Fuzzy/Neural Congestion Control for Integrated Voice and Data DS-CDMA/FRMA Cellular Networks

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***Abstract*—The paper proposes congestion control using fuzzy/neural techniques for integrated voice and data direct-sequence code division multiple access/frame reservation multiple access (DS-CDMA/FRMA) cellular networks. The fuzzy/neural congestion controller is constituted by a pipeline recurrent neural network (PRNN) interference predictor, a fuzzy performance indicator, and a fuzzy/neural access probability controller. It regulates traffic input to the integrated voice and data DS-CDMA/FRMA cellular system by determining proper access probabilities for users so that congestion can be avoided and throughput can be maximized. Simulation results show that the DS-CDMA/FRMA fuzzy/neural congestion controllers perform better than conventional DS-CDMA/PRMA with channel access function in voice packet dropping ratio, corruption ratio, and utilization. In addition, the neural congestion controller outperforms the fuzzy congestion controller.**

***Index Terms*—Congestion control, direct sequence-code division multiple access/frame reservation multiple access (DS-CDMA/FRMA) cellular networks, fuzzy/neural techniques.**

I. Introduction

The DIRECT-SEQUENCE code division multiple access (DS-CDMA) is a preferable candidate for the third-generation cellular systems. One characteristic of DS-CDMA is that by separation of pseudonoise (PN) codes, many users can transmit at the same time within the same frequency band. It manifests advantages in many aspects such as high spectrum efficiency, soft limit on capacity, wide bandwidth (or frequency diversity), multipath mitigation, interference suppression, inherent privacy, lower transmit power requirements, and unity reuse factor.

It has been recognized that CDMA capacity is only interference limited; any reduction of interference for CDMA systems can convert directly and linearly into an increment of capacity [1]. When the number of users becomes large, congestion occurs and transmission corruption happens due to multiple access interference (MAI). Congestion is an inherent problem for networks with multiple user access when the load exceeds what can be handled. Many air interface protocols were presented to lower the possibility of congestion and to increase system utilization. In [2], a rough comparison was made among packet reservation multiple access (PRMA), frame reservation multiple access (FRMA), circuit reservation multiple access (CRMA), burst reservation multiple access (BuRMA), and so forth, and it was concluded that PRMA and FRMA would be better choices for integrated voice and data systems. In [3], an FRMA protocol was proposed to reduce receiver activity for the integration of voice and data over PRMA. In [4], the permission probability of DS-CDMA/PRMA protocol was controlled by a piece-wise linear function. However, when fading is taken into consideration, the piece-wise linear function fails to catch characteristics of time-varying fluctuate traffic (interference). Thus, it is somewhat difficult to make a good decision under such a nonstationary situation.

In the past decade, fuzzy systems have replaced conventional technologies in many scientific applications and engineering systems, especially in control systems and pattern recognition. They can provide decision-support and expert systems with powerful reasoning capabilities bound by a minimum of rules. The major feature of the fuzzy logic is its ability to express the amount of ambiguity in human thinking and subjectivity in a comparatively undistorted manner. When a mathematical model of the process does not exist, it is appropriate to use fuzzy logic [5]. On the other hand, neural networks are a new generation of information processing systems that are constructed to utilize some of the organizational principles which characterize the human brain. They are able to learn arbitrary nonlinear input–output mapping directly from training data; they can sensibly interpolate input patterns that are new to the network; and they can automatically adjust their connection weights to optimize their behaviors as controllers, predictors, pattern recognizers, decision makers, etc. Neural networks are good at tasks such as pattern matching and classification, function approximation, optimization, vector quantization, and data clustering [5]. Both fuzzy systems and neural networks are numerical model-free estimators and dynamical systems; they are the intelligent techniques that can improve systems working in uncertain and nonstationary environments.

Therefore, in this paper we propose fuzzy/neural-based congestion control for integrated voice and data DS-CDMA/FRMA cellular systems by providing adequate access probability for users. The fuzzy/neural congestion controller is designed to contain a pipeline recurrent neural network (PRNN) interference predictor, a fuzzy performance indicator, and an access probability controller. The PRNN is adopted to predict the interference so as to achieve good nonlinear prediction capability and fast convergence time [6], [7] because the uplink interference process in a DS-CDMA/FRMA cellular system is non-

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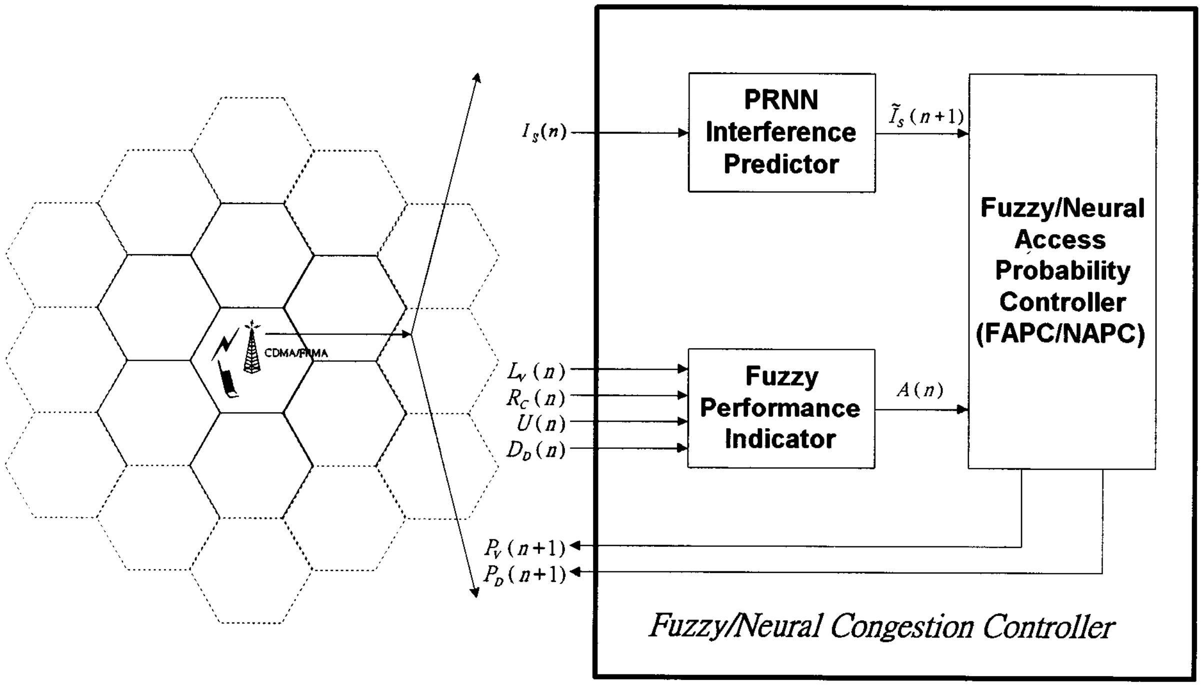

Fig. 1. A DS-CDMA/FRMA cellular system with the fuzzy/neural congestion controller.

linear and nonstationary. The fuzzy performance indicator considers the system effective measures such as voice packet dropping probability, packet corruption ratio, data packet delay, utilization, and issues an overall performance indication as feedback so that the fuzzy/neural congestion controller would be a stable closed-loop system. Also, the access probability controller, based on the predicted next-step interference sample and the system performance indication, determines the access probabilities for users. We here consider two different designs for the access probability controller (APC): fuzzy access probability controller (FAPC) and neural-net access probability controller (NAPC). FAPC uses fuzzy logics to realize, while NAPC adopts radial-basis function network (RBFN) to implement. Simulation results show that the DS-CDMA/FRMA fuzzy/neural congestion controllers with intelligent techniques overrides the conventional DS-CDMA/PRMA congestion controller with channel access function [4] in the overall performance; and NAPC outperforms FAPC.

The rest of the paper is organized as follows. The system model of the fuzzy/neural congestion controller in an integrated voice and data DS-CDMA/FRMA cellular system is introduced in Section II. The design of the PRNN interference predictor, the fuzzy performance indicator, and the access probability controllers using fuzzy logic techniques or neural networks are described in Section III. Simulation results are presented and discussed in Section IV. Section V gives some concluding remarks.

II. System Model

The system model of a DS-CDMA/FRMA cellular communication system with a fuzzy/neural congestion controller is shown in Fig. 1. The fuzzy/neural congestion controller consists of a PRNN interference predictor, a fuzzy performance indicator, and a fuzzy/neural access probability controller (FAPC/NAPC). The cellular system contains K cells, where each cell has separate uplink band and downlink band. PN codes are assumed to be enough to support all users which are uniformly distributed within a cell.

In both uplink and downlink, the DS-CDMA/FRMA protocol has a time-division frame structure which consists of N slots per frame time T. Each slot has several CDMA code channels for users to transmit their packets. As shown in Fig. 2, the first slot of every uplink (downlink) frame is designed for contention (signaling), and the remaining slots of the uplink (downlink) frame are for reservation (information). The uplink contention slot is for contention users, defined as those who have packets to transmit but who have not yet not attained reservation; the uplink reservation slots are for reservation users, defined as those who have successfully contended and have obtained a reservation. The uplink information packets include not only the information bits, but also some signaling bits to notify the base station whether the user wants to continue transmitting or release the reservation in the next frame. The downlink signaling slot contains the message of access probability for uplink contending users, contention result in the previous frame, and slot position for uplink reservation users. The downlink information slots are used by the base station to transmit downlink information packets to mobile users. Note that the downlink signaling slot in frame $(n+1)$ contains the contention result of the uplink contention slot in frame n and the slot position for reservation users in frame $(n-1)$'s slot N and frame (n)'s slots $2 \sim N$. Such a design is because of a time slot shift between uplink and downlink frames. In this case, if a reservation user transmits the reservation release signal in its last packet in slot N of frame $(n-1)$, the capacity will still be reserved in frame n and is actually released in frame $(n+1)$.

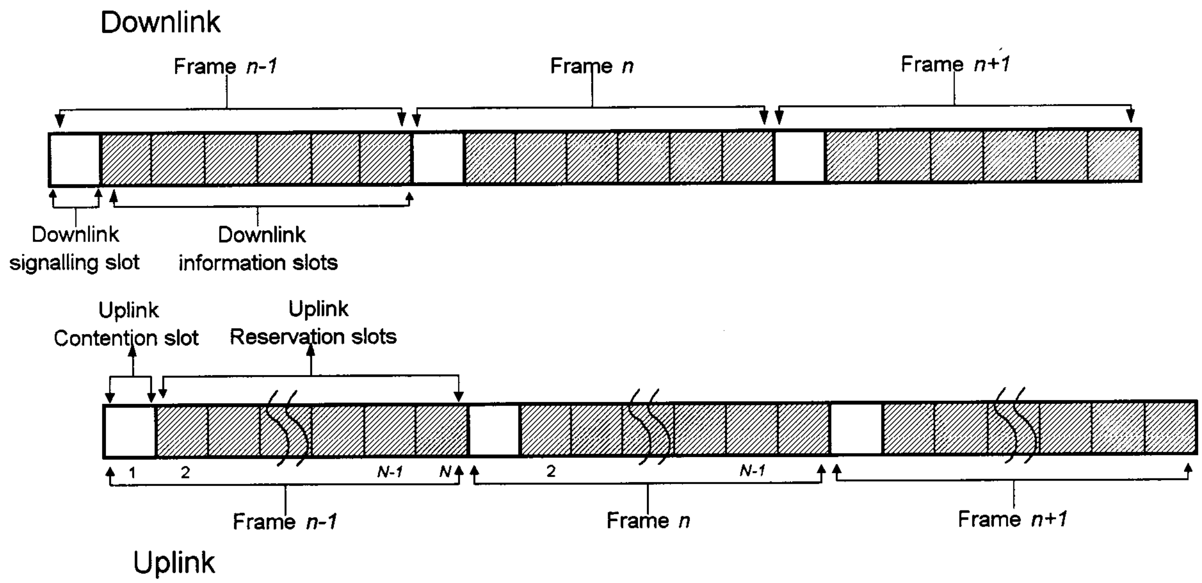

Fig. 2. The frame structure of the DS-CDMA/FRMA protocol.

If a contention user wants to transmit information packets, it first transmits a contention information packet at the contention slot according to its access probability. The voice (data) access probability for $(n+1)$th frame is denoted by $P_V(n+1)$ ($P_D(n+1)$). If the user's contention information packet is successfully received at base station, the base station will reserve a CDMA code of a time slot for the user and the user transmits information packets in the reservation slot of the next frames accordingly. If the contending information packet is corrupted because of MAI or not admitted to transmit, voice users have different treatment from data users. For voice users, the contention information packet will be queued to transmit in the next frame. If the contending voice packet has no chance to succeed until delay limit time T_D, the packet will be discarded and the next voice packet will try contention in the next frames. For data users, the contention information packet will be queued to transmit until final success.

The newly successful user is first allocated with a CDMA code in the slot which has more free capacity. When the system incurs a situation such that the reservation capacity required is more than the total capacity in reservation slots due to the increase of reservation users, some bandwidth of the contention slot will be borrowed for temporary use by some reservation users. In this case, the access probability will be decreased. The reservation packets that are permitted to temporarily use the contention slot should be voice packets only because of the delay sensitivity of voice users. When the reservation load becomes low, the reservation users in the contention slot will be rearranged into reservation slots.

The radio propagation model here contains two main loss factors: mean path loss and log-normal shadowing. Thus the average received power can be expressed as [1]

$$\Gamma(r) = P \cdot r^{-\theta} \cdot 10^{\zeta/10} \tag{1}$$

where P is the transmitted power, r is the distance between the base station and the user, θ is the path loss exponent, and ζ is the log-normal random variable. For simplicity, the whole system is assumed to be under perfect power control so that the slow fading can be equalized and thus the received power at the base station is a constant value S.

As the interference power of user j at any time instant n in base station k is considered, it is composed of the home-cell interference, the first-tier adjacent-cell interference, and the background noise (additive white Gaussian noise), denoted by $I_{H,k}(n)$, $I_{A,k}(n)$, and ψ, respectively. Generally speaking, the home-cell interference and the adjacent-cell interference are much larger than the background noise, thus we ignore ψ here. Assume that there are $N_{v,k}$ ($N_{d,k}$) voice (data) users in cell k and the voice (data) traffic activity factor is denoted by ν_i (δ_i). Then $I_{H,k}(n)$ for a voice user j within a basic channel (time slot) can be expressed as [1]

$$I_{H,k}(n) = S\left[\sum_{i=1,\, i\neq j}^{N_{v,k}} \nu_i + \sum_{i=1}^{N_{d,k}} \delta_i\right] \tag{2}$$

where the first (second) term in the bracket is the total interference coming from the other voice users (all data users). $I_{A,k}(n)$ is given by [1]

$$I_{A,k}(n) = S\sum_b \left[\sum_{i=1}^{N_{v,b}} \nu_i \cdot \left(\frac{r_{ib}}{r_{ik}}\right)^{\theta} \cdot 10^{(\zeta_{ik}-\zeta_{ib})/10} + \sum_{i=1}^{N_{d,b}} \delta_i \cdot \left(\frac{r_{ib}}{r_{ik}}\right)^{\theta} \cdot 10^{(\zeta_{ik}-\zeta_{ib})/10}\right] \tag{3}$$

where the first (second) term in the bracket is the total interference coming from all voice (data) users in cell b, $b \in \{$ the first-tier adjacent cells neighboring to cell $k\}$, r_{ik} is the distance of user i in cell b to the base station of cell k, and r_{ib} is the distance of user i to the base station of its home cell. Since perfect power control is assumed, $I_{H,k}(n)$ is the same for all users. The interference power in a basic channel at time instant n, denoted by $I_S(n)$, is the summation of $I_{H,k}(n)$ and $I_{A,k}(n)$. In this paper, $I_S(n)$ is periodically measured every frame time nT at base station and is chosen as an input variable for the PRNN interference predictor.

Voice source model is characterized as a two-state (talkspurt and silence) Markov chain and will generate one packet in each frame time T. The talkspurt and silence periods are assumed to be exponentially distributed with mean $1/\alpha$ and $1/\beta$, respectively. Data source model is assumed to be in Poisson process with mean arrival rate λ_d. Voice (data) packets will be put into voice (data) queue with capacity B_V (B_D) before being transmitted. If the queue is full or the packet cannot be successfully received at the base, the packet is considered dropped.

III. Fuzzy/Neural Congestion Controller

The building blocks for the fuzzy/neural congestion controller are the PRNN interference predictor, the fuzzy performance indicator, and the fuzzy/neural access probability controller. Detailed designs are described in the following.

A. PRNN Interference Predictor

PRNN is a pipelined structure of recurrent neural network (RNN). It has good prediction capability and fast converges speed, with real-time recurrent learning (RTRL) algorithm [8]. In the PRNN interference predictor, the predicted interference sample at frame $(n+1)$, $\tilde{I}_S(n+1)$, can be obtained from p previously measured interference samples $I_S(i)$, $n-p+1 \le i \le n$ and q prediction errors $\tilde{e}(j)$, $n-q+1 \le j \le n$, based on a nonlinear ARMA (NARMA) model of process. $\tilde{I}_S(n+1)$ can be expressed as

$$\tilde{I}_S(n+1) = h\left(I_S(n), \ldots, I_S(n-p+1); \tilde{e}(n), \ldots, \tilde{e}_(n-q+1)\right) \tag{4}$$

where $h(\cdot)$ is an unknown nonlinear function and $\tilde{e}(j) = I_S(j) - \tilde{I}_S(j)$. To approximate the nonlinear function $h(\cdot)$ by RNN with RTRL algorithm, inputs of RNN cannot be error samples [7]. So we reformulate the above recursive formula to be a new function H, which is expressed as

$$\tilde{I}_S(n+1) = H\left(I_S(n), \ldots, I_S(n-p+1); \tilde{I}_S(n), \ldots, \tilde{I}_S(n-q+1)\right). \tag{5}$$

A fully connected RNN structure has M neurons and $p+q+M$ input nodes, as shown in Fig. 3. The first p input nodes are the external inputs which are the measured interference signals from $I_S(n)$ to $I_S(n-p+1)$. There is a bias input value which is always 1. The next q input nodes are the predicted signals from

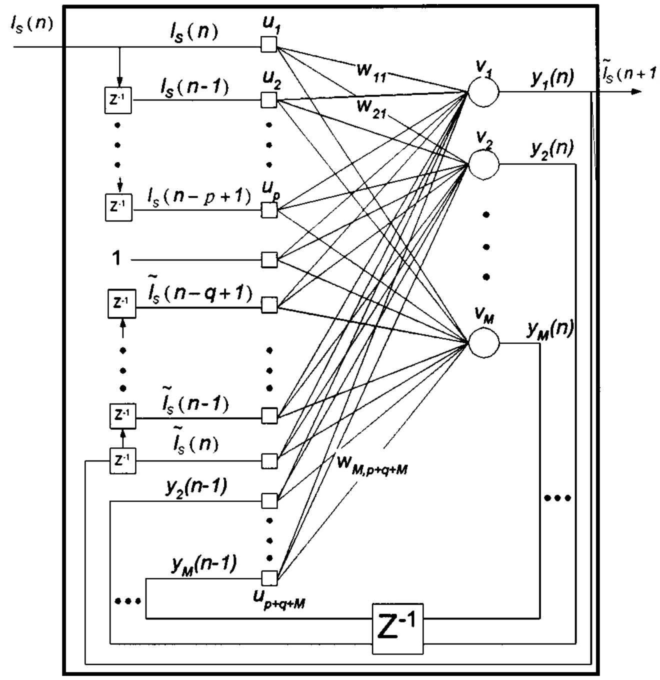

Fig. 3. The RNN structure.

$\tilde{I}_S(n)$ to $\tilde{I}_S(n-q+1)$. There are $M-1$ feedbacks from neuron outputs: $y_2(n-1) \sim y_M(n-1)$. w_{ji} represents the weight of the connection from the ith input node to the jth neuron, $1 \le i \le p+q+M$, $1 \le j \le M$. The jth neuron calculates a weighted sum, denoted by $v_j(n)$, as

$$v_j(n) = \sum_{i=1}^{p+q+M} w_{ji}(n) u_i(n) \tag{6}$$

where $u_i(n)$ represents the ith input node. Then, it transforms $v_j(n)$ by a sigmoidal activation function $\varphi(\cdot)$ to an output $y_j(n)$ given by

$$y_j(n) = \varphi(v_j(n)) = \frac{1}{1+\exp(-v_j(n))}. \tag{7}$$

In this way, $\tilde{I}_S(n+1)$ can be obtained by

$$\begin{aligned}\tilde{I}_S(n+1) &= y_1(n) \\ &= \varphi\left(\sum_{i=1}^{p} w_{1i}(n) I_S(n+1-i) + w_{1,p+1}(n) \right. \\ &\quad + \sum_{i=p+2}^{p+q+1} w_{1i}(n) \tilde{I}_S(n-i+p+2) \\ &\quad \left. + \sum_{i=p+q+2}^{p+q+M} w_{1i}(n) y_{i-p-q}(n-1) \right) \\ &= \hat{H}\left(I_S(n), \ldots, I_S(n-p+1), \tilde{I}_S(n), \ldots, \right. \\ &\quad \left. \tilde{I}_S(n-q+1)\right)\end{aligned} \tag{8}$$

where $\hat{H}(\cdot)$ is the nonlinear approximated function of $H(\cdot)$.

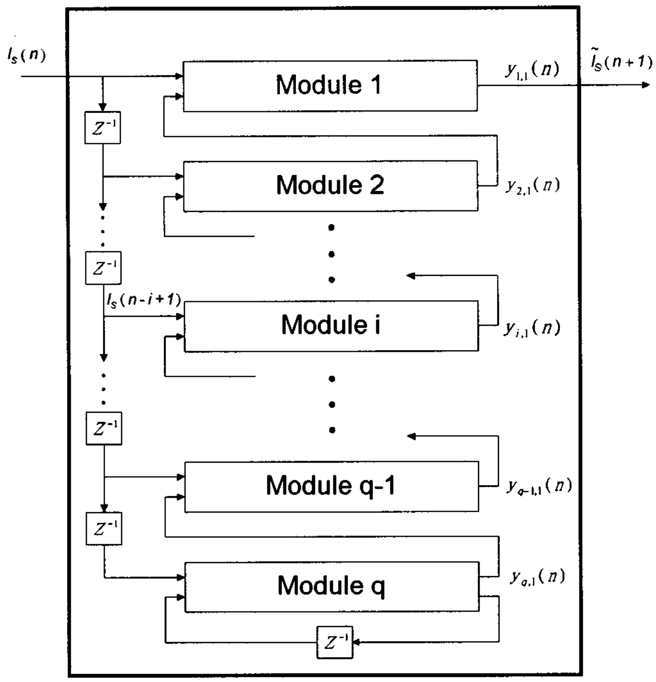

Fig. 4. The PRNN structure.

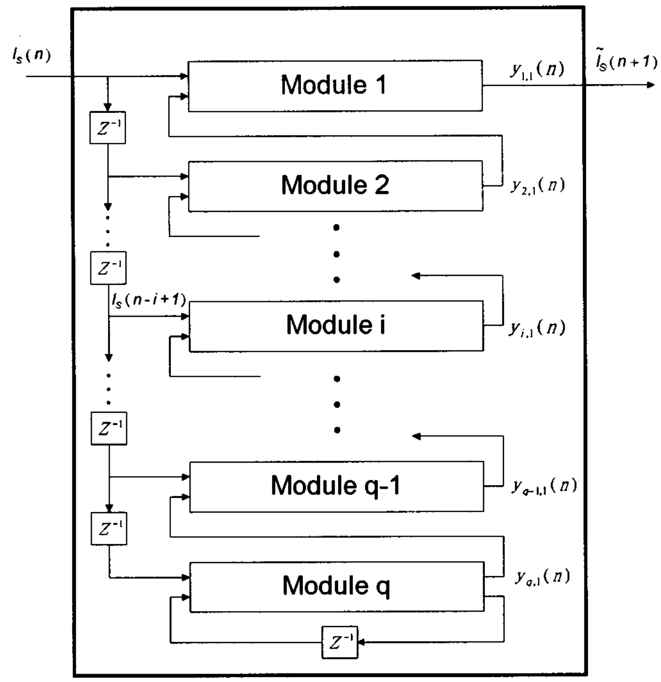

Fig. 5. The small RNN module i.

The incremental change of weight w_{ij} is according to the steepest decent method in the RTRL algorithm [8]

$$w_{ij}(n+1) = w_{ij}(n) - \eta \frac{\partial C(n)}{\partial w_{ij}} \tag{9}$$

where η is the learning rate parameter, $C(n)$ is the cost function defined as

$$C(n) = \sum_{i=1}^{q} \lambda_n^{i-1} \hat{e}^2(n-i+1) \tag{10}$$

and λ_n is an exponential forgetting factor which is bounded in [0, 1]. Note that the computation of the RNN prediction is proportional to M^4 [6], [8].

The PRNN structure, which divides the RNN structure into q small RNN modules, is shown in Fig. 4, and each small RNN module i has a structure similar to that of RNN [6]. As shown in Fig. 5, the small RNN module i consists of M' neurons and $(d + M' + 1)$ input nodes, where $q \times M' = M$ and $d = p - q + 1$. For the ith module, the first d input nodes are the external inputs which are the delayed signals from $I_S(n-i+1)$ to $I_S(n-i-d+2)$; the $(d+1)$th input node is a constant 1. The $(d+2)$th input node is the first neuron's output of the $(i+1)$th module: $y_{i+1,1}(n)$ if $i \neq q$ or the feedback signal from the first neuron's output of module q in time $(n-1)$. $y_{q,1}(n-1)$ if $i = q$, and the rest $(M'-1)$ input nodes are the feedbacks of $2 \sim M'$ neurons in the same module: $y_{i2}(n-1) \sim y_{iM'}(n-1)$. w_{ij} is the weight of connection from the ith input node to the jth neuron. Finally, the output of the first neuron in the first module represents the PRNN prediction output at time instant $(n+1)$. Note that the computation of the PRNN prediction is proportional to $q \times M'^4 = M^4/q^3$, thus PRNN is much faster than RNN. And the PRNN interference predictor operates not only with preliminary learning phase but also with adaptive learning during working.

B. Fuzzy Performance Indicator

The system performance is usually described by measures such as the voice packet dropping ratio L_V, the contention corruption ratio R_C, the system utilization U, and the data packet delay D_D. Neither of them can represent the system performance alone without the consideration of others. We use fuzzy logics to get an overall system performance indication A, based on the four performance measures mentioned above as input linguistic variables. Thus the congestion controller has a concluding performance indication feedback so that it is a closed-loop system and has stable and robust operations.

We define the term set of L_V as $T(L_V) = \{\text{Low, High}\} = \{\text{Lo, Hi}\}$, R_C as $T(R_C) = \{\text{Little, Big}\} = \{Lt, Bg\}$, U as $T(U) = \{\text{Small, Large}\} = \{Sm, La\}$, and D_D as $T(D_D) = \{\text{Short, Long}\} = \{Sh, Lg\}$. The membership functions for $T(L_V)$, $T(R_C)$, $T(U)$, and $T(D_D)$ are defined as $M(L_V) = \{\mu_{Lo}, \mu_{Hi}\}$, $M(R_C) = \{\mu_{Lt}, \mu_{Bg}\}$, $M(U) = \{\mu_{Sm}, \mu_{La}\}$, and $M(D_D) = \{\mu_{Sh}, \mu_{Lg}\}$, where

$$\mu_{Lo}(L_V) = g(L_V;\, L_{V,\min},\, Lo_e,\, 0,\, Lo_w) \tag{11}$$
$$\mu_{Hi}(L_V) = g(L_V;\, Hi_e,\, L_{V,\max},\, Hi_w,\, 0) \tag{12}$$
$$\mu_{Lt}(R_C) = g(R_C;\, R_{C,\min},\, Lt_e,\, 0,\, Lt_w) \tag{13}$$
$$\mu_{Bg}(R_C) = g(R_C;\, Bg_e,\, R_{C,\max},\, Bg_w,\, 0) \tag{14}$$
$$\mu_{Sm}(U) = g(U;\, U_{\min},\, Sm_e,\, 0,\, Sm_w) \tag{15}$$
$$\mu_{La}(U) = g(U;\, La_e,\, U_{\max},\, La_w,\, 0) \tag{16}$$
$$\mu_{Sh}(D_D) = g(D_D;\, D_{D,\min},\, Sh_e,\, 0,\, Sh_w) \tag{17}$$
$$\mu_{Lg}(D_D) = g(D_D;\, Lg_e,\, D_{D,\max},\, Lg_w,\, 0) \tag{18}$$

and $L_{V,\min}$, $L_{V,\max}$, $R_{C,\min}$, $R_{C,\max}$, $U_{\min}$, $U_{\max}$, and $D_{D,\min}$, $D_{D,\max}$ are the minimum and maximum possible values for L_V, R_C, U, and D_D, respectively, and $g(\cdot)$ is a trapezoidal function defined as

$$g(x; x_0, x_1, a_0, a_1) = \begin{cases} \frac{x-x_0}{a_0}+1, & \text{for } x_0-a_0 < x \le x_0 \\ 1, & \text{for } x_0 < x \le x_1 \\ \frac{x_0-x}{a_1}+1, & \text{for } x_1 < x \le x_1+a_1 \\ 0, & \text{otherwise.} \end{cases} \tag{19}$$

The output linguistic variable is the performance indicator A. The term set of A is defined as $T(A) = \{A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8\}$, and the membership function of A is denoted by $M(A) = \{\mu_{A_1}, \mu_{A_2}, \mu_{A_3}, \mu_{A_4}, \mu_{A_5}, \mu_{A_6}, \mu_{A_7}, \mu_{A_8}\}$, where

$$\mu_{A_1}(A) = f(A; A_{1,c}, 0, 0) \tag{20}$$
$$\mu_{A_2}(A) = f(A; A_{2,c}, 0, 0) \tag{21}$$
$$\mu_{A_3}(A) = f(A; A_{3,c}, 0, 0) \tag{22}$$
$$\mu_{A_4}(A) = f(A; A_{4,c}, 0, 0) \tag{23}$$
$$\mu_{A_5}(A) = f(A; A_{5,c}, 0, 0) \tag{24}$$
$$\mu_{A_6}(A) = f(A; A_{6,c}, 0, 0) \tag{25}$$
$$\mu_{A_7}(A) = f(A; A_{7,c}, 0, 0) \tag{26}$$
$$\mu_{A_8}(A) = f(A; A_{8,c}, 0, 0) \tag{27}$$

and $f(\cdot)$ is a triangular function defined as

$$f(x; x_0, a_0, a_1) = \begin{cases} \frac{x-x_0}{a_0}+1, & \text{for } x_0-a_0 < x \le x_0 \\ \frac{x_0-x}{a_1}+1, & \text{for } x_0 < x \le x_0+a_1 \\ 0, & \text{otherwise.} \end{cases} \tag{28}$$

We heuristically set $A_{i,c} = (0.5+0.5\times i), 1 \le i \le 8$ to reflect different degrees of the performance indication, and we denote $A_{4,c}$ in the middle to be the best performance.

Table I shows the rule structure. These rules are set according to experience and knowledge of that the contention corruption ratio R_C plays a dominant role and then the voice packet dropping ratio L_V does. We use the *max–min* inference method to calculate the membership value of each term in $T(A)$. Take rules 4 and 5, which have the same term A_2 for example. In the first step, the max–min inference method applies the *min* operator on membership values of associated term of all the input linguistic variables for each rule. We denote the weights of rules 4 and 5 by w_4 and w_5

$$w_4 = \min(\mu_{Hi}(L_V), \mu_{Lt}(R_C), \mu_{La}(U), \mu_{Sh}(D_D)) \tag{29}$$
$$w_5 = \min(\mu_{Lo}(L_V), \mu_{Lt}(R_C), \mu_{Sm}(U), \mu_{Lg}(D_D)). \tag{30}$$

TABLE I
THE RULE STRUCTURE FOR THE FUZZY PERFORMANCE INDICATOR

Rule	L_V	R_C	U	D_D	A
1	*Hi*	*Lt*	*Sm*	*Lg*	A_1
2	*Hi*	*Lt*	*La*	*Lg*	A_1
3	*Hi*	*Lt*	*Sm*	*Sh*	A_1
4	*Hi*	*Lt*	*La*	*Sh*	A_2
5	*Lo*	*Lt*	*Sm*	*Lg*	A_2
6	*Lo*	*Lt*	*La*	*Lg*	A_3
7	*Lo*	*Lt*	*Sm*	*Sh*	A_3
8	*Lo*	*Lt*	*La*	*Sh*	A_4
9	*Lo*	*Bg*	*Sm*	*Sh*	A_5
10	*Lo*	*Bg*	*La*	*Sh*	A_6
11	*Lo*	*Bg*	*Sm*	*Lg*	A_6
12	*Lo*	*Bg*	*La*	*Lg*	A_7
13	*Hi*	*Bg*	*Sm*	*Sh*	A_7
14	*Hi*	*Bg*	*La*	*Sh*	A_8
15	*Hi*	*Bg*	*Sm*	*Lg*	A_8
16	*Hi*	*Bg*	*La*	*Lg*	A_8

Then apply the *max* operator on w_4 and w_5 and yield the overall membership value of A_2, denoted by

$$w_{A_2} = \max(w_4, w_5). \tag{31}$$

Finally, the fuzzy performance indicator uses the *center of area* defuzzification method to obtain the performance indicator A by combining w_{A_i}, $1 \le i \le 8$

$$A = \frac{\sum_{i=1}^{8} w_{A_i} \times A_{i,c}}{\sum_{i=1}^{8} w_{A_i}}. \tag{32}$$

C. Fuzzy/Neural Access Probability Controller

From [12], $\overline{\text{SNR}}$ can be obtained by

$$\overline{\text{SNR}} = \sqrt{\frac{3\cdot S\cdot F}{I_S - S}} \tag{33}$$

where F is the spreading factor. The bit error probability P_e is approximated by

$$P_e \approx Q\left(\overline{\text{SNR}}\right) \tag{34}$$

where

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-y^2/2}\, dy. \tag{35}$$

If (L, B, ς) BCH-code is chosen, where L is the packet length, B is the number of information bits, and ς is the number of correctable error bits, then the packet error probability P_E is given by

$$P_E = 1 - \sum_{i=0}^{\varsigma} \binom{L}{i} (P_e)^i (1-P_e)^{L-i}. \tag{36}$$

If ${P_E}^*$ is the desired packet error probability in the air interface, I_S should be properly controlled under a maximum level ${I_S}^*$ so that $P_E \le {P_E}^*$.

Based on the knowledge, we hereafter design the access probability controllers using fuzzy logic theory and neural networks.

1) Fuzzy Access Probability Controller (FAPC): FAPC takes the predicted interference sample at frame $(n+1)$, $\tilde{I}_S(n+1)$, and the performance indicator at frame n, $A(n)$, as two input linguistic variables. We define the term set of $\tilde{I}_S(n+1)$ as $T(\tilde{I}_S) = \{\text{Low, Medium, High}\} = \{Lo, Me, Hi\}$ and the term set of $A(n)$ as $T(A) = \{\text{Small, Middle, Large}\} = \{Sm, Md, La\}$. Membership functions for $\tilde{I}_S(n+1)$ and $A(n)$ are defined as $M(\tilde{I}_S) = \{\mu_{Lo}, \mu_{Me}, \mu_{Hi}\}$ and $M(A) = \{\mu_{Sm}, \mu_{Md}, \mu_{La}\}$, where

$$\mu_{Lo}(\tilde{I}_S) = g(\tilde{I}_S; \tilde{I}_{S,\min}, Lo_e, 0, Lo_w) \tag{37}$$
$$\mu_{Me}(\tilde{I}_S) = f(\tilde{I}_S; Me_c, Me_{w0}, Me_{w1}) \tag{38}$$
$$\mu_{Hi}(\tilde{I}_S) = g(\tilde{I}_S; Hi_e, \tilde{I}_{S,\max}, Hi_w, 0) \tag{39}$$
$$\mu_{Sm}(A) = g(A; A_{\min}, Sm_e, 0, Sm_w) \tag{40}$$
$$\mu_{Md}(A) = f(A; Md_c, Md_{w0}, Md_{w1}) \tag{41}$$
$$\mu_{La}(A) = g(A; Lg_e, A_{\max}, Lg_w, 0) \tag{42}$$

where $\tilde{I}_{S,\min}$, $\tilde{I}_{S,\max}$, and $A_{\min}$, $A_{\max}$ are the minimum and maximum possible values for $\tilde{I}_S$ and A, respectively.

The output linguistic variable is here defined as the adjustment amount of $P_V(n)$, denoted by ΔP. We choose the term set for ΔP as $T(\Delta P) = \{\Delta P_1, \Delta P_2, \Delta P_3, \Delta P_4, \Delta P_5, \Delta P_6\}$ and denote the membership function of ΔP by $M(\Delta P) = \{\mu_{\Delta P_1}, \mu_{\Delta P_2}, \mu_{\Delta P_3}, \mu_{\Delta P_4}, \mu_{\Delta P_5}, \mu_{\Delta P_6}\}$. $\mu_{\Delta P_i}(\Delta P)$, $i = 1, \ldots, 6$, are given by

$$\mu_{\Delta P_1}(\Delta P) = f(\Delta P; \Delta P_1, 0, 0) \tag{43}$$
$$\mu_{\Delta P_2}(\Delta P) = f(\Delta P; \Delta P_2, 0, 0) \tag{44}$$
$$\mu_{\Delta P_3}(\Delta P) = f(\Delta P; \Delta P_3, 0, 0) \tag{45}$$
$$\mu_{\Delta P_4}(\Delta P) = f(\Delta P; \Delta P_4, 0, 0) \tag{46}$$
$$\mu_{\Delta P_5}(\Delta P) = f(\Delta P; \Delta P_5, 0, 0) \tag{47}$$
$$\mu_{\Delta P_6}(\Delta P) = f(\Delta P; \Delta P_6, 0, 0) \tag{48}$$

where ΔP_i, $1 \le i \le 6$, is the ith adjustment step. We heuristically set $-0.125 \le \Delta P_i \le 0.125$ and $\Delta P_i = (-0.175 + 0.05 \times i)$ to reflect different degrees of predicted interference and performance indication. As $\tilde{I}_S$ is low and A is in the middle, we choose $\Delta P = \Delta P_6$, denoting a larger increment for the access probability; as $\tilde{I}_S$ is large and A is large, we select $\Delta P = \Delta P_1$ denoting a larger decrement for the access probability. The rule structure is shown in Table II. Similarly, we use the max–min inference method to calculate the membership value for each term of $T(\Delta P)$ and then apply the center of area for defuzzification.

Once ΔP is obtained, we determine $P_V(n+1)$ by

$$P_V(n+1) = P_V(n) + \Delta P. \tag{49}$$

The access probability for data ready contention users $P_D(n+1)$ is then obtained by

$$P_D(n+1) = f_d \cdot P_V(n+1) \tag{50}$$

where f_d is a real number smaller than 1, denoting voice users have higher access priority than data users [4].

TABLE II
THE RULE STRUCTURE FOR FAPC

Rule	I_S	A	ΔP
1	Hi	La	ΔP_1
2	Hi	Md	ΔP_1
3	Hi	Sm	ΔP_2
4	Me	La	ΔP_2
5	Me	Md	ΔP_3
6	Me	Sm	ΔP_4
7	Lo	La	ΔP_5
8	Lo	Md	ΔP_6
9	Lo	Sm	ΔP_6

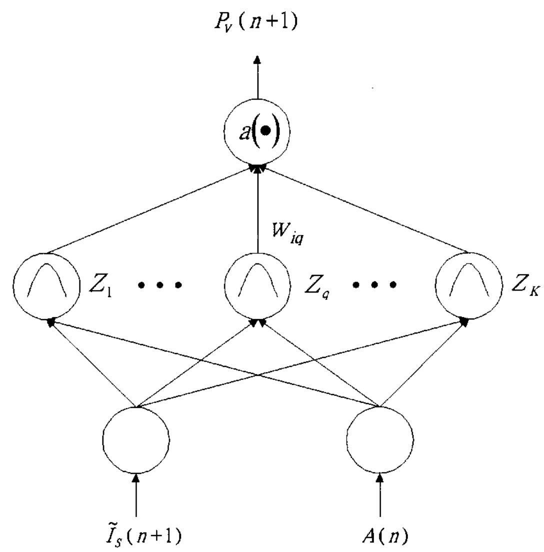

Fig. 6. The structure of RBFN for NAPC.

2) Neural-Network Access Probability Controller (NAPC): NAPC adopts RBFN to design. RBFN has a wide variety of usage in many applications such as signal processing, pattern recognition, control, and function approximation. It can fit any arbitrary function with just one hidden layer. RBFN generally cannot quite achieve the same accuracy as the backpropagation network, but it can be trained several order faster than the backpropagation network. In addition, RBFN's have a great potential to relax the size growing and learning difficulty encountered in feedforward neural networks [5]; they have powerful adaptive and learning capabilities.

The structure of RBFN for NAPC is shown in Fig. 6. The hidden node q in the RBFN performs the normalized Gaussian activation function

$$z_q \equiv \frac{\exp\left[-|\vec{x} - \vec{m}_q|^2 / 2\sigma_q^2\right]}{\sum_{\ell=1}^{k} \exp\left[-|\vec{x} - \vec{m}_\ell|^2 / 2\sigma_\ell^2\right]}, \qquad 1 \le q \le k \tag{51}$$

where $\vec{x}$ is the input vector, $\vec{m}_q$ (σ_q) is the mean (variance) of the qth Gaussian function, and k is the number of hidden nodes. In this way, hidden node q has its own receptive field centered on $\vec{m}_q$ with size proportional to σ_q, and it will give a maximum response to the input vector closest to $\vec{m}_q$. For an input vector $\vec{x} = (\tilde{I}_S(n+1), A(n))$ lying somewhere in the input space, the receptive fields which are close to it will be properly activated. The output of RBFN, $P_V(n+1)$, is simply the mapping of the weighted sum of the hidden node outputs by

$$P_V(n+1) = a\left(\sum_{q=1}^{k} w_{iq} z_q\right) \tag{52}$$

where $a(\cdot)$ is the output activation function. That is to say, the function of RBFN is to group the input vectors which are close to each other and then teaches every group to which output level it belongs.

Generally speaking, RBFN can be trained by either the hybrid learning rule or the error backpropagation rule. The former is composed of unsupervised learning in the input layer and supervised learning in the output layer. The latter is a purely supervised learning rule. If RBFN is trained by the error backpropagation learning rule, it does not learn appreciably faster than the backpropagation network and it may encounter large-width problem. Therefore, the hybrid learning network is chosen in the following design for NAPC.

In the unsupervised learning phase to train RBFN in NAPC, the task is to determine the receptive field center $\vec{m}_q$ and the width σ_q. The adjustment of $\vec{m}_q$, denoted by $\Delta\vec{m}$, can be simply found by

$$\Delta\vec{m} = \eta(\vec{x} - \vec{m}_{\text{closest}}) \tag{53}$$

where $\vec{m}_{\text{closest}}$ is the center of the receptive field closest to the input vector and other centers remain unchanged. The width σ_q can be determined by the mean distance to the first few nearest neighbors

$$\sigma_q = \frac{\sum_{i=1}^{\gamma} |\vec{m}_q - \vec{m}_i|}{\gamma} \tag{54}$$

where γ is the number of the first few nearest neighbors.

In the supervised learning to train RBFN in NAPC, it must know the correct (optimal) value of the target output for each input pattern. However, in NAPC, there does not exist an optimal value of access probability which we can measure to obtain. The only information we can have is the system performance measures and the interference level for the determined access probability. That is to say, the system only provides evaluative signals instead of instructive signals for NAPC. For this reason, we utilize a *reinforcement learning algorithm* [5], [8]–[11] to solve the learning problem.

Fig. 7 shows the interaction between RBFN and its controlled communication network, using the reinforcement learning algorithm. The reinforcement learning algorithm calculates the cost function in term of an evaluative signal. This evaluative signal is to indicate the deviation of the system performance from the desired (optimal) one and is the so-called *reinforcement signal*. It is to associate the input pattern and the output pattern; then weights of RBFN in NAPC can be dynamically adjusted so that the cost is minimized in the supervised learning phase.

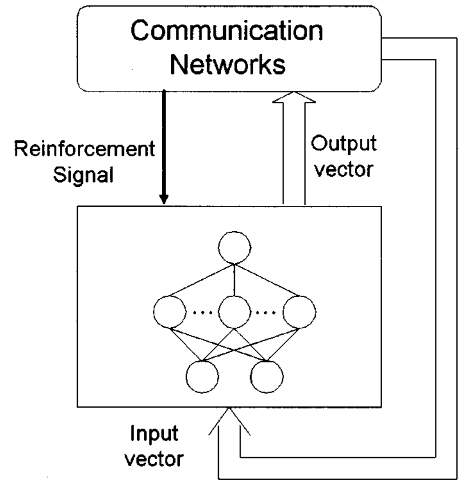

Fig. 7. A basic reinforcement learning structure.

In other words, the cost function in backpropagation learning rule should have defined as [5]

$$E = \tfrac{1}{2}(\hat{P}_V - P_V)^2 \tag{55}$$

where $\hat{P}_V$ is the optimal output value that NAPC should have. The adjustment of weights can be obtained by

$$\Delta w_{iq} = \eta \cdot \frac{\partial E}{\partial w_{iq}} = \eta \cdot (\hat{P}_V - P_V) \cdot a'\left(\sum_q w_{iq} z_q\right) \cdot z_q \tag{56}$$

where η is the learning rate. However, since $(\hat{P}_V - P_V)$ is not obtainable, it is substituted by a reinforcement signal R. We define $R = (\hat{R}_C - R_C)$ $(R = (\hat{I}_S - I_S))$ if $I_S \le \hat{I}_S$ $(I_S > \hat{I}_S)$. Here $\hat{R}_C$ is the required corruption ratio of the whole system when the corruption ratio of voice contention packets approximates 10^{-2}, and $\hat{I}_S$ is the interference threshold obtained from simulation experience. Usually, $\hat{I}_S$ is set smaller than $I_S{}^*$. Therefore (56) becomes

$$\Delta w_{iq} = \begin{cases} \eta_{R_C} \cdot (\hat{R}_C - R_C) \cdot a'\left(\sum_q w_{iq} z_q\right) \cdot z_q, & \text{if } I_S \le \hat{I}_S \\ \eta_{I_S} \cdot (\hat{I}_S - I_S) \cdot a'\left(\sum_q w_{iq} z_q\right) \cdot z_q, & \text{if } I_S > \hat{I}_S \end{cases} \tag{57}$$

where η_{R_C} and η_{I_S} are two different learning rates for cases of $I_S \le \hat{I}_S$ and $I_S > \hat{I}_S$, respectively. The weights can then be updated by

$$w_{iq} = w_{iq} + \Delta w_{iq}. \tag{58}$$

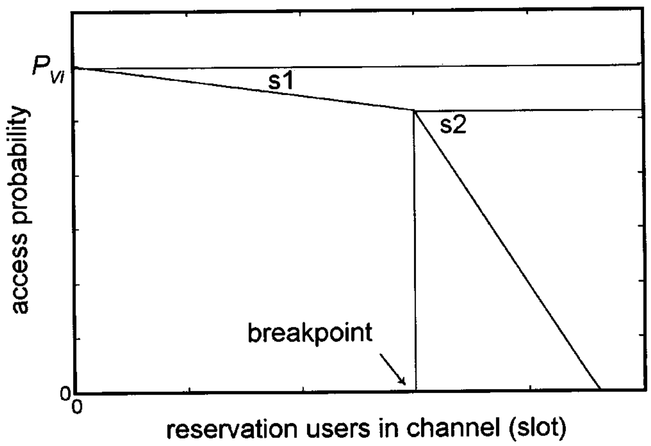

Fig. 8. The channel access function for DS-CDMA/PRMA system.

After obtaining $P_V(n+1)$, the access probability for data ready contention users, $P_D(n+1) = f_d \cdot P_V(n+1)$, as given in (50).

IV. Simulation Results and Discussions

We show the performance comparison of these two DS-CDMA/FRMA fuzzy/neural congestion controllers with FAPC and/or NAPC and the conventional DS-CDMA/PRMA system with channel access function.

DS-CDMA/PRMA has the same frame structure and time slots as DS-CDMA/FRMA, but all the time slots in DS-CDMA/PRMA can be used for transmission of either contention packets or reservation packets. If a user wants to contend for reservation, it first transmits a contention packet at any time slot with a given access probability. Once contending successfully, it can begin transmitting its information packet at the same time slot in the next frame. If the contention is failed, the user can try at the next time slot. In [4], a channel access function was defined to relate the voice access probability to the number of reservation users. As Fig. 8 shows, the function is assumed to contain two linear piecewise segments of voice access probability versus the number of reservation users with the following parameters: the initial large access probability for voice users at very light traffic load P_{V_i}; the slopes of the two linear segments $s1$ and $s2$ (in unit of access probability/users); and the position of breakpoint (in the number of users). If the number of reservation users is smaller (larger), more (fewer) contention users are allowed. Therefore, the slope of the first segment $s1$ was designed to be smaller than the slope of the second segment $s2$. If the breakpoint is chosen larger, the channel access function is more generous in the sense that the system would allow more contention users; however, it might cause higher corruption ratio. If it is chosen smaller, the access function is more restrictive in the sense that the system would allow fewer contention users; however it might cause the increment of packet delay. These parameters were set according to the simulation experiences so that the channel access function is effective and can yield a good trade-off between corruption ratio and packet delay. Afterwards, the access probability of data users is that of voice users multiplied by a ratio f_d.

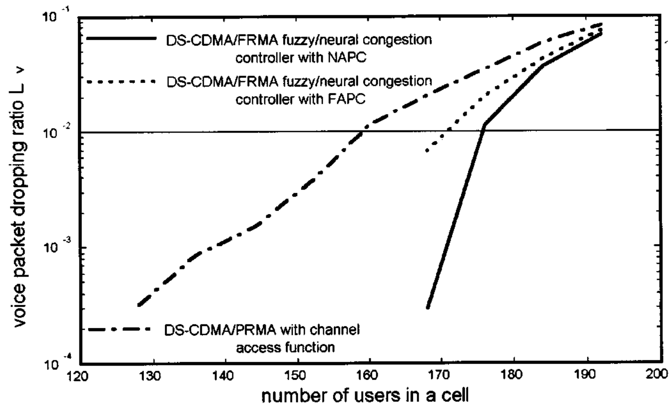

Fig. 9. The voice packet dropping ratio L_V versus the number of users in a cell.

The simulation environment is defined as: $K = 49, \theta = 4$, standard deviation of ζ is 8 dB, $T = 20$ ms, $N = 10, 1/\alpha = 0.44$ s, $1/\beta = 0.56$ s, $1/\lambda_d = 0.04, F = 15, T_D = 40$ ms, $B_V = 12$, $B_D = 200$, and the RBFN output activation function $a(x)$ is taken to be $1/[1+\exp(-x)]$. The voice source rate is 8 kbit/s and thus generates 160 information bits per frame time. Adding 64 header bits, we choose ($L = 511, M = 229, \varsigma = 38$) BCH-code. The total bandwidth is 3.8325 MHz. We set $P_E{}^* = 0.01, I_S{}^* = 16 \times S$. According to simulation experience, $P_{V_i} = 0.3, s1 = 0.007$, $s2 = 0.08$, breakpoint $= 6$, and f_d is set to be 0.25.

Fig. 9 shows the voice packet dropping ratio L_V versus the number of users in a cell. Here L_V includes voice packets dropping due to buffer overflow and voice packets discarding due to too much contention delay. It can be seen that the DS-CDMA/FRMA fuzzy/neural congestion controller with either FAPC or NAPC performs much better than the DS-CDMA/PRMA system with channel access function. If the voice dropping ratio is set to be 10^{-2} (note that we did not take it as a requirement in the design), we see that the DS-CDMA/FRMA fuzzy/neural congestion controller with NAPC can accommodate 176 users/cell, which is five users/cell more than the one with FAPC and is 17 users/cell more than the DS-CDMA/PRMA system with channel access function. The main reason is that the fuzzy/neural congestion controller adopts intelligent techniques such as fuzzy logic control and neural networks; thus it has more powerful capability to determine proper access probabilities and more adaptive to time-varying traffic. The other reason is that in DS-CDMA/FRMA protocol, the contention packets and the reservation packets are separated so that the fluctuation of contention packet traffic would not influence the transmission of reservation packets. However, in DS-CDMA/PRMA protocol, the contention packets and the reservation packets can be transmitted in the same time slot, so that the reservation packets are influenced by the contention packets. It can also be seen that NAPC outperforms FAPC. The main reason is that NAPC utilizes RBFN which has powerful and adaptive learning capability to give more appropriate access probability than FAPC.

The contention corruption ratio R_C versus the number of users in a cell is shown in Fig. 10. Here R_C denotes the corruption ratio in the contention slot. It can be found that the DS-CDMA/FRMA fuzzy/neural congestion controller has significantly small corruption ratio, while the DS-CDMA/PRMA system with

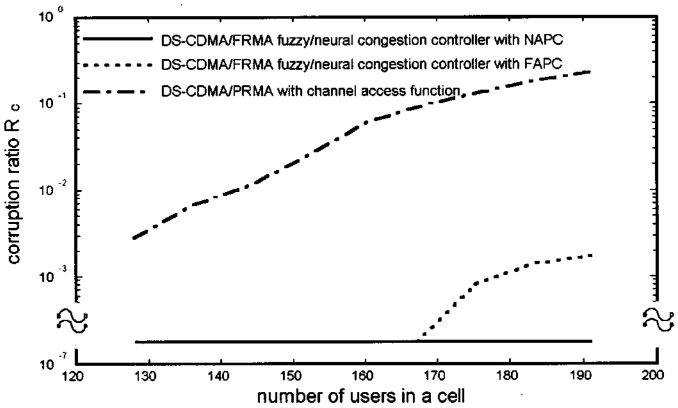

Fig. 10. The corruption ratio R_C versus the number of users in a cell.

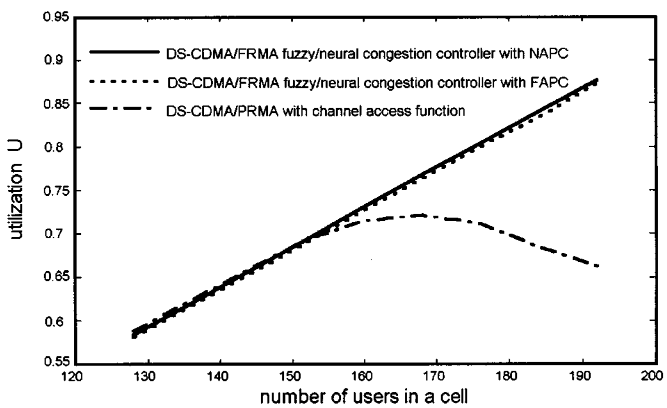

Fig. 11. The utilization U versus the number of users in a cell.

channel access function has a noticeably high corruption ratio. This demonstrates that the former can regulate input traffic so well that it has almost no contention failure. This is because the fuzzy/neural congestion controller is intelligent to adaptively adjust the access probability and the DS-CDMA/FRMA protocol separates the violently changing contention traffic from the smoothly changing reservation traffic.

Fig. 11 shows the utilization U versus the number of users in a cell. Here U is defined as the used capacity divided by the total capacity. In the low traffic load, the utilization of DS-CDMA/PRMA system is almost the same as the DS-CDMA/FRMA system. This is because in low traffic load, both DS-CDMA/PRMA system and DS-CDMA/FRMA systems can accommodate well. However, when the traffic load grows up, the DS-CDMA/FRMA system with fuzzy/neural congestion controller has better utilization. It is because the DS-CDMA/FRMA system with fuzzy/neural congestion controller can regulate input traffic better than the DS-CDMA/PRMA system with channel access function, and thus the former has lower corruption ratio than the latter. Though the utilization of the two fuzzy/neural congestion controllers is almost the same, NAPC still has utilization about 0.3% higher than FAPC.

Fig. 12 shows the data packet delay D_D versus the number of users in a cell. Here D_D counts the time from the data packet arrival at the user's terminal to its successful contention. In all traffic loads, the DS-CDMA/PRMA system performs better than the two DS-CDMA/FRMA systems. This is due to that

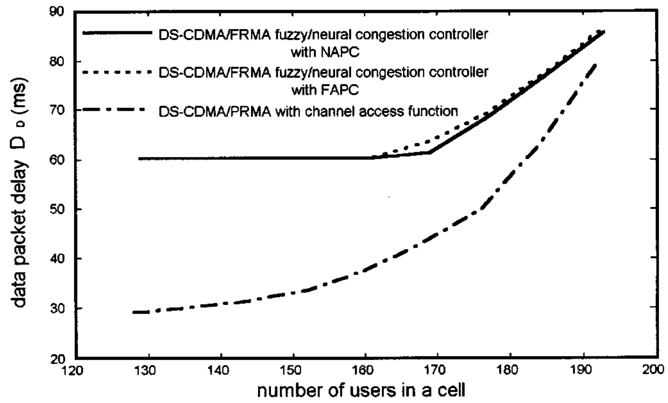

Fig. 12. The data packet delay D_D versus the number of users in a cell.

the DS-CDMA/PRMA protocol allows users to contend at any time slot, while the DS-CDMA/FRMA protocol allows contention users only at the first time slot of a frame. Though the DS-CDMA/FRMA protocol performs worse than the DS-CDMA/PRMA protocol in this aspect, it still has other advantages mentioned above over the DS-CDMA/PRMA protocol.

V. Concluding Remarks

In the paper, we propose a congestion controller using fuzzy/neural intelligent techniques for DS-CDMA/FRMA cellular systems. The fuzzy/neural congestion controller contains a PRNN interference predictor, a fuzzy performance indicator, and a fuzzy/neural access probability controller. The fuzzy/neural access probability controller denotes two alternative designs: FAPC using fuzzy logic system and NAPC adopting RBFN.

Simulation results show that the DS-CDMA/FRMA system with fuzzy/neural congestion controller performs much better than the DS-CDMA/PRMA system with channel access function in the voice packet dropping ratio, the corruption ratio, and the utilization, for all traffic loads. It is because the fuzzy/neural congestion controller can intelligently compute to predict the next-step interference sample, to support the overall system performance indication as a control feedback, and to determine an appropriate access probability for users; therefore it can effectively regulate contending users at the contention slots, thus maximizing the throughput. It is also because the DS-CDMA/FRMA system only allows contention users to contend at the beginning of a frame, and it separates the violently changing contention traffic from the reservation traffic; while the DS-CDMA/PRMA system allows contention users to contend at any time slot of a frame, and thus reservation packets may be corrupted by contention packets in some slots, especially in heavy traffic. Furthermore, NAPC outperforms FAPC in all performance measures. It is because neural networks have powerful adaptive and learning capabilities, while fuzzy logic systems are inflexible in a sense, that parameters of membership functions are fixed whenever chosen, compared to neural networks.

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REFERENCES

[1] K. S. Gilhousen, I. M. Jacobs, R. Padovani, A. J. Viterbi, L. A. Weaver, Jr, and C. E. Wheatley, III, "On the capacity of a cellular CDMA system," *IEEE Trans. Veh. Technol.*, vol. 40, pp. 303–312, May 1991.

[2] P. Taaghol, R. Tafazolli, and B. G. Evans, "On the reservation multiple access protocols for future mobile communication systems," in *Proc. IEEE VTC 97*, vol. 3, 1997, pp. 1523–1527.

[3] P. Narasimhan and R. D. Yates, "A new protocol for the integration of voice and data over PRMA," *IEEE J. Select. Areas Commun.*, vol. 14, pp. 623–631, May 1996.

[4] A. E. Brand and A. H. Aghvami, "Performance of a joint CDMA/PRMA protocol for mixed voice/data transmission for third generation mobile communication," *IEEE J. Select. Areas Commun.*, vol. 14, pp. 1698–1707, Dec. 1996.

[5] C. T. Lin and C. S. G. Lee, *Neural Fuzzy Systems*. Englewood Cliffs, NJ: Prentice-Hall, 1996.

[6] S. Haykin and L. Li, "Nonlinear adaptive prediction of nonstationary signals," *IEEE Trans. Signal Processing*, vol. 43, pp. 526–535, Feb. 1995.

[7] P. R. Chang and J. T. Hu, "Optimal nonlinear adaptive prediction and modeling of MPEG video in ATM networks using pipeline recurrent neural networks," *IEEE J. Select. Areas Commun.*, vol. 15, pp. 1087–1100, Aug. 1997.

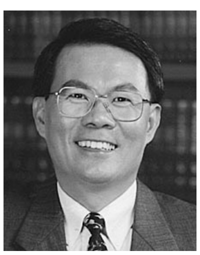
[8] R. J. Williams and D. Zipser, "A learning algorithm for continually running fully recurrent neural networks," *Neural Comput.*, vol. 1, pp. 270–280, 1989.

[9] A. A. Tarraf, I. W. Habib, and T. N. Saadawi, "Reinforcement learning-based neural network congestion controller for ATM networks," in *Proc. IEEE MILCOM*, vol. 2, 1995, pp. 668–672.

[10] C. S. Lin and Y. H. E. Cheng, "Radial basis function networks for adaptive critic learning," in *Proc. IEEE Int. Conf. Neural Networks*, vol. 2, 1994, pp. 903–906.

[11] C. T. Lin and C. S. G. Lee, "Reinforcement structure/parameter learning for neural-network-based fuzzy logic control systems," *IEEE Trans. Fuzzy Systems*, vol. 2, pp. 46–63, Feb. 1994.

[12] M. B. Pursley, "Performance evaluation for phase-coded spread spectrum multiple-access communication—Part I: System analysis," *IEEE Trans. Commun.*, vol. COM-25, pp. 795–799, Aug. 1997.



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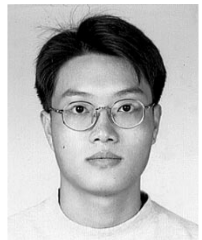

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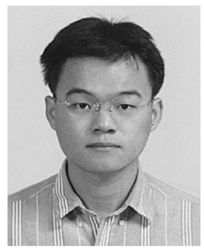

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