

Neural Network Based LTE Throughput Estimation in Two-Tier Femtocell Networks

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ABSTRACT: Femtocells are a promising technology that benefits both mobile user and operators by providing economical voice and high speed data service particularly at indoor. Femtocells overlaid on existing macrocell forms a two-tier network and it may be considered as a heterogeneous network. Close access mode working of Femtocell Access Points (FAPs) and sharing radio resource allocation between existing macrocell and femtocells causes both cross-tier and co-tier interference. Achieved user throughput estimation at user equipment and FAP is a key parameter to implement an efficient interference mitigation scheme in the said networks. A neural network based SINR-to-Channel Quality Index (CQI) mapping and the throughput estimation scheme is proposed in this work. Femtocell user SINR and throughput estimated using a Neuro-controller estimated CQI are compared with theoretical and actual values. The simulation results obtained verifies the validity of the proposed throughput estimation scheme.

KEYWORDS: Femtocell, macrocell, LTE, Throughput, cross-tier Interference, Co-tier Interference.

I. INTRODUCTION

Research studies from various Mobile Experts have shown that global mobile traffic reached 1,000 petabytes per month and is anticipated to grow multi-fold in the coming years. To meet this rapid growth of mobile data demand, cellular networks are evolving from 3G to 4G LTE and the network topology is also shifting to a heterogeneous network of femtocells complementing macro cells to improve throughput, coverage and user experience specifically at indoors [1]. Femtocell Access Points (FAPs), foreseen as a cost effective indoor coverage solution, serve as low-power, short range data access points that are overlaid on the macrocell networks. Since it connects users to the core service network by utilizing high speed broadband connections such as DSL, cable modem or RF, it can provide improved coverage and increased throughput for home users, while off-loading traffic from expensive macrocell radio access networks onto the low-cost public internet. Overlaying femtocells on macrocells will improve spatial reuse and spectral efficiency. Moreover, they will provide power and battery savings due to the short range of transmission.

In spite of these benefits, fruitful launch of femtocell technology is not yet achieved in a full-fledged manner. The key technical challenge is interference management in the two-tier femtocell networks and availability of more number of literatures indicates the same. It is preferred for the femtocells to share the frequency band with the existing macrocell network, as the licensed band a scarce resource is highly populated. Moreover, the access mode in which femtocells operate is also a main cause of interference. Operators cannot manage femtocell interference using the classic centralized frequency planning/optimization, because they do not know the exact number and position of femtocells and may not own the femtocell backhaul. Hence, the development of distributed radio resource management techniques is necessary to handle femtocell interference. As an initial step to design an efficient cross-tier interference mitigation scheme LTE throughput estimation in two-tier femtocell networks is an important task.

Recent investigations regarding femtocell networks have shown that one of the key technical implementation challenges is the cross-tier interference between existing macrocell and femtocell networks [2]. Chandrasekhar et al. proposed orthogonal and partially shared spectrum to avoid cross-tier interference [3]. However, considering the scarcity of radio resources and the difficulty of deployment, utilization of the same bandwidth is preferable. Chandrasekhar et al. also investigated a non-cooperative power allocation with utility-based signal to interference and noise ratio (SINR) adaptation for co-channel deployed femtocells to alleviate the uplink interference suffered by

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macrocells [4], but they have assumed femtocell users know the channel state information (CSI) of the interfering channel to the macrocell base station in the uplink. This assumption is not applicable in the case of a frequency division duplex (FDD) system [5 add it]. In order to address the femtocell interference problem in Orthogonal Frequency Division Multiple Access (OFDMA) based networks, several schemes have already been proposed in the literature. In [5], in order to allow for a better spatial reuse, the maximum DL transmit power of femtocells is tuned to guarantee a constant femtocell coverage radius according to the received signal strength from the closest macrocell. In [6], user measurements are used to estimate the interference at user locations, and SCs with the lowest interference are allocated to users. None of these schemes use per SC power control, or takes the mentioned one-MCS-per user constraint into account. In [7], a Stackelberg-game-based power control was formulated to maximize femtocell's capacity under cross-tier interference constraints. However, subchannel allocation was not considered there. In [8], Shen and Lok investigated the problem of cross-tier and intercell interference for a two-tier femtocell network. In this investigation, the macro- and femto-tiers were assumed to share the same spectrum, and the femto-tiers were further assumed to use a closed-access scheme. The game theory and variation inequality theory were used to achieve femto-tier optimality and reduce cross-tier interference quickly. However, in these works, joint subchannel and power allocation with the users' quality of service (QoS) and cross-tier interference considerations were not studied. Another possible approach for solving the interference management problem in the literature is the concept of coordinated multi-point transmission/reception (CoMP). The basic idea is to utilize multiple transmitting BS nodes to cover cell-edge UEs (user equipments) that have poor reception. In this context, there are a variety of CoMP techniques among which the most popular techniques are coordinated scheduling/ beamforming (CS/CB), joint transmission (JT), and dynamic cell selection [9]. Although the concept of CoMP can enhance cell coverage and increase system throughput, it has a number of challenges for practical implementation. These challenges include determining the collaborating BSs, synchronization among the collaborating BSs, channel estimation at the collaborating BSs, and more importantly, increased traffic on the backhaul. In [10], the authors proposed a scheme for beamforming codebook restriction at the macrocell base station (MBS) which allows both macrocell and femtocell users to select the best channel that is robust to cross-tier interference prior to transmission. Beamforming codebook restriction is performed based on codeword correlation with a reference codeword vector generated according to a predetermined pseudo-random sequence for each channel. This scheme, however, requires the coordinated BSs to know the channel state information (CSI) of the interference channel prior to transmission which incurs a considerable amount of feedback signaling over the backhaul. In [11], the authors proposed a CoMP scheme that selects the optimal antenna patterns combination of all femtocells with the objective of maximizing network capacity. The proposed solution searches for the optimal antenna pattern combinations of all femtocells using simulated annealing. Both the works in [10] and [11] consider the interference among different femtocells but are not concerned about the cross-tier interference between femtocells and MBSs as in our work. A comprehensive study and survey on the downlink interference management in the said femtocell networks is given in [12]. The two-tier femtocell network indicating downlink cross-tier and co-tier interference scenarios is shown in Figure 1.

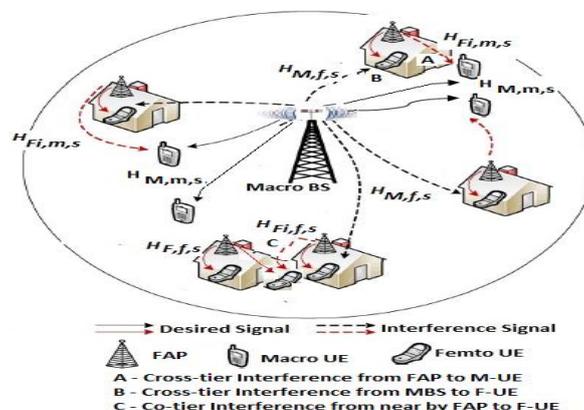


Figure 1. Two-Tier Femtocell Network Illustrating Interference in Downlink

The main contribution of this work is a neural network based LTE throughput estimation which needs to be performed for development of an efficient cross-tier interference mitigation scheme in two-tier femtocell networks. Existing conventional throughput estimation methods for power control schemes and subchannel allocation are not directly

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related to this proposed scheme. This key advantage of this scheme lies in the fact that it does not require any additional feedback from users regarding channel conditions. A neuro-control algorithm formed for throughput estimation works well with the already available quantized channel information, the channel quality index (CQI) which is feedback by user equipment (UE). The neuro-controller implemented in UE estimates the CQI and as a part of uplink transmission and transmits the encoded CQI within Physical Uplink Control Channel (PUCCH) to the base station as a closed loop feedback mechanism. The BS receives and then decodes the PUCCH information to obtain the channel measurements. In the base station the decoded CQI information is used to estimate the user achieved throughput and based on which further decision on allocation of MCS and radio resource is performed to enhance the Quality of Service (QoS). The neural network implemented in the UE and BS is off-line trained for SINR-to-CQI mapping and CQI-to-SINR mapping and then the throughput is estimated. Usage of neural network speeds up the training and the convergence of the said process. The proposed method does not need any hardware change either at the base station or at UE.

The rest of the paper is organized as follows: Section II describes the two-tier femtocell network system model considered in this work. Section III describes proposed neural network based throughput estimation scheme. Simulation results and discussion are presented in section IV and concluding remarks are given in section V.

II. SYSTEM MODEL

The downlink of an LTE - macrocell network with a central base station (macrocell BS - MBS) equipped with N_m transmit antennas is considered in this work. K_m macrocell users are uniformly distributed in the macrocell's coverage region \mathbb{M} , which is assumed to be a circular disc with radius R_m and area $|\mathbb{M}| = \pi R_m^2$. The macrocell is overlaid with single antenna- equipped Femtocell APs, each with coverage of radius R_f . The set of femtocells is $F = \{F_1, \dots, F_m, \dots, F_n, \dots, F_F\}$, and set of users of femtocell is $Fm: Um = \{Um1, \dots, Um_u, \dots, Um Um\}$. Since femtocell APs are deployed randomly in densely populated areas, the distribution of FAPs is assumed to be a homogeneous Spatial Poisson Point Process (SPPP) Π_f . Let FBSs are distributed in each macrocel with intensity λ_f and it is considered to be the spatial density. It is expressed as the average number of FAPs per unit. The average number of FAPs in a macrocell coverage region $F = \lambda_f |\mathbb{M}|$. The FAPs are assumed to provide closed access to users that are members of a particular subscriber group or in other words registered indoor users who fall within the range of each femtocell coverage area. Both macrocell and femtocell users are assumed to be equipped with single-antenna receivers. The total system bandwidth B is divided into orthogonal sub-carriers, which in turn are combined into N_p sub-channels (SCs) or Resource Blocks (RBs). A RB is the coarse unit of radio resource that can be assigned to a user; in other words, it is the basic time-frequency unit corresponding to 0.5 msec and 180 KHz frequency band. A proportional fair scheduler is employed to assign the available SCs among N_m macro users and N FAPs. Each user (macrocell / femtocell) is allocated with only one sub-channel p , containing OFDM symbols, in each frame. A perfectly synchronized OFDMA network is assumed.

FAPs may be deployed in middle service area of macrocells mainly for offloading the congested mobile traffic. Since the MBS operates at a much higher transmit power compared to the FAP, the MBS transmission causes interference to the downlink reception at the F-UE, especially if the FAP is not very far from the MBS. Hence, under co-channel resource assignment, the transmission from an FAP to the F-UE is caused by interference from MBS. In other words, with an assignment of a same SC p by MBS and FAP to M-UE and F-UE respectively, the transmission from MBS creates cross-tier interference on F-UE. Additionally, in sub-urban areas where more number of femtocell are expected in the near future, co-tier interference from nearby FAPs may also be there. Hence the SINR of femto user F-UE $f \in N_f$ served by FAP $F_j \in N$, allocated with SC p is given by

$$\gamma_{F_j, f, p} = \frac{P_{tF} \cdot \Gamma_{F_j, f, p}}{N_o \cdot \Delta f + \sum_{\substack{i=1 \\ i \neq j}}^N P_{tF} \cdot \Gamma_{F_i, f, p} + P_{tM}} \quad (1)$$

where P_{tm} and P_{tf} are the transmit powers of MBS and FAPs respectively, N_o is the received noise power, $\Gamma_{F_j, f, p}$ represent the link gain between the FAP F_j and its femto user f ; while $\Gamma_{F_i, f, p}$ represent the link gain of the interference that nearby FAP $F_i \in N$ impose on femto user f and $\Gamma_{M, f, p}$ represent the link gain of the interference that MBS M impose on femto user f on SC p . The link gain Γ , which is dominantly affected by path loss, can be expressed as $\Gamma = 10^{-PL/10}$, where PL is the path loss between a base station and a UE. Path loss models relevant to a particular link given in [13] can be used.

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The achieved user throughput of femto user f is given by

$$T_{f,p} = B \times \Delta f \times \log_2(1 + \alpha \cdot \gamma_{Fj,f,p}) \quad (2)$$

where, $\alpha = -1.5/\ln(5BER)$ a constant for a target bit error rate (BER) and Δf is sub-carrier spacing frequency. Here bandwidth $B = N_{pf} \cdot b_s$, where N_{pf} number subcarriers per femto user and b_s is the number of bits per symbol. Then Number of subcarriers per user $N_{pf} = SRB \cdot R'$, where SRB is the number of subcarriers per Resource Block and R' is number of Resource Blocks.

III. NEURAL NETWORKS BASED THROUGHPUT ESTIMATION IN TWO-TIER FEMTOCELL NETWORKS

An artificial neural network, which is a parallel data processing system that has learning and self-organizing ability can be used for estimation of throughput in a two-tier femtocell network. The input-output data necessary for the off-line training of the neural network have been obtained in the present work using the lookup table for mapping SINR estimate to modulation scheme and coding rate [14]. A back-propagation algorithm is used for training of the created network. The LEARNGDM function which has a gradient descent with momentum weight / bias learning is used in this work. Learning occurs according to the learning parameters: learning rate=0.01 and momentum constant $t = 0.9$. MSE is the performance criteria used in this work that evaluates the network, according to the mean of the square of the error between the target and computed output. The minimum MSE that can be achieved in this work is $1e-2$. For a back-propagation training algorithm, the derivative of the activation function is needed. Therefore, the activation function selected must be differentiable. The sigmoid function satisfies this requirement and it is the commonly used soft-limiting activation function. It is also quite common to use linear output nodes to make learning easier and using a linear activation function in the output layer does not 'squash' (compress) the range of output [15]. Hence, a bipolar sigmoid activation function and a linear activation function are used for the hidden and output layers, respectively. Trials have been carried out to obtain maximum accuracy with a minimum number of neurons per layer. The feed forward neural network developed consists of one neuron in the input layer, eight neurons in the hidden layer and one neuron in the output layer.

The CQI, a measure of downlink radio channel quality that specifies the best modulation constellation and coding rate to match the link quality. The value of this one is computed such that the transport block error rate will not exceed 10% [14]. The higher the value of the CQI measure, the higher the modulation order and the higher the coding rate. The threshold values mapping SINR values to the spectral efficiency are based on a simple lookup table is given in Table 1. It is also be used as a lookup table for mapping SINR estimate to modulation scheme and coding rate. Technically, the CQI index 0 signals an out-of-range message and does not participate in modulation mapping. The higher the value of the CQI measure, the higher the modulation order and the higher the coding rate.

Table I. Lookup table for mapping SINR estimate to modulation scheme and coding rate [14]

CQI index	Modulation	Coding Rate	Spectral Efficiency (bps/Hz)	SINR estimate (dB)
1	QPSK	0.0762	0.1523	-6.7
2	QPSK	0.1172	0.2344	-4.7
3	QPSK	0.1885	0.3770	-2.3
4	QPSK	0.3008	0.6016	0.2
5	QPSK	0.4385	0.8770	2.4
6	QPSK	0.5879	1.1758	4.3
7	16QAM	0.3691	1.4766	5.9
8	16QAM	0.4785	1.9141	8.1
9	16QAM	0.6016	2.4063	10.3

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10	64QAM	0.4551	2.7305	11.7
11	64QAM	0.5537	3.3223	14.1
12	64QAM	0.6504	3.9023	16.3
13	64QAM	0.7539	4.5234	18.7
14	64QAM	0.8525	5.1152	21.0
15	64QAM	0.9258	5.5547	22.7

In a typical link adaptation process at subframe (n), the downlink BS forms the resource grid from the user data Physical Downlink Shared Channel, (PDSCH) and the Downlink Control Information, (DCI) in the Physical Downlink Control Channel (PDCCH). The DCI contains the scheduling assignments that help the UE correctly decode the subframe information. The information contained in the PDCCH includes the MCSs, the precoder matrix, rank information, and the MIMO mode used. The UE can then perform the critical step of channel condition measurement as part of the process of decoding the received resource grid. In this process, it estimates channel quality measurements that include the CQI, the precoder matrix estimation (PMI), and the rank estimation (RI). In this work CQI alone is considered in throughput estimation. As part of uplink transmission, the UE may embed the channel quality measures within the PUCCH and transmit to the BS as a closed-loop feedback mechanism. The base station can then decode the PUCCH information to obtain channel measurements. In fact, this information available enables the system scheduler to decide whether or not to adapt various system parameters in the next frame as a result of feedback received from downlink channel quality. At the base station in the downlink transmitter operations for the next subframe ($n+1$), the scheduling decisions and the new MCS allocated based on channel conditions are encoded into the PDCCH information and transmitted to the mobile terminal [14].

Initially, a neuro-controller which is a feedforward neural network trained for the lookup table given in Table 1 using back propagation learning algorithm is used for SINR to CQI mapping. The SINR and throughput achieved by the user terminal and the same estimated by the said neuro-controller are simulated. Another neuro-controller implemented in FAP performs demapping of CQI-to-SINR and it can be used for throughput estimation. Based on this alone FAP takes decision on whether to adjust its transmission power or to go for reallocation of radio resources allocated to that particular user.

IV. SIMULATION RESULTS

The performance of the proposed neural network based throughput estimation scheme is verified by simulation of the system model described in section II and III. It is assumed that in a single macrocell, FAPs which has coverage of 30m radius and macro users and femto users reside outdoor and indoor, respectively. It is also assumed that the MBS and FAP serve N_m macro users and N_f femto users, respectively. The proposed throughput estimation at UE and FAP are compared with theoretical one. The SINR of femtocell user who is 400m away from macrocell and 15m from interfering co-channel base stations are shown in Figure 4 and 6 respectively. Similarly, the achieved user throughput estimated at UE and Throughput estimated at FAP using neuro-controller estimated CQI with cross-tier interference from MBS and one interfering FAP are shown in Figure 5 and 7 respectively.

The estimated throughput is close to the theoretical value and the simulation results obtained verifies the validation of the proposed throughput estimation scheme. It may be desirable for the FAP to adjust the transmit power to provide better QoS to its users while minimizing the interference to nearby femto users. The control of transmit power is based on the measurement report to satisfy the minimum target spectral efficiency (e.g. ≥ 1 b/s/Hz near the indoor cell edge). Moreover, change in scheduling radio resources is also considered based on the CQI. Hence the estimation of throughput using neuro-controller estimated CQI, which is close to the theoretical values may be considered as a initial step for an efficient interference mitigation scheme.

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TABLE II. SIMULATION PARAMETERS

Parameter	Value
Carrier Frequency	2 GHz
System Bandwidth	20 MHz
Number of subcarriers per RB	12
Number of RBs	100
Modulation	64 QAM
Target BER	10^{-6}
Noise Power	-174 dBm / Hz
Macrocell Radius	500 m
Femtocell Radius	30m
MBS Transmit Power	20 W
FAP Transmit Power	100Mw
Number of macro users	50
Number of femto users per FAP	4
Penetration loss of outer wall	20 Db
Penetration loss of inner wall	5 dB

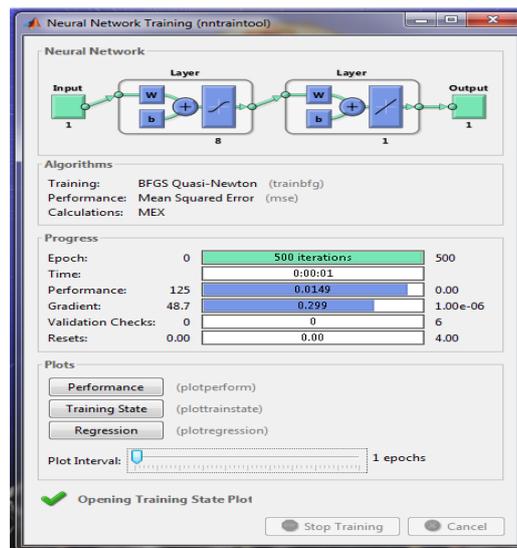


Figure 2. Neural Network Training of the proposed Throughput Estimation Scheme

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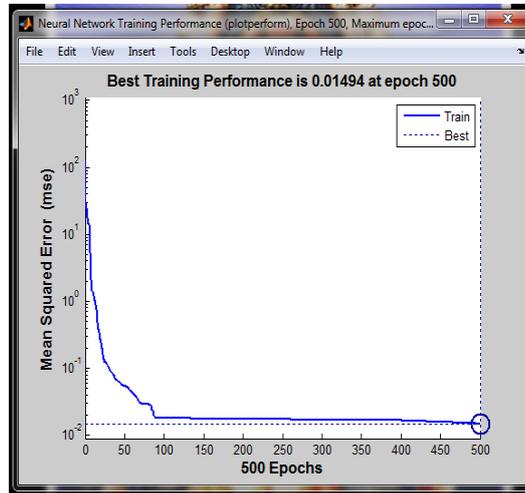


Figure 3. Neural Network Training Performance

Initially a two-tier femtocell network with cross-tier interference is modeled; SINR and achieved user throughput are simulated. The simulation parameters used in this work are given in Table II. The neural network in UE is off-line trained with SINR-CQI values and another neural network in FAP is also off-line training with CQI-SINR values. Based on the SINR estimated by the neuro-controller, femtocell user throughput is estimated. The neural network with 8 hidden neurons is trained for 500 epochs. The neural network training (nn training tool) and performance are shown in Figure 2 and 3 respectively. The minimum MSE that can be achieved in this work is $1e-2$.

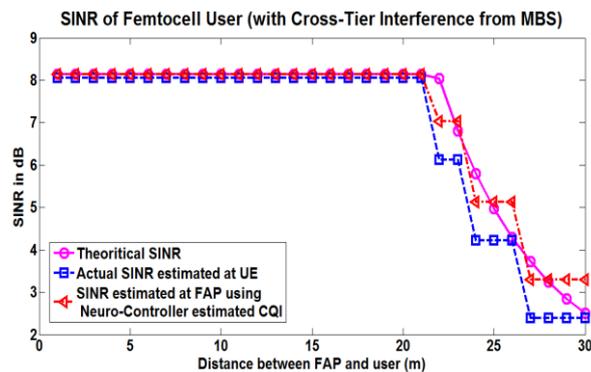


Figure 4. SINR of Femtocell User Estimated at UE and FAP using Neuro-Controller estimated CQI (with Cross-Tier Interference from MBS)

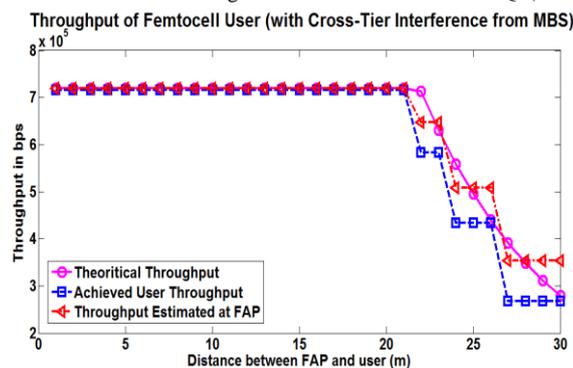


Figure 5. Throughput of Femtocell User Estimated at UE and FAP using Neuro-Controller estimated CQI (with Cross-Tier Interference from MBS)

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The SINR and throughput of femtocell user with cross-tier interference from MBS are shown in figure 4 and 5 respectively. It is observed, the SINR and throughput of user 20m away from FAP are reduced significantly. The actual values estimated at UE and the same estimated at FAP using proposed Neuro-Controller estimated CQI are close to the theoretical values calculated using equations (1) and (2). User 25m away from his serving FAP experience poor QoS and captured in coverage hole. He can get uninterrupted service only the interference generated by MBS downlink is removed, which can be done by rescheduling the radio resource allocated to that particular user. The FAP initiates this action using the neuro-controller estimated CQI, SINR and throughput.

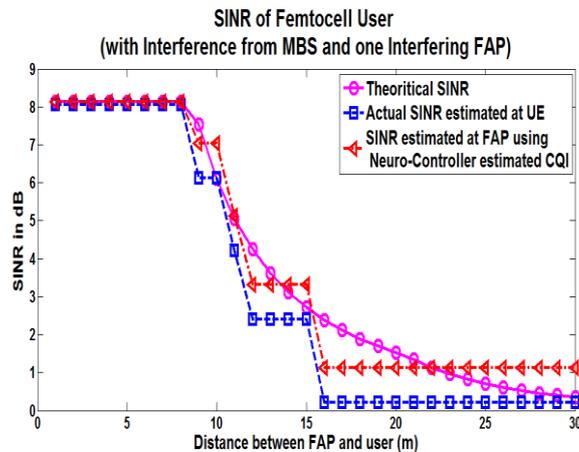


Figure 6. SINR of Femtocell User Estimated at UE and FAP using Neuro-Controller estimated CQI (with Interference from MBS and one interfering FAP)

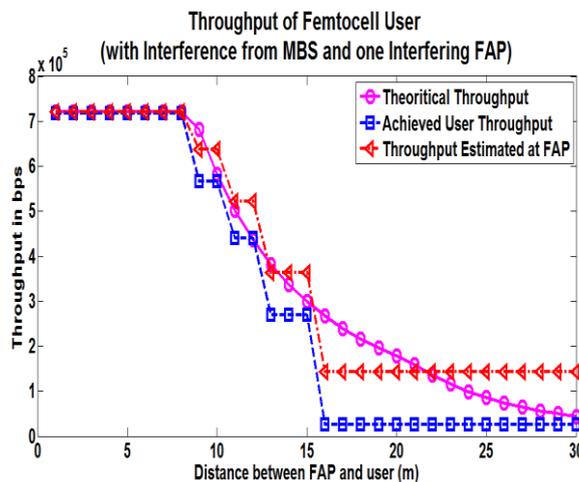


Figure 7. Throughput of Femtocell User Estimated at UE and FAP using Neuro-Controller estimated CQI (with Interference from MBS and one interfering FAP)

Similarly, the SINR and throughput of femtocell user with interference from MBS and one FAP (least case) are shown in figure 5 and 7 respectively. It is observed, the SINR and throughput of user just 10m away from FAP are reduced significantly. This indicates the rigorousness of both cross-tier and co-tier interference and stress the need for an efficient interference mitigation scheme to ensure the better QoS to all users.

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V. CONCLUSION

In this paper, a neural network based throughput estimation scheme is proposed. The simulation results of femtocell user SINR and throughput with cross-tier interference from MBS and interference from one co-channel FAP are presented. In fact the estimated throughput is utilized for taking decision about FAP transmission power control and / or change in assignment (or rescheduling) of radio resource allocated the femtocell users. Since the throughput estimated using neuro-controller estimated CQI is close to the theoretical value, it can be utilized for the said interference mitigation process. Nevertheless, the LTE throughput estimation is not yet standardized particularly for two-tier femocell networks. Hence the proposed neural network based throughput estimation scheme is an efficient, fast and accurate, and it can be implemented in FAP.

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