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A Comparison of Adaline and MLP Neural Network-based Predictors in SIR Estimation in Mobile DS/CDMA Systems

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Abstract**—**In this paper we compare the response of linear and nonlinear neural network-based prediction schemes in prediction of received Signal-to-Interference Power Ratio (SIR) in Direct Sequence Code Division Multiple Access (DS/CDMA) systems. The nonlinear predictor is Multilayer Perceptron MLP and the linear predictor is an Adaptive Linear (Adaline) predictor. We solve the problem of complexity by using the Minimum Mean Squared Error (MMSE) principle to select the optimal predictors. The optimized Adaline predictor is compared to optimized MLP by employing noisy Rayleigh fading signals with 1.8 GHZ carrier frequency in an urban environment. The results show that the Adaline predictor can estimates SIR with the same error as MLP when the user has the velocity of 5 km/h and 60 km/h but by increasing the velocity up-to 120 km/h the mean squared error of MLP is two times more than Adaline predictor. This makes the Adaline predictor (with lower complexity) more suitable than MLP for closed-loop power control where efficient and accurate identification of the time-varying inverse dynamics of the multi path fading channel is required.

Keywords**—**Power control, neural networks, DS/CDMA mobile communication systems.

I. Introduction

THE user capacity and quality of service in a DS/CDMA system crucially depends on the levels of interference from other users and perfect power control plays a very important role in a CDMA system. The open loop power control is designed to over-come the near-far and shadowing problems on the reverse link of a CDMA system, while the closed-loop power control and feedback procedure eliminates the received signal fluctuation due to the small scale propagation loss [1],[2]. The inherent problem in a closed-loop power control algorithm is feedback delay. Therefore, to compensate the uplink fading, the uplink channel information must be estimated at the base station and then feedback to the mobile station, so that, the mobile station can adjust its transmit power according to the feedback information [3]. A closed loop power control model for the reverse link is illustrated in Fig. 1.

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In this model the signal strength or SIR is first estimated at the base station for every time slot and then is compared with the desired or the target level and so that the received power is kept almost equal. In addition, power control on SIR is more suitable than that based on signal strength because CDMA system is interference limited [4], [5], [6]. Neural networks are well suited to be utilized as nonlinear predictive filters because of their distinguished approximation and generalization capabilities [7], [8], [9]. We use the MLP as a nonlinear neural network-based predictor and Adaline predictor as a linear neural network-based predictor.

An important but difficult problem in designing the neural network is to determine the optimal structure for successful prediction. In this paper, we have used MMSE principle to solve the problem of complexity or the length of predictor. A hybrid and Modified Elmann Neural Network (MENN) and Heinonen-Neuvo prediction were proposed in [10], [11], [12] to predict signal strength and they used Predictive Minimum Description Length (PMDL) method to find the optimal neural network. The structure of MLP and Adaline predictors are first optimized off-line for different velocities and the performance of all mentioned structures are evaluated in terms of bias and MSE then use the optimal predictor with on-line learning and adaptation in the real situation.

A Rayleigh fading channel simulator and SIR estimator technique are described in section II. In section III we discuss the topology of Adaline and MLP neural network-based power prediction and the applied learning algorithm. The optimized neural predictor is found off-line and applied to predict SIR in a Rayleigh fading channel. An illustrative simulation is demonstrated in section IV. Finally, we conclude this paper with a few remarks in section V.

II. Rayleigh Fading Power Signal and SIR Estimator

One of the most commonly used method to simulate a Rayleigh fading channel is described in [13] and is referred to as the Jake's method. A simplified channel simulator often assumes the superposition of plane waves, whose arrival angles are uniformly distributed and associated with different Doppler shifts, ranging from the minimum to the maximum specified by the mobile speed. The Jake's method assumes that the line-of-sight component is absent. When the number of paths is large enough, the base band signal received from a multi path fading channel is approximately a complex Gaussian process and it invoke central limit theorem.

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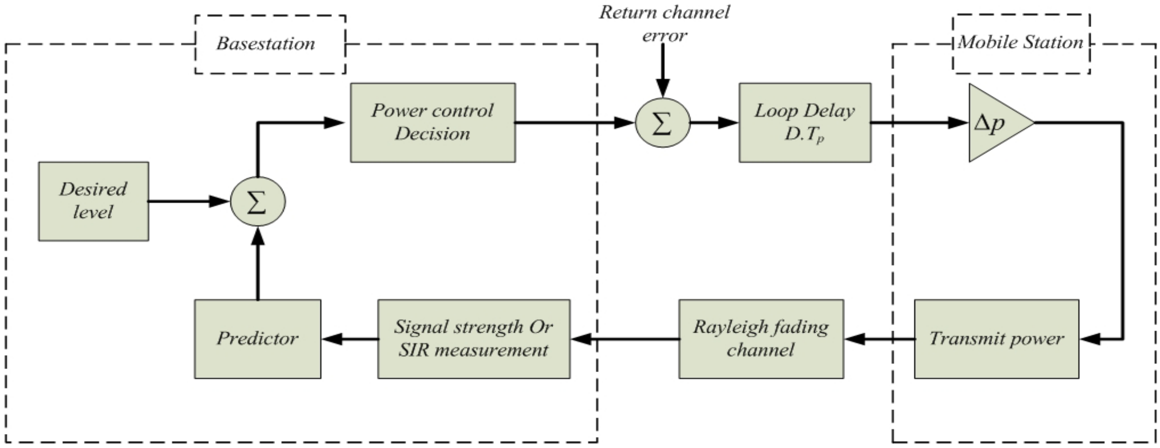

Fig. 1 Closed loop power control model

We can write the amplitude fluctuation of the base band signal as follows

$$\beta(t)=\frac{1}{\sqrt{L}}\left\{\sum_{l=1}^{L/2-1}\left[e^{j2\pi\left(f_D\cos\psi_l t-f_c\tau_l\right)}+e^{-j2\pi\left(f_D\cos\psi_l t-f_c\tau_{-l}\right)}\right]+ e^{j2\pi\left(f_D t-f_c\tau_L\right)}+e^{-j2\pi\left(f_D t-f_c\tau_{-L}\right)}\right\} \quad (1)$$

Here $\beta(t)$ is amplitude fluctuation, L is the number of paths , f_c is carrier frequency, f_D is Doppler frequency, $\psi_l(t)$ has a uniform distribution in $[0,2\pi]$ and $\tau_l << T_s$ (T_s is the sample duration) in frequency- nonselective channel [14]. The jth user's signal strength is attenuated by the factor $\frac{1}{M}$ (cross correlation between spreading sequences) after dispreading by the kth users spreading sequences [15],[16],[17]. The SIR of the kth user during one symbol period can be expressed as follows

$$\gamma_k(n)=\frac{\left|A_k\beta_k(n)\right|^2}{\frac{1}{M}\sum_{j\neq k}\left|A_j\beta_j(n)\right|^2+\sigma_k^2(n)}. \quad (2)$$

Here $\beta_k(n)$ is the fading channel coefficient and $\sigma_k(n)$ is the standard deviation of the Additive White Gaussian Noise (AWGN). The simulated fading envelope for a vehicle with speed of 10km/h and its corresponding SIR are shown in Fig.2. We used all data symbols in the time slot to estimate the SIR. The chip rate is assumed $R_c = 3.84\ Mcps$ as given in the 3G specification for uplink data channel. Therefore, 40 binary symbols per time slot are available for the SIR estimation.

III. Neural Network Selection

Consider a feed forward multilayer perceptron with one hidden layer and q hidden nodes, and an Adaline neural network as predictive filters. They have p input nodes $x(n), x(n-1),\ldots, x(n-p+1)$, and the single node in the output layer represents the one-step-ahead prediction.

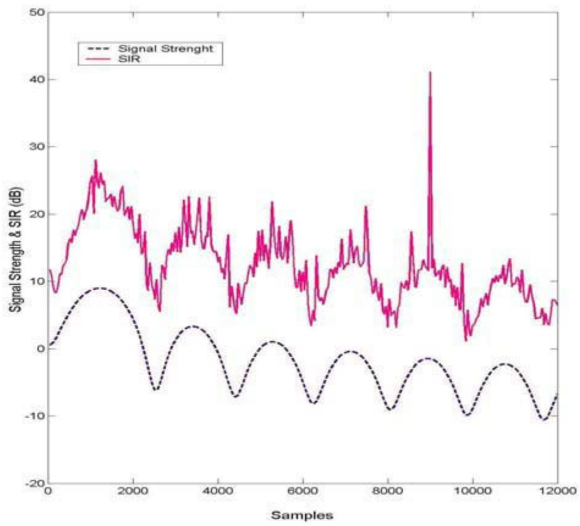

Fig. 2 SIR in Rayleigh fading channel ($f_D = 17Hz$ and $K = 12$)

In this application, MLP and Adaline predictors are given in Figs. 3 and 4, respectively. In MLP structure, the hyperbolic tangent sigmoid functions are used as the nonlinear transfer function of the hidden nodes, and the transfer function of the output node is linear. There are many ways to maximize the predictor's generalization.

From the network structure's point of view, we may select the optimal number of input and hidden nodes, or assume partial connections between different nodes and apply some pruning methods to eliminate very small weights in order to simplify the network structure [18], [19]. The number of hidden nodes q, in MLP model, and the number of input nodes should be optimized. There are two principles to find the optimal predictor. Two criteria, Minimum Mean Squared error (MSE) and Minimum Description Length (MDL) criteria [20], [10] are used for filter design parameter selection.

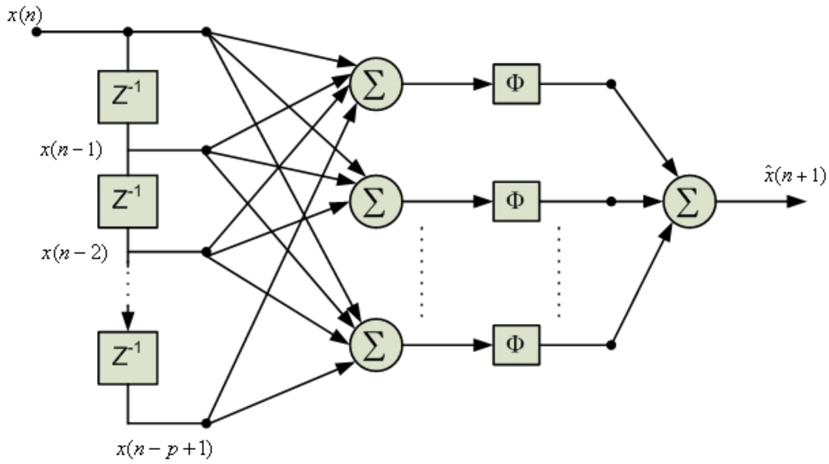

Fig. 3 The structure of the MLP neural- network-based predictor

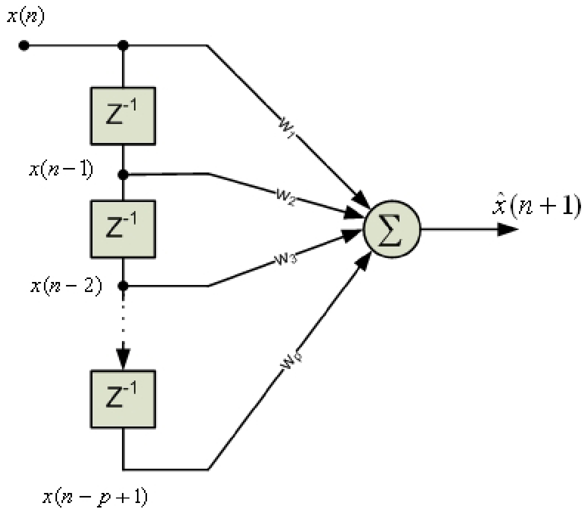

Fig. 4 The structure of the Adaline neural- network-based predictor

In this paper we used MSE principle to find the optimal structure or the length of predictor because MDL is actually a criterion to used for finding the order of the Autoregressive (AR) and Auto Regressive Moving Average (ARMA) models and our Rayleigh fading channel predictor is not an AR process, therefore MDL criteria cannot be expected to give exact results[21], [22]. MSE principle is given as

$$MSE = \frac{1}{N}\sum_{n=0}^{N-1}\left[\hat{x}(n+1) - x(n+1)\right]^2 \tag{3}$$

Here $x(n), n = 1,2,\ldots,N$ are the samples values of the time series to be predicted. In MLP predictor, we have

$$u_i(n) = \sum_{j=1}^{p} w_{ji}\, x(n-j) \qquad i = 1,2,\ldots,q \tag{4}$$

$$z_i(n) = \tanh\left[u_i(n)\right] \tag{5}$$

$$\hat{x}(n+1) = \sum_{i=1}^{q} v_i z_i(n) \tag{6}$$

The output of Adaline predictor is

$$\hat{x}(n+1) = \sum_{j=1}^{p} w_j\, x(n-j) \tag{7}$$

We divided $\{x(n)\}$ into $k_{\max} = \frac{N}{d}$ consecutive segments where d represents the length of prediction and $k_{\max}$ is an integer number. We train each network with p inputs and q hidden nodes using the back propagation learning algorithm [23] to minimize the mean squared error in each segment.

$$ES_{kd} = \sum_{n=kd}^{kd-1}\left[\hat{x}(n+1) - x(n+1)\right]^2 \tag{8}$$

Then we use the obtained optimal weights and bias to predict the points $x(n+1), n = kd, kd+1, \ldots, (k+1)d-1$ in the following subsequent (k+1)th segment to maintain the actual mean squared prediction error

$$E_{(k+1)} = \frac{1}{d}\left[x_{(k+1)}(n+1) - \hat{x}_{(k+1)}(n+1)\right]^2 \qquad (9)$$

In this prediction the parameters of the predictor are determined and updated using the past data. The predictions of the data points in the very first segment are taken as zero. This procedure is continued until the mean squared errors for all the segments are found. Then we calculate the total actual mean squared error for MLP predictor as

$$E_{per} = \frac{1}{(k_{\max}-1)} \sum_{k=1}^{k_{\max}-1} E_{(k+1)} \qquad (10)$$

We find different E_{per} for the network with the p input nodes and q hidden nodes. Due to the local minima problem with neural networks, minimization of (10) must be handled carefully .If a deterministic optimization algorithm, such as the conventional back propagation is used, the above procedures should be repeated many times, each of which has random initialization values. The final MSE of each model is the averaged MSE of all the experiments. If a stochastic search algorithm, such as the simulated annealing algorithm [25], is used, the *temperature* must be decreased as slowly as possible so that a global minimum, or at least a relatively good local minimum could be achieved. When we repeated the above procedure for B times we got

$$\overline{E}_{per} = \frac{1}{B} \sum_{b=1}^{B} E_{per}(b) \qquad (11)$$

Here b is the bth repetition. We select the network with the minimum E_{per} as the optimal predictor structure.

IV. Simulation Result

A. Off-line Optimization of Neural-Network

Due to the time-varying and mobile speed-dependent characteristics of the power response of the Rayleigh fading channel, it is not practical to optimize the predictor structure for a power signal covering the whole speed range. Therefore, we only consider the optimization of the network structures under three extreme conditions when the vehicle speed is 5, 60 and 120 km/h. The additive noise used is zero mean white Gaussian noise. We use $\overline{x} = (x_n, \ldots, x_{n+p-1})$ from a segment of a received SIR, as shown in Figs. 3 and 4. This time series has 600 samples and the segment length d here is 200. In MLP predictor, the computational complexity will be increased drastically by increasing the number of hidden nodes. A large number of hidden nodes is rarely used, and we change q in a small range, i.e. , q=1,2,3. The mean squared errors and the prediction output of different MLP structures for different vehicle speeds 5 km/h , 60 km/h and 120 km/h have been achieved in [26]. The MSE of all models candidates in Adaline at the speed of 5, 60, 120 km/h are given in Figs. 5, 6, 7, respectively. It is easy to find that the optimal Adaline has nine input nodes at the speed of 5 km/h, and for vehicle's speed of 60 km/h it has 5 input nodes, and with 18 input nodes turns out to be the best structure for the speed of 120 km/h.

B. Real-Time Prediction with On-Line Adaptation

As the fading signals are highly nonstationary, which is the case in mobile communication applications, the learning must be adaptive. We have used *on-line* back propagation algorithm with a moving window. This allows the predictor to adapt new data quickly while adequately forgetting the old data [24]. The structure of MLP and Adaline predictors are first optimized *off-line* using the procedures described above. The obtained optimal predictors are then used for prediction of SIR. At the speeds of 5, 60, 120 km/h , the output of the Adaline are shown in Figs. 8, 9, 10, respectively. The results show that the optimal MLP and Adaline predictors can predict SIR with the same MSE values of about 0.02, 0.25 at the urban mobile speeds of 5 km/h, 50 km/h, respectively. But by increasing the mobile velocity until 120 km/h, the MSE value for Adaline predictor is 0.2 and this value for MLP predictor is approximately 0.4.

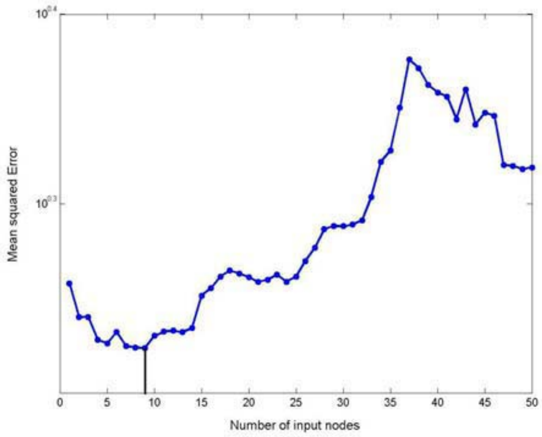

Fig. 5 MSE of different Adaline models at the speed of 5km/h

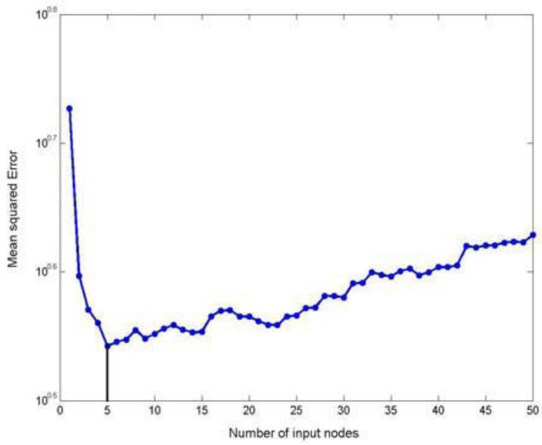

Fig. 6 MSE of different Adaline models at the speed of 60km/h

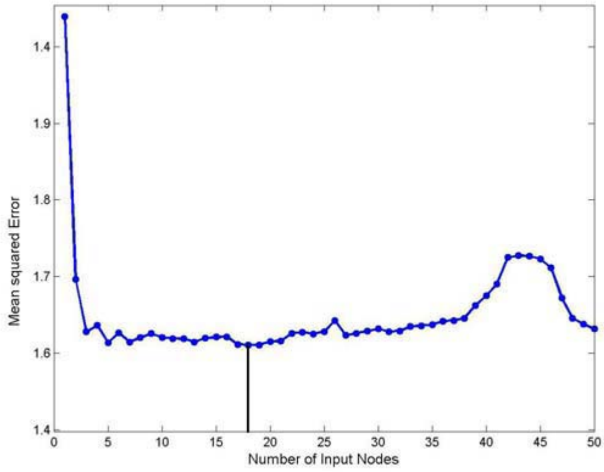

Fig. 7 MSE of different Adaline models at the speed of 120km/h

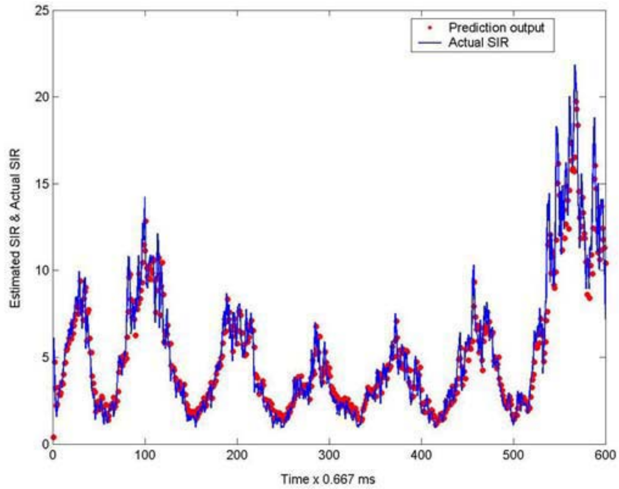

Fig. 8 The Adaline predictor output of SIR at the speed of 5 km/h along with the actual SIR

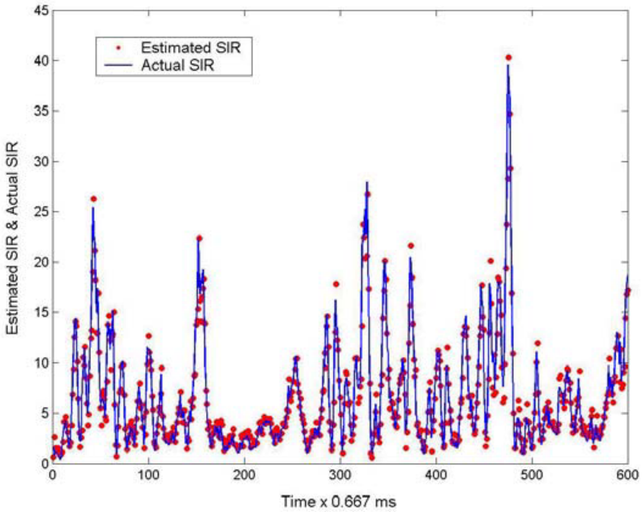

Fig. 9 The Adaline predictor output of SIR at the speed of 60 km/h along with the actual SIR

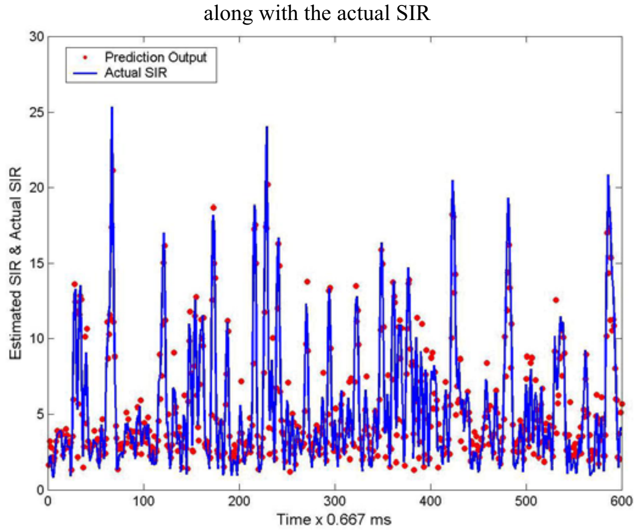

Fig. 10 The Adaline predictor output of SIR at the speed of 120 km/h along with the actual SIR

V. CONCLUSION

In this paper, we compared the linear and nonlinear neural network predictors for SIR estimation in DS/CDMA systems. Simulation results show that the optimized Adaline neural network structure is more capable in identifying the time-varying inverse dynamics of the multi path fading channel than the optimized MLP predictor at high vehicle speeds. The great advantage of neural network-based predictor is that the Adaline neural predictor with the lower complexity and shorter training time could provide better identification results. Although the neural predictor has high computational complexity, it is feasible from the application point of view, because the required sampling rate is only 1.5 KHz. Therefore, custom VLSI and DSP processors are the potential implementation platforms of our adaptive predictor. The presented neural predictors are the natural preprocessing stages for advanced fuzzy and neural power controllers.

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