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Wireless Channel Prediction Using Artificial Intelligence with Constrained Data Sets

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CISTER-TR-220609

2022

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Abstract

This work deals with the study of artificial intelligence (AI) tools for purposes of vehicular wireless channel prediction. The objective is to test the ability of different types of AI and machine learning (ML) algorithms under different types of implementation constraints. We focus particularly in highly changing scenarios where the channel state information changes relatively fast and therefore the relevant measurements or long-term statistical models are therefore scarce. This means that the training of our models can be potentially inaccurate or incomplete and we need to investigate which AI algorithm behaves better in this challenging condition. In future work we aim to investigate also computation complexity constraints, real-time deadlines, and outdated/distorted or noisy data set samples. We also aim to correlate the main properties of the well-known Jakes' channel model with the effectiveness of the type of prediction and the parameters of the different algorithms being tested. The objective of channel prediction in vehicular networks is to reduce allocation and transmission errors, thereby reducing latency and improving message transmission reliability, which is crucial for future applications such as autonomous vehicles. Results show that even in situations with incomplete data sets, AI can provide good approximate predictions on the channel outcome,

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***Abstract*—The work in this paper deals with the study of artificial intelligence (AI) tools for purposes of vehicular wireless channel prediction. The objective is to test the ability of different types of AI algorithms under different types of implementation constraints that will be typical of vehicular applications. We focus particularly in scenarios where the channel changes relatively fast and therefore the relevant measurements or long-term statistical models are scarce. This means that the training of our models can be potentially inaccurate or incomplete and we need to investigate which AI algorithm behaves better in this challenging condition. In future work we aim to investigate also computation complexity constraints, real-time deadlines, and outdated/distorted or noisy data set samples. We also aim to correlate the main properties of the well-known Jakes' channel model with the effectiveness of the type of prediction and the parameters of the different algorithms being tested. The objective of channel prediction in vehicular networks is to reduce allocation and transmission errors, thereby reducing latency and improving message transmission reliability, which is crucial for future applications such as autonomous vehicles. Results show that even in situations with incomplete data sets, AI can provide good approximate predictions on the channel outcome. LSTM in multi-step and CNN in single-step between implemented algorithms have better performance and lower error in prediction.**

***Index Terms*—channel prediction, artificial intelligence, Jake's model.**

I. Introduction

The proliferation of the Internet of Things (IoT) in industrial applications has revealed the importance of a wireless layer that provides ubiquitous, reliable and real-time connectivity. One important aspect of this wireless layer is the ability to detect/estimate/predict channel propagation variations and respond effectively to such changes (adaptation). Channel prediction can be used for a variety of purposes that range from reduction of training bandwidth, improved channel estimation or equalization, improved resource allocation, reduced latency, anomaly detection, obstacle prediction, etc.

The majority of works on channel prediction has considered ideal scenarios with complete data sets that capture the majority of statistics and variations of channel components. However, in practice, particularly in vehicular networks with high Doppler shifts, channel statistics can change too fast, and therefore the amount of data to perform the correct scenario detection, training model selection and/or training process are incomplete and/or inaccurate.

The paper in [1] focused on multi-step prediction for Rayleigh channels using convolutional neural networks (NNs) and deep learning. The paper in [2] has focused on the existing prediction schemes based on statistical modeling and neural networks(NNs) for fading channels and impact of outdated channel state information (CSI) on the performance of a wide range of wireless systems. The authors not only investigated the existing neural network(NN) algorithms for channel prediction but they proposed a novel MIMO (multiple-input multiple-output) channel predictor build on a deep recurrent neural network(NN) that incorporates LSTM (long short-term memory) or GRU (gated recurrent memory) cells. Deep learning channel prediction for railway MIMO communications has been presented in [3]. Channel prediction based on NNs for dedicated short range networks in real time is presented in [4]. Massive MIMO prediction for mm-wave channels has been presented in [5].

This paper attempts a comparison between different types of algorithms for channel prediction particularly when the data sets for training are incomplete or when the only information available is a few channel measurements collected by the terminal. We provide bench marking with the conventional linear regression tools. The channel used is the well-known Jake's model that consists of a sum of sinusoids which generates an equivalent Rayleigh fading channel. The objective of our work is to investigate complexity and practical implementation issues. This means we look at practical constraints such as reduced data sets, noisy samples, and under-sampled channel functions. This paper reports the initial stage of this task in the context of the European research project InSecTT (Intelligent Secure Trustable Things) [6], which aims to bring realistic AI tools for different applications of the Internet of Things, with high emphasis on reliable and trusted AI layers.

The organization of this document is as follows. Section II describes the vehicular scenario with constrained data sets for channel prediction. Section III introduces the channel model to be used. Section IV presents the summary of the different algorithms used for channel prediction and preliminary results. Finally, Section V provide the final view and discussion of the presented results as well as future problems to be addressed with the the research project InSecTT.

Notation. Scalar variables are denoted by lower case letters.

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The variable i represents the imaginary number $\sqrt{-1}$, $E[\cdot]$ is the statistical average operator, $\mathcal{CN}(\mu, \sigma^2)$ denotes a complex circular Gaussian distribution with mean μ and variance σ^2.

II. Scenario description

We consider a vehicular networking scenario with one base station and a constant speed vehicle as shown in Fig. 1. It is assumed that the channel samples are measured by the receiver at a given sampling rate $f_s = 1/T_s$. Fig. 1 shows two options to achieve channel prediction. The more conventional approach (show on the left hand side of the figure) consists of a feature extraction mechanism that allows us to select a long term channel statistics and thus use a pre-trained neural network or machine learning model. The second approach which involves less computational complexity is to use the available channel samples to perform the training of the model. The intention is to achieve a prediction with only a few samples and without the need to select the pre-trained model. The argument is that the first option is optimum for channels that do not change rapidly in time, while the second option can be used in highly changing scenarios that are typical of vehicular networks with high vehicle speeds. This paper focuses on the second option, where the available channel samples are used instantly to train an AI model that is used to predict future samples.

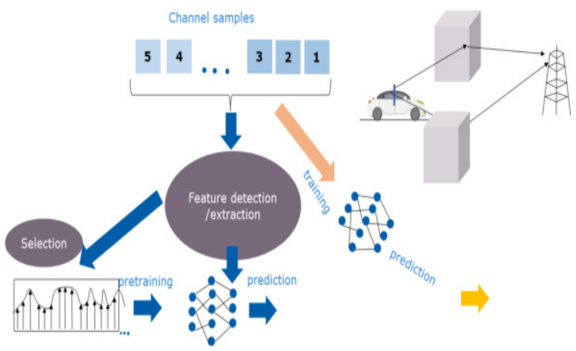

Fig. 1. Scenario for vehicular channel prediction using AI.

III. Channel model

The Jakes' channel model is perhaps one of the most basic channel models used in the literature of wireless communications. It consists of a sum of sinusoids (complex) with random phase, mimicking an environment with isotropic and uniform scattering [7].

$$h(t) = \sum_{k=1}^{N_s} C_k e^{i\pi F_d \cos(\alpha_k)t + \theta_k}, \quad (1)$$

where F_d is the maximum Doppler frequency, θ_k is a random phase, N_s is the number of scatterers, C_k is a normalization

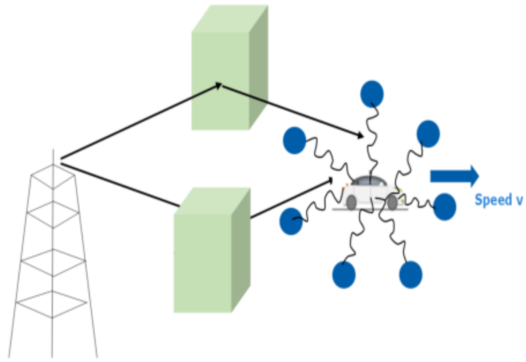

Fig. 2. Channel model

factor, t is the time domain variable (real number), and α_n is the angle of arrival of the signal of the kth ray (See Fig. 2).

Thanks to the central limit theorem, when the number of scatterers is high, the received signal in the Jakes' model tends to a circular Gaussian complex random variable, which is also known as Rayleigh fading channel. This means $h(t) \sim \mathcal{CN}(0, 1)$. This model generates a cross-correlation function given by the Bessel function of order zero $R(\tau) = E[h^*(t - \tau)h(\tau)] = J_0(F_d\tau)$. The spectral characteristics of the Jake's model provide us with the first hint on the performance of channel prediction. If the channel process is under-sampled or below the maximum Doppler frequency, errors in the recovery of the waveform will start to arise. In general, communication systems are designed for packet and training sequence transmission that correlate with the channel coherence time. This ensures that the sampling frequency is enough to recover the waveform. However, high Doppler scenarios could lead to the problem of under-sampling and thus prediction errors will increase. In all the results of this paper we assume a vehicle speed of 30 km/hr using an operational frequency of 6GHz and a sampling period of 2 ms. In all cases, it is assumed that the terminal only has a handful of channel measurements to perform the prediction operation using either conventional regression of artificial intelligence algorithms.

The properties of the data set are given in table I. In the remainder of this paper, the sampled channel amplitude $h(nT_s)$ can be simply regarded as the variable y and the time variable t as the x variable to simplify representation on the Cartesian coordinates.

TABLE I
DATASET SETTING

Parameter	Value(unit)
vehicle speed	30 (km/hr)
frequency	6 (GHz)
sampling period	2 (ms)
number of scatterers	20
number of samples	29

IV. Prediction Algorithms

A. Linear and polynomial regression

Linear regression is a basic and widely use type of predictive analysis which usually works on continuous data [8]. The model assumes a linear relationship between the input variables x and the single output variable $y = |h(t)|^2$. Input variables are independent of each other. Linear and polynomial regression are used to predict channel values in Fig. 3. In this case, the polynomial regression with 10 degree can follow the train data better, and the MSE (mean square error) achieved by this algorithm is 0.2781 for training data and 241.3399 for testing data. Due to the error being too much, the regression cannot be used to predict the next step of the channel.

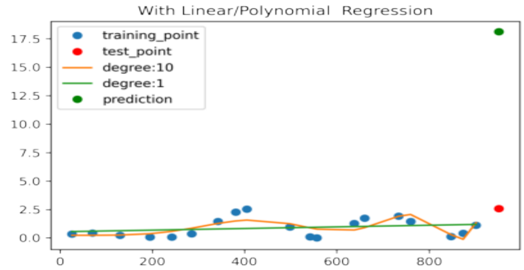

Fig. 3. Channel pred. by using Linear and Polynomial Regression.

B. B-Spline interpolation method

B-spline or basis spline is a curve approximation method based on given coefficients. Any spline function of given degree can be expressed as a linear combination of B-splines of that degree, as shown in $y(x) = \sum_{j=0}^{n-1} c_j B_{j,k,t}(x)$, where $B_{j,k,t}(x)$ are B-spline basis functions with k degree and knots t, and c_j are the spline coefficients or control points. The result of implementation of B-Spline interpolation algorithm is depicted in Fig. 4. In this method, the MSE obtained was 0.0611 for training data and 1.9517 for testing data.

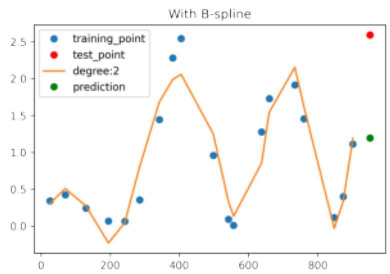

Fig. 4. Channel prediction by using B-Spline interpolation algorithm.

C. Convolutional Neural Network (CNN)

In the following we use the forecasting time series idea by implementing CNN algorithm, built through the TensorFlow library in Python.

CNNs are very similar to ordinary Neural Networks(NNs). They are made up of neurons that have learnable weights and biases. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity.

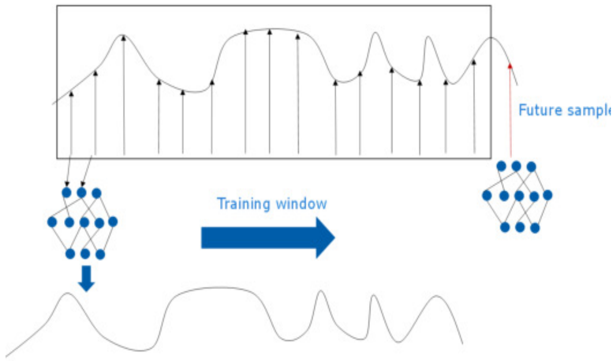

Fig. 5. Prediction with NNs

In forecasting time series, it is possible to employ two type of models: single and multi-time step. In single step model, only a single future point is predicted but a multi-step model predicts a sequence of the future values. The first can use a single feature or all features, and the second can use single-shot, i.e. make predictions all at once or use auto-regressive, where one prediction is obtained at a time and its value is fed to the model. AN example with single step is shown in Fig. 5.

We use CNN and a traditional fully connected layers architecture with ReLu as activation function in all neurons. First, the CNN was implemented using single step. By compiling the model and fitting it to our train data, we can predict the next window as shown in Fig. 6. In this case, the MSE is 0.1144, and the loss is 0.0132.

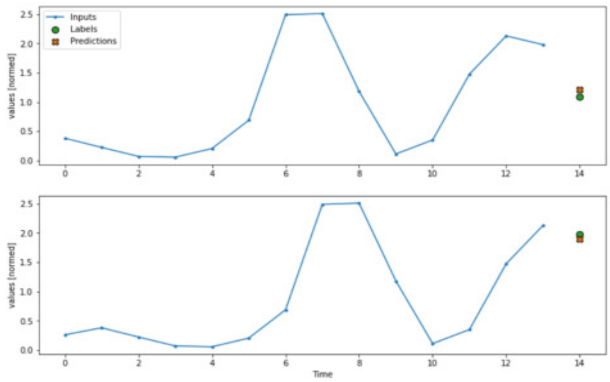

Fig. 6. Prediction with CNN by using single step

D. Recurrent Neural Networks (RNN),k (LSTM)

RNN is a good choice because this architecture has the capability to process sequential data by storing indefinite historical information in its internal state [9]. The key of RNNs is to apply the same type of operations (weight sharing) at each time instant (recurrence) by involving the state as well as the currently available input vectors. LSTM architecture introduce special units called memory cells in the recurrent hidden layer and multiplicative gates that regulate the information flow. The result of implementing RNN-LSTM algorithm with TensorFlow library in Python is shown in Fig. 7 with 100 epoch (number of iterations over the entire training set), where the loss is 2.5856 and has 1.2737 of mean absolute error. Fig. 8 shows that if we increase the epoch, prediction becomes more accurate, but we see overfitting (the model does not generalize well from training data to unseen data) in our training data.

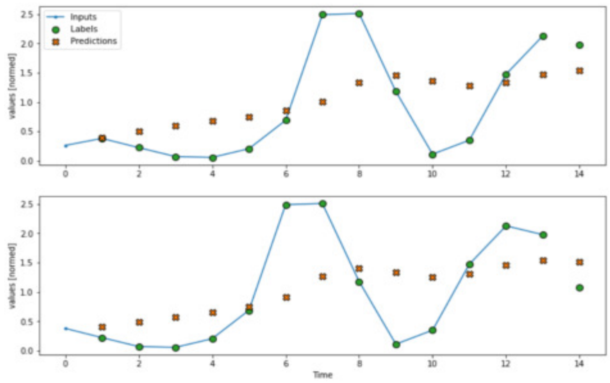

Fig. 7. Prediction by using RNN-LSTM single step with 100 epoch.

Finally, we do the simulation by implementing CNN and RNN-LSTM algorithms with multiple step. The results are shown in Figs 9 and 10. The loss and the MSE for CNN was 0.7852 and 0.6930 respectively, while for RNN was 0.3915 and 0.5320, respectively. Being demonstrated that the algorithm that offers better predictions of the channel behavior is RNN-LSTM in multiple step, based on the evaluated parameters. Also, it is possible to get better prediction by increasing the number of epoch, but again the overfitting problem is present.

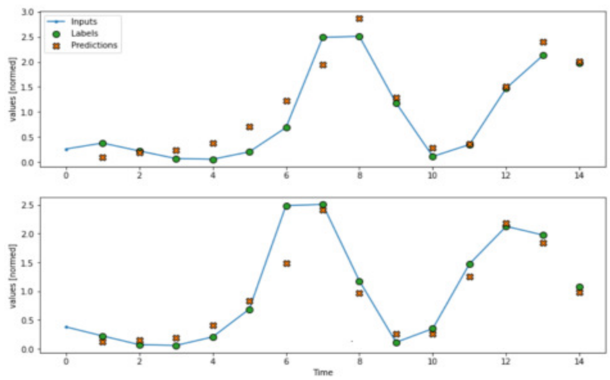

Fig. 8. Prediction by using RNN-LSTM single step with 150 epoch.

V. Discussion on Results

In this study, some NNs and forecasting algorithms were implemented for predicting channel behavior in vehicular

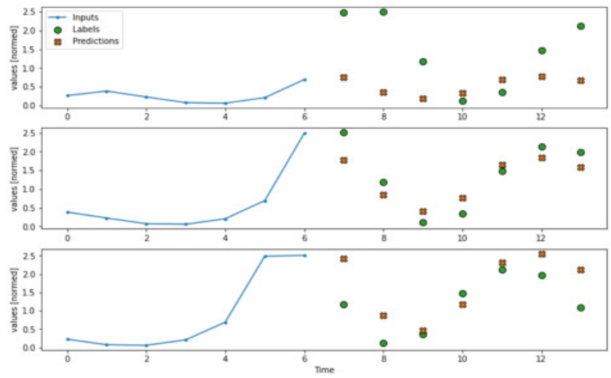

Fig. 9. Prediction by using CNN multiple step with 50 epoch

networks using the well known Jakes' model. Some regression algorithms for predicting channel in the future, were examined. It was concluded that the B-spline had better performance and higher accuracy in comparison with polynomial regression. Also, based on the error computation of CNN and RNN algorithms which were also implemented for prediction of the channel, CNN in single-step and LSTM in multi-step forecasting, have shown better performance. The mean squared error of implemented algorithms compares in table II. As for future work, the number of layers and some main parameter of the neural network(NN) could be evaluated considering the real conditions, to find the best approach for predicting.

TABLE II
MSE comparison of different algorithms

Algorithm	MSE
polynomial regression	241.3399
B-spline	1.9517
CNN (single step)	0.1144
LSTM (single step)	1.2737
CNN (multiple step)	0.6930
LSTM (multiple step)	0.5320

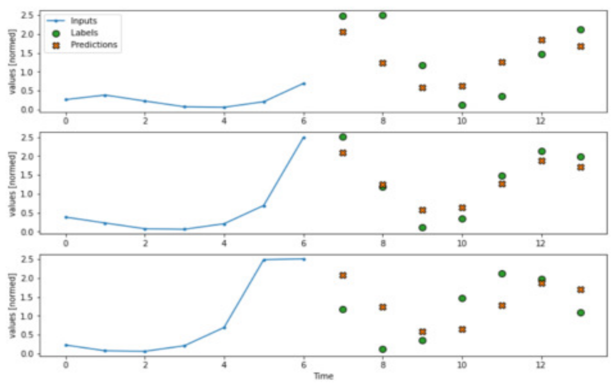

Fig. 10. Prediction by using RNN-LSTM multiple step with 100 epoch

VI. Acknowledgment

This work was partially supported by National Funds through FCT/MCTES (Portuguese Foundation for Science and Technology), within the CISTER Research Unit (UIDP/UIDB/04234/2020); also by the Operational Competitiveness Programme and Internationalization (COMPETE 2020) under the PT2020 Agreement, through the European Regional Development Fund (ERDF), and by FCT, under project POCI-01-0145-FEDER-032218 (5GSDN); also by FCT and the ESF (European Social Fund) through the Regional Operational Programme (ROP) Norte 2020. InSecTT project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No. 876038. The JU receives support from the European Union's Horizon 2020 research and innovation programme and Austria, Sweden, Spain, Italy, France, Portugal, Ireland, Finland, Slovenia, Poland, Netherlands, Turkey. Disclaimer: The document reflects only the author's view and the Commission is not responsible for any use that may be made of the information it contains.

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