Intelligent Call Admission Control for Wideband CDMA Cellular Systems

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***Abstract*—In this paper, we propose intelligent call admission control for wideband code-division multiple-access (CDMA) cellular systems to support differentiated quality-of-service (QoS) requirements, guarantee the forced termination probability of handoffs, and maximize the spectrum utilization. The intelligent call admission controller (ICAC) contains a fuzzy call admission processor to make admission decision for a call request by considering QoS measures such as the forced termination (drop call) probability of handoff, the outage probability of all service types, the predicted next-step existing-call interference, the link gain, and the estimated equivalent interference of the call request. The pipeline recurrent neural network (PRNN) is used to accurately predict the next-step existing-call interference, and the fuzzy logic theory is applied to estimate the new/handoff call interference based on knowledge of effective bandwidth method. Simulation results indicate that ICAC achieves system capacity higher than conventional CAC schemes by an amount of more than 10% in both low and high moving speed cases. Moreover, ICAC can cope with the unpredictable statistical fluctuation of wireless multimedia traffic; it always fulfill QoS requirements for all service types and keep the forced termination probability satisfied, while the CAC of multimedia calls (MCAC) and SIR-based CAC with intercell interference prediction (PSIR-CAC) fail to adapt to the variation of traffic conditions.**

***Index Terms*—Call admission control, equivalent interference, fuzzy logic, handoff, neural network.**

I. Introduction

With desired features such as high system capacity (soft capacity), low power transmission, soft handoff, multipath mitigation, and interference suppression [1], code-division multiple access (CDMA) has been adopted for third-generation wireless communication systems. The third generation wideband CDMA cellular system must be able to support integrated services with differentiated *quality-of-service* (QoS) requirements. Thus, a sophisticated call admission control (CAC) is needed so that the system can satisfy various QoS constraints such as the forced termination (drop call) probability for handoffs and the outage probabilities for different services, and maximize the spectrum utilization.

Liu and Zarki [2] proposed an uplink signal-to-interference (SIR)-based CAC, which adopted a *residual capacity* algorithm, for a direct sequence code-division multiple-access (DS-CDMA) cellular system with pure voice traffic. However, the QoS requirement was not guaranteed. Kim *et al.* [3], and Ishikawa and Umeda [4] extended and developed the admission control work in [2], but integrated traffic and differentiated QoS requirements were not studied.

Evans and Everitt [5] utilized an effective bandwidth concept [10] to transform the traffic generated by a user into an equivalently occupied bandwidth in an integrated services system. The per class outage requirement was not supported, and the system state dimensions grew with an increasing number of cells, making the computational complexity intractable. Kim and Han [6] also proposed a CAC scheme that considered dual classes of services. This scheme measured the received interference and estimated the power requirement for the new user to predict the resulting SIR. The outage probability might overwhelm in some traffic load region.

Also, there were literatures working on the CAC problem with further consideration of handoff protection. Shin *et al.* [7] proposed to reserve a number of radio channels to protect handoff calls in DS-CDMA cellular systems, where the amount of interference of a connection is quantized as one radio channel. The number of reserved channels for handoff was derived as it was done in TDMA systems. The interference to the destination cell before and after the handover in the CDMA air interface was not correctly considered. Jeon and Jeong [8] utilized the property of soft capacity in CDMA systems, and designed prioritization by setting SIR threshold of handoff calls lower than that of new calls.

The wideband CDMA systems will turn out to be within a *dynamic, imprecise, and bursty environment* because of the *unpredictable statistical fluctuations* in the flow of wireless multimedia traffic. To that end, we here adopt intelligent techniques such as fuzzy logic systems and neural networks to cope with the traffic uncertainty. The fuzzy logic systems have replaced conventional technologies in many scientific applications and engineering systems, especially in control systems. They appear to provide a robust mathematical framework for dealing with real-world imprecision; and they can also provide decision support and expert systems with powerful reasoning capabilities bound by a set of fuzzy rules. When a mathematical model of a process does not exist, it is appropriate to use fuzzy logic systems. On the other hand, neural networks are

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information processing systems that are constructed to characterize the human brain. They are able to learn arbitrary nonlinear input–output mapping directly from training data; they can automatically adjust their connection weights to achieve optimality for controllers, predictors, etc. Both fuzzy logic and neural networks are numerical model-free and dynamical estimators. They can improve systems working in uncertain and unstationary environments.

Therefore, the paper proposes an *intelligent call admission control* (ICAC) method for wideband CDMA cellular systems to support differentiated QoS requirements such as the forced termination probability of handoffs and the outage probability for all service types, and maximize the spectrum utilization. The ICAC contains *fuzzy call admission processor* together with *fuzzy equivalent interference estimator* and *pipeline recurrent neural network (PRNN) interference predictor*. It decides whether to accept the new or handoff call based on not only the estimated equivalent interference and the predicted mean interference of existing calls but also the QoS measures such as the outage probabilities of all service types and the forced termination probability as system feedbacks. In addition, the link gain of the call request, denoting a good or bad user, is further considered.

The ICAC is justified by comparing it with some conventional CAC schemes such as the SIR-based CAC with intercell interference prediction (PSIR-CAC) proposed in [3] and the CAC of multimedia calls (MCAC) proposed in [8]. Simulation results indicate that ICAC can always fulfill the multiple QoS requirements under all traffic load conditions, while these conventional CAC schemes fail in heavy traffic load condition. In particular, ICAC achieves system capacity higher than the PSIR-CAC and MCAC by more than 10% in traffic ranges where the QoS requirements are kept. Effects of adoption of PRNN interference predictor and the link gain of new call request on the capacity are also investigated. It can be found that PRNN can facilitate ICAC in a highly variant interference environment, and the consideration of the link gain can benefit ICAC in low mobility case. Moreover, from the proposed fuzzy rule structure of *fuzzy call admission processor*, QoS measures acts as feedbacks to ICAC indicating current system conditions, and ICAC is more adaptive and stable than PSIR-CAC and MCAC.

The rest of the paper is organized as follows. Section II describes the system model of a wideband CDMA cellular system and functional blocks within ICAC. Section III gives the designs for the fuzzy equivalent capacity estimator, the PRNN interference predictor, and the fuzzy call admission processor contained in ICAC. Simulation results and discussions are presented in Section IV. Finally, conclusions are remarked in Section V.

II. System Model

Fig. 1 depicts the system model of a wideband CDMA cellular system with ICAC. The model considers K cells, where mobile users communicate with each other via air interface to base station (BS), and BSs are connected to a base station controller (BSC) or a radio network controller (RNC) containing the ICAC.

Input traffic generated within mobile users is categorized as real-time voice (type-1) and nonreal-time data (type-2). New voice and data calls arrive at the system according to Poisson distributions with average arrival rates of λ_v and λ_d, respectively. Herein, the voice source is characterized by a two-state discrete-time Markov chain traffic model and generates an air-interface packet in each frame duration of T during ON state (talkspurt) but none during OFF state (silence). The mean durations of talkspurt and silence periods are assumed to be exponentially distributed with $1/\alpha$ and $1/\beta$, respectively. The data source is characterized by a batch Poisson process with an average message arrival rate of A_d. The size of data message is assumed to be a positive-valued random variable which is generally distributed. The data message will further be segmented into a number of air-interface packets according to the processing gain set for the service. Each terminal supports two finite separate buffers for voice and data services.

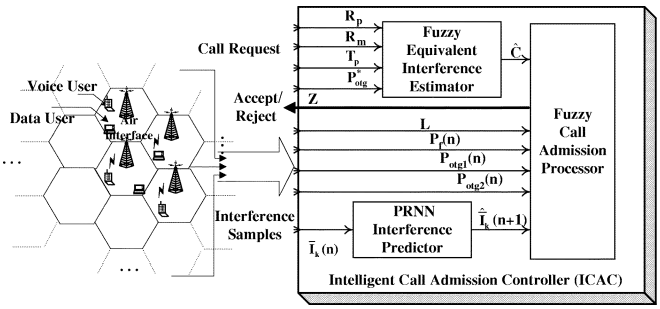

Fig. 1. System model.

For differentiated bit-error-rate (BER) requirements set for the type-1 and the type-2 traffic, we define their individual processing gains, denoted by G_1 and G_2. The G_1 and G_2 are chosen to be the closest integer greater than the required spreading factor. Corresponding to each specific BER requirement and processing gain, the signal-to-interference ratio (SIR) threshold values of type-1 and type-2 traffic, denoted by SIR_1^* and SIR_2^*, can be obtained. Two basic transmission rates (basic channels) are supported: 1) $R_1 = R$, which is dedicated to active voice users and is equal to the voice coding rate and 2) $R_2 = R \cdot G_1/G_2$, which is dedicated to active data users. If a data user requires a transmission rate X higher than the basic transmission rate R_2, this rate will be quantized into M times of R_2, where $M = \lceil (X)/(R_2) \rceil$ and $\lceil \cdot \rceil$ denotes the smallest integer greater than or equal to the argument, and each R_2 is encoded with a different pseudonoise (PN) code. Under this circumstance, the data connection transmits with M basic channels ($M \geq 1$) simultaneously for communications, and the total transmission power is M times to the power of single code channel.

In the radio propagation, the significant loss is assumed to contain the path loss and the shadowing. The short-term fading is averaged out by a window to form the interference measurement samples, and thus, we here ignore the effect of short-term fading for the CAC. The generally accepted radio propagation (link gain) model $L(r)$ is then the product of the θth power of the distance and a correlated shadowing random variable $\zeta(r)$ of log-normal distribution with standard deviation σ_0 dB [1], which is given by

$$L(r) = 10^{\frac{\zeta}{10}} r^{-\theta} \tag{1}$$

where r is the distance between the mobile user and the base station. The $\zeta(r)$ has an auto-correlation function given as

TABLE I
RULE STRUCTURE FOR THE FUZZY CAPACITY REQUIREMENT ESTIMATOR

	Elements of Term Sets	Membership Function
R_p	Small (Sm)	$\mu_{Sm}(R_p) = h(\log(R_p); \log(R_{p,min}), Sm_e, 0, Sm_w)$
	Medium (Me)	$\mu_{Me}(R_p) = f(\log(R_p); Me_c, Me_{w0}, Me_{w1})$
	Large (La)	$\mu_{La}(R_p) = h(\log(R_p); La_e, \log(R_{p,max}), La_w, 0)$
R_m	Low (Lo)	$\mu_{Lo}(R_m) = h(\frac{R_m}{R_p}; 0, Lo_w, 0, Lo_e)$
	High (Hi)	$\mu_{Hi}(R_m) = h((\frac{R_m}{R_p}); Hi_e, 1, Hi_w, 0)$
T_p	Short (Sh)	$\mu_{Sh}(T_p) = h(\log(T_p); \log(T_{p,min}), Sh_e, 0, Sh_w)$
	Middle (Me)	$\mu_{Me}(T_p) = f(\log(T_p); Md_c, Md_{w0}, Md_{w1})$
	Long (Lg)	$\mu_{Lg}(T_p) = h(\log(T_p); Lg_e, \log(T_{p,max}), Lg_w, 0)$
P^*_{otg}	Strict (St)	$\mu_{St}(P^*_{otg}) = f(\log P^*_{otg}; \log P^*_{otg2}, S1, S0)$
	Loose (Ls)	$\mu_{Ls}(P^*_{otg}) = f(\log P^*_{otg}; \log P^*_{otg1}, S0, S1)$

$E[\zeta(r_1)\zeta(r_2)] = \sigma_0^2 e^{-(r_{\rm E}-r_{\rm I})/r_{\rm T}}$, where r_0 denotes the decay of the correlation [9]. All users in their home cell are assumed to be perfectly power-controlled. During the connection, as the user detects the pilot strength of another cell stronger than that of original cell by φ dB, the handoff procedure is performed.

The proposed ICAC mainly consists of a *fuzzy equivalent interference estimator*, *PRNN interference predictor*, and *fuzzy call admission processor*. The *fuzzy equivalent interference estimator* estimates the equivalent interference of a call request, denoted as $\hat{C}$, from its claimed traffic parameters: peak rate R_p, mean rate R_m, peak rate duration T_p, and its outage probability requirement $P^*_{\rm otg}$. The *PRNN interference predictor* takes the interference mean of cell k at the present time instant n, $\bar{I}_k(n)$, as an input variable to accurately predict the interference mean at the next time instant $(n+1)$, $\hat{\bar{I}}_k(n+1)$. The $\bar{I}_k(n)$ is obtained by $\bar{I}_k(n) = \frac{\sum_{j=0}^{N-1} I_k(n-jT)}{N}$, where N is the size of time window, and $I_k(m)$ is the received interference power at time instance m. And the *fuzzy call admission processor* chooses the forced termination probability for handoffs measured at present time n, denoted by $P_f(n)$, the outage probabilities of type-1 and type-2 services measured at the present time n, denoted by $P_{\rm otg1}(n)$ and $P_{\rm otg2}(n)$, the link gain L in (1), $\hat{\bar{I}}_k(n+1)$, and $\hat{C}$ as input variables to determine the acceptance for the call request. In the paper, the required outage probability for type-i traffic, denoted by $P^*_{{\rm otg}i}$, is set to be the system QoS requirements, instead of SIR^*_i. Furthermore, in order to protect the handoff connection against forced termination, the required probability of forced termination, denoted by P^*_f, is also set to be the QoS requirement.

III. INTELLIGENT CALL ADMISSION CONTROLLER

A. Fuzzy Equivalent Interference Estimator

Assume there is a call request with traffic parameters: the peak rate R_p, the mean rate R_m, the peak rate duration T_p, and the required outage probability $P^*_{\rm otg1}(P^*_{\rm otg2})$, in the cell k. Similar to the effective bandwidth method used in high-speed networks [10], [11], the equivalent interference of call request (type-1 or type-2), denoted by $\hat{C}$ ($\hat{C}_1$ for type-1, $\hat{C}_2$ for type-2) can be obtained by Gaussian approximation given in the Appendix.

Since the fuzzy approach exhibits a soft behavior that means having a great ability to deal with the real-world imprecise, uncertain traffic, we here adopt fuzzy implementation of the *fuzzy equivalent interference estimator*. The equivalent interference estimator takes R_p, R_m, T_p, and $P^*_{\rm otg}$, claimed by a call request, as four input linguistic variables. The link gain variable is not considered here, but considered in the *fuzzy call admission processor*. This is because in this paper, equal received power control is assumed, and the link gain variable affects only the adjacent cell interference but not the home cell interference.

A fuzzy logic system contains fuzzifier, inference engine, and defuzzifier. To design the fuzzy logic controller, a set of input and output variables are first selected, and each variable has its term set to cover all corresponding situations. Several fuzzy inference rules are then established, based on the knowledge obtained from the numerical results of above derivations, to associate the decision to the current input values. First, the fuzzifier maps each input values to the values of corresponding term sets. The inference engine then obtains the output terms according to the input terms from fuzzifier and the rule base. Finally, the defuzzifier converts the output terms into a crisp value presenting the decision result. The design of the *fuzzy equivalent interference estimator* is as follows [12].

Term sets for R_p, R_m, T_p, and $P^*_{\rm otg}$ and membership functions for these term sets are defined in Table I, in which triangular function $f(x; x_0, a_0, a_1)$ and trapezoidal function $h(x; x_0, x_1, a_0, a_1)$ are chosen to be the membership functions, where x_0 in $f(\cdot)$ is the center of the triangular function, $x_0(x_1)$ in $h(\cdot)$ is the left (right) edge of the trapezoidal function, and $a_0(a_1)$ is the left (right) width of the triangular or the trapezoidal function. In the parameters setting for membership functions, $R_{p,\min}, R_{p,\max}, T_{p,\min}$, and $T_{p,\max}$, are the minimum and the maximum possible values for R_p and T_P, respectively; $P^*_{\rm otg1}$ and $P^*_{\rm otg2}$ are the desired QoS requirements of outage probability for type-1 and type-2 traffic; $S0$ and $S1$ are the two boundaries for the membership function of $\mu_{Ls}(P^*_{\rm otg})$ and $\mu_{St}(P^*_{\rm otg})$ such that these two membership function are mutually mirrored. Since R_p, T_p, and $P^*_{\rm otg}$ vary widely from different traffic sources, a logarithm function is employed. According to numerical results, proper boundary values of the membership functions are set to characterize R_p, R_m, and T_p. Also, $Sm_w = Me_{w0} = Me_c - Sm_e, La_w = Me_{w1} = La_e - Me_c$,

TABLE II
TERM SETS AND THEIR MEMBERSHIP FUNCTION FOR INPUT VARIABLES

Rule	R_p	R_m	T_p	P^*_{otg}	$\hat{C}$	Rule	R_p	R_m	T_p	P^*_{otg}	$\hat{C}$
1	*Sm*	*Lo*	*Sh*	*Ls*	C_1	19	*Me*	*Hi*	*Sh*	*Ls*	C_4
2	*Sm*	*Lo*	*Sh*	*St*	C_2	20	*Me*	*Hi*	*Sh*	*St*	C_5
3	*Sm*	*Lo*	*Md*	*Ls*	C_1	21	*Me*	*Hi*	*Md*	*Ls*	C_5
4	*Sm*	*Lo*	*Md*	*St*	C_2	22	*Me*	*Hi*	*Md*	*St*	C_6
5	*Sm*	*Lo*	*Lg*	*Ls*	C_1	23	*Me*	*Hi*	*Lg*	*Ls*	C_5
6	*Sm*	*Lo*	*Lg*	*St*	C_2	24	*Me*	*Hi*	*Lg*	*St*	C_7
7	*Sm*	*Hi*	*Sh*	*Ls*	C_2	25	*La*	*Lo*	*Sh*	*Ls*	C_3
8	*Sm*	*Hi*	*Sh*	*St*	C_3	26	*La*	*Lo*	*Sh*	*St*	C_4
9	*Sm*	*Hi*	*Md*	*Ls*	C_3	27	*La*	*Lo*	*Md*	*Ls*	C_5
10	*Sm*	*Hi*	*Md*	*St*	C_4	28	*La*	*Lo*	*Md*	*St*	C_6
11	*Sm*	*Hi*	*Lg*	*Ls*	C_3	29	*La*	*Lo*	*Lg*	*Ls*	C_6
12	*Sm*	*Hi*	*Lg*	*St*	C_4	30	*La*	*Lo*	*Lg*	*St*	C_7
13	*Me*	*Lo*	*Sh*	*Ls*	C_1	31	*La*	*Hi*	*Sh*	*Ls*	C_6
14	*Me*	*Lo*	*Sh*	*St*	C_2	32	*La*	*Hi*	*Sh*	*St*	C_7
15	*Me*	*Lo*	*Md*	*Ls*	C_3	33	*La*	*Hi*	*Md*	*Ls*	C_7
16	*Me*	*Lo*	*Md*	*St*	C_4	34	*La*	*Hi*	*Md*	*St*	C_8
17	*Me*	*Lo*	*Lg*	*Ls*	C_4	35	*La*	*Hi*	*Lg*	*Ls*	C_8
18	*Me*	*Lo*	*Lg*	*St*	C_5	36	*La*	*Hi*	*Lg*	*St*	C_8

$Lo_w = Hi_w = Hi_e - Lo_e, Sh_w = Md_{w0} = Md_c - Sh_e$, and $Lg_w = Md_{w1} = Lg_e - Md_c$ are set and fine-tuned. The output linguistic variable is the equivalent interference $\hat{C}$ ($\hat{C}_1$ or $\hat{C}_2$); its term set is defined as $T(\hat{C}) = \{C_i, i = 1, \ldots, 8\}$. The membership function of $T(\hat{C})$ is denoted by $M(\hat{C}) = \{\mu_{C_i}, i = 1, \ldots, 8\}$, where $\mu_{C_i}(\hat{C}) = f(\hat{C}; C_{i,c}, 0, 0), i = 1, \ldots, 8$, and $C_{1,c} = R_m$, and $C_{i,c} = C_{i-1,c} + (R_p - R_m)/7, i = 2, \ldots, 8$.

According to the fuzzy set theory, the fuzzy rule base forms a fuzzy set with dimensions $|T(R_p)| \times |T(R_m)| \times |T(T_p)| \times |T(P^*_{\text{otg}})|$ ($|T(x)|$ denotes the number of terms in $T(x)$). Therefore, there are a total of 36 fuzzy inference rules. Table II lists these fuzzy inference rules, which are set based on knowledge described by examples as follows. In rule 31, rule 32, and rule 35, the peak rate is large and the mean rate is high. The resulting interference in rule 31, which has a short peak rate duration, is thus expected to be less than that in rule 35, which has a long peak rate duration. And rule 31, which has a loose QoS requirements, is considered to have lower resulting interference than rule 35, which has a strict QoS requirement.

In the inference process, the max–min inference method is adopted. The max–min inference method initially applies the min operator on membership values of terms of all input linguistic variables for each rule and then applies the max operator to yield the overall membership value, for each output term. For example, there are rule 2, rule 4, rule 6, rule 7, and rule 14 which have the same term C_2. Results of the min operator for rule 2, rule 4, rule 6, rule 7, and rule 14, denoted as w_2, w_4, w_6, w_7, and w_{14}, are expressed as

$$w_2 = \min(\mu_{Sm}(R_p), \mu_{Lo}(R_m), \mu_{Sh}(T_p), \mu_{St}(P^*_{\text{otg}})) \quad (2)$$
$$w_4 = \min(\mu_{Sm}(R_p), \mu_{Lo}(R_m), \mu_{Md}(T_p), \mu_{St}(P^*_{\text{otg}})) \quad (3)$$
$$w_6 = \min(\mu_{Sm}(R_p), \mu_{Hi}(R_m), \mu_{Lg}(T_p), \mu_{St}(P^*_{\text{otg}})) \quad (4)$$
$$w_7 = \min(\mu_{Sm}(R_p), \mu_{Hi}(R_m), \mu_{Sh}(T_p), \mu_{Ls}(P^*_{\text{otg}})) \quad (5)$$
$$w_{14} = \min(\mu_{Me}(R_p), \mu_{Lo}(R_m), \mu_{Sh}(T_p), \mu_{St}(P^*_{\text{otg}})). \quad (6)$$

Then, the result after the max operator, for the term C_2, denoted as $w_{C_{\text{I}}}$, can be obtained by

$$w_{C_{\text{I}}} = \max(w_2, w_4, w_6, w_7, w_{14}). \quad (7)$$

The center of area defuzzification method is used for the defuzzifier owing to its computational simplicity. This defuzzification method obtains the equivalent interference $\hat{C}$ by combining $w_{C_1}, w_{C_2}, w_{C_3}, w_{C_4}, w_{C_5}, w_{C_6}, w_{c_7}$, and w_{c_8} as

$$\hat{C} = \frac{\sum_{i=1}^{8} w_{C_i} \times C_{i,c}}{\sum_{i=1}^{8} w_{C_i}}. \quad (8)$$

B. PRNN Interference Predictor

Many adaptive filtering algorithms were proposed for one-step prediction, e.g., *Kalman filter* [13], *recursive least-squares algorithms* [14], and *neural networks*. Among those techniques, neural networks belong to nonlinear adaptive filtering class, and neural networks have the learning capability and can dynamically adjust connection weights to achieve optimality for prediction [14]. The interference process is assumed to be in a nonlinear auto-regressive moving average (NARMA) model. Approximating the NARMA model in the least mean square error sense allows us to express the one-step prediction of the mean interference as a function of p measured interference powers and q previously predicted interference powers. That is,

$$\hat{\bar{I}}_k(n+1) = H(\bar{I}_k(n), \ldots, \bar{I}_k(n-p+1); \hat{\bar{I}}_k(n), \ldots, \hat{\bar{I}}_k(n-q+1)) \quad (9)$$

where $\hat{\bar{I}}_k(i)$ is the previously predicted mean interference sample at time $i, n-q+1 \leq i \leq n$, in cell k, $\bar{I}_k(i)$ is the measured mean interference sample at time $i, n-p+1 \leq i \leq n$, and $H(\cdot)$ is an unknown nonlinear function to be determined.

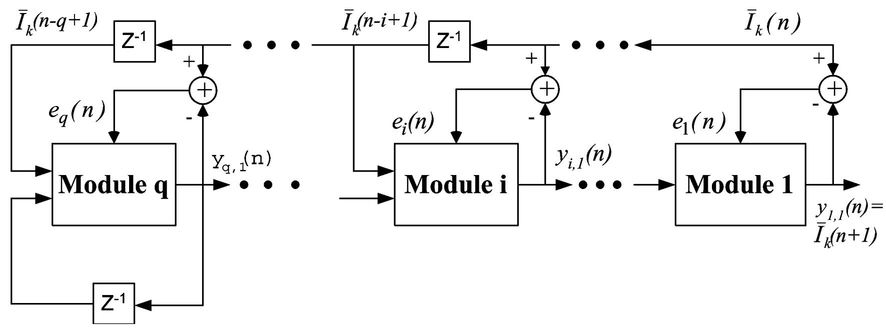

Fig. 2. Structure of the PRNN interference predictor.

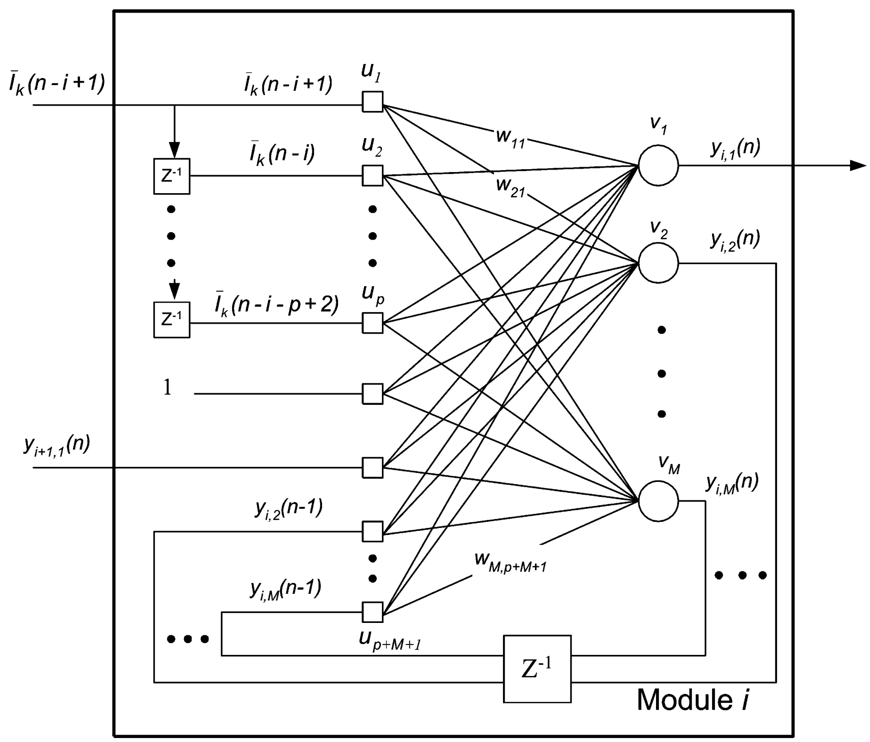

Fig. 3. The ith small RNN module in the PRNN interference predictor.

Applying PRNN to the NARMA prediction yields a high prediction accuracy, fast convergent speed, and low computation complexity [17]. Thus, PRNN is adopted herein to approximate the $H(\cdot)$ function.

Fig. 2 shows the architecture of PRNN interference predictor, which involves a total of q levels of processing. Each level has an identical neural module and a subtractor. For level i, two external inputs are fed into the module: the delayed version of the measured interference sample $\bar{I}_k(n-i+1)$ and the first output of the preceding level $y_{i+1,1}(n)$, and the output of this module subtracted from $\bar{I}_k(n-i+2)$ forms an error signal $e_i(n)$. The error signal is used to adjust the synaptic weights in the ith neural module. Consequently, the output of the first module $y_{1,1}(n)$ is the desired next-step interference prediction $\hat{\bar{I}}_s(n+1)$.

Fig. 3 depicts the detailed structure of module i, which is constituted by a two-layer recurrent neural network. The output vector, $\vec{y}_i(n) = [y_{i,1}(n), \ldots, y_{i,M}(n)]$, consists of M elements, among which, $(M-1)$ outputs are fed back to the input, and the first output, $y_{i,1}(n)$, is applied directly to the next module $i-1$. The input vector $\vec{u}_i(n)$ consists of three parts: the p-tuple external input vector $[\bar{I}_k(n-i+1), \ldots, \bar{I}_k(n-i-p+2)]$, a bias input whose value is always maintained at $+1$, a feedforward input from the preceding level $y_{i+1,1}(n)$, and the M-tuple feedback vector $[y_{i,2}(n-1), \ldots, y_{i,M}(n-1)]$. The details can be referred to [15]–[17].

To adjust the synaptic weights, we define a cost function based on these error signals, which is given by

$$\mathcal{E}(n) = \sum_{i=1}^{q} \lambda^{i-1} e_i^2(n) \tag{10}$$

where λ is an exponential weighting factor of the range $(0 < \lambda \leq 1)$ [15]. The factor λ^{i-1} weighs the memory of module i in the PRNN. Notably, $e_i(n) = \bar{I}_k(n-i+2) - y_{i,1}(n)$. Because $y_{i,1}(n)$ is limited in amplitude within the range (0, 1) due to the characteristics of sigmoidal activation function, $\bar{I}_k(n-i+2)$ is normalized before being actually put into the PRNN predictor.

TABLE III
TERM SETS AND THEIR MEMBERSHIP FUNCTION FOR INPUT VARIABLES

	Elements of Term Sets	Membership Function
P_f	Satisfied (Sa_f)	$\mu_{Sa_f}(P_f(n)) = h(P_f(n); 0, Sa_{e_f}, 0, Sa_{w_f})$
	Not Satisfied (Ns_f)	$\mu_{Ns_f}(P_f(n)) = h(P_f(n); Ns_{e_f}, 1, Ns_{w_f}, 0)$
P_{otg1}	Satisfied (Sa_1)	$\mu_{Sa_1}(P_{otg1}(n)) = h(P_{otg1}(n); 0, Sa_{e1}, 0, Sa_{w1})$
	Not Satisfied (Ns_1)	$\mu_{Ns_1}(P_{otg1}(n)) = h(P_{otg1}(n); Ns_{e1}, 1, Ns_{w1}, 0)$
P_{otg2}	Satisfied (Sa_2)	$\mu_{Sa_2}(P_{otg2}(n)) = h(P_{otg2}(n); 0, Sa_{e2}, 0, Sa_{w2})$
	Not Satisfied (Ns_2)	$\mu_{Ns_2}(P_{otg2}(n)) = h(P_{otg2}(n); Ns_{e2}, 1, Ns_{w2}, 0)$
$\hat{\bar{I}}_k(n+1)$	Small (Sm)	$\mu_{Sm}(\hat{\bar{I}}_k(n+1)) = h(\hat{\bar{I}}_k(n+1); 0, Sm_e, 0, Sm_w)$
	Large (Lg)	$\mu_{Lg}(\hat{\bar{I}}_k(n+1)) = h(\hat{\bar{I}}_k(n+1); I_o, \infty, Lg_w, 0)$
L	Strong (Sr)	$\mu_{Sr}(L) = h(L/L_0; 0, Sr_e, 0, Sr_w)$
	Weak (Wk)	$\mu_{Wk}(L) = h(L/L_0; Wk_e, \infty, Wk_w, 0)$
$\hat{C}$	Small (Sc)	$\mu_{Sc}(\hat{C}) = h(\hat{C}; 0, Sc_e, 0, Sc_w)$
	Large (Lc)	$\mu_{Lc}(\hat{C}) = h(\hat{C}; Lc_e, Lc_{e1}, Lc_w, 0)$

The synaptic weights are adjusted by using an RTRL algorithm [16], [17]. For a synaptic weight $w_{\zeta,\xi}$, the incremental change $\triangle w_{\zeta,\xi}(n)$ at time n according to the steepest descent method is expressed as

$$\triangle w_{\zeta,\xi}(n) = -\eta \frac{\partial \mathcal{E}(n)}{\partial w_{\zeta,\xi}} = 2\eta \sum_{i=1}^{q} \lambda^{i-1} e_i(n) \cdot \frac{\partial y_{i,1}(n)}{\partial w_{\zeta,\xi}}. \quad (11)$$

The training of PRNN consists of two stages. During the *off-line* training phase, interference samples using typical system parameters and traffic load are generated. The PRNN, fed with these samples, adjusts the synaptic weights recursively until the root mean square error (RMSE) of the desired prediction output is lower than the criteria. During the *on-line* training phase, the PRNN interference predictor obtains the interference predictions for existing calls at time instant $(n+1)$, $\hat{\bar{I}}_k(n+1)$, from the output of the first neuron of the first module, and measures the interference sample $\bar{I}_k(n+1)$; then it adjusts the synaptic weights using the RTRL algorithm. Due to the on-line learning capability, PRNN can adapt its wights to the current load conditions other than those set in off-line training phase.

C. Fuzzy Call Admission Processor

The *fuzzy call admission processor* is responsible for the determination of the acceptance of a new or handoff call request. For the new call request, the processor considers the $P_f, P_{\rm otg1}, P_{\rm otg2}, \hat{\bar{I}}_s(n+1), L$, and $\hat{C}$ as its input linguistic variables which indicate the system performance measures, the predicted system load, the link quality, and the estimated equivalent interference generated by the call. For the handoff call request, the processor considers the same input variables as for the new call request except that the link quality L is not taken into account since the handoff call is definitely on the cell boundary.

According to the domain knowledge from simulations, term sets and membership functions of input linguistic variables $P_f, P_{\rm otg1}, P_{\rm otg2}, \hat{\bar{I}}_s(n+1), L$, and $\hat{C}$ are defined in Table III, where $h(\cdot)$ is the trapezoidal function as defined in Table I. As for the parameter setting for these membership functions, Ns_{e_f} is set to be P_f^* minus a safety margin, and Sa_{e_f} is a value less than Ns_{e_f} by a safety amount for separating the satisfactory region and the violation region; $Ns_{e1}(Ns_{e2})$ is set to be $P^*_{\rm otg1}(P^*_{\rm otg2})$ minus a safety margin, and $Sa_{e1}(Sa_{e2})$ is also set to a value less than $Ns_{e1}(Ns_{e2})$ for the same reason as the safety amount for Sa_{e_f}; I_o is the tolerable interference power corresponding to the minimal signal-to-interference power ratio SIR_1^*, and Sm_e would be set to be a fraction of I_o; L_0 is the reference link gain within which the mobile user is regarded as to be far from the base station and the interference to the adjacent cells is greater, and $Sr_e \geq 1$ and $Wk_e \leq 1$. We also set $Sc_w = Lc_w = Lc_e - Sc_e, Sm_w = I_0 - Sm_e = Lg_w$ to simplify the design of fuzzy logic parameters. The other endpoints of Sc_e, Lc_e, Lc_{e1}, and the widths of the membership function of $Sa_{w_f}, Ns_{w_f}, Sa_{w1}, Ns_{w1}, Sa_{w2}, Ns_{w2}, Sr_w$, and Wk_w must be fine-tuned to proper values during simulations.

The term set for the output linguistic variable of new call request $T(Z = Z_n) = \{$Straightly Accept, Weakly Accept, Weakly Reject, Straightly Reject$\} = \{\mathrm{SA}_n, \mathrm{WA}_n, \mathrm{WR}_n, \mathrm{SR}_n\}$. Membership functions for Z_n are denoted by $M(Z_n) = \{\mu_{\mathrm{SA}_n}, \mu_{\mathrm{WA}_n}, \mu_{\mathrm{WR}_n}, \mu_{\mathrm{SR}_n}\}$, where $\mu_X(Z_n) = f(Z_n; X, 0, 0)$, and X is $\mathrm{SA}_n, \mathrm{WA}_n, \mathrm{WR}_n$, or SR_n. A new call request can be accepted if the output of the fuzzy call admission processor Z_n is greater than an acceptance threshold $z_{na}, \mathrm{SR}_n \leq z_{na} \leq \mathrm{SA}_n$. Without a loss of generality, $\mathrm{SR}_n = 0, \mathrm{SA}_n = 1$, and let $\mathrm{WR}_n = (\mathrm{SR}_n + z_{na})/2, \mathrm{WA}_n = (\mathrm{SA}_n + z_{na})/2$. Similarly, the term set for the output linguistic variable of handoff call request $T(Z = Z_h) = \{\mathrm{SA}_h, \mathrm{WA}_h, \mathrm{WR}_h, \mathrm{SR}_h\}$, and membership functions for Z_h are denoted by $M(Z_h) = \{\mu_{\mathrm{SA}_h}, \mu_{\mathrm{WA}_h}, \mu_{\mathrm{WR}_h}, \mu_{\mathrm{SR}_h}\}$, where $\mu_X(Z_h) = f(Z_h; X, 0, 0)$, and X is $\mathrm{SA}_h, \mathrm{WA}_h, \mathrm{WR}_h$, or SR_h. A handoff call request can be accepted if the output of the fuzzy call admission processor Z_h is greater than an acceptance threshold $z_{ha}, R_h \leq z_{ha} \leq A_h$. Similarly, we set $R_h = 0, A_h = 1, \mathrm{WR}_h = (R_h + z_{ha})/2$, and $\mathrm{WA}_h = (A_h + z_{ha})/2$.

TABLE IV

RULE STRUCTURE OF THE FUZZY CALL ADMISSION PROCESSOR FOR NEW CALL REQUEST

Rule	P_f	P_{otg1}	P_{otg2}	$\hat{\bar{I}}_{n+1}$	L	$\hat{C}$	Z_n	Rule	P_f	P_{otg1}	P_{otg2}	$\hat{\bar{I}}_{n+1}$	L	$\hat{C}$	Z_n
1	Sa_h	Sa_1	Sa_2	Sm	-	-	SA_n	20	Sa_h	Ns_1	Ns_2	Sm	Sr	Lc	WR_n
2	Sa_h	Sa_1	Sa_2	Lg	Sr	Sc	SA_n	21	Sa_h	Ns_1	Ns_2	Sm	Wk	-	SR_n
3	Sa_h	Sa_1	Sa_2	Lg	Sr	Lc	WA_n	22	Sa_h	Ns_1	Ns_2	Lg	Sr	-	SR_n
4	Sa_h	Sa_1	Sa_2	Lg	Wk	-	WR_n	23	Sa_h	Ns_1	Ns_2	Lg	Wk	-	SR_n
5	Sa_h	Sa_1	Ns_2	Sm	Sr	Sc	SA_n	24	Na_h	Sa_1	Sa_2	Sm	-	-	WA_n
6	Sa_h	Sa_1	Ns_2	Sm	Sr	Lc	WA_n	25	Na_h	Sa_1	Sa_2	Lg	Sr	-	WA_n
7	Sa_h	Sa_1	Ns_2	Sm	Wk	Sc	WA_n	26	Na_h	Sa_1	Sa_2	Lg	Wk	-	WR_n
8	Sa_h	Sa_1	Ns_2	Sm	Wk	Lc	WR_n	27	Na_h	Sa_1	Ns_2	Sm	Sr	-	WA_n
9	Sa_h	Sa_1	Ns_2	Lg	Sr	Sc	WA_n	28	Na_h	Sa_1	Ns_2	Sm	Wk	Sc	WR_n
10	Sa_h	Sa_1	Ns_2	Lg	Sr	Lc	WR_n	29	Na_h	Sa_1	Ns_2	Sm	Wk	Lc	SR_n
11	Sa_h	Sa_1	Ns_2	Lg	Wk	Sc	WR_n	30	Na_h	Sa_1	Ns_2	Lg	Sr	Sc	WR_n
12	Sa_h	Sa_1	Ns_2	Lg	Wk	Lc	SR_n	31	Na_h	Sa_1	Ns_2	Lg	Sr	Lc	SR_n
13	Sa_h	Ns_1	Sa_2	Sm	Sr	Sc	WA_n	32	Na_h	Sa_1	Ns_2	Lg	Wk	-	SR_n
14	Sa_h	Ns_1	Sa_2	Sm	Sr	Lc	WR_n	33	Na_h	Ns_1	Sa_2	Sm	Sr	-	WR_n
15	Sa_h	Ns_1	Sa_2	Sm	Wk	Sc	WA_n	34	Na_h	Ns_1	Sa_2	Sm	Wk	Sc	WR_n
16	Sa_h	Ns_1	Sa_2	Sm	Wk	Lc	WR_n	35	Na_h	Ns_1	Sa_2	Sm	Wk	Lc	SR_n
17	Sa_h	Ns_1	Sa_2	Lg	Sr	-	WR_n	36	Na_h	Ns_1	Sa_2	Lg	-	-	SR_n
18	Sa_h	Ns_1	Sa_2	Lg	Wk	-	SR_n	37	Na_h	Ns_1	Ns_2	-	-	-	SR_n
19	Sa_h	Ns_1	Ns_2	Sm	Sr	Sc	WA_n								

TABLE V

RULE STRUCTURE OF THE FUZZY HANDOFF ADMISSION PROCESSOR FOR HANDOFF CALL REQUEST

Rule	P_f	P_{otg1}	P_{otg2}	$\hat{\bar{I}}_{n+1}$	$\hat{C}$	Z_h	Rule	P_f	P_{otg1}	P_{otg2}	$\hat{\bar{I}}_{n+1}$	$\hat{C}$	Z_h
1	Sa_f	Sa1	Sa2	Sm	Sc	SA_h	17	Ns_f	Sa1	Sa2	Sm	Sc	SA_h
2	Sa_f	Sa1	Sa2	Sm	Lc	SA_h	18	Ns_f	Sa1	Sa2	Sm	Lc	SA_h
3	Sa_f	Sa1	Sa2	Lg	Sc	SA_h	19	Ns_f	Sa1	Sa2	Lg	Sc	SA_h
4	Sa_f	Sa1	Sa2	Lg	Lc	SA_h	20	Ns_f	Sa1	Sa2	Lg	Lc	SA_h
5	Sa_f	Sa1	Ns2	Sm	Sc	WA_h	21	Ns_f	Sa1	Ns2	Sm	Sc	SA_h
6	Sa_f	Sa1	Ns2	Sm	Lc	WR_h	22	Ns_f	Sa1	Ns2	Sm	Lc	SA_h
7	Sa_f	Sa1	Ns2	Lg	Sc	WR_h	23	Ns_f	Sa1	Ns2	Lg	Sc	WA_h
8	Sa_f	Sa1	Ns2	Lg	Lc	WR_h	24	Ns_f	Sa1	Ns2	Lg	Lc	WR_h
9	Sa_f	Ns1	Sa2	Sm	Sc	WR_h	25	Ns_f	Ns1	Sa2	Sm	Sc	SA_h
10	Sa_f	Ns1	Sa2	Sm	Lc	WR_h	26	Ns_f	Ns1	Sa2	Sm	Lc	SA_h
11	Sa_f	Ns1	Sa2	Lg	Sc	SR_h	27	Ns_f	Ns1	Sa2	Lg	Sc	WA_h
12	Sa_f	Ns1	Sa2	Lg	Lc	SR_h	28	Ns_f	Ns1	Sa2	Lg	Lc	WR_h
13	Sa_f	Ns1	Ns2	Sm	Sc	SR_h	29	Ns_f	Ns1	Ns2	Sm	Sc	SR_h
14	Sa_f	Ns1	Ns2	Sm	Lc	SR_h	30	Ns_f	Ns1	Ns2	Sm	Lc	SR_h
15	Sa_f	Ns1	Ns2	Lg	Sc	SR_h	31	Ns_f	Ns1	Ns2	Lg	Sc	SR_h
16	Sa_f	Ns1	Ns2	Lg	Lc	SR_h	32	Ns_f	Ns1	Ns2	Lg	Lc	SR_h

Tables IV and V present the rule structure of *fuzzy call admission processor* for the new (handoff) call request. It can be found from Table IV that the more (less) satisfied the $P_f, P_{\rm otg1}, P_{\rm otg2}$ are and the smaller (larger) the $\hat{\bar{I}}_{n+1}$ is, the higher (lower) likelihood the system can accept the new call request. As P_f is not satisfied but $P_{\rm otg1}, P_{\rm otg2}$, and $\hat{\bar{I}}_{n+1}$ indicate the light system load, the system will tend to accept the new call request to enhance the utilization since the relief from a temporary congestion may happen. At any specific system load condition, the system will tend to reject the bad users with poor signal quality and the more heavy loaded users according to L and $\hat{C}$. Also, it can be found in Table V that the system tends to accept the handoff call as the P_f is not satisfied more likely than as P_f is satisfied to protect the ongoing call anyway except the condition that the traffic load is very heavy. And the larger $\hat{\bar{I}}_{n+1}, P_{\rm otg1}$, and $P_{\rm otg2}$ imply the heavier traffic load, then the system tends to reject the handoff call request. Notice that these system QoS performance measures such as $P_f(n), P_{\rm otg1}(n)$, and $P_{\rm otg2}(n)$ act as a metric to reflect system performance and play as feedback signals for ICAC. Consequently, ICAC is a closed-loop control system in which system stability can be ensured and QoS requirements can be satisfied.

Similarly, the $max\text{–}min$ inference method is employed herein to calculate the membership value for each term of

$T(Z_n)(T(Z_h))$ and the center of area method is then applied for defuzzification.

IV. Simulation Results and Discussion

In the simulations, $K = 49$ hexagonal cells, E_b/N_0 of type-1 connection $\gamma_1^* = 7$ dB, E_b/N_0 of type-2 connection $\gamma_2^* = 10$ dB, the spreading factor of each basic code channel $\mathrm{SF} = 256$, and the frequency spectrum bandwidth $W = 3.84$ MHz are selected. The QoS requirements of outage probability are set to be $P_{\mathrm{otg1}}^* = 2\times 10^{-2}$ and $P_{\mathrm{otg2}}^* = 5\times 10^{-3}$, and the QoS constraint of forced termination probability is defined as $P_f^* = 5 \times 10^{-5}$. To achieve the required outage requirement of type-2 connections, the processing gain ratio is chosen to be $(R_{\mathrm{I}})/(R_{\mathrm{E}}) = 3$, and therefore the SIR threshold before despreading are set to be $SIR_1^* = -14$ dB, $SIR_2^* = -17$ dB. The filtering factor (the exponential decay factor) to obtain the interference mean estimation is 0.02. The voice source model is assumed to be with $1/\alpha = 1$ s and $1/\beta = 1.35$ s, while the data source model is assumed to be with $1/A_d = 0.1$ and the size of data message is in a geometric distribution with mean 2 and maximum length 10. The mean holding times for both voice and data services are 90 s. The moving speed of each mobile user V has two simulation cases. In the low mobility case, the speed of a mobile user is randomly selected from 0 km/h or 5 km/h. In the high mobility case, the speed of mobile users is either $V_1 = 20$ km/h or $V_2 = 60$ km/h with equal probability. The moving direction is modeled by the angle τ with uniform distribution. The radio propagation parameters of θ and ζ are set to be 4 and 8 dB [1], and the handoff margin is set to be 3 dB.

The effectiveness of the proposed ICAC is tested by comparing it with the SIR-based CAC with intercell interference prediction (PSIR-CAC) proposed in [3] and the CAC for multimedia calls (MCAC) proposed in [8]. For PSIR-CAC [3], the call request is accepted if the minimum residual capacity of each cell among the active sets is positive. The SIR threshold is set to be -14 dB. For MCAC, E_b/N_0 threshold values for the type-1 and type-2 services, denoted by γ_0 and γ_1, are set to be 7 and 10 dB, respectively. This algorithm accepts a call request of type $i, i = 1$ or 2, if the condition for type k connection satisfies

$$\left(\left(\frac{E_b}{N_0}\right)_{k,i}^{-1} + \sum_{j=1}^{M_c} 1/\mathrm{SF}_{i,j}\right)^{-1} \geq \gamma_k^* \cdot \beta_i^x, \quad k = 1, 2, \quad (12)$$

where $\beta_i^x, x = n$ or h for new or handoff call request, is the admission margin parameter to give different priorities for new or handoff call requests of type-i class, and $(E_b/N_0)_{k,i}$ is the measured mean E_b/N_0 of type k, M_c is the number of code channels, and $\mathrm{SF}_{i,j}$ is the spreading factor of channel j for the call request of type i. We set $\beta_1^n = 1.25, \beta_2^n = 1.3, \beta_1^h = 1.05$, and $\beta_2^h = 1.1$. In the original scheme [8], single code and variable spreading factor transmission was used. Here, we extend it to a multicode transmission system, using the same design concept. Thus, $\mathrm{SF}_{i,j}$ of each code is 256, but multicode channels are used to carry the information bits.

We first demonstrate the effects of the adoption of PRNN interference prediction and the link gain on the system capacity. Fig. 4 shows the mean number of accommodation users versus the traffic intensity ρ for ICAC with and without PRNN interference predictor. It can be found that in the low mobility case, the ICAC equipped with PRNN interference predictor can attain maximal 5% gain of system capacity at $\rho = 1.3$, compared with the ICAC without PRNN interference predictor. In the high mobility case, the gain of system capacity achieved by ICAC with PRNN interference predictor is above 5% after $\rho \geq 0.91$. The gain of system capacity increases along with the increment of traffic load, and the gain of system capacity in high mobility case is more than that in low mobility case. The larger the variance of interference power received at the base station is, the more significantly the PRNN interference predictor can facilitate the estimation.

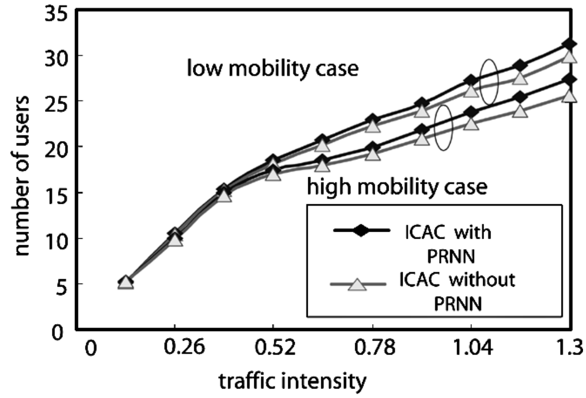

Fig. 4. Mean number of accommodation users versus traffic intensity for ICAC with and without PRNN interference predictor.

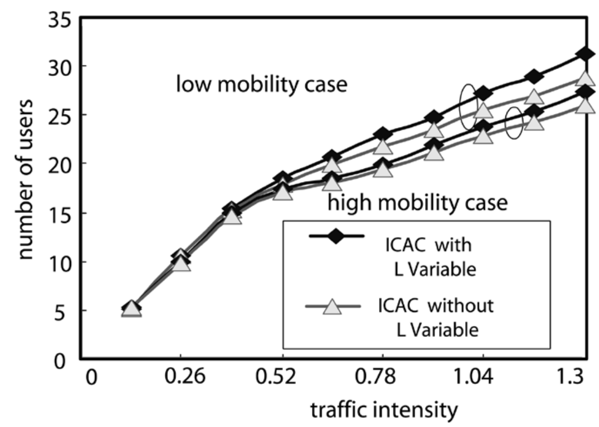

Fig. 5. Mean number of accommodation users versus traffic intensity of ICAC with and without link gain L variable.

Fig. 5 shows the mean number of accommodation users versus traffic intensity for ICAC with and without link gain L variable. In the low mobility case, the system capacity of ICAC with link gain achieves improvement by above 5% more than that of ICAC without link gain as $\rho \geq 0.78$. In the high mobility case, the gains of system capacity are 2.5% as $\rho = 0.78$ and about 5% as $\lambda = 1.3$. And the capacity gain increases as the traffic load becomes heavy in both low and high mobility cases. It is because the ICAC scheme with L can reject bad users and accept good users at heavy traffic conditions, while the ICAC scheme without L variable has no such information to make a decision. But in the high mobility case, the capacity gain is reduced since good users are more likely to become

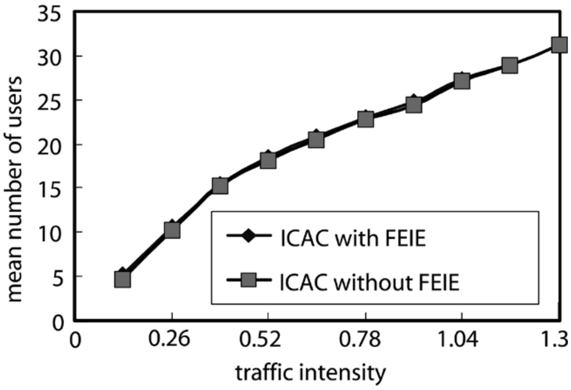

Fig. 6. Mean number of accommodation users versus traffic intensity of ICAC with and without FEIE.

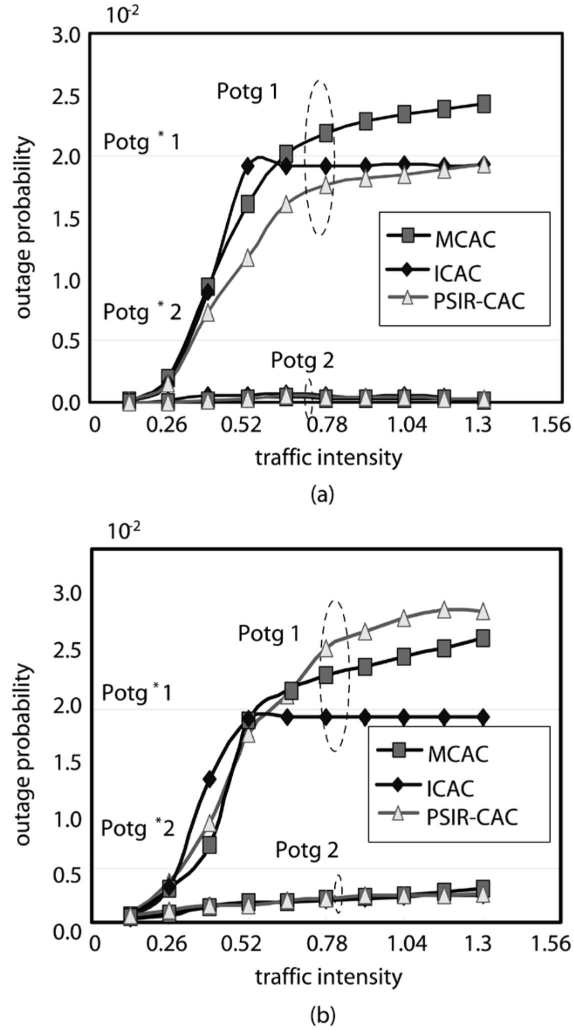

Fig. 7. Outage probabilities versus traffic intensity (a) low mobility case and (b) high mobility case.

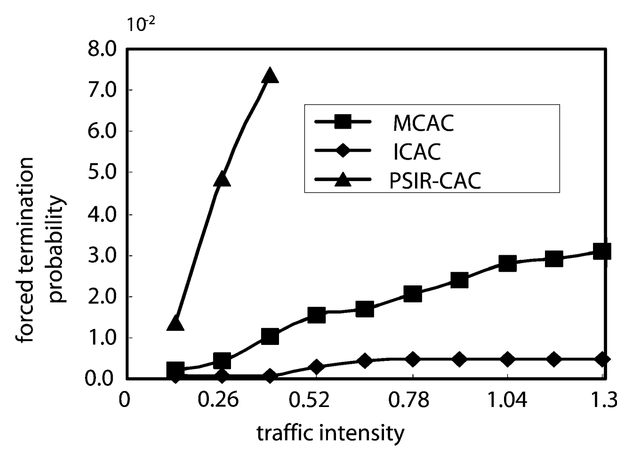

Fig. 8. Forced termination probabilities versus new call arrival rate.

bad users and the interference will deteriorate. Moreover, the ICAC with the link gain variable can implicitly avoid over interfering adjacent cells. As noted, the predicted interference received at base station reflects partly the traffic load of the adjacent cells; and ICAC rejects the highly interfered users (bad users) to avoid serious interference to the adjacent cells if the predicted interference is large. We have simulated the case of hot spot. The result shows that the hot spot cells are not too aggressive to suppress the accommodation users in the adjacent cells. Therefore, ICAC with the link gain variable has taken the interference of adjacent cells into considerations.

Fig. 6 show the number of accommodation users versus traffic intensity for ICAC with and without fuzzy equivalent interference estimator (FEIE). The ICAC without FEIE is simulated by feeding the equivalent interference obtained in the Appendix to the fuzzy call admission processor. It can be found that they have the similar performance. However, the former uses simple logic to get the equivalent interference, while the later obtains the equivalent interference by complicated computation.

Fig. 7 illustrates the outage probabilities versus traffic intensity for ICAC, MCAC, and PSIR-CAC in (a) low and (b) high mobility cases. It can be seen that ICAC can always guarantee QoS requirements of outage probabilities for all traffic types and all traffic load conditions; PSIR-CAC cannot keep the type-1 outage probability guaranteed in the high mobility case due to the more unpredictable change of interference received at the base station; and MCAC cannot guarantee the type-1 outage probabilities as traffic load gets heavier in both low and high mobility cases. It can also be found that the outage probability of ICAC is the highest in the QoS-guaranteed region ($\rho \leq 0.52$) than those in other two schemes, and is almost kept constant at 0.02 after $\rho > 0.52$. It is because that ICAC adopts intelligent techniques such as fuzzy logic systems and neural networks, which have powerful reasoning capabilities and learning ability, respectively, to cope with the variant interference of uncertain traffic; and ICAC adopts measures of the outage probabilities of each type of traffic as input linguistic variables. But MCAC and PSIR-CAC do not take the outage probability and system load variation into account. ICAC can adapt to fluctuating traffic load situations and fulfill the requirements.

Fig. 8 shows the forced termination probability of handoff call requests versus traffic intensity for ICAC, MCAC, and PSIR-CAC in low mobility case. It can be found that ICAC can always keep the forced termination probability of handoff calls under the constraint no matter how the traffic load is; MCAC, which simply sets the priority for handoff call over new call, cannot always guarantee the forced termination probability requirement except that the admission margin parameter for

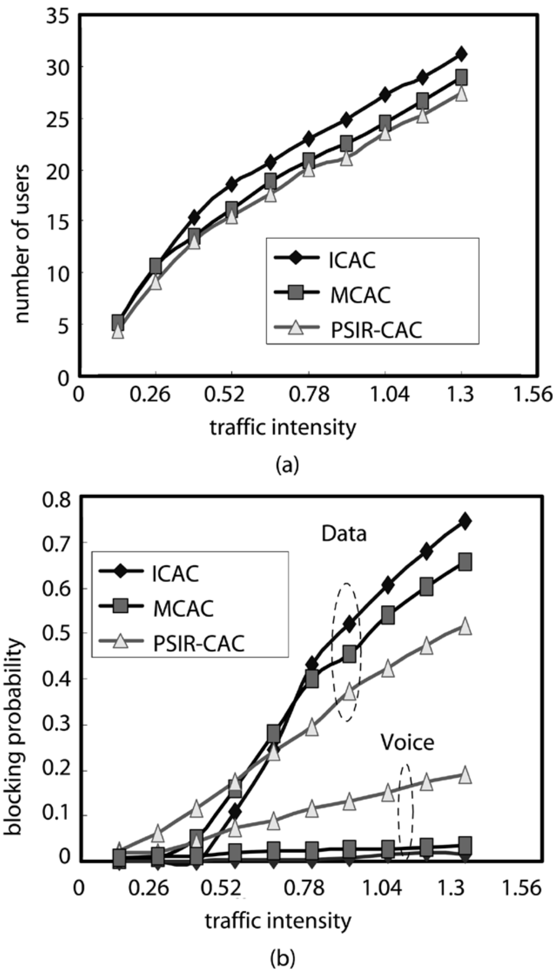

Fig. 9. (a) Number of accommodation users and (b) new call blocking probability versus traffic intensity in low mobility case.

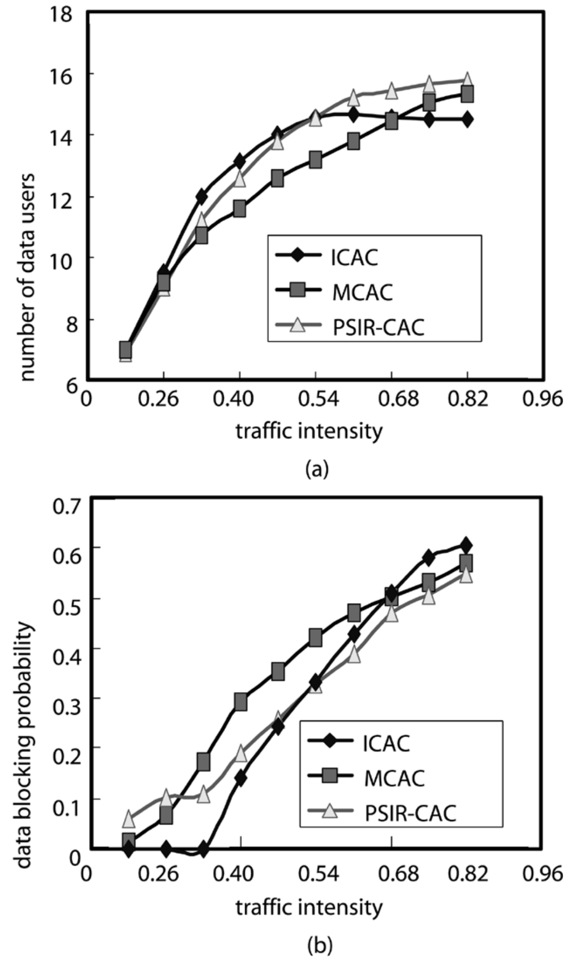

Fig. 10. (a) Number of accommodation data users and (b) blocking probability of data users versus the new call arrival rate of data users where voice arrival rate is fixed at 0.1 per frame time.

handoff calls in MCAC is adjusted for different traffic conditions; and PSIR-CAC extremely violates the constraint because it does not take this constraint into consideration.

Fig. 9 illustrates (a) the number of users and (b) the new call blocking probabilities of voice and data users versus traffic intensity for ICAC, MCAC, and PSIR-CAC in low mobility case. It can be found that ICAC accepts users more than PSIR-CAC and MCAC by an amount of around 13% and 10%, respectively. And in the $\rho \leq 0.52$ region where all these three schemes can keep QoS guaranteed, the blocking probability of ICAC is the lowest; but out of the region, say $\rho \geq 0.78$, the blocking probability of data users for ICAC is the largest, while that of voice users for ICAC is still the smallest. This is because, as $\rho \leq 0.52$, ICAC can precisely predict the system load condition and thus fully utilize the resource; but in the heavy-load condition, ICAC tends to reject bad users, hence the adjacent cell interference is significantly reduced and the system capacity grows up continuously. Notice that the equivalent interference of data connection is larger due to the higher burstiness and the stricter requirement, and they are likely to be bad users. In the high mobility case, similar phenomena are observed.

Fig. 10 shows (a) the number of accommodation data users and (b) the blocking probability of data users versus traffic intensity of data users where the voice arrival rate is fixed to be 0.1 per frame time and no voice users are allowed to be blocked. It can be seen that the mean number of accommodation data users of ICAC is 7% and 11% more than those of MCAC and PSIR-CAC at $\rho < 0.40$ where all these three schemes can guarantee the requirements of outage probabilities. As $0.40 \leq \rho \leq 0.54$ where MCAC and PSIR-CAC begin to violate the QoS requirements, ICAC still attains more number of data users by the amount 5% and 9% than MCAC and PSIR-CAC, respectively. After $\rho \geq 0.54$, the accommodation data users of ICAC remains constant in order to keep QoS requirements guaranteed and the blocking probability of ICAC grows higher than those of MCAC and PSIR-CAC, while the numbers of data users of MCAC and PSIR-CAC continue increasing but their QoS requirements keep deteriorating. Therefore, it can be concluded that ICAC can precisely estimate the system condition to admit more users than MCAC and PSIR-CAC as these three schemes satisfy the QoS requirements; and ICAC accepts reasonable users into the system to keep the requirement guaranteed while the MCAC and PSIR-CAC violate the requirement.

V. CONCLUSION

This paper presents an intelligent call admission controller (ICAC) for wideband CDMA cellular systems to support differentiated QoS provisioning, satisfy the system QoS constraints, and maximize the spectrum utilization. ICAC is applied with both fuzzy logic control and PRNN techniques, thus contains a fuzzy equivalent interference estimator, a PRNN interference predictor, and a fuzzy call admission processor. The fuzzy equivalent interference estimator determines the interference power caused by the new call request, based on the domain knowledge on effective bandwidth method. The PRNN interference predictor forecasts the system interference mean at the next time period, and it can achieve additional gain in system capacity by an amount of 5%. The fuzzy call admission processor considers the system QoS performance measures of each traffic type and the link gain of the call request to determine whether to accept the call request, based on the estimated equivalent interference generated by the call and the predicted next-step interference caused by existing calls. The further consideration of the variable of link gain of the new call request can make ICAC capable of rejecting bad users and accepting good users to improve the system capacity. Therefore, ICAC can achieve system capacity higher than PSIR-CAC and MCAC by an amount of more than 10% in regions where QoS requirements are guaranteed. ICAC is indeed effective for differentiated QoS provisioning for wireless multimedia CDMA systems.

Appendix I
Derivation of $\hat{C}_1$ and $\hat{C}_2$

Let Ω_k be the aggregation traffic process of voice and data calls in the cell k, which can be expressed as $\Omega_k = \sum_{i=1}^{N_{\mathrm{E},k}} \nu_{i,k} + \sum_{i=1}^{N_{\mathrm{I},k}} \delta_{i,k} \cdot R_G \cdot M_{i,k}$, where $\nu_{i,k}(\delta_{i,k})$ denotes the type-1 (type-2) traffic activity factor, $N_{1,k}(N_{2,k})$ is the number of type-1 (type-2) users, $M_{i,k}$ is the number of basic code channels needed by type-2 user i, in home cell k for communication, and $R_G = R_2/R_1$. In order to fulfill the QoS requirements of outage probabilities, the process Ω_k should satisfy the following constraints:

$$\Pr\{\Omega_k > 1/SIR_1^*\} < P_{\mathrm{otg1}}^* \tag{I.1}$$

$$\Pr\{\Omega_k > R_G/SIR_2^*\} < P_{\mathrm{otg2}}^* \tag{I.2}$$

$$N_{1,k}\hat{C}_1 + N_{2,k}\hat{C}_2 < \min\left\{\frac{1}{SIR_1^*}, \frac{R_G}{SIR_2^*}\right\}. \tag{I.3}$$

Assume that Ω_k possesses Gaussian property; its mean μ_{Ω_k} and the variance σ_{Ω_k} are the summation of the mean and the variance of each individual connection, respectively, given by $\mu_{\Omega_k} = N_{1,k} \cdot R_{m,1} + N_{2,k} \cdot R_{m,2}$, and $\sigma_{\Omega_k}^2 = N_{1,k} \cdot \sigma_1^2 + N_{2,k} \cdot \sigma_2^2$. The $R_{m,1}(R_{m,2})$ and $\sigma_1(\sigma_2)$ are the mean and the variance of the rate generated by a type-1 (type-2) call. Since the type-1 and type-2 source models are herein assumed to be an ON–OFF process and a batch Poisson process, respectively, the σ_1 and σ_2 can be obtained by $\sigma_1^2 = (R_{p,1} - R_{m,1})R_{p,1}, \sigma_2^2 = (R_G^{\mathrm{I}} \cdot R_{m,2}^{\mathrm{I}})/((T_{p,2} - 1))$, where $R_{p,1}$ is peak rate of a voice call and $T_{p,2}$ is the peak rate duration of a data call. By normalizing the variable Ω_k, (I.1) can be written as $P\{\Omega_k' > ((1/SIR_{\mathrm{E}}^*) - \mu_{\Omega_k})/(\sigma_{\Omega_k})\} < P_{\mathrm{otg1}}^*$, where Ω_k' is a normalized Gaussian random variable. Let β_1 be a constant such that $Q(\beta_1) = P_{\mathrm{otg1}}^*$, and the condition $((1/SIR_{\mathrm{E}}^*) - \mu_{\mathrm{L}_k})/(\sigma_{\mathrm{L}_k}) > \beta_1$ must be satisfied. By substituting μ_{Ω_k} and $\sigma_{\Omega_k}^2$ into the above condition, the constraint for type-1 traffic becomes

$$(1/SIR_1^*) - N_{1,k} \cdot R_{m,1} + N_{2,k} \cdot R_{m,2} > \beta_1 \cdot \left(N_{1,k} \cdot \sigma_1^2 + N_{2,k} \cdot \sigma_2^2\right)^{1/2}. \tag{I.4}$$

Similarly, the constraint for type-2 traffic can be obtained by

$$(R_G/SIR_2^*) - N_{1,k} \cdot R_{m,1} + N_{2,k} \cdot R_{m,2} > \beta_2 \cdot \left(N_{1,k} \cdot \sigma_1^2 + N_{2,k} \cdot \sigma_2^2\right)^{1/2} \tag{I.5}$$

where β_2 is a constant such that $Q(\beta_2) = P_{\mathrm{otg2}}^*$. Consequently, $\hat{C}_1$ and $\hat{C}_2$ can be obtained from the four constraints as given in (I.4), (I.5), and (I.3).

To derive $\hat{C}_i$ in the case of more traffic types, bandwidth allocation is required to define the resource partition policy among different types of connections, and linear or nonlinear programming techniques can be used.

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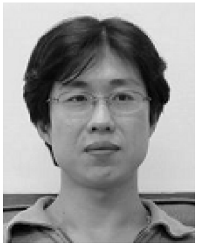

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