SINR-based Network Selection for Optimization in Heterogeneous Wireless Networks (HWNs)

Abubakar M. Miyim, Mahamod Ismail & Rosdiadee Nordin

Department of Electrical, Electronics and Systems Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia 43600 Bangi, Selangor DE
Email: ammiyim@eng.ukm.my

Abstract. To guarantee the phenomenon of "Always Best Connection" in heterogeneous wireless networks, a vertical handover optimization is necessary to realize seamless mobility. Received signal strength (RSS) from the user equipment (UE) contains interference from surrounding base stations, which happens to be a function of the network load of the nearby cells. An expression is derived for the received SINR (signal to interference and noise ratio) as a function of traffic load in interfering cells of data networks. A better estimate of the UE SINR is achieved by taking into account the contribution of inter-cell interference. The proposed scheme affords UE to receive high throughput with less data rate, and hence benefits users who are located far from the base station. The proposed scheme demonstrates an improved throughput between the serving base station and the cell boundary.

Keywords: *intercell; interference; prediction; SINR; throughput; vertical handover.*

1 Introduction

As a result of high demand and competition, wireless communication services have been witnessing an exponential growth in recent years. This development has led to the convergence of multiple wireless (LTE/LTE-A, cellular, WLAN and satellite) networks to form one pervasive wireless access point in providing diverse services [1]. The major concern, however, is how to harmonize the divergence of the networks available in managing user mobility as each network differs in data rate, transmission range, traffic class, etc. [2].

Vertical handover, defined as the handover of resources between the radio base stations (RBSs) of diverse wireless access technologies, is assumed to be the solution for optimizing the handover decision algorithm [3]. Many of the research works related to horizontal handover are about the evaluation of RSS for the mobile user equipment (UE) but the factors used in RSS comparison and evaluation do not suffice for optimization of the performance of wireless networks. Metrics such as system performance, service aggregation, network conditions, service cost, mobile host and user preferences need to be accorded attention [4]. Since RSS-based VHO is not a QoS aware scheme, it cannot

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provide better QoS to the user to support multimedia services [1,3]. Furthermore, the achievable data rate for the UE is a function of the received signal to interference and noise ratio (SINR). Therefore, a SINR based VHO is not only expected to achieve maximum throughputs and minimum dropping probabilities but also to provide a unified radio resource for the heterogeneous wireless networks. With the proposed vertical handover algorithm, the future RSS can be predicted and it calculates the service cost to determine the right choice of the network to be handed over to. Being triggered at the end of the handover procedure, the algorithm is employed to take an optimum decision in evaluating the input parameters of the candidate target networks.

The rest of this paper is organized as follows: Section 2 reviews related works, while Section 3 discusses SINR prediction using GM (1, 1) and a neural network. Section 4 evaluates the performance of the proposed Predictive SINR Handover Algorithm (PSHA). Simulation set-up and analysis of the results obtained therein are discussed in Section 5. The conclusions of the paper are drawn in Section VI.

2 Related Works

In order to make possible seamless access in multi-access wireless networks, designing an efficient vertical handover (VHO) algorithm is always considered critical. Nowadays, the attention of researchers has shifted to the design and deployment of seamless heterogeneous wireless network technologies with various works that have appeared covering vertical handover (VHO) algorithms. However, many of the earlier studies on vertical handover considered the received signal strength (RSS) as the main decision indicator. Two handover classes of handover procedures exist with RSS as the major criterion: 1) handover decided by comparing RSS with a predefined threshold value [5,6]; and 2) RSS as an entity used to initiate and trigger handover [7,8]. In [5], a vertical handover decision-making algorithm is formulated, adopting a Markov decision process (MDP) to maximize the expected total rewards per connection. The proposed approach in [6-8] determines the optimal target network through polynomial regressive RSS prediction and MDP analysis. The TCP sender is capable of accurately predicting the bandwidth available in order to enhance the network throughput by using a cross-layer approach. RSS and service type were combined to optimize the VHO decision mechanism as formulated in [9]. A fuzzy logic system is considered when selecting cells from WLAN/WiMAX/ LTE networks, while the RSS threshold for the VHO decision remains unperturbed thereby aggravating the ping-pong effect.

The aforementioned vertical handover schemes using RSS as an indicator have their advantages. The attainable data rates of the UE can be expressed as a function of the received signal to interference plus noise ratio (SINR) [10]. In addition, the use of SINR in integrated wireless networks can provide a solution for handover optimization. Unlike RSS-based vertical handovers, SINR can provide a higher average throughput for the user and achieve the best possible performance of the system. Furthermore, an SINR-based vertical handover is more desirable to support better multimedia QoS. As expected, the combined SINR-based vertical handover (CSVH) discussed in [11] does acquire a higher throughput compared with an RSS-based vertical handover, but the algorithm gives no consideration to other QoS parameters. Thus, we propose multi-dimensional predictive SINR-based vertical handover (MPSVH) algorithm to provide a seamless vertical handover that supports multi-attribute QoS.

In line with the four classes of service defined by the Third Generation Partnership Project (3GPP), SINR, user preferences, cost and available bandwidth of each WLAN access point (AP) and LTE eNodeB radio base station (RBS) were given consideration. The proposed scheme comprises: 1) the combination of SINR prediction by GM (1, 1) and back propagation (BP) neural network to fix the appropriate time for triggering handover. Additionally, a stability period to reduce unnecessary handovers is also considered. The obtained results demonstrate an improvement not only in selecting the optimal network while considering user preferences and network conditions, but the scheme also performs well with regards to system throughput.

3 SINR Prediction Model {GM(1, 1) and ANN (Back Propagation)}

Most of the time, successful handover execution is largely dependent on the accuracy of the predicted SINR. On the other hand, wrong or faulty handover decisions occur when the SINR estimation is inaccurate. This phenomenon is prevalent with networks that adopt only one single prediction method for SINR estimation. Reducing randomness by using more than one method helps to significantly improve the accuracy of prediction because the information acquired is a combination of the results from the various prediction methods [6]. The grey model GM(n, m), which describes the dynamic conduct of the grey system and is widely established as GM(1, 1), is quite suitable for prediction of highly noisy data such as the SINR, as discussed in [7] and [9]. However, the results obtained by using GM(1, 1) prediction cannot meet the requirements in actual situations as SINR change is highly nonlinear because of the complexity of the wireless environment. For a network to approximate complex non-linear functions, it requires a learning process. Therefore, in this work, a multi-layer neural network (MLNN) that employs a back propagation algorithm and is capable of parallel distribution and self-training was chosen to determine the relationship between the neurons [12], even though residual errors are most likely to occur. Correcting such anomalies (errors) asks for the coupling of two or more variant models that complement one another. The GM(1, 1) model was found to be the perfect choice to enhance the reliability of the prediction results. Exploring the qualities of the two model networks – GM(1, 1) and the artificial neural network – led to the birth of a nonlinear model that is just perfect to predict the SINR and enhance the accuracy of the prediction, as depicted in Figure 1.

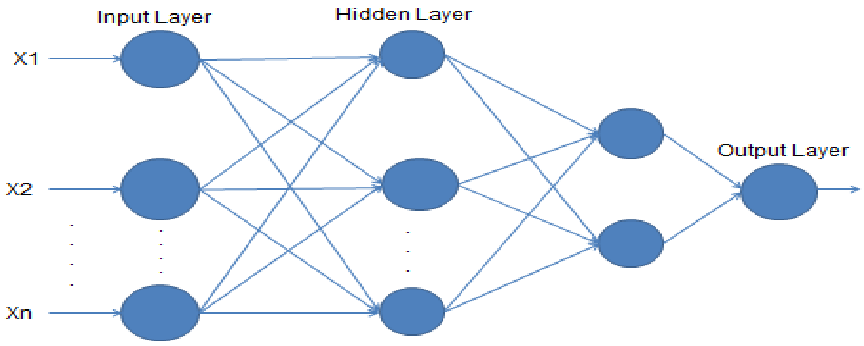

Figure 1 Architecture of MLNN with back propagation model.

4 Proposed Prediction Techniques

The inputs in Figure 1 represent the prediction values of multiple layers of GM(m, n). The GM(1, 1) together with a multiple-layer artificial BP neural network is used to predict SINR. The following factors are considered during the modelling and prediction processes: 1) time series prediction of SINR accomplished by GM(1, 1); 2) establishment of ANN-BP, initialization of weight, and offset value; 3) updating the weights and offset values of the ANN through repeated training until the error between output value and target value drops below a certain fixed value; 4) employment of the prediction model by applying the predicted components of GM(1, 1) as input data for the BP neural network in order to obtain the output data. It is indeed clear that the traffic on the downlink requires a higher bit rate (bandwidth) than the uplink traffic and this is in agreement with the requirement of multimedia services. Therefore, the assumption is that all candidate eNodeB stations and access points (APs) of a heterogeneous wireless network of *m* eNodeBs (BS) and *n* APs may be indexed by 1 to $m + n$ and arranged in a set:

$$Z = [BS_1, BS_2, \ldots, BS_m, AP_1, AP_2, \ldots, AP_n] \tag{1}$$

The moment the combined prediction A produces an SINR that is lower than the defined threshold, triggering of the handover is set. Determining the network optimization depends on a cost function for every network user based on the vertical handover algorithm regarding attributes like: user preferences, SINR, bandwidth availability and monetary cost of traffic for users.

4.1 Signal to Interference plus Noise Ratio (SINR)

It is possible to obtain the maximum attainable data rate for the given carrier bandwidth and SINR when the Shannon capacity formula is applied. The highest data rate attainable (Δ_{AP} and Δ_{BS}) from WLAN and LTE-A networks respectively for a connected mobile user are easily replicated by the received SINR from the two networks ζ_{AP} and ζ_{BS} respectively:

$$\Delta_{AP} = \kappa_{AP} \log_2 \left(1 + \frac{\zeta_{AP}}{\Phi_{AP}} \right) \tag{2}$$

$$\Delta_{BS} = \kappa_{BS} \log_2 \left(1 + \frac{\zeta_{BS}}{\Phi_{BS}} \right) \tag{3}$$

Φ_{AP} and Φ_{BS} are the loss factors of the channel codes for both WLAN and LTE-A networks respectively.

When downlink traffic has the same data rate, i.e. $\Delta_{AP} = \Delta_{BS}$ and is offered users by the two (WLAN and LTE-A) networks, then an expected relationship is established between ζ_{AP} and ζ_{BS}, which is expressed thus:

$$\zeta_{BS} = \Phi_{BS} \left\{ \left(1 + \frac{\zeta_{AP}}{\Phi_{AP}} \right)^{\frac{\kappa_{AP}}{\kappa_{BS}}} - 1 \right\} \tag{4}$$

At a certain moment in time, the values of the received SINR from LTE-A eNodeB$_j$ by a user *i* can be expressed as:

$$\zeta_{BS_{j,i}} = \frac{G_{BS_{j,i}} P_{BS_{j,i}}}{P_0 + \sum_{k=1, k \neq j}^{m} \left(G_{BS_{k,i}} P_{BS_k} \right) + G_{BS_{j,i}} \chi \left(P_{BS_j} - P_{BS_{j,i}} \right)} \tag{5}$$

The SINR ($\zeta_{AP_{j,i}}$) received from the WLAN by a user *i* is expressed as:

$$\zeta_{AP_{j,i}} = \frac{G_{AP_{j,i}} P_{AP_j}}{P_{BS} + \sum_{k=1, k \neq j}^{n} \left(G_{AP_{k,i}} P_{AP_k} \right)} \tag{6}$$

In order to achieve the same data rate via eNodeB (BS), the received SINR from APs ($S_{Ap,\,i}$) is considered as the input and so becomes the SINR:

$$S'_{AP,i} = \Phi_{BS}\left(\left(1+\frac{S_{AP,i}}{\Phi_{AP}}\right)^{\frac{\kappa_{AP}}{\kappa_{BS}}} - 1\right) \tag{7}$$

To determine the propagation condition, a macro-cell propagation model with path loss is adopted here for urban and suburban areas [13].

$$PL(dB) = 58.8 + 21\log(f_c) + 37.6\log(d) + S(dB) \tag{8}$$

Where f_c is the carrier frequency, d is the distance between the user and BS or AP, and S corresponds to the log-normal shadowing with $s = 10$ dB standard deviation.

4.2 SINR Estimation

Referring to Figure 2, consider a terminal located in sector 0 and assume that the terminal is being served by base station 0. Assume that in addition to BS 0, the terminal has BSs 1 and 2 and are in its active set. The active set of a terminal is the set of BSs whose pilot signal can be correctly decoded by the terminal. The terminal receives inter-cell interference from sectors 1 and 2. Let α_i be the forward link SINR of sector i as measured by the terminal using the current scheme [8], [14] (i.e. by using Eq. (4) and assuming 100% load in the rest of the sectors).

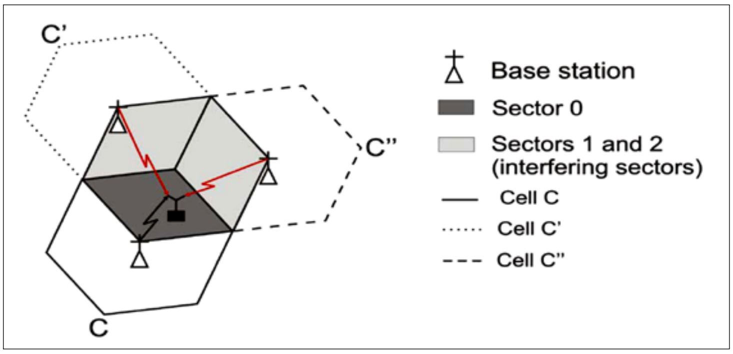

Figure 2 Topology of a typical cell [9].

$$\begin{bmatrix}\alpha_0\\ \alpha_1\\ \alpha_2\end{bmatrix}=\begin{bmatrix}\dfrac{G_0^2A^2T_c}{\frac{1}{3}AT_c\left(G_1^2+G_2^2\right)+2N_0}\\ \dfrac{G_1^2A^2T_c}{\frac{1}{3}AT_c\left(G_0^2+G_2^2\right)+2N_0}\\ \dfrac{G_2^2A^2T_c}{\frac{1}{3}AT_c\left(G_0^2+G_1^2\right)+2N_0}\end{bmatrix} \tag{9}$$

In our proposed scheme, the terminal uses the above values of α_i that are known from pilot measurements. The above sets of equations are then solved to obtain the channel gains G_i as follows:

$$\begin{bmatrix}G_0^2\\ G_1^2\\ G_2^2\end{bmatrix}=\begin{bmatrix}1-\frac{1}{3}\alpha_0-\frac{1}{3}\alpha_0\\ -\frac{1}{3}\alpha_1 1-\frac{1}{3}\alpha_1\\ -\frac{1}{3}\alpha_2-\frac{1}{3}\alpha_2 1\end{bmatrix} \tag{10}$$

Let the actual SINR at the terminal for the forward link of sector *i* be β_i. This SINR takes into account the traffic load in the interfering sectors. Using Eq. (4), we obtain:

$$\begin{bmatrix}\beta_0\\ \beta_1\\ \beta_2\end{bmatrix}=\begin{bmatrix}\dfrac{G_0^2A^2T_c}{\frac{1}{3}AT_c\left(G_1^2+G_2^2\right)+2N_0}\\ \dfrac{G_1^2A^2T_c}{\frac{1}{3}AT_c\left(G_0^2+G_2^2\right)+2N_0}\\ \dfrac{G_2^2A^2T_c}{\frac{1}{3}AT_c\left(G_0^2+G_1^2\right)+2N_0}\end{bmatrix} \tag{11}$$

Since G_i is already known from (6), the actual SINR, β_i, for each of the sectors can be obtained by using the above expressions once ρ_i are known. Thus, we do not propose altering the current implementation of the pilot measurement procedure, which makes our SINR estimation scheme easy to implement within the current framework. However, it is required of each eNodeB to keep track of its traffic load (ρ_i) since the derivation of Eq. (2) requires the probability of the time slot being busy. Even with multi-slot packets, the load measurement scheme only needs to know whether a time slot is empty or busy. A long-term averaging exponential filter can then be used by each BS_i to determine its average load as explained in the following section.

4.3 Cell Selection

The fact that the terminals see a time-varying wireless channel over the link should be taken into account when scheduling data. In all the aforementioned works, as well as several other related works, no special consideration is given to the fact that the inter-cell interference has an important role to play in determining the SINR of a user. In the previous section, SINR estimation used a scheme that is disadvantaged as it does not provide an accurate estimate of the inter-cell interference in the SINR. This is because under the scheme, users located near the cell boundary may report a lower data rate than the actual supportable rate as a result of inaccurate rate estimation.

When a user is about to hand over to a neighbouring sector using cell-selection, it measures the SINR of all the BSs in its active set to determine the best serving sector. It is possible that due to proximity, the SINR of the UE for BS 0 tends to be higher than that of BS 1 ($\alpha_0 > \alpha_1$). However, the real SINR of the UE for BS 1 may be higher than that of BS 0 ($\beta_1 > \beta_0$). Thus, the user continues to remain in sector 0 instead of handing over to sector 1. Illustrating the simulation results using αi instead of β_i may result in sub-optimum cell selection, where the resultant SINR of the UE in the chosen cell may be lower when α_i are used for cell selection criterion instead of β_i.

5 Simulation Setup

While it is easy to extend the simulation settings to account for more than two interfering sectors, we note that the signals of two neighbouring sectors are substantially stronger than the interfering signal received from other distant sectors; hence, only two interfering sectors were simulated. Corresponding to each user and each base station (serving and interfering base stations), a time-varying channel gain G_i was generated in each time slot. The user SINR was a function of random variables G_i, and G_{2i} expressed as:

$$G_i^2 = cd_i^{-n} * \left(10^{\frac{\varsigma_i}{10}}\right) * W_i^2 \mathrm{G}_i \tag{12}$$

In Eq. (7), the first term in the product is deterministic (for a fixed user location) corresponding to path loss, while the second term is a random variable corresponding to lognormal shadowing loss. Here, ξ_i is a Gaussian random variable with mean 0 and variance σ. ITU path loss models for vehicular (120 kmph) and pedestrian (3 kph) users [7] were adopted. Shadowing was correlated over each time slot depending on the speed of the user as per Gudmundson's model [7]. The shadow correlation distance was the same for both the vehicular and the pedestrian model, and depended only on the environment (urban or suburban). Time correlation of Rayleigh fading was determined by the speed of the terminal and simulated using the filtered Gaussian noise technique from [15]. The simulation parameters are listed in Table 1.

Table 1 Simulation Parameters.

Parameters	Values
Carrier frequency, f_c	2600 MHz
Log-normal shadowing, σ	12 dB
Shadow correlation distance	25.0 m
Noise spectral density, N_0	-174 dBm/Hz
Radius of the sector, R	1 Km
R_0 of cell coverage	0:90R = 0:90 Km
Penetration loss (pedestrian only)	12 dB
Pedestrian path loss in dB	30 log10(f_0) + 49 + 40 log10(d)
Vehicular path loss in dB	21 log10(f_0) + 58:83 + 37:6 log10(d)

User locations were selected equidistantly from the two interfering base stations. At each UE terminal, the SINR prediction scheme was simulated. In this scheme, the terminal has an averaging filter bank for each packet type. The filter bank uses the SINR measurements from the past to predict the future SINR for each packet type. In a real-time network, in addition to the SINR prediction algorithm, there is a control loop that adjusts the predicted SINR values based on measured packet error rate. The UE makes the SINR predictions more conservative when the measured packet error rate is high.

5.1 Simulation Results

In all our simulations, although the time variations of the user channel as a function of user speed were simulated (time-varying shadowing and fading), it was assumed that the location of the mobile user did not change. This is because the objective of our study was to demonstrate that the users located near the boundary of the cell benefit from our proposed scheme. Such an approach is often used by network designers to study how throughput degrades as a function of the distance of the user from the serving base station. Figure 3 shows the received signal strength with and without noise generation for a single user. Spreading the signals transmitted in the channel led to reconstruction of the RSS from noise generated with maximal length sequence.

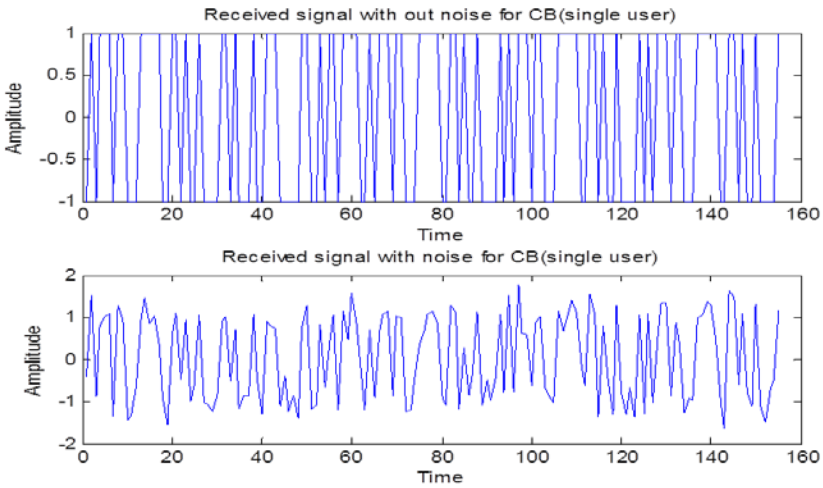

Figure 3 RSS of channel bandwidth with and without noise as a function of time.

The bit error rate (BER) curve is steaper and comes to zero quickly. For keeping the desired BER at an acceptable level of 0.1, a corresponding -11.5dB of data interference and -10dB of interference level at rate 2R were needed. Figure 4 is a graph of the BER plotted as a function of the SINR where a 3.5 dB level with less network load indicates a significant improvement in the SINR.

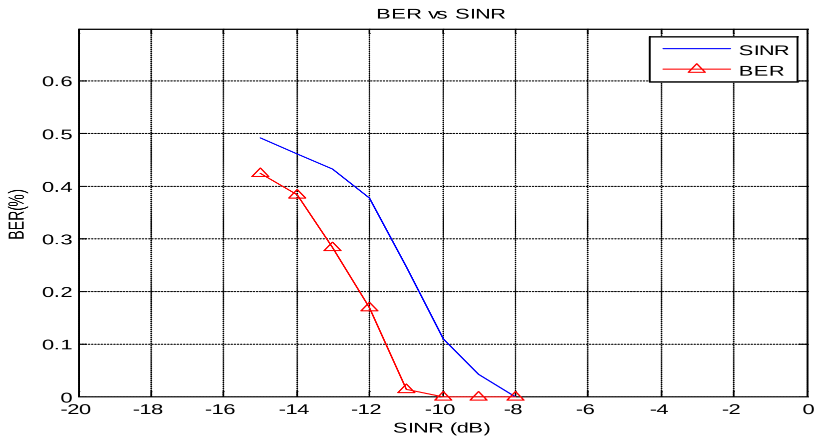

Figure 4 Comparison of retransmission packets.

Figure 5 shows a sharp linear plot of data rate against SINR. With the SINR at -12.5, a corresponding value of 1Kbps was recorded. The plot linearly increases until the data rate reaches 2Kbps at -10dB SINR, indicating minimum packet error rate. Using the scheme along with hybrid ARQ, a good throughput improvement was obtained. However making use of two schemes for almost all the settings, the packet error rates were kept below 1% and never went above 2%, as can be seen in Figure 6. Thus the proposed scheme enhanced the functioning of hyrbrid ARQ by providing more accurate initial SINR estimates.

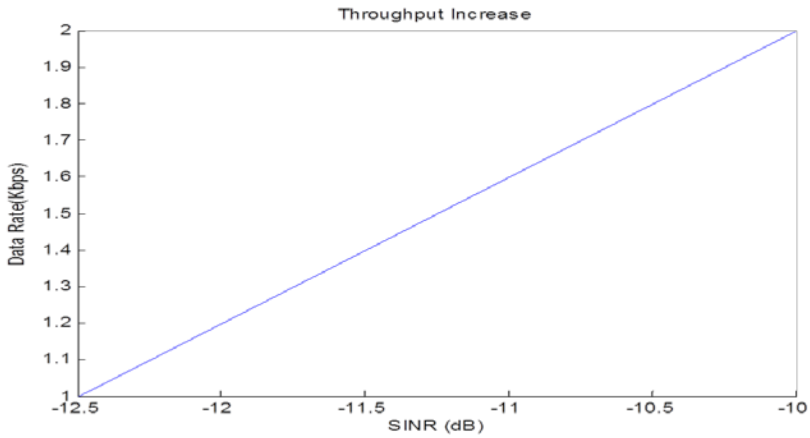

Figure 5 Data rate as a function of SINR.

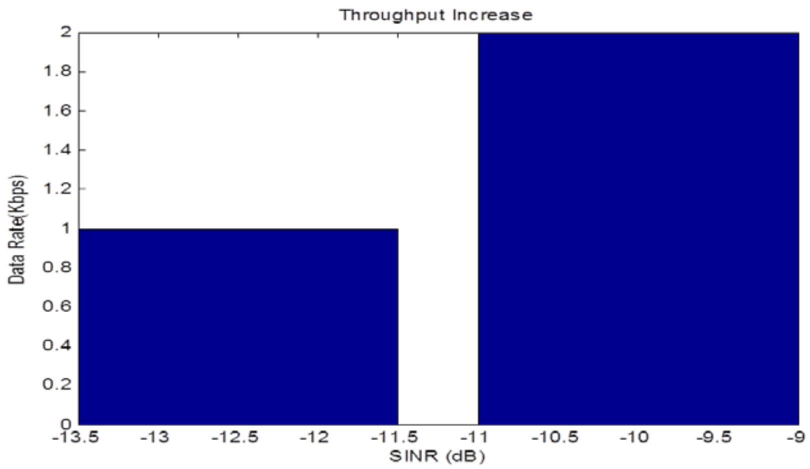

Figure 6 Increased throughput.

Using a different scheme for SINR estimation (i.e. using α_i as SINR estimates) instead of the known method (i.e. using β_i as SINR estimates), the set of simulations yielded sub-optimum cell selection. The network loads in the three sectors were $\rho_0 = 0.3$, $\rho_1 = 1.0$, $\rho_2 = 0.3$. These load values were chosen to illustrate the UE's nearest to BS 0 ($\alpha_0 > \alpha_1, \alpha_2$) as well as the effect of network load that results in SINR β_i such that $\beta_1 > \beta_0, \beta_2$. This is demonstrated in Figure 7 with plot α_0, α_1, β_0 and β_1 indicating that instantaneous SINR estimates are time averaged values.

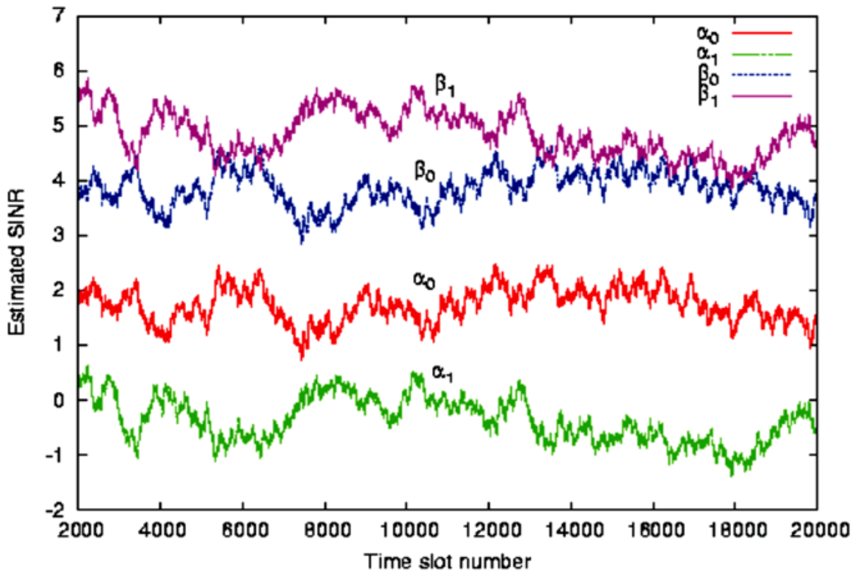

Figure 7 Predicted SINR for different cells.

Using β_i to make cell selection decisions, the UE would then hand over to sector 1 instead of staying in sector 0, thereby having a higher SINR (β_1). Thus the proposed scheme can prove beneficial to users during cell selection.

6 Conclusions

A scheme to improve SINR estimation at the user terminal, where the measurements take into account the actual (and not the worst-case) inter-cell interference, has been described. The proposed scheme requires the base stations to use traffic measurement (network load) and send this information to the mobile terminals. The terminals then use this information along with an improved SINR estimation scheme to obtain an accurate estimate of their current channel state. In simulations, the proposed scheme outperformed other SINR estimation schemes by providing better throughput to users, especially the ones located farther from the serving base station. Also observed is that the gains of the proposed scheme are more pronounced for vehicular users than for pedestrian users. The proposal is more beneficial to users when making cell selection choices during handover.

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