td>$X = {G, C_{x,y,z}}$</td>
<td>Non-spatial methods. $G$ in block model is usually subjected to smoothening.</td>
</tr>
<tr>
<td>4</td>
<td>NA</td>
<td>$X = {G, C_{x,y,z}, P}$</td>
<td>$X = {G, C_{x,y,z}}$</td>
<td>Both spatial and non-spatial methods.</td>
</tr>
<tr>
<td>5</td>
<td>$X = {G, P}$</td>
<td>$X = {G, C_{x,y,z}}$</td>
<td>$X = {C_{x,y,z}}$</td>
<td>Non-spatial methods can be used to populate geological database with $P$. Spatial methods shall be used to populate blocks of the block model.</td>
</tr>
</tbody>
</table>

Symbols:
- $C_{x,y,z}$: coordinates $x$, $y$, $z$
- $P$: measured process properties
- $G$: elemental and/or mineral grades

Figure 3: Selection of the modelling method based on the available information (some possible scenarios). Note: coordinates describing spatial location of samples in samples of the geological database and blocks of the block model can always assumed to be known.

Figure 4: Building geometallurgical block model.
Iron ore prices for different ores are mainly based on natural iron content and quality (penalties or/and premiums). The main quality parameters for iron ore to be considered are SiO₂, Al, P, S, Mn, Ti, basic oxides (CaO and MgO), alkalis (Na₂O and K₂O), V, Cu, Moisture, PSD. (Poveromo, 2000).

The increased variability in iron ore quality, processing of new iron ore types, increased production volumes and increased requirements from steel makers have created a niche for iron ore geometallurgy (Ramanaidou et al., 2012). Applying geometallurgy in iron ore production for maintaining reasonable production performance (recoveries, throughput) and desired products quality can be achieved through the geometallurgical program (Parian, 2017). Some examples of developing and applying geometallurgical programs in iron ore production are summed up in Table 7.

Table 7 Geometallurgy of iron ore – case studies (based on (Lishchuk, 2016; Parian, 2017)).

<table>
<thead>
<tr>
<th>Case study</th>
<th>Location</th>
<th>Targeted</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carol lake</td>
<td>Canada</td>
<td>Energy required in milling (crushing, grinding)</td>
<td>(Canada) (Bulled et al., 2009)</td>
</tr>
<tr>
<td>Hannukainen</td>
<td>Finland</td>
<td>LIMS concentrate grade and recovery</td>
<td>(Lascelles et al., 2008)</td>
</tr>
<tr>
<td>Kiirunavaara</td>
<td>Sweden</td>
<td>Penalty material (SiO₂ grade), throughput</td>
<td>(Niiranen, 2015; Niiranen and Böhm, 2013; Niiranen and Fredriksson, 2012; K. K. Niiranen and Böhm, 2012)</td>
</tr>
<tr>
<td>Malmberget</td>
<td>Sweden</td>
<td>Recovery</td>
<td>(Lund, 2013)</td>
</tr>
<tr>
<td>Nkout</td>
<td>Cameroon</td>
<td>Metallurgical and environmental responses (iron oxides liberation)</td>
<td>(Anderson et al., 2014, 2013)</td>
</tr>
<tr>
<td>Pau Branco Mine</td>
<td>Brazil</td>
<td>Quality of iron lumps</td>
<td>(Gomes et al., 2016, 2015)</td>
</tr>
<tr>
<td>Putu</td>
<td>Liberia</td>
<td>Metallurgical and environmental responses</td>
<td>(Anderson et al., 2013)</td>
</tr>
<tr>
<td>Solomon project</td>
<td>Australia</td>
<td>Concentrate grade and yield (recovery)</td>
<td>(Vatandoost et al., 2013)</td>
</tr>
<tr>
<td>Stora Sahavaara</td>
<td>Sweden</td>
<td>LIMS concentrate grade and recovery</td>
<td>(Antonsson, 2011; Baker et al., 2010)</td>
</tr>
<tr>
<td>Storforshei iron</td>
<td>Norway</td>
<td>Grindability</td>
<td>(Kristine Togersen et al., 2018)</td>
</tr>
<tr>
<td>formation (IF)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tapuli</td>
<td>Sweden</td>
<td>Grinding, Magnetic separation</td>
<td>(Baker et al., 2010)</td>
</tr>
<tr>
<td>West Australian Iron</td>
<td>Australia</td>
<td>Crushing</td>
<td>(Wright et al., 2013)</td>
</tr>
<tr>
<td>Ore (WAIO)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2.2.1. Geometallurgical tools in iron ore processing

Magnetic separation is the primary separation technique employed in iron ore concentrators. Depending on the ore properties and processing target grade, magnetic separation can be done as either a wet or a dry process, with either low- or high-intensity magnetic fields. In this thesis, the focus is on the WLIMS as the primary method used to upgrade the iron ore from Leveäniemi deposit. Normally, a lab scale WLIMS drum apparatus is the main tool for simulating iron ore behaviour in a WLIMS process. Both WLIMS and DT are wet magnetic separation techniques.
The DT (Davis, 1923, 1921; Oberteuffer, 1974; Schulz, 1963; Svoboda, 2004) is a standard tool for estimating the highest possible concentrate grade in magnetic separation (Cheng and Misra, 1999; Niiranen, 2015) and estimating the amount of magnetically recoverable iron in the ore. There are two types of parameters, which affect the DT performance: material properties and the operational settings of the apparatus. The DT works with particles mixed with water. Particles fed to the tube are separated based on their structure (Schulz, 1963), liberation (Schulz, 1963; Schulz and Lex, 1967), composition (Schulz, 1963; Schulz and Lex, 1967), magnetic susceptibility (Eloranta, 1983; Farrell and Miller, 2011; Guarin et al., 2009; Rayner and Napier-Munn, 2000) and particle size (Rayner and Napier-Munn, 2000; Svoboda, 2004). Only two operational parameters are reported as having rather strong impact on the DT performance: the magnetic field strength and the amount of water flushed through the tube (Schulz, 1963). The water rate (flow speed) was reported to be insignificant by Schulz, (1963) and Ahmed (2010).

In geometallurgy, DT is used as a proxy to WLIMS, i.e., quality control tool. Dworzanowski (2012) has used the DT to simulate best possible iron recovery evaluating options to maximise recovery of fine iron ore. Niiranen, (2015) used the DT to predict concentrate cleanness in WLIMS with a focus on silica content. Murariu and Svoboda (2003) found that DT tests can be used to estimate the efficiency of a conventional ferrite drum separator, operated at 0.1 T. Using DT test as a proxy to WLIMS is because DT requires a small sample size, is a wet technique, and according to Oberteuffer (1974) the DT accounts for drag forces, such as friction and hydrodynamics. Additionally, a DT, unlike other competitive techniques such as SATMAGAN (Saturation Magnetization Analyser) and MAGNASAT (Magnetic Susceptibility Meter), produces separate products (Farrell and Miller, 2011). SATMAGAN is a magnetic balance which measures the force acting on the sample in a magnetic field with a spatial gradient (Raspiscan systems, 2018). MAGNASAT measures the change that materials cause to an alternating current (AC) magnetic field (Ultradynamics, 2018). However, the DT, unlike WLIMS, lacks mechanical forces, has much higher degree of water drag forces, can be operated at different magnetic fields and has originally been designed only for testing fine materials.

2.2.2. Mineralogical characterisation - Fe-oxides minerals liberation

Mineralogical studies are an essential part of the metallurgical testwork and optimising the recovery processes (Dominy et al., 2018). Liberation analysis is normally an expensive and time-consuming procedure of mineralogical characterisation. In iron ore production, mainly complex problems may justify high costs of preparing resin mounts and running scanning electron microscopy. One alternative may be semi-automated optical microscopy based on analysis of digital images obtained using a reflected light optical microscope (Delbem et al., 2015) or optical image analysis (Donskoi et al., 2016). However, this method requires laborious sample preparation.

The first relevant study of Fe-oxides liberation using the DT was conducted by Wiegel (1975). He discussed the binary system of magnetite and non-magnetite and concluded that the choice of comminution techniques, exclusive of pebble grinding, do not have a significant effect on liberation. The model described in Wiegel, (1975) was further developed in Wiegel, (2011) to
provide guidance in simulation of processing of low-grade ores. Additionally, Wiegel's model was used to carry out simulations, where liberation based models were used for taconite (Ersayin, 2007). Despite advanced mathematical modelling, this study was dealing only with low-grade ores. Fully liberated magnetite and mixed particles were not distinguished. The mineralogical complexity of the tested materials was not fully considered.

The impact of liberation properties on magnetic separation was studied by Leißner et al. (2013). The process evaluator $Z$ was calculated for a greisen-type ore with a ring-type magnetic separator at different field strengths. Only feed samples were analysed by mineral liberation analysis.

The empirical model developed by Ersayin, (2004) is based on a pseudo-liberation approach and correlates liberation data to feed grade. It establishes a relationship between feed grade, particle size, and magnetite recovery. Although the model was used for simulation, it has not been validated.

The Kiruna iron ore was studied for the chemical composition and separation properties by Niiranen, (2015). DT tests of seven drill core samples and Henry-Reinhardt charts (HRC) were used as the main tools in this geometallurgical study. It assumed that HRC provides a characterisation of liberation. The liberation study was done with Automated Scanning Electron Microscopy (Auto-SEM). Three samples, representing different ore types, were sieved into two size fractions (less than 40 µm, 40-100 µm) and each size fraction tested in DT at four current strengths (0.12 A, 0.18 A, 0.225 A, 1.78 A). Four other samples, representing variability inside one of the ore types, were sieved into three size fractions (less 40 µm, 40-63 µm, larger than 63-80 µm) and each size fraction was tested in DT at three current strengths (0.1 A, 0.2 A and 1.8 A). However, there was no systematic comparison between HRC and liberation measurements from an Auto-SEM.

2.2.3. Reference case: Malmberget

Development of geometallurgical program starts from the proper mineralogical characterisation. Lund, (2013) has characterised the mineralogical, chemical and textural properties and established the geological model consisting of modal mineralogy and mineral textures of the Malmberget iron ore deposit.

The massive ore is defined by its high Fe content (55-60%) and low SiO$_2$ content. In the eastern part of the deposit the massive ore is surrounded by semi-massive mineralisation, characterised by a lower Fe grade (<55%) and higher SiO$_2$ content. The semi-massive zone can be several tens of meters thick, occurring as rims or as inclusions in the massive ore. Mineralogically, the ore is composed of magnetite and hematite as the main minerals and apatite and amphibole-pyroxene as typical gangue minerals. The semi-massive ore contains various proportions of silicates, i.e., feldspars (albite and orthoclase), amphibole, quartz, and biotite, which display a broad variation of more or less complex mineral-texture relationships (Lund, 2013).

The metallurgical testwork was conducted on five different sample batches of >100 kg which reflects and represents the main ore types of Malmberget deposit. A textural classification was
established for the massive and semi-massive ore to include both mineral- (mineral phases, mineral chemistry, and modal mineralogy) and textural information (grain size, shape, associating mineral). Due to the overall relatively high Fe-oxide content in the ore, the main gangue minerals for each ore type (normalised value) were used as a key feature to identify a variation between the textural types (each mineral selected, was related to the ore processing). The challenge was to create a geological model that offers quantitative information to be used in a process model. As mineral ore/textural type is usually descriptive, it is assumed that there is a close relationship between mineral liberation and mineral textural type. Therefore, classification of the ore handles the textural information from a processing point of view, in this case, incorporating the particle liberation distribution for each textural type and sample (by size) (Table 8). The feldspar rich textural type (Fsp) is typical for the lower grade magnetite ore (semi-massive), the amphibole rich textural type (Amph-(Ap-Bt)) is widespread in the massive ore together with another common apatite-bearing textural type (Ap-(Amph)) (Figure 5), details in (Lund et al., 2015).

### Table 8 The geometallurgical framework of how to simulate and forecast the metallurgical variation of ore deposit variables (based on Lund, (2013)).

<table>
<thead>
<tr>
<th>Ore type</th>
<th>Main associating minerals</th>
<th>Textural type name</th>
<th>Modal composition (average bulk), wt.%</th>
<th>Liberation distribution of Mgt, (Average bulk), %</th>
<th>Grade, %</th>
<th>Recovery, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semi massive</td>
<td>Ab, Qtz, Bt, Amph</td>
<td>Fsp</td>
<td>Mgt 55.1 Ab 35.0 Act 7.6 Ap 0.4 Bt 1.8</td>
<td>Liberated Mgt 95.9 Ab 2.2 Act 1.1 Ap 0.5 Bt 0.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Massive</td>
<td>Amph</td>
<td>Amph-(Ap, Bt)</td>
<td>Mgt 66.4 Ab 2.9 Act 23.0 Ap 1.3 Bt 6.4</td>
<td>Liberated Mgt 94.5 Ab 0.5 Act 3.8 Ap 0.4 Bt 0.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ap, Amph</td>
<td>Ap – (Amph)</td>
<td>Mgt 86.6 Ab 0.1 Act 3.3 Ap 7.1 Bt 2.8</td>
<td>Liberated Mgt 89.2 Ab 0.8 Act 0.9 Ap 6.0 Bt 3.0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The process model in Lund et al., (2013) for each sample was made using a one-unit concentration model to quantify the mineral processing performance (grades for Fe, Si, P and Fe-recovery) in Table 8. The process model uses textural type and modal mineralogy of the sample as inputs. The output of the model by Lund et al., (2013) (Figure 6) was the forecast of elements’ and minerals’ recoveries to concentrate, and the concentrate’s chemical and mineralogical composition. The estimated error of the outputted elements was the lowest for iron and did not exceed 3% for gangue elements (Table 9).

### 2.3. Testing production scenarios by simulating synthetic data

Modelling by simulation is a well-documented practice commonly used in the mining industry to evaluate alternative process designs (Everett, 1997; Everett and Howard, 2011; Jupp et al., 2013). Such modelling is typically undertaken at operating mines where production records are available for the actual short-term grade variability. In these cases, the real data are used as an input into the simulation of different scenarios.
Previously synthetic geological data has been studied by Malmqvist et al. (1980) for improving sampling techniques. The focus was on mineral exploration and sampling for mineral resource estimation of deep-seated sulphide ore bodies. More recent examples of simulation for reproduction of complex geological structures and behaviour of spatial geological data can be found in Chatterjee and Dimitrakopoulos, (2012) and Mustapha and Dimitrakopoulos, (2011). Jupp et al., (2013) created a synthetic ore body model and used it for geometallurgy to study variability reduction problem in daily scheduling system.

Traditionally, the modelling of an ore body has been restricted to the geological domain (the definition of physical regions with homogeneous properties based on lithology, mineral grade and style of mineralisation (Schouwstra et al., 2013), densities, and elemental grades. The processing properties have been almost totally neglected. However, a simulated synthetic ore body, as defined here, must satisfy three conditions: include processing properties; show realistic variability within synthesised data and impose spatial cohesion between data. Additional parameters, such as constraints by a mining method, processing performance, and economic response will produce more realistic output. The selection of a modelling approach (Table 10) to simulate geological and propagate mineral processing properties in a three-dimensional physical space involves a trade-off between geological realism and conditioning capabilities.

### Table 9: Relative standard deviations (RSD) of the XRF assay analysis, % (Lund, 2013).

<table>
<thead>
<tr>
<th>Element</th>
<th>Fe</th>
<th>Ti</th>
<th>V</th>
<th>Si</th>
<th>Al</th>
<th>Ca</th>
<th>Mg</th>
<th>Na</th>
<th>K</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSD</td>
<td>0.1</td>
<td>1.0</td>
<td>1.4</td>
<td>1.0</td>
<td>2.0</td>
<td>3.2</td>
<td>2.8</td>
<td>2.0</td>
<td>2.4</td>
<td>0.7</td>
</tr>
<tr>
<td>Classification of the Methods</td>
<td>References</td>
<td>Number of Data Points</td>
<td>Smoothing</td>
<td>Realism</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>-----------------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>-----------------------</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Geostatistics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Estimations</strong> (e.g., univariate, indicator, co-, and block kriging)</td>
<td>(Chiles and Delfiner, 2012; Gandhi and Sarkar, 2016; Isaaks and Srivastava, 1989; Mariethoz and Caers, 2015; Matheron, 1963; Sarma, 2009)</td>
<td>Large</td>
<td>High</td>
<td>Low/Medium</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Simulations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Stochastic</strong> (e.g., LU, sequential Gaussian, and Block error simulations)</td>
<td>(Chiles and Delfiner, 2012; Mariethoz and Caers, 2015; Remy et al., 2009)</td>
<td>Medium</td>
<td>Low</td>
<td>Medium/High</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Process</strong> (e.g., process based, process-mimicking)</td>
<td>(Mariethoz and Caers, 2015; Michael et al., 2010)</td>
<td>Small</td>
<td>Low</td>
<td>High</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Statistics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Univ., Bivariat</strong> (e.g., Inverse distance weighting, nearest neighbour, polynomial regression, splines)</td>
<td>(Smith et al., 2018; Watkins et al., 2008)</td>
<td>Medium/Large</td>
<td>High</td>
<td>Low</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Multivariate</strong> (e.g., K-means clustering, PLS regression)</td>
<td>(Eriksson et al., 2013)</td>
<td>Medium/Large</td>
<td>Medium</td>
<td>Medium</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Non-geostatistics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Unsupervised</strong>: clustering (e.g., K-means)</td>
<td></td>
<td>Medium</td>
<td>Medium</td>
<td>Medium</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Supervised</strong>: regression (e.g., Neural networks) and classification (e.g., nearest neighbours, decision trees)</td>
<td>(Aggarwal, 2014; Frank et al., 2016a; Suthaharan, 2016)</td>
<td>Large</td>
<td>Medium</td>
<td>Medium/High</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

One possible solution to the incomplete data and above posed questions could be in creating a simulator (synthetic testing environment) for generating a synthetic ore body. In such a case, it would be possible to assign as many properties to the synthetic ore as needed for using the synthetic model as a decision-supporting tool. A synthetic ore body may provide an environment where different production scenarios can be numerically tested in an effective way, with consideration of impact from all the upstream and downstream processes. The outcome of the sampling campaign can be tested and predicted with synthetic drilling, and results can be used for planning and correcting actual drilling campaigns. The model may contain multiple realizations with different resolutions and a reference case. Comparison between realizations and reference case give an idea about additional sampling needed and uncertainties in processing and mining related to the voxels location in the ore body. However, in this thesis only one realization is used, since studying uncertainties is beyond the scope of the study.
3.1. Leveäniemi case study

Leveäniemi is the third largest apatite-iron ore in Norrbotten area, Sweden. It is located 40 kilometres southeast of Kiruna, in northern Sweden (Figure 7) and was discovered in 1897 (Bremer, 2010). Leveäniemi is an open-pit mine operated by LKAB with proven reserves of 91 Mt @ 47.3% and probable reserves of 7 Mt @ 39.4% Fe (LKAB, 2017). Leveäniemi was in operation between 1964 and 1983, when it was put on hold, and re-opened in 2015. (Gustafsson, 2016; Niiranen, 2015).

The Leveäniemi ore is a high-grade magnetite ore. Genetically, it is described as a combination of both tabular stratiform-stratabound and breccia-style apatite iron ores. The character of the host rocks is felsic-mafic and intermediate volcanic (trachyandesitic) (Martinsson et al., 2016). Apart from the magnetite ore, other ore types can be distinguished in this area, i.e., calcareous magnetite ore, hematite-altered ore and brecciated ore (Frietsch, 1966). The main ore mineral is magnetite, but there are also smaller amounts of hematite. The gangue minerals include apatite, biotite, calcite, quartz, chalcopyrite, pyrite, amphiboles, micas (e.g., biotite), potassium feldspar, and plagioclase (e.g., albite). (Gustafsson, 2016; Lund et al., 2013; Martinsson et al., 2016).

The Leveäniemi deposit shares multiple similarities with Malmberget deposit, since both belong to the apatite iron ore type deposit. The geometallurgical ore types (GEM) classification developed by Lund, (2013) was also applied in an attempt to link Malmberget and Leveäniemi deposits by their geometallurgical properties (Appendix I).

3.2. Metallurgical methods and apparatus

Detecting new patterns in iron ore processing in the case study would enable enhancement of the predictability of the process performance. To the best of my knowledge, there are no validated results on how the DT may be applied efficiently in process modelling. The testing procedure included sampling, metallurgical testwork, mineralogical characterisation and modelling (Figure 8).
Thirteen representative composite iron ore samples (each a minimum of 60 kg) were used in this thesis. Ten drill core samples and three pit grab samples were collected by the mine geologist to cover the full geological variation of the deposit.

Figure 7 Leveäniemi location, geological setting and location (modified after Allen et al., 2004).

Figure 8 Flowchart of the testwork.
**Sample preparation.** Samples for the DT and WLIMS were crushed in a lab scale jaw crusher to <3.35 mm and then split into batches for the WLIMS and DT feed. The WLIMS subsamples were later ground for 5 min in a rod mill and for 60 min in a ball mill to P80 80 µm. The DT subsamples were ground in a laboratory stainless steel ball mill (CAPCO or GCT mill) for 11 min. The GCT procedure is described in Mwanga et al., (2017, 2015). The small mill was used to minimize mass losses of the fine fraction during size reduction.

**WLIMS** was conducted in a single step using bulk material. The average sample size was 10 kg to ensure a stable and repeatable result. The material was fed to the WLIMS with a rate of 0.5 kg/min at water rate of 3 l/min and drum rotation speed of 60 rpm. Two products were obtained from the test: concentrate and tailings. The WLIMS testing setup is shown in the Figure 9. The WLIMS tests were conducted at LTU mineral processing laboratory.

**DT test.** The DT test was conducted on three different size fractions: fine, medium and coarse (Table 11). Due to the DT geometric limitations, the fraction coarser than 106 µm was not tested.

<table>
<thead>
<tr>
<th>Size fraction, µm</th>
<th>Name adopted in the thesis</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>less than 38</td>
<td>fine</td>
<td>f</td>
</tr>
<tr>
<td>38-75</td>
<td>medium</td>
<td>m</td>
</tr>
<tr>
<td>75-106</td>
<td>coarse</td>
<td>c</td>
</tr>
<tr>
<td>0-106</td>
<td>bulk</td>
<td>b</td>
</tr>
</tbody>
</table>

![Figure 9 WLIMS: Left - schematic view, Right - experimental setup (A - feed input, B - feeder, C - magnet drum, D - concentrate outlet, E - flow control knob, F - pump, G - tailings outlet, H - water tank, I - tailings tank).](image)

The tests were done using a minimum weight of 60-80 g per sample, to ensure sufficient product (min 20 g) for mineralogical characterisation. However, since the DT is most efficient at sample weight below 20 g, the test for each sample was conducted in several batches 10-15 g each. The
water flow was set to 0.3 l/min, the tube angle – 45 degrees, and tube oscillations – 45 min⁻¹. The
tests were done at LKAB’s R&D Laboratory at Malmberget, Sweden. A standard DT apparatus
was used (Figure 10 - left).

The DT tests were run in three steps utilizing a staged rougher approach (Figure 10 - right). First,
the material was fed to the DT at current strength of 0.1 A, it extracted the particles with the
highest magnetic volumes (highly liberated magnetite particles). Then, the tailings of the first run
were fed to the DT at 0.2 A current strength. Finally, the tailings of the second run was fed to the
DT at 0.5 A. Duration of each test run was 130 seconds.

**Figure 10 Davis tube: Left - testing setup
(A - inlet for sample and water, B - magnets, C - glass tube, D - outlet used for both
concentrate and tailings), Right - Davis tube test procedure.**

GCT has been developed at LTU as proxy test for estimating the Bond ball mill work index
(Mwanga et al., 2015). GCT is done by using a small 1.4 l CAPCO® laboratory ball mill (Figure
11).

### 3.3. Analytical methods

**Optical microscopy.** Optical microscopy, using a Nikon Eclipse E600, was applied for
identification of mineralogy, alterations, grain size distribution and textural properties of the DT
feed samples.

**Auto-SEM-EDS (i.e., QEMSCAN).** Modal mineralogy and liberation analyses of the DT feed
were done on a QEMSCAN system. Fifty-two polished resins blocks representing four size
fractions (less than 38 µm, 38-75 µm, 75-106 µm, larger than 106 µm) of 13 ore type samples were
analysed. The average number of measured particles per sample was 5000. The tests were done at
LKAB’s R&D Laboratory at Malmberget, Sweden. Minerals considered to be of a minor
importance and minerals, which could not be efficiently distinguished with Auto-SEM-EDS were
grouped together, e.g., Fe-oxides for magnetite and hematite.
Figure 11 CAPCO® laboratory ball mill used for GCT.

Data post-processing was performed with HSC Chemistry software (Outotec, 2017) under the following conditions:

- The minimum amount of mineral in a particle to be considered as liberated (Lib Threshold) is 100%; and
- The minimum amount of mineral in a particle to be treated as binary, ternary, complex (tolerance) is 1%.

**Chemical assays.** Chemical assays were prepared and analysed by ALS-Geochemistry (Piteå, Sweden) and the Technical Laboratory at LKAB (Malmberget, Sweden).

The amount of magnetic iron was measured with an electromagnetic method using a SATMAGAN (Stradling, 1991; Wiegel, 1975). SATMAGAN results were delivered as corresponding to the Fe$^{2+}$ content ($Sat_{Fe^{2+}}$) in magnetic fraction. For samples with high iron grades, it can be assumed that $Sat_{Fe^{2+}}$ is proportional to the magnetite (Mgt) grade (Gustafsson, 2018; Lund et al., 2013; Parian et al., 2015), and therefore calculated as (1):

$$Mgt\% = \frac{Sat_{Fe^{2+}}\%}{24.3\%} \cdot 100\%$$  \hspace{1cm} (1)

where 24.3% is Fe(II) content in pure magnetite.

In addition to the chemical assays, some process performance parameters were used in modelling (Table 12). The Difference Index (DI) is the same term as the Separation Efficiency put forward by Schulz (1970), but it is a name describes better the built of the index.
### Table 12 Secondary variables used in the modelling.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Formula</th>
<th>Variables</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recovery, %</td>
<td>( R = \frac{C}{F} )</td>
<td>Mass pull, %</td>
<td>( M = \frac{\text{Conc}}{\text{Feed}} )</td>
</tr>
<tr>
<td>Cumulative recovery, %</td>
<td>( R_{\text{cum}} = \sum \frac{C}{F} )</td>
<td>P80, ( \mu \text{m} )</td>
<td></td>
</tr>
<tr>
<td>Difference index, %</td>
<td>( D_{I,Fe} = R_{Fe} - R_{Oth} )</td>
<td>( X_{\text{LTU}}, % )</td>
<td>( X_{\text{LTU}} = \frac{\text{Fe}_{\text{Feed}}}{M} - 0.724 )</td>
</tr>
</tbody>
</table>

\( C \) is mass of element of interest in concentrate [g], \( F \) is mass of element of interest in feed [g], \( R_{Fe} \) is recovery of iron [%], \( R_{Oth} \) is recovery of any other element [%], \( \text{Conc} \) is mass of concentrate [g], \( \text{Feed} \) is mass of feed [g], \( \text{Fe}_{\text{Feed}} \) is iron content in feed [%], \( M \) is a mass pull [%], 0.724 is the iron content of stoichiometric magnetite. The cumulative recovery, mass pull and difference index from DT tests received corresponding indices, i.e., “12” for the results from the first two runs, and “13” from the first three runs.

### 3.4. Materials

#### 3.4.1. Process data

Composition characterisation include chemical assays, modal mineralogy, and liberation distribution of iron oxides and measurements of magnetic iron in samples. The process parameters (expressed as a variable \( Y \)) selected for modelling include iron recovery both in WLIMS (\( R_{Fe}^{WLIMS} \)) and DT (\( R_{Fe}^{DT} \)), and mass pull in WLIMS (\( M^{WLIMS} \)) and DT test (\( M^{DT} \)), \( P_{80} \) (80th percentile of the particle size distribution) after 11 minutes of grinding material in a laboratory scale ball mill, and degree of liberation of iron oxides after grinding (magnetite and hematite) (\( L_{Fe-ox} \)).

#### 3.4.2. Spatial data

The spatial geological data is available as a production block model from LKAB Leveäniemi with iron grades estimated by kriging from geologically logged and chemically assayed drill cores. Totally, the geological database includes information from 82 drill cores divided into 5550 samples and assayed for 24 elements (Al, As, Ba, CaO, Cl, Co, Cr2O3, Cu, Fe, K2O, MgO, Mn, Na, Ni, P, Pb, S, SiO2, Sn, Sr, TiO2, V, Zn, Zr), and specific gravity (Table 13). Each sample in the database has a unique ID number and can be spatially identified with its orthogonal coordinates \((x, y, z)\).

### Table 13 Basic statistics of the chemical assays and density for the samples from the geological database.

<table>
<thead>
<tr>
<th></th>
<th>P, %</th>
<th>TiO2, %</th>
<th>V, %</th>
<th>SiO2, %</th>
<th>Fe, %</th>
<th>Al, %</th>
<th>CaO, %</th>
<th>MgO, %</th>
<th>Mn, %</th>
<th>Na, %</th>
<th>K2O, %</th>
<th>Cu, ppm</th>
<th>S, %</th>
<th>density, t/m³</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>0.38</td>
<td>0.40</td>
<td>0.09</td>
<td>25.63</td>
<td>39.12</td>
<td>7.32</td>
<td>3.49</td>
<td>3.09</td>
<td>0.06</td>
<td>1.62</td>
<td>1.28</td>
<td>853</td>
<td>0.09</td>
<td>3.71</td>
</tr>
<tr>
<td>median</td>
<td>0.25</td>
<td>0.36</td>
<td>0.08</td>
<td>25.80</td>
<td>38.33</td>
<td>7.10</td>
<td>3.10</td>
<td>3.14</td>
<td>0.05</td>
<td>1.06</td>
<td>1.00</td>
<td>320</td>
<td>0.03</td>
<td>3.50</td>
</tr>
<tr>
<td>stdev</td>
<td>0.42</td>
<td>0.26</td>
<td>0.06</td>
<td>18.81</td>
<td>21.30</td>
<td>5.88</td>
<td>2.10</td>
<td>1.69</td>
<td>0.03</td>
<td>1.71</td>
<td>1.29</td>
<td>1,610</td>
<td>0.16</td>
<td>0.77</td>
</tr>
<tr>
<td>max</td>
<td>4.92</td>
<td>2.13</td>
<td>0.25</td>
<td>94.70</td>
<td>70.19</td>
<td>20.20</td>
<td>36.70</td>
<td>15.10</td>
<td>0.49</td>
<td>7.63</td>
<td>6.29</td>
<td>8,540</td>
<td>4.59</td>
<td>5.19</td>
</tr>
<tr>
<td>min</td>
<td>0.00</td>
<td>0.02</td>
<td>0.00</td>
<td>0.32</td>
<td>0.92</td>
<td>0.17</td>
<td>0.03</td>
<td>0.19</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
<td>0</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>
CHAPTER 4  METHODOLOGY

“Highly organized research is guaranteed to produce nothing new.”

Frank Herbert, Dune

4.1. Classification of geometallurgical programs (Paper A)

A geometallurgical program aims at the development and use of geometallurgical models. Geometallurgical models should provide reliable forecast for the variation in production performance by linking it to the variability in the upstream processes. Knowing the magnitude and implications from the variations in production allows for informed decision-making at managerial level regarding the actions required for better production planning. However, all mines are different and consequently the commodity, the process, the working culture, and the local environmental regulations etc., will differ in different mines. Accordingly, each mine represents a unique case that is likely to require customized geometallurgical solution for the production problems. The aim of the classification is therefore to investigate different application levels of geometallurgy in order to identify gaps in the applied methods with the overall purpose of finding ways to increase the predictability of the process, and thus indicate areas where development is called for. Filling in gaps allows to measure and model the impact of geological variability in the feed on the variability in the process performance, when such impact is significant. Possible gaps are: (1) less costly and simpler mineralogical characterisation techniques; (2) geometallurgical tests which would allow to capture the variability in the process (i.e., new tools for conducting tests or a new testwork routine for measuring desirable parameters); (3) process models which could explain the behaviour of the ore in a particular part of the process; (4) process simulation with relevant models implemented in a simulation software; and (5) spatial modelling methods adequate for the reviewed case.

4.1.1. Collecting information on industrial practices of geometallurgy

This thesis is based on cross-disciplinary research, involving an extensive literature review (38 cases) as well as semi-structured interviews (14 cases) (Appendix III) and a cross-sectional survey (Lishchuk, 2016) to validate the notion of a geometallurgical program. 52 case studies (Lishchuk, 2016) were reviewed to develop an analytical framework for the assessment of geometallurgical programs. The cases were selected on the basis of the (alleged) existence of geometallurgical activities. Selection of interviewees and survey participants was based on personal contacts. The survey serves the purpose of structuring the geometallurgical data (sampling, models, and
simulations) in a way which would facilitate identifying the gaps in available technologies (e.g., mineralogical characterisation, geometallurgical tests, process models). Identifying those gaps will show where the development is needed for constructing a geometallurgical program. An online questionnaire (Lishchuk, 2016) form linked to the database was developed in Google Forms. The questionnaire form was grouped by seven chapters:

1. Respondent information, i.e. information about the person who was filling the form;
2. General information on the mine project;
3. Production information to collect data about the most common production parameters, i.e., ore type, main product etc.;
4. Deposit model to cover availability and potential for application of the geological and geotechnical data for geometallurgical modelling;
5. Geometallurgy level to obtain existing information regarding the geometallurgical purposes;
6. Implementation of geometallurgical information in order to collect answers regarding the information depth of application of geometallurgy;
7. Application of geometallurgical approach. Self-evaluation. The purpose of this section was to double check results by asking questions in a graphical way.

The survey included 14 participants (mining and mineral processing engineers, process mineralogists, researchers, trainees, master students) at companies in Europe (Sweden, Poland, Finland, Russia), Americas (Canada, USA, Brazil) and Africa (Namibia, and one unspecified country in Africa). The participants have in-depth knowledge of the mine production, processing, production planning, the level of implementation of geometallurgy at their companies, and were, therefore, suitable to validate the notion of geometallurgical program. The interaction with the respondents for the cases Mine-1, Mine-2, Mine-3, and Mine-4 was via face-to-face communication, and interaction with other respondents was via mail, or social networks (Facebook).

4.1.2. Information treatment

The information collected was used to classify the case studies according to the respective approaches, i.e., traditional, proxy or mineralogical and levels of applications (Figure 12).

While it is necessary to more clearly define the notion of geometallurgical programs, there is a risk of misinterpreting the collected information. Some of the main challenges (sources of possible errors) of the survey are difference in terminology used in different geographical locations and different meanings for the same term applied in different areas (e.g., recovery in mining means proportion of the ore extracted after accounting for mining losses, while recovery in mineral is the percentage of the total metal contained in the ore that is recovered to the concentrate).
4.1.3. **Classifying according to approaches**

The type of approach is defined by the data used in the geometallurgical program (Figure 13). Three different geometallurgical approaches could be distinguished: traditional (elemental), proxy, and mineralogical.

The classification of the approach is based on the traceable component: e.g., chemical composition, metallurgical response, mineralogy and is thus affected by the methods for sampling and analysis. The sampling frequency and types of tests used for defining metallurgical responses also varied between the identified geometallurgical approaches. Therefore, the case studies were classified into the traditional approach if they were using chemical (chemical composition) and qualitative mineralogical (list of minerals) information (corresponding characterisation techniques are listed in Table 3). The case studies which used quantitative mineralogical (modal mineralogy) information (Table 3) were classified into the mineralogical approach. Finally, case studies, where geometallurgical tests (some of such tests are listed in Table 2) were combined with chemical (chemical composition) and qualitative mineralogical (list of minerals) information, were classified into the proxy approach.

4.1.3.1 **Traditional approach**

In the traditional approach, chemical assays and chemical composition of the ore form the basis of the program. Metallurgical response is calculated from the chemical composition of the ore collected by chemical assays of samples. Simple recovery functions are used for this purpose, i.e., elemental recovery is a function of the elemental content in the ore. The functions are developed by using metallurgical testing and statistical analysis to define the correlation between the metallurgical response and feed properties i.e., chemical composition. Traditional approach is common for commodity types where ore grades are high. It is also a common method for the early
stages of the mining projects, i.e., conceptual study stage and pre-feasibility study. Often the development of geometallurgical program starts from traditional approach.

![Diagram of Linkage between geology and process via geometallurgical approaches.](image)

**4.1.3.2 Proxy approach**

The proxy approach uses geometallurgical tests or other indirect measurements of metallurgical response to characterise the metallurgical behaviour of ore for large number of samples in different processing stages. The geometallurgical test is a small-scale test which indirectly measures the metallurgical response (Table 2). Normally, the geometallurgical test results must be converted with certain correction factors (often called scale up factors) to give estimate of the metallurgical results at the plant. Examples of geometallurgical tests are DT (Niiranen and Böhm, 2012) and SPI (Kosick et al., 2002). Geometallurgical tests need to be applied early in the ore characterisation in order to collect information on the ore variability (Mwanga et al., 2015). Such tests are cheap and rapid, in comparison to laboratory scale metallurgical tests, and usually require special equipment. They can be performed on samples of a small size and should correlate reasonably well with conventional tests and metallurgical results of the plant (Chauhan et al., 2013). It is the application of geometallurgical tests in connection with elemental grades and without connection to mineral-related behaviour of the ore, which distinguishes proxy approach from the mineralogical one.

**4.1.3.3 Mineralogical approach**

The mineralogical approach refers to geometallurgical programs where a geometallurgical model, i.e., deposit and process model, is built based primarily on quantitative mineralogical information. The process simulation in the mineralogical approach must be capable of handling unit process models at the particle level (Parian, 2017). This often means that accurate information on modal mineralogy is needed for the whole ore body (Lamberg et al. 2013). Thus, mineralogical data has to be quantitative and the collection of information has to be continuous throughout the life of the mine (Hunt and Berry, 2017) and systematic. Lund (2013) and Lamberg (2011) demonstrate
how a geological model and a process model can be linked using mineralogical information. Bonnici et al., (2008) highlight the implications of mineralogical information (textural attributes) for processing behaviours such as comminution, liberation and recovery.

4.1.4. Classifying according to applications

To become an industrial geometallurgical program, the geometallurgical model has to be used in production. The depth of the applicability of the program is defined by how geometallurgical data may be used in production management. The depth of the geometallurgy application shows the level of geometallurgy involvement in production management decisions and is divided into passive, semi-active and active level of use. This depends on the sophistication of the model, the depth of its use, the main involved players at the site, the complexity of managerial tasks involved, and if a corrective or preventive approach is used to solve production issues. The conditions for placing the case study on a certain level of application of geometallurgical program are listed in Table 14. Fulfilling more technical requirements from the list in Table 14 (e.g., creating geological database, conducting metallurgical tests, building process models, continuity of the program etc.) does not necessary lead to a more advanced level of application, but creates such a possibility. The number of participants involved in the geometallurgical program changes with the depth of the program. A deeper (more advanced) level of geometallurgy corresponds to deeper integration and cooperation between the involved parts of the mineral production chain, i.e., geology (exploration and production), mining, production maintenance, sales etc.

Table 14 Application levels of geometallurgical program.

<table>
<thead>
<tr>
<th>Level</th>
<th>Name</th>
<th>Geological database</th>
<th>Metallurgical testing</th>
<th>Model</th>
<th>Simulation</th>
<th>Actions</th>
<th>Players</th>
<th>Mapping</th>
<th>Continuity</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>None</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td>None</td>
<td></td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Data collecting</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td>geologist and mineral processing engineers</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>2</td>
<td>Visualization</td>
<td>X</td>
<td>X</td>
<td>Y*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Forecasting</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Changing process</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>Corrective</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Constraining</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td>and mining engineer</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Production planning</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>Y*</td>
<td>Preventive</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Managing production scenarios</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>and QEHS** engineer, environmentalists, sellers of concentrate, product buyers, metallurgists, shareholders</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*“Y” is not obligatory; **QEHS - Quality, Environmental, Health and Safety
4.1.4.1  Level 0 - None

Level 0 - None means that no geometallurgical data is collected and neither a geometallurgical program nor a geometallurgical model exist. This is the starting level of every geometallurgical program.

4.1.4.2  Level 1 - Data collecting

At the level 1 geometallurgical data is collected systematically but is not used for any production planning purposes or visualization of the information. Collecting geometallurgical data requires collaboration between the geologist and the processing engineer. At this level, the ore has to be tested for either a feed-forward effect on the variability in metallurgical response in laboratory conditions, or for feedback connection between variability in metallurgical response at the plant that can be consciously linked to the geological variability. The latter can be optionally achieved by thorough empirical plant observations in operating mines. The basis for the future geometallurgical model is created at this level. The existence of geometallurgy at this stage does not lead to any noticeable actions.

4.1.4.3  Level 2 - Visualization

At level 2, the variability within the ore body is visualized based on the collected geometallurgical data. The data is stored in numerical form; thus, special software has to be used. The data is used by visualizing the variability in presentations, meetings and discussions. At this level, also people outside processing and geology should have access to it. A geometallurgical model may exist at this stage, but it is not used for any production-related purposes. Besides that, a geometallurgical program at this stage inherits all the features of the level 1 “Data collecting”.

4.1.4.4  Level 3 - Forecasting

Level 3 uses geometallurgical data to forecast production. The information is used to raise awareness amongst other players without any active actions for production. Information may be used in tailings management and concentrate marketing and shipping, i.e., information is taken but no actions exist to change mining, ore blending or processing. Commonly, the geologist and the processing engineer remain the only active participants of the geometallurgical program.

4.1.4.5  Level 4 - Changing process

At level 4, information on the variability in feed quality is used to make changes to the process. At this stage only corrective but no preventive actions are taken. Corrections may be planned beforehand; however, they impact only a limited part of the process (a section) and involve a limited number of people. Level 4 is a transitional stage between passive and active application of geometallurgy.
4.1.4.6 Level 5 - Constraining

At level 5 data is used to define feed quality constraints and production limitations of the process. This is the lowest level of active use of geometallurgy including typically some preventive actions. It is also the first level on which geometallurgical program has to be continuous and is often also constantly improved. Typically, this level includes limitations on the feed properties, e.g., titanium grade must be below 0.9 wt% in the feed; the mass proportion of talc bearing country rock must be lower than 4% of the feed. Therefore, changes are typically made on the mining side or in feed blending to mitigate the negative impact of the problematic components in the downstream process. Changes include such actions as ore blending, selective mining, and small changes in the production flowsheet. Level 5 requires a larger group of participants with obligatory involvement of mining engineer and production planner, besides geologist and metallurgist.

4.1.4.7 Level 6 - Production planning

At level 6, the production plan is based on geometallurgical data. A wide range of players, including (besides geologist, metallurgist and mining engineer) maintenance and automation engineers. Also, economists benefit from the geometallurgical results and actively contribute to the utilisation and development of the geometallurgical program. At this level, often both geological variables and geometallurgical indices are included in block model (3D). Therefore, a block model is continuously maintained and updated. In some cases, simulations of alternative scenarios are done, although not on a regular basis. Effective application of geometallurgy at this level requires advanced online measurement tools (e.g., measurement while drilling system) and real-time update of the geometallurgical model, block model and mine production plan. Both geological and processing simulations are utilized. Involvement of economists and finance specialists allows for production benefit estimation in terms of cash flow and projected cash flows, including both discounted cash flow and net present value (NPV).

4.1.4.8 Level 7 - Managing production scenarios

At the highest level 7, managing production and geometallurgical data form a vital basis of the decision making, e.g., investments, selection of alternative technologies, production interruptions (or production speed-ups), merging of companies, expansion and investments. Such flexibility is achieved through active use of simulation and active involvement of wide range of stakeholders. Both upstream and downstream processes are affected by geometallurgy. Effective application of geometallurgy at this level requires advanced online measurement tools and real-time update of the geometallurgical model, block model and mine production plan.

4.2. Preliminary testing of a geometallurgical program (Papers C, D, E)

A classification system of geometallurgical programs helped to identify tools and models needed for the geometallurgical program. However, before starting the development of the
geometallurgical program, it is important to investigate the impact of the future actions. Such testing could be done in a synthetic environment – synthetic ore body model.

A process-mimicking approach was selected for modelling in this thesis due to its relative simplicity and high realism. The algorithm was implemented in a MATLAB code.

### 4.2.1. Synthetic ore body model

The synthetic ore body model includes two modules: the synthetic deposit module and the synthetic sampling module (Figure 14). Each module is comprised of a spatial component, which considers location of each point in a physical space, and a database, which carries non-spatial quantitative and qualitative information for each point. Spatial and non-spatial information is connected by a unique ID number assigned to each point of the model in physical space and a corresponding record in the database. Both databases (deposit module and sampling module) have the same metadata and carry the same type of information (elemental composition, mineralogy, recoveries, throughput, mining cost, value etc.) about each block of the synthetic deposit and each segment of a synthetic drill core.

![Figure 14 Structure of the synthetic ore body model.](image)

### 4.2.2. Synthetic deposit module

The Synthetic Deposit Module is described with a three-dimensional voxel model and database. The Synthetic Deposit Module focuses on outlining the deposit’s borders and assigning geological, mining, processing and economic properties to each voxel of the voxel model. In practice, the uncertainty of the ore response in the process may also be impacted by extraction sequence, processing available, operators team working at the plant, and batch with which the extracted block was blended during the process.
4.2.2.1 Spatial data

The spatial part of the deposit module for the synthetic ore body is a three-dimensional voxel model, where each voxel corresponds to a minable block of the deposit. The size of the voxels can be set to any constant value. The location of each voxel is described by the coordinates $x, y, z$. The $x$ and $y$ coordinates are planar, and $z$ represents height. The coordinate system follows the left-hand rule. Therefore, the centre of the coordinates lies in the lower left corner of the voxel model and values of the coordinate $z$ increase upwards.

4.2.2.2 Database

A database of voxel properties describes geological, mineralogical, mining, mineral processing and economic properties of each voxel (Figure 15). Each voxel gets one entry in a database with complete information about its properties. The geological data in the database are derived from the three-dimensional voxel model.

The voxel model represents the extent of the mineral deposit including both ore body and country rock. The geological domains, mineralogical and elemental properties are the key geological features chosen for modelling synthetic deposits. Generated mineralogical and chemical information is inputted to the mineral processing model implemented in HSC simulation software (Outotec, 2017) for each block. Alternatively, other pieces of software may be used (see Table 4). Process parameters estimated for each block are constrained with a mining method, since sequencing of the blocks sent to the process depends on the production plan of the selected mining method. Process performance, e.g., concentrate quality, throughput, mining cost, dilution etc. provide inputs for the economical assessment of the designed mine. Geological, production and economic information about each block is stored in a database and linked to the block with unique identification number.

![Figure 15 Structure of the deposit module of the synthetic ore body model.](image)

4.2.3 Database description

4.2.3.1 Geology

Domains: Physical space. The general term “domain” here refers to a volume or physical space with homogeneous properties, e.g., mineral distribution, rock density, grindability, commodity material recovery, or texture. In other words, voxels belonging to the same ore type, adjacent to each other and showing spatial continuity of any properties (e.g., geological, metallurgical
properties) inside the ore body are referred to as domains (David, 2007; Sanchidrián et al., 2012). Ore types, alteration zones, mineral grade distributions, and weathering zones are called geological domains. Domains used to model process parameters are referred to as geometallurgical domains.

The complex shape of the domains is modelled (approximated) with simple geometrical bodies. Traditional geological modelling software, e.g., Dassault Systems, (2018), Maptek, (2017) deal with 3D domains by using solids generated from wireframes or through implicit modelling. However, an ellipsoid (Figure 16 and eq. (2)) is chosen here, since it is a common shape used in geosciences, i.e., geostatistics. Other geometric shapes may be used in modelling domains as well (e.g., cubes, spheres and their sectors). It might be enough to use one ellipsoid to approximate each domain:

\[
(x - x_0)^2/a + (y - y_0)^2/b + (z - z_0)^2/c = 1
\] (2)

Here (see also Figure 16) \(o = (x_0, y_0, z_0)\) is the centre of the ellipsoid; \(a, b, c\) are its semi-axes. The spatial orientation can also be given by Euler rotation angles \(\alpha, \beta, \gamma\).

![Figure 16 Ellipsoid used to model domains.](image)

However, cases that are more complex may require usage of combination of multiple ellipsoids. Interactions or conflicting overlaps between different domains are resolved by applying Boolean operations (Figure 17).

![Figure 17 Examples of Boolean operations.](image)

The physical location of each domain (ellipsoid) in relation to other domains is defined by aligning ellipsoid centres along an auxiliary design line or placed individually by the model user. The auxiliary design line is used as reference for the ellipsoids’ locations and does not have any particular geological meaning.

Rock types, the same as other spatially continuous variables, are defined by modelling domains and encoding them with a unique identifier for the particular rock type. One voxel of the synthetic ore body model is occupied only by one rock type (ore type, ore class, weathering type etc.).

**Mineralogy.** Modal mineralogy is defined for the mineral grade model by considering mineralogical difference between geological domains and preserving relevant quantities,
distribution, and composition of the minerals. Firstly, a complete list of minerals for the entire model is identified. Then an appropriate sub-list of minerals is defined for each geological domain. It is assumed that a mineral can occur in the orebody due to any one or more of several mineralization effects. Therefore, overlapping generations of the same mineral should be modelled as separate objects. Mineral grades from different populations of the same mineral can be summed up and given a new name (e.g., Magnetite_Sum) or kept separately in the database (e.g., Magnetite_1, Magnetite_2, Magnetite_3).

Mineral distribution for each voxel is modelled as a function of coordinates of the voxel in the block model (Figure 18). When extension of the mineral inside the block model is known, the physical space of the actual mineral distribution can be restricted by geological domains (ellipsoids) and scaled correspondingly. Mineral quantity distribution can also be complex since they represent several overlapping distributions with a drift. Initial hypothesis about mineral distribution is expressed as a generalized additive model (GAM) shown below by eq. (3).

\[
M = T + S + N = \begin{cases} 
  T = f_T(x, y, z), & \min T = a_T, \max T = b_T \\
  S = f_S(x, y, z), & \min S = a_S, \max S = b_S \\
  N = f_N(x, y, z), & \min N = a_N, \max N = b_N 
\end{cases}
\]

where, \( M \) is a mineral grade in a given voxel scaled to the interval of minimum and maximum values defined for the mineral; \( T \) is a trend function; \( S \) is a systematic error; \( N \) is a random error; \( T, S, N \) are functions of coordinates \((x, y, z)\) of the voxel. Each \( f_T(x, y, z), f_S(x, y, z), f_N(x, y, z) \) can be chosen as follows, eq. (4), where each choice for the function \( f \) defines a different hypothesis for mineral distribution and mineralisation.

\[
f = \begin{cases} 
  r^n; \\
  \sin(r^n); \\
  \cos(r^n); \\
  \text{normal random value} \ (\mu, \sigma); \\
  \text{standard normal random value} \ [0,1]; 
\end{cases}
\]

where \( r \) is defined as the distance (e.g., Euclidian or Manhattan) in 1-, 2- or 3-dimensional space between the voxel of interest and the centre of the geological domain (ellipsoid):

\[
r = \left( (x - x_o)^n + (y - y_o)^n + (z - z_o)^n \right)^{\frac{1}{n}} 
\]

where \( n \) is any real number; \( x, y, z \) are coordinates of the voxel’s locations and \( x_o, y_o, z_o \) are coordinates of the center of the geological domain (as shown in Figure 16).

In this thesis, mineral grades were expressed as: \( M = T + S + N = r^n + \sin(r^n) + \text{normal random value} \ (\mu, \sigma) \).
Describing minerals independently from each other might lead to a severe over or under estimation of mineral proportions for some voxels. This problem is avoided by using a two-step approach: commodity minerals are modelled independently from each other summing up to a value $A\%$, the rest (gangue) minerals, are modelled as a fraction of available space remaining, defined as $100\%-A\% = B\%$.

Mineral chemical composition can vary from deposit to deposit or even within the same deposit. Thus, the mineral composition is described with the elemental grades being a function of a mineral grain’s spatial location in the voxel model. Modelling of the minerals distribution is done by considering the following aspects:

- **Stationarity** is insured by modelling the “stationarity ellipsoids”. A stationarity ellipsoid is a geometry where the mineral distribution is the same for a given mineral throughout the portion of the voxel model enclosed by this stationarity ellipsoid. The algorithm of describing stationarity ellipsoids is identical to the one used for describing geological domains. Stationarity allow for describing anisotropy of the mineral distributions within the ellipsoids’ dimensions and orientations;
- **Spatial conflicts** between geological domains and stationarity ellipsoids are resolved with Boolean operations (Figure 17);
- Minerals modelled with eq. (3) - (5) may have compositions which are outside the normal

**Figure 18 Applying geological domains to model rock types and property (e.g., mineral grade, elemental grade, density etc.) inside the rock type.**
range of values. Therefore, a certain minimax range can be imposed by rescaling (or truncating) the mineral distribution; and

- **The total sum** of mineral grades should be closed to 100%. Normalisation of values to a constant sum is also called a closure and forces negative correlations (Aitchison and Egozcue, 2005; Butler, 1976; Chayes, 1960; Pawlowsky-Glahn and Egozcue, 2016, 2011). The significance of closure problem for environmental data was emphasized by Filzmoser et al., (2009) and Reimann et al., (2012), and for compositional geochemical data by Makvandi et al., (2016). In this work, closure can be done either by scaling minerals’ grades proportionally to their values, or by assigning the rest to “unspecified gangue”.

**Chemical composition.** A voxel’s chemical composition depends on the modal mineralogy and chemical composition of the minerals. Each mineral within a geological domain has a defined chemical composition. If the chemical composition of a mineral varies, then several mineral species may have to be modelled, e.g., amphibole 1, amphibole 2, amphibole 3. The vector of chemical composition (v) of a voxel is calculated from modal mineralogy and the chemical composition of minerals, eq. (6):

\[ v = A \cdot x \]  

where \( A \) is a matrix of chemical composition of minerals (sometimes also called mineral matrix), and \( x \) is a vector of mass proportions of minerals in a voxel.

**Density.** The density of a voxel point is based on the densities of each of the separate minerals as a weighted harmonic mean assuming zero porosity of the rock, eq. (7):

\[ \rho = \frac{\sum_{i=1}^{m} wt_{i} \% \rho_{i}}{\sum_{i=1}^{m} wt_{i} \%} \]  

where, \( \rho_{i} \) is the density of the mineral \( i \), \( wt_{i} \% \) is the weight fraction of the mineral \( i \). The non-zero porosity can be considered by multiplying by the corresponding coefficient \( a \in (0,1] \).

Other geological (e.g., alterations, mineral textures), mineralogical (e.g., modal mineralogy, mineral liberation, grain size distribution), geophysical (e.g., magnetic susceptibility, porosity, dielectric permittivity, electrical conductivity) and geotechnical (e.g., Poisson’s ratio) properties might be considered in the future.

### 4.2.3.2 Production

**Mining.** A mining plan defines the ore sequence prior to coming to the processing plant. The mining plan is determined by the mining method. To enable the mining module, the voxel model is transformed into the resource block model by giving dimensions to voxels. For simplicity, and for preserving the maximum resolution of the model, the conversion is made by assigning one voxel to one block. However, for low variability models, the properties of one block can be retrieved by averaging the properties of several voxels.
Mining constraints for the synthetic ore body model can be introduced by applying a mining method, which may be either surface mining or underground mining. The mining constraints can also be omitted (thereby assuming zero ore dilution, and zero ore losses). The time constraint of the mining production can be modelled by applying, for example, a series of pushbacks in an open pit mining (Figure 19). Each following pushback is represented by a cone of a larger size with preserved slope angle (ratio between cone’s diameter and height). Blocks enclosed in mining area of the synthetic deposit are extracted at once. Ore can be sequenced based on metal grade, mineral grade, processing cost, commodity recovery in the separation process, or by any other desirable property.

For the mine scheduling and open pit optimization, there are several methods available such as floating cone (Laurich, 1990), Lerchs–Grossman algorithm (Lerchs and Grossmann, 1965), network flow approaches (Picard, 1976), Dagdelen–Johnson Lagrangian Parametrization (Dagdelen and Johnson, 1986). Meagher et al., (2014) and Newman et al., (2010) provide a review of those and some more methods for the open pit optimization and mine planning. In this thesis, the optimization step was done by approximating open pit by a cone enveloping the whole ore body. The pushbacks are simply the sequential cones allocated with equal intervals from the bottom to the top of the ore body.

![Figure 19 The sequential open pit mining (pushbacks).](image)

**Processing.** The process model is implemented through process simulation in the HSC Sim 7.1 process simulator (Outotec 2012). The simulation is done by considering the liberation and distribution of the mineral particles, and the process simulator is capable of handling liberation information and multiphase particles. The process model treats each voxel separately. The voxel information is retrieved from the synthetic ore body model and the time aspect is controlled by
the mining model. The information on the plant feed, gathered through geological information from each voxel, enables the utilisation of particle-based models (Koch and Rosenkranz, 2017; Lamberg and Lund, 2012; Lamberg and Vianna, 2007). As the material enters the plant, it is converted to particles by applying the liberation distribution of the corresponding geometallurgical domain. The modal composition of a block and the geometallurgical domain may be different; the mass proportions of particles in the particle population are adjusted using eq. (8) (Lund et al., 2015):

\[ \hat{p}_j = p_j \cdot \sum_{i=1}^{L} (\chi(i)_j \cdot \kappa_i) \]  

(8)

where \( \hat{p}_j \) is the iteratively adjusted mass proportion of the mineral grades; \( p_j \) is the mass proportion of the mineral grades before adjustment; \( \chi(i)_j \) is the mass proportion of mineral in a particle; \( L \) is a total number of minerals; and the correction factor \( \kappa_i \) is calculated for each mineral \( i \) before each iteration round as follows, eq. (9):

\[ \kappa_i = \frac{M(i)}{\sum_{j=1}^{N} (p(j) \cdot \chi(i)_j)} \]  

(9)

where \( M(i) \) is a mineral grade in the sample; \( N \) is number of particles; and \( p \) refers to the mass proportion of particle in a size class. So, the denominator is the mineral grade back-calculated from the liberation data.

The unit process models contain a description of the behaviour of each particle based on one or several properties: density, size, mineral composition, and shape (Lamberg, 2010). For each processed voxel or block the process model returns product quantities and qualities (elemental grades, mineral grades, particle size distribution (PSD), mineral liberation information) with processing information (time spent on processing the block, processing costs and consumables quantities required for processing the block.)

The process model uses the geological information modelled in the synthetic ore body model from the previous steps (see 4.2.3.1 Geology) as an input (in other words, feed stream). The geological information of each voxel is fed to the beneficiation simulation separately (no blending). The output of the beneficiation simulation includes the composition of all the process streams; recoveries, mass pulls of the separation processes; throughputs and energy consumption calculated for each voxel. Beneficiation information produced at this step can be added to the database and be linked to the spatial part of the model by a unique ID.

For the beneficiation simulation done at an elemental level, an input would include elemental composition of the voxel, i.e., Fe, Si, Al etc. At a mineralogical level, such input would include modal mineralogy of the voxel, i.e., commodity mineral (e.g., magnetite) and gangue minerals (e.g., biotite, quartz etc.). Beneficiation simulation by size is possible if mineral distributions in the synthetic ore body model are simulated by size. Alternatively, a fragmentation model may be applied over the synthetic data, c.f. Ouchterlony, (2005); Sanchidrián et al., (2012).
In order to design a beneficiation simulation model, process performance information is needed for the similar ore types. Such information can include lab scale tests (e.g., WLIMS, DT, flotation, BWi test), pilot plant tests, or plant survey.

### 4.2.3.3 Economics

The final performance of every mining project is always estimated economically. Conclusions can be drawn by comparing costs related to the implementation of the project and operating mining production, and revenues obtained from the sold final material. Capital and operating costs of production can be estimated from cost models (e.g., InfoMine, (2018); Sayadi et al., (2014)) and revenues – from the historical commodity prices taken at any date (e.g., Kitco Metalc Inc., (2017); LME, (2018)). While revenues are directly connected to the recoverable commodity grade, operating cost cannot be estimated so easily. Firstly, mining operating cost is linked to the ease of extraction of each block and the cost of transportation to the processing plant. For each mining method, there is a mineral recovery and dilution; and mining layout also has an influence (Table 15).

#### Table 15 Ore recovery and dilution for different mining methods (modified after Darling, 2011).

<table>
<thead>
<tr>
<th>Mining method</th>
<th>Relative cost</th>
<th>Flexibility</th>
<th>Selectivity</th>
<th>Recovery, %</th>
<th>Dilution, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface mining</td>
<td>0.10</td>
<td>moderate</td>
<td>moderate</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Room-and-pillar (coal)</td>
<td>0.30</td>
<td>high</td>
<td>high</td>
<td>50-80</td>
<td>20</td>
</tr>
<tr>
<td>Stope-and-pillar</td>
<td>0.30</td>
<td>high</td>
<td>high</td>
<td>75</td>
<td>15</td>
</tr>
<tr>
<td>Sublevel caving</td>
<td>0.40</td>
<td>low</td>
<td>low</td>
<td>75</td>
<td>15</td>
</tr>
<tr>
<td>Shrinkage stoping</td>
<td>0.50</td>
<td>moderate</td>
<td>moderate</td>
<td>80</td>
<td>10</td>
</tr>
<tr>
<td>Cut-and-fill</td>
<td>0.60</td>
<td>moderate</td>
<td>high</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>Longwall</td>
<td>0.20</td>
<td>low</td>
<td>low</td>
<td>80</td>
<td>10</td>
</tr>
<tr>
<td>Sublevel caving (top slicing)</td>
<td>0.50</td>
<td>low</td>
<td>low</td>
<td>90</td>
<td>20</td>
</tr>
<tr>
<td>Block caving</td>
<td>0.20</td>
<td>low</td>
<td>low</td>
<td>90</td>
<td>20</td>
</tr>
</tbody>
</table>

Depending on the mining method (Table 15), the cost of separate block extraction can have a connection to the cost of extraction of neighbouring blocks. Hardness and mass of the volume unit would be another parameter to control. Process operating costs will depend on the energy used in comminution and the chemicals and energy costs for separation processes.

The mining cost solution implemented in the synthetic ore body model accounts for the depth of the mining and density of the extracted material. The cost solution implemented in the synthetic ore body model accounts for the depth of the mining and its density. The processing cost per tonne is considered to be a constant value. Present value (PV), future value (FV) and NPV of the material (concentrate or metal) produced by the process are calculated as shown by eq. (10). The results from the economic model can be used for comparison between different scenarios, or for estimating the impact of managerial decisions.
where \( j \) is a period \([1,N]\); \( d \) is a discounting rate, %; \( P \) is the metal price; \( C_s \) is the sales cost; \( Q_r \) is the material recovered in mining and process, units per period; \( C_p \) is the processing cost; \( Q_p \) is the processed amount of material, units per period; \( C_m \) is the mining cost; \( Q_m \) is the mined amount of material, units per period.

### 4.2.4. Sampling module

Sampling is the main source of information on the deposit’s geology, mineralogy and processing properties. Synthetic sampling is implemented by simulating synthetic drill cores. Mathematically they can be represented as infinitesimally thin cylinders, or as lines, eq. (11):

\[
\frac{x - x_0}{l} = \frac{y - y_0}{m} = \frac{z - z_0}{n}
\]

where \((x_0, y_0, z_0)\) is some point on the line, and \((l, m, n)\) are non-zero numbers where \(l\) is an \(x\)-intercept, \(m\) is an \(y\)-intercept, and \(n\) is an \(z\)-intercept.

The sampling module (Figure 20) enables the investigation of different drilling patterns, orientations, and sampling densities. The spatial part of the sampling module includes X, Y, Z coordinates of each sample. For sampling with drillholes, coordinates X, Y, Z correspond to the location of the section of the drill core. The coordinate system used in a sampling module is the same as for the Deposit module described in 4.2.2.1 Spatial data.

The difference between a drill core, and reverse circulation (RC) chips may be considered by selecting the sample sizes (half core, quarter core) and sample preparation methods. Sample size in the drillholes is defined by the sample or composite length. A smaller composite length allows better capturing of the variability of the studied parameter, e.g., magnetite grade, BWi, etc. A larger composite size would smooth the data. The advantage of larger sample size is the lower total number of samples needed to assay or test all the drill cores and thus lower cost. The synthetic
sampling module does not have any sample size limitation and allows simulation of infinitely small samples. This will lead to a larger number of records in the database of the sampling module.

The difference between sampling methods is implemented through the errors ($\varepsilon$) added to the sampled values eq. (12). This allows for studying different sampling strategies. The number of vertical drillholes is limited by the number of voxels covering the horizontal cross-section of the block model. A single sample can consist of one or several voxels. Non-vertical drillholes are described with dip and azimuth in addition to the total depth and collar coordinates. Synthetic drill cores are extracted as composites where composite length can be defined depending on the variability in the deposit and purpose of the study.

Synthetic element composition in a drill core sample is obtained by transferring values from the nearest voxel in a voxel model to the segments of the synthetics drill cores. Those chemical compositions do not account for the error of the assaying methods, i.e., XRF. Therefore, chemical compositions of the synthetic drill core samples are converted to chemical assay values by applying an error model. The error model is based on the precision and accuracy information for chemical analyses, e.g., for XRF, eq. (12):

$$G_{XRF} = G_{true} \pm \varepsilon$$

where $G_{XRF}$ is a component’s grade analysed by synthetic XRF; $G_{true}$ is a synthetic value of the component grade of the sample; $\varepsilon$ is the measurement error which can be described by a normal distribution with standard deviation $\sigma$ and expected value 0.

The standard deviation for each elemental assay ($\sigma_{El}$) is computed as a product of elemental grades ($G_{true}$) and relative standard deviation ($RSD_{El}$) as shown in eq. (13).

$$\sigma_{El} = G_{true} \cdot RSD_{El}$$

4.2.5. Reference case: Malmberget

A synthetic iron ore body model is created based on results from previous extensive and careful characterisations of the structural and mineralogical information from Malmberget iron ore deposit in Northern Sweden (see, 2.2.3 Reference case: Malmberget). The deposit, upon which the model is based, consists of several tabular to stock-shaped ore bodies of massive to semi-massive magnetite and/or hematite deformed into a synformal shape (Bauer et al., 2018; Lund, 2013).

4.2.6. Tested strategies

4.2.6.1 Sampling program (Paper C)

Assays from the drill core samples were used to select the samples for geometallurgical testing. Geometallurgy suggests that metallurgical performance can be linked to the geological properties
of the ore, i.e. geometallurgical ore types. Thus, geological parameters were isolated by clustering technique and assays of the drill core samples were classified by k-mean clustering algorithm (MacQueen, 1967). The Euclidean distance between the multivariate means of the n=2..N clusters was used as an indication of the difference between the geological parameters. Clustering was performed on normalised data by computing a standard score for each input according to (14):

\[ Z = \frac{X - \mu}{\sigma} \]  

(14)

where, \( \mu \) is the arithmetic average, \( \sigma \) is the standard deviation.

The results of the virtual DT tests for selected samples were created using HSC Sim 7.1 process simulator (Outotec, 2012). For each sample sent for the virtual DT test both modal composition and textural class information was provided. Based on this information the particle population of about 350 particles was generated in the simulator for given particle size distribution with \( P_{80} = 100 \) microns. For more information on how modal composition and liberation information of an archetype was combined for defining the feed stream see Lund et al., (2015). In the magnetic separation the separation of minerals was set perfect: for fully liberated minerals 100% of magnetite was recovered into the concentrate and 100% of gangue minerals ended into the tailing. For composite particles the simulator calculated the distribution value (recovery) based on recoveries of fully liberated particles and their mass proportions in a composite particle. The final outcome of the virtual DT test was the concentrate grade (Fe), its quality (P and Si contents), mass pull and iron recovery. Chemical composition of the concentrate produced was assayed by virtual XRF including the above described error model, thus the result generated in the virtual DT included experimental error.

Real processing parameters were calculated in the same manner (but without experimental error) for all the voxels of the synthetic ore body. These parameters are referred as “real parameters” or real case scenario (RCS). Geometallurgical sampling procedure was repeated several times by gradual increase of n from 2 to N, until results from the testwork converged RCS. Results from the final iteration (N) were used to build a predictive geometallurgical model.

In reality the DT results are further scaled-up to forecast the full-scale production results. Here a simplification was made that DT equals to the metallurgical result in a full-scale process.

Two different approaches were used to build a geometallurgical predictive model: mineralogical – based on mineral grades; and elemental – based on elemental grades. Therefore, EMC was done for obtaining modal composition for the ore body and DT concentrate. The predictive model was based on the nearest neighbour algorithm and was predicting performance of each voxel based on Fe, P, and Si grade for the elemental approach and Mgt, Ap, and Si grades for the mineralogical approach.
4.2.6.2 Economic performance (Paper D)

Five different scenarios (Difference between production scenarios) forecasting the production were assessed with the help of the synthetic orebody. Variation of two parameters was included in the scenarios: existence of geometallurgical program and possibility for stockpiling. The first set of scenarios examined the production approach. ‘A’ and ‘B’ scenarios assumed perfect stockpiling conditions, which implied that there was no limitation to the sequence of sending ore to the processing plant. ‘C’ and ‘D’ scenarios assumed no stockpiling; thus the mined block was immediately sent to the plant.

The other set of scenarios reviewed the presence or the absence of the geometallurgical program. ‘A’ and ‘C’ scenarios didn’t include geometallurgical program and therefore optimisation of the mining was done through head grade and assumption on constant recovery. ‘B’ and ‘D’ scenarios assumed perfect geometallurgical program. For each block complete information of its value was available through process simulation and this was used for optimisation. ‘B’ and ‘D’ were based on a mineralogical approach, which meant that instead of metal recoveries, mineral recoveries were considered, and processing the recovery model itself was built on mineralogy rather than metal accounting.

<table>
<thead>
<tr>
<th>Production scenarios</th>
<th>Usage of geometallurgy</th>
<th>Stockpiling</th>
</tr>
</thead>
<tbody>
<tr>
<td>‘A’</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>‘B’</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>‘C’</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>‘D’</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>‘E’</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

Forecasts were evaluated in two ways based on:

1. The internal rate of return (IRR) and NPV with the annual discretisation for each case;
2. The second set of NPV values for the block-based discretisation (focuses on optimisation of time required to process each block). Finally, all four scenarios ‘A’, ‘B’, ‘C’ and ‘D’ were compared to the scenario ‘E’. Scenario ‘E’ represented the geometallurgical scenario where discounted cash flow was optimised. Thus, ‘E’ was designed to give the best possible outcome.

For better understanding of the model, the difference between cash flows for ‘A’ versus ‘B’, and ‘C’ versus ‘D’ production scenarios was reviewed. To make the scenarios more realistic premiums and penalties were set on quality of the produced concentrate and were included in the economic model. Premiums were added under the condition that concentrate met the following requirements: P% < 0.025, SiO₂% < 0.80, Al₂O₃ % < 0.28, MgO% < 0.35, TiO₂ % < 0.45, Na₂O% < 0.06, CaO% < 0.20.

Penalties were applied under the condition that concentrates met the following requirements: P% > 0.075, SiO₂% > 4.00, Al₂O₃% > 0.70, MgO% > 1.00, TiO₂ % > 0.40, Na₂O% > 0.22, CaO% >
1.90. Amount of penalties paid was dependent of the total number of breached conditions. For example, P% > 0.075 meant that only 75% of the concentrate value could be paid, CaO% > 1.90–0% of the concentrate value could be paid. The economic parameters are summarised in Table 17.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iron price, $/t</td>
<td>53.16</td>
<td>Processing operating cost, $/t</td>
<td>17.1</td>
</tr>
<tr>
<td>Freight charge, $/t</td>
<td>8</td>
<td>Premium, $/t</td>
<td>5.0</td>
</tr>
<tr>
<td>Discount rate, %</td>
<td>10</td>
<td>CAPEX, M$</td>
<td>20.0</td>
</tr>
</tbody>
</table>

### 4.3. Process modelling (Paper B)

#### 4.3.1. $X_{LTU}$ - Ore classification

In processing, the DT tests are done on drill cores, and the minimum available information includes a mass pull and rough estimate of the feed composition from the geological database or handheld XRF analyser. The handheld XRF analyser can be used when data from the database is not easily accessible. Based on this knowledge, a new quality estimator ($X_{LTU}$) for classifying ore types was proposed. The $X_{LTU}$ classifies the ore considering both its composition and behaviour in magnetic separation. The idea is that if all available magnetite in the ore is reporting to the DT concentrate as pure magnetite, then $X_{LTU}$ will be zero:

$$X_{LTU} = F_e^{Feed} - MP \cdot 0.724$$  \hspace{1cm} (15)

Positive values of $X_{LTU}$ appear when iron content in DT concentrate is less than expected. Therefore, in this case, some iron is lost to the tailings. Negative values of $X_{LTU}$ appear when the mass pull (MP) is larger than expected. In this case, it means that concentrate is not as clean as expected.

#### 4.3.2. Fe recovery in WLIMS

Separation in WLIMS, i.e., iron recovery, is controlled mainly by magnetic, gravity, drag, and mechanical forces. While in the DT, separation is due to magnetic, gravity, and drag forces. Therefore, iron recovery for WLIMS may be written as:

$$R_{WLIMS}^{Fe} = R_{DT}^{Fe} + t + n_r$$  \hspace{1cm} (16)

where, $R_{WLIMS}^{Fe}$ is iron recovery in WLIMS; $R_{DT}^{Fe}$ is iron recovery in DT; $t$ is a systematic component which considers non-magnetic forces involved in separation performance in WLIMS; $n_r$ is a random noise, which can be neglected since it is averaged to zero. Therefore:

$$R_{WLIMS}^{Fe} - R_{DT}^{Fe} = \Delta R \rightarrow if \ n_r \approx 0, then \ \Delta R = t$$  \hspace{1cm} (17)
So, knowing the iron recovery in DT and being able to explain the recovery difference $\Delta R$ via the trend function $t$, allows one to forecast the iron recovery in WLIMS, provided the test settings of the DT, i.e., magnetic field strength, correspond with the magnetic force in WLIMS.

### 4.3.3. Fe-oxides liberation with PCA/PLS

Any potential proxy tool for the Fe-oxides liberation prediction should be capable of a rough forecast using as little information as possible, so that additional work and costs related to the extra analysis for chemical assays or mineralogical studies will not be needed. When the DT is used for predicting liberation, the simplest data may include mass pull and possibly feed composition, if the latter is available from drill core logging or portable XRF. More complex predictions require chemically assayed DT products, and process performance parameters, i.e., difference indices, and recoveries. Additionally, information by size and applying different magnetic fields strengths can be used. This thesis focused on considering fully liberated Fe-oxides. Studying liberation properties of mixed particles would require a more extensive sampling campaigns, with additional metallurgical testing and mineralogical characterisation.

PCA and PLS methods were used for pattern recognition. PCA handles large number of interrelated variables by reducing dimensionality of the original data set. Dimensionality reduction is achieved by transforming the data set to the principal components (PCs) which cover most of the variation of the original data set. (Jackson, 1991; Jolliffe, 2002; Shlens, 2014). Steps for performing PCA can be found in the literature (Keho, 2012; Legendre and Legendre, 1998; Shlens, 2014; Vidal et al., 2016). Here, the software SIMCA ver. 14 (Eriksson et al., 2013) was used for modelling. Confidence levels were left at the default value 95%.

PLS is an extension of PCA and was used as a mathematical tool for relation recognition in this thesis. PLS works as a regression model which links primary variables $x$ and response variables $y$. Difference and relationships between PCA and PLS as well as their usage is well covered in the literature, e.g., Godoy et al., (2014), Kettaneh et al., (2005). The quality of modelling was evaluated with the goodness values of cumulative explained variation ($R^2_X$ and $R^2_Y$), and the cumulative predicted variation ($Q^2$) of the total variance. The higher values of $R^2_X$, $R^2_Y$, $Q^2$ the better is a model.

PCA/PLS have been widely used in mineral processing. Pourghahramani et al., (2008) has used PCA and PLS to study relationship between grinding variables and structural changes during mechanical activation of hematite concentrate. (Tungpalan et al., 2015b) used PCA to create predictive models for relating mineralogical and textural characteristics to the copper recovery. Finally, PCA and PLS were used by Gallmeier et al., (2017) in predicting the extractability of hydrocarbons from shales. Rincon et al., (2019a) used PCA to link mineralogical features and flotation recovery.
4.4. Spatial modelling (Paper F)

The spatial model of the process properties is built by the methodology illustrated in Figure 21. First, the ore samples are characterised mineralogically (liberation analysis in Table 23) and chemically ($X_{PS}$, in Table 24), and then are subjected to the mineral processing testwork (Table 23). Second, the process ($Y_{PS}$) and chemical ($X_{PS}$) properties of the ore samples (the first dataset) are used to build non-spatial process models. Third, the geological database is populated with process properties estimated from the non-spatial process models ($Y_{PS}$) and using chemical assays from the geological database (second dataset) as input variables. The geological database with estimated process properties is referred to as the updated geological database. Fourth, the process properties, iron grades, and coordinates of each drill core sample contained in the updated geological database are extracted and form a third dataset ($X_{DHD}$). The third data set is used to build spatial process models ($Y_DHD$). Those models can be used for populating production block model (geometallurgical block model) or drillholes not assayed for the chemical elements other than iron grade.

![Figure 21 Development of a spatial model for the process properties.](image)

To the best of our knowledge, machine-learning has not been widely applied to the spatial modelling of process properties. The most common techniques to model process properties spatially till now have been regression models (Macmillan et al., 2011), multivariate statistics, such as principal component analysis and partial least square methods (Keeney et al., 2011; Keeney and Walters, 2011; Newton and Graham, 2011), and geostatistical methods such as kriging (Preece, 2006). The advantage of using machine-learning methods is fast processing and the capability to manage multi-dimensionality, while the main drawback is a need for large training data sets for the prediction.

The inputs and outputs of models and how the process properties measured in ore samples are integrated into geological database and to the spatial model are shown in Figure 22. The process properties ($\{R_{Fe^{W/IM}}, R_{Fe^{DT}}, M_{W/LMS}, M_{DT}, P_{80}, L_{Fe-oxy}\}$) of the ore samples are not linked to a special location and exist in one dimensional space of point samples (1D). Ore samples have small volume (mass of each ore sample is approximately 60 kg, and even smaller volumes are used in testwork). The small volume means that samples have a small support size in spatial planning. Support is an average volume over which the data are measured or defined (Chilès and Delfiner, 2012). When process properties ($Y_{PS}$) are modelled as functions of the chemical composition of the feed ($X_{PS}$), cf. Table 24, and are deployed into the updated geological database, the process properties can be referred to as existing in two-dimensional space (2D). Support of those samples may increase compared to the ore samples if their composite length is high enough. If coordinates of the drill core collars are known, then the process properties can be referred to as existing in three-dimensional space (3D). When the process properties deployed into the updated geological
database are modelled ($Y_{DHD}$) as function of samples’ coordinates and iron grade only, then the process properties can be referred to as existing in three-dimensional space (3D). Since blocks in the block model always have a larger volume than composites from the geological database, the support of the blocks will increase. The spatial model can be used for populating spatial objects (geological database or block model) with process parameters assuming spatial correlation of the process properties. Special attention should be paid to the change of support, which can be source of additional errors.

All the modelling is done with the WEKA software package (Frank et al., 2016b) using default settings for the models parameters. Both population and extraction processes are done by using machine-learning methods listed in Table 18. The methods included eight individual models for building both non-spatial and spatial process models. Amalgamating the various outputs into a single prediction may increase accuracy (Witten et al., 2017). Therefore, two additional models were used in spatial process modelling - meta-models built as an aggregation by computing average and median of the eight individual models. Only raw data are used as model input variables; thus, no data transformation is applied.
4.4.1. Non-spatial process modelling

Eight modelling methods (see Table 18) are used for modelling six process properties \( Y_{PS} \) (Figure 22) measured from the ore samples \( \{ R_{Fe}^{W L I M S}, R_{Fe}^{D T}, M_{W L I M S}, M_{DT}, P_{B0}, L_{Fe-DX} \} \), see Table 23. The elemental grades of the ore samples are used as primary input variables \( X_{PS} \) (Table 24).

Table 18 Machine learning modelling methods from WEKA.

<table>
<thead>
<tr>
<th>ID</th>
<th>Models / Abbreviation</th>
<th>Description</th>
<th>Classifier type</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Elastic Net / EN</td>
<td>EN is a regression model with the elastic net penalty determined as a combined penalty of lasso and ridge methods.</td>
<td>Function*</td>
<td>(Zou and Hastie, 2005)</td>
</tr>
<tr>
<td>2</td>
<td>Linear regression / LR</td>
<td>LR is expressed as linear combination of attributes with predominant weights.</td>
<td>Function*</td>
<td>(Frank et al., 2016b; Witten et al., 2017)</td>
</tr>
<tr>
<td>3</td>
<td>Sequential minimal optimization for support vector regression / SMO</td>
<td>SMO uses linear models to implement nonlinear class boundaries. Essentially, SMO is an iterative algorithm for solving the regression problem using support vector machine (SVM).</td>
<td>Function*</td>
<td>(Shevade et al., 1999; Smola and Schölkopf, 2004; Witten, 2017)</td>
</tr>
<tr>
<td>4</td>
<td>Instance-bases learning with parameter k / IBk</td>
<td>IBk assumes that similar instances will have similar classifications. The method is sensitive to the number of irrelevant attributes.</td>
<td>Lazy*</td>
<td>(Aha et al., 1991)</td>
</tr>
<tr>
<td>5</td>
<td>K* instance-based classifier / K*</td>
<td>K* is an instance-based classifier uses entropy as a distance measure.</td>
<td>Lazy*</td>
<td>(Cleary and Trigg, 1995)</td>
</tr>
<tr>
<td>6</td>
<td>M5Rules / M5</td>
<td>M5 builds model trees repeatedly, and the best rule is selected at each iteration.</td>
<td>Rules*</td>
<td>(Holmes et al., 1999; Quinlan, 1992; Wang and Witten, 1997; Frank et al., 2016)</td>
</tr>
<tr>
<td>7</td>
<td>Random forest / RF</td>
<td>RF is a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. The generalization error for forests converges to a limit so the number of trees in the forest becomes large. The drawback is lack of interpretability.</td>
<td>Trees*</td>
<td>(Breiman, 2001)</td>
</tr>
<tr>
<td>8</td>
<td>M5P/ M5P</td>
<td>M5P uses a decision-tree induction algorithm to a build tree. Method does not maximise the information gain at each interior node. It uses splitting criterion that minimizes the intra-subset variation in the class values down each branch. Consideration is given to pruning the tree back from each leaf.</td>
<td>Trees*</td>
<td>(Quinlan, 1992; Wang and Witten, 1997)</td>
</tr>
<tr>
<td>9</td>
<td>AVE</td>
<td>AVE is an arithmetic average from EN, LR, SMO, IBk, K*, M5, RF and M5P</td>
<td>Meta</td>
<td>-</td>
</tr>
<tr>
<td>10</td>
<td>MED</td>
<td>MED is a median estimated from EN, LR, SMO, IBk, K*, M5, RF and M5P.</td>
<td>Meta</td>
<td>-</td>
</tr>
</tbody>
</table>

* Classification for lazy, trees, functions and rules is adopted from Frank et al., (2016): Lazy are instance-based classifiers; Trees are based on decision trees; Function can be written down as mathematical equations in a reasonably natural way; Rules are similar to trees although are more unsupervised (more on the differences between rules and trees in Ordonez and Zhao, (2011)).

The modelling results are assessed using \( k \)-fold cross-validation with 10 folds. In \( k \)-fold validation, the original dataset is randomly divided into \( k \) subsets of equal size. One out of ten \( k \) subsets are
retained for testing the model. The remaining \( k-1 \) subsets are used for model training. The cross-validation process is repeated \( k \) times and each subset is used only once for validation.

4.4.2. Populating geological database

Derived models are compared in terms of RSD ((18) and the most suitable model is used for populating the geological database with the process properties \((Y_{DS})\). The selected method is also improved by applying selection of the significant variables, which is also known as feature selection or variable selection. The number of variables higher than optimal (subset of the variables at which accuracy of the classifier is maximal) may decrease the accuracy in machine-learning methods. The optimal number of variables can be reached by applying the significant variable (variables with low signal-to-noise ratio) selection (Kohavi et al., 1997). The updated geological database allows for spatial modelling of process properties, since each sample in the geological database contains corresponding coordinates of the samples location in 3D physical space \((x, y, z)\).

\[
RSD = \frac{\sigma}{\mu} \cdot 100\% \tag{18}
\]

where, \( \sigma \) is standard deviation, and \( \mu \) is mean of population.

4.4.3. Spatial process modelling

The modelling methods (see Table 18) are also used to extract process properties and build spatial process models \(Y_{DHD}\) using coordinates \((x, y, z)\) and iron grades from the positions in geological database as primary input variables \(X_{DHD}\). The grade of iron was used in building the spatial process models, since it is the only element estimated in the block model and it has been verified by a competent person. The obtained models \(Y_{DHD}\) for the process properties are used to do geometallurgical mapping – populating geological block model, or geological database for newly added drillholes with process properties. Introducing additionally AVE and MED models may yield more robust estimate of the process properties by mitigating the impact of extreme values (potential outliers) in prediction.

The spatial process modelling results are assessed with verification by splitting the updated geological database into training and testing subsets. The testing subset is formed by selecting positions in the geological database, which correspond to a single drillhole. All other positions in the geological database, excluding the one selected for testing subset, form training subset. The spatial process modelling is performed on the training subset and then process properties are predicted for the testing subset \((\hat{Y}_{DHD})\). The newly predicted process properties \((\hat{Y}_{DHD})\) are compared to the ones already available at the geological database \((Y_{DHD})\). The procedure is repeated three times, by selecting different drillholes to be excluded from the updated geological database for each verification round. The drillholes chosen for verification 13008, 14031, and 14057b represent different parts of the ore body, and were selected based on the number and average length of the composites, and average iron grade (Table 19).
The precision is measured with RSD (Irvin, 1970). The machine-learning methods are considered to be good enough if the upper bound limit of RSD is below 25 % (David, 2013). RSD values below 5% suggests that the machine-learning method is excellent (Grubbs, 1969) for spatial modelling of the assessed process property.
"Stupidity is doing same thing and expecting different results"

Unknown (Not Einstein)

5.1. Classification of geometallurgical programs (Paper A)

The classification system developed here (Figure 23) has two dimensions: the first dimension is the type of geometallurgical approach and the second dimension is the depth of application of geometallurgy.

![Figure 23 Selected mines arranged in classification matrix.](image)

LEGEND

Continents:
- Europe
- Southern America
- Northern America
- Africa
- Australia and Oceania

Commodities:
- Precious metals (e.g., Au, Ag, PGM)
- Base metals (e.g., Cu, Ni, Zn)
- Ferrous (Fe)
- Polymetallic (e.g., Au and Cu; Ag, U and Fe)
- Non-metals (e.g., diamonds, coal, phosphates)
5.1.1. Approaches

The classification system shown in Figure 23 is essential for identification of different ways to connect geological information and ore performance in the process. Three geometallurgical approaches were systematized in this thesis to classify case studies shown in Figure 23: traditional, proxy and mineralogical. Each geometallurgical approach is divided into two sub-approaches: domained and global. The domaining sub-approach implies a more advanced use of a block model, while a global sub-approach does not require a block model at all. In other words, mines that follow the domained geometallurgical approach in Figure 23, generally have more capabilities towards developing a more advanced geometallurgical program.

5.1.2. Applications

The depth of the geometallurgy application, described in Figure 23, shows the level of geometallurgy involvement in production management for the selected case studies. The practical use of this classification system becomes obvious when there is a need to either change a geometallurgical approach (e.g., from traditional to proxies or from proxies to mineralogical) or to go to a more advanced level of the geometallurgy application. Eight levels of application were identified (Figure 23 and cf. Table 14) in the order of increasing involvement in production management ranging from the simplest (level 0) to the more advanced (level 7): (0) none, (1) data collecting, (2) visualization, (3) forecasting, (4) changing process, (5) constraining, (6) production planning and (7) managing production scenarios. Normally, the more advanced level includes all features of the lower levels.

5.2. Preliminary testing of a geometallurgical program with synthetic data (Papers C, D, E)

5.2.1. Geological model

The synthetic ore body model was created in MATLAB. The deposit has three textural types, i.e., Amph-(Ap-Bt), Ap-(Amph) and Fsp (Figure 24) were spatially modelled based on characterisation described earlier for the Malmberget reference case. Spatial distribution of the textural types was arranged according to the distribution suggested by Lund, (2013).

![Figure 24 Spatial distribution of textural types in cross-sections generated from the synthetic ore body. A – in a plane XZ, B – in a plane YZ, C – in a plane XY.](image-url)
5.2.2. Mining model

The synthetic ore body is modelled as a surface deposit, therefore open pit mining is used as the mining constraint, which is approximated with a cone model. Mining and time constraints are modelled as 13 sequential cones, representing pushbacks in a synthetic open pit mine. The overall slope angle of this open pit model is 40°. Mined cones set the time variable in the later process simulation, when blocks are sent to the processing according to the mining plan. A production plan was generated from the mining model (Figure 25). In Figure 25, an interesting pattern emerges, where mining of the synthetic ore body shows considerable variations in the ore fed to the concentrator. This is based only on the assumed geological model and textural information.

![Figure 25 Production plan generated from the mining model.](image)

5.2.3. Process model

The process model used for this case study is based on Lund, (2013) and is comprised of two main sections: dry processing and wet processing. Dry processing includes cobbing and size reduction in a cone crusher. Wet processing has three stages of WLIMS and two stages of grinding and dewatering. Here, the final concentrate is the feed to the pellets plant and recycled water is returned to the head of the process.

The simulation used to create the process performance forecasts was run for 12,231 blocks, using five iterative calculation rounds. The outcome of the simulation model was an amendment to the stream file, and included information on the concentrate: modal mineralogy, chemical composition, recoveries of main commodity minerals and elements, processing time, concentrate tonnage per hour and feed tonnage per hour. These values were used as an input to the economic model. The simulated magnetite recoveries (Figure 27) show that there are three distinctive populations of the process responses influenced by textural differences (Amph-(Ap-Bt), Ap-(Amph) and Fsp). The dispersion of the simulated recoveries is due to the texture differences of the different textural types.

![Figure 27 Simulated magnetite recoveries](image)
Validation of the synthetic ore body model was done by visual comparison of the geological structures (textural types) proposed by Lund, (2013), shown in Figure 5, and the textural types generated from the synthetic ore body model, shown in Figure 24. Comparison between the predicted and measured commodity recoveries was done based on Figure 6 and Figure 27. Additional possible validation could be done using geostatistical methods by comparing variograms. Variograms of the real case study and variograms of the synthetic ore body could be compared for the entire ore body, for selected zones (e.g., oxidation zones, ore types), or for drillholes. However, the exact locations of the Malmberget samples’ origin in the ore body are not known. Therefore, there is no possibility to construct validation variograms from the real-life case study.

5.2.4. Sampling module

Two synthetic sampling campaigns were produced to illustrate the flexibility of the synthetic drilling in terms of drillhole spacing and assayed parameters. In both campaigns, drill cores are dipping vertically and have regular pattern of collar locations. The first (Figure 28 - A) comprised a 25 drillholes pattern, where thicker composites represent higher iron grade. The second pattern (Figure 28 - B) comprised of 81 drillholes, with thicker composites representing higher magnetite grade and a colorbar showing the actinolite grade. The composite length for both campaigns was chosen as 1/3 of the voxel size (25/3 = 8.33 m). Higher iron/magnetite grades identify the extent of the ore body thus showing efficiency of the sampling campaign in outlining the deposit. The sampling database contains the same information as deposit database (Figure 14): mineralogical, mining, process and economic information about each part of the drill core. All those parameters can be easily included and visualised by the sampling campaign.
Figure 27 Mgt recoveries predicted with the HSC based process simulation from the synthetic ore body model. (Abbreviations: Mgt - magnetite; Ap - apatite; Bt – biotite; Amph – amphiboles; Fsp – K feldspars).

Figure 28 Simulated drill core samples. A (left) - 25 (5×5) drill cores with thicker composites representing higher iron grade. B (right) - 81 (9×9) drill cores of the synthetic ore body with thicker composites representing higher Mgt, % and colorbar showing Act, %.

5.2.5.1 Sampling (Paper C)

Clustering for N=10 is presented in Figure 29, where elemental and mineral based approaches give almost identical results in classification.
A total of 200 sampling & geometallurgical testing campaigns were simulated ranging from 2 to 201 samples. Ten geometallurgical predictive models based on the nearest neighbour algorithm (for 2, 5, 10, 15, 20, 25, 30, 50, 100, 200 samples) were investigated and compared. Comparison was made for the prediction of concentrate quality and quantity, see Table 20. Prediction for iron recovery and total concentrate tonnages reaches acceptable level (<5%) already when 10 samples are used as a base of the prediction. Whether the estimate is done based on mineral or elemental grades does not show any significant difference. However, the prediction of the concentrate quality in terms of detrimental components, i.e. phosphorous and silica, is much more sensitive. Even with 100 samples the error in the estimates of production of different quality products is quite bad, >5%. Only in 200 samples the required accuracy is reached.

5.2.5.2 Economic performance (Paper D)

Although Malmberget has very homogeneous and high-quality ore, the difference between prediction and production scenario performances was extensive (see Table 21). In both production options (with stockpile management and without) ‘A’ and ‘C’ (scenarios with optimised head grade) showed lower NPV and IRR values compared to scenarios ‘B’ and ‘D’. Scenarios ‘B’ and ‘D’ have also shown overall economic performance that was very close to the most realistic scenario ‘E’.
Table 20 Prediction of metallurgical performance based on 2-200 samples using elemental approach. Error gives difference between the real case scenario and forecast (100*[forecast-RCS]/RCS).

<table>
<thead>
<tr>
<th>Sample</th>
<th>Prediction based on N samples</th>
<th>Error compared to RCS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HQ</td>
<td>RQ</td>
</tr>
<tr>
<td>2</td>
<td>0.0</td>
<td>36.4</td>
</tr>
<tr>
<td>5</td>
<td>9.7</td>
<td>19.1</td>
</tr>
<tr>
<td>10</td>
<td>25.9</td>
<td>24.8</td>
</tr>
<tr>
<td>15</td>
<td>22.0</td>
<td>22.2</td>
</tr>
<tr>
<td>20</td>
<td>25.9</td>
<td>20.5</td>
</tr>
<tr>
<td>25</td>
<td>25.0</td>
<td>21.6</td>
</tr>
<tr>
<td>30</td>
<td>22.9</td>
<td>27.5</td>
</tr>
<tr>
<td>50</td>
<td>23.9</td>
<td>25.8</td>
</tr>
<tr>
<td>100</td>
<td>23.9</td>
<td>27.2</td>
</tr>
<tr>
<td>200</td>
<td>24.7</td>
<td>25.0</td>
</tr>
<tr>
<td>RCS</td>
<td>25.9</td>
<td>24.8</td>
</tr>
</tbody>
</table>

Abbreviations: HQ is high quality product, RQ is regular quality product, LQ is low quality product.

Table 21 Performance of five examined production scenarios.

<table>
<thead>
<tr>
<th>Production scenarios</th>
<th>NPV, M$</th>
<th>Cumulative cash flow, M$</th>
<th>IRR, %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>By year</td>
<td>By block processing time</td>
<td></td>
</tr>
<tr>
<td>‘A’</td>
<td>5.4</td>
<td>6.7</td>
<td>13.5</td>
</tr>
<tr>
<td>‘B’</td>
<td>10.3</td>
<td>11.9</td>
<td>19.3</td>
</tr>
<tr>
<td>‘C’</td>
<td>4.0</td>
<td>5.2</td>
<td>13.5</td>
</tr>
<tr>
<td>‘D’</td>
<td>8.1</td>
<td>9.6</td>
<td>19.3</td>
</tr>
<tr>
<td>‘E’</td>
<td>11.7</td>
<td>13.4</td>
<td>19.3</td>
</tr>
</tbody>
</table>

Two methods were used for NPV discretisation to compare also the production scenarios. The first NPV type (by year) was discretised by number of production years. And the NPV by block processing time was discretised by the time required to process each block separately. It was clear that planning based on annual discretisation tends to underestimate NPV. Difference in cash flow can be explained by difference in magnetite recoveries assigned for each block. In geometallurgical production scenarios recoveries were taken from the mineral processing simulation. Thus, recoveries in geometallurgical approach were different for each block.

On the other hand, fixed recoveries were used in non-geometallurgical production scenarios. Non-geometallurgical approaches don’t assume predictive recovery model, which explains utilisation of the fixed recoveries. In addition to high NPV shown by scenario ‘E’, it also exhibited shorter than any other production scenario payback time (Figure 29).
Figure 30 Cash flow (CF) and discounted cash flow (DCF) for the investigated production scenarios.

5.3. Process models in magnetic separation of Leveäniemi ore – results and discussions (paper B)

5.3.1. Mineralogical characterisation and process testwork

The ore samples can be classified into two geologically different types based on the drill core assessment/logging (Table 22): massive and semi-massive ore. Both ore types have low amount of P₂O₅ (1.1 %). The massive ore has a high iron content and a low amount of SiO₂. It is characterised by finely grained magnetite with amphibole and apatite as the main gangue minerals. Both amphiboles and apatite have fine and coarse grain intergrowths. Calcite veining is another important but minor textural type. Semi-massive ore has a lower content of iron (less than 50%) and the main non-iron minerals are silicates. Semi-massive ore, unlike massive ore, has a wider variation of minerals and textures. Magnetite is fine-grained and biotite, feldspars (i.e., albite, K-Fsp) and quartz are the main gangue minerals.

The quantified mineralogy (Figure 31) for each sample reconfirms the previously defined two ore classes. Massive ore is Fe-oxide-rich (>90% Mgt, Hem) mainly with the higher content of amphiboles and apatite distributed in the finest size fraction. Semi-massive ore, on the other hand, has a lower Fe-oxides grade, however it contains silicates (predominantly biotite), which are more evenly distributed between the size fractions. The liberation distribution of Fe-oxides (Figure 32) is higher for the finer size fractions for all the ore classes. Sample 12, classified as rich semi-massive ore, is the only sample that equally well might fall into either massive or semi-massive ore class.

The mineralogical analysis can explain difference in mass pull, recoveries or liberation of the material. For instance, iron in amphiboles in mixed particles or as entrainment would give a false prediction of the magnetic separation if it is only based on the iron head grade.

The results of the metallurgical testwork and liberation analysis that are used in further modelling, are summarised in Table 23. The semi-massive ore samples have shown lower mass pull in WLIMS
and DT and also lower recovery in DT than massive. Liberation of iron oxides was higher for massive samples. Iron recovery in WLIMS was higher for massive samples. No connection was found between $P_{80}$ and ore type.

**Table 22 A classification of Leveäniemi ore based on mineral and textural variations.**

<table>
<thead>
<tr>
<th>ID</th>
<th>Ore classes</th>
<th>Iron % in drill core</th>
<th>Textural type</th>
<th>Main associated minerals</th>
</tr>
</thead>
<tbody>
<tr>
<td>13s</td>
<td>Semi-massive ore</td>
<td>&lt;20</td>
<td>Disseminated/Veiny</td>
<td>Mgt+Bt+Ah+Qtz</td>
</tr>
<tr>
<td>1s</td>
<td>Massive ore</td>
<td>20-40</td>
<td>Veiny/Granular</td>
<td>Mgt+Bt+Kfsp+Qtz</td>
</tr>
<tr>
<td>6s</td>
<td>Patchy</td>
<td>20-40</td>
<td>Mgt+Bt+Amph+Qtz+Ap</td>
<td></td>
</tr>
<tr>
<td>9s</td>
<td>Banded</td>
<td>60-70</td>
<td>Mgt+Bt+Kfsp+Qtz</td>
<td></td>
</tr>
<tr>
<td>12s</td>
<td>Rich semi-massive ore</td>
<td>40-50</td>
<td>Coarse-grained amphibole rich</td>
<td>Mgt+Ap+Ah+Bt+Qtz</td>
</tr>
<tr>
<td>5m</td>
<td>Massive ore</td>
<td>&gt;50</td>
<td>Fine-grained amphibole/Calcite rich</td>
<td>Mgt+Amph+Ap+Cal</td>
</tr>
<tr>
<td>8m</td>
<td>Massive ore</td>
<td>&gt;50</td>
<td>Fine-grained amphibole/Calcite rich</td>
<td>Mgt+Amph+Bt+Qtz+Cal</td>
</tr>
<tr>
<td>10m</td>
<td>Massive ore</td>
<td>&gt;50</td>
<td>Coarse-grained amphibole rich</td>
<td>Mgt+Amph+Ap</td>
</tr>
<tr>
<td>11m</td>
<td>Massive ore</td>
<td>&gt;50</td>
<td>Coarse-grained amphibole rich</td>
<td>Mgt+Amph+Ap</td>
</tr>
<tr>
<td>2m</td>
<td>Coarse-grained apatite rich</td>
<td>Mgt+Amph+Ap</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4m</td>
<td>Coarse-grained apatite rich</td>
<td>Mgt+Amph+Ap</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7m</td>
<td>Coarse-grained apatite rich</td>
<td>Mgt+Amph+Ap</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3m</td>
<td>Fine-grained hematite</td>
<td>Mgt+Ap</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Abbreviations: Mgt-Magnetite; Hem-Hematite; Amph-Amphibole; Cal-Calcite; Bt-Biotite; Ab-Albite Qtz-Quartz; K-Fsp-K-Feldspar.

**Figure 31 Modal mineralogy of the treated samples.**

**Figure 32 Fe-oxides liberation for treated samples and size fractions.**

Chemical assays of the feed samples included 13 elements (P, TiO$_2$, V, SiO$_2$, Fe, Al, CaO, MgO, Mn, Na, K$_2$O, Cu, S - Table 24). Drill core samples, listed in geological database, were assayed for 24 elements (Al, As, Ba, CaO, Cl, Co, Cr$_2$O$_3$, Cu, Fe, K$_2$O, MgO, Mn, Na, Ni, P, Pb, S, SiO$_2$, Sn, Sr, TiO$_2$, V, Zn, Zr) and density. Since the ore samples were assayed only for 13 elements, the same 13 out of 24 elements from geological database were used in modelling (Table 24).
Table 23 Mineral processing properties of the process samples.

<table>
<thead>
<tr>
<th>ID</th>
<th>Ore type</th>
<th>$M^{WLIMS},%$</th>
<th>$R^{WLIMS},%$</th>
<th>$M^{DT},%$</th>
<th>$R^{DT},%$</th>
<th>$P_{80},\mu m$</th>
<th>$L_{Fe-ox}%$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1s</td>
<td>Semi-massive</td>
<td>45.5</td>
<td>90.0</td>
<td>44.27</td>
<td>86.33</td>
<td>395</td>
<td>42.21</td>
</tr>
<tr>
<td>2m</td>
<td>Massive</td>
<td>94.8</td>
<td>82.5</td>
<td>90.62</td>
<td>98.39</td>
<td>1,014</td>
<td>78.27</td>
</tr>
<tr>
<td>3m</td>
<td>Massive</td>
<td>69.4</td>
<td>54.9</td>
<td>60.13</td>
<td>63.65</td>
<td>458</td>
<td>79.54</td>
</tr>
<tr>
<td>4m</td>
<td>Massive</td>
<td>96.3</td>
<td>89.9</td>
<td>92.63</td>
<td>99.16</td>
<td>605</td>
<td>75.73</td>
</tr>
<tr>
<td>5m</td>
<td>Massive</td>
<td>89.7</td>
<td>89.1</td>
<td>86.93</td>
<td>98.80</td>
<td>292</td>
<td>79.26</td>
</tr>
<tr>
<td>6s</td>
<td>Semi-massive</td>
<td>69.8</td>
<td>92.4</td>
<td>40.23</td>
<td>90.00</td>
<td>608</td>
<td>55.47</td>
</tr>
<tr>
<td>7m</td>
<td>Massive</td>
<td>95.9</td>
<td>84.7</td>
<td>93.17</td>
<td>98.72</td>
<td>1,945</td>
<td>82.47</td>
</tr>
<tr>
<td>8m</td>
<td>Massive</td>
<td>88.7</td>
<td>86.4</td>
<td>86.79</td>
<td>98.23</td>
<td>187</td>
<td>78.96</td>
</tr>
<tr>
<td>9s</td>
<td>Semi-massive</td>
<td>57.7</td>
<td>91.2</td>
<td>54.12</td>
<td>93.14</td>
<td>217</td>
<td>49.75</td>
</tr>
<tr>
<td>10m</td>
<td>Massive</td>
<td>91.6</td>
<td>90.5</td>
<td>86.34</td>
<td>98.90</td>
<td>419</td>
<td>81.41</td>
</tr>
<tr>
<td>11m</td>
<td>Massive</td>
<td>93.1</td>
<td>79.8</td>
<td>92.56</td>
<td>99.17</td>
<td>205</td>
<td>84.33</td>
</tr>
<tr>
<td>12s</td>
<td>Rich semi-massive</td>
<td>74.2</td>
<td>93.8</td>
<td>66.83</td>
<td>97.29</td>
<td>248</td>
<td>71.39</td>
</tr>
<tr>
<td>13s</td>
<td>Semi-massive</td>
<td>29.1</td>
<td>95.3</td>
<td>29.18</td>
<td>87.54</td>
<td>194</td>
<td>52.35</td>
</tr>
</tbody>
</table>

Table 24 Basic statistics of the chemical assays and density for the ore samples.

<table>
<thead>
<tr>
<th></th>
<th>P, %</th>
<th>TiO₂, %</th>
<th>V, %</th>
<th>SiO₂, %</th>
<th>Fe, %</th>
<th>Al, %</th>
<th>CaO, %</th>
<th>MgO, %</th>
<th>Mn, %</th>
<th>Na₂O, %</th>
<th>K₂O, %</th>
<th>Cu, ppm</th>
<th>S, %</th>
<th>density, t/m³</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>0.50</td>
<td>0.29</td>
<td>0.11</td>
<td>15.29</td>
<td>51.21</td>
<td>2.32</td>
<td>3.04</td>
<td>2.34</td>
<td>0.05</td>
<td>0.60</td>
<td>179</td>
<td>0.04</td>
<td>4.70</td>
<td></td>
</tr>
<tr>
<td>median</td>
<td>0.50</td>
<td>0.29</td>
<td>0.13</td>
<td>6.34</td>
<td>62.13</td>
<td>0.85</td>
<td>2.86</td>
<td>1.98</td>
<td>0.06</td>
<td>0.12</td>
<td>98</td>
<td>0.03</td>
<td>4.96</td>
<td></td>
</tr>
<tr>
<td>stdev</td>
<td>0.23</td>
<td>0.15</td>
<td>0.04</td>
<td>14.73</td>
<td>16.95</td>
<td>2.45</td>
<td>0.82</td>
<td>0.26</td>
<td>0.02</td>
<td>0.79</td>
<td>1.01</td>
<td>0.04</td>
<td>0.48</td>
<td></td>
</tr>
<tr>
<td>max</td>
<td>0.84</td>
<td>0.59</td>
<td>0.17</td>
<td>48.05</td>
<td>66.90</td>
<td>7.72</td>
<td>4.88</td>
<td>4.63</td>
<td>0.08</td>
<td>2.77</td>
<td>2.81</td>
<td>9.05</td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td>min</td>
<td>0.10</td>
<td>0.08</td>
<td>0.04</td>
<td>2.07</td>
<td>16.16</td>
<td>0.24</td>
<td>2.12</td>
<td>0.80</td>
<td>0.02</td>
<td>0.05</td>
<td>0.01</td>
<td>43</td>
<td>0.01</td>
<td></td>
</tr>
</tbody>
</table>

5.3.2. $X_{LTU}$

Modal mineralogy and mineral liberation allow ore classification solely based on mineralogical variability. $X_{LTU}$ was designed as a metric for classifying ore considering both processing properties i.e., magnetic separation in DT and iron grade in feed. When $X_{LTU}$ is plotted against Fe-oxides liberation (Figure 33), it is possible to conclude whether process performance has been impacted by liberation or other factors. For instance, in the case of sample 3 (black ellipse in Figure 33), the high values of $X_{LTU}$ are caused by a high hematite content. Additional examples are the fine fractions of samples 2, 8, 10, 12 (grey rounded rectangle in Figure 33), whose high values of $X_{LTU}$ may be due to a different mineralogical texture in the feed (for the same degree of Fe-oxides liberation) and thus higher iron grades in material are not reporting to concentrate. This was also confirmed by the mineralogical study of the feed, which showed that most of the amphibole is distributed into the finest size fraction.
Fe recovery in WLIMS

The overall comparison of iron recovery in WLIMS against iron recovery in the DT shows no clear correlation (Figure 34). However, there are groups of samples that seem to be dependent on the magnetic current strength. The important observation is that DT cumulative iron recovery exhibits much higher variability for the test conducted at 0.2 A than at 0.1 A and 0.5 A.

The $\Delta R$ function was estimated from the DT test at 0.2 A, due to the highest variability of the iron recovery response in DT at this current strength (Figure 34). PLS was used here to connect the $\Delta R$ variable (response variable $y$) and other iron related process variables (main variables $X$). The $x$ variables included (Table 25): SATMAGAN values of the feed (Feed_Sat), iron in feed (Feed_Fe), iron recoveries (Rec12_Fe), and mass pull (Conc12) in DT. Cumulative mass pull and iron recovery in DT (at 0.1 A and 0.2 A) were included in the model to cover the difference in magnetic and mechanical forces. SATMAGAN values and iron head grade of the DT/WLIMS, were included to cover the differences between massive and semi-massive samples in the feed. PLS analysis produced a model with three statistically significant PCs.

Figure 34 WLIMS iron recovery vs cumulative DT iron recovery at different current strengths at 0.1 A, 0.2 A, and 0.5 A.
Table 25 Input X and Y variables into PLS model of $\Delta R$ (the average values).

<table>
<thead>
<tr>
<th>Parameters, %</th>
<th>Mass pull</th>
<th>Iron recovery</th>
<th>Iron in feed</th>
<th>Satmagan in feed</th>
<th>$\Delta R$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Codes used in modelling</td>
<td>Conc12</td>
<td>Rec12_Fe</td>
<td>Feed_Fe</td>
<td>Feed_Sat</td>
<td>WLIMSminDT</td>
</tr>
<tr>
<td>X/Y variable</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Massive ore samples</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>90.6</td>
<td>98.4</td>
<td>64.8</td>
<td>17.7</td>
<td>52.1</td>
</tr>
<tr>
<td>3</td>
<td>60.1</td>
<td>63.7</td>
<td>62.1</td>
<td>5.5</td>
<td>53.5</td>
</tr>
<tr>
<td>4</td>
<td>92.6</td>
<td>99.2</td>
<td>65.7</td>
<td>20.5</td>
<td>45.4</td>
</tr>
<tr>
<td>5</td>
<td>86.9</td>
<td>98.8</td>
<td>60.4</td>
<td>18.9</td>
<td>48.7</td>
</tr>
<tr>
<td>7</td>
<td>93.2</td>
<td>98.7</td>
<td>66.9</td>
<td>19.3</td>
<td>4.2</td>
</tr>
<tr>
<td>8</td>
<td>86.8</td>
<td>98.2</td>
<td>62.2</td>
<td>19.5</td>
<td>41.9</td>
</tr>
<tr>
<td>10</td>
<td>86.3</td>
<td>98.9</td>
<td>62.2</td>
<td>19.5</td>
<td>-5.9</td>
</tr>
<tr>
<td>11</td>
<td>92.6</td>
<td>99.2</td>
<td>64.2</td>
<td>20.4</td>
<td>41.2</td>
</tr>
<tr>
<td>Semi-massive ore samples</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>44.3</td>
<td>86.3</td>
<td>30.7</td>
<td>9.1</td>
<td>22.2</td>
</tr>
<tr>
<td>6</td>
<td>40.2</td>
<td>90.0</td>
<td>26.1</td>
<td>7.7</td>
<td>8.8</td>
</tr>
<tr>
<td>9</td>
<td>54.1</td>
<td>93.1</td>
<td>37.9</td>
<td>11.1</td>
<td>53.1</td>
</tr>
<tr>
<td>12*</td>
<td>66.8</td>
<td>97.3</td>
<td>46.3</td>
<td>14.8</td>
<td>47.0</td>
</tr>
<tr>
<td>13</td>
<td>29.2</td>
<td>87.5</td>
<td>16.2</td>
<td>5.8</td>
<td>65.3</td>
</tr>
</tbody>
</table>

* Rich semi-massive

The loading plot (Figure 35) shows that the first PC is covering primarily the variability in the process behaviour (mass pull and iron recovery). The second PC is covering primarily the ore type simply through the iron grade and SATMAGAN value. The simplest separation between massive and semi-massive is made by establishing thresholds based on the iron grades and SATMAGAN values. From the loading plot, iron recovery and mass pull are located far from origin; therefore, have the highest impact on the model. The close location of those two variables to each other also suggests positive correlation between them. SATMAGAN values positively correlate with the iron concentration in feed and are strongly linked to the ore type. Massive ore will have higher SATMAGAN values than semi-massive ore.

The score plot of t1/t2 (Figure 36) reveals full separation between hematite (sample 3) and other massive ore samples. Massive and semi-massive ores are well separated in this plot by the second PC, while the transitional sample 12 is very close to the origin.

The comparison of the loading (Figure 35) and score (Figure 36) plots shows that samples 3 and 13 contribute more to the highest positive value $\Delta R$. Those are also samples with the lowest mass pull and iron recovery. In case of sample 13, the reason for being an outlier could be in a poorer control of the sampling quality, since it was a grab sample. It is also clear that there is no strong impact of the ore type (massive, semi-massive) on $\Delta R$. The statistical values suggest a very good model with cumulative explained variation of $R^2_X = 99\%$, $R^2_Y = 91\%$ and the cumulative predicted variation of $Q^2 = 89\%$ of the total variance.
Finally, the predicted $\Delta R$ values were compared against measured. The comparison is shown in Figure 37. The general fit is very good and is independent of geological ore types.

5.3.4. Fe-oxides liberation

One of the aims of this thesis was to develop a proxy model for predicting the Fe-oxides liberation by use of the DT. Having a proxy model for Fe-oxides liberation will contribute to process modelling and simulation with mixed particles. Mineral liberation information deployed in a block model may also have an impact on production planning and mine scheduling.
Modelling was performed in two steps. First, PLS was used to predict Fe-oxides liberation using all the data types (chemical assays, difference indices, recoveries, concentrate quality and mass pull), and tendencies were studied with loading and score plots. Second, the most influential data type was selected for building a simplified model to predict Fe-oxides liberation using PLS. The first step is well covered in the Paper B. Therefore, only second step is presented here.

In the second step, PLS was used to connect Fe-oxides liberation (response variable Y) and DT concentrate properties (main variables X) (Table 26).

The loading plot (Figure 38) shows that K₂O content in concentrate (X variable) is the strongest contributor for predicting the Fe-oxides liberation (Y variable). The two variables are negatively correlated. This can be explained by the high content of biotite and K-Feldspar in mixed particles. The first PC separates variables by the contribution of gangue elements, which are expressed as the variables (DT_C_MgO, DT_C_Al₂O₃, DT_C_K₂O) or Fe-oxides minerals (DT_C_Fe). The iron content in DT concentrate tends to correlate positively with the Fe-oxides liberation, since iron is the main component of Fe-oxides. Inverse correlation between iron and gangue elements MgO and Al₂O₃ in DT concentrate confirms presence of those elements in mixed ore–gangue particles. The score plot (Figure 39) shows clustering of the massive and rich semi-massive sample size fractions. The semi-massive ore size fractions are randomly dispersed to the left of the massive samples and are confined to a dense class. For both massive and semi-massive samples, coarser size fractions tend to be further from origin. However, only the coarse fractions of the semi-massive fall outside the confidence ellipse. Here, sample 12 tends to be more similar to the massive samples, since all three points corresponding to the coarse, medium and fine size fractions are within the limiting ellipse. The first PC shows separation between samples by the degree of liberation of Fe-oxides. Samples with higher liberation of Fe-oxides tend to be located to the right of the vertical axis and those with lower liberation of Fe-oxides tend to be located to the left.

The comparison of loading (Figure 38) and score (Figure 39) plots confirms that coarser particles contribute more to the DT concentrate impurities and gangue elements recovery, while finer particles tend to contribute more to the separation efficiency evaluated by means of the difference index. It is important that particle size correlates negatively with the degree of liberation of the Fe-oxides, meaning that smaller particles will tend to be more liberated. Fe-oxides liberation is higher for massive ore than for semi-massive, which is in accordance with quantitative mineralogy measurements (Figure 32). The possibility of modelling Fe-oxides liberation is promising. As follows from Figure 38, it should be possible to obtain a fair model by including only DT concentrate properties (Table 26) as model variables. For the semi-massive ore, the similarities between alignment of the observations on the score plot and differences indices at loading plot suggest that a model partially explaining Fe-oxides liberation could be constructed from those variables. The PLS model for predicting Fe-oxides liberation based on DT concentrate properties (Fe, K₂O, Al₂O₃ and MgO grades) yielded, in a two significant component model, R²ₓ=89%, R²ᵧ=89%, and Q²=88%.
Table 26 Input X and Y variables into PLS model of the Fe-oxides liberation (the average values of DT concentrate chemical assays).

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Fe, %</th>
<th>K₂O, %</th>
<th>Al₂O₃, %</th>
<th>MgO, %</th>
<th>Fe-Oxides liberation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Codes used in modelling for the parameters</td>
<td>DT_C_Fe</td>
<td>DT_C_K₂O</td>
<td>DT_C_Al₂O₃</td>
<td>DT_C_MgO</td>
<td>Lib_FeOxid</td>
</tr>
<tr>
<td>X/Y variable</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>Y</td>
</tr>
</tbody>
</table>

**Massive ore samples**

<table>
<thead>
<tr>
<th></th>
<th>Fe</th>
<th>K₂O</th>
<th>Al₂O₃</th>
<th>MgO</th>
<th>Fe-Oxides liberation</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>69.8</td>
<td>0.0</td>
<td>0.4</td>
<td>0.4</td>
<td>85.6</td>
</tr>
<tr>
<td>3</td>
<td>66.9</td>
<td>0.0</td>
<td>0.6</td>
<td>0.5</td>
<td>87.7</td>
</tr>
<tr>
<td>4</td>
<td>70.3</td>
<td>0.0</td>
<td>0.3</td>
<td>0.4</td>
<td>81.9</td>
</tr>
<tr>
<td>5</td>
<td>69.1</td>
<td>0.0</td>
<td>0.6</td>
<td>0.6</td>
<td>85.8</td>
</tr>
<tr>
<td>7</td>
<td>71.3</td>
<td>0.0</td>
<td>0.3</td>
<td>0.3</td>
<td>90.8</td>
</tr>
<tr>
<td>8</td>
<td>69.7</td>
<td>0.1</td>
<td>0.5</td>
<td>0.4</td>
<td>83.5</td>
</tr>
<tr>
<td>10</td>
<td>70.0</td>
<td>0.0</td>
<td>0.5</td>
<td>0.5</td>
<td>87.2</td>
</tr>
<tr>
<td>11</td>
<td>70.3</td>
<td>0.0</td>
<td>0.4</td>
<td>0.4</td>
<td>89.7</td>
</tr>
</tbody>
</table>

**Semi-massive ore samples**

<table>
<thead>
<tr>
<th></th>
<th>Fe</th>
<th>K₂O</th>
<th>Al₂O₃</th>
<th>MgO</th>
<th>Fe-Oxides liberation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>63.0</td>
<td>0.6</td>
<td>2.1</td>
<td>0.9</td>
<td>60.9</td>
</tr>
<tr>
<td>6</td>
<td>62.9</td>
<td>0.2</td>
<td>2.4</td>
<td>0.7</td>
<td>66.4</td>
</tr>
<tr>
<td>9</td>
<td>65.8</td>
<td>0.5</td>
<td>1.5</td>
<td>0.4</td>
<td>65.8</td>
</tr>
<tr>
<td>12*</td>
<td>68.0</td>
<td>0.1</td>
<td>0.8</td>
<td>0.6</td>
<td>79.1</td>
</tr>
<tr>
<td>13</td>
<td>59.5</td>
<td>0.3</td>
<td>3.2</td>
<td>0.6</td>
<td>62.0</td>
</tr>
</tbody>
</table>

* Rich semi-massive

Figure 38 Step two – PLS loading plot of the variables projected into two dimensions for Fe-oxides liberation model.

Figure 39 Step two – PLS score plot of the observations projected into two dimensions for Fe-oxides liberation model.
5.4. Spatial models (paper F)

This thesis can be used as a guideline for selecting suitable machine learning tool for modelling process data. The study used samples from the Leveäniemi iron ore mine in Sweden. Modelling was done in two steps. First, the process properties were deployed into a geological database by building multivariate models. The data for modelling were obtained by conducting process testwork and mineralogical characterisation of samples. Second, process properties estimated in the geological database were extracted together with coordinates (x, y, z) and iron grades forming a new data set. Then spatial process models were built using extracted coordinates (x, y, z) and iron grades as input variables. Modelling methods were evaluated and compared in terms of relative standard deviation (RSD).

5.4.1. Comparing mineralogical and elemental approaches

Two approaches, elemental (traditional) and mineralogical, were tested for being used in populating geological database with process parameters. Analysis was based on 12 samples representing the geological variability in the Leveäniemi apatite iron ore deposit for Fe-oxides liberation, WLIMS mass pull, DT mass pull, Fe recovery in DT, Fe recovery in WLIMS, and $P_{80}$ were modelled. The hematite sample 3 was excluded from modelling. Additionally, a general PLS model was built for more detailed analysis and the model included all process parameters excluding $P_{80}$. $P_{80}$ was excluded, since number of samples used in modelling (12 samples) did not allow to build a model with acceptable quality. The prediction quality for separate PLS models and for the general model of the process parameters based on elemental and mineralogical approaches is compared in Table 27.

Comparison of the elemental and mineralogical approaches (Table 27) has shown that mineralogical approach outperforms elemental in predicting mass pull and iron recovery in WLIMS, and iron recovery in DT. There was almost no difference between the approaches in predicting liberation of Fe-oxides and mass pull in DT. The elemental approach was markedly better than mineralogical in predicting $P_{80}$. Finally, there was no difference observed between approaches in a general model. The loading plot (Figure 40) shows that Fe and V grade in feed (X variable) are the strongest contributors for predicting the Fe-oxides liberation, WLIMS mass pull, DT mass pull and Fe recovery in DT (Y variable). The iron recovery in WLIMS positively correlates with the gangue elements and correlate negatively with Fe and V in feed. The score plot (Figure 41) shows clustering of the massive and rich semi-massive samples alone the first PC. It seems that there is larger difference between semi-massive samples than between massive samples, since they are more scattered. Sample 12 could be identified as both massive and semi-massive, since it is located very close to the vertical axis.
Table 27 Comparison between elemental and mineralogical approaches in process modelling with PLS regression.

<table>
<thead>
<tr>
<th>Process parameters</th>
<th>Elemental approach</th>
<th>Mineralogical approach</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PCAs</td>
<td>R2X</td>
</tr>
<tr>
<td>$L_{Fe-ox}$</td>
<td>2</td>
<td>0.733</td>
</tr>
<tr>
<td>$M^{DT}$</td>
<td>3</td>
<td>0.828</td>
</tr>
<tr>
<td>$R_{Fe}^{wLIMS}$</td>
<td>3</td>
<td>0.745</td>
</tr>
<tr>
<td>$M_{wLIMS}^{Fe}$</td>
<td>3</td>
<td>0.796</td>
</tr>
<tr>
<td>$P_{B0}$</td>
<td>4</td>
<td>0.873</td>
</tr>
<tr>
<td>General (excl. $P_{B0}$)</td>
<td>2</td>
<td>0.754</td>
</tr>
</tbody>
</table>

The loading plot (Figure 42) shows that Fe-oxides grades, SATMAGAN and specific gravity in feed (X variable) are the strongest contributors for predicting the Fe-oxides liberation, WLIMS mass pull, DT mass pull and Fe recovery in DT (Y variable). Similarly to the elemental approach, the iron recovery in WLIMS positively correlate with the gangue elements and correlate negatively with Fe-oxides grades, SATMAGAN and specific gravity in feed. The score plot (Figure 43) shows clustering similar to the clustering for the elemental approach, where massive and rich semi-massive samples in the first principle component show larger variability in semi-massive samples than in massive samples. Mineralogically, sample 12 could be identified rather as massive.

The comparison of loading plots for elemental (Figure 40) and mineralogical (Figure 42) approaches, and score plots for elemental (Figure 41) and mineralogical (Figure 43) approaches shows that massive ore samples tend to have a higher degree of liberation for Fe-oxides, mass pulls and iron recovery in DT. Semi-massive samples, especially samples 6, 12 and 13 tend to have higher Fe recoveries in WLIMS.
5.4.2. Process modelling

Eight methods were used to build process models ($Y_{PS}$) for populating a geological database with process properties. At this stage, there was no improvement of the model by selecting significant variables. The methods which showed the lowest errors for particular process properties are highlighted (* - <15%, ** - <10%) in Table 28.

Table 28 RSD, % of the modelled process properties $\tilde{Y}_{PS}$(best predictions are highlighted: * - <15%, ** - <10%).

<table>
<thead>
<tr>
<th>ID</th>
<th>Modelling methods</th>
<th>$M^W{\text{LIMS}}$</th>
<th>$R^W{\text{LIMS}}_{Fe}$</th>
<th>$M^D{T}$</th>
<th>$R^F{\text{LIMS}}_{Fe}$</th>
<th>$P_{80}$</th>
<th>$L_{Fe-ox}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>EN</td>
<td>13.2*</td>
<td>4.1**</td>
<td>3.3**</td>
<td>2.1**</td>
<td>106.1</td>
<td>12.1*</td>
</tr>
<tr>
<td>2</td>
<td>LR</td>
<td>26.0</td>
<td>4.9**</td>
<td>17.2</td>
<td>5.2**</td>
<td>123.5</td>
<td>20.5</td>
</tr>
<tr>
<td>3</td>
<td>SMO</td>
<td>17.9</td>
<td>4.9**</td>
<td>3.8**</td>
<td>2.6**</td>
<td>94.4</td>
<td>6.4**</td>
</tr>
<tr>
<td>4</td>
<td>IBk</td>
<td>24.2</td>
<td>3.8**</td>
<td>13.8*</td>
<td>3.3**</td>
<td>120.5</td>
<td>7.2**</td>
</tr>
<tr>
<td>5</td>
<td>K*</td>
<td>18.2</td>
<td>3.3**</td>
<td>15.3</td>
<td>3.9**</td>
<td>128.0</td>
<td>10.4*</td>
</tr>
<tr>
<td>6</td>
<td>M5</td>
<td>12.2*</td>
<td>6.7**</td>
<td>5.5**</td>
<td>3.3**</td>
<td>108.0</td>
<td>10.4*</td>
</tr>
<tr>
<td>7</td>
<td>RF</td>
<td>17.9</td>
<td>4.3**</td>
<td>10.0*</td>
<td>2.6**</td>
<td>92.7</td>
<td>8.3**</td>
</tr>
<tr>
<td>8</td>
<td>M5P</td>
<td>12.2*</td>
<td>6.3**</td>
<td>5.5**</td>
<td>3.3**</td>
<td>97.2</td>
<td>10.5*</td>
</tr>
</tbody>
</table>

The RSD provided an advantage when comparing the obtained results for the modelled process properties with one another. The predictions for iron recoveries are better than mass pulls in WLIMS and DT for all eight methods. Good predictions were obtained for the iron oxides liberation, where all the methods except for Linear have shown RSD below or very close to 10%.

No single method gave reasonably good prediction for the $P_{80}$. The possible reasons for such bad prediction could be statistically insignificant number of samples used in modelling and low average $P_{80}$ compared to the maximum $P_{80}$ values occurring in the deposit.
5.4.3. Updated geological database

Overall, the results suggest that the EN, M5, M5P, and SMO have the lowest average RSD. None of the methods had a better RSD for predicting all the process properties. SMO was randomly selected for populating the geological database with the process properties.

The SMO method was improved before applying it for populating the geological database (reduced SMO). The reduced SMO model was obtained by selecting significant variables prior to modelling, therefore “reduced SMO = variable selection + SMO”. The significant variables selection was done by applying wrapper approach to feature subset selection (WAFSS) (Kohavi et al., 1997), which is a supervised type of filter for variable selection. WAFSS selects significant variables by dividing variables into subsets, evaluating each subset based on cross-validation, and selecting the variables which yield into the most accurate model.

5.4.4. Spatial process model and cross-validation

Eight machine-learning modelling methods and two additional meta-methods listed in Table 18 were compared for building spatial process models ($Y_{DHD}$). The process properties extracted from the geological database ($Y_{DHD}$) were modelled as a function of the coordinates and iron grade only ($X_{DHD} = \{x, y, z, \%Fe\}$). Then, the verification was performed by splitting data into three pairs of training and testing subsets and predicting process properties for the testing data set. Results of the verification are shown in Figure 44. Each plot represents modelling for the separate process property. Vertical axis shows RSD expressed in %. Horizontal axis lists modelling machine-learning methods. The data points on each plot represent RSD for each machine-learning method for each testing subset: 13008, 14031, and 14057b. The drillholes chosen for verification from the updated geological database represent randomly selected drillholes from the opposite edges of the deposit and from the central part of the Leveäniemi deposit.

Excellent results in terms of RSD (<5%) was achieved for modelling iron recovery in WLIMS and DT, and mass pull in DT (except for IBk for test dataset 13008) and the iron oxides liberation (<10% RSD), while higher than the other tests, still falls into the good range for RSD values (except for IBk for test dataset 13008). Deviations in prediction for the drillhole 13008 may be due to an overrepresented number of composites with low iron grade (median and average iron grades are significantly lower than average in the deposit), (Table 19). This suggests that any of the tested machine-learning methods can be used for spatial modelling of iron recovery in WLIMS and DT and iron oxides liberation. The results for modelling mass pull in WLIMS were poorer with RSD >10% for all eight machine-learning methods. However, the results still can be used as trend indicators since all the machine-learning methods (except for IBk for test dataset 14031) have RSD <25%. Drillhole 14031 has a slightly larger average composite size (larger support) than the average composite sample in the geological database, which may be a source of the poorer performance of the machine-learning methods for predicting WLIMS mass pull. A possible reason for the better prediction for mass pull in DT is a relation between iron grade in the feed and mass
pull that is closely linear. Modelling of \( P_{80} \) has not yielded a good model and cannot be further used. A possible explanation for that could be lack of spatial correlation for \( P_{80} \).

The methodology for integrating process data into a spatial model enables geometallurgical spatial mapping, which is the ultimate product of a geometallurgical program. The results and discussions presented in this paper indicate that machine-learning methods are good for building spatial geometallurgical models for mass pulls, recoveries and iron oxides liberation (Table 29).

![Figure 44 RSD of the spatial process models obtained from cross-validation on the testing data sets: • 13008, ▲ 14031, ◆ 14057b.](image)

More investigation is needed for spatial modelling of comminution properties of the ore, e.g., \( P_{80} \), energy consumption, Bond work Index etc. The lower RSD for the decision tree methods suggests that those methods may be the most suitable for modelling non-additive variables (recoveries),
while functions are more suitable for modelling additive variables (feed rate). AVE and MED may be a good choice for modelling when the additivity properties of the modelled process parameters are not known. IBk performed the worst on the given data set. The nearest neighbour group of methods (such as IBk) is considered to be a good method for geological data, since nearest neighbour is often implemented as a part of geological modelling software as one of the methods for populating a geological block model. However, its drawback is that the method is sensitive to the selected number of the nearest neighbours (k value) and distance definition (Euclidian, Manhattan, Chebyshev, Minkowski).

Table 29 Advantages and disadvantages of proposed methods (* - the worst, ** - the average, ***- the best, A – acceptable for being used in spatial modelling, N – non-acceptable for being used in modelling).

<table>
<thead>
<tr>
<th>Process parameter</th>
<th>functions</th>
<th>Trees</th>
<th>Lazy</th>
<th>Ave/med</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{L}_{Fe-ox}$</td>
<td>***(A)</td>
<td>***(A)</td>
<td>*(A)</td>
<td>***(A)</td>
</tr>
<tr>
<td>$M_{DT}$</td>
<td>***(A)</td>
<td>**(A)</td>
<td>*(A)</td>
<td>**(A)</td>
</tr>
<tr>
<td>$M_{WLIMS}$</td>
<td>**(A)</td>
<td>***(A)</td>
<td>*(A)</td>
<td>***(A)</td>
</tr>
<tr>
<td>$P_{80}$</td>
<td>**(N)</td>
<td>**(N)</td>
<td>*(N)</td>
<td>**(N)</td>
</tr>
<tr>
<td>$R_{Fe}$</td>
<td>*(A)</td>
<td>***(A)</td>
<td>**(A)</td>
<td>***(A)</td>
</tr>
<tr>
<td>$P_{WLIMS}$</td>
<td>*(A)</td>
<td>***(A)</td>
<td>*(A)</td>
<td>***(A)</td>
</tr>
</tbody>
</table>
CHAPTER 6  DISCUSSIONS

“Discussion is impossible with someone who claims not to seek the truth, but already to possess it.”

Romain Rolland,
Above the Battle

6.1. General

According to the reviewed literature, establishing geometallurgical programs is assumed to be beneficial for certain types of deposits. The theoretical gap in research is the lack of tools and methods for planning geometallurgical programs in an efficient way, which in turn would ensure predictability.

Therefore, this thesis is aimed to provide a new framework for doing geometallurgy with better predictability. Bringing predictability to geometallurgical programs shall be started early by planning how much geometallurgy is needed (Objective 1), estimating whether there would be any benefits from geometallurgy (Objective 2) and only then proceed with actual sampling, testwork, and development of technical process models (Objective 3) and spatial models (Objective 4). It is a requirement of engineering background of this thesis to place emphasis on the major technical developments made by the author, in context of the geometallurgical programs, cf. Table 30. The questions (objectives) are further discussed in following sections.

6.2. Geometallurgical approach

6.2.1. Classification

The organisational and interdisciplinary aspects of geometallurgy have received less attention than the technical aspects (Jackson et al., 2011). This thesis aspires to address this gap. The recommendations to enhance the decision-making in geometallurgy presented here are based on the literature review, and on interviews with geometallurgy specialists within the mining sector. The main usage of the developed classification is linking geological information with metallurgical responses and identifying gaps where improvement is needed for better predictability. The main difference between the previous systems for structuring geometallurgical programs presented by others (i.e., Bridge et al., 2014; Dunham et al., 2011; Jackson et al., 2011; Sola and Harbort, 2012; Vann et al., 2011) and the one presented in this thesis is the classification under traditional, mineralogical and proxy approaches, which clarifies how to collect and use the geological and process information for further planning. Such a classification allows for the investigation of the
more practical issues related to the ge metallurgical programs: which analytical instruments (e.g., XRF or XRD) and process tests should be used (e.g., DT, WLIMS, flotation); how the geometallurgical model can be applied in production; which actors have to be involved in the geometallurgical program; etc.

Table 30 Correspondence between elements of a geometallurgical program and technical improvements made in the thesis.

<table>
<thead>
<tr>
<th>Elements of the geometallurgical program structure</th>
<th>Developments made</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geological data</td>
<td>Ore classification with $X_{LRU}$</td>
</tr>
<tr>
<td>Sampling</td>
<td>Synthetic data</td>
</tr>
<tr>
<td>Testwork</td>
<td>DT testing procedure with 3 current strength</td>
</tr>
<tr>
<td>Mineralogical characterisation</td>
<td>Iron-oxides liberation model</td>
</tr>
<tr>
<td>Process modelling</td>
<td>Iron recovery in WLIMS based on DT</td>
</tr>
<tr>
<td>Process simulation</td>
<td>N/A</td>
</tr>
<tr>
<td>Geometallurgical spatial modelling</td>
<td>Applying machine learning methods for non-spatial and spatial process modelling</td>
</tr>
</tbody>
</table>

Based on the data collected on different geometallurgical programs, a trend was identified that the more advanced levels of geometallurgical programs tend to use a mineralogical approach. The traditional elemental approach is used more in the less advanced levels of geometallurgical programs and the proxy approach is applied in between these levels. The explanation is that the development of a geometallurgical program usually starts with a systematic collection of numerical data - chemical assays from the drill core samples - with high data collection frequency. This information is often defective for the purposes of metallurgical model development, because a metallurgical response is likely to be more dependent on mineralogy than on the chemical composition of the ore. Thus, once the geometallurgical program goes to a more advanced level, the use of mineralogical information increases.

In the thesis, geometallurgy is viewed as a paradigm change in mining industry from just problem solving to a holistic variability management and problem prevention. This shift has prompted the inclusion into geometallurgy of a wide range of disciplines, i.e., spatial modelling, economical modelling; and a dispersion of responsibilities across a wider range of actors.

6.2.2. Synthetic ore body

A synthetic ore body modelling framework, developed within this thesis, allows for supported decision making in planning, sampling, testing, and beneficiation model building. Using synthetic data makes it possible to investigate the impact of the future actions before starting the development of the geometallurgical program. Therefore, a more educated guesses can be made about details of the geometallurgical program before starting to implement it. However, this approach is not a substitute for the existing geostatistical approaches or process models; rather it is a tool for testing the sensitivity of the project to constraints at different stages and different parts
of the mining value chain. The impact of the variability in an ore deposit can be traced through the whole mining value chain, down to the concentrate and tailings quality. Potentially, the impact can be traced to the smelter, and the environmental parameters may also be considered.

The synthetic framework differs from the previously used geometallurgical synthetic data sets (Jupp et al., 2013) and integrated approaches (Tungpalan et al., 2015a). First, the ore body modelling was taken to a mineralogical level and the quantitative information such as the modal composition and mineral texture was assigned to each voxel. Second, the process was modelled and simulated on the mineral liberation level. This gives access to the ore variability at scale which is significant for the metallurgical response, but challenging to map in the ore body. Therefore, the use of a synthetic ore body gives a realistic environment to test different essential questions in mineral production.

The reference case study of the Malmberget apatite iron ore is used in the synthetic ore body modelling to define whether commencing geometallurgical modelling for the Leveäniemi apatite iron ore case would be beneficial.

6.3. Modelling

6.3.1. Process

The availability of low-cost and sufficiently accurate geometallurgical tests for quantification of different ore properties (physical and process behaviour) is yet another cornerstone of a successful geometallurgical program. Benefits of using geometallurgical tests for reinforcing a geometallurgical program have been previously described (e.g., Mwanga (2014)). In this thesis, existing geometallurgical tests are collected and classified in Table 2.

This thesis is an attempt to develop testwork and models for filling in gaps in the geometallurgy for predicting iron ore process performance based on a proxy tool, i.e., DT, and mineralogical information. Therefore, the developed models fall into the mineralogical approach.

Firstly, $X_{LTU}$ is proposed for simple ore classification. Implementation of $X_{LTU}$ is simple, since it requires only separation results from DT and iron grade in the feed. The $X_{LTU}$ estimator may be used to identify samples with potential processing problems or that have been misclassified.

Secondly, a low labour-intensive alternative is proposed for predicting iron-oxides liberation using PCA/PLS. The method deals with high grade ore and considers fully liberated and mixed particles, which can be seen as advantage compared to Wiegel, (1975). The hallmark of the method is its low cost compared to other techniques, such as MLA/QEMSCAN, semi-automated optical microscopy (Delbem et al., 2015), or optical image analysis (Donskoi et al., 2016). The exact areas of usage for the developed method can be defined through additional studies, where accuracy and precision of the developed method will be compared against the other techniques. In deposits where magnetite has significant amounts of elements other than iron deployed in the lattice, the model might require additional calibration in order to reach higher accuracy of the predicted iron-
oxides liberation. In this thesis the liberation of the iron-oxides is explained through the ore behaviour in magnetic separation. Similar work done by Leißner et al. (2013) explained magnetic separation with regard to liberation. Niiranen, (2015) has shown that HRC can be used in characterising liberation by applying a similar approach to using DT. However, in those papers, neither a numerical model, nor validation with Auto-SEM were developed for describing liberation.

Thirdly, the suggested approach for modelling WLIMS recovery can be used to reduce the amount of testwork in the mine laboratory and may also be used in cases when the available sample size is not sufficient (<<10 kg) for a laboratory scale WLIMS test. To use the DT results for predicting WLIMS performance, the magnetic field of the DT must be fine-tuned to get maximum variation in the iron recovery for the tested samples. This is contrary to the way DT is normally used for checking the achievable concentrate quality. In mine production, if the DT separation results are available for a large number of samples with known location of the samples (e.g., tests done on segments of the drill cores), then the WLIMS recovery model may be applied for deploying iron recovery from WLIMS into a production block model.

Massive ores do not exhibit a large enough variation in liberation, DT recoveries, and mass pulls that exceeds experimental noise. Therefore, the DT should only be applied for studying marginal ores. When the DT performance parameters are deployed in a block model, constant values for liberation, recoveries and mass pulls can be assigned to the blocks containing massive ore.

All models developed here are based on DT measurements. Those data are normally obtained in production on an everyday basis. Therefore, the methods are low-cost and do not require much investment for deployment.

6.3.2. Spatial

The possibility to forecast ore behaviour in the process, before it is sent to the plant, and even before it is extracted from the mine, is the main objective of the geometallurgical spatial modelling. Therefore, creating spatial process models, which may be used for populating a block model or geological database are crucial for increasing the predictability of geometallurgical programs.

Linear geostatistical methods (i.e., kriging) are commonly used in block modelling. However, those methods are not suitable for non-additive variables (Deutsch, 2015; Dunham and Vann, 2007). Instead, machine learning methods can be applied in spatial modelling. One of the main advantages of using machine-learning methods in the spatial modelling of process properties is the capacity of these methods to deal with the additivity issue. RSD suggest that Tree-based methods are to be preferred among other machine learning methods when modelling non-linear process properties. Tree-based methods have several advantages over other methods: they tolerate missing values; can handle both continuous and categorical data, and are robust (Henderson et al., 2004). Random forest methods are particularly good since they do not have requirements to consider the probability distribution and they deal efficiently with non-linear (non-additive) data (Hengl et al., 2015).
Applying a two-step approach (first deploying the process properties into a geological database with non-spatial process models and then building the spatial process models) seems to be a solution for sparse data. Alternatively, sparse data can be used for the domaining (David, 2007; Sanchidrián et al., 2012) of the deposit and assigning constant values to each domain (cf. Appendix II for more examples of domaining). The advantage of the two-step approach is that process properties, which were measured for the samples with unknown location, are linked to the spatial coordinates \((x, y, z)\) in the ore body by deploying those properties into a geological database. The process properties and coordinates contained in the updated geological database form a new dataset for building spatial process models.

### 6.4. Synthesis

#### 6.4.1. Benefits

The findings of the thesis have considerable managerial implications:

- Increasing the predictability of geometallurgical programs by applying the developed classification framework for planning a geometallurgical program at its early stages.

- The economics of the project can be improved by investing only those areas where development is needed. Such areas are defined by the depth of application of the geometallurgical program (levels 0-7).

- Preventing unnecessary investment in methods and techniques which might have low or no positive effect on the project’s economy. This can be achieved by using synthetic data for estimating the benefits from implementing geometallurgy at a mine site. Additionally, the benefits can be compared for different strategies in sampling, mineralogical characterisation, testwork and production.

- Less data/labour is needed for running geometallurgical programs. This can be achieved by estimating iron oxides liberation and iron recoveries in WLIMS from the models, instead of expansive testwork.

- Getting more out of the data: the data already routinely collected at magnetite iron ore mines with DT can be utilised for ore classification, iron recoveries prediction for WLIMS and iron oxides liberation.

#### 6.4.2. Implementation

The implementation of the framework presented in the thesis may be achieved by selecting the level of geometallurgical application and identifying actors whose interests have to be represented. A new approach is presented here since the traditional approach of handling geometallurgical programs is not sufficient. Synthetic deposit modelling should involve all of the future participants in the geometallurgical program. This will estimate whether the investment into development of a geometallurgical program (i.e., sampling, testwork, mineralogical studies, modelling and simulation, salaries, etc) can be justified by potential gains (i.e., lower penalty materials in
concentrate, higher throughput, higher recoveries, more even production, etc). Additionally, creating synthetic data will help develop the common language between actors and avoid future misunderstanding due to different technical jargons (Dunham and Vann, 2007). Once it is confirmed by testing the different production strategies with the synthetic data, the geometallurgy can enter the next phase, which is the actual development (see Figure 1). If a geometallurgical program is developed for a magnetite iron ore deposits, then some process properties, such as ore classification, throughput and iron recoveries in DT and WLIMS, and iron-oxides liberation can be forecasted by calibrating the models presented in this thesis. The geologists and process engineers must be involved in the calibration process. After calibration, these process properties can be deployed into a production block model using machine learning methods. The geologist, process engineer, mining engineer, and data analysis specialist all have to be involved in the geometallurgical block modelling. Models developed in the thesis have to be calibrated when used for other types of deposits or for process properties not covered here.

The decision whether a geometallurgical program shall be implemented as a one-off or continuous geometallurgical program depends on the deposit type, geological knowledge, stage of the production (i.e., feasibility, production, or closure), available funding, severity of the problem. A one-off solution is preferable closer to the end of mine life and for simple deposits with well-known geology. A continuous program would offer more even and distributed cost allocation over a longer time for development of the geometallurgical program. However, the beginning (first iteration) of a continuous program would be identical to the one-off program, with following updates.

A continuous geometallurgical program allows for parallel flow of tasks. This means that several elements of the geometallurgical program can be done simultaneously: collecting additional samples, conducting test-work and mineralogical characterisation, estimating the added value of additional geometallurgical work and updating the geometallurgical (non-spatial and spatial) process models.

6.4.3. Challenges

The main challenges encountered in the thesis can be summed in several bullet points:

- A geometallurgical program becomes more complex as the number of actors increases, processes become more complex and feed quality gets more variable. The participation of a broad range of actors (e.g., geology, metallurgy, mine planning, environment, and commercialisation specialists together with managers (Beniscelli, 2011)) is necessary to avoid opposition to the implementation of geometallurgy. Involving new actors into geometallurgical program includes identification of important actors and their role in decision-making. Additional questions are: therefore how to identify those actors?, whose interests are more important than others?, and are they adequately represented? Including more actors is expected to lead to more informed decisions by considering more opinions, interests, and knowledge, which might be crucial for the mine performance. The actors involved in the geometallurgical program may change through the life of mine, due to
changes in upstream and downstream processes, i.e., geological knowledge, feed, mine method, process, regulations etc. There are no one-fits-all criteria for the selection of participants, since each type of production problem may require a different level of expertise in mining, processing, geology, environmental issues or economics.

- The issue of up-scaling of the process properties in synthetic data modelling is not addressed here, since, the breakage model implemented in the simulation is specific to the ore types and the magnetic separation process does not face upscaling problem (Koch et al., 2015). However, the importance of upscaling has been widely discussed in the literature (Boogaart and Tolosana-Delgado, 2018; Coward et al., 2009; Sepulveda et al., 2016; Tolosana-Delgado et al., 2015). One possible solution proposed by (Coward et al., 2009) is to use primary-response framework to reduce the bias of non-linear scaling up.

- The major challenge of the technical part of the thesis is that proof of concept was done only for magnetite iron ores.

- Applying the iron-oxide liberation model for predicting liberation properties of concentrate and tailings would extend the usage of the model. This, however, would require additional mineralogical studies on separation products (concentrate and tailings), to find the patterns for linking DT performance with liberation properties of concentrate and tailings. Predicting mixed particles using DT would allow to reduce mineralogical studies at mines.

- A good spatial model for $P_{88}$ was not achieved in this thesis. The main reason for that was lack of good predictors which could be utilised for building a predictive model (e.g., density, hardness, grain size distribution). Another reason may be low number of ore process samples; therefore, more investigation is needed for spatial modelling of the comminution properties of the ore.

- A small number of samples imposes several limitations on a geometallurgical program. First, outliers may have overwhelming impact on the model’s quality. Second, some ore types may have been missed during sampling. Third, different process properties require different number of samples due to difference in the (a) sampling and analytical methods, (b) magnitudes of measured values and errors, (c) distribution of measured values and errors (d) error types (systematic, random, outliers). Despite all those limitations, the process modelling yielded reasonably good models and may be used for improved process predictability.
Chapter 7  Conclusions

“Everything has its limit - iron ore cannot be educated into gold.”

Mark Twain

Returning to the hypothesis, it is now possible to state that the predictability of the geometallurgical program was enhanced by developing a classification system for the geometallurgical programs, a synthetic testing environment, and process and spatial models.

Objective 1. A new two-dimensional classification system of geometallurgical approaches enables:

- Identifying different ways to link geological information with metallurgical responses: mineralogical, traditional, proxy approaches.
- Suggesting areas where the development for the improved predictability of the geometallurgical program is needed.

Objective 2. Synthetic data was presented for studying the benefits of the future geometallurgical programs before the actual implementation. It can be used for evaluating different strategies for sampling, modelling, production, and economic assessment; and it was shown for the iron ore case study that process properties (recovery and throughput) require fewer samples for making reliable process prediction for the spatial modelling than concentrate quality.

Objective 3. Novel models were developed for ore classification ($X_{LTU}$), mineralogical characterisation (Iron oxides liberation predictive proxy model), and process prediction (iron recovery in WLIMS model based on the DT). Additionally, it was concluded that:

- DT may be applied only for studying marginal ores.
- The mineralogical approach often outperforms elemental in predicting non-spatial process properties.

Objective 4. Development of the spatial process models lead to the following conclusions:

- Machine learning methods can be used for spatial process modelling with high precision.
- Tree classifiers handle non-additive process properties better than functions and lazy methods.
- More robust estimate of the process properties in spatial modelling can be achieved by aggregated models.
CHAPTER 8  FUTURE RESEARCH AND RECOMMENDATIONS

“My interest is in the future because I am going to spend the rest of my life there.”

Charles Franklin Kettering

The methodology developed here can be used in implementing geometallurgical programs in a more predictable way by considering the planning of the program with the classification system, testing the benefits of geometallurgy with synthetic data, and applying models developed within this thesis to the iron ore. Several questions, which were beyond the scope of the thesis, may be suggested for future development:

- More detailed study on the various actors involved in the process, to determine whose interests are more important than others’, and are they adequately represented in geometallurgical context? For this it would be necessary to identify the roles of the actors, their power in relation to the deposit and process types, production issues, geographic location of the mine, cultural differences, and other aspects which might be difficult to foresee?

- Extend synthetic data usage to other deposit types, (e.g., VMS, IOCG) and broader value chain (e.g., geophysics, process metallurgy, and environmental assessment).

- Develop a generic error model covering the whole mining value chain.

- Extend the usage of the process models developed in the thesis to other magnetic ore types (e.g., monoclinic pyrrhotite); and extend the usage of liberation predictive process models for concentrate and tailing, and for mixed particles.

- Study how fast, low-cost and precise the geometallurgical tests must be to be competitive in comparison with traditional ore characterization techniques.

- Comparison between machine learning and geostatistical methods for geometallurgical spatial modelling.


Curry, D.C., Keith, A.C., Jackson, J., 2013. Is a 2.5 per cent success rate good enough? Traditional mine development methods have the tail wagging the dog, in: The Second AUSIMM International Geometallurgy Conference/ Brisbane, QLD, 30 September-2 October 2013. Brisbane, QLD, Australia, pp. 113–128.


McKee, D.J., 2013. Understanding Mine to Mill. The Cooperative Research Centre for Optimising Resource Extraction (CRC ORE), University of Queensland, St Lucia, Brisbane, Australia, St Lucia, Brisbane, Australia.


Appendix I: GEM-type classification

The mineralogical study has serendipitously revealed that Leveäniemi ore can be classified according to the classification developed by Lund, (2013) for the Malmberget case study. The classification has shown that presence of Bt rich samples at Leveäniemi deposit (Figure Ia), which was not samples and analysed by Lund, (2013). All the Bt rich samples belong to the semi-massive ore type and non Bt rich ore type was found in massive ore (Table AI.1). The classification is based on the normalized values for the gangue minerals (Table AI.2). Therefore, a link has been established between classification of Leveäniemi ore samples presented in Table 22 (supported by mineralogical and liberation measurements) and classification developed by Lund, (2013) for Malmberget deposit and applied here for the Leveäniemi deposit (Figure Ia).

Figure Ia. Classifying Leveäniemi ore samples according to the geometallurgical ore types (GEM-type) classification scheme (Lund, 2013).
### Table AI.1 Description of the Leveäniemi ore samples according to the ge metallurgical ore types (GEM-type) (Lund, 2013).

<table>
<thead>
<tr>
<th>Ore type</th>
<th>Ore mineral</th>
<th>GEM type</th>
<th>GEM sub-type</th>
<th>GEM code</th>
<th>Leveäniemi samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Massive</td>
<td>Mgt</td>
<td>Amph+Ap+Bt+Py</td>
<td>Amph</td>
<td>2b</td>
<td>2, 8</td>
</tr>
<tr>
<td></td>
<td>Hcm</td>
<td>Amph</td>
<td>2b</td>
<td></td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Mgt</td>
<td>Ap</td>
<td>2c</td>
<td></td>
<td>4, 5, 7, 10, 11</td>
</tr>
<tr>
<td>Rich semi-massive</td>
<td>Mgt</td>
<td>Qtz</td>
<td>-</td>
<td>3</td>
<td>12</td>
</tr>
<tr>
<td>Semi-massive</td>
<td>Mgt</td>
<td>Amph+Ap+Bt+Py</td>
<td>Bt</td>
<td>2d</td>
<td>1, 6</td>
</tr>
</tbody>
</table>

### Table AI.2 Normalized gangue mineral grades for Leveäniemi samples.

<table>
<thead>
<tr>
<th>ID</th>
<th>Ab</th>
<th>Qtz</th>
<th>K-Fsp</th>
<th>Grt</th>
<th>Amph/Px</th>
<th>Ap</th>
<th>Bt</th>
<th>FeTi-oxides</th>
<th>Sulp.</th>
<th>Cal</th>
<th>Amph+Ap+Bt+Py</th>
</tr>
</thead>
<tbody>
<tr>
<td>1b</td>
<td>0.2</td>
<td>19.2</td>
<td>6.9</td>
<td>0.4</td>
<td>5.0</td>
<td>4.9</td>
<td>60.0</td>
<td>0.0</td>
<td>2.1</td>
<td>1.2</td>
<td>72.0</td>
</tr>
<tr>
<td>2b</td>
<td>0.0</td>
<td>0.5</td>
<td>0.2</td>
<td>1.3</td>
<td>75.3</td>
<td>13.6</td>
<td>1.1</td>
<td>1.1</td>
<td>0.5</td>
<td>6.2</td>
<td>90.5</td>
</tr>
<tr>
<td>3b</td>
<td>0.7</td>
<td>0.2</td>
<td>3.5</td>
<td>12.7</td>
<td>5.9</td>
<td>43.0</td>
<td>8.5</td>
<td>0.2</td>
<td>1.8</td>
<td>23.4</td>
<td>59.2</td>
</tr>
<tr>
<td>4b</td>
<td>0.0</td>
<td>10.9</td>
<td>0.4</td>
<td>0.1</td>
<td>3.3</td>
<td>50.7</td>
<td>6.5</td>
<td>1.0</td>
<td>2.3</td>
<td>24.7</td>
<td>62.8</td>
</tr>
<tr>
<td>5b</td>
<td>0.0</td>
<td>8.4</td>
<td>1.2</td>
<td>0.2</td>
<td>24.4</td>
<td>52.3</td>
<td>5.1</td>
<td>1.0</td>
<td>0.6</td>
<td>6.8</td>
<td>82.4</td>
</tr>
<tr>
<td>6b</td>
<td>2.6</td>
<td>19.6</td>
<td>1.3</td>
<td>0.2</td>
<td>15.3</td>
<td>14.4</td>
<td>45.0</td>
<td>0.0</td>
<td>0.1</td>
<td>1.4</td>
<td>74.8</td>
</tr>
<tr>
<td>7b</td>
<td>0.2</td>
<td>0.1</td>
<td>0.2</td>
<td>0.3</td>
<td>3.2</td>
<td>83.8</td>
<td>1.0</td>
<td>0.6</td>
<td>0.5</td>
<td>10.0</td>
<td>88.6</td>
</tr>
<tr>
<td>8b</td>
<td>0.0</td>
<td>12.2</td>
<td>3.4</td>
<td>1.3</td>
<td>46.1</td>
<td>4.9</td>
<td>19.9</td>
<td>0.4</td>
<td>1.2</td>
<td>10.8</td>
<td>72.0</td>
</tr>
<tr>
<td>9b</td>
<td>0.4</td>
<td>17.1</td>
<td>26.4</td>
<td>0.1</td>
<td>6.1</td>
<td>1.5</td>
<td>46.3</td>
<td>0.0</td>
<td>0.9</td>
<td>1.2</td>
<td>54.7</td>
</tr>
<tr>
<td>10b</td>
<td>0.1</td>
<td>5.7</td>
<td>0.9</td>
<td>1.3</td>
<td>33.6</td>
<td>40.5</td>
<td>2.6</td>
<td>0.7</td>
<td>0.6</td>
<td>14.1</td>
<td>77.2</td>
</tr>
<tr>
<td>11b</td>
<td>1.6</td>
<td>8.4</td>
<td>2.3</td>
<td>0.1</td>
<td>6.2</td>
<td>58.5</td>
<td>15.3</td>
<td>4.1</td>
<td>0.9</td>
<td>2.5</td>
<td>81.0</td>
</tr>
<tr>
<td>12b</td>
<td>22.8</td>
<td>11.0</td>
<td>1.5</td>
<td>0.2</td>
<td>5.9</td>
<td>32.4</td>
<td>22.5</td>
<td>0.7</td>
<td>1.2</td>
<td>1.8</td>
<td>61.9</td>
</tr>
<tr>
<td>13b</td>
<td>30.6</td>
<td>11.4</td>
<td>3.2</td>
<td>0.2</td>
<td>1.7</td>
<td>8.2</td>
<td>43.8</td>
<td>0.0</td>
<td>0.2</td>
<td>0.7</td>
<td>53.9</td>
</tr>
</tbody>
</table>
### Appendix II: Case studies of mining data integration

<table>
<thead>
<tr>
<th>Case study</th>
<th>Location</th>
<th>Method used</th>
<th>Predicted</th>
<th>Comment</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anonymous, Cu–Mo porphyry</td>
<td>South America</td>
<td>Multivariate geostatistical simulation using an intrinsic super secondary approach</td>
<td>Grades and comminution indices</td>
<td>Process properties are frequently unequally sampled and sampled at scales much larger than typical assay measurements. Handling multivariate data was a challenge</td>
<td>(Deutsch et al., 2016)</td>
</tr>
<tr>
<td>Anonymous, phosphate mine (flotation &amp; magnetic separation)</td>
<td>Brazil</td>
<td>Multiple regression of elements</td>
<td>Mass recovery of the plant based on the chemical assays of the feed</td>
<td>Model was intended for the block model, but implementation is not reported</td>
<td>(Fernandes and Cabral, 2016)</td>
</tr>
<tr>
<td>Cadia East, porphyry Cu–Au</td>
<td>Australia</td>
<td>Multivariate statistical methods (PCA) for spatial domain modelling, regression model based on minerals</td>
<td>$A \times b$, BWi, SPI</td>
<td>-</td>
<td>(Keeney et al., 2011; Keeney and Walters, 2011; Newton and Graham, 2011)</td>
</tr>
<tr>
<td>Escondida, porphyry Cu</td>
<td>Chile</td>
<td>Kriging</td>
<td>BWi, SPI</td>
<td>-</td>
<td>(Preece, 2006)</td>
</tr>
<tr>
<td>Finney’s Hill, Cu porphyry associated skarn deposit</td>
<td>Based on anonymous data</td>
<td>Process (circuit) simulation</td>
<td>Strategies for mineral production</td>
<td>No spatial modelling done</td>
<td>(Tungpalan et al., 2015a)</td>
</tr>
<tr>
<td>La Colosa, porphyry Au</td>
<td>Colombia</td>
<td>PCA, regression models, domain modelling on previous modelling</td>
<td>Comminution variability: BWi, $A \times b$</td>
<td>Integrated geometallurgical method (IGM) outlined was applied</td>
<td>(Montoya et al., 2011)</td>
</tr>
<tr>
<td>Mogalakwena, Platinum Mine, PGE</td>
<td>South Africa</td>
<td>Geochemical domain modelling and regression</td>
<td>Blasting parameters, throughput and plant recoveries</td>
<td>-</td>
<td>(Schouwstra et al., 2013)</td>
</tr>
<tr>
<td>Morro do Ouro, related to hydrothermal fluids rich in Au–Pb–Zn</td>
<td>Minas Gerais State, Brazil</td>
<td>Domaining based on lithology</td>
<td>Acid neutralised capacity (ANC) and Au recovery</td>
<td>-</td>
<td>(Esper et al., 2013)</td>
</tr>
<tr>
<td>Olympic Dam, Cu-Au-U-Ag</td>
<td>South Australia</td>
<td>Linear regression model of minerals, Mineralogy algorithm to calculate minerals</td>
<td>Tailings leach acid consumption = $a + b \times (%$ chlorite) + $c \times (%$ carbonates) + $d \times (%$ sericite)</td>
<td>-</td>
<td>(Macmillan et al., 2011)</td>
</tr>
<tr>
<td>Olympic Dam, IOCG-U (Cu-U-Au-Ag deposit)</td>
<td>South Australia</td>
<td>Sequential Gaussian simulation with a subsequent regression.</td>
<td>Plant performance: Cu &amp; U recoveries, DWi, BMWi, Acid consumption, Net recovery</td>
<td>Prediction = $a \times A + b \times B + c \times V + d \times D$. Reliance on the multivariate Gaussian distribution after univariate transformation was a limitation factor</td>
<td>(Boisvert et al., 2013)</td>
</tr>
<tr>
<td>Radomiro Tomic, porphyry Cu</td>
<td>Chile</td>
<td>Domaining and later ordinary co-kriging by domain</td>
<td>Recovery of bioleach tests and</td>
<td>Recovery is predicted indirectly through the ratio between soluble Cu (Cu$<em>{24h}$) and total Cu (CuT) - Cu$</em>{24h}$/CuT</td>
<td>(Riquelme et al., 2009)</td>
</tr>
<tr>
<td>Case study</td>
<td>Location</td>
<td>Method used</td>
<td>Predicted</td>
<td>Comment</td>
<td>Reference</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>---------------</td>
<td>----------------------------------------------------------------------------</td>
<td>-----------------------------</td>
<td>------------------------------------------------------------------------</td>
<td>---------------------</td>
</tr>
<tr>
<td>Red Dog, Zn-Pb</td>
<td>Alaska, USA</td>
<td>PCA classification for each block in a block model and regression model for different classes</td>
<td>Zn recovery, throughput and specific power</td>
<td></td>
<td>(Newton and Graham, 2011)</td>
</tr>
<tr>
<td>Chelopech</td>
<td>Bulgaria</td>
<td>Linear equations</td>
<td>$A \times b$ and operating work (OWi) indices</td>
<td></td>
<td>(Rincon et al., 2019b)</td>
</tr>
<tr>
<td>Seven anonymous case studies, porphyry ore</td>
<td>Unknown</td>
<td>Linear regression</td>
<td>BWi, DWi</td>
<td>Note: comminution samples tend to overestimate comminution energy by up to 20 per cent</td>
<td>(Harbort et al., 2013)</td>
</tr>
<tr>
<td>Synthetic deposit model, AIO</td>
<td>Sweden</td>
<td>Process simulation applied to every block. Nearest neighbor, linear prediction for data propagating.</td>
<td>Throughput, recovery</td>
<td>NPV, IRR were estimated</td>
<td>(Lishchuk et al., 2016a, 2016b)</td>
</tr>
</tbody>
</table>
Appendix III: Interview questionnaire

<table>
<thead>
<tr>
<th>Details</th>
<th>Answer</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Contact details</td>
<td></td>
</tr>
<tr>
<td>2. Company name</td>
<td></td>
</tr>
<tr>
<td>3. Mine site name</td>
<td></td>
</tr>
<tr>
<td>4. Country</td>
<td></td>
</tr>
<tr>
<td>5. Commodity</td>
<td></td>
</tr>
<tr>
<td>6. Main minerals</td>
<td></td>
</tr>
<tr>
<td>7. <strong>Process include</strong> (e.g., open pit mine, grinding, flotation, filtering, leaching):</td>
<td></td>
</tr>
<tr>
<td>8. Geometallurgy is <strong>applied</strong> in for the following parts of the process (e.g., flotation, grinding, dewatering, etc)</td>
<td></td>
</tr>
<tr>
<td>9. <strong>Tools</strong> used (e.g., XRF, MLA, XRD, ICP, Hyperspectral imaging, optical microscopy)</td>
<td></td>
</tr>
<tr>
<td>10. <strong>Tests</strong> used (e.g., BWi, batch flotation, DT etc.)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Name</th>
<th>Yes</th>
<th>No, but intended</th>
<th>No</th>
<th>No information</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>11. Geological <strong>database</strong> exists and is used in geometallurgy</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12. <strong>Metallurgical tests</strong> are conducted for capturing variability</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13. Geometallurgical model exists</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14. <strong>Simulation</strong> is used (for which parts of the value chain)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15. Metallurgical response or indicators of the metallurgical response are <strong>visualised in a block model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16. Geometallurgical model is continuously updated and edited</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**PLEASE CHOOSE APPLICABLE:**

17. Active participants of the geometallurgy:

- Geologist
- Processing engineer
- Mining engineer
- Automation engineer
- Maintenance engineer
- Environmentalist
- Product buyer
- Economist
- Shareholders

18. **Approach used in geometallurgy:**

- **Traditional** (Based on elemental grades)
- **Proxy** (based on abstract properties, e.g., DT)
- **Mineralogical** (based on mineral properties, e.g., liberation)

19. Geometallurgy is used to:

- Not used
- Used to correct problems
- Used to prevent problems

20. Managerial function of geometallurgy:

- None
- Data collecting
- Visualization
- Forecasting
- Changing process
- Constraining
- Production planning
- Managing production scenarios
## Appendix IV: Data integration issues associated with geostatistics

<table>
<thead>
<tr>
<th>Term</th>
<th>Description</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Declustering</td>
<td>Declustering corrects the variable’s distribution by minimizing the effects of biased spatial distribution of the variable of interest. However, declustering does not solve the problem for short distances due to oversampling.</td>
<td>(Chilès and Delfiner, 2012; Sinclair and Blackwell, 2004)</td>
</tr>
<tr>
<td>Decorrelation</td>
<td>Decorrelation is a procedure of data transformation for generating a new set of variables which are independent from each other. Decorrelation can be used in a conditional simulation or modelling non-additive variables. Decorrelation could be performed with MAF method (maximal autocorrelation factors) or PCA (principal component analysis).</td>
<td>(Chilès and Delfiner, 2012; Deutsch et al., 2016)</td>
</tr>
<tr>
<td>Domains</td>
<td>Domain is volumes with a variable ( Z(u) ) (mineral grade, BWI etc) having homogeneous distribution. It is characterised by uniform characteristics (e.g., geological) and is equivalent to geostatistically stationary areas. Modelled domain must be larger than selective mining units otherwise it is worthless to delineate domain.</td>
<td>(Rossi and Deutsch, 2014; Sinclair and Blackwell, 2004)</td>
</tr>
<tr>
<td>Ergodicity</td>
<td>A single sample would reflect the statistical character of the random function. The more continuous the covariance and the larger the covariance range, the larger the area A has to be before ergodicity is achieved. In other words, mean of a sample can be approximated by the mean of an actual realization over a sufficiently large domain.</td>
<td>(Deutsch and Journel, 1998; Welhan, 2004)</td>
</tr>
<tr>
<td>Kriging</td>
<td>Kriging is an interpolation linear method (ordinary, simple kriging) for estimating ( Z(u) ) in a non-sampled location ( u ). Kriging has been introduced in Kriege, (1951). Kriging has a smoothing effect.</td>
<td>(Chilès and Delfiner, 2012)</td>
</tr>
<tr>
<td>Kriging (Ordinary)</td>
<td>Ordinary kriging is an interpolation method for situations where the slowly varying mean is unknown.</td>
<td>(Mariethoz and Caers, 2015)</td>
</tr>
<tr>
<td>Kriging (Simple)</td>
<td>Simple kriging is an interpolation method where the variogram and the mean are stationary. The mean is known over the area A.</td>
<td>(Mariethoz and Caers, 2015)</td>
</tr>
<tr>
<td>Random function</td>
<td>Random function is a probabilistic description of the distribution of variable ( Z(u) ) within area A at location ( u ). Both ( u ) and ( Z(u) ) belong to the same statistical population. Area A is considered stationary. RF considers both random and structured components of the spatial variability of the variable.</td>
<td>(Bardossy, 1997; Rossi and Deutsch, 2014; Sinclair and Blackwell, 2004)</td>
</tr>
<tr>
<td>Simulation</td>
<td>Simulation is procedure to obtain interpolation reproducing the variogram of the original variable. Simulation applies a probabilistic model of the variables ( Z(u) ) and generates a set of possible values for each block.</td>
<td>(Bardossy, 1997; Rossi and Deutsch, 2014)</td>
</tr>
<tr>
<td>Stationarity</td>
<td>Stationarity represents a statistically homogeneous population (the same population) in the area A, and is a property of the random function. Stationarity may not be a physical property, but a characteristic of the chosen estimation method.</td>
<td>(Isaaks and Srivastava, 1989; Rossi and Deutsch, 2014)</td>
</tr>
<tr>
<td>Support</td>
<td>Support is a size of the 1-, 2-, or 3-dimensional space (length, area, volume) over which the data are measured or defined. Referring estimates to a size different from the size of given samples is called support problem. Constructing (compositing) of larger support from grades of smaller supports leads to smoothing of the original data values.</td>
<td>(Chilès and Delfiner, 2012; Garrido et al., 2019; Isaaks and Srivastava, 1989; Sinclair and Blackwell, 2004; Welhan, 2004)</td>
</tr>
<tr>
<td>Variography</td>
<td>Variography is used measure spatial similarity of a regionalized variable and can be defined as a statistical description of how the values at two points become different as the separation between these points changes. Other alternative functions to measure autocorrelation are (e.g., covariogram, correlogram). The variogram shows how different sample become when distance between them increases.</td>
<td>(Chilès and Delfiner, 2012; Sinclair and Blackwell, 2004)</td>
</tr>
</tbody>
</table>
Appendix V: Data integration issues associated with metallurgical data

<table>
<thead>
<tr>
<th>Considerations</th>
<th>Description</th>
<th>Solutions</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Additivity</strong></td>
<td>Complex nonlinear averaging of response (metallurgical) parameters</td>
<td>Conditional simulation</td>
<td>(Keeney et al., 2011)</td>
</tr>
<tr>
<td></td>
<td>Biased estimates with kriging</td>
<td>Modelling response variables by using additive variables</td>
<td>(Deutsch et al., 2016)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Non-linear transformation</td>
<td>(Deutsch, 2013)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Decorrelation using PCA</td>
<td>(Chilès and Delfiner, 2012; Deutsch et al., 2016)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Develop models which express process parameter as a function of additive properties, i.e., metal and mineral grades</td>
<td>(Ehrig, 2013)</td>
</tr>
<tr>
<td><strong>Overfitting</strong></td>
<td>Overfitting occurs at overly complex models and is a phenomenon when statistical model describes random error/noise instead of desired relationship and exaggerates minor fluctuations in the data</td>
<td>Cross-validation</td>
<td>(Kittler et al., 2011; Windle et al., 2016)</td>
</tr>
<tr>
<td><strong>Support</strong></td>
<td>Biased variance of the population due to unequal support</td>
<td>Compositing Declustering</td>
<td>(Krige, 1951; Matheron, 1963)</td>
</tr>
<tr>
<td></td>
<td>Support is not constant and changes between tests, selective mining unit and daily production. Blurry definition of support when metallurgical samples are composited from different locations</td>
<td>Compositing Declustering</td>
<td>(Carrasco et al., 2008; Riquelme et al., 2009)</td>
</tr>
<tr>
<td><strong>Smoothening effect</strong></td>
<td>Some response variables can possibly be controlled by extremes but not averages in population, e.g., liberation</td>
<td>Geostatistical simulation Indicator geostatistics</td>
<td>(Chilès and Delfiner, 2012; Dunham and Vann, 2007; Goovaerts, 1997)</td>
</tr>
<tr>
<td><strong>Missing data</strong></td>
<td>Incomplete data due to high cost of the metallurgical tests</td>
<td>Gibbs sampler Gaussian simulation</td>
<td>(Deutsch, 2013)</td>
</tr>
<tr>
<td></td>
<td>Cause problems in data transformations</td>
<td>Imputing zeros by a constant fraction of the detection limit OR Multiple imputation. Note: Using constant values, regression, or co-kriging imposes risk of altering multivariate special relationships (Deutsch, 2013).</td>
<td>(Boisvert et al., 2013; Lopez et al., 2016; Tolosana-Delgado et al., 2015)</td>
</tr>
<tr>
<td></td>
<td>Problem in compositional regression modelling</td>
<td>Removing sample with missing values</td>
<td>(Boisvert et al., 2013)</td>
</tr>
<tr>
<td><strong>Communication</strong></td>
<td>Distrust between stakeholders: geologists, mining engineers, geostatistitians and metallurgical engineers</td>
<td>N/A</td>
<td>(Riquelme et al., 2009)</td>
</tr>
<tr>
<td><strong>Too few samples</strong></td>
<td>Available number of samples is not sufficient to do a proper assessment</td>
<td></td>
<td>(Carrasco et al., 2008)</td>
</tr>
<tr>
<td><strong>Closure problem</strong></td>
<td>Ratios (compositional data) do not sum up to 1. When summing up, histograms are distorted.</td>
<td>Complex multivariate relations must. PCA, MAF should be avoided</td>
<td>(Deutsch, 2013)</td>
</tr>
</tbody>
</table>
Appendix VI: Geometallurgical program – extended (areas where development was done within this theses is marked with green colour)
Appendix VII: Explanation to the picture on the title page

1. “Fe” in the middle means iron.
2. Figures that surround “Fe” represent participants and important actors in the geometallurgical program.
3. Diagram on the outside circle shows the flow of experimental work in the thesis and covers:

<table>
<thead>
<tr>
<th>#</th>
<th>Meaning</th>
<th>Picture</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Geological study</td>
<td>Deposit model</td>
</tr>
<tr>
<td>B</td>
<td>Sampling</td>
<td>Drill cores</td>
</tr>
<tr>
<td>C</td>
<td>Comminution and sample preparation</td>
<td>Ball mill</td>
</tr>
<tr>
<td>D</td>
<td>Geometallurgical testwork</td>
<td>Davis tube apparatus</td>
</tr>
<tr>
<td>E</td>
<td>Laboratory scale testwork</td>
<td>WLIMS apparatus</td>
</tr>
<tr>
<td>F</td>
<td>Mineralogical study</td>
<td>Liberation distribution for the sample 13 by size</td>
</tr>
<tr>
<td>G</td>
<td>Modelling</td>
<td>ΔR predicted vs. ΔR measured</td>
</tr>
<tr>
<td>A</td>
<td>Spatial and geological modelling (back to the beginning)</td>
<td>Deposit model</td>
</tr>
</tbody>
</table>
Appendix VIII: Paper A
THE GEOMETALLURGICAL FRAMEWORK. MALMBERGET AND MIKHEEVSKOYE CASE STUDIES

Viktor LISHCHUK*, Pierre-Henri KOCH, Cecilia LUND, Pertti LAMBERG
Luleå University of Technology, SE-971 87 Luleå, Sweden

Abstract: Geometallurgy is a growing area within a mineral processing industry. It brings together tasks of geologists and mineral processing engineers to do short and medium term production planning. However, it is also striving to deal with long term tasks such as changes in either production flow sheet or considering different scenarios.

This paper demonstrates capabilities of geometallurgy through two case studies from perspective of Minerals and Metallurgical Engineering division Lulea University of Technology. A classification system of geometallurgical usages and approaches was developed in order to describe a working framework. A practical meaning of classification system was proved in two case studies: Mikheevskoye (Russia) and Malmberget (Sweden) projects. These case studies, where geometallurgy was applied in a rather systematic way, have shown the amount of work required for moving the project within the geometallurgical framework, which corresponds to shift of the projects location within the geometallurgical classification system.

Keywords: geometallurgy, classification, proxies, mineralogy, case study, Malmberget, Mikheevskoye

1. WHAT IS GEOMETALLURGY?

A classical approach to model a deposit is to derive metal grades from chemical assays and build a 3D block model that includes geology and metal grades. However, the complexity of ores and deposits is increasing over the years and a need for enhanced models has emerged. In recent years several authors have proposed different definitions, all based on the close interaction between geology, mineral properties and...
behaviour of a feed in metallurgical operations (McQuiston and Bechaud, 1968; Vann et al., 2011). While the approach in itself is not new, recent advances in automated mineralogy, data processing and comminution testing have made it feasible in practice (Lamberg and Lund, 2012; Schouwstra et al., 2013).

Geometallurgy is a multi-disciplinary science that aims at integrating geology, mineralogy, mineral processing and metallurgy to build a spatially-based model for production management that quantitatively predicts:

- quality of concentrates and tailings,
- metallurgical performance, like metallurgical recoveries and throughput,
- environmental impact such as fresh water usage for tons produced.

To achieve these goals, a unified framework is needed to guide the practical work needed.

2. GEOMETALLURGICAL USAGE AND APPROACHES CLASSIFICATION

The data structuring and data modelling in geometallurgy heavily depend on geometallurgical approach used in the mine and final purpose of geometallurgy. When developing a geometallurgical program, i.e. industrial application of geology, one should have clear vision how this information will be used. To benchmark different geometallurgical programs we have developed a two dimensional classification system. The first dimension of the classification system is the type of geometallurgical approach and the second dimension is the depth of usage of geometallurgy (Fig. 1).

Fig. 1. Selected mines arranged in classification matrix
2.1. GEOMETALLURGY APPROACHES

The geometallurgical programs are divided in three approaches: traditional, proxies, mineralogical.

In **traditional approach** the metallurgical response of an ore in the mineral processing plant is calculated from the normal (chemical) assays using mathematical functions, which are often called as recovery functions. The functions are developed using variability testing and statistical analysis to define the correlation between the metallurgical response and feed properties (i.e. chemical composition).

**Proxies approach** uses geometallurgical tests for a large number of samples. The geometallurgical test is a small scale test which indirectly measures the metallurgical response. Normally the geometallurgical test results must be converted with certain correction factors to give an estimate on the metallurgical results of the plant. Examples of geometallurgical tests are Davis tube (Niiranen and Böhm 2012), Minnovex crus her index test (Kosick et al., 2002).

Continuous and systematic collection of quantitative mineralogical information is the main characteristic of the **mineralogical approach** in geometallurgy. An example how mineralogy can bridge geological model to model of mineral processing plant (Figs. 1, 2) is work done by Lamberg (2011) and Lund (2013).

Fig. 2. Role of particles in proposed geometallurgical approach (Lamberg, 2011, modified)

2.2. GEOMETALLURGY USAGES

Depth of usage in geometallurgy means how the geometallurgical data is used in the mine:

0. None (neither usage nor collection of geometallurgical data);
1. Collecting data (geometallurgical data is collected but not used);
2. Visualizing data (the variation within the ore body);
3. Defining production constraints (for example, cut-off grade);
4. Forecast production;
5. Making changes in process based on feed quality (changes are made in the process beforehand with the knowledge of geometallurgy);
6. Production planning;
7. Applying different production scenarios (geometallurgical data is used to make large scale decision of the future; e.g. when to invest, what alternative technologies is selected etc.).

The deeper the level of geometallurgy is, the deeper integration and cooperation between involved parts of the mineral production chain (geology exploration and production, mining, processing, sales etc.) are.

3. CASE STUDIES

3.1. MIKHEEVSKOYE

The Mikheevskoye geometallurgical model was developed by Lishchuk (2014). The aim of the study was to find a way for improving performance of the mineral processing plant through the better understanding of the variation in the ore body and mine planning of Cu-porphyry deposits. The aim of the study was reached by including information on hydrothermal alteration zoning in geological block modelling and geometallurgical zonality in estimates on operational costs.

The Mikheevskoye deposit is located in Chelyabinsk region, Russian Federation on the territory of the Varma municipality on the border with Kartaly municipality. The ore reserves of the Mikheyevsky deposit within the outlines of an initially planned open pit mine were approved by the State Commission for Mineral Reserves in July 2010 in an amount of 352 million tonnes (Mt) of categories A+B+C1+C2 (more about Russian resource and reserve categories could be found Henley, S., 2004) with an average copper content of 0.41% (Beloshapkov, 2012). Mikheevskoye could be considered as a greenfield project and commissioning was planned in 2013-2014.

The Mikheevskoye deposit demonstrates a typical alteration-mineralization zoning pattern for porphyry Cu deposits (Sillitoe, 2010). Zoning pattern forms a shape of a shell (Sillitoe, 1973). Alteration zones of Miheevskoye consist of the inner potassic and outer propylitic alteration zones. The zones of phyllic and argillic (clay rock) alteration are the part of the zonal pattern between the potassic and propylitic zones.

Copper mineralization occurs as chalcopyrite and bornite dissemination within the host lithology. Ore zones of the Mikheevskoye deposit have locally outlined, sometimes not well defined vertical mineral zonality (ore stratification) from the top to the bottom:

- The top layer consists of the shallow Cenozoic rocks (soil),
- Laterite zone (also known as supergene or oxidized zone - oxidized ore),
- Intermediate (oxidized/ cemented) zone - transitional (mouldy) ore,
The geometallurgical framework. Malmberget and Mikheevskoye case studies

- Hypogene (fresh) zone - sulphide (rocky) ore.

Initially, Mikheevskoye project did not have any geometallurgical model and the collected geological data had little use for mineral processing planning (level 0). Therefore, a project to develop a geometallurgical model was the set for the Mikheevskoye project. Two scenarios were evaluated for the project: the head grade based and geometallurgical based. The head grade scenario assumed that mine planning and feed quality would be forecasted based on ore metal grade. The geometallurgical based scenario assumed predictions based on geometallurgical domains. The geometallurgical domains were established for the ore zones which would behave homogeneously in the beneficiation process. The following objectives (Table 1) were formulated for the head grade scenario and geometallurgical program based on ideas developed in Lamberg, (2011).

Table 1. Objectives of the head grade and geometallurgical program scenarios

<table>
<thead>
<tr>
<th>Head grade scenario</th>
<th>Geometallurgical program scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>Investigation of feed quality needs of concentrator process (comminution and flotation departments usually have different needs)</td>
<td>Co-operate geological information about the deposit</td>
</tr>
<tr>
<td>Collect up-to-date geological information about the deposit</td>
<td>Conduct sampling campaign</td>
</tr>
<tr>
<td>Collect up-to-date topographic data from surveying</td>
<td>Model zonality of the ore body based on commodity grade</td>
</tr>
<tr>
<td>Model zonality of the ore body based on commodity grade</td>
<td>Model zonality of the ore body based on process behaviour of different ore types</td>
</tr>
<tr>
<td>Run open pit optimization</td>
<td>Develop optional open pit design based on commodity grade</td>
</tr>
<tr>
<td>Develop optional open pit design based on commodity grade</td>
<td>Develop mining plan and extraction schedule</td>
</tr>
<tr>
<td>Develop mining plan and extraction schedule</td>
<td>Estimate cost efficiency of the proposed solution</td>
</tr>
</tbody>
</table>

Application of the geometallurgical approach requires to link metallurgical and geological parameters. Williams and Richardson (2004) suggested using parameters listed in Table 2.

Table 2. Linkage between geological and metallurgical factors after Williams and Richardson (2004)

<table>
<thead>
<tr>
<th>Geological/mineralogical factor</th>
<th>Ore property</th>
<th>Metallurgical output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Grinding</td>
</tr>
<tr>
<td>Rock type</td>
<td>Hardness</td>
<td>X</td>
</tr>
<tr>
<td>Ore assemblage</td>
<td>Solubility, hardness</td>
<td>X</td>
</tr>
<tr>
<td>Alteration</td>
<td>Clays, hardness</td>
<td>X</td>
</tr>
<tr>
<td>Faulting</td>
<td>Clays, oxidation</td>
<td></td>
</tr>
<tr>
<td>Metamorphism</td>
<td>Clays, hardness</td>
<td>X</td>
</tr>
</tbody>
</table>
Mineral processing flow sheet suggested that hardness, oxidation and presence of magnetite were the most crucial parameters for the process performance. Some permutation of these parameters resulted in 13 geometallurgical domains and are presented in Table 3.

Table 3. Geometallurgical domains suggested for Mikheevskoye mine

<table>
<thead>
<tr>
<th>Cut-off 0.2% Cu</th>
<th>Hardness</th>
<th>Magnetite</th>
<th>Oxidation</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outside</td>
<td>Not relevant</td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Inside</td>
<td>Hard</td>
<td></td>
<td></td>
<td>2</td>
</tr>
<tr>
<td>Inside</td>
<td>Hard</td>
<td>X</td>
<td></td>
<td>3</td>
</tr>
<tr>
<td>Inside</td>
<td>Hard</td>
<td>X</td>
<td>X</td>
<td>4</td>
</tr>
<tr>
<td>Inside</td>
<td>Very hard</td>
<td></td>
<td></td>
<td>5</td>
</tr>
<tr>
<td>Inside</td>
<td>Very hard</td>
<td></td>
<td>X</td>
<td>6</td>
</tr>
<tr>
<td>Inside</td>
<td>Very hard</td>
<td>X</td>
<td></td>
<td>7</td>
</tr>
<tr>
<td>Inside</td>
<td>Very hard</td>
<td>X</td>
<td>X</td>
<td>8</td>
</tr>
<tr>
<td>Inside</td>
<td>Extremely hard</td>
<td></td>
<td></td>
<td>9</td>
</tr>
<tr>
<td>Inside</td>
<td>Extremely hard</td>
<td></td>
<td>X</td>
<td>10</td>
</tr>
<tr>
<td>Inside</td>
<td>Extremely hard</td>
<td></td>
<td>X</td>
<td>11</td>
</tr>
<tr>
<td>Inside</td>
<td>Extremely hard</td>
<td></td>
<td>X</td>
<td>12</td>
</tr>
<tr>
<td>Inside</td>
<td>Extremely hard</td>
<td></td>
<td>X</td>
<td>13</td>
</tr>
</tbody>
</table>

Two mining scenarios were calculated based on the metal grade and geometallurgical domains. The metal grade scenario assumed that the ore would be extracted by metal grade and the processing cost would be constant for each block. Geometallurgical domained approach assumed ore extraction by domains, which implies variable processing cost for different domains. Discretization of the mining schedule was done with one year frequency for the next five years.

Since the result of research was not used in production planning, this project was classified as visualization usage of geometallurgy (level 2, Fig. 1) and approach as traditional. It was also predicted that geometallurgical approach could potentially decrease the payback period for the project by 1.5 years and significantly increase the net present value.

3.2. CASE STUDY – MALMBERGET

Lund (2013) developed a geometallurgical framework established in three steps using the Malmberget iron ore deposit, northern Sweden, as a case study.

Malmberget deposit is a major iron ore source operated by LKAB located close to Gällivare in northern Norrbotten, Sweden. At the end of 2014, approximately 680 Mt of crude ore have been produced in open pits and underground workings and the reserves were estimated to 288 Mt with 42.1% Fe (LKAB, 2013).
The deposit consists of more than 20 sub-vertical ore bodies of hematite and magnetite occurring as massive lenses surrounded by an extensive brecciation. The origin is intensively debated and one of the prevailing theories is that the massive ore is formed as magmatic intrusions with the iron-enriched magma or high temperature hydro-thermal fluids circulation at 1.88-1.90 gigaannus (Geijer, 1930; Romer et al., 1994). The breccia (semi-massive) ore is suggested to have been formed by low-temperature hydro-thermal processes (Martinsson, 2004).

Lund (2013) showed that the reason behind the magnetite-hematite partition of the deposit might be oxidation of magnetite into hematite following an easterly to westerly direction.

The initial work focused on building the geological model in a geometallurgical context based on mineralogical characterization. This was done in several steps:

1. Ore characterization: gather chemical and mineralogical information on the ore and host rocks, as well as study their variations within the ore bodies
2. Quantification of mineralogy and textural information:
   a. Use chemical assays and element to mineral conversion (EMC) to evaluate mineral grades.
   b. Use optical microscopy and scanning electron microscopy (SEM) to evaluate the grain size (not particle size) of minerals. The association index (AI) and liberation data were used to build textural archetypes.
3. Definition of geometallurgical ore types (GEM-types): combine mineral grades and textural information to build GEM-types
4. Study comminution related to textural information: perform simple rock mechanics test and small-scale comminution tests to build a particle breakage model (establish liberation degree by size fraction). The particle breakage model follows the structure.
5. Test the applicability of the results using a metallurgical unit model: After converting un-sized modal composition to liberation distribution using textural archetypes (particle tracking algorithm based on Lamberg and Viana, 2007), a one-step dry magnetic separation (cobbing) was used.

Steps 1 to 3 yielded 6 different GEM-types for the Fabian and Prinzsköld ore bodies (Lund, 2013) and 5 textural archetypes. Step 4 gives an overall size distribution model, several lab-scale models linking mineralogy, comminution and limited liberation data, and provided classification into several grindability-liberation classes (Koch, 2013). Finally, Step 5 allowed validating the approach within a 2% error limit. These results validate the mineralogical approach to geometallurgy and indicate that, even with a limited number of samples and tests, it could be used to obtain geometallurgical parameters for the block model.

The approach in the Malmberget model is mineralogical and it enables production forecasting (level 4, Fid. 1).
3.3. DISCUSSION

Two case studies, Mikheevskoye and Malmberget, where geometallurgy was applied were reviewed in this paper. The purpose of these reviews was to show some capabilities and practical use of geometallurgy. Both case studies were initially at a low level of geometallurgy usage of. The low level of geometallurgy corresponded also to low predictability of production in these case studies.

The case studies demonstrate:

- With the right characterization and tests, even with limited samples, we can acquire quantitative information regarding the ore (hardness, modal mineralogy, grain size, degree of liberation and association index.
- Understanding on the behaviour of minerals and particles (of different sizes, modal mineralogy and textures in the beneficiation process is critical for creating reliable process model.
- Linking the information above enables to build a geometallurgical block model and use it as a production planning tool.

4. CONCLUSIONS

A modern mining industry faces new challenges which were not common several decades ago. Decreased ore grades, increased variability within ore body and highly fluctuating commodity prices have higher impact on the projects profitability and thus, require more accurate short and long term planning. One of the possible solutions for this is implementation of geometallurgy. Geometallurgy is instrument which allows connecting geological and mineral processing information for a predictive model to be used in short and medium term planning.

Geometallurgy has to cover all parts of mining production chain and take into account connections which exist between all production stages. Thus, more detailed and uniform descriptions of ore recourses, plant feed and process streams are required. Therefore, a two dimensional classification system of the geometallurgical approaches and usages was developed. This classification system was used to analyse typical geometallurgical data structure and applied over studied case studies. The practical use of this classification system becomes obvious when there is a need to either change geometallurgical approach (i.e., traditional, proxies, mineralogical) or go to the deeper level of the usage of geometallurgy. Information shown in Fig. 1 can also be used for benchmarking.

The potential impact of the geometallurgical program on production management was shown in two case studies: Mikheevskoye (Russian Federation) and Malmberget (Sweden). The result has proved to bring significant improvement in predictability of the feed quality and processing performance. For example, successful implementation of geometallurgical program in Mikheevskoye potentially decreases the payback peri-
od by 1.5 years. Both of these case studies were developed under the strong impact of research ideas and scientific approaches of the MiMeR (Mineral processing) division of the Lulea University of Technology (Sweden).

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Appendix IX: Paper B
Geometallurgical characterisation of Leveäniemi iron ore – Unlocking the patterns

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ARTICLE INFO
Keywords:
Davis tube
Magnetic separation
Liberation
Apatite iron ore
Leveäniemi

ABSTRACT
As part of a geometallurgical program for the Leveäniemi iron ore mine, the Davis tube was used as proxy to classify ore types, predict iron recoveries in wet low-intensity magnetic separation (WLIMS), and to estimate liberation of mixed particles. The study was conducted by testing 13 iron ore samples with a Davis tube and a laboratory WLIMS. Ore feed was studied for modal mineralogy and liberation distribution with Automated Scanning Electron Microscopy. Data analyses to detect the patterns and data dependencies were done with multivariate statistics: principal component analysis, and projection to latent structures regression. Results show that a simple index \(XLTU\) based on mass pull in the Davis tube is capable of easy classification of magnetite ores. Using Davis tube mass pull and iron recovery, together with iron and Satmagan head grades may predict iron recovery in WLIMS. Also, the variability in Fe-oxides liberation pattern for magnetite semi-massive ores can be explained with the chemical composition of the Davis tube concentrate. It is concluded that the Davis tube test is better used only for marginal ores, since iron oxide minerals tend to be fully liberated in high-grade magnetite massive ores after grinding. The developed models may be used in populating a production block model.

1. Introduction

Geometallurgy is an interdisciplinary approach, which aims at linking geological and mineral processing parts of the mining value chain by means of a spatial predictive model (Dunham and Vann, 2007; Lund and Lamberg, 2014; Vann et al. 2011). The increased variability in iron ore quality, new iron ore types, increased production volumes and increased requirements from steel makers have created a niche for iron ore geometallurgy (Ramanaidou et al., 2012). Applying geometallurgy in iron ore production for maintaining reasonable production performances (recoveries, throughput) and desired product qualities can be achieved through a geometallurgical program (Parian, 2017).

The project presented here aims to develop a geometallurgical program for the Leveäniemi apatite iron ore. Its ultimate goal is to build a geometallurgical block model. The Davis tube was chosen as a proxy tool for predicting process performance parameters (Lishchuk, 2016).

Davis tube is a standard tool for estimating the highest possible concentrate grade in magnetic separation (Cheng and Misra, 1999; Niiranen, 2015) and estimating the amount of magnetically recoverable iron in the ore. However, to the best of our knowledge, there are no validated results on how the Davis tube may be applied efficiently in process modelling.

The aim of this study is to find patterns in Davis tube performance connected to the mineralogical and textural description of the ore. It is assumed that the Davis tube is a nearly perfect magnetic separator without entrapment. This leads to the following hypotheses:

H 1: Davis tube test results may be used in ore classification.
H 2: There are similarities between the Davis tube and WLIMS in how the material is separated into concentrate and tailings. Thus, the Davis tube might be used to model WLIMS results.
H 3: Liberation of the feed might be predicted based on the Davis tube test results.

2. Literature review

2.1. Davis tube

The Davis tube (Davis, 1923, 1921; Obertueffer, 1974; Schulz, 1963; Svoboda, 2004) was selected here as a proxy because a Davis tube test uses a small sample size, is a wet technique, and according to Obertueffer (1974), the Davis tube accounts for drag forces, such as friction and hydrodynamics. Additionally, a Davis tube, unlike other competitive techniques such as Satmagan (Satisfaction Magnetization...
There are two types of parameters which impact the Davis tube performance: material properties and the operational settings of the apparatus. The Davis tube works with particles mixed with water. Particles fed to the tube are separated based on their structure (Schulz, 1963), liberation (Schulz, 1963; Schulz and Lex, 1967), composition (Schulz, 1963; Schulz and Lex, 1967), magnetic susceptibility (Eloranta, 1983; Farrell and Miller, 2011; Guarin et al., 2010; Rayner and Napier-Munn, 2000; Svoboda, 2004). Only two operational parameters are reported as having rather strong impact on the Davis tube performance: the magnetic field strength and the amount of water flushed through the tube (Schulz, 1963). The water rate (flow speed) was reported to be insignificant by Schulz, (1963) and Ahmed (2010).

The Davis tube is often used as a quality control tool for wet low-intensity magnetic separation (WLIMS). Dworzanski (2012) has used the Davis tube to simulate best possible iron recovery evaluating options to maximise recovery of fine iron ore. Niiranen, (2015) used the Davis tube to predict concentrate cleanness in WLIMS with a main focus on silica content.

2.2. Applying davis tube for assessment of WLIMS performance

Magnetic separation is the primary separation technique employed in iron ore concentrators. Depending on the ore properties and processing target grade, magnetic separation can be done as either a wet or dry process, with either low- or high-intensity magnetic fields. Both WLIMS and Davis tube accomplish wet magnetic separation. However, the Davis tube, unlike WLIMS, lacks mechanical forces, has much higher degree of water drag forces, can be operated at different magnetic fields and has originally been designed only for testing fine materials. In this study the focus is on the WLIMS as the primary method used to upgrade the iron ore from Leveäniemi deposit. Normally, a lab scale WLIMS drum apparatus is the main tool for simulating iron ore behaviour in a wet low-intensity magnetic separation process. Muririu and Svoboda (2003) found that Davis tube tests can be used to estimate the efficiency of a conventional ferrite drum separator, operated at 0.1 T.

2.3. Liberation of Fe-oxides

Mineral liberation properties can provide an estimation of the efficiency of the separation processes. Liberation based models are also common in mineral processing simulation (Ersayin, 2004; King and Schneider, 1995; Lambreg, 2011).

The first relevant study of Fe-oxides liberation using the Davis tube was conducted by Wiegel (1975). He discussed the binary system of magnetite and non-magnetite and concluded that comminution techniques, exclusive of pebble grinding, do not have a significant effect on liberation. The model described in Wiegel (1975) was further developed in Wiegel (2011) to provide guidance in simulation of processing of low-grade ores. Additionally, Wiegel's model was used to carry out simulations, where liberation based models were used for taconite (Ersayin, 2007). Despite highly advanced mathematical modelling, this study was dealing only with low-grade ores. Fully liberated magnetite and mixed particles were not distinguished. The mineralogical complexity of the tested materials was not fully considered.

The impact of liberation properties on magnetic separation was described as a combination of both tabular stratiform-stratabound and breccia-style apatite iron ores. The character of the host rocks are felsic and intermediate volcanic (trachyandesitic) (Martinsson et al., 2016). Apart from the magnetite ore, other ore types can be distinguished in this area, i.e., calcareous magnetite ore, hematite-altered ore and brecciated ore (Fritsch, 1966). The main ore mineral is magnetite, but there is also smaller amounts of hematite. The gangue minerals include apatite, biotite, calcite, quartz, chalcopyrite, pyrite, amphiboles, micas (e.g. biotite), potassium feldspar, and plagioclase (e.g. albite) (Gustafsson, 2016; Lund et al., 2013; Martinsson et al., 2016). The chemical composition of magnetite from Leveäniemi; (30.88% FeO/68.04 Fe₂O₃) with 0.15% Al₂O₃, 0.01% K₂O, 0.04% MgO and V₂O₅ 0.32% is close to stoichiometric values (Gustafsson, 2016).

3. Materials and methods

The testing procedure included sampling, metallurgical test-work, mineralogical characterisation and modelling (Fig. 1).

3.1. Sampling

Thirteen representative composite iron ore samples (each a minimum of 60 kg) were used in this study. Ten drill core samples and three pit grab samples were collected by the mine geologist to cover the full geological variation of the deposit.

3.2. Metallurgical characterisation

3.2.1. Sample preparation

Samples for the Davis tube and WLIMS were crushed in a lab scale jaw crusher to < 3.35 mm and then split into batches for the WLIMS and Davis tube feed. The WLIMS subsamples were later ground for 5 min in a rod mill and for 60 min in a ball mill to P80 80 µm. The Davis tube subsamples were ground in a laboratory stainless steel ball mill
(CAPCO or GCT mill) for 11 min. The GCT procedure is described in Mwanga et al. (2017, 2015). A small mill was used to minimize mass losses of the fine fraction during the size reduction. All analyses were done by size.

### 3.2.2. WLIMS

Wet low-intensity magnetic separation (WLIMS) was conducted in a single step using bulk material. The average sample size was 10 kg to ensure a stable and repeatable result. The material was fed to the WLIMS with a rate of 0.5 kg/min at water rate of 3 l/min and drum rotation of 60 rpm. Two products were obtained from the test: concentrate and tailings. The WLIMS testing setup is shown in Fig. 2. The WLIMS tests were conducted at Luleå University of Technology mineral processing laboratory.

### 3.2.3. Davis tube test

The Davis tube test was conducted on three different size fractions: −38 µm (fine), +38–75 µm (medium), and +75–106 µm (coarse). Due to the Davis tube geometric limitations, the fraction coarser than 106 µm was not tested. The tests were done using a minimum of 60–80 g per sample, to ensure sufficient product (min 20 g) for mineralogical characterisation. However, since the Davis tube is most efficient when the sample size is below 20 g, the test for each sample was conducted in several batches 10–15 g each. The water flow was set to 0.31/min, the tube angle − 45 degrees, and tube oscillations − 45 min⁻¹. The tests were done at LKAB’s R&D Laboratory at Malmberget, Sweden. A standard Davis tube apparatus was used (Fig. 3).

The Davis tube tests were run in three steps utilizing a staged rougher approach (Fig. 3), to check how the particles would respond to varying magnetic field intensity. First, the material was fed to the Davis tube at a current strength of 0.1 A, which extracted the particles with the highest magnetic susceptibility (highly liberated magnetite particles). Then, the tailings of the first run were fed to the Davis tube at 0.2 A current strength. Finally, the tailings of the second run was fed to the Davis tube at 0.5 A. Duration of each test run was 130 s.

### 3.3. Mineralogical characterisation

#### 3.3.1. Optical microscopy

Optical microscopy, using a Nikon Eclipse E600, was applied for identification of mineralogy, alterations, grain size distribution and textural properties of the Davis tube feed samples.

#### 3.3.2. Auto-SEM-EDS (QEMSCAN)

Modal mineralogy and liberation analyses of the Davis tube feed
were done on a QEMSCAN system. Fifty-two polished resins blocks representing four size fractions (−38 µm, 38–75 µm, 75–106 µm, + 106 µm) of 13 ore type samples were analysed. The average number of measured particles per sample was 5000. The tests were done at LKAB’s R&D Laboratory at Malmberget, Sweden. Minerals considered to be of a minor importance and minerals, which could not be efficiently distinguished with Auto-SEM-EDS were grouped together, e.g., Fe-oxides for magnetite and hematite.

Data post-processing was performed with HSC Chemistry software version 9 (Outotec, 2017) under the following conditions:

- the minimum amount of mineral in a particle to be considered as liberated (Lib Threshold) is 100%, and
- the minimum amount of mineral in a particle to be treated as binary, ternary, complex (tolerance) is 1%.

### 3.3.3. Chemical assays

Chemical assays were prepared and analysed by ALS-Geochemistry (Piteå, Sweden) and the Technical Laboratory at LKAB (Malmberget, Sweden) using XRF.

The amount of magnetic iron was measured with an electromagnetic method using a Satmagan (Stradling, 1991; Wiegell, 1975). Satmagan results were delivered as corresponding to the Fe²⁺ content (SatFe²⁺) in magnetic fraction. For samples with high iron grades, it can be assumed that SatFe²⁺ is proportional to the magnetite (Mgt) grade (Gustafsson, 2018; Lund et al., 2013; Parian et al., 2015), and therefore calculated as:

\[
Mgt[\%] = \frac{SatFe²⁺[\%]}{24.3[\%]} \times 100\%
\]

where 24.3[\%] is Fe²⁺ content in pure magnetite sample.

### 3.4. Data analyses

#### 3.4.1. Secondary variables

In addition to the chemical assays, some process performance parameters were used in modelling (Table 1). The Difference Index (Di) is the same as the Separation Efficiency put forward by Schulz (1970), but it is a name better describing the built of the index.

#### 3.4.2. Ore classification

In processing, the Davis tube tests are done on drill cores, and the minimum available information includes a mass pull and rough estimate of the feed composition from the geological database or handheld XRF analyser. The handheld XRF analyser can be used when data from the database is not easily accessible. Based on this knowledge, a new quality estimator \(X_{LTU}\) for classifying ore types was proposed. The \(X_{LTU}\) classifies the ore considering both its composition and behaviour in magnetic separation. The idea is that if all available magnetite in the ore is reporting to the Davis Tube concentrate as pure magnetite, then \(X_{LTU}\) will be zero:

\[
X_{LTU} = \frac{Fe_{Feed} - MP - 0.724}{MP - 0.724}
\]

Positive values of \(X_{LTU}\) appear when iron content in DT concentrate is less than expected. Therefore, in this case, some iron is lost to the tailings. Negative values of \(X_{LTU}\) appear when the mass pull is larger than expected. In this case, it means that concentrate is not as clean as expected.

#### 3.4.3. WLIMS recovery prediction

Separation in WLIMS, i.e., iron recovery, is controlled mainly by magnetic, gravity, drag, and mechanical forces. While in the Davis tube, separation is due to magnetic, gravity, and drag forces. Therefore, iron recovery for WLIMS may be written as:

\[
R_{WLIMS}^{Fe} = R_{WLIMS}^{Fe} + t + n
\]

where \(R_{WLIMS}^{Fe}\) is iron recovery in WLIMS; \(R_{WLIMS}^{Fe}\) is iron recovery in Davis tube; \(t\) is a systematic component which considers non-magnetic forces involved in separation performance in WLIMS; \(n\) is a random noise, which can be neglected since it is averaged to zero. Therefore:

\[
R_{WLIMS}^{Fe} = R_{WLIMS}^{Fe} + n = R_{WLIMS}^{Fe} + \Delta R - \Delta R = t + n
\]

So, knowing the iron recovery in DT and being able to explain the recovery difference \(\Delta R\) via the trend function \(t\), allows one to forecast the iron recovery in WLIMS, provided the test settings of the Davis tube, i.e., magnetic field strength, correspond with the magnetic force in WLIMS.

#### 3.4.4. Fe-oxides liberation

Any potential proxy tool for the Fe-oxides liberation prediction should be capable of a rough forecast using as little information as possible, so that additional work and costs related to the extra analysis for chemical assays or mineralogical studies will not be needed. When the Davis tube is used for predicting liberation, the simplest data may include mass pull and possibly feed composition, if the latter is available from drill core logging or portable XRF. More complex predictions require chemically assayed Davis tube products, and process performance parameters, i.e., difference indexes, and recoveries. Additionally, information by size and applying different magnetic fields strengths can be used. This study focused on considering fully liberated Fe-oxides. Studying liberation properties of mixed particles would require a more extensive sampling campaigns, with additional metallurgical testing and mineralogical characterisation.

#### 3.4.5. PCA/PLS – pattern recognition

Principal component analysis (PCA) and projection to latent structures (PLS) methods were used for pattern recognition. PCA handles large number of interrelated variables by reducing dimensionality of the original data set. Dimensionality reduction is achieved by transforming the data set to the principal components (PCs) which cover most of the variation of the original data set (Jackson, 1991; Jolliffe, 2002; Shiens, 2014). Steps for performing PCA can be found in the literature (Keio, 2012; Legendre and Legendre, 1998; Shiens, 2014; Vidal et al., 2016). Here, the software SIMCA ver. 14 (Eriksson et al., 2013) was used for modelling. Confidence levels were left at the default value 95%.

PLS is an extension of PCA and was used as a mathematical tool for relation recognition in this study. PLS works as a regression model which links primary variables X and response variables Y. Difference and relationships between PCA and PLS as well as their usage is well covered in the literature, e.g., Godoy et al. (2014), Kettaneh et al. (2005).

PCA/PLS have been widely used in mineral processing. Pourghahramani et al. (2008) has used PCA and PLS to study
relationship between grinding variables and structural changes during mechanical activation of hematite concentrate. Tungpalan et al. (2015) used PCA to create predictive models for relating mineralogical and textural characteristics to the copper recovery. Finally, PCA and PLS were used by Gallmeier et al. (2017) in predicting the extractability of hydrocarbons from shales.

### 4. Results and discussion

#### 4.1. Mineralogical characterisation

The ore samples can be classified into two geologically different types based on the drill core assessment/logging (Table 2): massive and semi-massive ore. Both ore types have low amount of P₂O₅ (1.1%). The massive ore has a high iron content and a low amount of SiO₂. It is characterized by finely grained magnetite with amphibole and apatite as the main gangue minerals. Both amphiboles and apatite have fine and coarse grain intergrowths. Calcite veining is another important but minor textural type.

Semi-massive ore has a lower content of iron (< 50%) and the main non-iron minerals are silicates. Semi-massive ore, unlike massive ore, has a wider variation of minerals and textures. Magnetite is fine-grained and biotite, feldspars (i.e., albite, K-Fsp) and quartz are the main gangue minerals.

The quantified mineralogy (Fig. 4) for each sample reconfirms the previously defined two ore classes. Massive ore is Fe-oxide-rich (> 90% Mgt, Hem) mainly with the higher content of amphiboles and apatite distributed in the finest size fraction. Semi-massive ore, on the other hand, has a lower Fe-oxides grade, however it contains silicates (predominantly biotite), which are more evenly distributed between the size fractions. The liberation distribution of Fe-oxides (Fig. 5) is higher for the finer size fractions for all the ore classes. Sample 12, classified as rich semi-massive ore, is the only sample that equally well might fall into either massive or semi-massive ore class.

The mineralogical analysis can explain difference in mass pull, recoveries or liberation of the material. For instance, iron in amphiboles in mixed particles or as entrapment would give a false prediction of the magnetic separation if it is only based on the iron head grade.

#### 4.2. Ore classification with XLTU

Modal mineralogy and mineral liberation allow ore classification solely based on mineralogical variability. XLTU was designed as a metric for classifying ore considering both processing properties i.e., magnetic separation in Davis tube and iron grade in a feed. When XLTU is plotted against Fe-oxides liberation (Fig. 6), it is possible to conclude whether process performance has been impacted by liberation or other factors. For instance, in the case of sample 3 (black ellipse in Fig. 6), the high

<table>
<thead>
<tr>
<th>Sample ID</th>
<th>Ore classes</th>
<th>Fe-mineral</th>
<th>Iron % in drill core</th>
<th>Textural type</th>
<th>Main associated minerals</th>
</tr>
</thead>
<tbody>
<tr>
<td>13</td>
<td>Semi-massive ore</td>
<td>Mag</td>
<td>&lt; 20</td>
<td>Disseminated/Veiny</td>
<td>Mgt + Bt + Ab + Qtz</td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
<td>20–40</td>
<td>Veiny/Granular</td>
<td>Mgt + Bt + Kfsp + Qtz</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
<td>40–50</td>
<td>Fine-grained amphibole/Calcite</td>
<td>Mgt + Amp + Ab + Bt + Qtz</td>
</tr>
<tr>
<td>12</td>
<td>Rich semi-massive ore</td>
<td>Mag</td>
<td>40–50</td>
<td>Coarse-grained amphibole rich</td>
<td>Mgt + Amp + Ab + Bt + Qtz</td>
</tr>
<tr>
<td>5</td>
<td>Massive ore</td>
<td>Mag</td>
<td>&gt; 50</td>
<td>Coarse-grained amphibole rich</td>
<td>M gt + Calcite + Ap + Cal</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td>Fine-grained amphibole rich</td>
<td>Mg t + Amp + Ap + Cal</td>
</tr>
<tr>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td>Coarse-grained amphibole rich</td>
<td>Mgt + Amp + Ap</td>
</tr>
<tr>
<td>11</td>
<td></td>
<td></td>
<td></td>
<td>Fine-grained amphibole rich</td>
<td>M gt + Amp + Ap + Calcite</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td>Coarse-grained apatite rich</td>
<td>M gt + Amp + Ap + Calcite</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td>Coarse-grained apatite rich</td>
<td>M gt + Amp + Ap + Calcite</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td>Coarse-grained apatite rich</td>
<td>M gt + Amp + Ap + Calcite</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td>Coarse-grained apatite rich</td>
<td>M gt + Amp + Ap + Calcite</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td>Coarse-grained apatite rich</td>
<td>M gt + Amp + Ap + Calcite</td>
</tr>
</tbody>
</table>

Table 2. A classification of Leveäniemi ore based on mineral and textural variations.

Abbreviations: Magnetite-Mgt; Hematite-Hem; Amphibole-Amph; Calcite-Cal; Biotite-Bt; albite-Ab; Quartz-Qtz; K-Feldspar-K-Fsp.
values of $X_{LTU}$ are caused by a high hematite content. Additional examples are the fine fractions of samples 2, 8, 10, 12 (grey rounded rectangle in Fig. 6), whose high values of $X_{LTU}$ may be due to a different mineralogical texture in the feed (for the same degree of Fe-oxides liberation) and thus higher iron grades in material are not reporting to concentrate. This was also confirmed by the mineralogical study of the feed, which showed that most of the amphibole is distributed into the finest size fraction. For the materials with a lower degree of liberation, and potentially with higher gangue content, $X_{LTU}$ does not signal any problems.

4.3. WLIMS performance assessment with Davis tube

The overall comparison of iron recovery in WLIMS against iron recovery in the Davis tube shows no clear correlation (Fig. 7). However, there are groups of samples that seem to be dependent on the magnetic current strength. The important observation is that Davis tube cumulative iron recovery exhibits much higher variability for the test.
conducted at 0.2 A than at 0.1 A and 0.5 A.

The ΔR function was estimated from the Davis tube test at 0.2 A, due to the highest variability of the iron recovery response in Davis tube at this current strength (Fig. 7). PLS was used here to connect the ΔR variable (response variable Y) and other iron related process variables (main variables X). The X variables included (Table 3): Satmagan values of the feed (Feed_Sat), iron in feed (Feed_Fe), iron recoveries (Rec12_Fe), and mass pull (Conc12) in Davis tube. Cumulative mass pull and iron recovery in Davis tube (at 0.1 A and 0.2 A) were included in the model to cover the difference in magnetic and mechanical forces. Satmagan values and iron head grade of the Davis tube/WLIMS, were included to cover the differences between massive and semi-massive samples in the feed. Satmagan values here cover hematite presence and iron grade considers head grade variability. PLS analysis produced a model with three statistically significant principal components.

The loading plot (Fig. 8) shows that the first principal component is covering primarily the variability in the process behaviour (mass pull and iron recovery). The second principal component is covering primarily the ore type simply through the iron grade and Satmagan value. The simplest separation between massive and semi-massive is made by establishing thresholds based on the iron grades and Satmagan values. From the loading plot, iron recovery and mass pull are located far from origin; therefore have the highest impact on the model. Close location of those two variables to each other also suggests positive correlation between them. Satmagan values positively correlate with the iron concentration in feed. Satmagan also is strongly linked to the ore type. Massive ore will have higher Satmagan values than semi-massive ore.

The score plot of t1/t2 (Fig. 9), reveals full separation between hematite (sample 3) and other massive ore samples. Massive and semi-massive ores are well separated in this plot by the second principal component, while the transitional sample 12 is very close to the origin.

The comparison of the loading (Fig. 8) and score (Fig. 9) plots shows that samples 3 and 13 contribute more to the highest positive value ΔR. Those are also samples with the lowest mass pull and iron recovery. In case of sample 13, the reason for being an outlier could be in a poorer control of the sampling quality, since it was a grab sample. It is also clear that there is no strong impact of the ore type (massive, semi-massive) on ΔR. The statistical values suggest a very good model with cumulative explained variation of R2X = 99%, R2Y = 91% and the

Table 3
Input X and Y variables into PLS model of ΔR (the average values).

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<th>Parameters</th>
<th>Codes used in modelling for the parameters</th>
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<td>Mass pull, %</td>
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<td>X</td>
<td>Iron recovery, %</td>
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<td>Iron in feed, %</td>
<td>Feed_Fe</td>
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<td>X</td>
<td>Satmagan in Feed, %</td>
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<td>X</td>
<td>ΔR, %</td>
<td>WLIMSminDT</td>
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<tr>
<td>Y</td>
<td>RΔ, %</td>
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<th>Sample ID</th>
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<td>53.5</td>
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Fig. 8. PLS loading plot of the variables projected into two dimensions.

Fig. 9. PLS score plot of the observations projected into two dimensions (t1/t2) generated for ΔR model. The identifiers for the PSD next to the sample numbers stand for: f – fine; m – medium; c- coarse size fractions.
cumulative predicted variation of Q2 = 89% of the total variance.

Finally, the predicted $\Delta R$ values were compared against measured. The comparison is shown in Fig. 10. The general fit is very good and is independent of geological ore types.

4.4. Liberation prediction enhanced by Davis tube

One of the aims of this study was to develop a proxy model for predicting the Fe-oxides liberation by use of the Davis tube. Having a proxy model for Fe-oxides liberation will contribute to process modeling and simulation with mixed particles. Mineral liberation information deployed in a block model may also have an impact on production planning and mine scheduling.

Modelling was performed in two steps. First, PLS was used to predict Fe-oxides liberation using all the data types (chemical assays, difference indices, recoveries, concentrate quality and mass pull), and tendencies were studied with loading and score plots. Second, the most influential data type was selected for building a simplified model to predict Fe-oxides liberation using PLS.

In the first step, PLS was used to connect the Fe-oxides liberation variable (response variable Y) and other process variables (main variables X). The X variables included (Fig. 11): chemical assays and Satmagan values of the feed (Feed_Fe, Feed_K2O, Feed_Al2O3, Feed_MgO, Feed_Sat), difference indices (DI13_Fe, DI13_K2O, DI13_Al2O3, DI13_MgO), recoveries (REC13_Fe, REC13_K2O, REC13_Al2O3, REC13_MgO), concentrate quality (DT_C_Fe, DT_C_K2O, DT_C_Al2O3, DT_C_MgO) and mass pull (Conc13) of the Davis tube. For studying liberation with the Davis tube, it is required to maximise the number of the liberated and mixed magnetic particles in the concentrate, while tailings should be comprised solely of gangue minerals. Such separation in the Davis tube can be achieved at the highest magnetic field strength, which corresponds to a current strength of 0.5 A. Cumulative chemical assays, recoveries, difference indices and mass pulls from the final Davis tube test run (at 0.5 A) were used in the modelling. The final PLS model resulted, in a two significant component model, R2X = 75%, R2Y = 92%, and Q2 = 89%. The VIP (variable importance for projection) plot shows that Fe, K2O, Al2O3, MgO content of the Davis tube concentrate are the most influential factors in the model. This can be explained by the principles of Davis tube performance. A Davis tube concentrate may be considered free of liberated gangue particles; most of the gangue elements are either in the lattice of Fe-oxides or in a combination of gangue minerals or in mixed Fe-oxides-gangue particles. Therefore, K2O, Al2O3 and MgO of the Davis tube concentrate were defined as the most influential factors and main contributors to mixed particles of Fe-oxides intergrown with silicate gangue particles, i.e., biotite, K-Feldspar and amphiboles. SiO2 was excluded from the model, since it is a too strong variable which measures the same underlying aspect as iron and therefore overemphasizes its contribution.

The score plot (Fig. 12) reveals a clear separation between two geological ore classes (massive and semi-massive) along the first principal component. The only exception is sample 12, which exhibits properties of both massive and semi-massive ore. Sample 12 has a relatively high Fe-oxides content compared with the semi-massive samples. The second principal component shows separation between
samples by size. Finer particles tend to be located above the origin, while coarser are below the origin. Samples 1c and 13c seem to be outliers, since they are located outside the Hotelling $T^2$ ellipsoid. The Hotelling $T^2$ ellipsoid corresponds to the significance level of 0.05.

According to the loading plot (Fig. 11), the Davis tube concentrate composition of gangue elements is clustered far from origin, therefore has high influence on the model. The iron in the Davis tube concentrate correlates positively with the Fe-oxides liberation, due to iron being the main component of Fe-oxides minerals. Feed, together with difference indices for gangue elements, cluster separately from Fe, Satmagan in feed, mass pull, and gangue elements recoveries.

The comparison of loading (Fig. 11) and score (Fig. 12) plots confirms that coarser particles contribute more to the Davis tube concentrate impurities and gangue elements recovery, while finer particles tend to contribute more to the separation efficiency evaluated by means of the difference index. It is important that particle size correlates negatively with the degree of liberation of the Fe-oxides, meaning that smaller particles will tend to be more liberated. Fe-oxides liberation is higher for massive ore than for semi-massive, which is in accordance with quantitative mineralogy measurements (Fig. 5).

The possibility of modelling Fe-oxides liberation is promising. As follows from Fig. 11, it should be possible to obtain a fair model by including only Davis tube concentrate properties (Table 4) as model variables. For the semi-massive ore, the similarities between alignment of the observations on the score plot and differences indices at loading plot suggest that a model partially explaining Fe-oxides liberation could be constructed from those variables.

In the second step, PLS was used to connect Fe-oxides liberation (response variable $Y$) and Davis tube concentrate properties (main variables $X$) (Table 4).

The loading plot (Fig. 13) shows that K2O content in concentrate (X variable) is the strongest contributor for predicting the Fe-oxides liberation ($Y$ variable). The two variables are negatively correlated. This can be explained by the high content of biotite and K-Feldspar in mixed particles. The first principal component separates variables by the contribution of gangue elements which are expressed as the variables (DT_C_MgO, DT_C_Al2O3, DT_C_K2O) or Fe-oxides minerals (DT_C_Fe). The iron content in Davis tube concentrate tends to correlate positively with the Fe-oxides liberation, since iron is the main component of Fe-oxides. Inverse correlation between iron and gangue elements MgO and Al2O3 in Davis tube concentrate confirms presence of those elements in mixed ore–gangue particles.

The score plot (Fig. 14) shows clustering of the massive and rich semi-massive sample size fractions. The semi-massive ore size fractions are randomly dispersed to the left of the massive samples and are confined to a dense class. For both massive and semi-massive samples, coarser size fractions tend to be further from origin. However, only the coarse fractions of the semi-massive fall outside the confidence ellipse. Here, sample 12 tends to be more similar to the massive samples, since all three points corresponding to the coarse, medium and fine size fractions are within the limiting ellipse. The first principal component shows separation between samples by the degree of liberation of Fe-oxides. Samples with higher liberation of Fe-oxides tend to be located to the right of the vertical axis and those with lower liberation of Fe-oxides tend to be located to the left.

The comparison of loading (Fig. 13) and score (Fig. 14) plots confirms observations made from Figs. 11 and 12 and does not reveal new trends. The PLS model for predicting Fe-oxides liberation based on Davis tube concentrate properties (Fe, K2O, Al2O3 and MgO grades) yielded, in a two significant component model, $R^2_X = 89\%$, $R^2_Y = 89\%$, and $Q^2 = 88\%$.

![Fig. 13. Step two – PLS loading plot of the variables projected into two dimensions for Fe-oxides liberation model.](image)

### Table 4

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<td>Fe-oxides liberation</td>
<td>Lib_FeOxid</td>
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<td>87.7</td>
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parameter, which helps to establish a con-

shown that samples with high
is supported by a mineralogical study with Auto-SEM-EDS. It was
model is based on the
tend to have higher amphibole contents.
tube iron recoveries and
recoveries in WLIMS can be calculated from summation of the Davis
Leveäniemi ore type classi-
quality problems such as hematite or higher amphibole content in a
sample, as is the case in some of the Leveäniemi ore samples. The
Leveäniemi ore type classification, based on the $X_{LTU}$ quality estimator is supported by a mineralogical study with Auto-SEM-EDS. It was
shown that samples with high $X_{LTU}$ values are hematite samples and
samples with low positive $X_{LTU}$ values are magnetite samples which
tend to have higher amphibole contents.

A prediction model for iron recovery in WLIMS is proposed. The
model is based on the $\Delta R$ parameter, which helps to establish a con-
nection between iron recoveries from Davis tube and WLIMS. PLS
modelling suggests that $\Delta R$ may be explained with mass pull and iron
recovery from the Davis tube, together with iron and Satmagan head
grades. Since $\Delta R$ can be predicted from the developed model, then iron
recoveries in WLIMS can be calculated from summation of the Davis
tube iron recoveries and $\Delta R$.

A prediction model for the Fe-oxides liberation distribution is pro-
posed. PLS modelling has shown that Davis tube concentrate chemical
assays correlate strongly with Fe-oxides liberation distribution mea-
sured by Auto-SEM-EDS and they provide enough information for
building a good model. Since the prediction does not require any pre-
vious knowledge of feed composition or recoveries, the developed
method may become a low-cost proxy for more expensive techniques,
e.g. Auto-SEM-EDS.

The main conclusion, which follows from this study, is that Davis
tube may be applied only for studying marginal ores. Massive ores do
not exhibit large enough variation in liberation, Davis tube recoveries and
mass pulls. Thus, when Davis tube performance parameters are
deployed in a block model, constant values for liberation, recoveries
and mass pulls can be assigned to the blocks containing massive ore.

The findings can be applied in production planning and optimization.
The $X_{LTU}$ estimator may be used to identify samples with potential

processing problems or that have been misclassified. An iron recovery
model for WLIMS can be applied in a spatial predictive model (block
model). The predictive liberation model might be used for beneficiation
simulation of mixed ore-gangue particles. The predictive liberation
model may also be used in block modelling and contribute to the mine
scheduling as one of the targeted production parameters.

These results create a perspective for extending the model usage to
other magnetic ore types, such as ores with significant amounts of other
ferromagnetic minerals (e.g., monolyc pyrrhotite, chromite) and ores
which also include para-magnetic iron bearing minerals (e.g., goethite,
hematite). The future studies can also be extended to coarser particle
sizes (> 106 µm), which might require adjustments of the Davis tube
test to allow for processing of coarser particles.

Acknowledgments

We would like to express our gratitude for support and permission
to publish to LKAB, particularly Kari Niiranen, Therese Lindberg and
Lewis Wild. Special acknowledgments are to Perti Lamberg for his
valuable ideas and to Abdul Mwanga and Mehdi Parian for their con-
tribution to our understanding of geometallurgical tests. Thanks are
also due to Efrain Cardenas and Kartikay Singh for assistance with ex-
periments. This research is a part of the PREP project and financed by
VINNOVA (Sweden) project nr. 2014-01933, which is highly ac-
knowledged.

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Appendix X: Paper C
EVALUATION OF SAMPLING IN GEOMETALLURGICAL PROGRAMS THROUGH SYNTHETIC DEPOSIT MODEL

V. Lishchuk, P. Lamberg, C. Lund
Luleå University of Technology
Luleå, Sweden

ABSTRACT

The main purpose of geometallurgy is to develop a model to predict the variability in the mineral processing performance within the ore body. Geometallurgical tests used for developing such a model need to be fast, practical and inexpensive and include as an input data relevant and measurable geological parameters like elemental grades, mineral grades and grain size. Important in each geometallurgical program is to define the number of samples needed to be sent for geometallurgical testing to enable reliable metallurgical forecast. This is, however, a complicated question that does not have a generic answer.

To study the question on sampling a simulation environment was built including a synthetic ore body and sampling & assaying module. A synthetic Kiruna type iron oxide - apatite deposit was established based on case studies of Malmberget ore. The synthetic ore body includes alike variability in rock types, modal mineralogy, chemical composition, density and mineral textures as its real life counterpart. The synthetic ore body was virtually sampled with different sampling densities for a Davis tube testing, a geometallurgical test characterising response in magnetic separation. Based on the test results a forecast for the processing of the whole ore body was created. The forecasted parameters included concentrate tonnages, iron recovery and concentrate quality in terms of iron, phosphorous and silica contents.

The study shows that the number of samples required for forecasting different geometallurgical parameters varies. Reliable estimates on iron recovery and concentrate mass pull can be made with about 5-10 representative samples by geometallurgical ore type. However, when the concentrate quality in terms of impurities needs to be forecasted, the sample number is more than 20 times higher. This is due to variation in mineral liberation and shows the importance of developing techniques to collect qualitative information on mineral and ore textures in geometallurgy.

KEYWORDS

Sampling, synthetic ore body, simulation, geometallurgical testing framework.
INTRODUCTION

In developing the mineral resource estimates the information on the processability and its variability is collected quite late. Scoping studies deals almost only with geological data and the processing and mining information is considered only in pre-feasibility and feasibility study stages (The Australasian Institute of Mining and Metallurgy, 2012). Introduction of geometallurgy at early stages of the project can decrease level of uncertainty in the future project stages and consequently in production (Dominy, 2013).

Geometallurgy aims to develop a predictive model which combines geological and mineral processing information. This model is used in production planning, designing and management. It is expected to give benefits especially in low grade ores showing high variability in their processing properties. Such ores have high production risks which can manifest as low or negative profit margins if the operation is managed in a traditional way.

Development of a geometallurgical model requires access to a large number of samples that specify the processing properties. The basic knowledge and sample material collected by drilling, drill core logging and chemical assays is not sufficient. Additional characterisation techniques are needed. Geometallurgical tests, i.e. small tests which characterize the metallurgical properties and thus give quantitative information on the variability are commonly used. They need to be fast and inexpensive, they should use only small amount of sample but still they should reliably characterise processability. A number of geometallurgical tests are available for different areas of beneficiation. For comminution they include tests characterising crushability, grindability and forecasting throughput. Examples of such are geometallurgical comminution test (GCT) developed by Mwanga et al., (2015) and GeM Commination index (GeMCi) described by Kojovic et al. (2010). For magnetic separation Davis tube test is frequently used (Murariu and Svoboda, 2003); for leaching different alternatives of leach performance test are available (e.g. Kuhar et al., 2011). For gravity separation the sample size is a problem, e.g. in the GRG test (Dominy, 2013; Zhou and Cabri, 2004). For flotation “shaker test” has been proposed by Vos et al. (2014) but it has not gained popularity.

Based on the test results a predictive model is created. As input parameters the model takes properties provided in the geological data set. Parameters like elemental grades (e.g. Cu wt%), mineralisation type and hosting lithology are commonly used. As an output the model gives production forecast: throughput, concentrate tonnages (mass pull), metal recoveries, concentrate quality parameters, tailing properties and economic key figures.

One problem in collecting such a data set is to select how many samples are needed for different assays and techniques to develop reliable geometallurgical model. If the number of samples is too small then the model can be inaccurate or even defective. By increasing the samples at some point the gain in prediction accuracy don’t justify the costs and time spent. Good sampling strategy is needed. It must take into account geological and metallurgical variability together with sampling (Gy, 1976; Minnitt et al., 2007), analysis and modelling errors (Bulled and Mcinnes, 2005).

Number of required samples for different characterisation methods in geometallurgical programs is a widely discussed topic. David (2014) recommended up to 30 variability samples for metallurgical testing in different mine design stages. Williams and Richardson (2004) assumed several hundred of samples for metallurgical and geometallurgical testing, more than a thousand of samples for mineralogical study and more than ten thousand of samples for traditional chemical assays. In a mineralogical approach the mineralogical information: mineral grades and texture properties, are required for several thousand of samples (Parian et al., 2015).

Adequate geometallurgical sampling requires good knowledge of the ore body. Geological database and block model accompanied by internal company expertise on both ore body and beneficiation process often provide solid basis for planning and conducting sampling campaigns. Yet, the fact that geological information is mostly qualitative and its quality if difficult to estimate, is a challenge. Therefore
primary sampling, mainly by drilling, and secondary sampling for geometallurgical testing is often an iterative process. Geological information is used as default information in classification and domaining but they are critically evaluated against the results of the geometallurgical tests.

There are several unanswered questions around the development of a geometallurgical model. How many samples are required? How the samples should be assayed? What kind of geometallurgical tests should be used and how many samples are needed? How qualitative information can and should be used? Is mineralogical information needed or does it give some benefits? How the domaining should be done or is it really needed at all? How the modelling should be done? In what details the model should go? How to estimate the error in the whole chain? What kind of error can be accepted in different stages?

It is obvious that there are no universal answers to above posed questions but they vary from case to case. Studying different alternatives and finding feasible solutions is slow and tedious with real case studies. A synthetic ore body and corresponding geometallurgical system could provide an environment where different scenarios could be tested effectively.

Previously the sampling problem has been studied with synthetic geological data by and Malmqvist et al. (1980). The focus was in mineral exploration and sampling for mineral resource estimation of deep sited sulphide ore bodies. More recent examples of simulation for reproduction of complex geological structures and behaviour of the spatial geological data can be found in Chatterjee and Dimitrakopoulos (2012) and Mustapha and Dimitrakopoulos (2011). Modelling by simulation is a well-documented practice commonly used in the mining industry to evaluate alternative process designs (see Everett 2001, 2007; Howard et al., 2005; Everett et al., 2010, Jupp et al. 2013a). Such modelling is typically undertaken as an optimisation study to increase the efficiencies and productivity of operating mines where actual short-term grade variability data are available from production records. In these cases the real data is used as an input data into the simulation of different scenarios. Jupp et al. (2013b) created a synthetic ore body model and used it in geometallurgy to study the most effective way to reduce the variability in daily scheduling system.

In all the previous studies the modelling of the ore body has been restricted to lithology, density and elemental grades. The processing properties have been almost totally excluded and therefore as such they are not suitable for a test bed to study different geometallurgical questions listed earlier. A simulated synthetic ore body for geometallurgy must satisfy three conditions: it must include processing properties; it must show realistic variability within synthesised data and there must be spatial cohesion between data. Additional parameters, such as constraints of a mining method, processing performance, and economic response would produce more realistic output. A synthetic geometallurgical testing framework (SGTF) is described in this paper as a solution for answering different geometallurgical problems. The framework comprises of synthetic ore body together with processing and economic models to represent the major part of the mine-to-metal value chain. The aim of this paper is to describe a new technique for planning geometallurgical sampling, testing and model building by application of the synthetic framework. This allowed describing the effect of geological and metallurgical variability on sampling strategy. Malmberget iron ore deposit in Sweden (Lund et al., 2013) was selected for the ore type to mimic.

**METHODOLOGY**

A geometallurgical system is a complex value chain comprised of geological, mining, mineral processing and other metallurgical downstream processes. The simulation environment developed here for studying geometallurgical questions is called synthetic geometallurgical testing framework (SGTF). Three modules of the synthetic framework were used in this study: synthetic ore body, sampling & assay module and process simulation. Study conducted within the developed framework included three phases: sampling; geometallurgical testing; sample re-classification and metallurgical testing (see Figure 1).
Synthetic Ore Body

Synthetic ore body of the framework was developed in Matlab. It allows generating a geological model of an ore body using mineralogical approach (Hoal et al., 2013; Lamberg et al., 2013; Lishchuk et al., 2015b). Geological description is a spatial model represented by the cloud of points within a defined volume. The smallest units, points, are called voxels and their size should be smaller or equal than smallest possible sample to be collected by drilling and sampling from the synthetic ore body. Description of the geological properties is given for each voxel including information on lithology, mineralogy, chemical composition, mineral textures (textural archetype) and specific gravity.

The lithology is modelled as a set of geometric shapes enclosing voxels. The grade of each commodity mineral in any given voxel is defined based on spatial grade model:

\[
\tilde{M}^D = P + S + T \rightarrow \begin{cases} 
\tilde{P} = f_P(x, y, z), & \min P = a_P, \max P = b_P \\
\tilde{S} = f_S(x, y, z), & \min S = a_S, \max C = b_S \\
\tilde{T} = f_T(x, y, z), & \min T = a_T, \max T = b_T 
\end{cases} \quad (1)
\]

where, \( \tilde{M}^D \) is mineral grade in a given voxel; \( P \) is primary, \( S \) secondary and \( T \) is tertiary component. \( P, T \) and \( S \) are functions of coordinates (x, y, z) of the point, \( a \) and \( b \) are the minimum and the maximum values of each component. \( \tilde{\ } \) indicates that parameter was not scaled to the defined range and \( f_P(x, y, z), f_S(x, y, z), f_T(x, y, z) \) are trigonometric functions that describe \( P, T \) and \( S \). The commodity mineral can be represented fully independent on lithologies. The reason behind generating commodity minerals separately from the lithology minerals was to have capability to describe the grade distribution of important minerals accurately.

After defining the grade of the main commodity minerals in each voxel the remaining mass differing from 100% is filled with lithology based minerals. For each lithology the average grade and standard deviation is provided for each mineral present. This information together with normal distributed random numbers is used to complete the modal composition.

The textural information of each voxel is provided by textural archetypes. For each type full mineral liberation information in certain particle size (distribution) is provided in a global library. Chemical composition of minerals by lithology is also provided in library. Derivatives of voxels like chemical composition, specific gravity, magnetic susceptibility and other mineral based properties are calculated for each voxel from the modal composition and the library data.
Using Malmberget as a Case Study

Synthetic ore body for this study was created based on Malmberget iron ore deposit located in northern Sweden (Lund, 2013). Malmberget ore is comprised of several ore bodies, mainly of massive magnetite. Iron ore grade is high, 51-61 % Fe. Magnetite and hematite are the main ore minerals. Apatite and actinolitic amphibole comprise main gangue minerals. The accessory minerals include biotite, albite, pyrite, chalcopyrite and titanite. The massive ore, high in Fe and low in SiO$_2$, is surrounded by a semi-massive mineralisation. The semi-massive mineralisation can be several tens of meters thick, occurring as rims or as inclusions in the massive ore with a decreasing iron grade. The main gangue minerals of the semi-massive ore are silicates, i.e. feldspars (albite and K-feldspar), amphibole, quartz and biotite in various proportions.

The massive ore has broad variation of mineral-texture relations. Both fine- and coarse-grain textures exist. Mineralogically semi-massive ore is composed of several different mineral assemblages, i.e. lithologies, with more complicated textures than the massive ore itself. Lund (2013) identified two main textural types of the massive ore: Amp-(Ap-Bt) and Ap-(Amp), and one textural type of semi-massive ore - Fsp.

The synthetic ore body was created by using one commodity mineral, magnetite, and three lithologies (Fsp, Amp and Ap) equalling three textural archetypes. These are referred as geometallurgical ore types. Four gangue minerals (albite, actinolite, apatite and biotite) were included. The average modal composition of each lithology type without commodity mineral (magnetite) is given in Table 1. The average composition of the ore after modelling the full mineralogy is given in Table 1. Mode of occurrence of magnetite in one size fraction (75-150 microns) of an average ore is given in Table 1 to illustrate how mineral liberation information was included in the model. The chemical composition of the minerals was taken from Lund (2013) and was defined to be identical in all lithologies. Spatial distribution of lithologies, i.e. textural types, in Malmberget (Lund 2013) and in the generated synthetic ore body is compared in Figure 2. The synthetic ore body mimics reasonably well the lithological variation in Malmberget.

Figure 2 – Spatial distribution of lithologies, the left image is from Lund (2013) and the right image was generated within the synthetic ore body.
Table 1 – Average modal composition of lithologies and average modal composition of ore types and mode of occurrence of magnetite in one size fraction, 75-150 microns.

<table>
<thead>
<tr>
<th>Lithology</th>
<th>Fsp</th>
<th>Amp</th>
<th>Ap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Albite</td>
<td>52.1</td>
<td>9.6</td>
<td>7.7</td>
</tr>
<tr>
<td>Actinolite</td>
<td>25.5</td>
<td>68.7</td>
<td>8.6</td>
</tr>
<tr>
<td>Apatite</td>
<td>13.0</td>
<td>8.1</td>
<td>56.0</td>
</tr>
<tr>
<td>Biotite</td>
<td>9.4</td>
<td>13.6</td>
<td>27.7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Geometallurgical ore type</th>
<th>Fsp</th>
<th>Amp</th>
<th>Ap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Magnetite</td>
<td>75.7</td>
<td>71.6</td>
<td>75.8</td>
</tr>
<tr>
<td>Albite</td>
<td>12.7</td>
<td>2.7</td>
<td>1.9</td>
</tr>
<tr>
<td>Actinolite</td>
<td>6.2</td>
<td>19.5</td>
<td>2.1</td>
</tr>
<tr>
<td>Apatite</td>
<td>3.2</td>
<td>2.3</td>
<td>13.6</td>
</tr>
<tr>
<td>Biotite</td>
<td>2.3</td>
<td>3.9</td>
<td>6.7</td>
</tr>
</tbody>
</table>

Mode of occurrence of magnetite in 75-150 microns size fraction in an average ore

<table>
<thead>
<tr>
<th>Geometallurgical ore type</th>
<th>Fsp</th>
<th>Amp</th>
<th>Ap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liberated</td>
<td>95.9</td>
<td>94.5</td>
<td>89.2</td>
</tr>
<tr>
<td>In composite particles with albite</td>
<td>2.2</td>
<td>0.5</td>
<td>0.8</td>
</tr>
<tr>
<td>In composite particles with actinolite</td>
<td>1.1</td>
<td>3.8</td>
<td>0.9</td>
</tr>
<tr>
<td>In composite particles with apatite</td>
<td>0.5</td>
<td>0.4</td>
<td>6.0</td>
</tr>
<tr>
<td>In composite particles with biotite</td>
<td>0.4</td>
<td>0.8</td>
<td>3.0</td>
</tr>
</tbody>
</table>

Sampling and Assaying within the Synthetic Geometallurgical Testing Framework

Geometallurgical sampling within the synthetic geometallurgical testing framework implied two separate actions: primary sampling by drilling and secondary sampling by selecting parts of the drill cores. Simulated drill cores were created in MATLAB environment by giving the collar coordinates, final depth of the drill core, azimuth and dip of each individual drill core. Each drill core retrieved information available from the crosscut voxels of the synthetic ore body (Figure 3).

Voxels belonging to the same geometallurgical ore type, adjacent to each other and showing spatial continuity of metallurgical properties inside the ore body were referred to as domains (Hunt et al., 2014 and David, 2007). Assaying of simulated drill cores was performed by applying an error model for the chemical analysis. The error model was based on the precision and accuracy information given by Lund (2013) for XRF analyses. Standard deviation for each assay was computed as Hadamard product of elemental grades (G) and relative standard deviation (RSD) matrices (Equation 2). RSD for each element is given in equation (3).

$$\begin{bmatrix} G_{Si} & G_{Ca} & G_{Ti} & G_{Na} \\ G_{K} & G_{Mg} & G_{V} & G_{Fe} \end{bmatrix} \ast \begin{bmatrix} RSD_{Si} & RSD_{Ca} & RSD_{Ti} & RSD_{Na} \\ RSD_{K} & RSD_{Mg} & RSD_{V} & RSD_{Fe} \end{bmatrix} = \begin{bmatrix} \sigma_{Si} & \sigma_{Ca} & \sigma_{Ti} & \sigma_{Na} \\ \sigma_{K} & \sigma_{Mg} & \sigma_{V} & \sigma_{Fe} \end{bmatrix}$$

$$\begin{bmatrix} RSD_{Si} & RSD_{Ca} & RSD_{Ti} & RSD_{Na} \\ RSD_{K} & RSD_{Mg} & RSD_{V} & RSD_{Fe} \end{bmatrix} = \begin{bmatrix} 1.0 & 3.2 & 1.0 & 2.0 \\ 2.4 & 2.8 & 1.4 & 0.1 \end{bmatrix}$$

$$\begin{bmatrix} RSD_{Si} & RSD_{Ca} & RSD_{Ti} & RSD_{Na} \\ RSD_{K} & RSD_{Mg} & RSD_{V} & RSD_{Fe} \end{bmatrix} = \begin{bmatrix} 2.0 & 1.1 & 0.7 & 6.5 \end{bmatrix}$$
Assays from the drill core samples were used to select the samples for geometallurgical testing. Initial hypothesis suggested that metallurgical performance can be linked to the lithology, i.e. geometallurgical ore types. Thus, geological parameters were isolated by clustering technique and assays of the drill core samples were classified by k-mean clustering algorithm (MacQueen, 1967). The Euclidean distance between the multivariate means of the $n=2..N$ clusters was used as an indication of the difference between the geological parameters. Clustering for $N=10$ is presented in Figure 4, where elemental and mineral based approaches give almost identical results in classification.

Clustering was performed on normalised data by computing standard score for each input according to equation

$$z = \frac{x - \mu}{\sigma}$$  \hspace{1cm} (4)

where, $\mu$ is the arithmetic average, $\sigma$ is the standard deviation.

The results of the virtual Davis tube tests for selected samples were created using HSC Sim 7.1 process simulator (Outotec, 1974). For each sample sent for the virtual Davis tube test both modal composition and textual class information was provided. Based on this information the particle population of about 350 particles was generated in the simulator for given particle size distribution with P80=100 microns. For more information on how modal composition and liberation information of an archetype was combined for defining the feed stream see Lund et al. (2015). In the magnetic separation the separation of minerals was set perfect: for fully liberated minerals 100% of magnetite was recovered into the concentrate and 100% of gangue minerals ended into the tailing. For composite particles the simulator calculated the distribution value (recovery) based on recoveries of fully liberated particles and their mass proportions in a composite particle. The final outcome of the virtual Davis Tube test was the concentrate grade (Fe), its quality (P and Si contents), mass pull and iron recovery. Chemical composition of the concentrate produced was assayed by virtual XRF including the above described error model, thus the result generated in the virtual Davis tube included experimental error.

Real processing parameters were calculated in the same manner (but without experimental error) for all the voxels of the synthetic ore body since. These parameters are referred as “real parameters” or real case scenario (RCS). Geometallurgical sampling procedure was repeated several times by gradual increase.
of \( n \) from 2 to \( N \), until results from the test work converged with the real case (RCS). Results from the final iteration (\( N \)) were used to build a predictive geometallurgical model.

Figure 4 – Classification of geometallurgical samples for mineralogical approach in top row (classification by magnetite (Mgt), apatite (Ap) and silica (Si) content); and for traditional head grade-approach in bottom row (classification by iron, phosphorous and silica content). Crosses show centres of different classes.

Geometallurgical Model

The main purpose of geometallurgy is to build a predictive model (Lamberg, 2011), and mineralogical approach is often used (Hoal et al., 2013; Lamberg et al., 2013; Lishchuk et al., 2015a, 2015b). In reality the Davis tube results are further scaled-up to forecast the full scale production results (Niiranen and Böhm, 2012). Here a simplification was made that Davis tube equals to the metallurgical result in a full scale process.

Two different approaches were used to build a geometallurgical predictive model: mineralogical – based on mineral grades; and elemental – based on elemental grades. Therefore, element to mineral conversion (EMC) (Parian et al., 2015) was done for obtaining modal composition for the ore body and Davis tube concentrate. Predictive model was based on the nearest neighbour algorithm and was predicting performance of each voxel based on iron, phosphorous, silica grade for the elemental approach and magnetite, apatite and silica grades for the mineralogical approach.

RESULTS

A total of 200 sampling & geometallurgical testing campaigns were simulated ranging from 2 to 201 samples. Ten geometallurgical predictive models based on the nearest neighbour algorithm (for 2, 5, 10, 15, 20, 25, 30, 50, 100, 200 samples) were investigated and compared. Comparison was made for the prediction of concentrate quality and quantity, see Table 3. Prediction for iron recovery and total concentrate tonnages reaches acceptable level (<5%) already when 10 samples are used as a base of the prediction. Whether the estimate is done based on mineral or elemental grades does not show any significant difference. However, the prediction of the concentrate quality in terms of detrimental
components, i.e. phosphorous and silica, is much more sensitive. Even with 100 samples the error in the estimates of production of different quality products is quite bad, >5%. Only in 200 samples the required accuracy is reached.

Table 3 – Prediction on metallurgical performance based on 2-200 samples. Error gives difference between the real case scenario (100*[forecast-RSC]/RSC).

<table>
<thead>
<tr>
<th>Samples N=</th>
<th>Prediction based on N samples</th>
<th>Error compared to RCS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>% of ore gives Fe Rec, Conc, kt</td>
<td>% of ore gives Fe Rec, Conc, kt</td>
</tr>
<tr>
<td>2</td>
<td>0.0 36.4 63.6 94.5 1244</td>
<td>-100.0 46.5 29.3 1.1 5.1</td>
</tr>
<tr>
<td>5</td>
<td>9.7 19.1 71.3 89.1 1026</td>
<td>-62.7 -23.3 44.8 -4.7 -13.3</td>
</tr>
<tr>
<td>10</td>
<td>25.9 24.8 49.2 94.3 1208</td>
<td>0.0 0.0 0.0 0.9 2.0</td>
</tr>
<tr>
<td>15</td>
<td>22.0 22.2 55.7 93.9 1211</td>
<td>-15.1 -10.5 13.2 0.4 2.3</td>
</tr>
<tr>
<td>20</td>
<td>25.9 20.5 53.6 92.5 1158</td>
<td>-0.1 -17.6 8.9 -1.1 -2.2</td>
</tr>
<tr>
<td>25</td>
<td>25.0 21.6 53.4 94.0 1203</td>
<td>-3.6 -12.8 8.4 0.5 1.6</td>
</tr>
<tr>
<td>30</td>
<td>22.9 27.5 49.7 94.5 1211</td>
<td>-11.8 10.6 0.9 1.1 2.3</td>
</tr>
<tr>
<td>50</td>
<td>23.9 25.8 50.3 93.7 1186</td>
<td>-7.9 4.1 2.1 0.2 0.2</td>
</tr>
<tr>
<td>100</td>
<td>23.9 27.2 48.9 93.4 1179</td>
<td>-7.9 9.7 -0.7 -0.1 -0.4</td>
</tr>
<tr>
<td>200</td>
<td>24.7 25.0 50.3 93.6 1187</td>
<td>-4.7 0.8 2.1 0.1 0.3</td>
</tr>
<tr>
<td>RCS</td>
<td>25.9 24.8 49.2 93.5 1184</td>
<td>0.0 0.0 0.0 0.0 0.0</td>
</tr>
</tbody>
</table>

*HQ = high quality product, RQ = regular quality product, LQ = low quality product.

CONCLUSIONS

The effect of geological variability on geometallurgical sampling within the ore body was assessed within synthetic geometallurgical testing framework. Synthetic ore body, a part of the framework, was used to critically evaluate the number of samples needed for geometallurgical testing to create reliable production forecast. For the iron ore case study it was concluded that the number of samples varies based on the parameter to be forecasted. For iron recovery and concentrate mass pull already 10 samples gave a good estimate in a system having three different geometallurgical types. The difference between the types in iron recovery was minor, but still significant, however the nearest neighbourhood method used in populating back the forecast worked well because of clear difference between the chemical compositions of the types. When the product quality was forecasted the number of samples for reliable forecast increased to 200. It may be possible to improve this by using different deployment algorithm, like multivariate statistic or principle component analysis (e.g., Keeney, 2010). However, this indicates that more accurate geological information on mineral textures and liberation would be needed. This leads to a conclusion that there is significant potential to increase the quality geometallurgical forecast by collecting quantitative information on ore and mineral textures. Currently techniques available for this are either poor in quality (drill core scanning) or expensive to use (automated mineralogy). This is clearly an area where development is needed.

The case study shows the strength of developed synthetic ore model. This study differs in couple of ways from previously used synthetic data sets in geometallurgy (Jupp et al. 2013b). First the ore body modelling is taken into mineral level, both the modal composition and quantitative data on mineral texture is assigned to each voxel. Second, the mineral processing (here Davis tube) is modelled and simulated on mineral liberation level. This gives access into a variability level which is very significant for metallurgical response but very challenging to map in the ore body. Therefore it gives realistic environment to test different important questions in geometallurgy.
REFERENCES


Lishchuk, V., Lamberg, P., Lund, C., 2015b. Classification of geometallurgical programs based on


Appendix XI: Paper D
Development of a Synthetic Ore Deposit Model for Geometallurgy

V Lishchuk¹, C Lund² and P Lamberg³

ABSTRACT

Geometallurgy aims to improve resource efficiency by creating a spatial model of an orebody in order to forecast ore processing behaviour. This enables calculation of the economic value of each ore block and the use of this information for production optimisation and hence an improved economic return. Modelling uses different approaches to link geological information with mineral processing: traditional approach uses chemical elements; proxy approach – small-scale geometallurgical tests; and mineralogical approach – minerals.

A geometallurgical model is obtained during execution of a geometallurgical program encompassing the entire value chain of ore processing. Available methods for establishing a geometallurgical model are in many cases limited and not yet comprehensively validated. Some of the limitations include: sampling density, assaying methods and quality, forecast accuracy block model content, geostatistical solutions for non-additive components, blending and assessment of positive impact of geometallurgy on the project. Synthetic ore models combined with process simulations and production scheduling, based on strong case studies, present a viable way to address these shortcomings. Such synthetic ore models will have realistic elemental and mineral distribution, textural attributes and 3D variability for input into the design of an appropriate geometallurgical program.

A synthetic orebody was created for an apatite-bearing iron deposit. Variability in modal mineralogy was described by geostatistical parameters combined by a set of linear and trigonometric functions. The generated synthetic deposit model was used to develop a mine production plan to generate a simulated process feed. The process feed had detailed information required for beneficiation process simulation: modal mineralogy, chemical composition of minerals, grain size and specific gravity. The synthetic system was used to measure benefits that a geometallurgical program developed for real cases could provide, compared to production where only head grade is optimised. These include a reliable sampling strategy and confidence in the feed-quality forecast for economic evaluation.

INTRODUCTION

Geometallurgy aims to creating a predictive model for mine-to-metal production chain through the combination of geological, processing and economic models (Figure 1). Highest returns on application of geometallurgy are expected to come from complex deposits with high variability in properties affecting its processing.

Geometallurgical predictive model (GPM) is to be established during development of a geometallurgical program (Lamberg, 2011). Establishment of the model requires involvement of various professionals from different disciplines (Lishchuk, Lamberg and Lund, 2015) and availability of harmonised modelling and simulation tools. The high-fidelity orebody model (Powell, 2013) with a high resolution and utility of the information and possible moves from indicators to predictors is a spatial basis for the geometallurgical program. In a high-fidelity geometallurgical program, the critical methodology selection, such as sampling design, components included in the block model and their assaying methods, and geostatistical solutions should be based on scientific principles. The benefits and limitations of program design vary from case to case and thus no single deterministic approach can be developed. In real cases comprehensive study of different alternatives is difficult. The use of a synthetic orebody model combined with process simulation and production scheduling, backed by validated case studies, offers an approach to improve the design, and cost-effectiveness of geometallurgical programs.

A wide variety of approaches has been developed to simulate ore deposits. Some of these models can be used for metallurgical and geometallurgical purposes. Chatterjee and

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3. Professor, Division of Minerals and Metallurgical Engineering, Department of Civil, Environmental and Natural Resources Engineering, Luleå University of Technology, Luleå, Sweden. Email: pertti.lamberg@ltu.se
Concentrate shipping and tailing treatment. In the following, were also created for the ore utilisation; ie mining, processing, the economic impact of a geometallurgical program. Models used to demonstrate the full impact of geometallurgy in the entire deposit. A tool to support a comprehensive approach empirically so that it could be applied reliably within an geometallurgical model (Vatandoost, 2010), developed into a statistical model, which is also called a universal approach to integrate distinct geometallurgical parameters into a geological database or in a block model. Information. Such geological information can be stored in a geometallurgical indices and spatially distributed geological information. These have focused on development of methods and geomaterials, such as mineralogy, hardness (Musafer et al, 2013; Preece, 2006), metal grades (Hosseini and et al, 2013; Lishchuk, Lamberg and Lund, 2015). Geology is described in the following hierarchy from largest to smallest significance for each spatial unit: (1) lithology, (2) mineralogy, (3a) chemical components and (3b) specific gravity (Figure 3).

The first level is lithology. The geometry of a lithology is defined by a combination of simple geometric shapes: here ellipsoid was used for simplicity. Position of each ellipsoid is described by coordinates of its centre (X0, Y0, Z0), Euler rotation angles (α, β, γ) semi-principal axes of length (a, b, c). Lithology is assigned in the lithology volume as a numeric code.

Dimitrakopoulos (2012); Mustapha and Dimitrakopoulos (2011) developed simulation approaches for reproduction of complex geological structures and good characterisation of the behaviour of the spatial architecture of geological data. Malmqvist (1979, 1973); Malmqvist, Malmqvist and Zweifel (1980) developed an approach to synthesise geological and sampling data for the purposes of exploration and feasibility study of a prospecting project for deep-seated sulfide orebodies.

Other relevant studies have been dedicated to linking geology with downstream processes. Journel (1974) linked geostatistical simulation of the orebodies with characteristics of the ore recovered by mining. Although the problems addressed cannot be considered as purely geometallurgical, the paper describes the implications of variability in metal grades and overburden thickness. Connecting grade variability with production planning was further considered by Jupp, Howard and Everett (2013). Short-term grade variability was the main concern of his study. Additionally, the problem of non-linearity or non-additivity was raised in connection with block modelling. Everett (2011) contributed to the determination of the mining sequence through the sequence simulation. It was done based on analysis of marginal value of the ore block to cover production-related costs. Iron grade was used as an input for defining the block’s value. The larger iron content corresponded to the larger value. Contaminants or penalty materials were reducing the block’s value proportionally to their grades.

There is a large body of research in spatial modelling on geometallurgical parameters, such as mineralogy, hardness (Musafer et al, 2013; Preece, 2006), metal grades (Hosseini and Asghari, 2014), work index, throughput and metal recovery (David, 2007; Deutsch, 2013; Keeney and Walters, 2009; Keeney, 2010). These have focused on development of methods and mathematical apparatus to connect metallurgical parameters (geometallurgical indices) and spatially distributed geological information. Such geological information can be stored in a geological database or in a block model.

Literature reviewed to date has not identified a systematic approach to integrate distinct geometallurgical parameters into a statistical model, which is also called a universal geometallurgical model (Vatandoost, 2010), developed empirically so that it could be applied reliably within an entire deposit. A tool to support a comprehensive approach would ease further evaluation of geometallurgy as it could be used to demonstrate the full impact of geometallurgy in the mine-to-metal value chain.

Here a synthetic orebody was created in order to evaluate the economic impact of a geometallurgical program. Models were also created for the ore utilisation; ie mining, processing, concentrate shipping and tailing treatment. In the following, ‘synthetic orebody’ refers to the geological model whereas ‘geometallurgical testing framework’ describes the whole system.

Geomattllurgy is claimed to help in optimisation of mineral resource utilisation (Philander and Rozendaal, 2013). According to Dunham and Vann (2007), geometallurgy can give increased total metal recovery and improved asset utilisation. In addition to these, Lamberg (2011) listed in his review that geometallurgy has potential to bring benefits such as better controlled ore deposit utilisation, higher flexibility in introduction of new technological solutions, lower operational risks and wider access to economical optimisation of the full operation. In literature reviewed there are currently a few case studies that state and demonstrate quantitatively the added value of geometallurgical programs. A mining project emulator called ‘Challenge Geometallurgy!’ developed for educational purposes at Luleå University of Technology, has demonstrated that the geometallurgical program can give up to 25 per cent shorter payback time compared to cases when no geometallurgical information is available. The value of geometallurgy for mining companies can also lie in shortened permitting times. Pure economical investigation would be still important to carry out in order to fully expose how much additional profit a geometallurgical program could allow during the mine lifetime.

METHODOLOGY

Synthetic orebody
The developed geometallurgical testing framework consists of several modules: geological model including geological (synthetic orebody – SOB), sampling and mining modules, mineral processing model and economic model. Structure of framework for evaluating geometallurgical programs with synthetic orebody model (geology) is shown (Figure 2).

Geological module – synthetic orebody
The geological module and synthetic orebody was developed based on mineralogical approach (Hoal, Woodhead and Smith, 2013; Lamberg et al, 2013; Lishchuk, Lamberg and Lund, 2015). Geology is described in the following hierarchy from largest to smallest significance for each spatial unit: (1) lithology, (2) mineralogy, (3a) chemical components and (3b) specific gravity (Figure 3).

The first level is lithology. The geometry of a lithology is defined by a combination of simple geometric shapes: here ellipsoid was used for simplicity. Position of each ellipsoid is described by coordinates of its centre (X0, Y0, Z0), Euler rotation angles (α, β, γ) semi-principal axes of length (a, b, c). Lithology is assigned in the lithology volume as a numeric code.
The second level is mineralogy. When generating information of modal mineralogy three separate steps are used (Figure 4). Each lithology consists of certain minerals. Two different types of minerals and mineral groups can be used. The first group is called here commodity minerals. The grade of each commodity mineral at any given point is defined based on spatial grade model:

\[
\tilde{M}^D = P + S + T \quad \begin{cases} 
\tilde{P} = f_P(x, y, z), \min P = a_P, \max P = b_P \\
\tilde{S} = f_S(x, y, z), \min S = a_S, \max S = b_S \\
\tilde{T} = f_T(x, y, z), \min T = a_T, \max T = b_T 
\end{cases}
\]

where:

- \(\tilde{M}^D\) is mineral grade in a given voxel
- \(P\) is a primary component
- \(S\) is secondary component
- \(T\) is a tertiary component

\(P, T\) and \(S\) are functions of coordinates \((x, y, z)\) of the point \(a\) and \(b\) are the minimum and the maximum values of each component

^ means that the parameter was not scaled to the defined interval

\(f_P(x, y, z), f_S(x, y, z), f_T(x, y, z)\) are functions to describe \(P, T, S\)

The reason for generating commodity minerals separately is to have the capability to describe the grade distribution of important minerals accurately.

The commodity mineral grade function parameters can be shared between different lithologies (Figure 3) or can be individual for different lithologies. Additionally, two or more different minerals can have similar grade function parameters. This gives the capability to generate natural positive relationships between different minerals. For example, in a breccia lithology, breccia components will have a positive correlation with each other and a negative correlation with matrix components. Another example is sulfide stockwork and dissemination where sulfide minerals will have positive correlation with each other and negative to silicate minerals.

The commodity mineral step (Figure 4) is aimed at setting grades for minerals with grades and spatial distribution independent of other minerals. Mineralisation can be generated so that it is an intrinsic part of a lithology, or else cut across several lithologies. Commodity mineral grades are propagated inside a shell comprising multiple ellipsoids (the same way as lithology). Intensity of mineralisation is given by Equation 1.

Spatially, each component of grade \((P, S, T)\) can be described by linear, trigonometric, exponential, logarithmic function or function of random numbers. This technique is a naïve deterministic approach to describe geological variability. In contrast to autoregressive models described by Sen (1990), or kriging models (Krige, 1999), parameters of the current approach are suggested by the experienced geologist instead of being estimated numerically. This means that mathematically each commodity mineral is described as the sum of trend and
randomness. After defining the components, each of them has to be scaled to the defined interval \([a, b]\). Thus, \(P\), \(S\), \(T\) have to be between the defined minimum \((a)\) and maximum \((b)\). Interval of minimum and maximum values is defined separately for each component. Hereafter, \(\hat{M}^{j}\) is scaled to the interval of minimum and maximum values defined for the mineral.

Second stage is to define the grade of other minerals:

\[
100\% - \sum_{j=1}^{n} a_{j} \geq 0 \%
\]

where:
\(v\) is the difference from 100%
\(M^{j}\) is the grade of a stochastic mineral

The third step is aimed at defining minerals that occupy unfilled part \(v\), per cent. The other (stochastic) minerals are defined by a function of normally distributed random numbers with predetermined average value and standard deviation. When all the minerals are defined, they are scaled to fit the unfilled part of the voxel \(v\), per cent:

\[
M_{i}^{v} = v \cdot \frac{\hat{M}_{i}^{k}}{\sum_{i=1}^{n} \hat{M}_{i}^{k}}
\]

where:
\(\hat{M}_{i}^{k}\) is a stochastic mineral \(k\) defined on a scale of 100%

Each mineral within a lithology has a fixed chemical composition. If the chemical composition of a mineral varies, it has to be modelled as multiple minerals (eg sphalerite 1, sphalerite 2, sphalerite 3). The chemical composition of a voxel is calculated from modal composition and chemical composition of minerals:

\[
b = A \cdot x
\]

where:
\(b\) is chemical composition of a voxel (vector)
\(A\) is chemical composition of minerals (matrix, sometimes called mineral matrix)
\(x\) are mass proportions of all minerals in a voxel (vector)

Specific gravity of a point is in turn based on specific gravity of separate minerals as a weighted harmonic mean:

\[
SG_{i} = \frac{\sum_{j=1}^{n} wt_{j} \cdot SC_{j}}{\sum_{j=1}^{n} wt_{j}}
\]

where:
\(SG_{i}\) is specific gravity of the mineral \(i\) in the voxel
\(wt_{j}\) is the weight fraction of the mineral \(j\)

The texture of each voxel is described by using archetypes utilising the concept developed by Lund, Lamberg and Lindberg (2015). The textural archetypes and names can be based on descriptions used in geology; ie ‘fine-grained’, ‘coarse-grained’, ‘porphyroblastic’, ‘hypidiomorphic’, or be just non-descriptive classes such as ‘A’, ‘B’, ‘C’. For each archetype information on mineral liberation exists. This can be simply a liberation measurement of a typical sample. The minerals in the archetype must have matched with the minerals in a lithology. A lithology can have one or several textural archetypes.

A point must have a volume greater than mineral grain size and therefore it is more appropriate to describe it as a cube and call it a voxel. Typical size for a voxel could be a size of a sample or smallest mineable unit depending on the case.

Therefore, each voxel of a synthetic orebody has the following information: spatial coordinates \((X, Y, Z)\), lithology \([\text{integer}]\), modal composition \([\text{mass proportion of each mineral}]\), density \([\text{double}]\) and archetype \([\text{string}]\). A library exists for the chemical composition of minerals and for liberation distribution of archetypes by size.

**Sampling module**

Sampling module simulates sampling by drilling. This enables investigation of different drilling patterns, orientations and densities. Within a drill core or RC chips the sample lengths, sample sizes (half core, quarter core), and sample preparation methods can be selected. This allows studying different sampling strategies. Number of drill holes is limited by the number of voxels covering the horizontal cross-section of the block model. The sample can consist of one or several voxels.

The samples are converted into analysis results in the assay level. For each analysis method their output parameters, detection limits and error model (standard deviation) is described. Thus, a sampling module sends a sample taking from an orebody. A sample includes the same information as a voxel. If it consists of several voxels, an average composition is used. For non-numeric information such as lithology, frequency information is delivered, eg sample consists of lithologies A (50 per cent), B (30 per cent) and C (20 per cent). For each analysis method the output parameters are calculated or derived from the voxel information. For example:

\[
C_{XRF}^{SiO_{2}} = C_{true}^{SiO_{2}} + \epsilon
\]

where:
\(C_{XRF}^{SiO_{2}}\) is X-ray fluorescence of \(SiO_{2}\)
\(C_{true}^{SiO_{2}}\) is a true \(SiO_{2}\) grade of the sample calculated from mineral grades and mineral library
\(\epsilon\) is the measurement error

**Production module**

For the production module the orebody needs to be divided into blocks. Blocks size can depend on mineralisation type and mining method. Production module sends a specific block in certain order to the production module. The open pit mine is approximated with a cone. Mine life is divided into periods and each period of production is reflected in a cone including blocks to be mined during the period with their mining order.
Mine operating expenses

Mine operating expenses module aims to estimate mining costs. In open pit this is based on depth of extraction. Assumed mining cost was scaled to the predefined minimum and maximum mining cost of one cubic metre of ore. The mining cost increased logarithmically with depth.

Process model

Process model consists of process simulation. The simulation is done on particle level therefore the process simulator must be capable of handling liberation information and multiphase particles. The process model treats each block separately. The block information is transferred from the synthetic orebody model and the time aspect is controlled by the production model. The information of the plant feed enabled the utilisation of particle-based models. As material enters into the plant, it is converted to particles by applying the liberation distribution of corresponding archetype. Because the modal composition of a block and the modal composition of the archetype are different, the mass proportions of particles in the particle population are adjusted using the formula given in Lund, Lamberg and Lindberg (2015). Unit process models describe the behaviour of each particle based on one or several of their properties: density, size, mineral composition, and shape (Lamberg, 2010). For each processed block, the process model returns product quantities and qualities (elemental grades, mineral grades, particle size distribution, mineral liberation information) with processing information: time spent processing a block, processing costs, consumables qualities and quantities required for processing the block.

Economic model

The economic model takes the information from the geological, mining and processing modules and offers bookkeeping. It also collects the time-cost information. The economic model can be used to forecast performance based on the selected scenario. Thus the main purpose of the economic model is comparison between different production scenarios based on different sampling designs but not optimisation.

SYNTHETIC IRON ORE CASE STUDY

A synthetic iron orebody was created based on geological and mineralogical information from Malmberget (Lund, 2013). The Malmberget iron ore deposit in Northern Sweden consists of several orebodies of massive magnetite and hematite, characterised by high Fe grade of 51–61 per cent and a varying P grade of <0.8 per cent (Lund, 2013). The main ore minerals are magnetite and hematite, and the gangue minerals are apatite and actinolitic amphibole. The accessory minerals include biotite, albite, pyrite, chalcopyrite and titanite. In the massive ore a broad variation of mineral-texture relations can be identified where magnetite has both fine- and coarse-grained texture with latter being the more common. Two main textural types, Amph-(Ap-Bt) and Ap-(Amph), were identified by Lund (2013). The massive ore, high in Fe and low in SiO₂, is surrounded in Malmberget by a semi-massive mineralisation that can be several tens of metres thick, occurring as rims or as inclusions in the massive ore with a decreasing iron grade. Mineralogically the semi-massive ore, texturally defined as Fsp type, is magnetite and/or hematite ore with an iron grade of less than 35 per cent Fe, and the main non-iron minerals being silicates; ie amphibole, feldspars (albite and K-feldspar), quartz and biotite in various proportions that generated several different mineral assemblages with more complicated textures than the massive ore.

For the synthetic orebody three lithologies were modelled: Fsp, Amph-(Ap-Bt) and Ap-(Amph). A total of one ore mineral and four main gangue minerals were included: Magnetite, albite, actinolite,apatite and biotite. Mineral distribution was different for each mineral in each texture thus each of them required unique model parameters. Chemical composition of the minerals was taken from Lund (2013) and was identical in all lithologies and textural types. Orientation and dimensions of the lithologies are shown in Figure 8. Ap-(Amph) is the most frequently occurring type of lithology, while Fsp is the least frequent one (Figure 6). Input values for the synthetic orebody, such as average values, standard deviation and minimum–maximum intervals, were based on three different geometallurgical textures by Lund (2013).

Magnetite (Mgt) grade variation is given as an example of a mineral distribution of commodity mineral (Figure 7). Magnetite grade and distribution depends on the lithology.

Element ratios within a synthetic orebody are shown in Figure 8. The modal chemistry might not always be strictly honoured, since variability in modal mineralogy Figure 8. Basic statistics for the both modal mineralogy and elemental composition of the synthetic orebody elements is summarised in Table 1. Magnetite is the commodity mineral and silicate minerals are the main lithology minerals (the others). Therefore, iron (Fe, main component in magnetite) has strong negative correlation with silica (Si). Negative correlation between Fe with most of other components is due to their existence in lithologies. When magnetite grade is high the grade of other minerals is low. Bimodal distribution in Fe-P diagram is due to the existence of higher grades of apatite in one of the lithologies as it was shown in Lund (2013). The deterministic character of the approach, allowed to control spatial distribution of the variables and match the basic statistics of those parameters from Lund (2013).

Specific gravity was defined based on Equation 6. It has bimodal distribution and ranges from 3.2 to 5.0 t/m³ for ore material excluding waste (see Figure 9).

The voxel size and the block size were selected to be equal in size, 5 × 5 × 5 m³. The actual mining operating cost was modelled as a function of depth at which block is located. Mining cost is increasing with depth and due to logarithmic distribution. Therefore, the number of blocks with lower mining operating cost is larger than number of blocks with higher operating cost (Figure 10).

The mineral processing model was implemented in HSC Sim 7.1a software developed by Outotec (2012). The mineral processing plant comprises two sections: dry cobbing plant and wet magnetic separation plant (Figure 11). The dry processing stage included screens, cone and autogenous crushers (vertical shaft impactor) and low-intensity magnetic separation (WLIMS). For the WLIMS a process model developed by Parian (2015) was used. The stream file included information about blocks of the orebody arranged in an order in which they would be fed to the processing plant. The following information was included for each block: ID, coordinates (X, Y, Z), lithology, modal mineralogy, chemical composition, specific gravity, mining operating cost and textural archetype.

Three different geometallurgical textures were the input to the process model. Each texture represented a population of particles that behaved differently in the process. Based on particle types and their mass proportions this will give different performance as the type and magnetite head grade varies as shown in Figure 12. Fsp texture type showed in
general higher recovery of magnetite, than Amph-(Ap-Bt) and Ap-(Amph). On the other hand, Ap-(Amph) had very narrow magnetite grade distribution and consequently also had the narrow distribution of magnetite recovery to the concentrate.

The forecast characterised performance of the beneficitation process and the mine blocks to be extracted and fed to the process. Values obtained from the forecast are given in Table 2 for the entire synthetic orebody without separation by lithologies or archetypes.

Simulation to create the forecasts was run for 12,231 blocks using five calculation rounds, thus iterations. The final outcome of the simulation model was an amendment to the stream file, which included information on the concentrate: modal mineralogy, chemical composition, recovery of main commodity minerals and elements, processing time, concentrate tonnage per hour and feed tonnage per hour. These values were used as an input to the economic model.

Economic model

Economic model was the last part of GPM. Five different scenarios forecasting the production were assessed with the help of the synthetic orebody and the evaluation framework. Variation of two parameters was included in the scenarios: existence of geometallurgical program and possibility for stockpiling. The first set of scenarios examined the production approach. ‘A’ and ‘B’ scenarios assumed perfect stockpiling conditions, which implied that there was no limitation to the sequence of sending ore to the processing plant. ‘C’ and ‘D’ scenarios assumed no stockpiling, thus the mined block was immediately sent to the plant.

The other set of scenarios reviewed the presence or the absence of the geometallurgical program. ‘A’ and ‘C’ scenarios didn’t include geometallurgical program and therefore optimisation of the mining was done through head grade and assumption on constant recovery. ‘B’ and ‘D’ scenarios assumed perfect geometallurgical program. For each block complete information of its value was available through process simulation and this was used for optimisation. ‘B’ and ‘D’ were based on a mineralogical approach (Lamberg et al., 2013; Lishchuk et al., 2015; Lishchuk, Lamberg and Lund, 2015), which meant that instead of metal recoveries, mineral recoveries were considered, and processing the recovery model itself was built on mineralogy rather than metal accounting.

Forecasts were evaluated in two ways based on:

1. the internal rate of return (IRR) and net present value (NPV) with the annual discretisation for each case
2. the second set of NPV values for the block-based discretisation (focuses on optimisation of time required to process each block).

Finally, all four scenarios ‘A’, ‘B’, ‘C’ and ‘D’ were compared to the scenario ‘E’. Scenario ‘E’ represented the geometallurgical scenario where discounted cash flow was
optimised. Thus, ‘E’ was designed to give the best possible outcome.

For better understanding of the model, the difference between cash flows for ‘A’ versus ‘B’, and ‘C’ versus ‘D’ production scenarios was reviewed.

To make the scenarios more realistic premiums and penalties were set on quality of the produced concentrate and were included in the economic model. Premiums were added under the condition that concentrate met the following requirements: $P\% < 0.025$, $SiO_2\% < 0.80$, $Al_2O_3\% < 0.28$, $MgO\% < 0.35$, $TiO_2\% < 0.45$, $Na_2O\% < 0.06$, $CaO\% < 0.20$. Penalties were applied under the condition that concentrates met the following requirements: $P\% > 0.075$, $SiO_2\% > 4.00$, $Al_2O_3\% > 0.70$, $MgO\% > 1.00$, $TiO_2\% > 0.40$, $Na_2O\% > 0.22$, $CaO\% > 1.90$. Amount of penalties paid was dependent of the total number of breached conditions. For example, $P\% > 0.075$ meant that only 75 per cent of the concentrate value could be paid, $CaO\% > 1.90$-0% of the concentrate value could be paid.

The economic parameters are summarised in Table 3.
RESULTS

Although Malmberget has very homogeneous and high-quality ore, the difference between prediction and production scenario performances was extensive (see Table 4). In both production options (with stockpile management and without) ‘A’ and ‘C’ (scenarios with optimised head grade) showed lower NPV and IRR values compared to scenarios ‘B’ and ‘D’. Scenarios ‘B’ and ‘D’ have also shown overall economic performance that was very close to the most realistic scenario ‘E’.

Two types of NPV discretisation were used to compare also the production scenarios. The first NPV type (by year) was discretised by number of production years. And the NPV by block processing time was discretised by the time required to process each block separately. It was very clear that planning based on annual discretisation tends to underestimate NPV.

Difference in cash flow can be explained by difference in magnetite recoveries assigned for each block. In geometallurgical production scenarios recoveries were taken from the mineral processing simulation. Thus recoveries in geometallurgical approach were different for each block.

<table>
<thead>
<tr>
<th>Element</th>
<th>Average</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Standard deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fe (%)</td>
<td>59.0</td>
<td>24.9</td>
<td>72.6</td>
<td>10.3</td>
<td>-0.9</td>
<td>2.8</td>
</tr>
<tr>
<td>Ti (ppm)</td>
<td>100.4</td>
<td>61.5</td>
<td>142.9</td>
<td>10.4</td>
<td>0.5</td>
<td>2.4</td>
</tr>
<tr>
<td>V (ppm)</td>
<td>294.0</td>
<td>119.9</td>
<td>373.3</td>
<td>59.1</td>
<td>-0.8</td>
<td>2.6</td>
</tr>
<tr>
<td>Si (%)</td>
<td>5.4</td>
<td>0.4</td>
<td>19.7</td>
<td>4.1</td>
<td>0.6</td>
<td>2.4</td>
</tr>
<tr>
<td>Al (%)</td>
<td>1.1</td>
<td>0.1</td>
<td>6.2</td>
<td>1.0</td>
<td>1.8</td>
<td>5.6</td>
</tr>
<tr>
<td>Ca (%)</td>
<td>2.9</td>
<td>0.2</td>
<td>12.3</td>
<td>1.2</td>
<td>1.5</td>
<td>7.4</td>
</tr>
<tr>
<td>Mg (%)</td>
<td>1.7</td>
<td>0.1</td>
<td>5.7</td>
<td>1.2</td>
<td>0.8</td>
<td>2.5</td>
</tr>
<tr>
<td>Na (%)</td>
<td>0.5</td>
<td>0.0</td>
<td>4.0</td>
<td>0.6</td>
<td>1.8</td>
<td>5.7</td>
</tr>
<tr>
<td>K (%)</td>
<td>0.3</td>
<td>0.0</td>
<td>1.5</td>
<td>0.2</td>
<td>1.4</td>
<td>5.9</td>
</tr>
<tr>
<td>P (%)</td>
<td>0.8</td>
<td>0.0</td>
<td>4.4</td>
<td>0.5</td>
<td>1.0</td>
<td>5.6</td>
</tr>
</tbody>
</table>
On the other hand, fixed recoveries were used in non-
geometallurgical production scenarios. Non-geometallurgical approaches don’t assume predictive recovery model, which explains utilisation of the fixed recoveries.

In addition to high NPV shown by scenario ‘E’, it also exhibited shorter than any other production scenario payback time (Figure 13).

CONCLUSIONS
Practical application of geometallurgy requires a number of specific tools to design effective programs and to quantify the impact that geometallurgy can have on project value. Such a tool has to be holistic and incorporate geological, processing, and economic data. In this study, such data was brought together and five different scenarios were evaluated under the geometallurgical scope. Scenarios differed by production approaches and application of geometallurgy.

The geological component of the geometallurgical model was based on a synthetic orebody. The developed framework is unique, since the geological information is taken down to mineralogical level. Both modal composition and texture is described for the whole deposit with high spatial resolution of one point per 125 m³. Synthesised geological data was used in process simulation and the metallurgical outcome supported economic calculations and comparison of the production scenarios. The synthetic orebody was also used to simulate simplified mining case, where feed optimisation was constrained by the mining plan (scenarios ‘C’, ‘D’).

The study has shown clear advantage of using geometallurgy in production planning. Geometallurgical production scenarios (‘B’, ‘D’) were characterised by both higher NPV and IRR since they took into account variability in throughput and recovery. Another conclusion was that optimisation based solely on head grade without application of variability in plant feed performance gives a less reliable forecast for the mining value chain.

Serendipitously, it was observed that economic performance parameters such as NPV are highly dependent on discretisation level. This observation could be potentially used in the future for error estimation of geometallurgical
Since most of the economic studies of mining projects are discretised by years, full value of geometallurgical economic model discretised by block processing time periods requires further investigation.

ACKNOWLEDGEMENTS

This study is part of the PREP project funded by Vinnova SIO STRIM – strategic innovation program for the mining and metallurgical industry.

REFERENCES


Appendix XII: Paper E
Simulation of a Mining Value Chain with a Synthetic Ore Body Model: Iron Ore Example

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Received: 15 August 2018; Accepted: 15 November 2018; Published: 18 November 2018

Abstract: Reconciliation of geological, mining and mineral processing information is a costly and time demanding procedure with high uncertainty due to incomplete information, especially during the early stages of a project, i.e., pre-feasibility, feasibility studies. Lack of information at those project stages can be overcome by applying synthetic data for investigating different scenarios. Generation of the synthetic data requires some minimum sparse knowledge already available from other parts of the mining value chain, i.e., geology, mining, mineral processing. The aim of the paper is to describe how to establish and construct a synthetic testing environment, or “synthetic ore body model” for data integration by using a synthetic deposit, mine production, constrained by a mine plan, and a simulated beneficiation process. The approach uses quantitative mineralogical data and liberation information for process simulation. The results of geological and process data integration are compared with the real case data of an apatite iron ore. The discussed approach allows for studying the implications in downstream processes caused by changes in upstream parts of the mining value chain. It also opens the possibility of optimising sampling campaigns by investigating different synthetic drilling scenarios including changes to the spacing between synthetic drill holes, composite length, drill hole orientation and assayed parameters. A synthetic deposit model can be a suitable tool for testing different scenarios for implementation of geometallurgical programs and also an educational tool for universities and companies.

Keywords: synthetic ore body; simulation; iron ore; prediction

1. Introduction

Geometallurgy aims to create a predictive model for mine-to-metal production chain through the combination of geological, processing and economic models. The highest returns on application of geometallurgy are expected to come from complex deposits with high variability in properties affecting its processing [1–3]. The geometallurgical predictive model is to be established during development of a geometallurgical program [1]. Establishment of the model requires involvement of various professionals from different disciplines and the availability of harmonised modelling and simulation tools. The high-fidelity orebody model [4] with a high resolution and utility of the information and possible moves from indicators to predictors is a spatial basis for the geometallurgical program. In a high-fidelity geometallurgical program, the critical methodology selection, such as sampling design, components included in the block model and their assaying methods, and geostatistical solutions should be based on scientific principles. The benefits and limitations of program design vary from case to case and thus no single deterministic approach can be developed. In real cases comprehensive study of different alternatives is difficult. The use of a synthetic orebody model combined with process
simulation and production scheduling, backed by validated case studies, offers an approach to improve the design, and cost-effectiveness of geometallurgical programs.

Geometallurgy is claimed to help in optimisation of mineral resource utilisation [5]. According to Dunham and Vann [6], geometallurgy can give increased total metal recovery and improved asset utilisation. In addition to these, Lamberg listed in his review that geometallurgy has potential to bring benefits such as better controlled ore deposit utilisation, higher flexibility in introduction of new technological solutions, lower operational risks and wider access to economical optimisation of the full operation [1]. In literature reviewed there are currently a few case studies that state and demonstrate quantitatively the added value of geometallurgical programs. A mining project emulator called “Challenge Geometallurgy!” developed for educational purposes at Luleå University of Technology, has demonstrated that the geometallurgical program can give up to 25% shorter payback time compared to cases when no geometallurgical information is available. The value of geometallurgy for mining companies can also lie in shortened permitting times. Pure economical investigation would be still important to carry out in order to fully expose how much additional profit a geometallurgical program could allow during the mine lifetime.

The outcome of the sampling campaign can be tested and predicted with synthetic drilling, and results can be used for planning and correcting actual drilling campaigns. The model may contain multiple realisations with different resolutions and a reference case. Comparison between realisations and reference case give an idea about additional sampling needed and uncertainties in processing and mining related to the voxels location in the ore body. However, in this work we use only one realisation, since studying uncertainties is beyond the scope of the study. Although the problem of upscaling was neglected in the study, its importance has been widely discussed in literature [7–10]. One possible solution proposed by Coward et al. [8] is to use primary-response framework to reduce the bias of non-linear scaling up. The framework suggests using primary additive variables, e.g., mineral grades, to predict non-linear response variables, e.g., recoveries.

A synthetic orebody was created with models for the ore utilisation; i.e., mining, and processing. Such an ore body model may provide an environment where different strategies for geometallurgical programs can be numerically tested in an effective way, with consideration of impact from all the upstream and downstream processes. The method presented in the paper is a proxy and simplified one, which might be applied for making rough estimates whether geometallurgy is needed or not. Synthetic data is also a valuable tool for educational purposes at universities and for production where complex concepts can be explained in a simple way. The paper describes both the algorithm and steps needed for building synthetic data. The usage of the synthetic ore body model is demonstrated through a case study of the Malmberget iron ore deposit, in Northern Sweden. Using mineralogical and liberation information for the spatial and process modelling makes the approach more realistic at higher level of process details.

2. How to Create a Synthetic Ore Body Model

2.1. Selection of the Modelling Approach

Modelling by simulation is a well-documented practice commonly used in the mining industry to evaluate alternative process designs [11–13]. Such modelling is typically undertaken at operating mines where production records are available for the actual short-term grade variability. In these cases, the real data is used as an input into the simulation of different scenarios. Previously synthetic geological data has been studied by Malmqvist [14,15] and Malmqvist et al. [16] for improving sampling techniques. The focus was on mineral exploration and sampling for mineral resource estimation of deep-seated sulphide ore bodies. More recent examples of simulation for reproduction of complex geological structures and behaviour of spatial geological data can be found in [17,18]. Jupp et al. [13] created a synthetic ore body model and used it for geometallurgy to study the variability reduction problem in the daily scheduling system.
Traditionally, the modelling of an ore body has been restricted to the geological domain (the definition of physical regions with homogeneous properties based on lithology, mineral grade and style of mineralisation [19,20], densities, and elemental grades). The processing properties have been almost totally neglected. However, a simulated synthetic ore body as defined in this paper must satisfy three conditions: Include processing properties; show realistic variability within synthesised data and impose spatial cohesion between data. Additional parameters, such as constraints by a mining method, processing performance, and economic response will produce more realistic output.

The selection of a modelling approach (Table 1) to simulate geological and propagate mineral processing properties in a three-dimensional physical space involves a trade-off between geological realism and conditioning capabilities. The number of data points, or number of samples, used in modelling is crucial when selecting the modelling method. The methods which are efficient with small number of data points can be used in geometallurgy, contrary to traditional resource estimate methods that work with large dataset. Prior knowledge about the studied phenomena and whether the modelling method is parametric or non-parametric may also have impact on number of data points [21]. Another parameter is a smoothing, which can be defined as whether the model smooths predictions at sampling locations or not [22]. Estimation methods such as kriging have a significant smoothing effect, while simulation techniques allow to produce values that are true to the fluctuations of the phenomenon [23]. Simulation techniques provide higher realism than traditional geostatistics [24,25]. A process-mimicking approach was selected for modelling in this study due to its relative simplicity, and that it does not require large number of data points has low smoothing and high realism. The algorithm was implemented in a MATLAB code and currently is not publicly available.

Table 1. Listing of spatial modelling approaches.

<table>
<thead>
<tr>
<th>Classification of the Methods</th>
<th>References</th>
<th>Number of Data Points</th>
<th>Smoothing</th>
<th>Realism</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geostatistics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimations (e.g., univariate, indicator, co-, and block kriging)</td>
<td>[23,24,26–29]</td>
<td>Large</td>
<td>High</td>
<td>Low/Medium</td>
</tr>
<tr>
<td>Stochastic (e.g., LU, sequential Gaussian, and Block Error simulations)</td>
<td>[23,24,30]</td>
<td>Medium</td>
<td>Low</td>
<td>Medium/High</td>
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<tr>
<td>Process (e.g., process based, process-mimicking)</td>
<td>[24,31]</td>
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<td>Low</td>
<td>High</td>
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<tr>
<td>Simulations</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Statistics</td>
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<tr>
<td>Uni-, Bivariate (e.g., Inverse distance weighting, nearest neighbour, polynomial regression, splines)</td>
<td>[32,33]</td>
<td>Medium/Large</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Multivariate (e.g., K-means clustering, PLS regression)</td>
<td>[34]</td>
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<td>Medium</td>
<td>Medium</td>
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<tr>
<td>Non-geostatistics</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Machine learning</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unsupervised: clustering (e.g., K-means)</td>
<td>[35–37]</td>
<td>Large</td>
<td>Medium</td>
<td>Medium/High</td>
</tr>
<tr>
<td>Supervised: regression (e.g., Neural networks) and classification (e.g., nearest neighbours, decision trees)</td>
<td></td>
<td>Medium</td>
<td>Medium</td>
<td>Medium</td>
</tr>
</tbody>
</table>

2.2. Synthetic Ore Body Model

The synthetic ore body model includes two modules: The synthetic deposit module and the synthetic sampling module (Figure 1). Each module is comprised of a spatial component, which considers the location of each point in a physical space, and a database, which carries non-spatial quantitative and qualitative information for each point. Spatial and non-spatial information is connected by a unique ID number assigned to each point of the model in physical space and a corresponding record in the database. Both databases (deposit module and sampling module) have the same meta data and carry the same type of information (elemental composition, mineralogy, recoveries, throughput, mining cost, value etc.) about each block of the synthetic deposit and each segment of a synthetic drill core.
2.3. Synthetic Deposit Module

The Synthetic Deposit Model is described with three-dimensional voxel model and database. The Synthetic Deposit Model focus on outlining the deposit’s borders and assigning geological, mining, processing and economic properties to each voxel of the voxel model. In practice, the uncertainty of the ore response in the process may also be impacted by extraction sequence, processing available, operators’ team working at the plant, and batch with which the extracted block was blended during the process. However, those factors would have a lower impact on the process performance in iron ore mining than in, for example, copper or gold ores.

2.3.1. Spatial Data

The spatial part of the deposit module for the synthetic ore body is a three-dimensional voxel model, where each voxel corresponds to a minable block of the deposit. The size of the voxels can be set to any constant value. The location of each voxel is described by the coordinates $x$, $y$, $z$. The $x$ and $y$ coordinates are planar, and $z$ represents height. The coordinate system follows the left-hand rule. Therefore, the centre of the coordinates lies in the lower left corner of the voxel model and values of the coordinate $z$ increase upwards.

2.3.2. Database

A database of voxel properties describes geological, mineralogical, mining, mineral processing and economic properties of each voxel (Figure 2). Each voxel gets one entry in a database with complete information about its properties. The geological data in the database are derived from the three-dimensional voxel model.

The voxel model represents the extent of the mineral deposit, including both ore body and country rock. The geological domains, mineralogical and elemental properties are the key geological features chosen for modelling synthetic deposits. Generated mineralogical and chemical information is inputted to the mineral processing model implemented in HSC simulation software [38] for each block. Alternatively, other software may be used: CEET, FLEET [39]; Cycad Process [40]; ECS/CEMulator [41]; IDEAS Integrated [42]; JKTech’s JKSimBlast, JKSimMet and JKSimFloat [43]; Microsoft Excel based simulator [44]; MinOOcad [45], MODSIM [46]; SimSci DYNSIM [47]. Process parameters estimated for
each block are constrained with a mining method, since sequencing of the blocks sent to the process depends on the production plan of the selected mining method. Process performance, e.g., concentrate quality, throughput, mining cost, dilution etc. provide inputs for the economical assessment of the designed mine. Geological, production and economic information about each block is stored in a database and linked to the block with a unique identification number.

2.3.2.1. Geology

**Domains: Physical space**

The general term “domain” here refers to a volume or physical space with homogeneous properties (e.g., mineral distribution, rock density, grindability, commodity material recovery, or texture). In other words, voxels belonging to the same ore type, adjacent to each other and showing spatial continuity of any properties (e.g., geological, metallurgical properties) inside the ore body are referred to as domains [48,49]. Ore types, alteration zones, mineral grade distributions, and weathering zones are called geological domains. Domains used to model process parameters are referred to as geometallurgical domains.

The complex shape of the domains is modelled (approximated) with simple geometrical bodies. Traditional geological modelling software, e.g., Maptek [50] and Dassault Systems [51] deal with 3D domains by using solids generated from wireframes or through implicit modelling. However, an ellipsoid (Figure 3 and Equation (1)) is chosen here, since it is a common shape used in geosciences, i.e., geostatistics. Other geometric shapes may be used in modelling domains as well (e.g., cubes, spheres and their sectors). It might be enough to use one ellipsoid to approximate each domain:

\[
\frac{(x - x_0)^2}{a} + \frac{(y - y_0)^2}{b} + \frac{(z - z_0)^2}{c} = 1
\]  

(1)

Here (see also Figure 3) \(o = (x_0, y_0, z_0)\) is the centre of the ellipsoid; \(a, b, c\) are its semi-axes. The spatial orientation can also be given by Euler rotation angles \(\alpha, \beta, \gamma\).

However, cases that are more complex may require usage of combination of multiple ellipsoids. Interactions or conflicting overlaps between different domains are resolved by applying Boolean operations (Figure 4).
Mineralogy

Modal mineralogy is defined for the mineral grade model by considering mineralogical difference between geological domains and preserving relevant quantities, distribution, and composition of the minerals. Firstly, a complete list of minerals for the entire model is identified. Then an appropriate sub-list of minerals is defined for each geological domain. It is assumed that a mineral of the same mineral can be summed up and given a new name (e.g., Magnetite_Sum) or kept separately in the database (e.g., Magnetite_1, Magnetite_2, Magnetite_3).

Mineral distribution for each voxel is modelled as a function of coordinates of the voxel in the block model (Figure 5). When extension of the mineral inside the block model is known, the physical space of the actual mineral distribution can be restricted by geological domains (ellipsoids) and scaled correspondingly. Mineral quantity distribution can also be complex since they represent several overlapping distributions with a drift. Initial hypothesis about mineral distribution is expressed as a generalised additive model (GAM) shown below by Equation (2).

\[
M = T + S + N \rightarrow \begin{cases} 
T = f_T(x, y, z), & \text{min}T = a_T, \ \text{max}T = b_T \\
S = f_S(x, y, z), & \text{min}S = a_S, \ \text{max}S = b_S \\
N = f_N(x, y, z), & \text{min}N = a_N, \ \text{max}N = b_N 
\end{cases} \tag{2}
\]

where, \(M\) is a mineral grade in a given voxel scaled to the interval of minimum and maximum values defined for the mineral; \(T\) is a trend function; \(S\) is a systematic error; \(N\) is a random error; \(T, S, N\) are functions of coordinates \((x, y, z)\) of the voxel. Each \(f_T(x, y, z), f_S(x, y, z), f_N(x, y, z)\) can be chosen as follows, Equation (3), where each choice for the function \(f\) defines a different hypothesis for mineral distribution and mineralisation.

\[
f = \begin{cases} 
\frac{r^n}{\sigma}, & \text{normal random value } (\mu, \sigma); \\
\sin(r^n), & \text{standard normal random value } [0, 1]; \\
\cos(r^n), & \text{standard normal random value } [0, 1]; 
\end{cases} \tag{3}
\]

where \(r\) is defined as the distance (e.g., Euclidian or Manhattan) in 1-, 2- or 3-dimensional space between the voxel of interest and the centre of the geological domain (ellipsoid):

\[
r = \left( (x - x_o)^n + (y - y_o)^n + (z - z_o)^n \right)^{\frac{1}{n}} \tag{4}
\]

where \(n\) is any real number; \(x, y, z\) are coordinates of the voxels locations; and \(x_o, y_o, z_o\) are coordinates of the center of the geological domain (as shown in Figure 3).
Figure 5. Applying geological domains to model rock types and property (e.g., mineral grade, elemental grade, density etc.) inside the rock type.

Describing minerals independently from each other might lead to a severe over or under estimation of mineral proportions for some voxels. This problem is avoided by using a simplified two-step approach: Commodity minerals are modelled independently from each other summing up to a value $A\%$, the rest (gangue) minerals, are modelled as a fraction of available space remaining, defined as $100\% - A\% = B\%$. However, this poses another problem of constructing the elemental and mineral grades since it introduces spurious correlations among data. The simplification was made here in light of the deposit type under the study with high grades of commodity mineral, and thus high iron grades, relatively high geological homogeneity.

Mineral chemical composition can vary from deposit to deposit or even within the same deposit. Thus, the mineral composition is described with the elemental grades being a function of a mineral grain’s spatial location in the voxel model. Modelling of the minerals distribution is done by considering the following aspects:

i. Stationarity is insured by modelling the “stationarity ellipsoids”. A stationarity ellipsoid is a geometry where the mineral distribution is the same for a given mineral throughout the portion of the voxel model enclosed by this stationarity ellipsoid. The algorithm of describing stationarity ellipsoids is identical to the one used for describing geological domains. Stationarity allow for describing anisotropy of the mineral distributions within the ellipsoids’ dimensions and orientations.

ii. Spatial conflicts between geological domains and stationarity ellipsoids are resolved with Boolean operations (Figure 4).

iii. Minerals modelled with Equations (2)–(4) may have compositions which are outside the normal range of values. Therefore, a certain minimax range can be imposed by rescaling (or truncating) the mineral distribution.
iv The total sum of mineral grades should be closed to 100%. Normalisation of values to a constant sum is also called a closure and forces negative correlations [52–56]. According to Aitchison [57] log-ratios should be used when it is needed to maintain the constant sum constraint. The significance of closure problem for environmental data was emphasised by Filzmoser et al. [58] and Reimann et al. [59], and for compositional geochemical data by Makvandi et al. [60].

Chemical composition

A voxel’s chemical composition depends on the modal mineralogy and chemical composition of the minerals. Each mineral within a geological domain has a defined chemical composition. If the chemical composition of a mineral varies, then several mineral species may have to be modelled, e.g., amphibole 1, amphibole 2, amphibole 3. The vector of chemical composition ($v$) of a voxel is calculated from modal mineralogy and the chemical composition of minerals, Equation (5):

$$v = A \cdot x$$

where $A$ is a matrix of chemical composition of minerals (sometimes also called mineral matrix), and $x$ is a vector of mass proportions of minerals in a voxel.

Density

The density of a voxel point is based on the densities of each of the separate minerals as a weighted harmonic mean assuming zero porosity of the rock, Equation (6):

$$\rho = \frac{\sum_{i=1}^{m} wt_i \cdot \%}{\sum_{i=1}^{m} \frac{wt_i \cdot \%}{\rho_i}}$$

where, $\rho_i$ is the density of the mineral $i$, $wt_i$, % is the weight fraction of the mineral $i$. The non-zero porosity can be considered by multiplying by the corresponding coefficient $a \in (0, 1]$.

Other geological (e.g., alterations, mineral textures), mineralogical (e.g., modal mineralogy, mineral liberation, grain size distribution), geophysical (e.g., magnetic susceptibility, porosity, dielectric permittivity, electrical conductivity) and geotechnical (e.g., Poisson’s ratio) properties might be considered in the future.

2.3.2.2. Production

Mining

A mining plan defines the ore sequence prior to coming to the processing plant. The mining plan is determined by the mining method. To enable the mining module, the voxel model is transformed into the resource block model by giving dimensions to voxels. For the simplicity, and for preserving the maximum resolution of the model, the conversion is made by assigning one voxel to one block. However, for low variability models, the properties of one block can be retrieved by averaging the properties of several voxels.

Mining constraints for the synthetic ore body model can be introduced by applying a mining method, which may be either surface mining or underground mining. However, the algorithm for implementation of underground mining remains to be developed. The mining constraints can also be omitted (thereby assuming zero ore dilution, and zero ore losses). The time constraint of the mining production can be modelled by applying, for example, a series of pushbacks in an open pit mining (Figure 6). Each following pushback is represented by a cone of a larger size with preserved slope angle (ratio between cone’s diameter and height). Blocks enclosed in mining area of the synthetic deposit are extracted at once. Ore can be sequenced based on metal grade, mineral grade, processing cost, commodity recovery in the separation process, or by any other desirable property.
For the mine scheduling and open pit optimization, there are several methods available such as floating cone [61], Lerchs–Grossman algorithm [62], network flow approaches [63], Dagdelen–Johnson Lagrangian Parametrization [64]. Newman et al. [65] and Meagher et al. [66] provide a review of those and some more methods for the open pit optimization and mine planning. In this study, the optimization step was done by approximating open pit by a cone enveloping the whole ore body. The pushbacks are simply the sequential cones allocated with equal intervals from the bottom to the top of the ore body.

**Processing**

The process model is implemented through process simulation in the HSC Sim 7.1 process simulator [38]. The simulation is done by considering the liberation and distribution of the mineral particles, and the process simulator is capable of handling liberation information and multiphase particles. The process model treats each voxel separately. The voxel information is retrieved from the synthetic ore body model and the time aspect is controlled by the mining model. The information on the plant feed, gathered through geological information from each voxel, enables the utilisation of particle-based models [67–69]. As the material enters the plant, it is converted to particles by applying the liberation distribution of the corresponding geometallurgical domain. The modal composition of a block and the geometallurgical domain may be different; the mass proportions of particles in the particle population are adjusted using Equation (7) [70]:

$$\hat{p}_j = p_j \cdot \sum_{i=1}^{L} \left( \chi(i, j) \cdot \kappa_i \right)$$  \hspace{1cm} (7)

where $\hat{p}_j$ is the iteratively adjusted mass proportion of the mineral grades; $p_j$ is the mass proportion of the mineral grades before adjustment; $\chi(i, j)$ is the mass proportion of mineral in a particle; $L$ is a total number of minerals; and the correction factor $\kappa_i$ is calculated for each mineral $i$ before each iteration round as follows, Equation (8):
\[ \kappa_i = \frac{M(i)}{\sum_{j=1}^{n} (p(j) \chi(i,j))} \]  

where \( M(i) \) is a mineral grade in the sample; \( n \) is number of particles; and \( p \) refers to the mass proportion of particle in a size class. As such, the denominator is the mineral grade back-calculated from the liberation data.

The unit process models contain a description of the behaviour of each particle based on one or several properties: Density, size, mineral composition, and shape [71]. For each processed voxel or block the process model returns product quantities and qualities (elemental grades, mineral grades, particle size distribution (PSD), mineral liberation information) with processing information (time spent on processing the block, processing costs and consumables quantities required for processing the block).

The process model uses the geological information modelled in the synthetic ore body model from the previous steps (see Section 2.3.2.1 Geology) as an input (in other words, feed stream). The geological information of each voxel is fed to the beneficiation simulation separately (no blending). The output of the beneficiation simulation includes the composition of all the process streams; recoveries, mass pulls of the separation processes; throughputs and energy consumption calculated for each voxel. Beneficiation information produced at this step can be added to the database and be linked to the spatial part of the model by a unique ID.

For the beneficiation simulation done at an elemental level, an input would include elemental composition of the voxel, i.e., Fe, Si, Al etc. At a mineralogical level, such input would include modal mineralogy of the voxel, i.e., commodity mineral (e.g., magnetite) and gangue minerals (e.g., biotite, quartz etc.). Beneficiation simulation by size is possible if mineral distributions in the synthetic ore body model are simulated by size. Alternatively, a fragmentation model may be applied over the synthetic data, c.f. [48,72].

In order to design a beneficiation simulation model, process performance information is needed for the similar ore types. Such information can include lab scale tests (e.g., WLIMS, Davis tube, flotation, Bond work index test), pilot plant tests, or plant survey.

2.3.2.3. Economics

The final performance of every mining project is always estimated economically. Conclusions can be drawn by comparing costs related to the implementation of the project and operating mining production, and revenues obtained from the sold final material. Capital and operating costs of production can be estimated from cost models (e.g., InfoMine [73] and Sayadi et al. [74]) and revenues—from the historical commodity prices taken at any date (e.g., Kitco Metalc Inc. [75] and LME [76]). While revenues are directly connected to the recoverable commodity grade, operating cost cannot be estimated so easily. Firstly, mining operating cost is linked to the ease of extraction of each block and the cost of transportation to the processing plant. For each mining method there is a mineral recovery and dilution; and mining layout also has an influence (Table 2).

| Table 2. Ore recovery and dilution for different mining methods (modified after Darling [77]). |
|---------------------------------|--------|--------|--------|--------|--------|
| Mining Method                   | Relative Cost | Flexibility | Selectivity | Recovery, % | Dilution, % |
| Surface mining                  | 0.10    | moderate | moderate | High     | Low     |
| Room-and-pillar (coal)          | 0.30    | high    | high     | 50–80    | 20      |
| Stope-and-pillar                | 0.30    | high    | high     | 75       | 15      |
| Sublevel caving                 | 0.40    | low     | low      | 75       | 15      |
| Shrinkage stopping              | 0.50    | moderate | moderate | 80       | 10      |
| Timbered square set             | 1.00    | moderate | high     | 100      | 0       |
| Longwall                        | 0.20    | low     | low      | 80       | 10      |
| Sublevel caving (top slicing)   | 0.50    | low     | low      | 90       | 20      |
| Block caving                    | 0.20    | low     | low      | 90       | 20      |
Depending on the mining method (Table 2), the cost of separate block extraction can have a connection to the cost of extraction of neighbouring blocks. Hardness and mass of the volume unit would be another parameter to control. Process operating costs will depend on the energy used in comminution and the chemicals and energy costs for separation processes.

The mining cost solution implemented in the synthetic ore body model accounts for the depth of the mining and density of the extracted material. The processing cost per tonne is considered to be a constant value. Present value (PV), future value (FV) and net present value (NPV) of the material (concentrate or metal) produced by the process are calculated as shown by Equation (9). The results from the economic model can be used for comparison between different scenarios, or for estimating the impact of managerial decisions.

\[
\begin{align*}
NPV &= \sum_{j=1}^{N} \frac{PV_j}{(1+d)^j} = \sum_{j=1}^{N} FV_j \\
FV_j &= \frac{PV_j}{(1+d)^j} \\
PV_j &= (P - s)Q_r - Q_c \cdot c - Q_m \cdot m
\end{align*}
\]

where \( j \) is a period \([1,N]\); \( d \) is a discounting rate, \%; \( P \) is the metal price; \( s \) is the sales cost; \( Q_r \) is the material recovered in mining and process, units per period; \( c \) is the milling cost; \( Q_c \) is the processed amount of material, units per period; \( m \) is the mining cost; \( Q_m \) is the mined amount of material, units per period per period.

### 2.4. Sampling Module

Sampling is the main source of information on the deposit’s geology, mineralogy and processing properties. Synthetic sampling is implemented by simulating synthetic drill cores. Mathematically they can be represented as infinitesimally thin cylinders, or as lines.

The sampling module (Figure 7) enables the investigation of different drilling patterns, orientations, and sampling densities. The spatial part of the sampling module includes \( x, y, z \) coordinates of each sample. For sampling with drill holes, coordinates \( x, y, z \) correspond to the location of the section of the drill core. The coordinate system used in a sampling module is the same as for the Deposit module described in Section 2.3.1. Spatial data.

![Figure 7. Structure of the sampling module and its connection to the synthetic ore body model.](image)

The difference between a drill core, and reverse circulation (RC) chips may be considered by selecting the sample sizes (half core, quarter core) and sample preparation methods. Sample size in the drill holes is defined by the sample or composite length. A smaller composite length allows better capturing of the variability of the studied parameter, e.g., magnetite grade, Bond Work Index, etc. A larger composite size would smooth the data. The advantage of larger sample size is the lower total number of samples needed to assay or test all the drill cores and thus lower cost. The synthetic sampling module does not have any sample size limitation and allows simulation of infinitely small samples. This will lead to a larger number of records in the database of the sampling module.

The difference between sampling methods is implemented through the errors \( \epsilon \) added to the sampled values Equation (10). This allows for studying different sampling strategies. The number of
vertical drill holes is limited by the number of voxels covering the horizontal cross-section of the block model. A single sample can consist of one or several voxels. Non-vertical drill holes are described with dip and azimuth in addition to the total depth and collar coordinates. Synthetic drill cores are extracted as composites where composite length can be defined depending on the variability in the deposit and purpose of the study.

Synthetic element composition in a drill core sample is obtained by transferring values from the nearest voxel in a voxel model to the segments of the synthetic drill cores. Those chemical compositions do not account for the error of the assaying methods, i.e., XRF. Therefore, chemical compositions of the synthetic drill core samples are converted to chemical assay values by applying an error model. The error model is based on the precision and accuracy information for chemical analyses, e.g., for X-ray fluorescence (XRF), Equation (10):

$$G_{XRF} = G_{true} \pm \epsilon$$  \hspace{1cm} (10)

where $G_{XRF}$ is a component’s grade analysed by synthetic XRF; $G_{true}$ is a synthetic value of the component grade of the sample; $\epsilon$ is the measurement error which can be described by a normal distribution with standard deviation $\sigma$ and expected value 0.

The standard deviation for each elemental assay ($\sigma_{El}$) is computed as a product of elemental grades ($G_{true}$) and relative standard deviation ($RSD_{El}$) as shown in Equation (11).

$$\sigma_{El} = G_{true} \cdot RSD_{El}$$  \hspace{1cm} (11)

3. How to Use Synthetic Data

3.1. Malmberget Case Study

A synthetic iron ore body model is created based on results from previous extensive and careful characterisations of the structural and mineralogical information from Malmberget iron ore deposit in Northern Sweden. The deposit, upon which our model is based, consists of several tabular to stock-shaped ore bodies of massive to semi-massive magnetite and/or hematite deformed into a synformal shape [70,78,79].

The massive ore is defined by its high Fe content (55–60%) and low SiO$_2$ content. In the eastern part of the deposit the massive ore is surrounded by semi-massive mineralisation, characterised by a lower Fe grade (<55%) and higher SiO$_2$ content. The semi-massive zone can be several tens of meters thick, occurring as rims or as inclusions in the massive ore. Mineralogically, the ore is composed of magnetite and hematite as the main minerals andapatite and amphibole-pyroxene as typical gangue minerals. The semi-massive ore contains various proportions of silicates, i.e., feldspars (albite and orthoclase), amphibole, quartz, and biotite, which display a broad variation of more or less complex mineral-texture relationships [78].

The metallurgical test work was conducted on five different sample batches of >100 kg which reflects and represents the main ore types of Malmberget deposit. A textural classification was established for the massive and semi-massive ore to include both mineral- (mineral phases, mineral chemistry, and modal mineralogy) and textural information (grain size, shape, associating mineral). Due to the overall relatively high Fe-oxide content in the ore, the main gangue minerals for each ore type (normalised value) were used as a key feature to identify a variation between the textural types (each mineral selected, was related to the ore processing). The challenge was to create a geological model that offers quantitative information to be used in a process model. As mineral ore/textural type is usually descriptive, it is assumed that there is a close relationship between mineral liberation and mineral textural type. Therefore, classification of the ore handles the textural information from a processing point of view, in this case, incorporating the particle liberation distribution for each textural type and sample (by size) (Table 3). The feldspar rich textural type (Fsp) is typical for the lower grade magnetite ore (semi-massive), the amphibole rich textural type (Amph-(Ap-Bt) is widespread in
the massive ore together with another common apatite-bearing textural type (Ap-(Amph) (Figure 8),
details in Lund et al. [70].

Table 3. The geometallurgical framework of how to simulate and forecast the metallurgical variation
of ore deposit variables.

<table>
<thead>
<tr>
<th>Step 1</th>
<th>Ore classification (Qualitative)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ore Type</td>
<td>Main Associating Minerals</td>
</tr>
<tr>
<td>Semi massive</td>
<td>Ab, Qtz, Bt, Amph</td>
</tr>
<tr>
<td>Massive</td>
<td>Amph</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Textural Type Name</th>
<th>Modal Composition (Average Bulk), wt.%</th>
<th>Liberation Distribution of Mgt, (Average Bulk), %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fsp</td>
<td>55.1 35.0 7.6 0.4 1.8</td>
<td>95.9 2.2 1.1 0.5 0.4</td>
</tr>
<tr>
<td>Amph-(Ap, Bt)</td>
<td>66.4 2.9 23.0 1.3 6.4</td>
<td>94.5 0.5 3.8 0.4 0.8</td>
</tr>
<tr>
<td>Ap – (Amph)</td>
<td>86.6 0.1 3.3 7.1 2.8</td>
<td>89.2 0.8 0.9 6.0 3.0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Grade, %</th>
<th>Recovery, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>68.2/2.7</td>
<td>93.6</td>
</tr>
<tr>
<td>64.3/5.2</td>
<td>88.8</td>
</tr>
<tr>
<td>66.0/4.4</td>
<td>90.0</td>
</tr>
</tbody>
</table>

Abbreviations: Mgt—magnetite; Ab—albite; Act—actinolite; Ap—apatite; Bt—biotite; Qtz—quartz; Amph—amphiboles.

Figure 8. Spatial distribution of textural types in cross-sections (Lund, 2013).

The process model in Lund et al. [78] for each sample was made using a one-unit concentration model to quantify the mineral processing performance (grades for Fe, Si, P and Fe-recovery) in Table 3.
The process model uses textural type and modal mineralogy of the sample as inputs. The output of the model by Lund et al. [78] (Figure 9) was the forecast of elements’ and minerals’ recoveries to concentrate, and the concentrate’s chemical and mineralogical composition [80].

The estimated error of the outputted elements was the lowest for iron and did not exceed 3% for gangue elements (Table 4).

### Table 4. Relative standard deviations (RSD) of the XRF assay analysis, % [80].

<table>
<thead>
<tr>
<th>Element</th>
<th>Fe</th>
<th>Ti</th>
<th>V</th>
<th>Si</th>
<th>Al</th>
<th>Ca</th>
<th>Mg</th>
<th>Na</th>
<th>K</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSD</td>
<td>0.1</td>
<td>1.0</td>
<td>1.4</td>
<td>1.0</td>
<td>2.0</td>
<td>3.2</td>
<td>2.8</td>
<td>2.0</td>
<td>2.4</td>
<td>0.7</td>
</tr>
</tbody>
</table>

Figure 9. Fe recoveries measured from Malmberget case study (based on [80]).

### 3.2. Geological Model

The synthetic ore body model was created in MATLAB. The deposit has three textural types, i.e., Amph-(Ap-Bt), Ap-(Amph) and Fsp (Figure 10) were spatially modelled based on characterisation described earlier for the Malmberget case study. Spatial distribution of the textural types was arranged according to the distribution suggested by Lund [80].

Figure 10. Spatial distribution of textural types in cross-sections generated from the synthetic ore body. A—in a plane xy, B—in a plane yz, C—in a plane xy.

The textural types were modelled with ellipsoids in several steps and were aligned along the centre line such that the centre of the ellipsoids were lying on the centre line. The centre line of the deposit was selected with a 15° dip that crosses the centre point of the voxel model (x = 25, y = 25, z = 25) mimicking the model proposed by [80]. This model is layered (Figure 10) with textural types changing with depth. The same pattern was mimicked in the synthetic ore body model with 20 layers:
7 layers for Ap-(Amph), 7 layers for Amph-(Ap-Bt) and 6 layers for to Fsp-type. The shape of the ore body (comprised of the layered textural types) was chosen to be ellipsoidal, with the widest part in the middle \((x = 25, y = 25, z = 25)\) and gradually narrowing with distance away from the centre. Where textural types modelled in the synthetic ore body model overlap, the assignment of a voxel to a specific textural type was made by applying priorities through the use of Boolean operations (Figure 4). The highest priority in spatial modelling was given to the Ap-(Amph), then to Amph-(Ap-Bt) and then to Fsp-type. The lowest priority was given to the country rock. For instance, when ellipsoids representing Ap-(Amph) and Fsp-types were overlapping, all the voxels inside the overlapped space were assigned to the Ap-(Amph) textural type. In reality the location of the geometallurgical domains does not always follow the regular pattern, i.e., domains centres are not aligned along a line and are not necessarily oriented and dipping in the exactly same direction. Therefore, noise was added to the dimensions and locations of the individual geometallurgical domains: \(\pm 1\) voxel to the location of the domain centres, \(\pm 1\) voxel to the size of semi-axis \((a, b, c)\) and \(\pm 10^\circ\) to the rotation of each geometallurgical domain in \(xz\) and \(yz\) planes. The resulting spatial distribution of textural types in the generated synthetic ore body is shown in Figure 10 and can be compared to the Figure 8 from Malmberget [80]. The synthetic ore body mimics reasonably well the actual variation of textural type in Malmberget.

3.3. Mining Model

The synthetic ore body is modelled as a surface deposit, therefore open pit mining is used as the mining constraint, which is approximated with a cone model. Mining and time constraints are modelled as 13 sequential cones, representing pushbacks in a synthetic open pit mine. The overall slope angle of this open pit model is 40°. mined cones set the time variable in the later process simulation, when blocks are sent to the processing according to the mining plan. A production plan was generated from the mining model (Figure 11). The mining plan includes textural ore composition and the total number of minable blocks extracted by every pushback. Synthetic blocks can be used for process simulation only after extraction from the synthetic mine. The applied mining constraint allows for consideration of dilutions from the country rock and losses due to mining method limitations. However, in order to convert the block model into a fully time indexed sequence of blocks fed to the processing plant, some other aspects (i.e., blasting, loading, muck-piling, blending, stockpiling management) need to be considered. In Figure 11, an interesting pattern emerges, where mining of the synthetic ore body shows considerable variations in the ore fed to the concentrator. This is based only on the assumed geological model and textural information.

![Figure 11. Feed forecast generated from the mining model.](image-url)
The number of mined blocks of ore increases during the early production stages, before pushback 5 (Figure 11), due to the larger volume included in each sequential pushback. In addition, the amount of waste rock in those pushbacks is relatively low compared to the amount of ore. The number of blocks of ore extracted with each pushback starts to decrease after pushback 5 (Figure 11), despite the increasing volume of the following pushbacks. The number of the ore blocks extracted over time decreases because the slope angle of the pushbacks is constant, the orebody is dipping vertically, and the slope angle of mineralization is lower than slope angle of the pushbacks. Thus, the extracted volumes of the pushbacks also contain waste rock blocks.

3.4. Process Model

The process model used for this case study (Figure 12) is based on [80] and is comprised of two main sections: dry processing and wet processing. Dry processing includes cobbing and size reduction in a cone crusher. Wet processing has three stages of WLIMS and two stages of grinding and dewatering. Here, the final concentrate is the feed to the pellets plant and recycled water is returned to the head of the process.

![Process model design of the Malmberget simplified flow sheet in HSC SIM used to populate the synthetic ore body model with process parameters.](image)

The simulation used to create the process performance forecasts was run for 12,231 blocks, using five iterative calculation rounds. The final outcome of the simulation model was an amendment to the stream file, and included information on the concentrate: modal mineralogy, chemical composition, recoveries of main commodity minerals and elements, processing time, concentrate tonnage per hour and feed tonnage per hour. These values were used as an input to the economic model. The simulated magnetite recoveries (Figure 13) show that there are three distinctive populations of the process responses influenced by textural differences (Amph-(Ap-Bt), Ap-(Amph) and Fsp). The dispersion of the simulated recoveries is due to the texture differences of the different textural types. The process performance metrics are listed in (Table 5).
Validation of the synthetic ore body model was done by visual comparison of the geological structures (textural types) proposed by [80], as shown in Figure 8, and the textural types generated from the synthetic ore body model, shown in Figure 10. Comparison between the predicted and measured commodity recoveries was done based on Figures 9 and 13. Additional possible validation could be done using geostatistical methods, e.g., comparing variograms. Variograms of the real case study and for the synthetic ore body could be compared for the entire ore body, for selected zones (e.g., oxidation zones, ore types), and for drill holes. However, this is not possible since the exact locations of the Malmberget samples’ origin in the ore body are not known.

3.5. Synthetic Sampling

The sampling module of the synthetic ore body model can be used to optimise the drilling campaign, depending on the purpose of the drilling. Drilling for resource estimation can use the cost of additional drilling as an optimisation parameter. The benefits of conducting synthetic drilling campaigns are the possibility to generate any number of drill holes, with any desirable orientation and length, and added accuracy from more dense sampling campaigns would suggest the optimum drilling density. Drilling for variability studies would rather focus on sample size (composite length) and cost of samples characterisation. Increasing the number of samples, thus decreasing the composite length, would allow finding the optimum sample size for mineral grade estimate or process characterisation. Synthetic drilling might also help to resolve the issue of change of support, since variability studies of geological and process variability may require different sample sizes. In both cases, the cost of additional actions (drilling, characterisation) compared with potential gain is a border condition for optimisation. Error studies on the synthetic resource estimate based on synthetic drilling is a good

Table 5. Basic statistics of the modal mineralogy and elemental composition of the produced concentrate.

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Modal Mineralogy, %</th>
<th>Elemental Composition, % (*—ppm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mgt</td>
<td>Ab</td>
</tr>
<tr>
<td>Average</td>
<td>98.1</td>
<td>0.2</td>
</tr>
<tr>
<td>Min</td>
<td>91.2</td>
<td>0</td>
</tr>
<tr>
<td>Max</td>
<td>99.4</td>
<td>0.7</td>
</tr>
<tr>
<td>Stdev</td>
<td>0.8</td>
<td>0.1</td>
</tr>
<tr>
<td>Skewness</td>
<td>−1.8</td>
<td>1.5</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>8</td>
<td>5.1</td>
</tr>
</tbody>
</table>

Figure 13. Mgt recoveries predicted with the HSC chemistry-based process simulation from the synthetic ore body model. (Abbreviations: Mgt—magnetite; Ap—apatite; Bt—biotite; Amph—amphiboles; Fsp—K feldspars).

Validation of the synthetic ore body model was done by visual comparison of the geological structures (textural types) proposed by [80], as shown in Figure 8, and the textural types generated from the synthetic ore body model, shown in Figure 10. Comparison between the predicted and measured commodity recoveries was done based on Figures 9 and 13. Additional possible validation could be done using geostatistical methods, e.g., comparing variograms. Variograms of the real case study and for the synthetic ore body could be compared for the entire ore body, for selected zones (e.g., oxidation zones, ore types), and for drill holes. However, this is not possible since the exact locations of the Malmberget samples’ origin in the ore body are not known.
way for project risk assessment and checking whether the project fulfils the accuracy requirements of
its development stage, e.g., pre-feasibility, feasibility or production stage.

Sampling optimisation is not the aim of this study. Instead, the ease of generating synthetic drilling
data is highlighted here. Multiple parameters can be selected and tested in synthetic drilling easily,
fast and with no additional cost: Spacing between collars, regular or irregular patterns, orientation for
individual drill cores (azimuth, dip), preferential composite length, assayed properties (e.g., commodity
elements, gangue minerals, grain size, recovery etc.). Therefore, two synthetic sampling campaigns
were produced to illustrate the flexibility of the synthetic drilling in terms of drill hole spacing and
assayed parameters. In both campaigns, drill cores are dipping vertically and have regular pattern of
collars locations. The first (Figure 14A) comprised a 25 drill holes pattern, where thicker composites
represent higher iron grade. The second pattern (Figure 14B) comprised of 81 drill holes, with
thicker composites representing higher magnetite grade and a colourbar showing the actinolite grade.
The composite length for both campaigns was chosen as 1/3 of the voxel size (25/3 = 8.33 m). Higher
iron/magnetite grades identify the extent of the ore body thus showing efficiency of the sampling
campaign in outlining the deposit. The sampling database contains the same information as deposit
database (Figure 1): Mineralogical, mining, process and economic information about each part of the
drill core. All those parameters can be easily included and visualised by the sampling campaign.

![Simulated drill core samples.](image)

**Figure 14.** Simulated drill core samples. **A** (left)—25 (5 × 5) drill cores with thicker composites
representing higher iron grade. **B** (right)—81 (9 × 9) drill cores of the synthetic ore body with thicker
composites representing higher magnetite grade and colourbar showing actinolite grade in %.

4. Implications and Limitations

The paper presents a synthetic ore body modelling algorithm which allows for data integration
and potentially may be developed for supporting decision making in planning, sampling, testing, and
beneficiation model building. The approach is not a substitute for the existing geostatistical approaches
or process models but is a tool for testing the sensitivity of the project to constraints at different stages
of the mining value chain. The impact of the variability in an ore deposit can be traced through the
whole mining value chain, down to the concentrate and tailings quality. Potentially, the impact can be
traced to the smelter and environmental parameters may also be considered.

The procedure presented here is aimed at geologists, geostatisticians, mining engineers, process
engineers, mine planners and economists. The main benefit for geologists is the possibility to develop
several hypotheses on ore classification and the drilling program. Selections of the grade estimation
method such as kriging, machine learning, multivariate statistics or domaining is easier with synthetic
data. Therefore, resource estimates made by geostatistics can be validated and supported. This may be done by designing several synthetic drilling scenarios with different drilling density and composite length, performing new grade estimates for each scenario, and comparing newly estimated grades with grades known from the synthetic ore body model. The mining engineers can test economic dependences of the project from mining methods and scheduling methods. Additionally, a guess can be made on possible ore losses and dilutions based on the block model resolution chosen for mine planning. Knowledge about rock properties can be used to model cracks and rock mechanical properties, which is important in blast design and rock support planning. The developed procedure is a step forward to improve blending strategies in mine planning and make an estimate of approximate grades and mineral associations to be sent to the process plant. The economic performance of the project may be estimated at different production stages, including pre-feasibility, feasibility studies, and production strategies. Finally, the sampling module may be a good proxy tool for drilling optimisation for the mining projects.

Uncertainty of the geological model (i.e., errors in sampling, measurements and geological modelling) was not addressed here. Applying simplified uncertainty or soft contacts (e.g., described by random error) may make the Figures 8 and 10 look more realistic; however, the model would lack physical realism. The elemental and mineral grades were constructed considering an apatite iron ore deposit type. Up-scaling of geometallurgical attributes was not considered since, the breakage model implemented in the simulation is specific to the ore types, and the magnetic separation process does not face an upscaling problem [81]. The mining method accounted only for the simplified open pit mining.

5. Conclusions

All data used in modelling come from the real-life case study of an iron ore. A complete chemical, mineralogical, mining, and processing information data set was generated with respect to the spatial constraints. Applying an algorithm for spatial constraints, including textural type allocation and mining production, makes this method more realistic compared to other studies, where only mineralogical and process parameters are considered for data integration. The uniqueness of this study is that the geological model is generated on a mineralogical level. Thus, modal composition and textural information are described quantitatively for the entire deposit. The resolution of the model is defined by the model designer and is reflected in the number of records in the deposit or sampling database. Thus, highly detailed models can be developed and studied with no additional costs.

The proposed approach allows for investigating various production strategies considering the impact of geological variability, mining constraints caused by mining method, and time constraints caused by mining plan on the process variability. Error properties, traced through the mining value chain simulated with this approach, can highlight the need for additional sampling and suggest techniques to be used in mineralogical characterisation. The approach can be used as a valuable tool in risk assessment at different stages of the mining projects or as a platform for testing different scenarios for the future geometallurgical program, or for educational purposes.

Future work should include creation of a deposit library covering VMS and porphyry deposits. More parts of the mining value chain can be included, i.e., geophysics, process metallurgy, environmental assessment, economic simulations. Adding a breakage model in blasting will improve production models.

**Author Contributions:** V.L. the model and computational framework and carried out the implementation. The author also took lead in writing the manuscript. C.L. provided case study data. E.M. assisted with mathematical interpretation of the data. P.L. supervised the project.

**Funding:** This research was part of the PREP (primary resource efficiency for enhanced prediction) research project supported by VINNOVA SIO STRIM project nr. 2014-01933.

**Acknowledgments:** The authors thank Bertil I Pålsson and Yousef Ghorbani for scientific guidance, writing assistance and technical editing that greatly improved the manuscript. Special acknowledgments are to Simon Michaux for his valuable ideas and comments that significantly assisted the research.
Conflicts of Interest: The authors declare no conflict of interest.

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EVALUATION AND COMPARISON OF DIFFERENT MACHINE-LEARNING METHODS TO INTEGRATE SPARSE PROCESS DATA INTO A SPATIAL MODEL IN GEOMETALLURGY

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ABSTRACT

A spatial model for process properties allows for improved production planning in mining by considering the process variability of the deposit. Hitherto, machine-learning modelling methods have been underutilised for spatial modelling in geometallurgy. The goal of this project is to find an efficient way to integrate process properties (iron recovery and mass pull of the Davis tube, iron recovery and mass pull of the wet low intensity magnetic separation, liberation of iron oxides, and $P_{90}$) for an iron ore case study into a spatial model using machine-learning methods. The modelling was done in two steps. First, the process properties were deployed into a geological database by building non-spatial process models. Second, the process properties estimated in the geological database were extracted together with only their coordinates (x, y, z) and iron grades and spatial process models were built. Modelling methods were evaluated and compared in terms of relative standard deviation (RSD). The lower RSD for decision tree methods suggests that those methods may be preferential when modelling non-linear process properties.

KEYWORDS

Data Integration, Spatial Model, WLIMS, Davis Tube, Iron Ore, Machine-learning, Geometallurgy.

1 INTRODUCTION

Geometallurgy is an interdisciplinary approach aimed at linking geological variability and variability in the beneficiation processes of the mining value chain by means of spatial and/or non-spatial predictive models (Lamberg 2011; Dunham and Vann, 2007; Lund and Lamberg, 2014; Vann et al., 2011; Lishchuk, 2016). Non-spatial models are used to predict process response based on the properties of the feed to the process. Spatial models predict process response based on the location of the sample in an ore deposit. The process of building such models is called a geometallurgical program (Lishchuk et al., 2015a, 2015b). The ultimate product of a geometallurgical program is geometallurgical spatial mapping (i.e., geometallurgical block model) (Figure 1), which integrates geological and process test data into a spatial process model (Dunham and Vann, 2007; Lund and Lamberg, 2014; Vann et al. 2011). Geometallurgical spatial mapping may be done by assigning process properties (e.g., recoveries, throughput, geometallurgical ore type, textural type) to drill core samples from a geological data base or minable blocks in a block model. A geological block model is a spatial numeric model which represents the variation of elemental grades and/or mineral grades in the ore body for production planning purposes (Darling, 2011). A typical block model is comprised of adjacent blocks which are described by the coordinates of their centroids and contain information on their geological and geotechnical properties, (i.e. chemical composition, modal mineralogy, lithological description, rock strength etc.). Process data (i.e., throughput, energy consumption, recoveries, product quality), on the other hand, are obtained from metallurgical test undertaken at any scale (laboratory, pilot, or plant).
Machine-learning is a part of computer science that focuses on studying mathematical models and algorithms to make predictions. Predictions are developed through the interpretation of data and patterns by connecting the data with the knowledge set and developing the learning algorithms (Oliver and Willingham, 2016; Suthaharan, 2016). Machine-learning methods have multiple advantages over other approaches (Table 1) particularly in geosciences, where it challenges geostatistical and Bayesian approaches (Daya et al., 2018). Machine-learning algorithms are widely used in applications such as predicting acid rock drainage chemistry (Betrie et al., 2014), resource model development (Oliver and Willingham, 2016), classification of drill core textures for process simulation (Tiu, 2017), and predictive modelling for spatial variables (Hengl et al., 2018). One of the main advantages of machine-learning methods is their capacity to deal with the additivity issue. Additivity is a mathematical property that allows the calculation of the mean of the variables by linear averaging (Carrasco et al., 2008; Coward et al., 2009). Some process parameters are not necessarily additive (Keeney, 2010), e.g., recoveries, throughput, and reagent consumption. Most common solutions for non-additive parameters are: expressing them as a function of additive properties, i.e., metal and mineral grades (Deutsch, 2013; Ehrig, 2013); applying alternate geostatistical methods using conditional simulation (Keeney et al., 2011; Deutsch et al., 2016); or decorrelation using Principal Component Analysis (Deutsch et al., 2016).

Building reasonable predictive model using machine-learning methods requires a trial and error approach using either supervised or unsupervised learning algorithms. Supervised learning assigns points to the classes based on class labels (pre-defined) classes. Unsupervised learning deals with segmenting feature space into classes without any previous training (Aggarwal, 2015; Suthaharan, 2016).

<table>
<thead>
<tr>
<th>Approaches</th>
<th>Spatial method</th>
<th>Additivity assumption</th>
<th>Number of samples</th>
<th>Missing values and zeros have impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Block calculation with regression model (multi-linear)</td>
<td>No</td>
<td>No</td>
<td>Low</td>
<td>Yes</td>
</tr>
<tr>
<td>Geostatistical (kriging)</td>
<td>Yes</td>
<td>Yes</td>
<td>High</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Table 1 Some classification methods for populating the block model with process properties.
The aim of this study is to develop a methodology for integrating process properties into a spatial model by using machine-learning methods and to compare performance of these machine-learning methods in terms of their precision. Precision here is expressed as relative standard deviation (RSD). The improvement of the machine-learning methods was not a part of the study, since machine-learning methods used here are well established. However, this study can be used as a guideline for selecting a suitable machine-learning tool for modelling process data. The study uses samples from the Leveäniemi iron ore mine in Sweden. Six process properties are tested integration into a spatial model using machine-learning methods: iron recovery, mass pull of Davis tube, wet low intensity magnetic separation, liberation of iron oxides, and \( P_{80} \). Modelling was done in two steps. First, the process properties were deployed into a geological database by building non-spatial process models. The data for the modelling were obtained by conducting process testwork and mineralogical characterisation of the samples. Second, process properties estimated in the geological database were extracted together with their coordinates \((x, y, z)\) and iron grades forming a new data set. Then the spatial process models were built using extracted coordinates \((x, y, z)\) and iron grades as input variables. Modelling methods were evaluated and compared in terms of RSD.

2 EXPERIMENTAL

2.1 Materials

The Leveäniemi iron ore mine (Figure 2) is the third largest apatite-iron ore deposit in Sweden. It is located 40 kilometres southeast of Kiruna in northern Sweden and was discovered in 1897 (Bremer, 2010). Leveäniemi is operated by LKAB with proven reserves of 93 Mt @ 47% iron and probable reserves 21 Mt @ 36% iron (LKAB, 2016). The main ore mineral is magnetite, with smaller amounts of hematite. The gangue minerals include apatite, biotite, calcite, quartz, chalcopyrite, pyrite, amphiboles (e.g., actinolite), micas (e.g., biotite), potassium feldspar, and plagioclase (e.g., albite) (Gustafsson, 2016; Lund, 2013; Martinsson et al., 2016).
The first data set is comprised of 13 ore samples. The selection of the samples is based on the geological variability of the ore body and controlled by the mine geologist. Each ore sample (feed) is subjected to metallurgical tests. As presented in Table 2, the metallurgical test work included wet low intensity magnetic separation (WLIMS), the Davis tube magnetic separation, and the geometallurgical comminution test (GCT). GCT was developed at Luleå University of Technology (LTU) for estimating the Bond ball mill work index for small batches of material/ore (Mwanga et al., 2015). The process properties selected for modelling are listed in Table 3. Each process property in Table 3 was modelled individually.

Table 2 Metallurgical test work.

<table>
<thead>
<tr>
<th>WLIMS</th>
<th>Davis Tube</th>
<th>Geometallurgical comminution test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aparatus</td>
<td>Feed</td>
<td>Concentrate</td>
</tr>
<tr>
<td></td>
<td>Flow control pole</td>
<td>Magnetic concentrate</td>
</tr>
<tr>
<td></td>
<td>Non-magnetic tail</td>
<td>Tailings</td>
</tr>
</tbody>
</table>

Figure 2 Leveäniemi location (modified from https://apps.sgu.se/kartvisare/kartvisare-malm-mineral.html#).
The test is conducted in a single step yielding to two products: concentrate and tailings. The material feed rate was 0.5 kg/min at water rate of 3 l/min and drum rotation of 60 rpm. The test is run for 130 sec, the apparatus was set for 0.3 l/min water flow, the tube angle is 45°, the current strength is 0.5 A, and the tube oscillations 45 min⁻¹. The GCT is done by using a small 1.4 l CAPCO® laboratory ball mill. More details are in Mwanga et al., (2015).

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<table>
<thead>
<tr>
<th>ID</th>
<th>Ore type</th>
<th>Fe, %</th>
<th>M&lt;sub&gt;WILMS&lt;/sub&gt;%,</th>
<th>R&lt;sub&gt;WILMS&lt;/sub&gt;%,</th>
<th>M&lt;sub&gt;DT&lt;/sub&gt;%,</th>
<th>R&lt;sub&gt;DT&lt;/sub&gt;%,</th>
<th>P&lt;sub&gt;80&lt;/sub&gt;, µm</th>
<th>L&lt;sub&gt;Fe-ox&lt;/sub&gt;%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Semi-massive</td>
<td>20-40</td>
<td>45.5</td>
<td>90.0</td>
<td>44.27</td>
<td>86.33</td>
<td>395</td>
<td>42.21</td>
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<td>2</td>
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<td>94.8</td>
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<td>3*</td>
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<td>69.4</td>
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<td>92.4</td>
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<td>90.00</td>
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<td>98.72</td>
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<td>82.47</td>
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<td>8</td>
<td>Massive</td>
<td>&gt;50</td>
<td>88.7</td>
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<tr>
<td>9</td>
<td>Semi-massive</td>
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<td>90.5</td>
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<td>98.90</td>
<td>419</td>
<td>81.41</td>
</tr>
<tr>
<td>11</td>
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<td>&gt;50</td>
<td>93.1</td>
<td>79.8</td>
<td>92.56</td>
<td>99.17</td>
<td>205</td>
<td>84.33</td>
</tr>
<tr>
<td>12</td>
<td>Rich semi-massive</td>
<td>40-50</td>
<td>74.2</td>
<td>93.8</td>
<td>66.83</td>
<td>97.29</td>
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<td>71.39</td>
</tr>
<tr>
<td>13</td>
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<td>&lt;20</td>
<td>29.1</td>
<td>95.3</td>
<td>29.18</td>
<td>87.54</td>
<td>194</td>
<td>52.35</td>
</tr>
</tbody>
</table>

M<sub>WILMS</sub> - mass pull in WLIMS; R<sub>WILMS</sub> - iron recovery both in WLIMS; M<sub>DT</sub> - mass pull DT test; R<sub>DT</sub> - iron recovery in DT; P<sub>80</sub> - 80<sup>th</sup> percentile of the particle size distribution after 11 min grinding in a CAPCO mill; L<sub>Fe-ox</sub> - degree of liberation of iron oxides after grinding (magnetite and hematite).

* Not used in modelling because dominated by hematite

Products of the tests and feed were subjected to mineral characterisation. The mineral characterisation included chemical assays (Table 4) for 13 elements (P, TiO₂, V, SiO₂, Fe, Al, CaO, MgO, Mn, Na, K₂O, Cu, S), modal mineralogy, liberation distribution of iron oxides, measurements of magnetic iron in feed samples, and density measurements. Chemical assays and density measurements were prepared and analysed by ALS-Geochemistry (Piteå, Sweden) and the LKAB’s R&D Laboratory (Malmberget, Sweden). Modal mineralogy and liberation analyses were performed on a QEMSCAN system. The amount of magnetic iron was measured with an electromagnetic method using a Saturation Magnetization Analyser (Satmagan) (Stradling, 1991; Wiegel, 1975). Modal mineralogy, liberation and amount of magnetic iron were analysed at LKAB’s R&D Laboratory (Malmberget, Sweden).

<table>
<thead>
<tr>
<th>ID</th>
<th>Ore type</th>
<th>Fe, %</th>
<th>T&lt;sub&gt;i&lt;/sub&gt;, %</th>
<th>TiO₂, %</th>
<th>V, %</th>
<th>SiO₂, %</th>
<th>Fe, %</th>
<th>Al, %</th>
<th>CaO, %</th>
<th>MgO, %</th>
<th>Mn, %</th>
<th>Na, %</th>
<th>K₂O, ppm</th>
<th>Cu, ppm</th>
<th>S, %</th>
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<tr>
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<td></td>
<td>Massive</td>
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<td>93.1</td>
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<td>Rich semi-massive</td>
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<td>52.35</td>
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</tbody>
</table>
The second dataset is comprised of spatial geological data, which is available as a production geological database and includes information from 82 drill cores divided into 5550 samples (positions in the database). Each sample in the database has a unique ID number and can be spatially identified with its orthogonal coordinates (x, y, z). Drill core samples, listed in the geological database, are assayed for 24 elements (Al, As, Ba, CaO, Cl, Co, Cr₂O₃, Cu, Fe, K₂O, MgO, Mn, Na, Ni, P, Pb, S, SiO₂, Sn, Sr, TiO₂, V, Zn, Zr) and density. Since the ore samples were assayed only for 13 elements (out of 24 elements in the geological database), these 13 were used in the modelling (Table 4).

### 2.2 Methods

The spatial model of the process properties is built by the methodology illustrated in Figure 3. First, the ore samples are characterised mineralogically (liberation analysis in Table 3) and chemically (Xₚₛ, in Table 4), and then are subjected to the mineral processing testwork (Table 3). Second, the process (Yₛₚ) and chemical (Xₛₚ) properties of the ore samples (the first dataset) are used to build non-spatial process models. Third, the geological database is populated with process properties estimated from the non-spatial process models (Yₛₚ) and using chemical assays from the geological database (second dataset) as input variables. The geological database with estimated process properties is referred to as the updated geological database. Fourth, the process properties, iron grades, and coordinates of each drill core sample contained in the updated geological database are extracted and form a third dataset (Xₕₒ). The third data set is used to build spatial process models (Yₒₕ). Those models can be used for populating production block model (geometallurgical block model) or drillholes not assayed for the chemical elements other than iron grade.

![Figure 3 Development of a spatial model for the process properties.](image)

To the best of our knowledge, machine-learning has not been widely applied to the spatial
modelling of process properties. The most common techniques to model process properties spatially till now have been regression models (Macmillan et al., 2011), multivariate statistics, such as principal component analysis and partial least square methods (Keeney et al., 2011; Keeney and Walters, 2011; Newton and Graham, 2011), and geostatistical methods such as kriging (Preece, 2006). The advantage of using machine-learning methods is fast processing and the capability to manage multi-dimensionality, while the main drawback is a need for large training data sets for the prediction.

The inputs and outputs of models and how the process properties measured in ore samples are integrated into geological database and to the spatial model are shown in Figure 4. The process properties ($R_{Fe}^{WLIMS}, R_{Fe}^{DT}, M_{Fe}^{WLIMS}, M_{Fe}^{DT}, P_{80}, L_{Fe-ox}$) of the ore samples are not linked to a special location and exist in one dimensional space of point samples (1D). Ore samples have small volume (mass of each ore sample is approximately 60 kg, and even smaller volumes are used in testwork, see Table 2). The small volume means that samples have a small support size in spatial planning. Support is an average volume over which the data are measured or defined (Chilès and Delfiner, 2012). When process properties ($Y_{PS}$) are modelled as functions of the chemical composition of the feed ($X_{PS}$), cf. Table 4, and are deployed into the updated geological database, the process properties can be referred to as existing in two-dimensional space (2D). Support of those samples may increase compared to the ore samples if their composite length is high enough. If coordinates of the drill core collars are known, then the process properties can be referred to as existing in three-dimensional space (3D). When the process properties deployed into the updated geological database are modelled ($Y_{DHD}$) as function of samples’ coordinates and iron grade only, then the process properties can be referred to as existing in three-dimensional space (3D). Since blocks in the block model always have a larger volume than composites from the geological database, the support of the blocks will increase. The spatial model can be used for populating spatial objects (geological database or block model) with process parameters assuming spatial correlation of the process properties. Special attention should be paid to the change of support, which can be source of additional errors.
Figure 4 Modelling process properties.

All the modelling is done with the WEKA software package (Frank et al., 2016) using default settings for the models parameters. Both population and extraction processes are done by using machine-learning methods listed in Table 5. The methods included eight individual models for building both non-spatial and spatial process models. Amalgamating the various outputs into a single prediction may increase accuracy (Witten et al., 2017). Therefore, two additional models were used in spatial process modelling - meta-models built as an aggregation by computing average and median of the eight individual models. Only raw data are used as model input variables; thus, no data transformation is applied.

Table 5 Machine-learning modelling methods from WEKA.

<table>
<thead>
<tr>
<th>ID</th>
<th>Models / Abbreviation</th>
<th>Description</th>
<th>Classifier type</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Elastic Net / EN</td>
<td>EN is a regression model with the elastic net penalty determined as a combined penalty of lasso and ridge methods.</td>
<td>Function*</td>
<td>(Zou and Hastie, 2005)</td>
</tr>
<tr>
<td>2</td>
<td>Linear regression / LR</td>
<td>LR is expressed as linear combination of attributes with predominant weights.</td>
<td>Function*</td>
<td>(Frank et al., 2016; Witten et al., 2017)</td>
</tr>
<tr>
<td>3</td>
<td>Sequential minimal optimization for support vector regression / SMO</td>
<td>SMO uses linear models to implement nonlinear class boundaries. Essentially, SMO is an iterative algorithm for solving the regression problem using support vector machine (SVM).</td>
<td>Function*</td>
<td>(Shevade et al., 1999; Smola and Schölkopf, 2004; Witten, 2017)</td>
</tr>
<tr>
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<td>---</td>
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</tr>
<tr>
<td>4</td>
<td>Instance-bases learning with parameter k / IBk</td>
<td>IBk assumes that similar instances will have similar classifications. The method is sensitive to the number of irrelevant attributes.</td>
<td>Lazy*</td>
<td>(Aha et al., 1991)</td>
</tr>
<tr>
<td>5</td>
<td>K* instance-based classifier / K*</td>
<td>K* is an instance-based classifier uses entropy as a distance measure.</td>
<td>Lazy*</td>
<td>(Cleary and Trigg, 1995)</td>
</tr>
<tr>
<td>6</td>
<td>M5Rules / M5</td>
<td>M5 builds model trees repeatedly, and the best rule is selected at each iteration.</td>
<td>Rules*</td>
<td>(Holmes et al., 1999; Quinlan, 1992; Wang and Witten, 1997; Frank et al., 2016)</td>
</tr>
<tr>
<td>7</td>
<td>Random forest / RF</td>
<td>RF is a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. The generalization error for forests converges to a limit so the number of trees in the forest becomes large. The drawback is lack of interpretability.</td>
<td>Trees*</td>
<td>(Breiman, 2001)</td>
</tr>
<tr>
<td>8</td>
<td>M5P / M5</td>
<td>M5P uses a decision-tree induction algorithm to build a tree. Method does not maximising the information gain at each interior node. It uses splitting criterion that minimizes the intra-subset variation in the class values down each branch. Consideration is given to pruning the tree back from each leaf.</td>
<td>Trees*</td>
<td>(Quinlan, 1992; Wang and Witten, 1997)</td>
</tr>
<tr>
<td>9</td>
<td>AVE</td>
<td>AVE is an arithmetic average from EN, LR, SMO, IBk, K*, M5, RF and M5P</td>
<td>Meta</td>
<td>-</td>
</tr>
<tr>
<td>10</td>
<td>MED</td>
<td>MED is a median estimated from EN, LR, SMO, IBk, K*, M5, RF and M5P</td>
<td>Meta</td>
<td>-</td>
</tr>
</tbody>
</table>

* Classification for lazy, trees, functions and rules is adopted by Frank et al., (2016): Lazy are instance-based classifiers; Trees are based on decision trees; Function can be written down as mathematical equations in a reasonably natural way; Rules are similar to trees although are more unsupervised (more on the differences between rules and trees in Ordonez and Zhao, (2011)).

2.2.1 Non-spatial process modelling

Eight modelling methods (see Table 5) are used for modelling six process properties ($Y_{PS}$) (Figure 4) measured from the ore samples ($\{R_{Fe}^{W/LIMS}, R_{Fe}^{DT}, M_{Fe}^{W/LIMS}, M_{Fe}^{DT}, P_{80}, L_{Fe=ox}\}$, see Table 3). The elemental grades of the ore samples are used as primary input variables $X_{PS}$ (Table 4).

The modelling results are assessed using k-fold cross-validation with 10 folds. In k-fold validation, the original dataset is randomly divided into k subsets of equal size. One out of ten k subsets are retained for testing the model. The remaining k−1 subsets are used for model training. The cross-validation process is repeated k times and each subset is used only once for validation.

2.2.2 Populating geological database

Derived models are compared in terms of RSD (eq. 1) and the most suitable model is used for populating the geological database with the process properties ($Y_{PS}$). The selected method is also improved by applying selection of the significant variables, which is also known as feature selection or variable selection. The number of variables higher than optimal (subset of
the variables at which accuracy of the classifier is maximal) may decrease the accuracy in
machine-learning methods. The optimal number of variables can be reached by applying the
significant variable (variables with low signal-to-noise ratio) selection (Kohavi et al., 1997).
The updated geological database allows for spatial modelling of process properties, since
each sample in the geological database contains corresponding coordinates of the samples
location in 3D physical space (x, y, z).

\[ RSD = \frac{\sigma}{\mu} \cdot 100\% \]  \hspace{1cm} \text{eq. 1}

where, \( \sigma \) is standard deviation, and \( \mu \) is mean of population.

2.2.3 Spatial process modelling

The modelling methods (see Table 5) are also used to extract process properties and build
spatial process models \( Y_{DHD} \) using coordinates (x, y, z) and iron grades from the positions in
geological database as primary input variables \( X_{DHD} \). The grade of iron was used in building
the spatial process models, since it is the only element estimated in the block model and it has
been verified by a competent person. The obtained models \( Y_{DHD} \) for the process properties are
used to do geometallurgical mapping – populating geological block model, or geological
database for newly added drillholes with process properties. Introducing additionally AVE
and MED models may yield more robust estimate of the process properties by mitigating the
impact of extreme values (potential outliers) in prediction.

The spatial process modelling results are assessed with verification by splitting the updated
geological database into training and testing subsets. The testing subset is formed by selecting
positions in the geological database, which correspond to a single drillhole. All other
positions in the geological database, excluding the one selected for testing subset, form
training subset. The spatial process modelling is performed on the training subset and then
process properties are predicted for the testing subset (\( \bar{Y}_{DHD} \)). The newly predicted process
properties (\( \bar{Y}_{DHD} \)) are compared to the ones already available at the geological database
(\( Y_{DHD} \)). The procedure is repeated three times, by selecting different drillholes to be excluded
from the updated geological database for each verification round. The drillholes chosen for
verification 13008, 14031, and 14057b represent different parts of the ore body, and were
selected based on the number and average length of the composites, and average iron grade
(Table 6).

<table>
<thead>
<tr>
<th>Parameters</th>
<th>13008</th>
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<th>14057b</th>
<th>Geological database</th>
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<tr>
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<td>6.2</td>
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<td>min, m</td>
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<td>1.4</td>
<td>0.9</td>
<td>0.1</td>
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<td>average, m</td>
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<td>2.7</td>
<td>2.6</td>
<td>2.7</td>
</tr>
<tr>
<td>median, m</td>
<td>2.6</td>
<td>3.0</td>
<td>2.7</td>
<td>2.7</td>
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</tbody>
</table>
The precision is measured with RSD (Irvin, 1970). The machine-learning methods are considered to be good enough if the upper bound limit of RSD is below \(25\%\) (David, 2013). RSD values below 5\% suggests that the machine-learning method is excellent (Grubbs, 1969) for spatial modelling of the assessed process property.

### 3 RESULTS AND DISCUSSIONS

#### 3.1 Process modelling

Eight methods were used to build process models \((Y_{ps})\) for populating geological database with process properties. At this stage, there was no improvement of the model by selecting significant variables. The methods which showed the lowest errors for particular process properties are highlighted (* - <15\%, ** - <10\%) in Table 7.

<table>
<thead>
<tr>
<th>ID</th>
<th>Modelling methods</th>
<th>(M_{Fe}^{WLIMS}, %)</th>
<th>(R_{Fe}^{WLIMS}, %)</th>
<th>(M_{Fe}^{DT}, %)</th>
<th>(R_{Fe}^{DT}, %)</th>
<th>(P_{80}, \mu m)</th>
<th>(L_{Fe-ox}, %)</th>
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<tbody>
<tr>
<td>1</td>
<td>EN</td>
<td>13.2%*</td>
<td>4.1%**</td>
<td>3.3%**</td>
<td>2.1%**</td>
<td>106.1%</td>
<td>12.1%*</td>
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<tr>
<td>2</td>
<td>LR</td>
<td>26.0%</td>
<td>4.9%**</td>
<td>17.2%</td>
<td>5.2%**</td>
<td>123.5%</td>
<td>20.5%</td>
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<td>3</td>
<td>SMO</td>
<td>17.9%</td>
<td>4.9%**</td>
<td>3.8%**</td>
<td>2.6%**</td>
<td>94.4%</td>
<td>6.4%**</td>
</tr>
<tr>
<td>4</td>
<td>IBk</td>
<td>24.2%</td>
<td>3.8%**</td>
<td>13.8%*</td>
<td>3.3%**</td>
<td>120.5%</td>
<td>7.2%**</td>
</tr>
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<td>5</td>
<td>K*</td>
<td>18.2%</td>
<td>3.3%**</td>
<td>15.3%</td>
<td>3.9%**</td>
<td>128.0%</td>
<td>10.4%*</td>
</tr>
<tr>
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<td>M5</td>
<td>12.2%**</td>
<td>6.7%**</td>
<td>5.5%**</td>
<td>3.3%**</td>
<td>108.0%</td>
<td>10.4%*</td>
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<td>7</td>
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<td>17.9%</td>
<td>4.3%**</td>
<td>10.0%*</td>
<td>2.6%**</td>
<td>92.7%</td>
<td>8.3%**</td>
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<td>8</td>
<td>MSP</td>
<td>12.2%*</td>
<td>6.3%**</td>
<td>5.5%**</td>
<td>3.3%**</td>
<td>97.2%</td>
<td>10.5%*</td>
</tr>
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</table>

The RSD provided an advantage when comparing the obtained results for the modelled process properties with one another. The predictions for iron recoveries are better than mass pulls in WLIMS and DT for all eight methods. Good predictions were obtained for the iron oxides liberation, where all the methods except for Linear have shown RSD below or very close to 10\%. No single method gave reasonably good prediction for the \(P_{80}\). The possible reasons for such bad prediction could be statistically insignificant number of samples used in modelling and low average \(P_{80}\) compared to the maximum \(P_{80}\) values occurring in the deposit.

#### 3.2 Updated geological database

Overall, the results suggest that the EN, M5, M5P, and SMO have the lowest average RSD. None of the methods had a better RSD for predicting all the process properties. SMO was
randomly selected for populating the geological database with the process properties.

The SMO method was improved before applying it for populating the geological database (reduced SMO). The reduced SMO model was obtained by selecting significant variables prior to modelling, therefore “reduced SMO = variable selection + SMO”. The significant variables selection was done by applying wrapper approach to feature subset selection (WAFSS) (Kohavi et al., 1997), which is a supervised type of filter for variable selection. WAFSS selects significant variables by dividing variables into subsets, evaluating each subset based on cross-validation, and selecting the variables which yield into the most accurate model.

3.3 Spatial process model and verification

Eight machine-learning modelling methods and two additional meta-methods listed in Table 5 were compared for building spatial process models ($Y_{DHD}$). The process properties extracted from the geological database ($Y_{DHD}$) were modelled as a function of the coordinates and iron grade only ($X_{DHD} = \{x, y, z, \%Fe\}$). Then, the verification was performed by splitting data into three pairs of training and testing subsets and predicting process properties for the testing data set. Results of the verification are shown in Figure 5. Each plot represents modelling for the separate process property. Vertical axis shows RSD expressed in %. Horizontal axis lists modelling machine-learning methods. The data points on each plot represent RSD for each machine-learning method for each testing subset: 13008, 14031, and 14057b. The drillholes chosen for verification from the updated geological database represent randomly selected drillholes from the opposite edges of the deposit and from the central part of the Leveââniemi deposit.
Excellent results in terms of RSD (<5%) was achieved for modelling iron recovery in WLIMS and DT, and mass pull in DT (except for IBk for test dataset 13008) and the iron oxides liberation (<10% RSD), while higher than the other tests, still falls into the good range for RSD values (except for IBk for test dataset 13008). Deviations in prediction for the drillhole 13008 may be due to overrepresented number of composites with low iron grade (median and average iron grades are significantly lower than average in the deposit), (Table 6). This suggests that any of the tested machine-learning methods can be used for spatial modelling of iron recovery in WLIMS and DT and iron oxides liberation. The results for
modelling mass pull in WLIMS were poorer with RSD >10% for all eight machine-learning methods. However, the results still can be used as trend indicators since all the machine-learning methods (except for IBk for test dataset 14031) have RSD <25%. Drillhole 14031 has a slightly larger average composite size (larger support) than the average composite sample in the geological database, which may be a source of the poorer performance of the machine-learning methods for predicting WLIMS mass pull. A possible reason for the better prediction for mass pull in DT is a relation between iron grade in the feed and mass pull that is closely linear. Modelling of $P_{80}$ has not yielded a good model and cannot be further used. A possible explanation for that could be lack of spatial correlation for $P_{80}$.

The methodology for integrating process data into a spatial model enables geometallurgical spatial mapping, which is the ultimate product of a geometallurgical program. The results and discussions presented in this paper indicate that machine-learning methods are good for building spatial geometallurgical models for mass pulls, recoveries and iron oxides liberation (Table 8). More investigation is needed for spatial modelling of comminution properties of the ore, e.g., $P_{80}$, energy consumption, Bond work Index etc. The lower RSD for the decision tree methods suggests that those methods may be the most suitable for modelling non-additive variables (recoveries), while functions are more suitable for modelling additive variables (feed rate). AVE and MED may be a good choice for modelling when the additivity properties of the modelled process parameters are not known. IBk performed the worst on the given data set. The nearest neighbour group of methods (such as IBk) is considered to be a good method for geological data, since nearest neighbour is often implemented as a part of geological modelling software as one of the methods for populating a geological block model. However, its drawback is that method is sensitive to the selected number of the nearest neighbours (k value) and distance definition (Euclidian, Manhattan, Chebyshev, Minkowski).

Table 8 Advantages and disadvantages of proposed methods (* - the worst, ** - the average, ***- the best, A – acceptable for being used in spatial modelling, N – non-acceptable for being used in spatial modelling) based on RSD values.

<table>
<thead>
<tr>
<th>Process parameter</th>
<th>Functions</th>
<th>Trees</th>
<th>Lazy</th>
<th>AVE/MED</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_{Fe-ox}$ – liberation of iron oxides</td>
<td>***(A)</td>
<td>***(A)</td>
<td>*(A)</td>
<td>***(A)</td>
</tr>
<tr>
<td>$M^{DT}_{Fe}$ – mass pull in Davis tube</td>
<td>***(A)</td>
<td>***(A)</td>
<td>*(A)</td>
<td>***(A)</td>
</tr>
<tr>
<td>$M^{WLIMS}_{Fe}$ – mass pull in WLIMS</td>
<td>***(A)</td>
<td>***(A)</td>
<td>*(A)</td>
<td>***(A)</td>
</tr>
<tr>
<td>$P_{80}$ - Size passing fraction = 80%</td>
<td>**(N)</td>
<td>**(N)</td>
<td>*(N)</td>
<td>**(N)</td>
</tr>
<tr>
<td>$R^{DT}_{Fe}$ – recovery in Davis tube</td>
<td>*(A)</td>
<td>***(A)</td>
<td>*(A)</td>
<td>***(A)</td>
</tr>
<tr>
<td>$R^{WLIMS}_{Fe}$ – recovery in WLIMS</td>
<td>*(A)</td>
<td>***(A)</td>
<td>*(A)</td>
<td>***(A)</td>
</tr>
</tbody>
</table>

Several limitations have to be highlighted when it comes to the application of the spatial process models to the population of the geometallurgical block model. When process properties are estimated in a block model, the machine-learning methods may be subjected to
a higher uncertainty than if estimation of the process properties is done for the drill cores of
the geological database. This is because the iron grades deployed in the block model are
estimated from the geostatistical models (smoothed), while iron grades in geological database
are measured. Difference in support may be another reason for difference between spatial
process models used for block models and the geological database. Increase of support (e.g.,
increase of a composite size, increase of a block size in a block model) causes lower variance
and induces a spatial smoothing effect (Chilès and Delfiner, 2012; Mery et al., 2017). So,
even though the average values of the process properties of drill core samples and mining
blocks will be similar, the variability will be smaller for larger supports (Dunham and Vann,
2007). This is due to the fact that the iron grades in geological database represent small
volumes of ore contained in 1-5 m long drillhole samples, the iron grades in a block model
represent volumes contained in blocks somewhere between 5x5x5 and 25x25x25 m.

4 CONCLUSIONS

The main goal of this paper was to find an efficient way of building spatial models for
metallurgical response using machine-learning tools by comparing ten machine-learning
methods (eight individual and two meta methods). Using freeware, such as WEKA, allowed
the production of fast and accurate models based on machine-learning methods for predicting
process properties for different zones in an ore body. The process properties were measured
for the composite samples collected at Leveäniemi iron ore mine in Sweden and included iron
recovery and mass pull of DT and WLIMS, liberation of iron oxides and $P_{80}$.

When building process models for populating the geological database, only iron recoveries
for DT and WLIMS were predicted with RSD below 10%, iron oxides liberation, and mass
pulls in DT and WLIMS had RSD below 20% (with slightly higher RSD for LR in iron
oxides liberation and WLIMS mass pull and IBk in WLIMS mass pull). These results need to
be interpreted with caution since a low number of samples implies that one significant outlier
may have overwhelming impact on the model’s error estimation. When building process
spatial models most of the process properties, except for mass pull in WLIMS and $P_{80}$, for
most of the machine-learning methods (except for IBk in iron oxides liberation) were
predicted with RSD smaller than 10%.

Spatial process models were developed as part of a geometallurgical program and can be used
for geometallurgical mapping. The results contribute to understanding of how to build
gemmetallurgical block models based on a limited number of not coordinated ore samples,
which are not additive in nature. The included process properties become spatial once they
are deployed into a geological database and allow further spatial modelling and deployment
into newly added drillholes to the geological database or in a geometallurgical block model.
Tree methods tend to perform better than function methods in predicting non-additive
variables (recoveries). Any uncertainties of the spatial model can be reduced if multiple
estimates of the process properties obtained with different methods are aggregated (e.g., with
AVE and MED methods) for each block, instead of trying to select the best modelling
method. Literature reports that geostatistical methods may give biased estimates of the non-
additive process properties. It remains for future studies to compare the difference between
machine-learning and geostatistical methods in geometallurgical spatial modelling. Since the number of ore samples is small, the resulting models would be mostly suitable for visualising trends and understanding spatial properties of the modelled process properties. Future studies may help to define the minimum sufficient number of samples needed for deploying process properties in a production block model and to further apply those data in mine production planning.

The machine-learning methods, especially trees, can benefit the non-spatial and spatial process modelling in geometallurgy. The usage of sparse data did not affect the results dramatically.

ACKNOWLEDGMENTS

We would like to express our gratitude for support and permission to publish to LKAB, particularly Mattias Gustafsson, Kari Niiranen, Therese Lindberg and Lewis Wild. Special acknowledgments are given to Pertti Lamberg and Bertil I Pålsson for their valuable ideas and proofreading. This research is a part of the PREP project and financed by VINNOVA project nr. 2014-01933, which is highly acknowledged.

NOMENCLATURE

- $L_{Fe-ox}$ – liberation
- of iron oxides
- $M_{Fe}$ – mass pull in Davis tube
- $M_{WLIMS}$ – mass pull in WLIMS
- $P_{80}$ – Size passing fraction = 80%
- $R_{Fe}$ – recovery in Davis tube
- $R_{WLIMS}$ – recovery in WLIMS
- $X_{DHD}$ – input variables to the spatial process model
- $X_{PS}$ – input variables to the non-spatial process model
- $Y_{DHD}$ – process model (spatial)
- $Y_{DHD}$ – process model (spatial) predicted for the testing subset
- $Y_{PS}$ – process model (non-spatial)
- AVE: Classifier is an arithmetic average from EN, LR, SMO, IBk, K*, M5, RF and M5P
- DT – Davis tube
- EN – Elastic Net
- GCT – geometallurgical comminution test
- IBk – Instance-bases learning with parameter k
- K* - K* instance-based classifier
- LKAB – Luossavaara-Kirunavaara AB
- LR - Linear regression
- LTU – Luleå University of Technology
- M5 – M5Rules
- M5P – lacks explanation in literature
- MED - Classifier is a median estimated from EN, LR, SMO, IBk, K*, M5, RF and M5P.
- PREP – primary resource efficiency for enhanced prediction
- QEMSCAN - Quantitative Evaluation of Minerals by Scanning electron microscopy
- RF - Random forest
- RSD – relative standard deviation
- Satmagan – Saturation Magnetization Analyser
- SMO - Sequential minimal optimization for support vector regression
- WEKA - Waikato Environment for Knowledge Analysis developed at the University of Waikato, New Zealand.
- WLIMS – wet low intensity magnetic separation
- $\mu$ is mean of population
5 REFERENCES


