Real-time Performance Evaluation of LTE for IIoT

Roman Zhohov*, Dimitar Minovski*[†], Per Johansson[†], Karl Andersson*

* Luleå University of Technology

[†] InfoVista Sweden AB

Skellefteå, Sweden

Email: *name.surname@ltu.se, [†]name.surname@infovista.com

Abstract—Industrial Internet of Things (IIoT) is claimed to be a global booster technology for economic development. IIoT brings bulky use-cases with a simple goal of enabling automation, autonomation or just plain digitalization of industrial processes. The abundance of interconnected IoT and CPS generate additional burden on the telecommunication networks, imposing number of challenges to satisfy the key performance requirements. In particular, the QoS metrics related to real-time data exchange for critical machine-to-machine type communication. This paper analyzes a real-world example of IIoT from a QoS perspective, such as remotely operated underground mining vehicle. As part of the performance evaluation, a software tool is developed for estimating the absolute, one-way delay in end-to-end transmissions. The measured metric is passed to a machine learning model for one-way delay prediction based on LTE RAN measurements using a commercially available cutting-edge software tool. The achieved results prove the possibility to predict the delay figures using machine learning model with a coefficient of determination up to 90%.

Keywords—IIoT, LTE, QoS, delay, jitter, real-time, critical IoT

I. INTRODUCTION

The fourth industrial revolution is predicted a priori and manifested as Industry 4.0. Smart Factories, Industrial Internet of Things (IIoT) and Cyber-Physical Systems (CPS) are main enabling components of Industry 4.0 which augment the industrial application scenarios and automation [1]. According to the predictions, implementation of IIoT will have a tremendous effect on the global economy [2]. PwCs 2016 Global Industry 4.0 survey respondents expect to see \$421 billion in cost reductions and \$493 billion in increased annual revenues p.a. [2].

The IIoT highly rely on the existing network infrastructure which enables the creation of private-networks transforming the entire manufacturing process into a smart environment [1]. Initially, conventional telecom networks could not cope with industry-specific requirements for reliable, predictable and efficient communication [3]. Industrial networks were mainly based on diverse deterministic bus technologies to satisfy strict requirements of hard real-time automation systems. IIoT technology offers a vast number of use-cases in the domain of healthcare, logistics, industrial production, supervisory control, robotics, etc. [4–6]. Several of such industrial services are engaging closely to the human lifestyle and privacy, to the extent that a life-threatening situation might occur if the delivered quality is not on the desired level. Thus, there is a growing necessity in providing and assuring a real-time exchange of information to guarantee safe operations.

On the other hand, recent advances in communication technologies, especially wireless solutions, and interconnection of numerous embedded systems, creating CPS, result in a convergence of the physical and virtual worlds [1]. It is evident that mobile communications will be a key enabler for IIoT, as a certain degree of QoS may be assured [7]. The study done by Ericsson forecasts around 29 billion connected devices by 2022, of which close to 18 billion will be related to IoT [8]. As the conventional LTE cannot cope with this forecast, one of the requirements for the upcoming 5G standard is supporting massive IoT devices [9]. Besides, 5G technology also addresses critical Machine Type Communication (MTC), which is defined as critical IoT [10]. However, in the context of this paper the definition of critical MTC is not limited to the life-threatening situation, but also includes the risks of interrupting industrial operation, causing significant losses for the business. The typical examples of critical IIoT include tele-remote vehicles, remote surgery, robotics, industrial automation, and control [10]. Such IIoT services pose strict quality requirements on the QoS parameters, such as delay, jitter and packet losses. Those QoS requirements are often addressed in the literature as ultra-reliable low-latency communications (URLLC) [7]. Nokia predicts that reliability and latency requirements will play a vital role in critical IoT communication [11]. For example, autonomous vehicles might require end-to-end latency to be less than 10 ms with block error rate (BLER) down to 10^{-6} [12]. As a result, evaluation and prediction of end-to-end latency of the underlying mobile network is a challenging task that becomes essential for both network provider and industrial stakeholder.

This paper offers a real-world case study of mission-critical IIoT that explores the potential of mine digitalization. For this purpose, a software tool was developed to continuously stream a typical sensor data over the LTE network. The absolute, one-way delay is captured per transmission and further coupled and analyzed with LTE RAN measurements. The idea is to explore the possibility of predicting the end-to-end latency that might occur in real-time transmission. The prediction, as a regression problem, is based on a machine learning model, which builds a knowledge base from the real-time radio measurements.

The rest of the paper is organized in the following order: Section II presents an industrial case-study, identifies types of traffic and the overall systems architecture; Section III reviews related work and discusses the importance of real-time sensor stream; Section IV proposes a tool for evaluation and

Fig. 1: Systems architecture

prediction real-time performance of LTE; Section V discusses results and application of the tool; Section VI concludes the paper.

II. CASE STUDY

A. Tele-remote mining vehicles

The underground mine is a hazardous environment with a risk of being injured. Moreover, work under these conditions can cause immediate (acute) or long-term (latency) health effects [13]. The motivation of this work is to examine the implementation of tele-remote operation of mining vehicles that will reduce the need for a human operator in the harsh environment of the underground mine.

From the industrial point of view, by introducing the IIoT mining industry may benefit from real-time monitoring, analytics, and control. Mining operations have a set of well-defined metrics such as uptime, productivity, fuel efficiency, etc. For instance, productivity is one important key performance indicator (KPI), defined as an amount of loaded material per hour. Real-time monitoring and data analytics can bring new insights into the best operation strategy based on productivity or fuel efficiency measurements [14].

B. Service components and types of traffic

Industrial use-case of remotely controlled vehicles offers a variety of traffic types and patterns including critical real-time data. Moreover, tele-remote operation and control have attracted significant attention of researchers in recent years [15–17]. The architecture of the system is shown in the Figure 1 and composes remote control station, remotely operated mining vehicle, and communication network. A typical control station for remotely operating vehicles includes:

- Displays showing the surrounding environment, typically including video streams from multiple cameras providing a certain field of view (FOV);
- Speakers providing audio feedback for better context awareness;
- Sensor view displaying metrics regarding vehicle operation and the conditions in the mine;
- Control devices, such as joysticks, wheels, pedals, etc., generating a control stream.
- Health status of the vehicle and the output of monitoring systems;
- Map that shows the machines position to provide situation awareness and facilitate navigation [16];

As a result, the utilized traffic in the system includes:

- Video stream from multiple cameras in uplink (UL);
- Audio stream from multiple microphones in UL;
- Sensor stream in UL from the monitoring systems, motor's controller, and various other externally deployed sensors capturing vehicle's operation and its health status;
- Control stream from the remote control station back to the vehicle in downlink (DL);

The scope of this study is limited to investigating how LTE RAN and radio metrics impact the QoS. The idea is first to examine how the experienced radio and LTE conditions at the end-user, in this case mining vehicles, affect the UL delay. Therefore, an emphasis is given on examining the sensor stream. The findings from this study might give insights in dealing with the complexity of measuring audio and video quality based on jitter, delays and packet losses. Thus, exploring the audio and video streams are left for future work.

III. REAL-TIME SENSOR STREAM

Sensor stream can be further split into two types: critical and non-critical stream. This is an important distinction in the requirements on reliability and end-to-end latency. The purpose of non-critical sensor stream is to periodically send information regarding machine's operation and surroundings. Typically, this data stream does not carry critical information for the machine operation or safety. Whilst, critical real-time sensor stream is sensitive to delays and packet losses since it might negatively affect the business and safety. In ideal case, the delay and jitter for this type of streaming should be upper-bounded following the principles of hard real-time system [18]. Moreover, a real-time sensor stream does not require significant throughput due to small sizes of data chunks [9]. Hence, it creates additional QoS requirements for the network.

Typical examples of critical real-time sensor data in remotely controlled mining vehicles include various vehicle and operation specific parameters, such as: time-to-collision, speed, positioning, motor's metrics, pressure and load on the fork-lift, etc. For instance, latency induced by the network and radio conditions might produce faulty measurement from the speed and proximity sensors, estimating time-to-collision. In addition, delayed sensor stream combined with bad video quality may delude the expert driver and compel a collision. Maximum working speed of the underground mining vehicles can vary up to 15-20 km/h. Simple calculations show that for 20 ms one-way delay and relatively low speed of 11 km/h

equals to approximately 6 cm of the displacement which can be critical for this industrial scenario. Thus, one may conclude that QoS degradation on the sensor stream may impact the overall QoE of the IIoT service.

Real-time sensor stream plays a significant role in industrial applications:

- Defines real-time strictness of the scenario and fundamental limitations on the communication technology, protocols, and network architecture;
- Defines the resolution and accuracy of the sensors, and impacts the overall QoE;
- Expands the user-interaction models and enriches the user experience by complementing the video and audio streams. For instance, reduced FOV, degraded depth perception, and image quality result in an inability to estimate speed, time-to-collision, perception of objects, locations and distance to obstacles, and the start of a sharp curve [19]. In such cases, the expert driver will heavily rely on the real-time sensor stream;
- Offers real-time monitoring of industrial processes, enabling to define novel KPIs regarding productivity, efficiency, safety, and reliability;

Studies on remote manipulative control strategies started in the 60s. Authors of [20] show how operators strategy changes with the time delay. Normally, when communication latency is about 1s, the drivers strategy changes to 'move and wait', instead of continuous control. In [21] is demonstrated that movement times increased by 64% and error rates increased by 214% when latency was increased from 8.3 to 225ms. Other studies [16], [17], [22], [23] show that varying delay largely degrades the driving performance compared to constant delay even with a higher magnitude. The unpredictability of time lag can cause over-actuation, such as repeating control commands and over-steering [16]. Performance of LTE network for remote driving was evaluated in [17] by testing the possibility of tele-remote operation of a vehicle under the state-of-the-art commercial LTE network conditions. However, authors have not discussed the evaluation of critical sensor communication.

IV. REAL-TIME PERFORMANCE EVALUATION AND PREDICTION

A. Background and system's architecture

Real-time performance of the underlying communication infrastructure is an integral part of QoS in industrial scenarios, due to the critical nature of the services. Evaluation of real-time sensor stream is a challenging task due to the absence of standards and recommendations. The QoS classes recommended by ITU-T in Y-1541 [24] does not address the identified IoT challenges on the communication infrastructure. Moreover, the ongoing work items within ITU addressing data transmission quality techniques, such as G.OM_HEVC, P.NATS, and G.vidmos [25–27] are not intended to assess critical real-time IIoT service. The cited recommendations are targeting multimedia systems, which poses different quality requirements in comparison to the IIoT. Also, utilizing round-trip time (RTT) measurements might not be the most suitable

techniques for IIoT due to the abundance of installed sensors and actuators.

To tackle this challenge, a Real-time Tool (RTOOL) was designed and developed as part of this study. RTOOL may periodically send a sensor stream from a source-node to a server (end-node), with a purpose to compute the one-way delay per transmission. Moreover, during the transmissions, the source-node collects radio and RAN measurements in real-time and further use these metrics to find the correlation with the one-way delay in post-processing analysis. The primary goal of RTOOL is to be able to predict the one-way delay in real-time at the source-node based on the collected radio and RAN logs. This prediction utilizes some of the most commonly used machine learning (ML) algorithms and evaluates performance in terms of coefficient of determination and Mean Absolute Error (MAE). Predicted figures for one-way delay could be used to calculate latency budgets for critical IoT, raise alarms, introduce possibilities to reduce latency and perform root-cause analysis.

Figure 1 depicts a high-level view of the utilized communication network. The IIoT case-study consists of remotely operated mining vehicle connected to the terminal (UE) in LTE RAN. Evolved packet system (EPS), which is composed of LTE RAN and EPC, forms the IIoT access network. The packet data network gateway (P-GW) provides connectivity to the public IP network, linking the mining vehicle with the remote control station. The mine where the experiments were carried on is located in the north of Sweden, with fully deployed LTE coverage inside. Radio dots from Ericsson [28] are used as small indoor cells, connected to the nearest outdoor eNB. From the eNBs, the UL traffic goes to the local core, located in Stockholm, from where enters the public Internet to find the end-node also hosted in Sweden but on a different network. The network infrastructure in the mine is designed to have a couple of handovers from one eNB to another. Hence, the Radio Dots are grouped and connected to different outdoor eNBs, for splitting the load.

Each element of the communication system introduces a varying delay due to the connectivity procedures, scheduling, and network fluctuations. Authors of [29] provide a detailed

Fig. 2: RTOOL architecture

overview of the latencies that can occur in LTE access domain. Connection establishment on the control and user plane is the most significant part of the latency in LTE access domain and can take up to 106 ms. Moreover, additional delays can be introduced because of scheduling, retransmission, and processing on user plane (up to 28 ms). However, these figures assume that the radio coverage is ideal and the quality of the signal is not degraded. In this paper, the aim is to analyze the delay which occurs due to the degraded radio conditions in LTE RAN. Evaluation of the control plane requires access to the core-network and analysis on metrics such as routing diagnostics, queuing length, load, bandwidth utilization, etc. Such quality metrics give insights to the performance of the network, but licensed RANs are typically complex and hardly accessible [30]. This means that performance evaluation of the control plane requires post-processing, offline analysis on the gathered core-network logs. Therefore, the latency induced by the control plane is out of scope for this study and the focus of the evaluation is on the user data plane. The main reason is the real-time access to the radio measurements at the source-node, such as Received-Signal-Strength-Indicator (RSSI), throughput, Signal-to-Interference+Noise-Ratio (SINR), etc. The hypothesis under test is a real-time analysis of the radio metrics and RAN events for predicting network performance parameters, such as the absolute delay, jitter and packet losses.

Delay figures of the IP backbone will vary depending on the region, network load and the number of hops between P-GW and application server. For instance, the delay can vary from 15 ms up to 150 ms in Europe [29]. In this work, we assume that application server (e.g., remote control station) is placed close to the P-GW and this delay is negligible.

B. Experiment setup

RTOOL is intended to mimic a sensor stream sent from real tele-operated mining vehicle. Logical components of the designed tool are illustrated in Figure 2. The software tool consists of following components: RTOOL Core, Adaptive NTP client for synchronization, logging system for post-processing and simple User Interface (UI). RTOOL Core has few configurable parameters for each logical element:

- Data Generator mimics a real sensor and generates sensor data with specific size, type, and format;
- A sampler which specifies the sampling rate of the sensor stream based on application requirements;
- Encoder which encrypts the sensor data and formats it according to the requirements;
- Multiplexer combines the data from several sensors into one stream;
- Socket is used to send sensor data from the phone to the server using a specified protocol, UDP by default;

End-to-end or OTT latency measurements refer to the time it takes to send a packet from the source-node until it is received at the end-node. These measurements are done by periodically sending UDP packets with a sensors payload from RTOOL to the end-node. The experiment is performed using

Fig. 3: NTP synchronization setup

different time periods (sampling rate) to send the data. Each UDP packet is time-stamped at RTOOL for seamless analysis at the end-node. Time-stamps and network measurements from TEMS Pocket are stored in log files for offline analysis.

RTOOL is envisioned to be part of a previously developed, commercially available software - TEMS Pocket [31]. It is described as a state-of-the-art phone-based test tool developed for measuring the performance and quality parameters of wireless networks. The main functionality of TEMS Pocket is the following:

- A real-time radio measurements and event data collection;
- Event data collection from the RAN;
- Indoor and outdoor testing of wireless networks;
- Drive testing capabilities with positioning;
- Storing the radio and event logs for post-processing using other TEMS-ecosystem tools such as TEMS Discovery [32];

Using TEMS Pocket limits the scope of implementation options which means that RTOOL must be implemented on commercial mobile phone or tablet under Android OS. Supported devices by TEMS Pocket are: Sony, HTC, LG, and Samsung. TEMS Pocket supports the following mobile technologies: LTE, WCDMA/HSDPA/HSUPA, GSM/GPRS/EDGE, and CDMA/EV-DO, with a possibility to lock specific radio access technology (RAT) and band. Moreover, TEMS Pocket has several control functions to modify the devices behavior in the LTE network. Control functions work in real-time and allow to perform quick and non-intrusive tests.

In a real-life scenario, it is envisioned a mobile phone to be physically placed on the mining vehicles and be remotely accessible. The user may start recording the radio conditions and RAN events, which will automatically calculate a predicted value of the delay in real-time. In the performed experiments to gather data for building the ML predictions, a Samsung Galaxy S9 mobile phone was equipped with RTOOL and TEMS Pocket. An overview of the experimental setup is depicted in the Figure 3. TEMS Pocket was locked to LTE network and was able to capture more than 1500 parameters explaining the radio and LTE RAN conditions. TEMS Pocket was configured to record those parameters every 5ms during the sensor streaming. RTOOL was set to periodically stream data on different intervals, every 20, 50, 100, and 200ms.

(a) Mobile operator A

(b) Mobile operator B

Fig. 4: Synchronization error

C. Time synchronization

Evaluation of real-time performance requires precise estimation of end-to-end delay between the control center and tele-remote vehicle. This task can be achieved by having two nodes perfectly synchronized with each other. Synchronization of the devices in the network is a complex task that can be done in two main ways:

- Synchronization over the network, using various protocols and services;
- Synchronization using external clock references, using signals from Global Navigation Satellite System (GNSS), atomic clocks, etc.;

Conventional approach is to synchronize two nodes by utilizing external references, such as GNSS signals from Global Positioning System (GPS), GLONASS, GALILEO or COMPASS. It is possible to provide accurate time synchronization typically better than 100 nanoseconds to UTC [33]. However, due to the inability to receive GNSS signals in underground environments, such a technique is not suitable for the mining industry. Thus, synchronization for our case-study may be only achieved using the existing LTE network. Main protocols that were developed to keep nodes over the network synchronized are Network Time Protocol (NTP) and Precision Time Protocol (PTP) known as IEEE Standard 1588-2008 [34].

NTP is de-facto time-keeping standard across the Internet [35]. NTP organizes clocks in a layered hierarchical way in terms of a stratum. The stratum level specifies the distance

between the reference clock and time server which is used for synchronization. The accuracy of the synchronization which might be achieved using NTP is less than 1ms in LAN and 10ms over WAN [35]. Compensation of the clock's offset is performed by measuring RTT to NTP server. The crucial assumption that NTP makes at this step is that the link is symmetrical and in ideal case UL and DL delays are equal.

For the purpose of the described case-study, a modified version of NTP is developed. Slightly changed topology is used since absolute synchronization to UTC time is not needed as long as NTP server and RTOOL are synchronized to each other. In conventional NTP topology, nodes synchronized to the NTP servers will have different clock errors due to the network fluctuations and clock offsets on the reference NTP servers. The proposed solution implements stand-alone NTP server and have its clock as a reference for the entire system. In this case, the error is completely mitigated on one side since synchronization error on the used server is equal to zero. Figure 3 shows proposed topology for experiment using NTP-based synchronization. RTOOL synchronizes phones hardware clock to NTP server adaptively which means that synchronization can be done only under excellent/good radio conditions (Table I).

TABLE I: LTE signal quality

Signal quality	Radio parameters		
	<i>RSRP</i> , dBm	<i>RSRQ</i> , dB	<i>CQI</i>
Excellent	>-90	>-9	>10
Good	-90 ... -105	-9 ... -12	9 ... 7
Fair	-106 ... -120	<-13	6 ... 1
Poor	<-120		0

It is important to outline that LTE wireless link is not symmetrical due to the differences in UL and DL radio technologies, scheduling mechanisms and bandwidth. However, measurements showed that clock error was acceptable for our scenario and provides the best effort that can be achieved in this specific use-case. Clock error was measured on the live network of two mobile operators by connecting phone directly to the NTP server using Android Debug Bridge (ADB). The results are shown in Figure 4.

D. Latency prediction

In recent years, ML models were successfully used in various applications from bioinformatics to speech and image recognition [36]. ML tries to construct data-driven models that can capture complex and sometimes hidden dependencies. ML is becoming increasingly useful with the recent developments of hardware (GPU and TPU), software (TensorFlow and Scikit-Learn) and distributed data-processing frameworks (Hadoop and Spark) [37–39].

The task of real-time network performance prediction from the radio measurements perfectly fits into the ML approach. Authors of [40] provide a general workflow (Figure 5) that can be used to build the ML model for predicting the one-way delay.

Fig. 5: The typical workflow of machine learning for networking [40]

D.1) Problem formulation and Data collection

The first step of the workflow is a problem formulation. As was stated earlier the goal is to predict network delay caused by the radio environment in LTE RAN. For the second step, as explained in Section IV-B, RTOOL and TEMS Pocket will be used to collect timestamps, radio measurements, RAN events and also send an IP sensor stream. Hence, there are two datasets, from RTOOL and TEMS Pocket.

D.2) Data processing and Feature extraction

As stated earlier, the latency is generated by several factors, but only a few of them (i.e., features) have the most effect on the target metric. The goal of the third step is to pre-process the data by cleaning, formatting and performing feature engineering. Captured radio metrics and end-to-end delay figures are presented as time-series data. End-to-end delay measurements are presented as a series of timestamps that were collected at the source-node and end-node. The time difference between two consecutive timestamps is defined by sampling period which can vary for different experiments. Missing data handling is one of the first steps of the data cleaning process. Commonly recommended ways for fixing missing data are [41]:

- Discarding observations that have missing value;
- Filling the missing values based on other data points, when appropriate;

In this work, both methods were utilized to pre-process measurements from TEMS Pocket. Observations that had less than two unique values were dropped from the dataset. The next step is the datasets alignment, as the TEMS Pocket measurements do not have the same timestamps and frequencies as the delay measurements. The collection of radio and RAN data happens every 5ms, while the delay measurements depend on the chosen sampling frequency. Therefore, the result RAN measurements were mapped to delay timestamps with Piecewise Aggregate Approximation (PAA) [42]. This means taking the median of the TEMS Pocket measurements for the duration of each transmission period of the sensor stream.

Feature engineering is the major step of the entire process of ML model creation. Better features utilization enables simpler models and produce improved results. Raw measurements should be transformed in certain ways to get better results. Considering the nature of radio and RAN measurements, there are several ways to create new features from time-series data:

- Lag features that represent measured values of the captured metrics at prior time samples.
- Window features that represent a value obtained from the values over a fixed window of prior time. Similarly to lag

features, this type of features are obtained by taking the mean value of measurements over the fixed window of prior time;

In practice, lag features are obtained by shifting original time series measurements. In general, the gathered data may succumb to stochastic or deterministic time series patterns of single or multiple seasonality, trends and cycles, which typically generate biased predictions [43]. Regarding the mining case-study, the presence of various trends and cycles are obvious, such as lunch breaks and shift changes. Also, the radio conditions inside the mine do not drastically change over time, as it is an isolated and constant environment. Thus, creating additional repetitive cycles. However, the monitored parameters heavily depend on the workflow of RAN, EPC and Public Internet. For instance, the recorded data may be different during the same experienced cycles due to heavy loaded or unloaded eNBs, EPC or Public Internet. This demands additional seasonal analysis on the mentioned entities, which is a complex topic that requires further research. For this reason, the computed lagged features are essential for capturing the relation between latency and RAN conditions that were before transmission.

Collected data have various features with values in different ranges. Most of the ML algorithms are sensitive to features scaling. All features and label (i.e. delay) were scaled using Standard scaler [44]. The scaled feature x' of original feature is given by:

$$x' = \frac{x - \bar{x}}{\sigma(x)}$$

where $\bar{x}$ is the mean value for x , and $\sigma(x)$ is the deviation.

As a result of feature engineering, a whole dataset consists of timestamps, delay measurements from RTOOL, original radio and RAN measurements from TEMS pocket, lag and window features that were obtained from the raw measurements. TEMS Pocket may collect more than 1500 parameters (i.e., features), but for latency prediction basic L1 radio measurements were utilized. These measurements are extensively described in following 3GPP standards [45–47] and detailed description of LTE L1 measurements is beyond the scope of this paper. Parameters such as RSRP, RSRQ, RSSI, SINR and physical throughput were considered as a features for the model construction. Main motivation for such feature selection is to enable less intrusive prediction and examine the possibility of predicting latency from L1 measurements from UE. Finally, a Pearson correlation coefficient was computed among all the recorded features [48]. From the results, the one-

way delay correlates the most with the physical throughput, and RSSI.

D.3) Model construction

The goal of the model construction step is to select an appropriate ML algorithm to get a reliable model with the best prediction. In this paper, we evaluated different ML-regressors from scikit library [49], with the most consistent validation results achieved from:

- Artificial Neural Networks (MLP);
- Decision Tree Regressor [50];
- Model ensembling: Bagging technique with a Decision Tree Regressor as a base for bagging ensembling.

Bootstrap aggregation, or bagging, is a technique that can be utilized with many classification and regression algorithms to reduce the variance associated with prediction, and as a result provide higher accuracy. Original dataset is divided into many bootstrap samples, after that base method is applied to each bootstrap sample and then the predictions are combined, by averaging for regression, to obtain the overall result, with smaller variance [51].

D.4) Model validation

The next step after model construction is its validation which is considered to be an important phase that verifies the model's accuracy and ensures that it does not overfit. Separate experiments on two live commercial LTE networks were performed to obtain datasets for training and validation. After all the measurements, all regressors were trained using the training set (80%) and evaluated against the testing set (20%).

Models were assessed by evaluating the accuracy of the delay prediction. Results for each sampling period are shown in Table II. More detailed discussion of the results follows in the next section. However, from the Table II it is obvious a linear decrease in the prediction accuracy as the sampling rate increases. Performance varies with a sampling rate due to the number of radio measurements and events collected within a time series. Lower sampling periods allow to monitor network with higher resolution and capture all fluctuations of the radio environment.

TABLE II: Prediction performance

Sampling period	R^2 (coefficient of determination)			Mean Absolute Error (MAE)		
	NN (MLP)	Decision Tree	Bagging Decision Tree	NN (MLP)	Decision Tree	Bagging Decision Tree
20 ms	82 %	82.2 %	90.7 %	0.23	0.11	0.091
50 ms	75.5 %	77.7 %	85.1 %	0.28	0.16	0.15
100 ms	73.7 %	67.3 %	81.8 %	0.29	0.19	0.13
200 ms	60 %	50 %	66.8 %	0.35	0.31	0.22

V. RESULTS AND DISCUSSION

Splitting the data-set into 80/20 for training and validation would mean predicting the one-way delay on 20% of the data-set. As it is difficult to find blind spots and lousy radio environment on a live commercial LTE network, the "silent"

(a) RF shield

(b) Drive test in the mine

Fig. 6: Experiments

box from the Figure 6(a) was used for generating training data. This radio frequency (RF) shield degrades signal quality or completely blocks it. Thus, it can produce a full range of radio conditions. A mobile phone will experience massive radio signal fluctuations when it is placed inside, while constantly opening and closing the box. Therefore, the TEMS Pocket data was recorded in this manner. The Figures 7(a) and 7(b) depicts massive fluctuations with the delay when the mobile phone streams sensor data while experiencing lousy radio conditions. At some point, the delay jumps all the way to 2000ms. The blue line on the Figure 7 is the true recorded delay, while the orange line is the predicted delay.

Real-Life underground drive tests as on Figure 6(b) were also performed to validate the prediction accuracies. Figure 7(c) illustrates the experienced delay while streaming from the mine. The values are relatively low and constant, with one recorded peak of 200ms during a handover. However, the prediction model was able to capture the handover and successfully predict the occurring delay. Again, the blue line is the true recorded delay, while the orange line is the predicted value. The benefit from such software implementation, prediction model and results is the ability to compute in real-time the one-way delay. A mobile phone with TEMS Pocket can be physically placed on the mining vehicle that will measure radio conditions and RAN events in real-time. These measurements are fed to the ML model which computes a prediction of the one-way delay. The predicted values may be plotted on one of the displays in the remote control room as a real-time gauge chart, to give better context awareness for the expert driver.

VI. CONCLUSION

The research community and the industry acceptance of IoT suggest rapid digitalization of industrial processes. Being applied in various domains, each IIoT service requires prioritization of different KPIs and service requirements. Thus, the network performance evaluation becomes linearly more complex as each IIoT requires different QoS assurances. In this work, a real-world industrial scenario was analyzed to evaluate the importance of critical real-time sensor streaming. For this purpose, a software tool was developed to capture the absolute, one-way delay for each transmission. The latency metrics

Fig. 7: Comparison of true delay and predicted delay figures

and further analyzed with various LTE RAN measurements. A machine learning technique is used to grasp the relation between the latency metrics and the captured radio measurements. The contribution of this study is a delay prediction for each transmission in real-time based on the correlation and learning processes. The initial results prove the possibility to estimate delay figures caused by the LTE RAN events and radio disturbances from the environment. The highest accuracy of the prediction is estimated at 90%.

The approach taken in this study is the first step in assessing the performance of an IIoT service. The achieved results enable further calculation of latency budgets for a given critical IoT service, as well as opens the possibilities to reduce latency and perform root-cause analysis.

ACKNOWLEDGMENT

This research work is financially supported by the Erasmus Mundus program PERCCOM [52], facilitated by the European Commission. The authors are grateful to the InfoVista Sweden AB that supported this work and provided access to TEMS products and research facilities. A special thanks to Niclas Ögren, network & protocols specialist, and Ulf Marklund, R&D manager, for helpful discussions and support.

REFERENCES

- [1] H. Kagermann, W. Wahlster, and J. Helbig, "Recommendations for implementing the strategic initiative industrie 4.0: Final report of the industrie 4.0 working group," April 2013.
- [2] PWC, "Industry 4.0: Building the digital enterprise."
- [3] M. Wollschlaeger, T. Sauter, and J. Jasperneite, "The Future of Industrial Communication: Automation Networks in the Era of the Internet of Things and Industry 4.0," *IEEE Industrial Electronics Magazine*, vol. 11, pp. 17–27, March 2017.
- [4] J. Marescaux, J. Leroy, M. Gagner, F. Rubino, D. Mutter, M. Vix, S. E. Butner, and M. K. Smith, "Transatlantic robot-assisted telesurgery," *Nature*, vol. 413, no. 6854, p. 379, 2001.
- [5] A. Sajid, H. Abbas, and K. Saleem, "Cloud-assisted IoT-based SCADA systems security: A review of the state of the art and future challenges," *IEEE Access*, vol. 4, pp. 1375–1384, 2016.
- [6] L. Sanchez, L. Muñoz, J. A. Galache, P. Sotres, J. R. Santana, V. Gutierrez, R. Ramdhany, A. Gluhak, S. Krco, E. Theodoridis, *et al.*, "Smart-Santander: IoT experimentation over a smart city testbed," *Computer Networks*, vol. 61, pp. 217–238, 2014.
- [7] Ericsson, "Manufacturing reengineered: robots, 5G and the industrial IoT," *Ericsson Business Review*, no. 4.
- [8] Ericsson, "Ericsson mobility report," 2017.
- [9] A. Osseiran, J. F. Monserrat, and P. Marsch, *5G Mobile and Wireless Communications Technology*. Cambridge University Press, 2016.
- [10] Q. Zhang and F. H. P. Fitzek, "Mission critical IoT communication in 5G," in *Future Access Enablers of Ubiquitous and Intelligent Infrastructures*, 2015.
- [11] Nokia, "White paper: 5G for mission critical communication achieve ultra-reliability and virtual zero latency," tech. rep., Nokia Solutions and Networks Oy, Espoo, Finland, 2016.
- [12] "METIS D1.1: scenarios, requirements and KPIs for 5G mobile and wireless system," tech. rep., 2013.
- [13] E. L. Petsonk, C. Rose, and R. Cohen, "Coal mine dust lung disease. New lessons from an old exposure," *American journal of respiratory and critical care medicine*, vol. 187, no. 11, pp. 1178–1185, 2013.
- [14] B. Frank, L. Skogh, and M. Alakla, "On increasing fuel efficiency by operator assistance systems in a wheel loader," in *Proceedings of International Conference on Advanced Vehicle Technologies and Integration*, July 2012.
- [15] C. Zhou, N. Damiano, B. Whisner, and M. Reyes, "Industrial internet of things: applications in underground coal mines," in *Mining engineering*, vol. 69, pp. 50–56, December 2017.
- [16] J. Y. C. Chen, E. C. Haas, and M. J. Barnes, "Human performance issues and user interface design for teleoperated robots," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 37, pp. 1231–1245, Nov 2007.
- [17] R. Liu, D. Kwak, S. Devarakonda, K. Bekris, and L. Iftode, "Investigating remote driving over the LTE network," in *Proceedings of the 9th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, AutomotiveUI '17, (New York, NY, USA), pp. 264–269, ACM, 2017.
- [18] P. A. Laplante and S. J. Ovaska, *Real-Time Systems Design and Analysis: Tools for the Practitioner*. Wiley-IEEE Press, 4th ed., 2011.
- [19] J. Bao, Z. C. Wu, J. J. Wu, P. P. Pei, and C. Liu, "The Impact of Image Parameters of Indirect Viewing Systems on Driver Fatigue and Task Performance," in *Advanced Information and Computer Technology in Engineering and Manufacturing*, Environmental Engineering, vol. 765 of *Advanced Materials Research*, pp. 2046–2050, Trans Tech Publications, 10 2013.
- [20] T. B. Sheridan and W. R. Ferrell, "Remote manipulative control with transmission delay," *IEEE Transactions on Human Factors in Electronics*, vol. HFE-4, pp. 25–29, Sept 1963.
- [21] I. S. MacKenzie and C. Ware, "Lag as a determinant of human performance in interactive systems," in *Proceedings of the INTERACT '93 and CHI '93 Conference on Human Factors in Computing Systems*, CHI '93, (New York, NY, USA), pp. 488–493, ACM, 1993.
- [22] B. Watson, N. Walker, W. Ribarsky, and V. Spaulding, "Effects of variation in system responsiveness on user performance in virtual environments," *Human Factors*, vol. 40, no. 3, pp. 403–414, 1998. PMID: 9849102.
- [23] J. C. Lane, C. R. Carignan, B. R. Sullivan, D. L. Akin, T. Hunt, and R. Cohen, "Effects of time delay on telerobotic control of neutral buoyancy vehicles," in *Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat. No.02CH37292)*, vol. 3, pp. 2874–2879, 2002.

- [24] ITU, "Recommendation Y.1541 Network performance objectives for IP-based services," recommendation, Telecommunication Standardization Sector (ITU-T), 12 2011.
- [25] ITU, "Recommendation P.1203.1: Parametric bitstream-based quality assessment of progressive download and adaptive audiovisual streaming services over reliable transport - Video quality estimation module," recommendation, Telecommunication Standardization Sector (ITU-T), 10 2017.
- [26] ITU, "Recommendation P.913 : Methods for the subjective assessment of video quality, audio quality and audiovisual quality of Internet video and distribution quality television in any environment," recommendation, Telecommunication Standardization Sector (ITU-T), 03 2016.
- [27] ITU, "Recommendation G.1071 : Opinion model for network planning of video and audio streaming applications," recommendation, Telecommunication Standardization Sector (ITU-T), 11 2016.
- [28] Ericsson, "Ericsson Radio Dot System, <https://www.ericsson.com/ourportfolio/radio-system/radio-dot-system>."
- [29] N. Nikaein and S. Krea, "Latency for Real-Time Machine-to-Machine Communication in LTE-Based System Architecture," in *17th European Wireless 2011 - Sustainable Wireless Technologies*, pp. 1–6, April 2011.
- [30] 3GPP, "Feasibility study for Further Advancements for E-UTRA (LTE-Advanced)," Technical Report (TR) 36.912, 3rd Generation Partnership Project (3GPP), 03 2017. Version 14.0.0.
- [31] InfoVista, "TEMS Pocket, <https://www.infovista.com/tems/products-for-radio-and-core-networks/radio-network-engineering/portable-testing-for-wireless-networks>."
- [32] InfoVista, "TEMS Discovery: Discover actionable insights into network performance, <https://www.infovista.com/tems/products-for-radio-and-core-networks/radio-network-engineering/ran-data-analysis-optimization>."
- [33] Endace, "IEEE 1588 PTP clock synchronization over a WAN backbone," whitepaper, Endace Technology Limited), 2016.
- [34] IEEE, "IEEE Standard for a Precision Clock Synchronization Protocol for Networked Measurement and Control Systems," *IEEE Std 1588-2008 (Revision of IEEE Std 1588-2002)*, pp. 1–300, July 2008.
- [35] P. Corcoran, "A Matter of Timing: Consumer Electronics and Network Time," *IEEE Consumer Electronics Magazine*, vol. 2, pp. 20–25, Oct 2013.
- [36] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016.
- [37] P. Sherkhane and D. Vora, "Survey of deep learning software tools," in *2017 International Conference on Data Management, Analytics and Innovation (ICDMAI)*, pp. 236–238, Feb 2017.
- [38] A. Parvat, J. Chavan, S. Kadam, S. Dev, and V. Pathak, "A survey of deep-learning frameworks," in *2017 International Conference on Inventive Systems and Control (ICISC)*, pp. 1–7, Jan 2017.
- [39] V. Sze, Y. H. Chen, J. Emer, A. Suleiman, and Z. Zhang, "Hardware for machine learning: Challenges and opportunities," in *2018 IEEE Custom Integrated Circuits Conference (CICC)*, pp. 1–8, April 2018.
- [40] M. Wang, Y. Cui, X. Wang, S. Xiao, and J. Jiang, "Machine learning for networking: Workflow, advances and opportunities," *IEEE Network*, vol. 32, pp. 92–99, March 2018.
- [41] A. Gelman and J. Hill, *Data Analysis Using Regression and Multi-level/Hierarchical Models*. Analytical Methods for Social Research, Cambridge University Press, 2006.
- [42] E. Keogh, K. Chakrabarti, M. Pazzani, and S. Mehrotra, "Dimensionality reduction for fast similarity search in large time series databases," *Knowledge and information Systems*, vol. 3, no. 3, pp. 263–286, 2001.
- [43] S. F. Crone and N. Kourentzes, "Feature selection for time series prediction—a combined filter and wrapper approach for neural networks," *Neurocomputing*, vol. 73, no. 10–12, pp. 1923–1936, 2010.
- [44] scikit learn, "sklearn.preprocessing.StandardScaler, <http://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html>."
- [45] 3GPP, "Physical layer procedures (FDD)," Technical Specification (TS) 25.214, 3rd Generation Partnership Project (3GPP), 03 2010. Version 8.9.0.
- [46] 3GPP, "Evolved Universal Terrestrial Radio Access (E-UTRA); Physical channels and modulation," Technical Specification (TS) 36.211, 3rd Generation Partnership Project (3GPP), 03 2017. Version 14.2.0.
- [47] 3GPP, "Evolved Universal Terrestrial Radio Access (E-UTRA); Physical layer procedures," Technical Specification (TS) 36.213, 3rd Generation Partnership Project (3GPP), 03 2017. Version 14.2.0.
- [48] T. M. Mitchell, *Machine Learning*. New York, NY, USA: McGraw-Hill, Inc., 1 ed., 1997.
- [49] scikit learn, "Scikit-learn: Machine Learning in Python, <http://scikit-learn.org/stable/>."
- [50] J. R. Quinlan, "Induction of decision trees," *Mach. Learn.*, vol. 1, pp. 81–106, Mar. 1986.
- [51] C. D. Sutton, "11 - classification and regression trees, bagging, and boosting," in *Data Mining and Data Visualization* (C. Rao, E. Wegman, and J. Solka, eds.), vol. 24 of *Handbook of Statistics*, pp. 303 – 329, Elsevier, 2005.
- [52] J. Porras, A. Seffah, E. Rondeau, K. Andersson, and A. Klimova, "Perc-com: A master program in pervasive computing and communications for sustainable development," in *2016 IEEE 29th International Conference on Software Engineering Education and Training (CSEET)*, pp. 204–212, April 2016.