A Sensitivity Analysis on the Potential of 5G Channel Quality Prediction

Sabari Nathan Anbalagan[1,*], Remco Litjens[2,3], Kallol Das[2], Alessandro Chiumento[1], Paul Havinga[1] and Hans van den Berg[2,4]

[1] *Pervasive Systems*, *University of Twente*, Enschede, The Netherlands
[2] *Department of Networks*, *TNO*, The Hague, The Netherlands
[3] *Department of EEMCS*, *TU Delft*, Delft, The Netherlands
[4] *Design and Analysis of Communication Systems*, *University of Twente*, Enschede, The Netherlands
{s.n.anbalagan, a.chiumento, p.j.m.havinga, j.l.vandenberg}@utwente.nl
{remco.litjens, kallol.das}@tno.nl
* corresponding author

2021 IEEE 93rd Vehicular Technology Conference (VTC2021-Spring) | 978-1-7281-8964-2/20/$31.00 ©2021 IEEE | DOI: 10.1109/VTC2021-Spring51267.2021.9448944

***Abstract*—With increasing network complexity, intelligent mechanisms to efficiently achieve the required quality of service of wireless-enabled applications are being developed, especially for industrial environments due to the onset of the fourth industrial revolution. In this paper, the potential benefits of wireless channel quality prediction for two of the three major use cases supported by 5G viz. enhanced Mobile BroadBand (eMBB) and Ultra-Reliable Low Latency Communication (URLLC) are quantified in an industrial indoor environment through simulations. Our analysis shows that the ability to perform perfect prediction improves the 10th user throughput percentile by up to 125% for eMBB use case and decreases the 90th resource utilization percentile by up to 37% for URLLC use case. Furthermore, the maximum tolerable prediction inaccuracy is found to be up to 5 dB and 0.35 dB for eMBB and URLLC use cases, respectively.**

***Index Terms*—Industrial IoT, Networking, Factories of the Future, 5G**

I. Introduction

Wireless communication plays an essential role in realizing the vision termed ‘Factories of the Future’ (FotF) [1]. The applications envisioned within FotF (industrial indoor environment) have (a combination of) different quality of service (QoS) requirements such as ultra-high reliability, low latency and high throughput. However, the industrial indoor environment has proven to be harsh and to have different propagation characteristics from other indoor environments [2] (e.g. office or residential environments), highlighting the need for intelligent techniques to achieve FotF applications’ QoS requirements.

Predicting the quality of wireless channels ahead of time leads to better resource allocation which improves the performance of the network. Because of its overarching benefits, channel quality prediction (CQP) has been an interesting research topic for more than a decade. As a result, several researchers have proposed CQP methods, which can be classified based on the technique used (such as polynomial fitting [3], Gaussian process regression [4], deep learning [5]) and/or the environment in which such techniques are applied (such as industrial [6], urban [4], highway [5]). Each of them reports the observed accuracy of their prediction while only a few include the performance improvement due to CQP for a chosen application. The true impact (or usefulness) of CQP for an application operating in a particular environment can only be gauged when the accuracy of CQP is linked with the corresponding performance improvement of the application. For example, a CQP method might claim a very high accuracy for a particular environment but it may turn out that the performance of the application of interest only increases by a very small margin. In such scenarios, the usefulness of the CQP, due to its modest impact, becomes debatable.

Although there are numerous works dedicated to predicting the channel quality, very few works determine its potential and limitations in an in-depth performance study. A notable work is by Zappone et al. [7] which discusses the usefulness of deep learning in network design. The problems associated with network design are mathematically modelled and the usefulness is evaluated. To the best of the authors’ knowledge, research on the impact of CQP on the performance of application is unavailable.

This paper quantifies the impact of CQP in a 5G industrial indoor environment for enhanced Mobile BroadBand (eMBB) and Ultra-Reliable Low Latency Communication (URLLC) use cases. For eMBB, the impact of CQP is measured in terms of throughput enhancement. For URLLC, the reduction in resource utilization (RU), as opposed to latency or reliability, is chosen as the metric for estimating the impact of CQP because the state of the art techniques achieve the latency & reliability constraint but utilize greater amount of resources. Therefore if CQP has to be impactful for URLLC use case, it has to reduce the amount of resources utilized, in addition to achieving the latency and reliability constraints. The benchmark chosen to evaluate our work is the state of the art link adaptation technique, as explained in Section II-B. Furthermore, the sensitivity of performance improvement w.r.t. prediction accuracy is analyzed. The major contributions of this paper are:

1) Quantifying the potential gain obtainable by CQP in a 5G industrial indoor environment for both eMBB and URLLC use cases;

978-1-7281-8964-2/21/$31.00 ©2021 IEEE

2) Deriving the maximum tolerable prediction inaccuracy for CQP to be beneficial.

The outline of the paper is as follows. The system model and assessment methodology used to achieve the mentioned objectives are presented in Section II. Subsequently, the results are presented and discussed in Section III. Finally, the derived conclusions are summed up in Section IV.

II. Methodology

The simulation setup is explained in Section II-A. The benchmark for our study is explained (in Section II-B) before explaining the methodologies in Section II-C.

A. Simulation Setup

To gauge the potential of CQP in industrial indoor environments, a factory hall of size 50m×50m×6m (length×width×height) is simulated. The base station (BS) is fixed on the centre of the simulated factory hall's ceiling. Simulations are repeated with varying User Equipment (UE) positions such that, every pixel in a 50×50-meter grid with a pixel size of 1×1-meter at a height of 1.5 m from the floor of the factory hall is covered. The channel model is generated using the quasi-deterministic radio channel generator (QuaDRiGa) [8] applying the propagation parameters for industrial indoor scenarios [9]. The simulation conditions are presented in Table I.

The two types of use cases analyzed are: 1) eMBB and 2) URLLC. Both are modelled as downlink traffic. For the modelled eMBB use case, a full transmit buffer is considered. Since a single-UE scenario is considered, full carrier bandwidth is available for the single UE. The Key Performance Indicator (KPI) for such an use case is the 10^{th} user throughput percentile.

The URLLC use case is modelled as a flow of 32-byte packets generated every 1 ms. The reliability constraint for URLLC is that at least 99.999% packets be successfully transmitted with a maximum radio transmission delay of 1 ms. Hence, the target Block Error Rate ($BLER_{target}$) is set to 10^{-5} . In this study, 5G numerology characterised by a 15 kHz sub-carrier spacing and a 1 ms slot duration is assumed. This implies that any retransmission of URLLC packets will result in a violation of latency constraint. As a consequence, the latency constraint is inherently achieved for every successfully transmitted packet. Therefore, effectively, the KPI observed for URLLC is the 90^{th} RU percentile when the reliability constraint is satisfied.

B. Outer Loop Link Adaptation

In its basic operation, each UE reports the observed channel quality to the BS in the form of Channel Quality Indicator (CQI) at periodic intervals (CQI periodicity). The CQI depends on the signal to noise ratio (SNR) measured by the UE. The BS processes the CQI reports received from the UE and selects the Modulation and Coding Scheme (MCS) corresponding to the reported CQI for downlink transmission. However, the reported CQIs may be inaccurate because there is an inherent

TABLE I
Simulation Parameters

Parameter	Value (range)	
Carrier frequency	3.5 GHz	
Bandwidth	5 MHz	
5G numerology	0 (sub-carrier spacing = 15 kHz)	
Transmit power	21 dBm	
OLLA step sizes (θ)	[10^{-7}, 10^{-6}, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 1, 2, 3, 4]	
UE speeds	[0.1, 0.3, 1, 3, 10] m/s	
CQI periodicity	[2, 5, 10, 20, 40, 80] ms	
Use Cases	**eMBB**	**URLLC**
$BLER_{target}$	10^{-1}	10^{-5}
KPI	10^{th} user throughput percentile	90^{th} resource utilization percentile
CQI levels	Table 5.2.2.1-3 (up to 256QAM) [10]	Table 5.2.2.1-2 (up to 64QAM) [10]

delay between the moment in which the UE measures the SNR and the moment that the correspondingly derived MCS is selected by the BS [11]. The channel quality can change during this delay leading to either unsuccessful or inefficient transmissions. If the BS chooses an MCS greater than that corresponding to the channel condition, the subsequent transmissions are likely to be unsuccessful. On the other hand, if the BS chooses a lower MCS, the subsequent transmissions are likely to be successful but inefficient. To overcome this, the BS uses another form of feedback received from the UEs viz., the ACK/NACK messages. A technique called the Outer Loop Link Adaptation (OLLA) combines the two mentioned feedbacks to help efficiently achieve the $BLER_{target}$ set by the use case.

OLLA introduces an offset (Δ) which is either increased by Δ_{up} upon successful transmission or decreased by Δ_{down} upon unsuccessful transmission. This offset is added to the CQI and then the resulting value is used for MCS selection [11]. In this study, the individual values for Δ_{up} and Δ_{down} are chosen as $(1 - BLER_{target}) \times \theta$ and $BLER_{target} \times \theta$, respectively, where θ is the OLLA step size. Therefore, the value of OLLA offset applied to the $(t + 1)^{st}$ transmission,

$$\Delta_{t+1} = \begin{cases} \Delta_t + (BLER_{target} \times \theta), & \text{if ACK} \\ \Delta_t - ((1 - BLER_{target}) \times \theta), & \text{if NACK.} \end{cases}$$

The step size θ has been proven to have significant effect on OLLA's performance [11] which is illustrated in Figure 1, where the 10^{th} user throughput percentile for eMBB use case is plotted against θ for UEs moving at a speed of 0.3 m/s and 1 m/s with a CQI periodicity set to 40 ms. The throughput increases with an increase in the OLLA step size θ up to a certain point and then starts to decrease. Initially, as θ increases, OLLA's throughput increases because OLLA is able to quickly converge to an optimal Δ for that particular scenario. However, after a certain value, an increase in θ causes the throughput to decrease because the Δ then tends to alternate between over- or undershooting w.r.t. the optimal value due to the greater step size θ. Furthermore, the maximum throughput values for the two scenarios plotted in Figure 1, are obtained for different values of θ because of different scenarios (UE speed in this case) and hence different degrees of outdatedness that the OLLA needs to compensate. This effect is also relevant for URLLC use case where overshooting and undershooting result in packet loss and greater RU, respectively. Therefore, the value of θ which maximizes the KPI for a particular use case, UE speed and CQI periodicity, is referred to as 'Optimal θ'. In our study, the simulations are run for the step sizes mentioned in Table I and the behaviour of OLLA with optimal θ for each scenario is chosen and used as the benchmark (referred to as *Optimal OLLA*). For instance, when the UE speed is 0.3 m/s, OLLA's performance with $\theta = 1$ is chosen as *Optimal OLLA* for the eMBB use case.

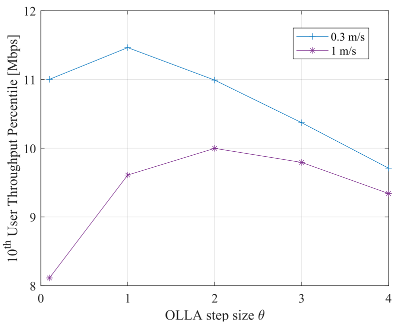

Fig. 1. Influence of the OLLA step size (θ) on the 10^{th} user throughput percentile (eMBB use case) for different UE speeds.

C. System Model

CQP algorithms predict the channel quality experienced by the UE with varying degrees of accuracy. For our study, prediction inaccuracies are modelled by artificially adding errors to the actual channel conditions within the simulation. These errors are considered to be zero-mean normally distributed around the actual channel quality. Therefore,

$$SNR_{predicted} = X + SNR_{actual},$$

where, $SNR_{predicted}$ is the predicted channel quality, SNR_{actual} is the actual channel quality, X represents a random variable which is normally distributed ($\mathcal{N}(0, \sigma^2)$) with zero mean and a standard deviation of σ. The BS chooses an MCS depending on $SNR_{predicted}$.

The potential of prediction can be observed when the prediction algorithms are 100% accurate. In other words, when $\sigma = 0$, the BS knows (by prediction) the channel quality perfectly and hence it can choose the highest MCS leading to a $BLER$ not exceeding the $BLER_{target}$. This scenario is referred to as *Perfect Prediction*. The difference between the KPI value observed with *Perfect Prediction* and *Optimal OLLA* is referred to as *'Prediction Potential'*.

For each use case (eMBB and URLLC) and scenario (a combination of UE speed and CQI periodicity), the standard deviation of prediction error σ, is varied and the corresponding KPI is observed. The value of σ at which the KPI of prediction is lower than that of *Optimal OLLA* is termed as '*Maximum Tolerable Prediction Inaccuracy*' (MTPI).

In our study, the speed of the user and CQI periodicity are varied. The faster the UE moves, the more quickly the channel conditions will vary. Longer CQI periodicity signifies then more outdated channel knowledge at the BS and a lower number of CQI reports. Therefore, a slow moving UE with short CQI periodicity correspond to small difference between the channel knowledge at the BS and the actual channel conditions; and greater signalling overhead due to CQI reporting. In this paper, the difference between the actual channel condition and that known by the BS is referred to as channel outdatedness. The analysis is performed for UE speeds up to 10 m/s which covers most practical scenarios within a factory [12].

III. Results & Discussion

The *prediction potential* and *MTPI* values for eMBB and URLLC use cases are presented and explained in Sections III-A and III-B respectively.

A. eMBB use case

Prediction Potential: The potential of channel prediction depends on the degree of channel outdatedness which, in turn depends on the UE speed and the CQI periodicity. In general, an increase in the degree of channel outdatedness decreases the throughput for *Optimal OLLA*. The difference between the 10^{th} user throughput percentile of *Perfect Prediction* and *Optimal OLLA* equates to the *prediction potential* (throughput gain) of CQP. Therefore, with an increasing degree of channel outdatedness, the *prediction potential* increases as shown in Figure 2.

It is observed that for slow moving UEs, the throughput gain of *Perfect Prediction* over *Optimal OLLA* is minimal. However, configuring the UE to report CQI every 2 ms introduces significant network overhead [13]. CQP reduces this overhead. Considering two scenarios with the same UE speed but different CQI periodicity, CQP's impact on signalling overhead can be explained. For an UE speed of 3 m/s, configuring the CQI periodicity to 20 ms instead of 2 ms would not only provide 60% throughput gain but also reduces the number of control

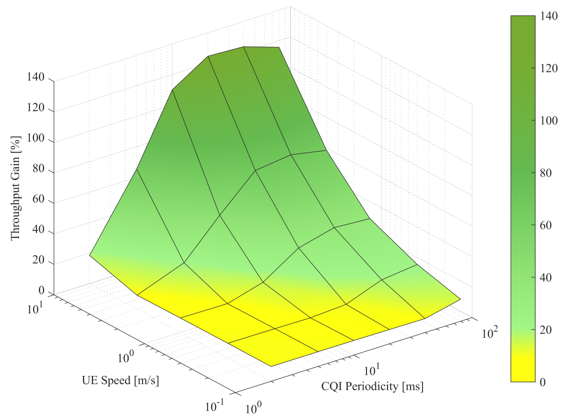

Fig. 2. Throughput gain (eMBB) of *Perfect Prediction* in relation to *Optimal OLLA*.

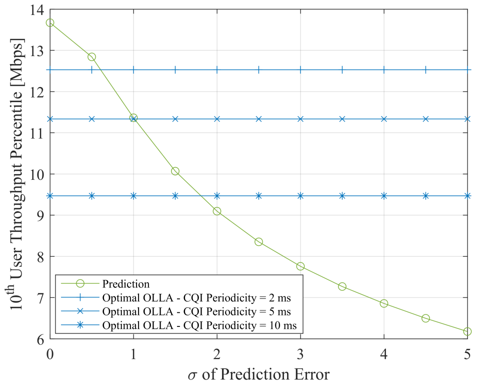

Fig. 3. Influence of prediction error on the 10^{th} user percentile throughput (eMBB) for UE Speed = 3 m/s.

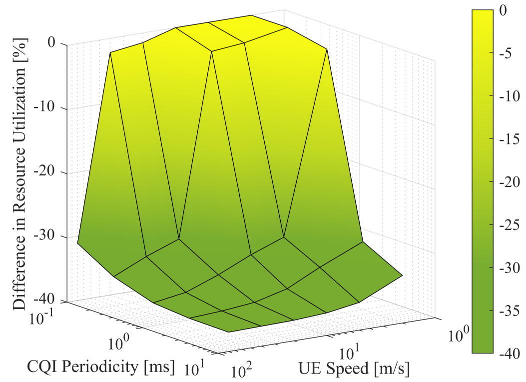

Fig. 5. Difference in resource utilization (URLLC) between *Perfect Prediction* and *Optimal OLLA*.

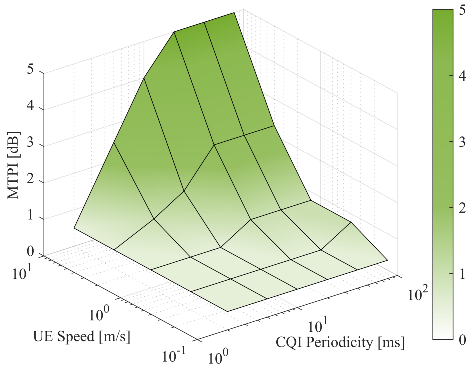

Fig. 4. MTPI for different scenarios considering eMBB use case.

packets required tenfold, theoretically. For fast moving UEs, *Optimal OLLA* is forced to choose a less aggressive MCS to cope with the channel outdatedness resulting in low throughput for the *Optimal OLLA* case, consequentially, the *prediction potential* is greatly positive.

MTPI: Naturally, the CQP techniques might not be 100% accurate. The more inaccurate they are, the less beneficial they become, as evident from Figure 3 where the 10^{th} user throughput percentile of prediction is plotted against a range of standard deviation (σ) along with that of *Optimal OLLA* for different CQI periodicities when the UE speed is 3 m/s. The 10^{th} user throughput percentile of *Optimal OLLA* does not depend on σ hence, the flat lines in Figure 3. However, as the CQI periodicity increases, the 10^{th} user throughput percentile achieved by corresponding *Optimal OLLA* reduces because the OLLA takes longer time to converge than when the degree of channel outdatedness is lower. As σ increases, the prediction error increases and consequently, the 10^{th} user throughput percentile decreases. For a UE moving at a speed of 3 m/s, a CQP technique with $\sigma \leq 1.5$ dB, would perform better than *Optimal OLLA* operating with a CQI periodicity of 10 ms. Thus, the MTPI equals 1.5 dB for this scenario.

Figure 4 presents the MTPI for different scenarios. This series follows a similar trend as the *prediction potential*. When the degree of channel outdatedness is low, the CQP has to be more accurate (σ = 0.5 dB) for it to be beneficial. On the other hand, when the degree of channel outdatedness is moderately high, a CQP technique with higher σ can outperform *Optimal OLLA*.

B. URLLC use case

Prediction Potential: The difference between the 90^{th} RU percentile of *Perfect Prediction* and that of *Optimal OLLA* to achieve the same BLER_{target} is shown in Figure 5 (Note: the X and Y axes' sequence of Figure 5 are different from that of the other figures). As in the case of eMBB, the KPI observed for *Perfect Prediction* is not influenced by the degree of channel outdatedness for URLLC use case either. However, as the degree of channel outdatedness increases, there is a steep increase in resources required by OLLA to achieve the BLER_{target} resulting in an increased difference in resource utilization between *Optimal OLLA* and *Perfect Prediction*. The reason is explained as follows. The *Optimal OLLA*, in an attempt to achieve the $BLER_{target}$, chooses a lower/robust MCS for transmission in order to overcome the outdated channel knowledge, resulting in an increased utilization of resources to transmit the same amount of data. The difference in RU tends to plateau because, the total number of CQI (and therefore, MCS) levels available are finite.

MTPI: Recall that the MTPI for URLLC use case is the maximum value of σ of prediction error that utilizes fewer resources while achieving the reliability constraint (99.999%). For URLLC use case, as the σ increases the reliability achieved decreases and, simultaneously, the RU increases. This effect is shown in Figure 6, where the influence of σ over reliability and RU for a UE speed of 3 m/s, is plotted. The increase in RU of prediction over the shown σ interval is insignificant when compared with the RU of *Optimal OLLA* for different CQI periodicities. In other words, from an RU perspective, prediction is always beneficial. However, the reliability of prediction drops with an increase in σ, and when $\sigma > 0.35$ dB, the $BLER_{target}$ is not achieved. Therefore, although the RU remains lower for higher values of σ, the MTPI for the scenario when UE speed is 3 m/s, is 0.35 dB. The prediction algorithms are required to be very accurate to

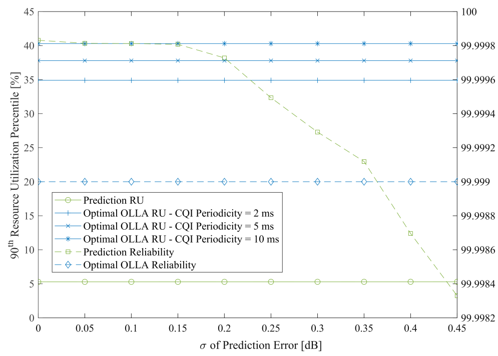

Fig. 6. Influence of prediction error on the 90^{th} resource utilization percentile (URLLC) and reliability (URLLC) for UE speed = 3 m/s.

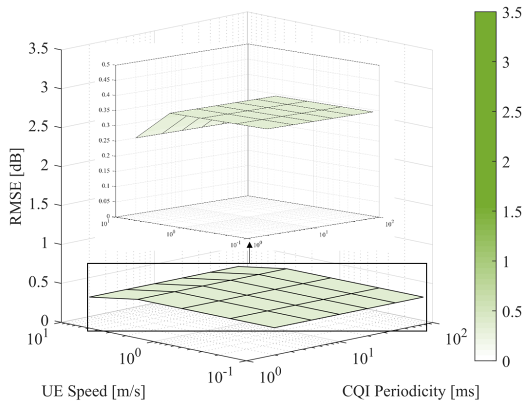

Fig. 7. MTPI for different scenarios considering URLLC use case.

an extent that the σ is expected to be between 0.25 and 0.35 dB as represented in Figure 7. It is interesting to note that when the degree of channel outdatedness is low, the prediction is required to be (slightly) more accurate than when the degree of channel outdatedness is high.

IV. Conclusions

Usefulness of CQP is analyzed for different UE speeds, CQI periodicity, and use cases. CQP is useful for eMBB in increasing the 10^{th} user throughput percentile (up to 125%) and reducing the number of CQI reports depending on the degree of channel outdatedness. Similarly, with URLLC use case, it is always beneficial to predict the wireless channel because it reduces the amount of resources required for communication (up to 37%). However, the CQP needs to be very accurate ($\sigma \leq 0.35$ dB) to reap the benefits, which is significantly more demanding than for eMBB use case where the CQP can be relatively inaccurate ($\sigma \leq 5$ dB). The results obtained serve as a guide to researchers in understanding the potential of CQP and thereby, aid in ascertaining the usefulness of novel ideas such as [14].

Acknowledgements

The authors would like to thank Maria Raftopoulou of TU Delft for generating the utilized BLER curves with The Vienna 5G Link Level Simulator [15] and Daan Middelkoop of the University of Twente for his analysis (even if excluded from the final version of the paper). This publication is funded partly by the Dutch Research Council (NWO) within the research programme Smart Industries under the project SUPREME (project No. 15467) and by the EU H2020 Research and Innovation Programme under the Clear5G project (grant agreement No. 761745)."

References

[1] 5G PPP, "5G and the Factories of the Future", 5G Infrastructure Public Private Partnership (5G PPP), Tech. Rep. [Online]. Available: https://5g-ppp.eu/wp-content/uploads/2014/02/5G-PPP-White-Paper-on-Factories-of-the-Future-Vertical-Sector.pdf 2015.

[2] P. Stenumgaard, J. Chilo, J. Ferrer-Coll and P. Angskog, "Challenges and conditions for wireless machine-to-machine communications in industrial environments", *IEEE Communications Magazine*, vol. 51, no. 6, 2013.

[3] Zukang Shen, J. G. Andrews and B. L. Evans, "Short range wireless channel prediction using local information", in *The Thirty-Seventh Asilomar Conference on Signals, Systems & Computers*, vol. 1, 2003.

[4] A. Chiumento, M. Bennis, C. Desset, L. Van der Perre and S. Pollin, "Adaptive CSI and feedback estimation in LTE and beyond: a Gaussian process regression approach", *EURASIP Journal on Wireless Communications and Networking*, no. 1, 2015.

[5] J. Joo, M. C. Park, D. S. Han and V. Pejovic, "Deep learning-based channel prediction in realistic vehicular communications", *IEEE Access*, vol. 7, 2019.

[6] J. Webber, N. Suga, S. Ano, Y. Hou, A. Mehbodniya, T. Higashimori, K. Yano and Y. Suzuki, "Machine learning-based RSSI prediction in factory environments", in *25th Asia-Pacific Conference on Communications (APCC)*, 2019.

[7] A. Zappone, M. Di Renzo and M. Debbah, "Wireless networks design in the era of deep learning: Model-based, AI-based, or both?" *IEEE Transactions on Communications*, vol. 67, no. 10, 2019.

[8] S. Jaeckel, L. Raschkowski, K. Börner and L. Thiele, "QuaDRiGa: A 3-D multi-cell channel model with time evolution for enabling virtual field trials", *IEEE Transactions on Antennas and Propagation*, vol. 62, no. 6, 2014.

[9] S. Jaeckel, N. Turay, L. Raschkowski, L. Thiele, R. Vuohtoniemi, M. Sonkki, V. Hovinen, F. Burkhardt, P. Karunakaran and T. Heyn, "Industrial indoor measurements from 2-6 GHz for the 3GPP-NR and QuaDRiGa channel model", in *IEEE 90th Vehicular Technology Conference*, 2019.

[10] 3GPP, "NR; Physical layer procedures for data", 3rd Generation Partnership Project (3GPP), Technical Specification (TS) 38.214. [Online]. Available: https://portal.3gpp.org/desktopmodules/Specifications/SpecificationDetails.aspx?specificationId=3216 2020.

[11] F. Blanquez-Casado, G. Gomez, M. del Carmen Aguayo-Torres and J. T. Entrambasaguas, "eOLLA: an enhanced outer loop link adaptation for cellular networks", *EURASIP Journal on Wireless Communications and Networking*, no. 1, 2016.

[12] E. A. Oyekanlu, A. C. Smith, W. P. Thomas, G. Mulroy, D. Hitesh, M. Ramsey, D. J. Kuhn, J. D. Mcghinnis, S. C. Buonavita, N. A. Looper, M. Ng, A. Ng'oma, W. Liu, P. G. Mcbride, M. G. Shultz, C. Cerasi and D. Sun, "A review of recent advances in automated guided vehicle technologies: Integration challenges and research areas for 5G-based smart manufacturing applications", *IEEE Access*, vol. 8, 2020.

[13] A. Chiumento, C. Desset, S. Pollin, L. Van der Perre and R. Lauwereins, "Impact of CSI feedback strategies on LTE downlink and reinforcement learning solutions for optimal allocation", *IEEE Transactions on Vehicular Technology*, vol. 66, no. 1, 2017.

[14] S. N. Anbalagan, F. Seraj and P. Havinga, "Towards factory schedule based adaptation for reliable networking in industrial IoT", in *IEEE 29th International Symposium on Industrial Electronics (ISIE)*, 2020.

[15] S. Pratschner, B. Tahir, L. Marijanovic, M. Mussbah, K. Kirev, R. Nissel, S. Schwarz and M. Rupp, "Versatile mobile communications simulation: The vienna 5g link level simulator", *EURASIP Journal on Wireless Communications and Networking*, vol. 2018, no. 1, pp. 1–17, 2018.