DESIGN OF CALL ADMISSION CONTROL TECHNIQUE BASED ON USER MOBILITY PREDICTION FOR NEXT GENERATION WIRELESS NETWORKS

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ABSTRACT

Next generation wireless networks integrating existing and new radio access technologies aim to provide improved Quality of Service (QoS) and efficient utilization of limited resources. It is designed to support variety of multimedia applications and thus require to ensure varied QoS requirements for different applications. In order to provide high QoS guarantee, many call admission control mechanisms have been proposed in the literature. Prediction based CAC algorithms have been proposed that aim to avoid unnecessary reservation of bandwidth resources. However, most of these CAC algorithms do not reflect the real behavior of mobile user and also very few studies have taken into consideration of time a user spends in a cell. In this paper, call admission control model based on artificial neural network (ANN) is proposed, wherein the main objective is to predict the user mobility and accordingly assign bandwidth resources to support different class of traffic types. The ANN based model is used to predict the user mobility so that the resources are not reserved unnecessarily and to achieve low call dropping probability for all traffic types, especially for high priority call requests.

Keywords: Quality of service; Call admission control, user mobility, Artificial neural network, next generation wireless networks.

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1. INTRODUCTION

With an emerging all IP networks, wireless communication technology has undergone rapid changes moving from the first generation to fourth generation and beyond. As a result of these changes, there is an increasing requirement for provision of seamless end-to-end quality of service (QoS) without any perceived service degradation. Next generation of traffic is likely to be based on multimedia applications like video on demand, images, voice, video streaming, internet browsing, fax etc. The QoS characteristics of these applications may involve intensive bandwidth requirement and different quality of service guarantees to support different multimedia applications. In light of this, ensuring QoS guarantees between the end systems becomes imperative in order to support wide variety of multimedia applications without service degradation using the available resources.

Quality of Service (QoS) guarantees can be ensured through an efficient call admission control (CAC) technique. The CAC must ensure that while admitting new calls, the desired QoS of existing calls in the system must be maintained and the system must provide the new call with its desired QoS. Because of the varied QoS requirements of multimedia applications (including video, audio, images, data etc.) and the coexistence of different radio access technologies in heterogeneous networks, makes the call admission control a challenging task. Furthermore, due to the limitations of radio spectrum, wireless systems are being designed based on micro/pico cellular structure to achieve higher capacity (Lee, 1991). However, because of the smaller coverage area, it will lead to higher rate of handoffs compared to macro cellular systems. Thus frequent handoffs and broad range of service requirements of multimedia applications pose great challenge in call admission control in cellular networks.

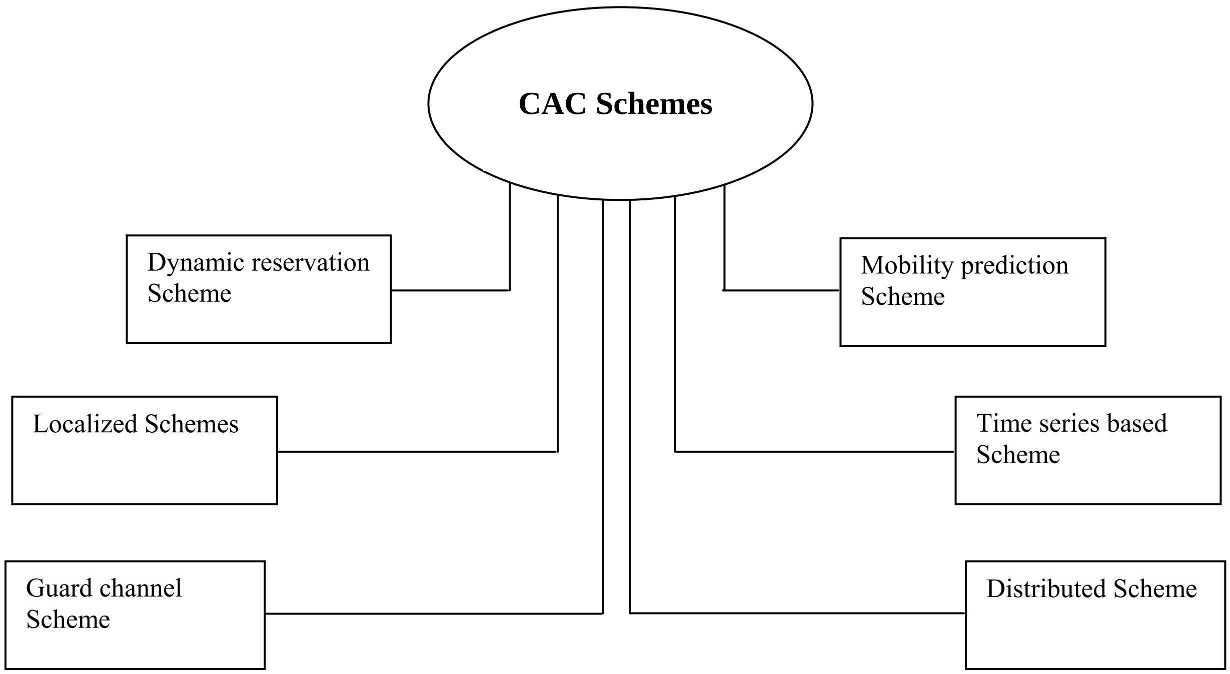
Many variations have been proposed in CAC schemes in the literature. Among these schemes, one of the simplest strategies is to reserve a fixed percentage of the base station's capacity for handoff connections and the scheme is often termed as fixed channel reservation or guard channel scheme. However, it has limitations in that this scheme cannot satisfy the hard constraint on the call dropping probability. Another approach for the CAC problem in cellular networks is shown by Haas *et al*. (2000) where the authors proposed a decision-theoretic approach based on Markov Decision Processes (MDP). The main difficulty is that the number of states of the Markov model becomes very large for real-life problems, which implies unacceptably high values for the time necessary to find a solution for the MDP problem. Further, these non-predictive techniques do not take into consideration of mobility information about the users. However, this information is one of the most important features in wireless networks as it has been shown to enhance the performance of radio resource and call admission control.

In addition to this, most of the prediction based CAC algorithms do not reflect the real behavior of mobile user and also very few studies have taken into consideration of time a user spends in a cell. In this paper, call admission control model based on artificial neural network (ANN) is proposed that make use of ANN to predict the user's path. Various researchers have used Artificial neural networks (ANN) as an alternative to prediction methods in different areas. It is shown by various researchers that the accuracy of the neural network model is comparable and even superior compared to other traditional models (Vilovic and Sipus, 2006; Stegmayer and Chiotti, 2005). Further it is also reported that NN Models can be used for single and Multi step forecasting and they are capable of learning the system and require low computation structures. Furthermore, call blocking probability (CBP), call dropping probability (CDP) and bandwidth utilization are the three important metrics for estimating the performance of any call admission scheme. Achieving CDP and CBP as low as possible while maximizing the bandwidth utilization is one of the biggest challenges in mobile networks (Islam *et al*., 2002; Kwon and Choi, 1999). In this paper, the main objective of the proposed ANN based scheme is to predict the user mobility and accordingly assign bandwidth resources to support different class of traffic types. The proposed model is used to predict the user mobility so that the resources are not reserved unnecessarily and to achieve low call dropping probability for all traffic types, especially for high priority call request and to maximize the bandwidth resource utilization.

The paper is organized as follows. Section 2 presents the related work in this field. The neural network based mobility prediction model is described in Section 3. Section 4, presents the concluding remarks and discusses future research work.

2 RELATED WORK

Admission control scheme decides whether to admit or to reject a user's call. An effective CAC scheme not only ensures that the network meets the QoS of the newly arriving calls if accepted, but also guarantees that the QoS of the existing calls does not deteriorate (Sutivong and Peha, 1997). Various CAC schemes have been proposed in the literature (Ramjee *et al*., 1996; Naghshineh and Schwartz, 1996, Soh *et al*., 2010) and a broader classification of these schemes is shown in Figure 1. Out of these, one of the simplest schemes is the fixed strategy based guard channel (GC) scheme (Hong and Rappaport, 1986). In this scheme, fixed numbers of channels in each cell are exclusively reserved for handoff calls. Guard channel scheme is simple in the sense that it does not require exchange of any control information between base stations or terminals. However, GC scheme is not flexible or adaptive to the varying traffic load.



Though the dynamic reservation strategies (Choi and Shin, 1998; Hou and Papavassiliou, 2003) have shown significant improvement in the performance compared to guard channel scheme. But these rely on handoff session rate estimates derived from the number of sessions in neighboring cells. In addition to this, for each call request, dynamic reservation requires high computational efforts and overhead signaling load on the system. Thus scalability of such CAC schemes for future micro/pico cellular all IP networks is doubtful.

Takagi and Takahashi (1991) proposed QoS provision framework for multimedia services. The framework used a bandwidth compaction technique in addition to bandwidth reservation and degradation and CAC to improve the spectrum utilization. However, the method proved to be difficult to implement, so the authors proposed partial compaction scheme for the spectrum. The main limitation of this scheme is redundant bandwidth that is reserved in all the six neighboring cells. Oliveira *et al*. (1998) proposed an admission control scheme based on adaptive bandwidth reservation to provide QoS guarantees for multimedia traffic. However, the proposed scheme allocates bandwidth to a connection in the cell where the connection request originates and also reserves bandwidth in all the neighboring cells, which may lead to wastage of resources in these cells. In (Zhang *et al*., 2001; Rozic and Kandus, 2004) authors used time series analysis based prediction for resource reservation for handoff calls. However, the performance results obtained can be achieved using simple prediction techniques and also this scheme required extensive computations to produce the predictions. Since user mobility has a profound effect on QoS provisioning, information relating to user mobility must be considered in the channel reservation process. Further, Prihandoko *et al*. (2003) proposed an adaptive QoS scheme to guarantee QoS for multimedia traffic. The study used traffic based bandwidth reallocation scheme that renegotiates the reserved and used bandwidth portions. Their results revealed that using bandwidth allocation level (BAL) scheme of 1 outperformed BAL scheme of 10 in terms of new call blocking probability (NCBP).

Kwon and Choi (2003) proposed a QoS provisioning scheme based on distributed CAC algorithm that guarantees upper bound of cell overload probability. However the authors considered the case of a single traffic class only. There have been other distributed call admission (DCA) schemes proposed in the literature (Naghshineh and Schwartz, 1996; Wu and Wong, 1998) in order to guarantee user connectivity and service quality. The proposed schemes make admission decision in a distributed manner based on status information exchanged between adjacent cells. The main features of DCA scheme is its simplicity in that the admission decision can be made in real time and does not require much computational efforts or directional environment information as in case of shadow cluster approach. However in most of these schemes resources are reserved in all the neighboring cells of user's current cell and these not only block the scarce resources but also increase signaling overhead.

The above described non-predictive techniques do not take into consideration of mobility information about the users. This mobility information is one of the most important features in wireless networks. It has been shown to enhance the performance of radio resource and hence call admission control (Yu, and Leung, 2001; Islam *et al*., 2003). Levine *et al* (1997) proposed predictive resource allocation and admission control scheme based on shadow cluster concept. In this scheme, the future resource requirement is estimated based on current movement pattern of the mobile users. However the scheme depends on the accuracy of the knowledge of each user's movement patterns, such as trajectory of mobile users and predicting the mobility pattern for each specific user in detail is quite difficult in real systems.

In (Islam *et al*., 2003) authors proposed radio resource management scheme based on three mobility parameters namely velocity, distance, and direction. This scheme attempts to solve the problem that occurs when the mobile user changes his/her direction and speed suddenly especially at the borders of the cells. However the approach does not consider previous history of the users which may enhance the performance of the network. Also it is not explained how to estimate velocity, distance and direction of the mobile terminals effectively.

In (Choi and Kin, 1998), a predictive and adaptive call admission technique is proposed in which the BTS calculates the bandwidth required to be reserved for handoff calls in the neighboring cells. The mobility of MS is estimated using the history of MS movements recorded in each cell. Using this information, the scheme predicts the handoff time and amount of bandwidth to be reserved. However the scheme considers only one dimensional case of cells (i.e. movement along the straight line). It does not consider different types of user's mobility patterns such as pedestrian and stationary mobiles. In (Choi and Kin, 2002) CAC algorithm is proposed that is based on mobility graph to predict the next cell. Each node in the graph represents a visited cell and edges represent the direction of the user. The prediction of next cell is estimated based on current BTS, previous BTS and the number of times the user has moved from the current to next cell. The scheme is suitable for multimedia and real time applications. But the applicability of the scheme is limited to short paths only (i.e. current, previous and next BTS).

It is seen that very few studies have taken into consideration of time a user spend in a cell. Furthermore, the most of the prediction based CAC algorithms do not reflect the real behavior of mobile user. Researchers (Rashad *et al*., 2006) have advocated the importance of this dwell time as it may lead to unnecessary reservations in the neighboring cells if it is not taken into consideration. To overcome the issues highlighted, in the present paper, artificial neural network based prediction model is proposed for call admission control. The following section gives a brief introduction about artificial neural networks in general followed by proposed ANN based user mobility prediction model.

3 ARTIFICIAL NEURAL NETWORKS

In this paper, neural network based user mobility prediction method is proposed for effectively handling the call blocking probability in multi class traffic heterogeneous network environment in order to enhance the resource utilization. Many researchers (Christodoulou and Georgipoulos, 2001; Vilovic and Sipus, 2006; Babu *et al*. 2009) have preferred NNs over other methods because of their speed in implementation and accuracy, and they have been successfully applied to wireless and Microwave applications (Babu *et al*., 2010; Agusti *et al*., 2004). According to Stegmayer and Chiotti (2005), the Neural Network model can be trained with input/output device measurements or simulations, and a very good accuracy can be obtained in the device characterization easily and rapidly.

A neural network is a simplified mathematical model of a biological neural network. It consists of a collection of interconnected neurons which is the basic component in the neural network model. Analogous to biological neuron, an artificial neuron receives input and each input is multiplied by the corresponding weights (i.e. the strength of the respective inputs) analogous to synaptic weights

All of these weighted inputs are then summed up and passed through an activation function to determine the output.

ANNs can be viewed as weighted directed graphs in which artificial neurons are nodes and directed edges (with weights) are connections between neuron outputs and neuron inputs. Based on the connection pattern (architecture), ANN's can be grouped into two categories :

- Feed-forward networks, in which graphs have no loops
- Recurrent (or feedback) networks, in which loops occur because of feedback connections.

In the most types of feed-forward networks, also called as multilayer perceptron, neurons are organized into layers that have unidirectional connections between them.

Generally speaking, feed-forward networks are static, that is, they produce only one set of output values rather than a sequence of values from a given input. Feed forward networks are memory-less in the sense that their response to an input is independent of the previous network state. Recurrent, or feedback, networks, on the other hand, are dynamic systems. Dynamic neural networks have memories and they are capable of memorizing the past information for long term as well as for short term periods.

In the proposed model, recurrent neural networks (RNN) would be used as they have superior capabilities compared to feed forward neural networks and have the ability to deal with time-varying input or output through their own natural temporal operation. Moreover; the RNNs demonstrate good control performance in the presence of un-modeled dynamics, parameter variations, and external disturbances (Lin *et al*., 2001). The RNN architecture can be classified into fully interconnected nets, partially connected nets and Locally Recurrent & Globally Feed-forward (LRGF) nets (Elman, 1990). The fully connected networks do not have distinct input layer/nodes. Each node has input from all other nodes. The partially connected RNN can be implemented by adding a feedback connection to the existing feed-forward NN to process the temporal information of the data. The feedback connection may be from hidden layer (Elman net) or from the output layer (Jordan net) (Jordon, 1989; Campolucci *et al*., 1990). In the LRGF nets, self connecting neuron layer is either present in the input or on the output side of the feed forward NN to process temporal information. The Recurrent Radial Basis Function Network (RRBFN) is a class of locally recurrent & globally feed-forward (LRGF) RNN. In LRGF network, the recurrent/self-connection is either in the input layer or in the output layer. RRBFN is having recurrent connection at the input layer.

Artificial Neural Networks can learn from a given data set and this initial learning process is called as training of NN. The main property of ANN is the ability to learn and ANN acquires knowledge about their environment during the iteration of learning process. The accuracy of a properly trained network depends on the accuracy of the data used to train the network (Patnaik *et al*. 2004). Therefore training data should be generated carefully either by simulation or experimentally. As the network size increases, the number of training patterns required for proper generalization also increases. Generation of data in wireless applications is quite expensive, so it is often desirable to develop the network with the minimum number of neurons in the hidden layers. Table 1 summarizes the different applications of neural networks in wireless communications engineering.

Table 1: Applications of neural networks in wireless communication

S.No.	Author, year	Application	Type of ANN model used
1.	Stegmayer and Chiotti (2005)	To predict dynamic behavior of non linear power amplifier in 3G transmitter.	Time Delayed NN using Hyberbolic tangent activation function.
2.	Babu *et al*. (2009)	Call admission control in heterogeneous wireless networks	Recurrent Radial Basis Function Networks (RRBFN)
3.	Babu *et al*. (2010)	QoS provisioning for beyond 3G	Recurrent Radial Basis

		networks	Function Networks (RRBFN)
4.	Vilovic and Sipus (2006)	for the prediction of the propagation characteristics in WLAN environment	Sigmoidal hyperbolic tangent function was used as activation function
5.	Patnaik *et al.* (2004)	Wideband antennas in wireless networks	Hyberbolic tangent activation function.
6.	Clarkson (1999)	Reviewed the applications of ANN in the fields like radio resource management, mobility management, equalizers, network design management, ATM network control, fault management etc	RBF neural network

3.1 Neural networks based Mobility Prediction Model

For the simulation purpose, consider the two dimensional cellular configuration as depicted in Figure 2 in which all the cells are indexed with numbers. It is assumed that cellular system uses fixed channel allocation scheme. Each MS collects the mobility data that is continually updated based on the user movements. This data builds up local mobility profile that is sent to the BTS at regular intervals. Each local profile recorded by MS comprises of IDs of current and previous base station. In addition to this it also contains the information regarding the duration of stay by MS in each cell. In order to do so, the mobility data of MS is collected at fixed time slots.

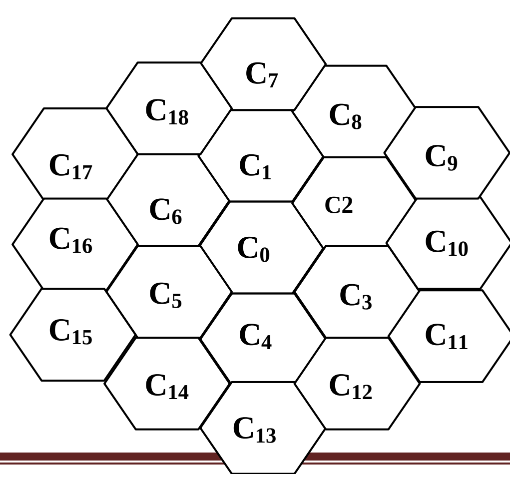


Fig. 2 Two dimensional cellular configuration

There are various topologies of neural networks reported in the literature for modeling of different types of systems with different kinds of linear and nonlinear behavior. In the case of heterogeneous a wireless network which is characterized by dynamic, non-stationary, non linear behavior, Recurrent Radial basis function network (RRBFN) is chosen for user mobility simulation.

The Radial Basis Function Network (RBFNN) is the type of NN that is composed of three fixed layers with a single hidden layer. Each node in the hidden layer has a parameter vector called as centre. These centres are used to compare with network input and produce radically symmetrical response. These responses are scaled by connection weights of the output layer and then produce network output. The hidden layer transforms the input space nonlinearly in a hidden space of higher dimensionality. Finally, the output layer performs a linear mapping. The total transformation made by the RBFNN is shown in the following equation:

$$y_k(\mathbf{x}) = w_{k0} + \sum_{j=1}^{M} w_{kj}\phi_j(\mathbf{x})$$

where □$_j$(x) is a nonlinear function, which is the Gaussian function as described as follows:

$$\phi_j(\mathbf{x}) = \exp\left(-\frac{\|\mathbf{x}-\boldsymbol{\mu}_j\|^2}{2\sigma_j^{\,2}}\right)$$

RBFN has a faster convergence property compared to a multilayer Perceptron (MLP) because it has a simple structure and the output value is calculated using the weighted sum method (Jordon, 1989; Campolucci *et al*., 1990). Following the scheme suggested by Rashad *et al.* (2006), the input layer of ANN receives location profile parameters of user mobility comprising of IDs of current (BS_i) and previous base station (BS_j), time stamp when the MS enters with BS_i (TSi), time stamp when the MS exits BS_i (TEi). The ANN network would be trained using these input samples until the network reaches a steady state where there are no significant changes in the synaptic weights. After training phase, the neural network would be tested with input data that is different from that used in the training process. If the outputs obtained are reasonable, the network generalizes well. For training purpose, the back propagation algorithm would be used as referred by many researchers (Vilovic and Sipus, 2006; Stegmayer and Chiotti (2005). The back propagation algorithm is based on the steepest descent gradient method applied to change the value of the each synaptic weight to minimize the output error (Haykin, 1999).

5.0 CONCLUDING REMARKS AND FUTURE WORK

In fourth generation wireless networks, it is required that they support a wide range of broadband services with a required level of quality of service (QoS). Since the QoS requirements of different multimedia applications (including video, audio, images, data etc.) vary and also due to the coexistence of different radio access technologies in heterogeneous networks, makes the call admission control a challenging task. In order to ensure that the QoS guarantees are provided at an acceptable level and support maximum subscribers, it becomes imperative to assign bandwidth resources efficiently to support different class of traffic types. In this regard the present work proposes a neural network based user mobility prediction model. The proposed model is used to predict the user mobility so that the resources are not reserved unnecessarily and to achieve low call dropping probability for all traffic types, especially for high priority call request and to maximize the bandwidth resource utilization. For this purpose, Radial basis function neural network (RBFNN) is chosen for user mobility prediction. According to this model, the mobility profile of MS in terms of parameters like IDs of current (BS_i), previous base station (BS_j), information regarding the duration of stay by MS in each cell collected at fixed time slots is sent to BTS at regular time intervals. The study can be extended for non stationary traffic load as the actual traffic load may deviate from the expected load.

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