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Fading Channel Prediction for 5G and 6G Mobile Communication Systems

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***Abstract*—Nowadays, there is a trend to employ adaptive solutions in mobile communication. The adaptive transmission systems seem to answer the need for highly reliable communication that serves high data rates. For efficient adaptive transmission, the future Channel State Information (CSI) has to be known. The various prediction methods can be applied to estimate the future CSI. However, each method has its bottlenecks. The task is even more challenging while considering the future 5G/6G communication where the employment of sub-6 GHz and millimetre waves (mmWaves) in narrow-band, wide-band and ultra-wide-band transmission is considered. Thus, author describes the differences between sub-6 GHz/mmWave and narrow-band/wide-band/ultra-wide-band channel prediction, provide a comprehensive overview of available prediction methods, discuss its performance and analyse the opportunity to use them in sub-6 GHz and mmWave systems. We select Long Short-Term Memory Recurrent Neural Network (RNN) as the most promising technique for future CSI prediction and propose optimising two of its parameters - the number of input features, which was not yet considered as an opportunity to improve the performance of CSI prediction, and the number of hidden layers.**

***Keywords*—5G, 6G, channel prediction, channel state information, sub-6 GHz, millimetre waves, neural network, artificial inteligence, narrow-band, wide-band, ultra-wide-band**

I. Introduction & Motivation

THE Adaptive System (AS) development is one of the leading researchers' interests in recent years [1] and it is also reasonable to employ it in mobile communication, e.g., for adaptive wireless transmission. However, the application of AS in the fast fading channels is challenging because the Channel State Information (CSI) is outdated in most of the communication systems [2], [3]. While considering the Ultra-Reliable Low-Latency Communication (URLLC) or the fragile communication in milimetre waves (mmWaves), the knowledge about CSI before sending the information seems to be very meaningful and can protect from losing information. Thus, the author analyses the opportunity to predict channels in sub-6 GHz and mmWave bands considered in 5G and 6G mobile communication networks. The analyses are expected to be applicable for adaptive control of mutliconnectivity that simultaneously employs sub-6 GHz and mmWaves, e.g., in remote surgery or robot control. In these applications, the sub-6 GHz is considered for robustness and mmWave for high data throughput.

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The fading channel prediction deep analysis was provided in 2007 [3]. The author presents the State-of-The-Art of currently available techniques for fading prediction and provides some simulation results. However, the analyses are considered for Rayleigh and Rician fading, and they are usually not directly applicable to mmWave communication. Furthermore, the paper does not cover the Artificial Intelligence based prediction methods which are available now. Another paper, [4], provides an overview of the applicability of Recurrent Neural Network (RNN) for CSI prediction. However, the paper highlights the applicability of RNN for fading prediction rather than provide a survey of available methods (e.g., Convolutional Neural Network - CNN - approaches are not presented). In [5], authors present some predictors of fading channel in 5G. In contrast to [5], we consider two types of channels: sub-6GHz and mmWave. Furthermore, we answer one of the authors' conclusions and provide the results of employing prediction on the measurement data. In this paper, we present the comprehensive overview of sub-6 GHz and mmWave prediction with some results of applying the methods to the measurement data. To the best of the author's knowledge, there is no up-to-date overview that provides all available methods and discusses various frequency bands, sub-6 GHz and mmWave, which are considered in 5G and 6G systems.

The paper is organised as follows. In Section II., the fast fading channel is described. Section III. provides the prediction methods. In Section IV., the available solutions are discussed. Section V. presents our results. Section VI concludes the paper.

II. Fast Fading Channel

The fading is caused by multipath propagation [3]. While sending the unmodulated carrier at the frequency f_c via fading channel, the received noiseless complex signal is as follows:

$$c(t) = \sum_{k=1}^{K} A_n e^{j(2\pi f_k t + \phi_k)} \tag{1}$$

where K, A_k, f_k and ϕ_k are the number of reflectors (scatterers), the amplitude, the Doppler frequency shift and phase ($\phi_k = k_0 d : k_0 = \frac{2\pi}{\lambda}$ - the wavenumber, d - the distance between transmitter and receiver [6]), respectively. It is worth to notice that the variables A_k, f_k and ϕ_k fluctuate slowly in comparison to variation of $c(t)$ [7]. The fading statistics depends on the frequency band and the received signal is different for various bandwidths.

The mmWaves communication is considered between 6 GHz and 100 GHz. The channel differs from channels in sub 6 GHz wireless communication [8]. The mmWaves are more affected by blockage, clustering and ground reflection than sub-6 GHz bands [9]. The propagation phenomena are strengthened with frequency growth. The scattering is larger in mmWave frequencies than in sub-6 GHz because scattering appears on objects with a size similar to wavelength (act as a point source). The diffraction is impaired in mmWaves, and thus, the shadowing effect enhances. The objects that are much larger than mmWave length cause reflections. Hence, the objects that cause scattering in sub-6 GHz provide reflections of mmWaves. The mmWaves entails different fading statistics parameters and, usually, different statistical models.

The future 5G and 6G communication are expected to employ various bandwidths depending on the scenario. Thus, it is necessary to consider narrow-band (NB), wide-band (WB) and ultra-wide-band (UWB) communication in analyses. The description of fading varies between the systems. In the NB system, only one bin is considered and all Multipath Components (MPCs) are there [10]. In the WB system, several bins are considered and we can describe the statistic in each bin. In UWB systems not all bins are filled with MPCs and signal distortion shall be considered (further reading: [10]).

III. Prediction

The goal of the prediction is to predict $c(t)$ from (1) in the n-th period [3]. The prediction range is expected from one millisecond to a few milliseconds and is much larger than channel estimation (the long-range prediction). The prediction Mean Square Error (MSE) usually rates the prediction. Nonetheless, the prediction MSE does not reflect system performance in all adaptive systems, e.g., in the transmission antenna selection [11], and another rating shall be considered, e.g., bit error rate. The currently available prediction methods can be distinguished into five categories Classical-estimation-based methods, AR-model-based methods, SOS model-based, Basic Expansion Techniques and AI-based methods.

1) Classical-estimation-based Methods: The prediction of the stochastic process can be considered as one of the estimation problem [12, p. 12.7]. The estimator can be directly applied and the estimation of future sample can be found. One of the application is shown in [13], where Minimum MSE estimator is used. The main drawback of the classical-estimation-based methods is that the autocorrelation has to be known. For more information, please see [12, p. 12.7] and [13].

2) AR-Model-Based/ARMA-Model-Based Methods: In the AR-Model-Based Methods, the autoregressive model of order P is employed [12] and the prediction is provided by $\widehat{c}[n] = \sum_{k=1}^{P} d_k[n]c[n-k]$ [3], where $c[n-1], \ldots, c[n-P]$ are the previous channel gains, and $d_1[n], \ldots, d_P[n]$ are the slowly time-variant coefficients. The coefficients can be calculated by employing the MMSE criterion [14]. Please notice that if the channel gains are jointly Gaussian (e.g., Rayleigh fading process), the predictor is the Linear MMSE (LMMSE) predictor, and it is the optimal MMSE [12], [15] . In the AR methods, knowledge about the channel gain correlation function is necessary and is employed to calculate the coefficients [3]. In general, the function is not known [16] and has to be found by using the noisy channel observations. The AR model parameters can be estimated by one of the block data algorithms or the sequential data algorithms which are also used in spectral analyses [16]. *The block data algorithms* take a fixed block of time samples, and they are convenient for the scenarios where we do not know which AR model order is best, and there is an opportunity to examine various orders. The most popular block data algorithms are : Yule-Walker Method, which is the correlation function estimation method, [17, sec.I.], [18, ch.3.4.1], [16, ch.8.3]; Burg Method, which is the reflection coefficient estimation method, [19, p.47-58], [20, Alg. 1]; Modified Covariance Method (MCM), which employs the combined minimization of the forward and backward linear prediction squared errors, [16, ch.8.5.2]; two methods, which use the separate minimization of the forward and backward linear prediction squared errors: Covariance Method (nonwindowed - only available data samples are used) [16, ch.8.5.1] and Autocorrelation Method (windowed - uses available and future data - unavailable data is set to zero) [16, ch.8.5.1]. The sequential data algorithms operate on the data sequentially and are advantageous in scenarios that include continuous tracking or adaptation of a slowly varying process. The three most common sequential data algorithms types are as follows: Least-Mean-Square (LMS) Methods, which is one of the gradient adaptive AR methods [16, ch 9.3]; Recursive Least Squares (RLS) Methods, e.g., Classical RLS method, Fast RLS methods, which uses RLS to estimate prediction parameters [16, p. 9.4]; Fast Lattice AR Methods, which employs lattice filter and reflection coefficients [16, ch 9.5]. The scenario shall drive the algorithm choice.

The AutoRegressive Moving Average (ARMA) model, which is the widely known model that describes time series (e.g. used in economy [21]) , is also the powerful tool for channel prediction [22], [23]. It is also possible to assume the channel impulse response as a sum of damped oscillators, and merge the AR part and Moving Average (AM) part to end with an ARMA innovation model (details in [24, ch 2.5]). The study of linear channel prediction by AR and ARMA models is provided in [24] which was published in 2002, and many hints for future prediction applications can be found.

3) SOS Model-Based or Parametric Radio Channel Model Prediction: The parametric radio channel (RC) model employs a physical propagation process approximation and is described by the transfer function $T(t, f_c) = T(t) = \sum_{i=1}^{d} \gamma_i e^{j2\pi v_i t}$ [25], where γ_i, v_i and d are the complex path weight, the Doppler Shift and the number of the most dominant multipath components, respectively. The most widely known spectral estimation methods are MUltiple SIgnal Classification (MUSIC) and Estimation of Signal Parameters via Rotational Invariance Technique (ESPRIT) [3]. In the MUSIC, an autocorrelation matrix and the eigenvalues are used [26]. There is also the modified version of algorithm, Root-MUSIC. For more information, please refer to [26, ch. 8.6.3] or [18, ch 4.5]. The application of the MUSIC and Root MUSIC methods for channel prediction are shown in [25], [27]–[31]. ESPRIT is based on the rotational transformation [18, ch.4.7]. The ESPRIT has similar accuracy to the MUSIC [18]. There are some modifications of ESPRIT as, e.g., Unitary-ESPRIT [32] or reduced complexity ESPRIT [28]. Another approach is to employ compressing sensing technique, as e.g., Fast Iterative Shrinkage-Thresholding Algorithm (FISTA) [33]. The FISTA algorithm spread the arrival signal into multipath components in the delay domain.

4) Basic Expansion Techniques: Basis Expansion Model is a deterministic model useful in scenarios with significant multipath signals [34]. The bases or base waveforms together with constant parameters (time-invariant) can describe the channel. Some papers [35]–[37] employ the band-limited stochastic process [3]. Another paper [38] uses the modal expansion method where the wave propagation physical equation is considered.

5) AI-based methods: The AI methods are applicable to wireless communication [39] and can be used to predict the wireless channel quality.

Neural Network Based Methods: The channel prediction problem is usually considered as a regression problem solved by learning-based reconstruction algorithm [39]. The problem can be analysed as the reconstruction of the signal propagation in an environment or a reconstruction of a time series.

The former concept requires information about scenario, e.g., transmitters, receivers, buildings, frequencies, and radio measurements. The solution effectiveness is verified in [39]. However, selecting the features, and the training algorithm is not trivial. The example of the solution is shown in [40], where the *CNN* is used. Although, the NN methods based on the signal propagation in an environment are not further discussed in this paper as it requires more data than the methods which consider CSI as a time series. For further reading, please refer to [39, ch. 3.3.1.2].

In the latter concept, we only require recent data of the time series we want to predict, e.g., SNR or CIR, and design the efficient NN method. The feature engineering is much easier as the input features are the time series old samples (only the number of features or their delays can be chosen). However, we still need to select the training algorithm and its parameters. The commonly used channel prediction NN is *RNN*. The opportunity to employ the RNN to predict the samples of time series is shown in [41]. In [2], the RNN prediction schemes are further discussed. Author rates the RNN as the efficient but the high computational complexity approach to predict future CSI. However, the computational burden is expected to be doable for an available commercial off-the-shelf hardware.

Another approach that employs time series concept is the application of *Feed Forward Neural Network (FFNN)* as proposed in [42]. However, the application of FFNN for prediction is not commonly used concept.

Support Vector Machine Based Methods: The Support Vector Machine (SVM) based methods find the mathematical function that described the channel [39]. The main advantage is that there are no local minima in the optimization process. Another benefit is the opportunity to control the error rate and the opportunity to find sparse solutions. The idea is to reconstruct the map of the signal propagation based on the function. Although, it is a very complex task. More information about this concept can be found in [39, ch. 3.3.1.1.].

Matrix Completion Based Methods The matrix completion methods are based on the concept of map reconstruction of the considered area [39]. The precision of the approaches is high. However, the cost is high complexity and issues with scalability. Some of the available algorithms are nuclear-norm-based algorithms, alternating projection methods. The methods are described in [39, ch. 3.3.1.3.] and the discussion is also provided.

IV. SOLUTIONS & PERFORMANCE

The solutions and results are analysed depending on their usability in future communication real applications. The analyses are divided into sub-6 GHz, mmWaves and separately for wide-band & ultra-wide-band systems.

1) Sub-6 GHz: In [29], authors analyse the simulation and performance bounds for NB fading channel real-time prediction for $f_c = 1.92$ GHz and $f_c = 5.9$ GHz. It is shown that the updates of fast fading parameters are necessary because the error grows when the statistic is outdated [29, Fig 2.]. The authors also presents the maximum prediction range based on Cramer Rao Lower Bound (CRLB) [29, Fig 3.]. They state that the prediction is feasible for NB fading channels.

[43] provides the results of the Rayleigh channel modelling by AR and SoS. The results show the impact of the AR model configuration and present a comparison of the aforementioned methods. From the perspective of the future system design, it is worth notice that the relation between model order and prediction MMSE is $\sigma_p^2 \sim k[sin(\pi f_d T)]^{2p}$ where σ_p^2 - one-step prediction MMSE, k - constant, p - model order, f_d – Doppler frequency, T – sampling period. It is shown that the SoS method is more complex than AR method.

In [25], authors examine some classical prediction approaches on Jakes's Model at the centre frequency 900 MHz and for measured real channel envelopes at the centre frequency 5.2 GHz (600 MHz bandwidth). In the Jakes's Model based analyses [25, Fig 1.], it is provided that the Unitary-ESPRIT has the best performance. It is also interesting that the performance for different prediction ranges is similar. In contrast to RC methods, the results of AR methods vary for different prediction ranges, and a shorter prediction range entails better performance. The best performance is achieved by the MCM for the AR model. However, the performance is still worse than the performance of Unitary-ESPRIT. Please notice that the MCM is usually used for the AR model but can also be used for the parametric radio channel model. While comparing the methods' envelope prediction range for different scenarios (based on Dersch's model) [25, Fig. 2], the MCM are efficient for almost all scenarios, and the Unitary-ESPIRIT performs well only for rural areas. [25, Fig. 2] is very interesting in terms of designing the system in the desired scenario.

Authors propose the technique for the channel estimation and long-range prediction for adaptive-orthogonal-frequency-division-multiplexing (AOFDM) in [44]. The frequency-selective wireless fading channel is described by the first-order

AR model (the tapped-delay-line-filter is employed). The AR coefficients are tracked by the generalised-variable-step-size LMNS (GVSS-LMS) based algorithm. The fading compensation is provided by a modified-Kalman-filter (MKF) based approach. The prediction is provided by numeric-variable-forgetting-factor RLS (NVFF-RLS) algorithm. The approach is compared with modified-Kalman-filtering [45], fixed-step-size LMS [26] algorithm with Fixed-Forgetting-Factor RLS (FFF-RLS) prediction [46] (MKF-FSS-LMS/FFF-RLS). The freshly designed MKFF-GVSS-LMS/NVFF-RLS outperforms MKF-FSS-LMS/FFF-RLS. The paper shows that there is still the opportunity to improve the classical methods.

In [47], the method to predict the NB channel is proposed and the impact of the training method on performance is examined. The Fully Connected RNN (FCRNN) is used together with three learning methods separately: the Real-Time Recurrent Learning (RTRL), the Global Extended Kalman Filter (GEKF) and the Decoupled Extended Kalman Filter (DEKF). It is shown that the RTRL complexity is reasonable in this application [37]. However, it uses the gradient method with first-order derivatives, and the convergence speed might be slow while comparing to the second-order derivatives based methods [48]. The basis of the second-order methods is formed by the Extended Kalman Filter (EKF). The main concept is to estimate the covariance matrix (which contains the second-order information about the training problem) and update it. The EKF is considered as a basis of computationally efficient NN training techniques (e.g., GEKF, DEKF) that enables FNNs and RNNS in various applications, e.g., pattern classification, channel equalization, control. It is shown that GEKF and DEKF converge faster than RTRL. The training is crucial in NN methods.

Authors in [49] propose to employ the Long Short-Term Memory (LSTM) based method, which is one of the RNN, for channel prediction in vehicular communication. The measurement samples of the IEEE 802.11p transmission with a centre frequency equal to 5.86 GHz are used for experiments. It is shown that the LSTM based approach outperforms the classical AR approach in both scenarios. It is worth noticing that the rapidly varying fading (high Doppler shift, dynamic scenario) is considered in the experiment.

In [50], authors develop another LSTM based prediction approach for vehicle-to-everything (V2X) communication system. The system is presented as an efficient approach for spatio-temporal channel parameters correlation analyses. The extensive simulations are performed, and the good performance of the approach is shown. Authors consider the Rayleigh fading. The analyses of the impact of speed of vehicle, SNR and Doppler frequency shift are shown. The speed of the vehicle and sampling rate do not affect the result significantly. The LSTM and ARIMA are more SNR sensitive than the SVR algorithm. All the methods' performances depend on the maximum Doppler frequency shift. However, the NMSE does not grow rapidly in all cases. In all results, we see that the LSTM outperforms other methods.

[42] compares the proposed BackPropagation Neural Network (BPNN) with Discrete Wavelet Transform – AR – Linear Regression (DWT-AR-LR, extension of AR model method) method, SVM method and Echo State Network (ESN) method. The BPNN outperforms the other methods, while holding low complexity. It is also shown that the method works best for Jakes's model while comparing to SCM Model and Clarke/Gan Model. It is also shown that the DWT-AR-LR prediction is more accurate than the prediction by classical AR model. The proposed method can be used together with a short pilot which matters in a resource-limited system.

2) mmWave: [51] provides the prediction of the mmWave channel downlink effective rate by employing Maximum Likelihood Estimator (MLE). They calculate the channel error covariance and use it to predict the future channel rate. The concept is verified by 28 GHz mmWave outdoor channel model-based simulations. The approach improves the effective downlink rate by reducing pilot transmissions.

In [52], authors analyse the channel prediction in the ground-to-air link under blockage in mmWave bands. The AR model with the Euclidean distance-based algorithm is used, and the ray-tracing simulations are performed. The comparison of the new prediction approach to the AR only based methods and RNN is provided. In terms of MSE and MAPE (Mean Absolute Percentage Error), the new prediction approach outperforms AR only and RNN methods. RNN performs better than AR only method. The cost of the new approach is increased complexity while comparing to other methods.

Authors provide LSTM based method for predicting multi-directional link quality in mmWave systems in [53]. The multi-connectivity is considered. The method is examined on the simulated data at 28 and 140 GHz and measurement data at 60GHz. In the prediction for one base station (BS) and a single trajectory at 28 GHz, LSTM outperforms the MA prediction. Furthermore, LSTM is less sensitive to modification of carrier frequency than the MA method. The received power is considered in analyses based on measurement data. The mean RMSE of LSTM is lower in all considered cases in comparison to the MA method results. The authors state that the prediction of mmWave link requires predicting link quality from multiple cells and multiple directions. The complex dependencies in time and across links shall be considered. Thus, the classical methods are challenging to apply.

The LSTM network for CSI prediction for a vehicular user is employed in [54]. The results are based on the ray-tracing simulation at 60 GHz, and the speeds between 10 m/s and 30 m/s are considered. The solution is used in Cloud/Centralized Radio Access Network (C-RAN). The vector of channel estimates of each BS is predicted, and the prediction values are used for beamforming. It is shown that the LSTM-based approach provides accurate prediction and provide a similar result to the traditional beam training scheme with lower pilot overhead.

In [55], authors examine Blind CSI Prediction Method based on NN (BCPMN, which employs CNN and LSTM) in Vehicle-to-Infrastructure (V2I) scenario. The paper employs Rician channel model, $f_c = 62.5$ GHz and $v = 320$ km/h. The weakness of the classical methods, e.g., ARIMA algorithms, is highlighted. The coherence time decreases with the increasing speed [56], and the mmWaves bands (high frequency) entails high Doppler spread. Thus, the classical approaches cannot track the rapidly changing channel impulse response. One of the main advantages of the BCPMN is that it does not need a pilot sequence to build channel statistics and predict the future CSI (it uses raw receive signal). The comparison to methods proposed in another papers (LSTM [49], [50]; OCEAN [57]) is shown. BPMN performs better than other methods, and the OCEAN method is still better than the LSTM method. Furthermore, for low SNR the difference in performance is smaller than for high SNRs. The prediction is feasible for the vehicle driving with 60 km/h, 120 Km/h and 320 km/h speed.

Authors in [57] discuss the CSI prediction for future 5G mobile communication systems ($f_c \in < 3, 300 > GHz$). They propose an online CSI prediction scheme (called OCEAN, which employs CNN and LSTM) and design a learning framework. The transmission and scenario parameters that have a major impact on the CSI and, in consequence, the prediction performance are highlighted (frequency band, location, time, temperature, humidity, weather). The parameters are considered in OCEAN design. The training approach is also proposed: the offline-online two-step training mechanism. The OCEAN method is examined in four case studies: a free space environment, outdoor environment with obstruction, workroom and building. The measurement data contains CSI data in 2.4 GHz and 5 GHz frequency bands (WiFi). The OCEAN method is almost as good as the ML-based algorithm in prediction accuracy and needs less computing time to predict the CSI for multiple channels. The MMSE-based method is much more accurate than OCEAN and ML-based approaches, but it needs more processing time.

3) Wide-band & ultra-wide-band: In [58], authors analyse the prediction in WB communication. The statical channel model is used and the velocity is constant. The ESPIRIT-type methods are employed and the results show that the prediction is more accurate than the prediction over a single frequency.

The SOS method is used in [33] for channel prediction of WB OFDM system. The simulation is based on 28 GHz non-light-of-sight model. Authors employ FISTA and compare the results to commonly used Inverse Discrete Fourier Transform (IDFT). It is shown that for bandwidth equal to 200 MHz and 400 MHZ both methods performs similarly. In the 800 MHz scenario the FIST method outperforms significantly IDFT method.

The analyses of UWB prediction is provided in [59]. The authors propose an efficient prediction framework for UWB and compare the performance to ITU-R UWB-CIR model. The prediction of CIR is provided by RLS algorithm. The analysis is based on measurement data of 2.2 GHz bandwidth at 3.1-5.3 GHz (outdoor environment). The proposed method achieves 15% lower prediction rate, and it is 12 times less complex than employing IRU-R UWB-CIR model.

Authors in [4] employ the prediction for a frequency-selective WB communication system. 3GPP Extended Vehicular A (EVA) and Extended Typical Urban (ETU) channel models are considered. The proposed RNN is expected to be used in MIMO-OFDM system. The Monte-Carlo simulations are used to examine the approach. The solution is effective, able to conduct multi-step prediction and more robust to

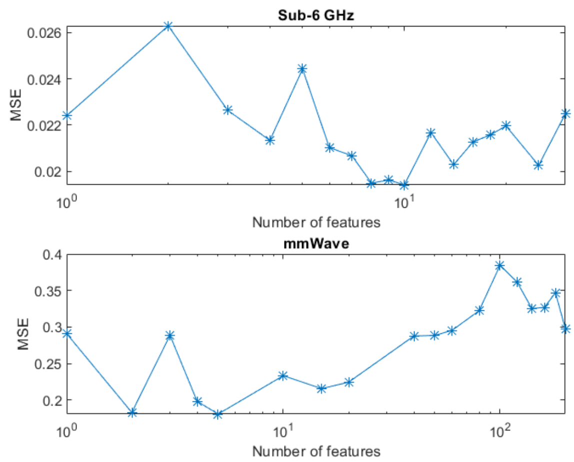

Fig. 1. The MSE for various number of LSTM input features; LSTM: 4 layers: sequence input, LSTM, fully connected, regression output; Adam (epochs: 300, grad. thresh.: 1, init. train. rate: 0.05, drop after 200 epochs, dropping factor: 0.2), init. weight: zeros, bias: one.

interpolation errors while comparing to the Kalman filter. However, the computational complexity is higher.

V. Our Results: LSTM

It was shown that the LSTM outperforms AR for both sub-6 GHz [49], [50] and mmWave frequencies [53]. The structure and description of LSTM can be found in [50, Fig.3] and [60]. The number of LSTM layers, the number of hidden units, the time step length of prediction is already compared for sub-6 GHz measured data [49]. The impact of the Tx/Rx speed, sampling rates, Doppler shifts and SNRs are analysed in [50] for simulated data (Rayleigh channel). In [53], it is shown that LSTM outperforms the MA method in the analyses based on measurement data (60 GHz). However, the LSTM network input size is constant in the aforementioned solutions, and its impact on the results is not examined. While considering the strongest correlation between consecutive samples (which might be not pointed enough in short memory), it is reasonable to use the last several samples for future values prediction. Thus, we examine the impact of the number of samples on results for both sub-6 GHz and mmWave bands. Moreover, we tested the impact of the number of hidden units in the mmWave band, which was not checked yet.

a) Sub-6 GHz: The measurement from University of California Santa Barbara is used [61]. The signals were measured in the building at 2.4 GHz (WiFi). The details about measurements can be found in [62]. We test the impact of input feature number and number of hidden units in LSTM. We expect to employ the robot's communication. It is assumed that the robot measures the short period of signal and then uses LSTM to predict the Signal-Noise-Ratio (SNR) for adaptive transmission to send crucial instructions.

The MSE varies for the different number of input features (Fig. 1, top).The lowest MSE is achieved for ten input features (0.0194). The second-best result is achieved for eight input features (0.0195). The MSE for single feature is higher (0.0224).

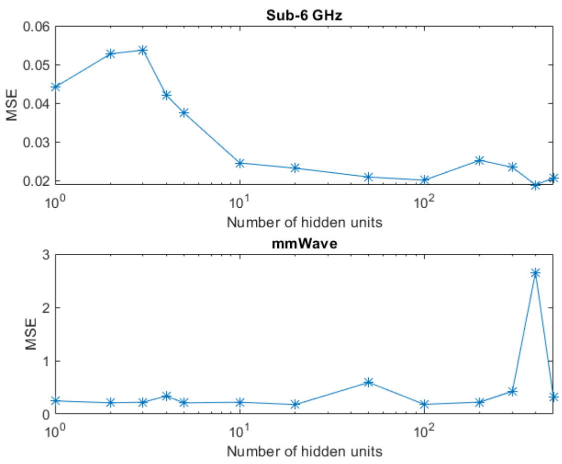

Fig. 2. The MSE for various number of LSTM hidden layers; network is same as for 1 and: features - mmWave: 5, features - sub-6 GHz: 10.

The MSE decreases when the number of hidden units grows over three (Fig. 2, top). The best result is achieved for 400 hidden units (0.0189). The MSE for one hidden unit is 0.0441. The second achieved result is for 100 hidden units (0.0202). It shall be considered that the training time increases while increasing the number of hidden units and the maximum is set to 500.

b) mmWave: The measurement from NG CMA database [63] is used. The measurement is provided by Department of Information Technology, Ghent University & IMEC, and was recorded in the working engine room of the vessel [64]. The carrier frequency is 60.48 GHz, and the transmission is based on IEEE802.11ad. More details can be found in [64] and in the measurements' folder on NG CMA website [63]. The impact of feature number and hidden units number are examined. We assume that the channel is measured for a short period, and then the SNR is predicted by LSTM to send the crucial data.

The MSE is different for the various number of features in Figure 1 - mmWave. It can be seen that one feature is not the best choice, and it is reasonable to improve the number of features. Figure 1 shows that the best choice for our scenario is 5 features (0.1807). It can also be seen that even if we increase the number of features to 2 (0.1828), the performance increases (1 feature: 0.291).

The hidden units are examined with constant training epochs number (300) to assume the limited time for training. The MSE varies for different number of hidden units (Figure 2,bottom). Some of the numbers yield very low performance (4: 0.336; 50: 0.5922, 400: 2,655). Three lowest MSE are: 0.1766 (20 hidden units), 0.1807 (100 hidden units), 0.2102 (5 hidden units).

VI. Conclusions

In this paper, a comprehensive overview of currently available prediction methods is provided. The analysis contains sub-6 GHz, mmWaves and various bandwidths. In most of the simulations, the RNN methods outperform other methods. The LSTM seems to be the most promising method for CSI prediction in sub-6 GHz and mmWaves. The employment of RNN is also reasonable in the wide-band communication system. However, classical methods are still most common in this application. The wide-band/ultra-wide-band is still not well investigated, and there is a potential to provide more experiments. Sub-6 GHz and mmWaves experiments are mainly carried out on the simulation data. More analyses on the measured data (especially for mmWave channel prediction) are expected to be beneficial for future system design.

In this paper, author used sub-6 GHz (2.4GHz) and mmWaves (60.48 GHz) measurement data and drew two conclusions. The performance of the LSTM can be improved by using more than one input feature in both bands: sub-6 GHz and mmWaves, and the number of hidden units have significant impact on the performance in sub-6GHz and mmWaves.

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