An Improvement Vertical Handover in HetNets Based on Alteration Channel Allocation Scheme

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***Abstract*—The efficient management of available radio resource utilization becomes crucial to maintain uninterrupted communication. So, the vertical handover decision process acts an important role to guarantee the seamless mobility for ubiquitous heterogeneous wireless networks in the next generation. The major contributions of this paper compose of the two topics. First, the Back-Propagation Neural Network (BPNN) is used for the channel allocation procedure in order to reduce the unnecessary handover, dropped call and data packet delay, respectively. Also, this algorithm can be increase the network throughput. Second, the merit function brings to use with the vertical handover decision management to provide the high Quality of Service (QoS). The simulation results as number of handover, dropping rate, data packet delay and throughput forms indicate that our proposed algorithm significantly enhance the overall performance compared with previous methods.**

***Index Terms*—back-propagation neural network, channel allocation, heterogeneous networks, ubiquitous, vertical handover**

I. Introduction

The continuity of communication without terminating services in anywhere and anytime is accelerating the technological development towards the heterogeneous network (HetNets) access and ubiquitous seamless, is called as “wireless broadband” for Next Generation Wireless Networks (NGWN). The coordination of different types of existing networks is the significant challenges in the future wireless systems as depicted in Fig. 1. The single mobile terminals can provide users with a wide range of services across different media in order to “Always Best Connected (ABC)”. Thus, the design of intelligent vertical handover decision algorithms as handover management schemes to enable the device to receive ongoing services even as it moves between different network or Access Points (APs) [1], [2]. Thus, the channel allocation approach provides the reserved channel for handover calls to increase the rate of successful access.

Dynamic and hybrid channel allocation are important in solve these problems [3]-[5]. However, these algorithms do not consider the access of different data services, so it cannot answer the satisfying requirements of multimedia services in personal communication.

Otherwise, many handover decision techniques have been proposed as RSS based approach; Analytic Hierarchy Process: AHP approach; Multiple Attribute Decision Making: MADM approach. RSS is the only main criterion for the handover decision process, so this algorithm is not practical because it should know how strong the RSS of the neighboring channel is to decide whether to handover earlier [6]. Additionally, the traveling time is used to minimize handover failure, unnecessary handover and connection breakdowns. But this method relies on sampling and averaging RSS points, which introduces increased handover delay [7]. AHP is proposed by [8]; the network with the highest performance score is selected on target network but this method ignores the wireless environment. Finally, MADM algorithm is a combination of methods and uses the many parameters at the same time (e.g. neural network, fuzzy logic, etc.) however this algorithm neglects the wireless surrounding, which may cause handover delay and increase the dropped call [9], [10]. To overcome these problems, the merit function is used for our proposed algorithm. In this paper, we consider the wireless surroundings as receiving signal strength in a large scale. The bandwidth, monetary cost and user preference is used to determine the handover decision process.

The rest of this paper is organized as follows. Section II presents the back propagation neural network. In Section III, the multiple signal classification approach is depicted. An improvement vertical handover in HetNets based on alteration channel allocation scheme is explained in Section IV. Finally, simulation results and conclusion are talked about Section V and VI, respectively.

II. Back-Propagation Neural Network

The Back-Propagation Neural Network (BPNN) is used to predict the Received Signal Strength (RSS) and allocate the channel. The Predictive RSS (PRSS) indicate in order to know whether a mobile node is moving closer to or away from the monitored network. Additionally, knowing the RSS of neighboring networks ahead of time and if the current RSS of the serving network is lower than the threshold, this allows the mobile node to perform a handover early. As a result, a connection is continuing

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to influence the lower dropping probability, especially while it is moving in the overlap area. Also, a good channel allocation is the crucial factor that yields seamless communication for ubiquitous wireless networks in order to receive a high Grade of Service (GoS) so that the allocating channel is given to handover requests which are first priority, more so than new call arrivals.

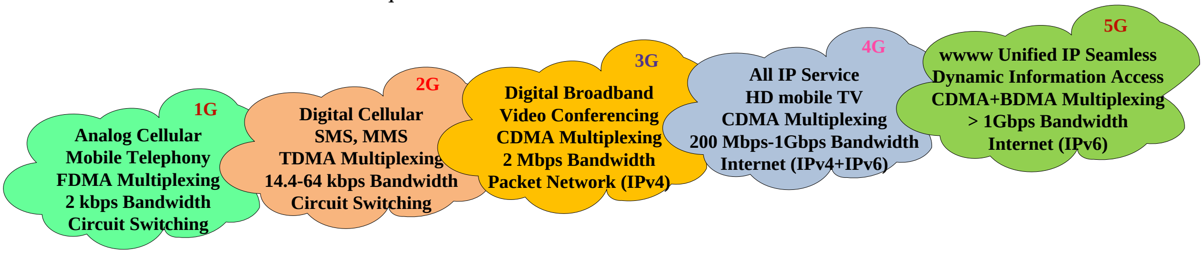

Figure 1. Evolution of wireless networks from 1G to 5G ubiquitous access.

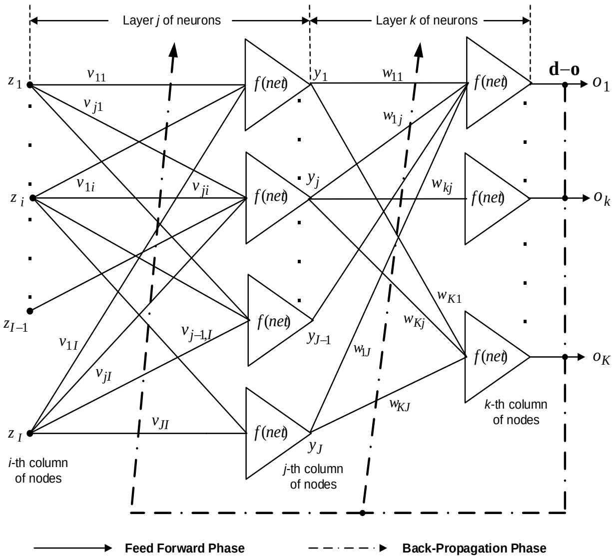

Figure 2. Back-propagation neural network.

The BPNN is learned for dynamic channel allocation. In Fig. 2, the input and output of the hidden layer are denoted as z_i and y_j while the output of the network is denoted as o_k for $i=1,2,\ldots,I$, $j=1,2,\ldots,J$ and $k=1,2,...,K$ arranged in a vector form as $\mathbf{z}=[z_1\, z_2 \ldots z_I]^t$, $\mathbf{y}=[y_1\, y_2 \ldots y_J]^t$, $\mathbf{o}=[o_1\, o_2 \ldots o_K]^t$. The weight v_{ji} connects the i^{th} input node to the j^{th} hidden node and the weight w_{kj} connects the output of the j^{th} neuron to the k^{th} neuron. Given P pairs of the training patterns include the input vector $(\mathbf{z}_P)$ and the desired output vector $(\mathbf{d}_P)$ form as $\{(\mathbf{z}_1,\mathbf{d}_1),(\mathbf{z}_2,\mathbf{d}_2),\ldots,(\mathbf{z}_P,\mathbf{d}_P)\}$, the weights are updated as follow [11]:

1. Initialize the weights v_{ji} and w_{kj} with small values between 0 and 1.

2. Submit a training pattern $\mathbf{z}_p$. The output responses of the hidden layer and output layer are shown as (1) and (2), respectively.

$$y_j = f\left(\sum_{i=1}^{I} v_{ji} z_i\right) \tag{1}$$

$$o_k = f\left(\sum_{j=1}^{J} w_{kj} y_j\right) \tag{2}$$

where $f(net)$ is a tangent-sigmoid transfer function as equal to $f(net) \triangleq \dfrac{2}{1+\exp(-\lambda net)}-1$, $\lambda>0$ and λ is a bias of network.

3. Calculate the error of the output layer depending on the different desired output and actual output as depicted in (3).

$$\delta_{ok} = \frac{1}{2}(d_k - o_k)(1-o_k^2) \tag{3}$$

where d_k is a desired output and o_k is an actual output of k^{th} neuron in the output layer, respectively.

In addition, the error of the hidden layer is computed as follows:

$$\delta_{yj} = \frac{1}{2}(1-y_j^2)\sum_{k=1}^{K}\delta_{ok} w_{kj} \tag{4}$$

4. Adjust the weights using the delta learning rule $w_{kj} \leftarrow w_{kj} + \eta\delta_{ok} y_j$, $v_{ji} \leftarrow v_{ji} + \eta\delta_{yj} z_i$; $\eta>0$, where η represents a learning rate between 0 and 1.

5. Increase $p=p+1$ and if $p<P$ then go to step 2. If $p=P$ and the cumulative error $E=\sum_{p=1}^{P}\frac{1}{2}\left\|\mathbf{d}_p-\mathbf{o}_p\right\|^2$ is below the acceptable maximum error, then stop the learning procedure, otherwise initiate the new training cycle.

To predict the RSS and allocate the channel of the n^{th} neighboring network, we use the input training pattern $\mathbf{z}_p$ consisting of the RSS, Mobile Speed (MS) and Bandwidth (BW) at the present time t and three past samples e.g. RSS parameter as (5). The output value is the predicted RSS $\mathbf{o}_p = R\hat{S}S_n[t+1]$ and it is compared to the actual RSS $\mathbf{d}_p = RSS_n[t+1]$.

$$\mathbf{z}_p = RSS_n[t], RSS_n[t-1], RSS_n[t-2], \ldots, RSS_n[t-I-1] \tag{5}$$

We use the number of nodes in the hidden layer that are 10 nodes that use a tangent sigmoid transfer function to connect them to all the input nodes. The output layer consists of one node which is obtained by a linearly weighted sum of the outputs of the hidden units. Note that the output of the network in this application is to decide whether the system needs a channel allocation as follows. If is 0, there is no channel allocation, but also is 1 then the system will reserve a channel for the mobile to the chosen base station. In our implementation, 700 samples are used for training the network and 300 samples are used to test the network. For each testing sample, square errors of actual output and desired output are calculated.

III. Multiple Signal Classification Approach

In this section, we use an antenna array with the MUltiple SIgnal Classification also known as MUSIC algorithm to estimate the mobile signal directions of arrival (DOA). In the first step, we consider the receiving signals at the L antennas which consist of the M source signals and noise, here is the form:

$$\mathbf{X}(t) = \sum_{m=1}^{M} \mathbf{a}(\theta_m) s_m(t) + \boldsymbol{\eta}(t) = \mathbf{A}(\Theta)\mathbf{s}(t) + \boldsymbol{\eta}(t) \quad (6)$$

where $\mathbf{A}(\Theta) = [\mathbf{a}(\theta_1),...,\mathbf{a}(\theta_M)]$ is an $L \times M$ matrix, which contains the steering vectors $\mathbf{a}(\theta_m)$ of the signal $s_m(t)$ that having the unknown angle of arrival, (θ_m). $\Theta = [\theta_1,...,\theta_M]$ is the direction of arrival of the M source signals. For the steering vectors of the antenna array will have phase a delay therefore the steering vector can be written as:

$$\mathbf{a}(\theta_m) = \begin{bmatrix} 1 \, e^{-j2\pi\frac{d}{\lambda}\sin\theta_m} \ldots e^{-j(L-1)2\pi\frac{d}{\lambda}\sin\theta_m} \end{bmatrix}^T \quad (7)$$

where λ is the wavelength of signal and d is the difference of distance between the antenna array. The source signal vector is a $1 \times M$ as $\mathbf{s}(t) = [s_1(t),...,s_M(t)]^T$. $\boldsymbol{\eta}(t) = [\eta_1(t),...,\eta_L(t)]^T$ is a $1 \times L$ noise vector which is correlated with the antenna. Note the number of antenna arrays is greater than the number of source signals $(L > M)$. We can find the correlation matrix of the antenna array by to using eigenstructure therefore the correlation matrix $\mathbf{R}$ can be written as:

$$\mathbf{R} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^H \quad (8)$$

where $\mathbf{U} = [\mathbf{u}_1,...,\mathbf{u}_L]_{L\times L}$ is a unitary matrix whose columns constitute eigenvectors and $\boldsymbol{\Lambda}$ is a diagonal matrix of real eigenvalues which have λ_i corresponding with the eigenvector $\mathbf{u}_i$ so $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_L > 0$. From that time; we divided the correlation matrix $\boldsymbol{R}$ as signal subspace: $\mathbf{S} = [\mathbf{u}_1,...,\mathbf{u}_M]$ and noise subspace: $\mathbf{N} = [\mathbf{u}_{M+1},...,\mathbf{u}_L]$, respectively. Thus, the matrix $\boldsymbol{R}$ is written as:

$$\mathbf{R} = \mathbf{S}\boldsymbol{\Lambda}_s\mathbf{S}^H + \mathbf{N}\boldsymbol{\Lambda}_n\mathbf{N}^H \quad (9)$$

Therefore, the MUSIC algorithm estimates the DOA of the source signals by finding M peaks of

$$P_{MUSIC}(\theta) = \frac{1}{\left|\mathbf{a}^H(\theta)\mathbf{N}\right|^2} \quad (10)$$

Because in practice, we cannot find the correlation matrix $\boldsymbol{R}$ in directly thus we will use the sampling signal for the estimate of $\boldsymbol{R}$ instead we use $\hat{\boldsymbol{R}}$ which is given as the following:

$$\hat{\mathbf{R}} = \frac{1}{N}\sum_{t=0}^{N-1} \mathbf{x}(t)\mathbf{x}^H(t) \quad (11)$$

In the simulation, we use the sampling signal N equal 1000 points. Fig. 3 shows the angle of arrival for the 10 users which are the difference of the directions as 3, 78, 104, 131, 170, 207, 258, 287, 321 and 348, respectively.

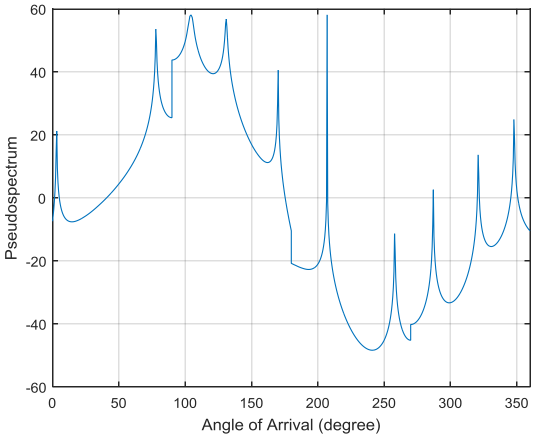

Figure 3. Angle of arrival for 10 users.

IV. An Improvement Vertical Handover in HetNets Based on Alteration Channel Allocation

Our proposed structure of IP-based mobile that joins with Long-Term Evolution (LTE) and Wireless Local Area Network (WLAN) and their fixed positions are illustrated in Fig. 4. WLAN and LTE can access via an IP network that is called loosely coupled. The loose coupling type provides a flexible and independent environment due to this scheme being based on mobile IP (MIP) [12], [13]. In the Mobile IP Regional Registration (MIP-RR), a visited domain consists of two hierarchy levels of foreign agents (FA) and Gateway FA (GFA). GFA is an entity located at the top of hierarchy whereas one or more FAs are organized under GFA. The benefit of the MIP-RR is to reduce the packet loss and signaling delay by only regionally registering to the GFA transparent to the Home Agent (HA). The protocols of the three cases in which handovers occur are considered. First, an upward vertical handover refers to handover from an Access Point (AP) of a smaller-size cell to a Base Station (BS) of a service with wider coverage. The second case is a downward vertical handover which takes place in reverse direction. Third, the Mobile Node (MN) moves and executes a handover from an AP to another AP which is called intrasystem handover.

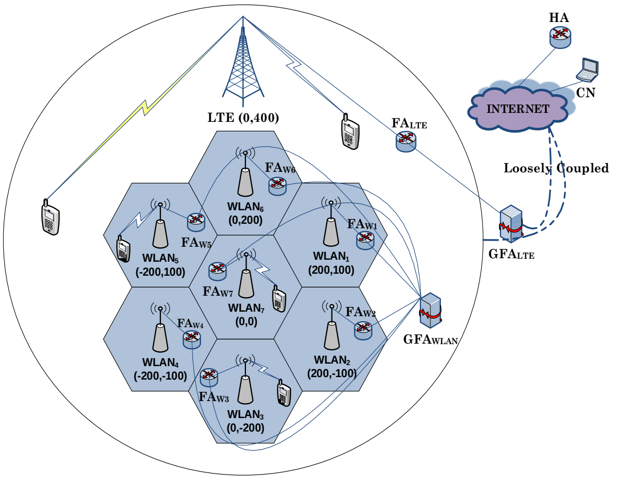

Figure 4. Heterogeneous networks cooperate with WLANs and LTE

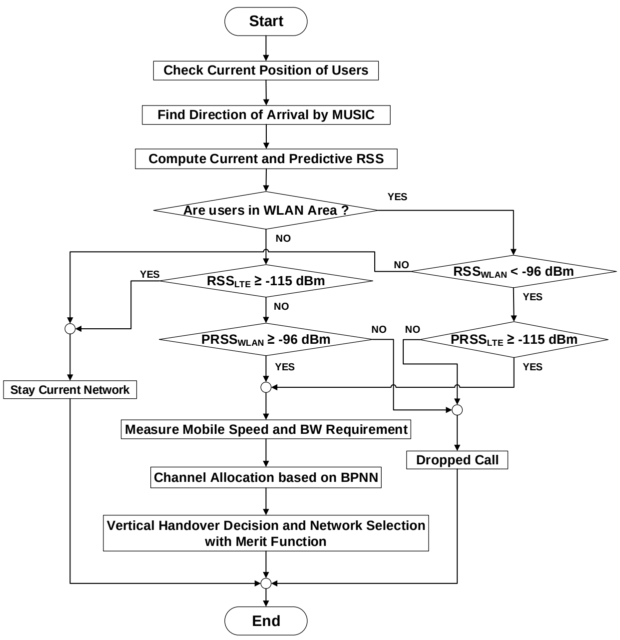

Figure 5. Vertical handover in HetNets based on alteration channel allocation scheme

The procedure of vertical handover in HetNets based on adjust channel allocation scheme is shown in Fig. 5. First, the process checks the user positions and direction of arrival; if the mobile users are in WLAN coverage area and the RSS from this network is less than the threshold then the MS and BW requirement of each users are measured. After that, this information is sent to the channel allocation based on BPNN process in order to adjust varying the environment. Finally, the vertical handover decision process selects the best candidate networks which are the highest score as following the merit function. The merit function of network n include available bandwidth (B_n), monetary cost (C_n) and user preference (U_n) can be computed as:

$$F_n = E_n\left(w_B \ln B_n + w_C \ln \frac{1}{C_n} + w_U \ln U_n \right) \qquad (12)$$

where E_n is the elimination factor of network n. The value of E_n is represented by zero or one to reflect whether the network n is suitable for the mobile node's request. The QoS factors are $q'_{n,1} = B_n$, $q'_{n,2} = \frac{1}{C_n}$ and $q'_{n,3} = U_n$. The weights are assigned as $(w_B, w_C, w_U) = (0.55, 0.25, 0.2)$.

V. Simulation Results

A. Received Signal Strength Indicator

This section evaluates the performance of the proposed algorithm that the RSS is sampled every 0.1 sec. The channel propagation model of the RSS received by a mobile node has different values in different types of networks. When the distance between a mobile node and a base station is d (meters), the $RSS(d)$ in LTE is given by [14].

$$RSS(d) = P_t - PL(d) \qquad (13)$$

where P_t is the transmit power, and $PL(d)$ is the path loss at distance d which is defined as

$$PL(d)_{\text{dB}} = S + 10n\log(d) + \chi_\sigma \qquad (14)$$

where S denotes the path loss constant, n denotes the path loss exponent and χ_σ represents the shadow effects which is a zero-mean Gaussian distributed random variable (in dB) with standard deviation σ (also in dB). We use $S=5$, $n=3.5$ and $\sigma = 6\,\text{dB}$, respectively.

In WLAN, the RSS received by the mobile node is computed based on the propagation model as following:

$$RSS(d)_{\text{dBm}} = 10\log\left(\frac{100}{(39.37d)^\gamma}\right) \qquad (15)$$

where γ denotes the environmental factors of transmissions which is set to 2.8.

B. Back-Propagation Neural Network Parameters

We use the received signal strength, bandwidth and mobile speed as the input of BPNN and these parameters are separated into 3 intervals such as low, medium and high as shown in Table I-Table III, respectively. Note that, each parameter is designed that is covered by both network characteristic. The condition of the network decision of WLAN and LTE are illustrated in Table IV-Table V.

TABLE I. Received Signal Strength Interval

Networks	Low (dBm)	Medium (dBm)	High (dBm)
WLAN	[-87, -85.34]	(-85.34, -83.67]	(-83.67, -82)
LTE	[-147, -145.67]	(-145.67, -144.34]	(-144.34, -143)

TABLE II. BANDWIDTH INTERVAL

Networks	Low (MHz)	Medium (MHz)	High (MHz)
WLAN	[0, 1]	(1, 20]	(20, 40]
LTE	[0, 1]	(1, 10]	(10, 20]

TABLE III. MOBILE SPEED INTERVAL

Networks	Low (m/s)	Medium (m/s)	High (m/s)
WLAN	[0, 0.9]	(0.9, 1.9]	(1.9, 3)
LTE	[0, 47]	(47, 93]	(93, 139)

TABLE IV. NETWORK DECISION FOR WLAN

MS (m/s)	L	L	L	M	M	M	H	H	H
BW (MHz)	L	M	H	L	M	H	L	M	H
Target	CH	CH	NO	CH	CH	NO	NO	NO	NO

TABLE V. NETWORK DECISION FOR LTE

MS (m/s)	L	L	L	M	M	M	H	H	H
BW (MHz)	L	M	H	L	M	H	L	M	H
Target	NO	NO	CH	NO	CH	CH	NO	NO	NO

Note that, L = Low, M = Medium, H = High, CH = Channel Allocation, NO = No Channel Allocation

C. *Performance Analysis*

To demonstrate the performance of the proposed an improvement vertical handover in heterogeneous wireless networks based on alteration channel allocation algorithm, number of handovers (unnecessary handover), dropping rate, data packet delay and throughput are evaluated. We assess the performance under different mean arrival times ranging from 5-30 sec. The average arrival rate of new calls is fixed at 10 calls/sec and average call holding time is 180 sec for each speed. The user's speed is a uniform distribution as equal to 1-30 m/s and user movement is modeled as the random waypoint mobility in 1500 (m) x 1500 (m) topology size for each speed.

Repeating the test to gain more accurate results, each point was run 10 times, and then we take their average based on OPNET simulator. Correspond to an actual situation for the simulating process, the Correspondent Node (CN) generates Constant Bit Rate (CBR) multimedia traffic using a 64-byte packet size and is sent every 0.1 sec and User Datagram Protocol (UDP) is the transport protocol applied between the networks that includes the detection of the new networks and the allocation of new IP address. These tasks are often handled by Dynamic Host Configuration Protocol (DHCP). The number of handovers, dropping rate, data packet delay and throughput in both networks under mean arrival time are illustrated in Fig. 6-Fig. 11, respectively. Fig. 6 shows the number of handovers as Predictive+BPNN that this proposed method has less value than Dynamic Channel Assignment (DCA) [4] algorithm since the proposed approach can predict the RSS of neighboring cell and can know the direction of users. Accordingly, the dropping calls mean the unsuccessful handover process causes the user to be disconnected and are the fewest by using the proposed algorithm as illustrated in Fig. 7. As a result, it yields the lowest data packet delay in WLAN and LTE networks of Predictive+BPNN that refers the channel allocation based on BPNN and cannot delay a vertical handover decision process as summarized in Fig. 8-Fig. 9. Packet delay is defined as the time interval between the correctly receiving of the last packet from the old AP and the completion of association with the new AP. In additional, we observe that the accumulated throughput in WLAN and LTE networks as demonstrate in Fig. 10-Fig. 11, so we meet the Predictive+BPNN approach yields the highest this value which refers the users can satisfy for your connection due that the data can send and receive completed.

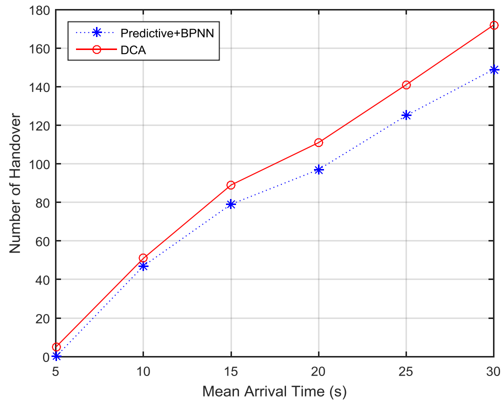

Figure 6. Number of handovers versus mean arrival time.

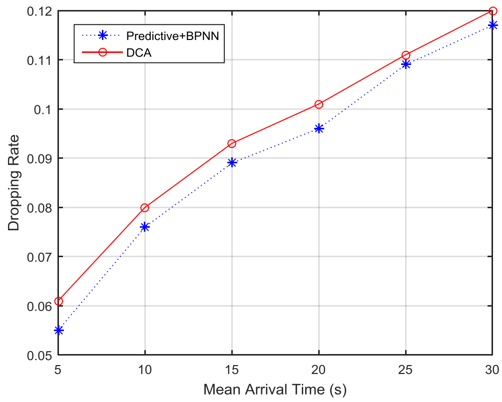

Figure 7. Dropping rate versus mean arrival time.

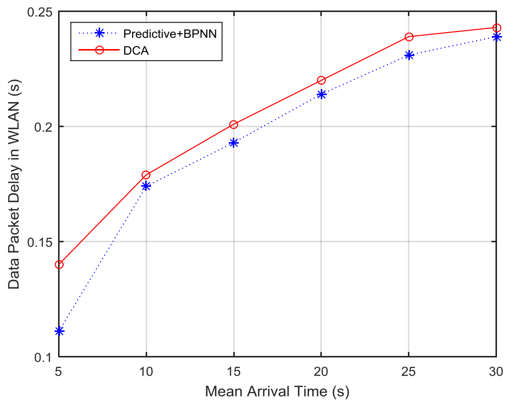

Figure 8. Data packet delay in WLAN versus mean arrival time.

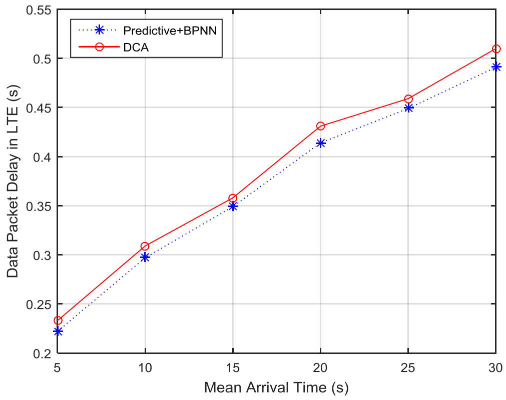

Figure 9. Data packet delay in LTE versus mean arrival time.

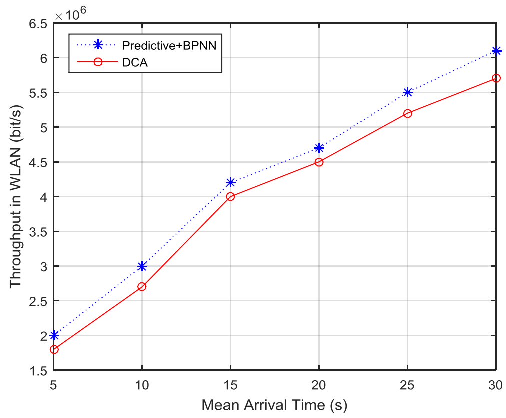

Figure 10. Throughput in WLAN versus mean arrival time.

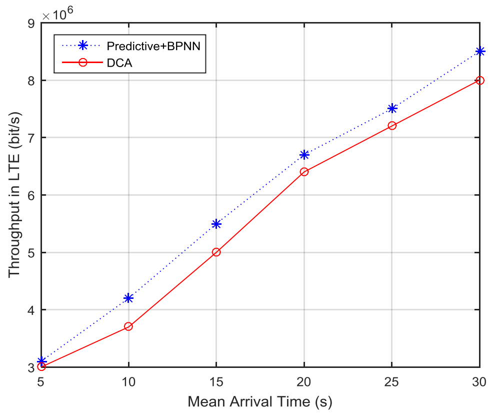

Figure 11. Throughput in LTE versus mean arrival time.

VI. Conclusion

We proposed the vertical handover in HetNets based on alteration channel allocation approach that is used to receive signal strength, mobile speed and bandwidth metrics as the input of the back-propagation neural network. The simulation results indicate the proposed scheme that outperforms another algorithm as reducing the unnecessary handovers, the dropping rate, data packet delay and throughput, respectively.

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