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Channel Prediction in Wireless Microcell and Picocell Systems Using Echo State Network

Nikola Sekulović1, Aleksandra Panajotović2, Miloš Banđur3, Đoko Banđur3 and Daniela Milović2

1College of Applied Technical Sciences Niš, Aleksandra Medvedeva 20, 18000 Niš, Serbia
2 Department of Telecommunications, University of Niš, Faculty of Electronic Engineering, Aleksandra Medvedeva 14, 18000 Niš, Serbia
3 Faculty of Technical Sciences, University of Priština, Kneza Miloša 7, 38220 Kosovska Mitrovica, Serbia
Corresponding Author: Nikola Sekulović

ABSTRACT: *Reservoir computing (RC) presents efficient approach for creating recurrent neural networks (RNN). RC encompasses echo state network (ESN) which has received increased attention owing to its effectiveness and relative simplicity due to fact that only connections from a reservoir to an output layer are trainable. This paper investigates the ESN-based prediction scheme for single-input single-output (SISO) systems in microcellular and picocellular environments using normalized mean squared error (NMSE) as a performance indicator. Presented simulation results show that gap between curves representing predicted and measured channel states is very small and no more than several neurons in input layer and several hundred neurons in reservoir should be used.*

KEYWORDS: *Channel prediction, Echo state network, Microcellular environment, Picocellular environment, Normalized mean squared error.*

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I. INTRODUCTION

In wireless communication systems, a state of channel changes very quickly. The system performance can be enhanced using channel prediction based on channel states in previous moments rather than using channel estimation. Namely, channel state obtained by channel estimation can become outdated due to delay caused by processing and feedback phases [1].

Autoregressive (AR) model, support vector machine (SVM) and discrete wavelet transform (DWT) method in combination with AR and linear regression (LR) algorithm (DWT-AR-LR) are widely explored in the open technical literature for channel predictions [2]-[4].

Echo state network (ESN) prediction model is a class of reservoir computing (RC) which is an alternative to gradient descent method for training recurrent neural networks (RNN) [5]. Due to its relative simplicity and efficiency, ESNs have attracted widespread application in time series prediction, nonlinear system modeling, speech and text processing, financial forecasting, localization and bio-medical applications. ESN consists of an input layer, a large RNN layer (reservoir) and an output layer. The weights in the input and reservoir layers are initialized randomly. The main part of the system is the reservoir of large number of sparsely connected neurons ensuring rich and long-term dynamics. The reservoir maps input sequences into high-dimensional projection. The weights in the nonlinear temporal kernel are not subjected to the training process. Learning is reduced to linear regression from the reservoir to the output. The output is linear combination of the echo states of the reservoir. Therefore, training procedure which is simplified because only the readout from the reservoir is trained, abundant nonlinar echo states and short memory are advantages of the model useful for modeling dynamical systems [6].

A channel prediction strategy based on ESN is proposed in [7]. Data set used for training and testing is obtained by simulation of Rician fading channel. It is shown that smaller prediction error can be attained in comparison with previous designs. Moreover, complexity of the ESN is less than complexity of the SVM and comparable to the complexities of AR and DWT-AR-LR. Motivated by these facts, in this paper, the effectiveness of prediction scheme based on the ESN is explored for microcellular and picocellular environments. Data sets used for training and testing contain measured signal-to-noise ratio (SNR) samples for scenarios described in details in [8]. Performance metrics used for analysis of the approach proposed is normalized mean squared error (NMSE).

This introduction ends with notational remarks. Vector and matrices are denoted by lower- and upper-case bold letters, respectively, while scalars are represented with non-bold letters. $(\cdot)^{\mathrm{T}}$ denotes transpose and $\mathbb{R}$ is the set of real numbers.

II. APPLICATION OF ESN MODEL FOR WIRELESS CHANNEL PREDICTION

A. Communication Scenario

A prediction scheme for a single-input single-output (SISO) channel is proposed and applied for two different environments:

1) B channel model represents a microcell environment where distance between mobile station (MS) and base station (BS) is in the order of 30 m. It assumes indoor-to-outdoor propagation with BS located outside and indoor environment usually consisted of several small offices.

2) E channel model represents a picocell environment in modern open office with windows metallically shielded. It refers to indoor-to-indoor scenario.

Data sets used for analysis in this work contain SNR channel values obtained based on measurement campaigns described in details in [8]. A series of SNR samples $\gamma(n) = \gamma(nT_s)$, $n = \overline{1, N_s}$, from [8], are used for network training and testing. Parameter T_s denotes sampling interval and parameter N_s is the total number of samples.

B. Prediction Framework

Having in mind its relative conceptual simplicity and computational inexpensiveness, the ESN model is proposed for channel prediction. The architecture of a multiple-input single-output ESN is illustrated through Fig. 1.

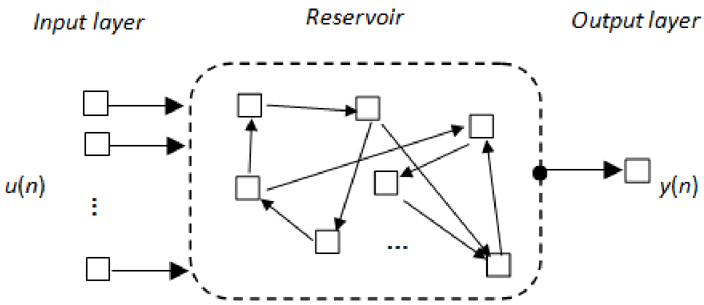

Fig. 1. Architecture of ESN

An input layer, an output layer and a large recurrent layer between them which is called internal reservoir form the ESN. Let N_u, N_x and N_y denote the number of neurons in the input layer, the internal reservoir and the output layer, respectively. The inputs, the reservoir states and the outputs are marked with **u**, **x** and **y**, correspondingly. The weights which describe connections among the neurons in the reservoir are collected into an internal matrix $\mathbf{W} \in \mathbb{R}^{N_x \times N_x}$. An input weight matrix $\mathbf{W}_{in} \in \mathbb{R}^{N_x \times (1+N_u)}$ describes relation between the input layer and the reservoir, while an output weight matrix $\mathbf{W}_{out} \in \mathbb{R}^{N_y \times (1+N_u+N_x)}$ defines optimal mapping of input and states of internal neurons into a N_y-dimensional variable. In our case, it is evident that N_y =1 holds.

At discrete time n, N_u samples of SNR are used as the input variables forming the input training vector $\mathbf{u}(n) \in \mathbb{R}^{N_u}$ which is expressed as

$$\mathbf{u}(n) = \left[\gamma(n), \gamma(n+1), \ldots, \gamma(n+N_u-1)\right]^{\mathrm{T}}. \quad (1)$$

The idea is to predict sample based on previous N_u samples

$$y(n) = \gamma(n+N_u). \quad (2)$$

The vector of reservoir neurons states $\mathbf{x}(n) \in \mathbb{R}^{N_x}$ at discrete time n is given by

$$\mathbf{x}(n)=\left[x_1(n),x_2(n),...,x_{N_x}(n)\right]^{\mathrm{T}}. \quad (3)$$

Generally, the ESN involves two phase. The first one assumes mapping of N_u-dimensional inputs into N_x-dimensional reservoir state space to obtain the echo states and to capture the dynamics of the inputs. The second one is to learn the output weight matrix. The mathematical formulations for the internal state update and the output are as follows [9]

$$\begin{aligned}\mathbf{x}(n)&=(1-\alpha)\mathbf{x}(n-1)+\alpha f\left(\mathbf{W}_{in}[1;\mathbf{u}(n)]+\mathbf{W}\mathbf{x}(n-1)\right)\\&=(1-\alpha)\mathbf{x}(n-1)+\alpha\tanh\left(\mathbf{W}_{in}[1;\mathbf{u}(n)]+\mathbf{W}\mathbf{x}(n-1)\right)\end{aligned}, \quad (4)$$

$$y(n)=g\left(\mathbf{W}_{out}\left[1;\mathbf{u}(n);\mathbf{x}(n)\right]\right)=\mathbf{W}_{out}\left[1;\mathbf{u}(n);\mathbf{x}(n)\right], \quad (5)$$

where $f(\cdot)$ is the non-linear activation function in reservoir, $g(\cdot)$ is the output function and α denotes the leaking rate. According to [10], $f(\cdot)$ and $g(\cdot)$ are hyperbolic tangent function and identity function, respectively. Typical values for leaking rate are $\alpha\in(0,1]$ and it is used for integrating reservoir states in two consecutive time steps.

C. Algorithm for Channel Prediction

In order to clearly illustrate the channel prediction scheme based on the ESN, a detailed procedure of the network initialization, training and testing is given step by step.

Step 1: The first N_{tr} samples are used to train the network, while the rest N_{te}=N_s-N_{tr} are test samples used to evaluate a prediction error.

Step 2: This step relates to the initialization of the ESN. Important parameters for this phase, known as global parameters, are input scaling factor (a) and spectral radius (ρ). The elements of the input weight matrix $\mathbf{W}_{in}$ are generated randomly from [-a, a]. Initialization of the internal reservoir matrix starts with a matrix $\mathbf{W}_{rand}$ generated according to the same type of distribution as $\mathbf{W}_{in}$. The procedure ends with scaling which is mathematically described as

$$\mathbf{W}=\rho\frac{\mathbf{W}_{rand}}{\lambda_{\max}\left(\mathbf{W}_{rand}\right)}, \quad (6)$$

where $\lambda_{\max}\left(\mathbf{W}_{rand}\right)$ is the largest eigenvalue of matrix $\mathbf{W}_{rand}$. Meeting the condition ρ<1 usually ensures ESN stability. The initial states of the internal neurons are all set as 0, i.e. $\mathbf{x}(0)=[0,0,...,0]^{\mathrm{T}}$.

Step 3: Samples from the training set excite the network changing the states of the internal neurons according to the state update function (4). From a certain sample N_c (N_c< N_{tr}), the states are stored into a matrix $\mathbf{X}\in\mathbb{R}^{(N_x+N_u+1)\times(N_{tr}-N_c+1)}$ given by

$$\mathbf{X}=\left[\mathbf{x}(N_c),\mathbf{x}(N_c+1),...,\mathbf{x}(N_{tr})\right]. \quad (7)$$

We use here a single **x** instead of [1;**u**;**x**] for notational brevity. In addition, the states of the output neuron are calculated using (5) and collected in vector row $\mathbf{y}\in\mathbb{R}^{N_{tr}-N_c+1}$ given by

$$\mathbf{y}=\left[y(N_c),y(N_c+1),...,y(N_{tr})\right]. \quad (8)$$

Step 4: Minimizing squared error between predicted and target signal value is done using direct ridge regression. The output weight vector is

$$\mathbf{W}_{out}=\mathbf{y}_{target}\mathbf{X}^{\mathrm{T}}\left(\mathbf{X}\mathbf{X}^{\mathrm{T}}+\beta\mathbf{I}\right)^{-1}, \quad (9)$$

where β is a regularization coefficient, **I** is the identity matrix and vector row $\mathbf{y}_{target}\in R^{N_{tr}-N_c+1}$ contains appropriate target values described by (2). The offline training algorithm ends by determining the output weight vector.

Step 5: The trained network is used for prediction and the network performance evaluation using the rest N_{te} labeled data. NMSE is used as a prediction error metrics and it is defined as

$$NMSE=\frac{\sum_{i=N_{tr}+1}^{N_s}\left(y_{target}(i)-y(i)\right)^2}{\sum_{i=N_{tr}+1}^{N_s}\left(y_{target}(i)\right)^2}. \quad (10)$$

III. III. SIMULATION RESULTS AND ANALYSIS

In this section of the paper, the performance of the proposed time-series prediction strategy is evaluated using data sets for SISO system obtained by measuring the instantaneous SNR values at the receiver side for the case when SNR at the transmitter side is 20 dB. Analysis is carried out using data sets containing N_s=4000 samples. The data sets are divided into two equal sets for training and testing (N_{tr}= N_{te}=2000). The states of internal neurons are memorized from N_c =100 sample (the washout length). The leaking rate and the regularization coefficient are set as α=0.3 and β=50, respectively. It is determined by simulation that there is no need to use more than 3 neurons in the input layer. This means that in the following analysis we use input vector which size is N_u=3.

The influence of the reservoir size N_x, as the main part of the network, is illustrated in Fig. 2 for both B and E channels. It is evident that the ESN with larger reservoir has better performance. We can also note that the curves enter saturation which implies that it is not rational to increase N_x uncontrolled. Namely, performance gain achieved in this way at the expense of computationally and memory efficiency is not justified. For both channels, the NMSE of the order of 10^{-3} can be expected. Figure also shows that the NMSE for B channel prediction is slightly lower.

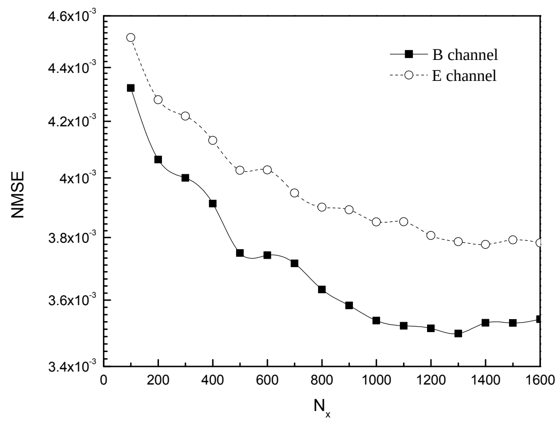

Fig. 2. NMSE versus number of internal neurons

Fig. 3 and Fig. 4 illustrate the target curve $y_{target}(n)$ and prediction curve $y(n)$, as well as absolute error between the curves

$$\Delta y = y_{target}(n) - y(n) . \qquad (11)$$

Fig. 3 contains examples for B channel, while Fig. 4 is related to E channel. Simulation results show that the gap between curves representing predicted and measured channel states is very small. We can draw indisputable conclusion that in microcell and picocell environments the proposed prediction scheme based on the ESN fits the chaotic time series very well with small errors.

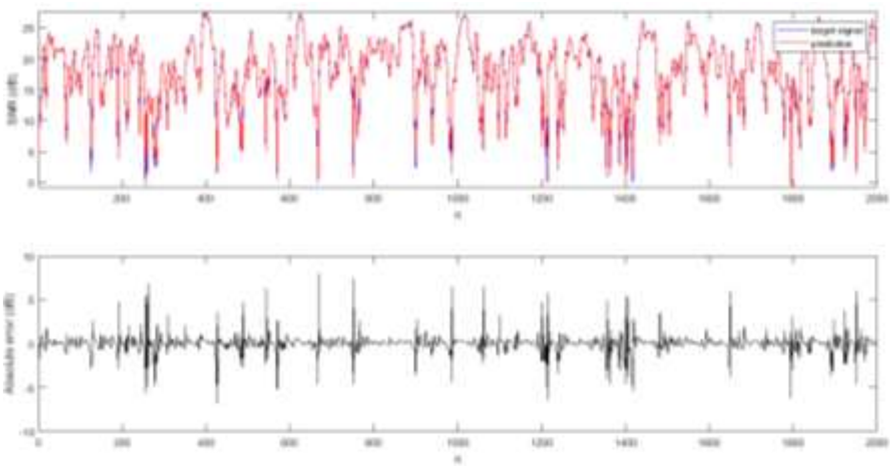

Fig. 3. Prediction curve and absolute error for B channel

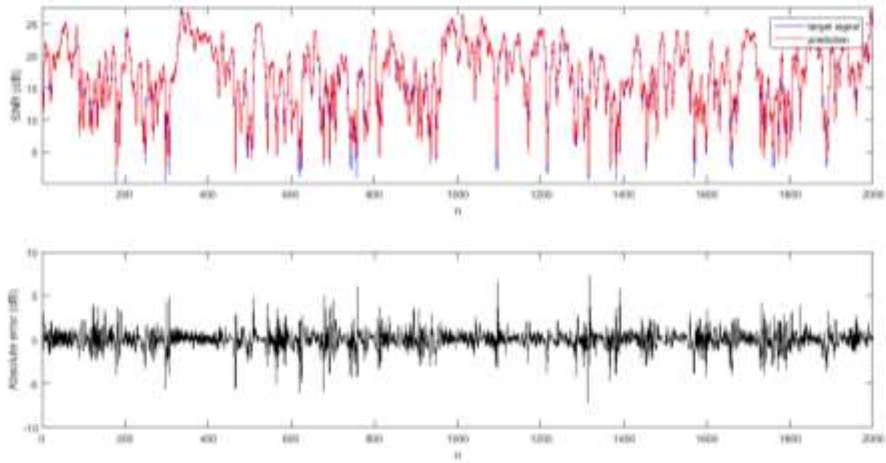

Fig. 4. Prediction curve and absolute error for E channel

IV. CONCLUSION

Reservoir computing is an efficient method to construct recurrent networks that model dynamical systems. This paper has investigated the ESN-based prediction scheme for SISO systems in microcellular and picocellular environments. The effectiveness of the framework has been confirmed using NMSE as a performance measure. Simulation results have shown that no more than several neurons in input layer and several hundred neurons in reservoir should be used. Further increasing the number of neurons will not result in significant prediction accuracy gain. The NMSE of the order of 10^{-3} can be expected.

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