

A Nonlinear Autoregressive Neural Network for Interference Prediction and Resource Allocation in URLLC Scenarios

Christian Padilla, Ramin Hashemi, Nurul Huda Mahmood, and Matti Latva-aho.

Centre for Wireless Communications (CWC), University of Oulu, Oulu, Finland,
Emails: {christian.padillaolivo, ramin.hashemi,nurulhuda.mahmood, matti.latva-aho}@oulu.fi

Abstract—Ultra reliable low latency communications (URLLC) is a new service class introduced in 5G which is characterized by strict reliability ($1 - 10^{-5}$) and low latency requirements (1 ms). To meet these requisites, several strategies like over-provisioning of resources and channel-predictive algorithms have been developed. This paper describes the application of a Nonlinear Autoregressive Neural Network (NARNN) as a novel approach to forecast interference levels in a wireless system for the purpose of efficient resource allocation. Accurate interference forecasts also grant the possibility of meeting specific outage probability requirements in URLLC scenarios. Performance of this proposal is evaluated upon the basis of NARNN predictions accuracy and system resource usage. Our proposed approach achieved a promising mean absolute percentage error of 7.8 % on interference predictions and also reduced the resource usage in up to 15 % when compared to a recently proposed interference prediction algorithm.

Index Terms—Interference prediction, Nonlinear Autoregressive Neural Network, ultra-reliable low-latency communications (URLLC).

I. INTRODUCTION

Ultra-reliable low-latency communication (URLLC) is a service class introduced in 5G that targets strict quality of service (QoS) requirements: reliability of $1 - 10^{-5}$ and latency of 1 ms [1]. These strict QoS guarantees can be achieved by over-provisioning of resources, i.e., allocating a large amount of resources in order to guarantee low outages [2]. However, such an approach is neither resource efficient nor scalable. Therefore it is necessary to develop a radio resource management (RRM) technique that overcomes these scalability and resource usage (RU) challenges while enabling URLLC [3].

Interference management has always been a challenge in wireless systems design [4]. Efficient interference management is among the possible ways to ensure efficient resource allocation (and to ensure scalability) for URLLC services. Having the ability to predict future interference is beneficial to tackle the effects of interference [5], resources can be allocated efficiently using this knowledge. Obtaining accurate forecasts of the interference power is a challenging task due to the time varying nature of wireless channels. Various researchers have proposed different interference prediction techniques.

This work was supported by the Academy of Finland 6Genesis Flagship project under grant 318927.

Haenggi et al. [6] used stochastic geometry to derive mean interference and probability distribution in wireless networks, Schmidt et al. [4] proposed the use of a recursive predictor to estimate future interference values by filtering the measured interference. Chinchali et al. [7] obtained promising results segmenting corrupted wireless transmissions into desired signal and interference estimate using Deep Learning.

Methodologically speaking, the interference power prediction can be statistical or AI-based. Statistical interference power prediction implies that some statistical properties of the interference power, such as mean interference, or even full probability distributions, are used to estimate future interference values. AI-based interference prediction consists on using a machine learning algorithm to approximate the behavior of the channel with a model that uses past interference values as inputs and future interference values as outputs. In this proposal we consider an AI-based solution since there is a broad study of statistics-based interference prediction techniques but there is scarcity in the application of AI for the same purpose.

A Nonlinear Autoregressive Neural Network (NARNN) has been chosen for interference prediction due to its high forecasting accuracy [8] and the fact that there is no need of a mathematical model of the process other than its own universal algorithm for future series prediction. A major benefit of NARNNs is that they accept dynamic inputs represented by time series sets where past values are used to predict future values in a time series set [9]. Several researchers have demonstrated promising prediction capabilities of NARNNs. Gairaa et al. [10] used a NARNN to predict global solar radiation levels, Ruiz et al. [9] used a NARNN to forecast energy consumption in public buildings and Sarkar et al. [8] studied the performance of NARNNs for long-term wind speed forecasting. The layout of this paper is as follows: the system model is presented in Section II. The NARNN design is described in Section III. In Section IV, the results are discussed. The conclusion of this proposal is presented in Section V.

II. SYSTEM MODEL

We consider the downlink of a typical multi-user wireless system in the two dimensional space organized by N transmitters (i.e., base stations (BS)), each of which serves

a single receiver. We focus our attention on a particular receiver of choice (denoted as user n), which is receiving a URLLC transmission in the presence of interference from the remaining $N - 1$ BSs. We assume that the transmitting BS of interest is the closest BS, while the remaining $N - 1$ interfering BSs are distributed across the service area at varying distances from the receiver of interest.

The corresponding channel responses between a transmitter and a receiver follows circularly symmetric complex Gaussian distribution. It is worth noting that the adaption of the channels' distribution can be generalized to more practical and complex scenarios without loss of generality. In order to keep the latency budget as low as possible, we assume that single-shot transmission. Therefore, the received signal at receiver is given by

$$r = h_n x_n + \underbrace{\sum_{k=1, k \neq n}^N h_k x_k}_{\text{Interference}} + w, \quad (1)$$

where $h_k \sim \mathcal{CN}(0, \beta_k)$, $\forall k \in \{1, \dots, N\}$ denotes the channel response between the k^{th} BS and the user n with path loss β_k . Also, the white Gaussian noise w has variance $\mathbb{E}[|w|^2] = \sigma^2$ and the symbols transmitted from BS to each user x_n where $\mathbb{E}[|x_n|^2] = p_n$ denotes the maximum transmit power. Thus, the signal-to-interference-plus-noise ratio (SINR) is defined as

$$\gamma_n = \frac{p_n |h_n|^2}{\sum_{k=1, k \neq n}^N |h_k|^2 p_k + \sigma^2}, \quad (2)$$

the objective of this work is to estimate the interference power such that the transmitter can effectively adapt its rate to minimize the unexpected interference power variations that affect the received signal quality and SINR. More specifically, in URLLC systems the amount of resources needed must be allocated depending on the outage probability requirement. The channel usage for user n is approximated as [11]

$$R_n \approx \frac{D}{C(\hat{\gamma}_n)} + \frac{Q^{-1}(\epsilon)^2 V(\hat{\gamma}_n)}{2C(\hat{\gamma}_n)^2} \left[1 + \sqrt{1 + \frac{4DC(\hat{\gamma}_n)}{Q^{-1}(\epsilon)^2 V(\hat{\gamma}_n)}} \right], \quad (3)$$

where

$$\hat{\gamma}_n = \frac{p_n |h_n|^2}{\hat{I}_n + \sigma^2}, \quad (4)$$

is the predicted SINR, \hat{I}_n is the predicted interference, D is the number of information bits with decoding probability ϵ , $C(\gamma) = \log_2(1 + \gamma)$ is the Shannon capacity of AWGN channels under infinite blocklength regime, $Q^{-1}(\cdot)$ is the inverse of the Q-function and $V(\gamma) = \frac{1}{\ln(2)^2} \left(1 - \frac{1}{(1 + \gamma)^2} \right)$ is the channel dispersion.

A model-based approach for interference prediction was recently presented by Mahmood et al. in [3]. The interference distribution was modeled using a DTMC and predictions were made in such a way that predicted interference is greater than the actual interference with probability \geq than confidence level η ; resources are calculated using (3). Results in [3] will be

used as performance benchmarks for the proposed NARNN and will be referred to as statistics-based prediction; for this reason, similar assumptions are considered in this paper: the desired channel has a mean SNR γ_D and the mean interference to noise ratio (INR) of each interfering link is uniformly distributed in the range $[\gamma_{I,\min}, \gamma_{I,\max}]$, the desired transmitter transmits packets of D bits with a target block error rate (BLER) ϵ .

Different from the aforementioned paper, we propose to employ a novel method to precisely estimate the interference power based on NARNNs. To do so, we first review fundamental concepts of NARNNs in the next section.

III. NAR MODEL

Interference power in a time series is difficult to forecast accurately due to the random nature of the wireless channel. A linear model would not be able to model the random variations in the wireless channel. For this reason, a NARNN has been used for effective time series prediction of interference. The NARNN is a recurrent dynamic network with feedback connections enclosing layers of the network; thus, the current output depends on the values of the past output [12]. The NARNN can be defined as [13]

$$y(t) = f(y(t-1), y(t-2), y(t-3), \dots, y(t-n)) + \epsilon(t), \quad (5)$$

where y is the data series for the combined interference values of $N-1$ interferers, $f(\cdot)$ is a transfer function that can be approximated by the neural network, n is the input delay of interference time series and ϵ is the approximation error.

Fig. 1 shows the architecture of the NARNN. It is composed of three layers: input, hidden and output layers. The NARNN architecture requires specific number of delays, hidden nodes, activation functions and an efficient training algorithm [14]. All these parameters can be optimized by trial and error [9]. We found 20 delays to be accurate enough for prediction of Rayleigh channel interference values. In addition, 16 neurons for hidden layer and both logsigmoid (f_1) and linear activation (f_2) function were used in hidden and output layers respectively. Levenberg-Marquadt back propagation (LMBP) was chosen as the training algorithm because of its fast convergence speed and accuracy [15], [16].

The necessary steps for implementing the NARNN are shown in Fig. 2. First, the time series data sets obtained in simulation was divided in two different sets: training and testing sets, this is the data pre-processing. NARNN weights and bias are later initialized with random values. LMBP was used to adjust their values in every iteration (epoch); as many iterations as needed should be performed to achieve a target error. The final step consists on using the test data to evaluate the performance and forecasting ability of the NARNN. Details about the performance of the NARNN will be discussed in the following sections. The open loop architecture (no feedback loop) was chosen over the closed-loop architecture because predictions were made one-step-ahead. Closed loop architecture is typically used for multistep-ahead predictions [8]. For this proposal, the NARNN training data sets consist

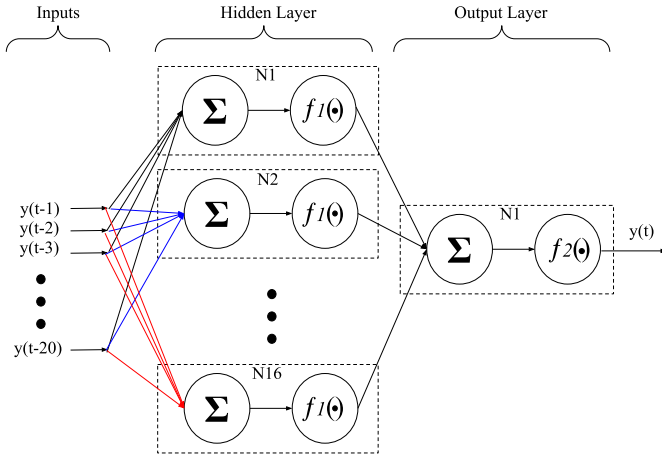


Fig. 1: NARNN architecture.

of interference power time series obtained from computer simulations of a downlink with $N-1$ interferers and a Rayleigh channel. Details on performance evaluation of the NARNN and resource allocation are discussed in the next section.

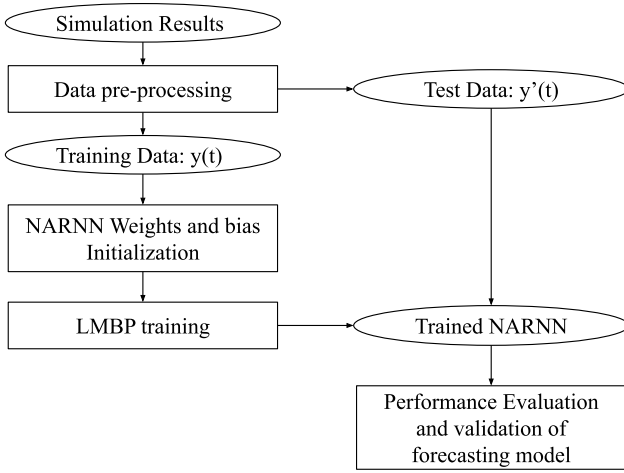


Fig. 2: NARNN training procedure.

IV. RESULTS AND DISCUSSION

This AI-based approach has two objectives. The first one is to predict the interference values using the developed NARNN; performance of the NARNN is evaluated by means of MAPE and MSE metrics. The second objective is to allocate resources depending on the NARNN output; performance is evaluated again after allocating resources by studying the resource usage and outage probabilities achieved by the NAR-based approach and comparing it to the statistics-based prediction in [3] where interference power value is predicted using a discrete time Markov chain (DTMC) and a configurable confidence level. With respect to resource allocation, the predicted interference power needs to be over-estimated to allow the system to meet target outage probabilities ranging from 10^{-1} to 10^{-5} . This

over-estimation can be accomplished by using an adjustable factor $1 < \alpha < 2$ to scale the NARNN output. We denominate this procedure as the Resource Control stage.

Fig. 3 shows the 2-stage process of the proposed NAR-based RRM technique. The NARNN is used in the first step for interference forecasting (namely prediction stage) and the adjustable factor α is used in the second step for regulating resource utilization.

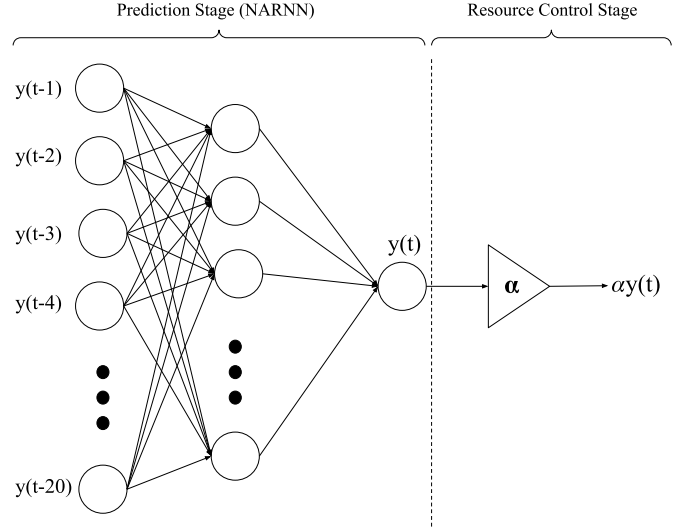


Fig. 3: Resource Management Model Proposal.

Regarding prediction stage, the NARNN was trained using data sets that consist of interference power time series obtained from computer simulations of a downlink with $N-1$ interferers operating in a Rayleigh channel. The prediction performance of the NARNN was evaluated using mean squared error (MSE) and mean absolute percentage error (MAPE). Mean square error is given by

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2, \quad (6)$$

MAPE makes comparisons easier because it is percentage-based [17]. Mean absolute percentage error is defined as

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \frac{|y_i - \hat{y}_i|}{y_i} \times 100, \quad (7)$$

The variables y_i and \hat{y}_i represent real and predicted interference values respectively. Impulse response corresponding to the NARNN in Prediction Stage is shown in Fig. 4. The best-performing NARNN was used to forecast interference power. For comparison purposes, the true values from simulations have also been plotted. The NARNN achieved a promising MSE of 0.5447 and MAPE of 7.816% in the optimal configuration. To find the optimal number of neurons tests were made with both log-sigmoid (namely logsig) and tangent hyperbolic sigmoid (namely tansig) functions. Table I shows the results of the test with a variable number of neurons with logsig and tansig functions as activation functions in the hidden layer.

These results show that there is not a significant benefit of increasing the number of neurons. Logsig performed at its best using 16 neurons with an MSE of 0.5447 while tansig reached peak performance with 14 neurons and an MSE of 0.5446. While there is a slight improvement with the tansig function with 14 neurons, we observed a higher number of epochs needed for training when compared to the logsig function. Tansig function required 64 epochs while logsig was trained with 19 epochs. It was concluded from this experiments that the developed NARNN required 16 neurons for the best overall performance.

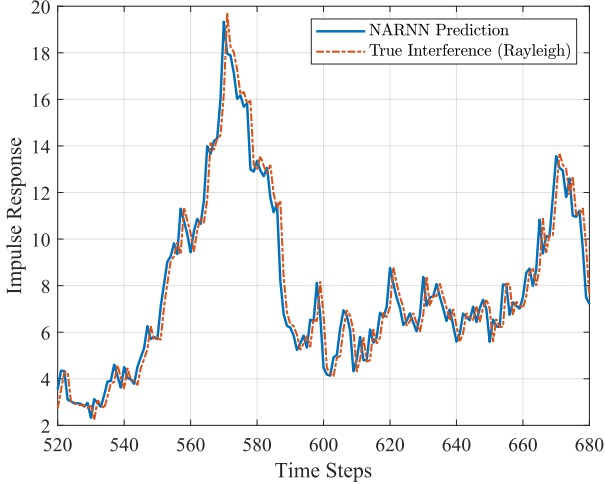


Fig. 4: NARNN predictions for a fixed range of time steps.

TABLE I
MSE AND MAPE FOR DIFFERENT NUMBER OF NEURONS

Activat. Funct.	Metric	Number of Neurons				
		8	12	14	16	18
Logsig	MSE	0.5449	0.5458	0.5455	0.5447	0.545
	MAPE	7.828	7.836	7.832	7.816	7.829
Tansig	MSE	0.5452	0.5449	0.5446	0.5454	0.5450
	MAPE	7.830	7.824	7.831	7.825	7.826

To study the effect of increasing the number of delays in the performance, multiple NARNN versions were trained with a different number of delay taps, specifically: 2, 20 and 50 delay taps. MSE was almost identical for these 3: 0.546, 0.5447 and 0.545 respectively with MAPEs around 7.8%. These results demonstrate that the NARNN is capable of modelling the Rayleigh channel with a small number of neurons and delays and that gains in performance are almost nonexistent when tuning these parameters. Given these results, 20 delays and 16 neurons were chosen to get a marginal improvement while keeping the complexity of the NARNN low.

With respect to the Resource Control Stage, α can be adjusted once a sufficient forecasting performance has been attained at the prediction stage, it is important to note that regulating α leads to changes in resource usage and outage probability. Since Resource Control Stage consists on a factor

multiplication, it is not possible to evaluate its performance, we rather exhibit the performance of the entire NAR-based approach in two ways. The first one, consists in adjusting the α factor to get the NARNN resource usage to equal the statistics-based estimate resource usage; in this scenario, the objective is to study the mean outage probability of these two techniques having the resource usage fixed. The second experiment is similar but instead of targeting the resource usage with α , we aim at the mean outage probability. The factor α is tuned to lower the resource usage of the NARNN while matching the statistics-based estimate mean outage probability. The objective is analogous to the first experiment, to study the resource usage of both techniques with a fixed mean outage probability.

Fig. 5 shows the ideal, statistics-based and the NAR-based prediction resource usage for outage probabilities ranging from 10^{-1} to 10^{-5} . It was found empirically that a value of $\alpha = 1.45$ equals the NARNN resource usage with the statistics-based prediction resource usage. Note that ideal resource usage has been calculated using a genie-aided estimator and is considered to be the optimum performance bound while the average interference is calculated using an IIR filter [3].

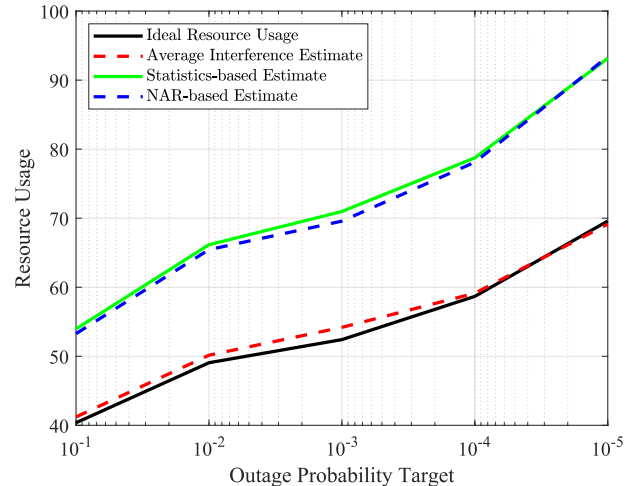


Fig. 5: Resource Usage of NAR-based estimate with $\alpha = 1.45$.

The mean outage probability of the NAR and statistics-based approaches for the same $\alpha = 1.45$ and the same range of target probabilities (10^{-1} to 10^{-5}) has been plotted in Fig. 6. This plot shows that the NAR-based approach is capable of reducing the mean outage probability considerably by using the same amount of resources as the statistical approach. There is a reduction in outage probability of factor up to 1/10 when using the NARNN with $\alpha = 1.45$. It is possible to target the outage probability of the statistical approach instead of the resource usage by choosing $\alpha = 1.2$. Fig. 8 shows mean outage probability for this α value. Both NAR and statistics-based estimates have similar outage probabilities but the resource usage of the NARNN went down by approximately 15% compared to the statistics-based estimate as seen on Fig. 7.

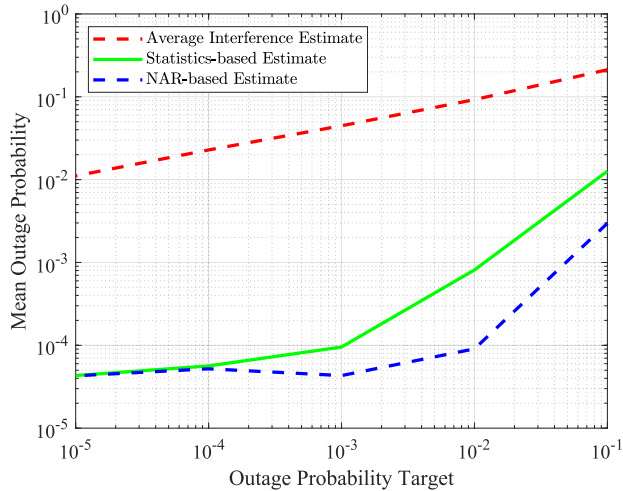


Fig. 6: Outage probability of NAR-based estimate with $\alpha = 1.45$.

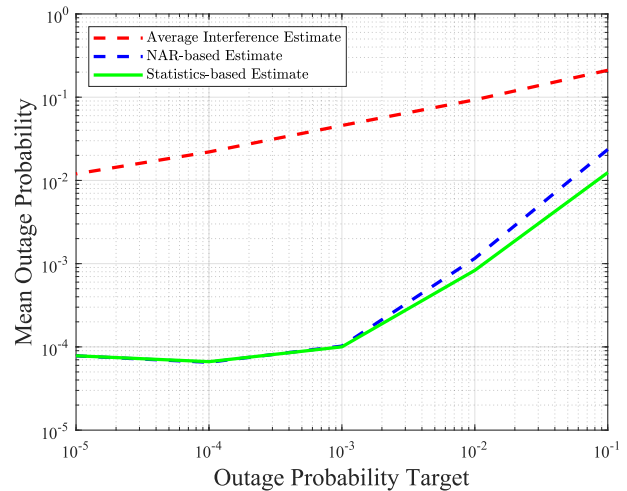


Fig. 8: Outage probability of NAR-based estimate with $\alpha = 1.2$.

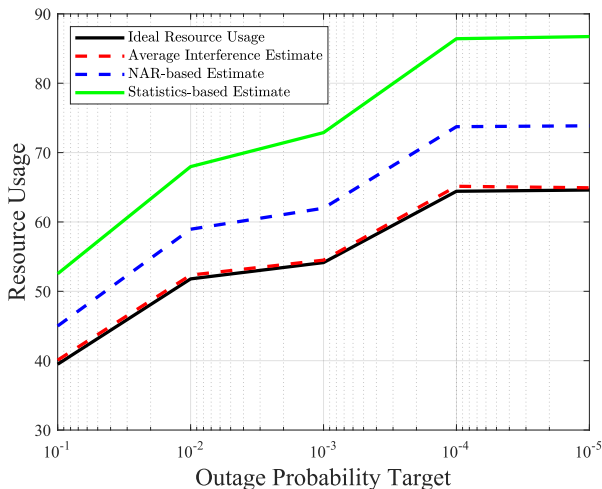


Fig. 7: Resource Usage of NAR-based estimate with $\alpha = 1.2$.

V. CONCLUSION

Having knowledge of the channel is of major importance to avoid high error rates and allocate resources accordingly. In addition, wireless channels behaviour is chaotic which makes prediction approaches very appealing. The focus of this proposal are URLLC scenarios, for this reason, predicting the channel behaviour is not the only objective, meeting URLLC target outage probabilities is also a major goal. To target these two objectives, we have proposed the use of a NAR-based RRM technique with two stages: interference prediction and resource control stages. For interference prediction, a NARNN was used due to its promising prediction capabilities. For resource control, a factor $1 < \alpha < 2$ is used to scale the output of the NARNN and to regulate resource usage. The NARNN provided very accurate predictions showing a promising MSE of 0.5447 and a MAPE of 7.816%. It was found by trial

and error that the optimal configuration for the NARNN was 16 neurons in hidden layer, 20 delays and a log-sigmoid activation function. The performance of the whole system (NARNN prediction and resource control) was compared to an statistics-based approach as depicted in Section II. For $\alpha = 1.2$, the NAR-based prediction matched the outage probability of the Statistics-based approach while using up to 15% less resources. For $\alpha = 1.45$ the NAR-based prediction matched the resource usage but outperformed the statistics-based based approach by reducing the outage probability in factor of up to 10 times. In summary, the developed NARNN showed promising predictions of interference and allowed a more efficient resource allocation when compared to statistics-based estimates. In this study NARNNs has been used to predict interference in a Rayleigh channel, however, further research is required to apply a NARNN to forecast interference when a more complex fading model is in use.

REFERENCES

- [1] J. Sachs, G. Wikstrom, T. Dudda, R. Baldemair, and K. Kittichokechai, "5g radio network design for ultra-reliable low-latency communication," *IEEE Network*, vol. 32, no. 2, pp. 24–31, 2018.
- [2] N. H. Mahmood, D. Laselva, D. Palacios, M. Emara, M. C. Filippou, D. M. Kim, and I. de-la Bandera, "Multi-channel access solutions for 5g new radio," 2019.
- [3] N. H. Mahmood, O. A. López, H. Alves, and M. Latva-Aho, "A predictive interference management algorithm for urllc in beyond 5g networks," *IEEE Communications Letters*, vol. 25, no. 3, pp. 995–999, 2021.
- [4] J. F. Schmidt, U. Schilcher, M. K. Atiq, and C. Bettstetter, "Interference prediction in wireless networks: Stochastic geometry meets recursive filtering," 2021.
- [5] G. Zheng, I. Krikidis, C. Masouros, S. Timotheou, D.-A. Toumpakaris, and Z. Ding, "Rethinking the role of interference in wireless networks," *IEEE Communications Magazine*, vol. 52, no. 11, p. 152–158, Nov 2014. [Online]. Available: <http://dx.doi.org/10.1109/MCOM.2014.6957156>
- [6] M. Haenggi, "Mean interference in hard-core wireless networks," *IEEE Communications Letters*, vol. 15, no. 8, pp. 792–794, 2011.
- [7] S. Chinchali and S. Tandon, "Deep learning for wireless interference segmentation and prediction."

- [8] R. Sarkar, S. Julai, S. Hossain, W. T. Chong, and M. Rahman, "A comparative study of activation functions of nar and narx neural network for long-term wind speed forecasting in malaysia," *Mathematical Problems in Engineering*, vol. 2019, p. 6403081, Mar 2019. [Online]. Available: <https://doi.org/10.1155/2019/6403081>
- [9] L. G. B. Ruiz, M. P. Cuéllar, M. D. Calvo-Flores, and M. D. C. P. Jiménez, "An application of non-linear autoregressive neural networks to predict energy consumption in public buildings," *Energies*, vol. 9, no. 9, 2016. [Online]. Available: <https://www.mdpi.com/1996-1073/9/9/684>
- [10] K. Gairaa, F. Chellali, S. Benkacali, Y. Messlem, and K. Abdallah, "Daily global solar radiation forecasting over a desert area using nar neural networks comparison with conventional methods," in *2015 International Conference on Renewable Energy Research and Applications (ICRERA)*, 2015, pp. 567–571.
- [11] A. Lancho, T. Koch, and G. Durisi, "On single-antenna rayleigh block-fading channels at finite blocklength," *IEEE Transactions on Information Theory*, vol. 66, no. 1, p. 496–519, Jan 2020. [Online]. Available: <http://dx.doi.org/10.1109/TIT.2019.2945782>
- [12] F. da Costa Lopes, E. H. Watanabe, and L. G. B. Rolim, "A control-oriented model of a pem fuel cell stack based on narx and noe neural networks," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 8, pp. 5155–5163, 2015.
- [13] Y. D. Nyanteh, S. K. Srivastava, C. S. Edrington, and D. A. Cartes, "Application of artificial intelligence to stator winding fault diagnosis in permanent magnet synchronous machines," *Electric Power Systems Research*, vol. 103, pp. 201–213, 2013. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0378779613001466>
- [14] R. Taherdangkoo, A. Tatomir, M. Taherdangkoo, P. Qiu, and M. Sauter, "Nonlinear autoregressive neural networks to predict hydraulic fracturing fluid leakage into shallow groundwater," *Water*, vol. 12, no. 3, 2020. [Online]. Available: <https://www.mdpi.com/2073-4441/12/3/841>
- [15] M. Hagan and M. Menhaj, "Training feedforward networks with the marquardt algorithm," *IEEE Transactions on Neural Networks*, vol. 5, no. 6, pp. 989–993, 1994.
- [16] D. W. Marquardt, "An algorithm for least-squares estimation of nonlinear parameters," *Journal of the Society for Industrial and Applied Mathematics*, vol. 11, no. 2, pp. 431–441, 1963. [Online]. Available: <https://doi.org/10.1137/0111030>
- [17] R. G. Kavasseri and K. Seetharaman, "Day-ahead wind speed forecasting using f-ARIMA models," *Renewable Energy*, vol. 34, no. 5, pp. 1388–1393, 2009. [Online]. Available: <https://ideas.repec.org/a/eee/rene/v34y2009i5p1388-1393.html>