A Channel Effect Prediction-Based Power Control Scheme Using PRNN/ERLS for Uplinks in DS-CDMA Cellular Mobile Systems

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***Abstract*—This paper proposes a channel effect prediction-based power control scheme using pipeline recurrent neural network (PRNN)/extended recursive least squares (ERLS) for uplinks in direct sequence code division multiple access (DS-CDMA) cellular mobile systems. Conventional signal-to-interference (SIR) prediction-based power control schemes may incur prediction mistakes caused by the adjustment of transmission power. The proposed power control scheme purely tracks the variation of channel effect and, thus, can be immune to any power adjustment. Furthermore, it adopts the PRNN with ERLS for predicting the channel effect. Simulation results show that the channel effect prediction-based power control scheme using PRNN/ERLS achieves a 40% higher system capacity and a lower outage probability than the conventional SIR prediction-based power control scheme using grey prediction method (*IEEE Trans. Veh. Technol.*, Vol. 49, No. 6, p. 2081, 2000).**

***Index Terms*—Channel effect prediction, direct sequence code division multiple access (DS-CDMA), extended recursive least squares (ERLS), power control, pipeline recurrent neural network (PRNN).**

I. Introduction

The direct sequence code division multiple access (DS-CDMA) cellular mobile system is an interference-limited system that requires power control to combat the multiple access interference (MAI) and near–far effect. The general concept of closed-loop power control for the reverse link in the DS-CDMA system is that the transmission power of a mobile is controlled within a required signal-to-interference (SIR) value received at the base station. Many uplink power control schemes have been proposed [1], [2]. However, they exhibit a loop delay. Thus, several prediction-based power control schemes have recently been proposed, including the fuzzy method [3] and grey method [4]. With *a priori* knowledge of the fading channel, these prediction-based power control schemes, employing predictors to compensate for delay, can reduce the power control error and outperform the non-prediction-based schemes.

The prediction objective of these prediction-based power control schemes is the SIR value. This received SIR value is affected not only by the channel effect, including the link gain and the interference fluctuation, but also by the transmission power, which is adjusted by the power control command. Notably, the transmission power may inhibit the SIR prediction-based power control scheme, as in [3], from generating a precise power control command. Consider an example in which the link gain declines at a deep fade period. The SIR prediction-based power control scheme first decides to send a positive command to increase the transmission power if the received SIR is lower than the desired threshold. The received SIR is thereby enhanced. Then, if the SIR predictor is misled and forecasts that the SIR value in the following cycle will exceed the desired SIR value, a negative command is sent to decrease the transmission power in the subsequent control cycle. However, the channel remains in a bad situation actually. In such a case, the received SIR value would exhibit zigzagging along a curve of deteriorated SIR value, and then it takes a long time to be restored to the desired SIR value. This is due to the fact that the transmission power interferes with the SIR prediction, and the SIR prediction-based scheme yields an inappropriate power control command for the adjustment of transmission power. The conventional SIR prediction-based power control schemes do not perform well. Wien *et al.* proposed a short-term fading prediction-based (SFP) power control scheme [5]. However, it was for downlinks, and only short-term fading needed to be considered.

In this paper, a channel effect prediction-based power control scheme for uplinks is proposed. This scheme tracks only the variation of the channel effect, including both the link gain and the MAI. Without the transmission power factor, the channel effect prediction-based power control scheme does not suffer from unsuitable impact by the transmission power. In addition, a pipeline recurrent neural network (PRNN) with extended recursive least squares (ERLS) [6] is employed for the predictor. The PRNN/ERLS predictor has been effectively and successfully applied to predict the MAI variation in the DS-CDMA/packet reservation multiple access (PRMA) system [7]. Simulation results show that the proposed scheme can improve the accuracy of power control and increase the system capacity.

II. Channel Effect Prediction-Based Power Control Scheme Using PRNN/ERLS Predictor

A. Channel Effect Prediction-Based Power Control Scheme

Fig. 1 depicts the block diagram of the channel effect prediction-based power control scheme using a PRNN/ERLS predictor. The channel effect $C_h(n)$ at time nT_p is designed as the prediction objective of the predictor, where T_p is the updating period. It is defined to be the ratio of link gain $G(n)$ to interference power $I(n)$, given by

$$C_h(n) = \frac{G(n)}{I(n)}. \quad (1)$$

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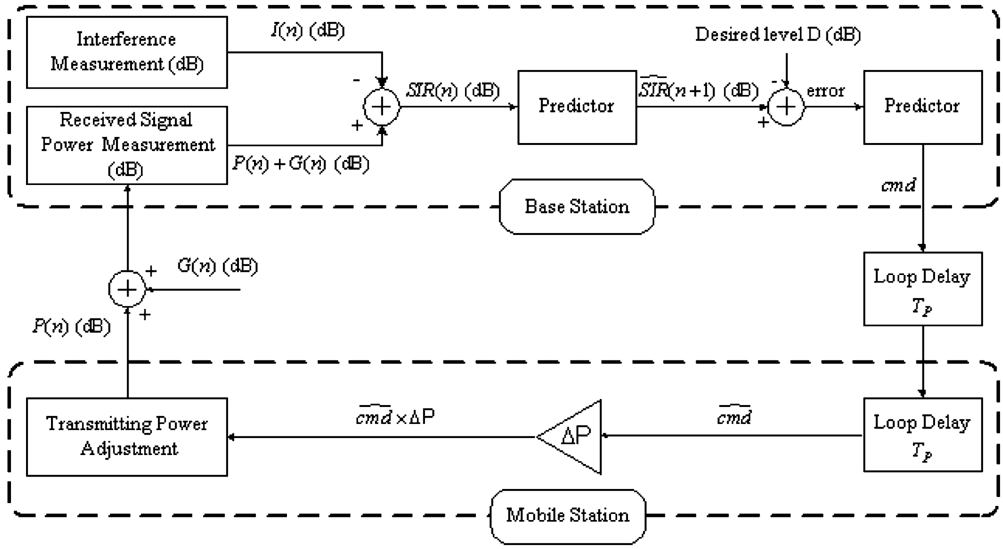

Fig. 1. Structure of Q-learning-based multirate transmission control (Q-MRTC) scheme.

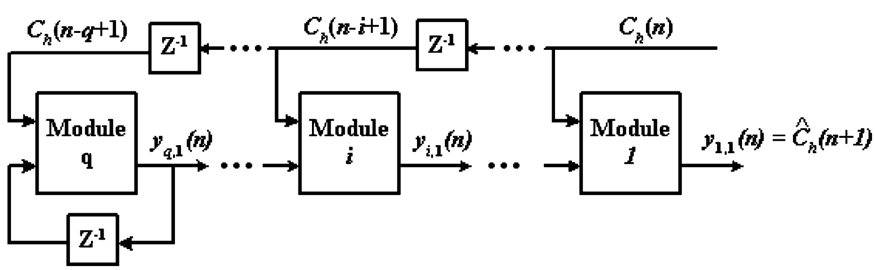

Fig. 2. PRNN structure.

As shown in the figure, at time nT_p, the mobile updates its transmission power $P(n)$; the base station measures the link gain $G(n)$ and the interference $I(n)$ for each user. The link gain can be measured from the signal strength of the common pilot channel. The channel effect $C_h(n)$ is then determined from $G(n) - I(n)$ in the decibel domain and fed into the PRNN/ERLS predictor for the next-cycle prediction. The PRNN/ERLS will yield a one-step predicted value of the channel effect $C_h(n+1)$. Furthermore, the measured transmission power $P(n)$ is determined by subtracting the received signal power from the link gain. The received SIR at the next time $(n+1)T_p$, $\widehat{\mathrm{SIR}}(n+1)$, defined as the product of the measured transmission power $P(n)$ and the predicted channel effect $\widehat{C_h}(n+1)$, can then be obtained. Comparing $\widehat{\mathrm{SIR}}(n+1)$ with the desired SIR level D yields an error value. If the error is nonnegative, then the power control command cmd is set to 1; otherwise, it is -1. The base station sends this command to the mobile. After a loop delay of T_p, the mobile detects the command $\widehat{\mathrm{cmd}}$ and adjusts the transmission power by an amount of $\Delta P \times \widehat{\mathrm{cmd}}$ dB.

B. PRNN Predictor

Consider a general sampled process of channel effect $\{C_h(n), n = kT_p, 0 \le k \le \infty\}$. According to the nonlinear autoregressive-moving average (NARMA) model of this process, with one-step prediction, the prediction value of the sample $\widehat{C_h}(n+1)$ at time $n+1$ can be determined from p previous measured samples $C_h(i)$, $n-p+1 \le i \le n$, and q prediction errors $\hat{e}(j)$, $n-q+1 \le j \le n$. It is expressed as

$$\begin{aligned}\widehat{C_h}(n+1) &= h\left(C_h(i); \hat{e}(j)\right)\\ &= h\left(C_h(n), \ldots, C_h(n-p+1)\right.\\ &\qquad \left.\hat{e}(n), \ldots, \hat{e}(n-q+1)\right)\end{aligned} \tag{2}$$

where $h(\cdot)$ is an unknown nonlinear function to be determined and $\hat{e}(j) = C_h(j) - \widehat{C_h}(j)$.

The recurrent neural network (RNN) is an approach well suited to fit the NARMA model [8]. Equation (2) should be reformulated as a new function H to enable RNN to be adopted with real-time recurrent learning algorithm (RTRL) to approximate $h(\cdot)$, given by

$$\begin{aligned}\widehat{C_h}(n+1) = H\Big(&C_h(n), \ldots, C_h(n-p+1)\\ &\widehat{C_h}(n), \ldots, \widehat{C_h}(n-q+1)\Big).\end{aligned} \tag{3}$$

In the implementation of the NARMA (p, q) prediction model, a fully connected RNN structure with M neurons and $p+q+M$ input nodes can be adopted. Several kinds of RNN have been applied to the power control prediction problem, such as the modified Elman neural network [9]; however, their computational complexities are pretty high. Instead, the PRNN structure is here considered for its computation efficiency. As depicted in Fig. 2, PRNN refers to the NARMA-based RNN predictor with a pipelined structure. PRNN divides the RNN structure into q small RNN modules [6], [7], whose structures are similar to that of the RNN. In our design, the ith small RNN consists of M' neurons and $(d + M' + 1)$ input nodes, where $q \times M' = M$ and $d = p - q + 1$. The first d input nodes are the external inputs, which are the delayed signals from $C_h(n - i + 1)$ to $C_h(n - d - i + 2)$; the $(d + 1)$th input node is constantly set to unity; the $(d + 2)$th input node is the output of the first neuron in the $(i + 1)$th module, $y_{i+1,1}(n)$, if $i \neq q$, or it is the feedback signal from the first neuron's output of module q in time $((n - 1)T_p)$, $y_{q,1}(n - 1)$, if $i = q$; and the remaining $(M' - 1)$ input nodes are feedbacked from $2 \sim M'$ neurons' output of the same module, $y_{i,2}(n - 1) \sim y_{i,M'}(n - 1)$. The weight of the connection from the jth input node to the kth neuron is given by $w_{kj}(n)$, $1 \leq j \leq d + M' + 1$, $1 \leq k \leq M'$.

The PRNN predictor yields $\widehat{C_h}(n + 1)$, which is the first output of the first module $y_{1,1}(n)$, given by

$$\widehat{C_h}(n+1) = \phi\left(\sum_{j=1}^{d} w_{i,j}(n)C_h(n-j+1) + w_{1,d+1} + w_{1,d+2}(n)y_{2,1}(n) + \sum_{j=d+3}^{d+M'+1} w_{1,j}(n)y_{1,j-d-1}(n-1)\right) \quad (4)$$

where $\phi(\cdot)$ is a sigmoid function of each neuron, expressed as

$$\phi(x) = \frac{1}{1 + exp(-x)}. \quad (5)$$

Ignoring the dependency of the updated weight matrix and recursively iterating $y_{i,1}(n)$ from $i = 2$ to $(q - 1)$ yields $\hat{C}_h(n + 1)$ as

$$\widehat{C_h}(n+1) = \hat{H}\Big(C_h(n), \ldots, C_h(n-p+1) \quad \widehat{C_h}(n), \ldots, \widehat{C_h}(n-q+1)\Big) \quad (6)$$

where $\hat{H}(\cdot)$ has a nested nonlinear property. $\hat{H}(\cdot)$ can accurately approximate the nonlinear function of $H(\cdot)$, which the NARMA-based RNN can provide.

C. ERLS Learning Algorithm

Here, the ERLS is applied as the learning algorithm for PRNN. The prediction errors for each module $e_i(n)$ and the PRNN predictor $E(n)$ are, respectively, defined as

$$e_i(n) = C_h(n - i + 1) - y_{i,1} \quad (7)$$

and

$$E(n) = \sum_{i=1}^{M} \xi^{i-1} e_i^2(n) \quad (8)$$

where $\xi \in (0, 1]$ is the forgetting factor. The term ξ^{i-1} is an approximate measure of the memory of the individual modules in the PRNN. The cost function of ERLS is defined as

$$\varepsilon_{\mathrm{ERLS}}(n) = \sum_{k=1}^{n} \xi^{n-k} E(k). \quad (9)$$

The ERLS algorithm minimizes the cost function (9) and then updates the weights of the neurons in the modules accordingly. For a detailed description of the learning algorithm, please see [6]. ERLS considers present and previous errors, so it outperforms the gradient decent algorithm which considers only the present error.

The PRNN with ERLS is well suited for prediction in a nonlinear and nonstationary radio channel environment because of the distributed nonlinearity built into its design and the capability of the neural network learning from the environment.

III. Simulation Results and Discussions

In the simulations, the DS-CDMA cellular mobile system is considered in a 19-cell hexagonal-grid configuration. The link gain $G(n)$ of the channel is determined by the long-term fading (free space loss and log-normal shadowing) and the short-term fading (Rayleigh fading). The data traffic is modeled as an ON–OFF source, which consists of two major parameter sets—the distributions of ON–OFF periods and the distribution of packet arrivals during an ON period. For simplicity, the transmission is assumed to be continuous during the ON period. The Pareto distribution is used, where the typical mean ON period is 7.2 s with a "heaviness" of $\rho = 1.7$ and the typical mean OFF period is 10.5 s with a "heaviness" of $\rho = 1.2$ [10]. Furthermore, the simulations ignore the effects of sectorization, handoff, branch diversity, and voice activity.

Every simulation result includes 100 simulation cycles, and each of which contains 1000 updating periods. Mobiles are randomly located at the beginning of each cycle and assumed to be fixed. As for the PRNN predictor, parameters are selected as: $M = 4$; $N = 2$; $p = 4$; and $\xi = 0.99$ [6].

The system performance measure considered herein is the average outage probability P_0, which is given by

$$P_0 = \Pr\{\mathrm{SIR}_r < \mathrm{SIR}_0\} \quad (10)$$

where SIR_r is the received SIR and SIR_0 is the minimum SIR required to achieve a desired bit error rate. $E_b/N_0 = \mathrm{SIR}_0 \times$ PG, where PG is the processing gain, so the value of SIR_0 for a service can be determined by the service's required E_b/N_0 and PG. For voice services, $\mathrm{SIR}_0 = -18$ dB is obtained if PG $= 256$ and the required $E_b/N_0 = 6$ dB. For multirate data services, the required E_b/N_0 is assumed to be 9 dB, the PG is assumed to be varied from 256 to 32, and then the SIR_0 is set accordingly. The desired level D is set to be 4 dB higher than SIR_0 in the simulation. In addition, the step size ΔP is set to 2 dB, and the number of mobile users in each cell is $K = 8$.

The proposed channel effect prediction-based power control scheme and the conventional SIR prediction-based power

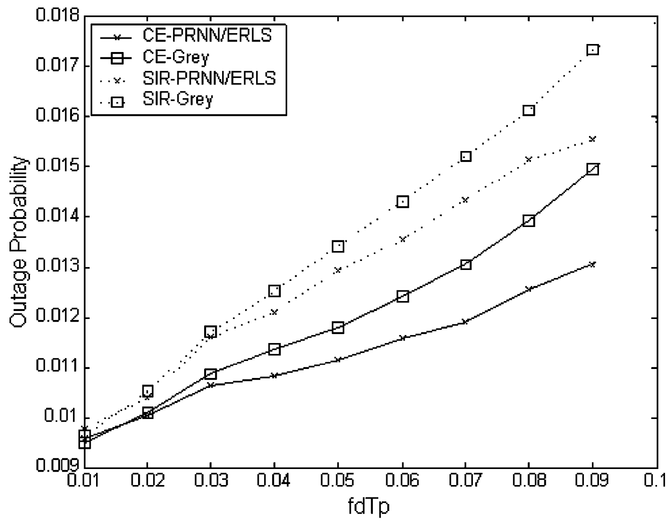

Fig. 3. Outage probabilities of power control schemes versus $f_D T_p$ for eight voice users in a cell.

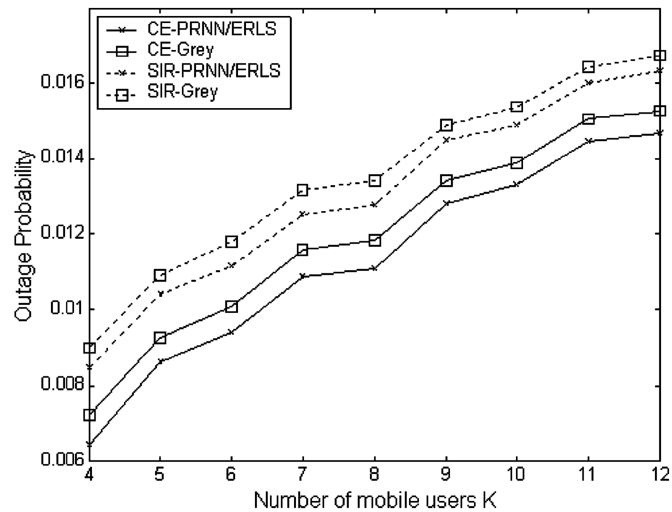

Fig. 4. Outage probabilities of power control schemes versus the number of voice-only mobile users in each cell with $f_D T_p = 0.05$.

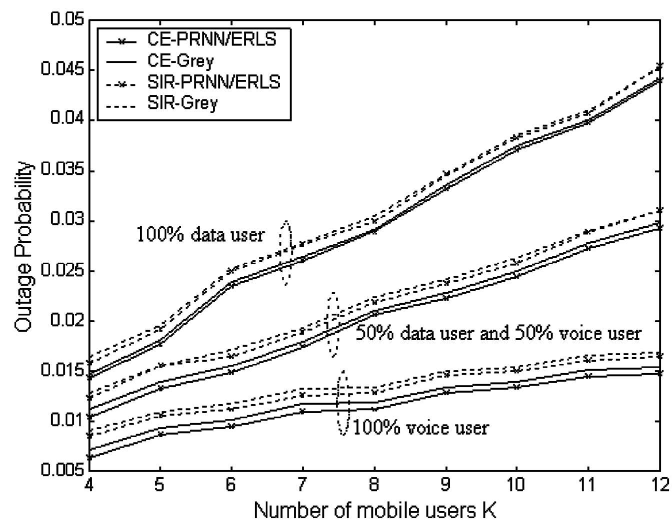

Fig. 5. Outage probabilities of power control schemes versus the number of mobile users in a cell with $f_D T_p = 0.05$.

control scheme are simulated for performance comparison. Both the PRNN/ERLS and the grey methods are adopted by these two schemes as a predictor. Hence, four schemes are investigated, namely: 1) the channel effect prediction-based scheme with PRNN/ERLS (CE-PRNN/ERLS); 2) the channel effect prediction-based scheme with grey (CE-Grey); 3) the SIR prediction-based scheme with PRNN/ERLS (SIR-PRNN/ERLS); and 4) the SIR prediction-based scheme with grey (SIR-Grey) [4].

Fig. 3 plots the outage probabilities versus the normalized Doppler frequency shift $f_D T_p$. The channel effect prediction-based power control schemes (CE-PRNN/ERLS and CE-Grey) outperform the conventional SIR prediction-based ones (SIR-PRNN/ERLS and SIR-Grey). This is due to the fact that the channel effect prediction-based scheme is related to the channel gain and the interference but is independent of the transmission power, especially for high-speed users. As mentioned above, if the transmission power is both the control objective and a component of the prediction objective, the situation could confuse the predictor regarding the real status of the radio channel. As a result, the SIR prediction-based power control scheme slowly converges to the desired SIR value D. Furthermore, PRNN/ERLS outperforms the grey method, given a prediction-based power control scheme. This is due to the fact that the PRNN/ERLS can capture the signal correlation more accurately than the grey method. The PRNN is basically a RNN and has an infinite memory of past signals. Moreover, the ERLS algorithm introduces the forgetting factor that assigns higher weights to recently received signals. This feature helps the PRNN/ERLS predictor to deal with nonstationary signals. On the contrary, the grey method only performs well in shorter learning windows (of three to six time intervals) [5].

Fig. 4 plots the outage probabilities versus the number of voice-only mobile users in each cell with $f_D T_p = 0.05$. The CE-PRNN/ERLS scheme outperforms the other schemes. If the quality of service (QoS) required outage probability for voice service is set to 1%, then the proposed CE-PRNN/ERLS can serve seven users in each cell, while the SIR-Grey scheme can only serve about five users. The CE-PRNN/ERLS yields a system capacity 40% higher than that given by the SIR-Grey. Fig. 5 plots the outage probabilities versus the number of voice and/or data users in each cell with $f_D T_p = 0.05$. It can be seen that the system performance deteriorates as the ratio of data users increases. The reasons are as follows: Data services require higher transmission rates and higher quality of communications; so the transmission power of data users must be increased. Furthermore, the traffic flows of data services are intermittent, corresponding to a relatively higher transmission variation. Hence, data services suffer a larger interference variation. The CE-PRNN/ERLS scheme, with the aid of channel effect prediction, can eliminate the interference associated with power control adjustment itself. Thus, it still can outperform the SIR-Grey scheme by an amount of 8% in a mixed mode scenario and 6.5% in a pure data scenario, given with a 2% outage probability requirement.

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