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Research Article

Active Learning Assisted Admission and Bandwidth Management in HWN for Facilitating Differential QoS under Multicriteria Factors

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Control of call admission and management of bandwidth are the two important functionalities to achieve higher call handling capacity in heterogeneous wireless networks (HWN). This work addresses the problem of supporting differential qualities of services (QoS) with adherence to multicriteria factors in addition to reducing call-dropping probability in HWN. Toward this end, learning-assisted admission and bandwidth management are proposed. The decision to control the call acceptance ratio and bandwidth allocation level is learned continuously based on current network dynamics and the differential QoS requirements of the current calls. This learning reduces the call drop probability and slippage in QoS for calls. The parameters employed for evaluation in the suggested approach for call admission control include call priority, service type, service delivery mode, bandwidth availability for scalable and nonscalable calls, QoS distortion rate, and call ratio.

1. Introduction

The rapid proliferation of mobile devices and Internet of things (IoT) devices are increasing mobile traffic exponentially. The demand for bandwidth-crunching services like video calls, video streaming, etc., creates congestion and reduces the quality of services in wireless networks [1]. The admittance of calls is based on several factors, including priority, service, network conditions, and load circumstances, with the ultimate objective of maximizing revenue. The training dataset can be changed to easily adapt the call admission control algorithm. This solution's proposed bandwidth adjustment features two modes—aggressive and nonaggressive—that are highly adaptable to the characteristics of a dynamic load. A heterogeneous wireless network combining multiple radio access technologies along with multimode terminals is one of the solutions to meet the huge bandwidth requirements. The goal for next generation wireless networks (NGWNs) include a core network including several radio access technologies (RATs) in a uniform and seamless manner. Wireless access networks are continually growing, constantly increasing both in coverage and offered bandwidth. In such a setting, providers using multi-RAT technologies will strive to maximize subscriber happiness while minimizing the strain on their subsystems. The multimode terminal can use one or more RAT coexisting in the same area either by selecting the most suitable RAT or by using multiple RATs in parallel. By making use of multiple RATs, cooperative heterogeneous wireless networks can reduce the call drop probability and meet the desired QoS of the users. Control of admission of joint calls (JCAC) and dynamics of bandwidths management are the two important functionalities that can support multiple services with differential QoS requirements over HWN [2]. JCAC decides to allow or reject new or handover calls to take optimum advantage of the availability of resources radio and ensure QoS is satisfied for all accepted calls [3]. Initial JCAC algorithms for HWN dropped the calls when none of the available individual RAT has enough bandwidth to support the calls [4–8]. JCAC algorithms later evolved to select multiple RATs for a single scalable call [9]. JCAS admits calls by giving more importance to handover calls compare with the new call. They do not the evaluate factors like the cost-benefit of admission, probability of QoS distortion based on the current network situation, etc., in their call admission decision. To increase call handling capacity in heterogeneous wireless networks, two crucial capabilities are call admission control and bandwidth management (HWN). In addition to lowering the likelihood of calls being dropped in HWN, this work addresses the issue of enabling varying quality of service (QoS) with adherence to multicriteria factors. By standard HWN bandwidth management, some of these bandwidths are made available to the still-applying, nonreal-time traffic class to meet bandwidth demands for changeover calls and new calls. By fusing cellular networks, wireless LANs, and ad hoc networks with the Internet, heterogeneous wireless networks (HWNs) offer flexible and varied wireless network access. Typical bandwidth management in HWN releases a few of these bandwidths for still under admission, not real-time traffic class to satisfy bandwidth requests of handover calls and new calls. This bandwidth management strategy does not give importance to the call characteristics (like a priority, the content of traffic-monetary, entertainment, etc). In short, there is no evaluation of admission and bandwidth management decisions based on multicriteria factors like cost benefits, priority, content characteristics, network situation on admission, etc., in most call admission and bandwidth management decision for multiple RAT selection HWN. To address this problem, active learning-assisted admission and bandwidth management solution is proposed in this work. The decision to admit calls and manage bandwidth is selected through a fuzzy logic classifier. The decisions are then fine-tuned continuously based on semi supervised feedback. The proposed model takes into account (i) the control of various network services and assurance levels to handle applications with different QoS requirements and traffic profiles; and (ii) the intradomain and end-to-end operation, controlling both the QoS levels in a domain and the sharing of the existing service level specifications (SLS) between domains to fulfill the end-to-end QoS requirements of the applications. Simplicity, ease of deployment, and Internet integration are the driving forces behind the model design. The proposal's adaptability and scalability in light of technological, service, and application evolution objectives have also been taken into account. These objectives are important for large-scale model deployment across several administrative domains with various QoS solutions.

The remaining paper's organization is like this. Sections 2 present the surveys of existing JCAC solutions along with their research gaps. Section 3 presents the proposed learning-assisted admission and bandwidth management solution and details the novel contributions of this work. Section 4 presents the results and comparison to state of art existing works. Section 5 presents the ending remark with the scope for future work.

2. Related Works

Khan et al. [10] solve this problem of admission control by programming mixed integers that are of nonlinearity for HetNet. For reducing the complexities of computation of comprehensive searches for the numerically larger user inside MINLP, the author proposes heuristics algorithms on basis of approximations. Admission control is based on throughput, traffic load imbalances, and the number of users. Badawy et al. [11] made admission control decisions in HWN based on mobile terminal modality (capability), network load, adaptive bandwidth of ongoing calls, and RAT terminal support index. Handoff calls are given more priority compared to normal calls without consideration of content characteristics. Bandwidth allocation is done in a distributed manner due to which, the solution cannot be applied in the case of scalable calls using multiple RATs. Khloussy et al. [12] proposed an admission control mechanism for specialized services based on revenue maximization. The bandwidth is reserved for specialized services in such a way as to maximize revenue. This reserved bandwidth can also result in loss, as they are dedicated only to specialized services. Kumar et al. [13] proposed an admission control scheme involving user preference-based RAT selection. The user expresses their preference among multiple RAT using weighted RAT parameters. This preference is used for checking bandwidth availability and the call is accepted on availability. Jabeena et al. [14] proposed a terminal modality-based joint call admission algorithm for HWN. The algorithm has two important processes: degradation and restoration. The degradation process involves taking the bandwidth of one going call to make way for a new call without degrading the QoS of the ongoing calls. The restoration process involves restoring available bandwidth to ongoing calls when the network is underutilized. The degradation or restoration is done with the same bandwidth step and this approach does not consider differential QoS. Mamman et al. [15] proposed a call admission control approach to increase the utilization of the resources and avoid starvation of best-effort traffic. Bandwidth degradation is applied to admit many users when there are insufficient network resources to accommodate many users. In addition to bandwidth degradation, adaptive thresholding of bandwidth for two services of real-time and best effort is implemented for efficient use of resources. Kim et al. [16] proposed a call admission control based on the location of the device within the cell. The user device is differentiated based on location within the cell as center or edge and the physical resources are allocated differentially to the user equipment. As UE approaches the center of the cell, it receives higher bandwidth, and its throughput increases. Xu et al. [17] proposed a call admission control algorithm based on game theory for cognitive HWN. The vacant spectrum to admit the call is decided based on the spectrum price at primacy channels, subchannel allocation price, and network selection. Bertrand's game theory is used to find the vacant spectrum price. The vacant spectrum satisfying the user's budget requirement is selected. Rahman et al. [18] proposed a call admission control scheme based on two dimensional Markov process called a defined limited fractional channel scheme. The channels are split into three parts: nonpriority, fractional priority, and integral priority. New call and handover calls are accepted with equal priority up to a certain first limit. After this first limit, till the second limit, hew calls are accepted with a certain acceptance ratio. After this second limit, only handover calls are accepted. This scheme differentiates only new and handover call and does not consider the call's QoS requirements. AlQahtani et al. [19] proposed a call admission control scheme based on delay and user categorization. The bandwidth allocation is adjusted dynamically based on current network conditions and the operator's revenue maximization. The users are categorized as gold and silver users. Services are classified as real-time and nonreal-time services. A priority score is given to calls based on user category and service type. This priority is dynamically adapted based on network conditions. Bandwidth is provisioned in proportion to the priority. Inaba et al. [20] proposed a fuzzy logic-based call admission control algorithm. The decision to accept/deny the call is made based on the user movement prediction, user security, and remaining capacity at the base station. The remaining capacity is categorized as real and nonreal-time capacity. The call drop probability is higher in this approach as there is no provision for bandwidth degradation to allow additional calls. Suresh et al. [21] proposed a call admission control algorithm combining an artificial fish swarm algorithm with a fuzzy inference system. The fuzzy decision to accept or deny the call is based on three input variables of effective capacity, service type, and normalized available capacity. Umar et al. [22] proposed an enhanced call admission control scheme with bandwidth reservation. Bandwidth degradation is done when there is no sufficient bandwidth for new calls. Nonreal-time calls are degraded ahead of real-time calls. Uchenna et al. [23] proposed an optimal dynamic priority call admission control for a universal mobile telecommunication system. This solution is based on renegotiation, exploring unused bandwidth, and claiming it for new/handover calls. Bandwidth is allocated to calls in proportion to the priority of the calls. Kumar et al. [24] modeled the channel allocation scheme for calls as an optimization problem on multiple objectives. Fitness function based on multiple objectives of minimizing call drop, increasing resource utilization, etc., is defined and optimization is done using Grey wolf optimizer. The computational complexity increases exponentially with the increase in the number of calls and this approach does not address this problem. Jadhav et al. [25] proposed an adaptive call admission control algorithm where the bandwidth is upgraded or downgraded adaptively. This scheme differentiates calls into real and nonreal-time calls. Calls from nonreal-time calls are degraded at a higher priority to make way for new or handover real-time calls. This scheme gives more importance to real-time calls without considering the nature of traffic of nonreal-time calls, the priority of users, and the revenue loss in degrading the call. Mohammed et al. [26] proposed a QoS-guaranteed call admission control algorithm. The algorithm is designed to maximize the system throughput, reduce new connection blocking rate, and increase per-flow throughput for both real and nonreal-time calls. But the scheme does not consider user characteristics and network characteristics in admission control decisions. Maitah et al. [27] proposed a call for admission control using the genetic neuro-fuzzy controller. The decision to accept or deny the call is decided based on the effective capacity and offered load. But it did not differentiate between the services of the calls and user characteristics.

From the survey, there are not many solutions addressing network dynamics and differential QoS in their call admission and bandwidth management decisions. Bandwidth degradation is done as a whole for service type without consideration for differential services and revenue loss. The existing approaches lack evaluation of admission and bandwidth management decisions based on multi-criteria factors like cost benefits, priority, content characteristics, network situation on admission, etc.

3. Proposed Solution

The choice of whether to accept, refuse, or wait is made in the learning assisted-call admission control depending on several factors including priority, service, network conditions, and load conditions. If it is determined to accept the call, aggressive bandwidth adjustment is started to free up bandwidth for a new call if one is not available. There will be no bandwidth modification if the call is judged to be denied. Nonaggressive bandwidth adjustment is triggered to provide room for the waiting call if it is determined that the call is on wait. The adjustment of the bandwidth is based on several criteria, including priority, the nature of the traffic, QoS distortion, etc.

The requested bandwidths are already being used for calls if the bandwidth for the incoming call is immediately accessible. If the incoming call's bandwidth is unavailable, the multifactor bandwidth adjustment is used. To make room for new or changeover calls, multifactor bandwidth adjustment degrades available bandwidth based on several parameters. There are two operating modes for bandwidth adjustment: aggressive and nonaggressive.

The architecture of the proposed learning-assisted admission and bandwidth management solution is given in Figure 1. As in Figure 1, the proposed solution has two important stages: active learning fuzzy logic-based call admission control and multifactor bandwidth adjustment in two modes aggressive and nonaggressive. In the fuzzy logic-based call admission control, the decision to admit, reject, or

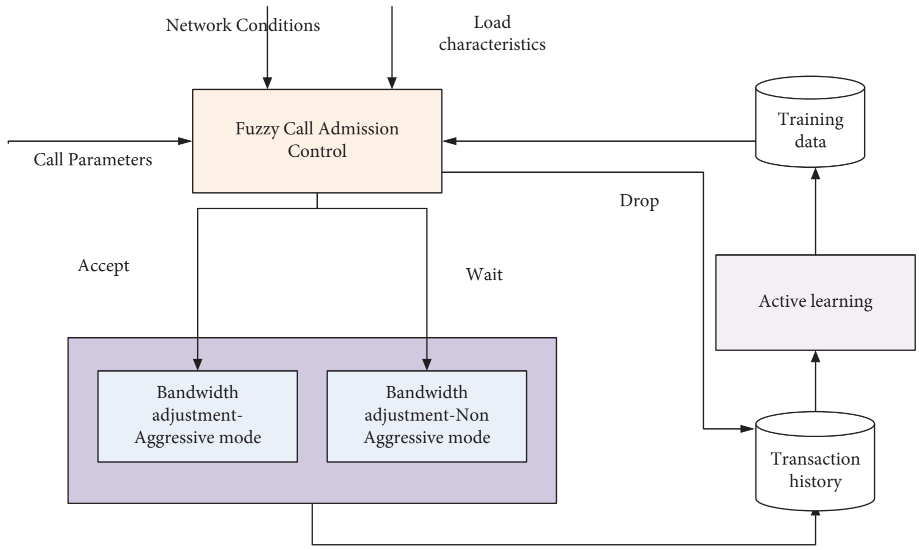

Figure 1: Architecture of active learning assisted admission and bandwidth management.

wait is based on multiple criteria of priority, service, network situation, and load conditions. If the call is decided to be accepted, aggressive bandwidth adjustment is triggered to make way for a new call in case bandwidth is not available. If the call is decided to be rejected, then there is no bandwidth adjustment invoked. If the call is decided to be in wait, nonaggressive bandwidth adjustment is trigged to make way for the waiting call. The bandwidth adjustment is based on multifactor of priority, traffic characteristics, QoS distortion, etc. Each of the stages of the proposed solution is detailed in the below subsections.

3.1. Active Learning Fuzzy Logic Call Admission Control. Call admission control (CAC) is a strategy that provides an efficient means of preventing network congestion and can be crucial in ensuring guaranteed QoS and preventing bandwidth traffic congestion. An accurate determination of whether a connection may be admitted into a resource-constrained network without going against the service guarantees made to the admitted connections is the fundamental purpose of a CAC algorithm. On the other hand, an effective CAC scheme strives to optimize call blocking probability (CBP), call-dropping probability (CDP), and system usage; however standard CAC schemes are not suitable for 5G communications. Fuzzy logic prevents uncertainties in HWN produced by conventional CAC methods. The active learning fuzzy logic call admission controller continuously learns to make the best admission control decision guided by active learning. The parameters used for call admission control in the proposed solution are the priority of the call, type of service, service delivery mode, bandwidth availability for nonscalable calls, bandwidth availability for scalable calls, QoS distortion rate, and the ratio of calls. The possible values for these parameters are given in Table 1. Fuzzy logic call admission control processes the incoming call and provides one of three outputs: accept, deny, or wait.

Typical fuzzy logic systems make the decision on output based on the rule set. Different from it, this work proposed an active learning-based fuzzy logic controller. A training dataset is initially prepared with expert guidance and instead of a rule set; the decision is made based on a labeled training set. The decisions are evaluated against the network situations and continuously updated. In this way, the fuzzy decision becomes adaptive without a fixed rule set. Another advantage of deriving the decision based on the training dataset is that it makes the fuzzy system extendable for new parameters. A training dataset D is created with each having values for input parameters $P1$ to $P8$ and output labels of accept (A), drop (D), and wait (W). This dataset is created by domain experts.

Fuzzy C mean clusterings are executed with datasets with the number of clusters P as 3. Clusters and centers following fuzzy C meaning clusterings are defined like:

$$\mathrm{D} = \left\{\mathrm{D}_{\mathrm{e,q}}\, , \mathrm{e} = 1, 2 \ldots P\, with\, q = 1, 2, 3\right\}, \tag{1}$$

with $\mathrm{D}_{\mathrm{e,q}}$ are qth coordinates for eth clusters.

Nearness of qth features of the r-th information q, r, f and q-th coordinates for e-th clusters are defined use of Gauss functions like in [28].

$$\mathrm{G}\left(\mathrm{f}_{\mathrm{r,q}}, \mathrm{D}_{\mathrm{e,q}}, \sigma_{\mathrm{e,q}}\right) = \mathrm{e}^{\left(\mathrm{f}_{\mathrm{r,q}} - \mathrm{D}_{\mathrm{e,q}}\right)^2/\sigma_{\mathrm{e,p}}^2}. \tag{2}$$

In which

$$\sigma_{\mathrm{e,q}} = \frac{1}{\mathrm{N_e}} \sum_{\mathrm{r}=1}^{\mathrm{N_e}} \left(\mathrm{f}_{\mathrm{r,q}} - \mathrm{D}_{\mathrm{e,q}}\right)^2. \tag{3}$$

Nearness of feature for r-th information toward e-th clusters produced like,

$$\Psi_{\mathrm{r,e}} = \prod_{\mathrm{q}=1}^{\mathrm{P}} \mathrm{G}\left(\mathrm{f}_{\mathrm{r,q}}, \mathrm{D}_{\mathrm{e,q}}, \sigma_{\mathrm{e,q}}\right). \tag{4}$$

Table 1: Admission control parameters.

Parameter	Details	Values
Priority of call ($P1$)	Priority of call is dependent on user type. User who pays a premium price for the services are of a higher priority compared to other users	This work provides two values for priority–high & low
Call category ($P2$)	Call can be a new call or handover call	New call, handover call
Type of service ($P3$)	The calls can be real-time tolerant (RT-TLR), real-time nontolerant (RT-NLR), and non-real-time (NRT)	NRT, RT-NLR, RT-TLR
Service delivery mode ($P4$)	Scalable calls can use multiple RATs in parallel. Nonscalable calls can use only one of RAT at a time	Scalable, nonscalable
Bandwidth availability for nonscalable calls ($P5$)	The total bandwidth available across all RAT	Absolute value
Bandwidth availability for nonscalable calls ($P6$)	The highest of bandwidth available across all the RAT	Absolute value
QoS distortion rate ($P7$)	The highest of QoS distortion across all the RAT	0 to 1
Ratio of calls ($P8$)	The ratio of NRT, RT-NLR, and RT-TLR	x: y: z with $x+y+z=1$

Outputs labels toward e-th clusters are got from the linearity regressions of incoming feature $\mathrm{f}_{\mathrm{r,q}}$ like:

$$\Phi_{\mathrm{r,e}} = \mathrm{W}_{\mathrm{e,0}} + \sum_{\mathrm{q=1}}^{\mathrm{P}} \mathrm{W}_{\mathrm{e,q,f_{r,q}}}. \tag{5}$$

In which, W is the coefficient of regressions coefficients for e-th clusters. As every one of r-th information had membership values for every P cluster, the finality of labeling for those exact links is produced through weights of this label of links and the values of its membership like:

$$\overline{\mathrm{N}}(\mathrm{r}) = \sum_{\mathrm{e=1}}^{\mathrm{P}} \Psi_{\mathrm{r,e}}\Phi_{\mathrm{r,e}}. \tag{6}$$

Magnitudes for $\overline{\mathrm{N}}(\mathrm{r})$ calculates up these might have errors w.r.t. $\mathrm{N}(\mathrm{r})$ from pieces of training. Total errors are evaluated like:

$$\mathrm{E} = \sum_{\mathrm{r=1}}^{\mathrm{N}} \|\overline{\mathrm{N}}(\mathrm{r}) - \mathrm{N}(\mathrm{r})\|^2. \tag{7}$$

The Gaussian parameters $\mathrm{D}_{\mathrm{e,q}}, \sigma_{\mathrm{e,q}}$ with the coefficient of regressions $\mathrm{W}_{\mathrm{e,p}}$ have been tuned toward reducing errors found like the use of methods of gradient descent.

$$\begin{aligned}
\mathrm{D}_{\mathrm{e,q}}(1+\mathrm{t}) &= \mathrm{D}_{\mathrm{e,q}}(\mathrm{t}) + \eta_{\mathrm{C}}\frac{\partial \mathrm{E}}{\partial \mathrm{D}_{\mathrm{e,q}}},\\
\sigma_{\mathrm{e,q}}(1+\mathrm{t}) &= \sigma_{\mathrm{e,q}}(\mathrm{t}) + \eta_{\sigma}\frac{\partial \mathrm{E}}{\partial \sigma_{\mathrm{e,q}}},\\
\mathrm{W}_{\mathrm{e,q}}(1+\mathrm{t}) &= \mathrm{W}_{\mathrm{e,q}}(\mathrm{t}) + \eta_{\mathrm{W}}\frac{\partial \mathrm{E}}{\partial \mathrm{W}_{\mathrm{e,q}}}.
\end{aligned} \tag{8}$$

In which t represents the index of iteration in which, η_C, η_σ, and η_W are the parameter of learning. Stopping interactions are implemented at times of the thresholds of errors getting touched. Beginning with the training in the Fuzzy Gauss member-based function are got to every level to accept, deny and wait in terms of the features $P1$ to $P8$.

For an incoming call I, the features $P1$ to $P8$ are extracted and Gauss-based memberships and functions that are fuzzy are invoked on every one of the classes. The decision for the incoming call is given as the class label of the maximum response Fuzzy Gaussian membership function.

$$I(r = P1, P2 \ldots . P8) = max\left(\Phi_{\mathrm{r,A}}, \Phi_{\mathrm{r,D}}, \Phi_{\mathrm{r,W}}\right). \tag{9}$$

The functions $\Phi_{\mathrm{r,A}}, \Phi_{\mathrm{r,D}}, \Phi_{\mathrm{r,W}}$ can be continuously adapted by modifying the training dataset. Active learning modifies the training dataset based on the evaluation of past actions against the revenue and modifying the labels of the existing tuple of the training dataset or adding new tuples.

Say the training dataset has n tuples and there were M calls over the last period collected in the transaction history. Each of the M calls has been marked with the decisions taken based on the fuzzy membership function derived from n tuples. The revenue gain achieved due to the past decision is calculated as G. A search is conducted for different combinations of decisions for the n tuples under the constraint of bandwidth to achieve higher revenue gain. Since this search is a combination explosion, the search is optimized using particle swarming optimizations.

PSOs are the intelligence of swarming algorithms simulating the socialist behaviors of the swarm of organisms. This method is popular for solving optimization problems due its simplicity, flexibility, and versatility. Organism goes randomly through differing velocities with uses this velocity for updating these positions individually. Every solution of candidates represents a “particle.” Every particle tries to attain the most optimum velocities based on its personal localized most optimum (p_{best}) magnitude with its neighbor’s global best (g_{best}). Each particle’s next position depends on these positions present conquering velocities under substant current velocity, distance from the current position to p_{best}, distance from the current position to g_{best}. The movement of a particle in its search space depends on its velocity. For a particle X, its current position X_i and current velocity U_i are updated as follows:

$$\begin{aligned}
X_i(1+t) &= X_i(t) + U_i(1+t),\\
U_i(t+1) &= wU_i(t) + r_1c_1\left(p_{besti}(t) - X_i(t)\right)\\
&\quad + r_2c_2\left(g_{besti}(t) - X_i(t)\right).
\end{aligned} \tag{10}$$

In the abovementioned equations, t is the iterative value. c_1, c_2 representing coefficients of accelerations. r_2, r_1

represents the random number, and w represents the weight of inertia. This iteration is repeated till the termination condition is met. In this work, a particle is an n item vector with values of A, D, or W. Initially K random particles are created in such a way that bandwidth consumption for the combination is fewer compared to the available net bandwidths in systems. The fitness function for the particle is the revenue for the decisions in that particle. PSO is initiated to find the optimal combination. The PSO iteration is stopped when there is no significant change in gain, between the previous iteration. If the gain achieved for the optimal combination is significantly higher than the gain G achieved over past execution, then the training dataset must be improved, else the training dataset is not updated. The training dataset is updated with labels as found from the optimal combination found by the PSO. Periodically, the past decision is evaluated and if it is suboptimal, it is refined to maximize the revenue.

3.2. Multifactor Bandwidth Adjustment. If the bandwidth for the incoming call is readily available, the requested bandwidths are under allocation toward calls. If the bandwidth for the incoming call is not available multifactor bandwidth adjustment is invoked. Multifactor bandwidth adjustment does bandwidth degradation based on multiple factors to make way for new or handover calls. The bandwidth adjustment works in two modes: aggressive and nonaggressive.

In aggressive mode, the need to accommodate calls is on an immediate basis, so the bandwidth must be claimed even if QoS distortion due to it is a little higher. In nonaggressive mode, the waiting time can be maximally utilized to provide bandwidth at far less QoS distortion rate. A multicriteria importance score is calculated for the ongoing calls based on the call's priority, traffic characteristics, and QoS distortion rate. Traffic characteristics are related to the type of transactions: fault tolerance or nonfault tolerance. Calls involving monetary like trading, and payments are nonfault tolerance. Calls relating to games, entertainment, etc., are fault tolerant. Fault-tolerant is given a score of 5 and nonfault tolerance is given a score of 10. QoS distortion rate is calculated in terms of the number of times the delay exceeded the required delay deadlines. The multicriteria importance score (MIS_i) calculated for each ongoing call is calculated as follows:

$$MIS_i = w_1 P_i + w_2 T_c + w_3 QR_i, \tag{11}$$

where $w_1 + w_2 + w_3 = 1$. P_i is the priority of the call, T_c is 5 or 10 depending on fault-tolerant or nonfault tolerant and QR_i is the QoS distortions so far. Once the calls are sorted on the important factor, the bandwidth adjustment is done on those calls.

The bandwidth to be taken from each call is reduced with the depth of the calls in the sorted list of calls (sorted on multicriteria importance score).

The bandwidth (B) to be taken from ongoing calls in case of aggressive mode is calculated as follows:

$$B = B_o e^{-x}, \tag{12}$$

where B_o is the maximum allowable bandwidth that can be taken from a call exceeding the minimal required capacity and x is the position in the sorted list [29–41].

As shown in Figure 2, as the length of importance increases or for calls deeper in the sorted list, the bandwidth to be taken from it is very less compared to the call in front.

In the case of nonaggressive mode, the bandwidth is taken in small steps expecting that within the wait time some other calls may be closed. So the bandwidth (B) to be taken from ongoing calls in the case of nonaggressive mode is calculated as follows:

$$B = \frac{B_o}{W} e^{-x}, \tag{13}$$

where W is the waiting time for the new call.

4. Results

The proposed solution is simulated in Matlab. The performance of the proposed solution is tested for a heterogeneous network involving 3GPP LTE RAT and IEEE 802.11n LAN RAT. The call is generated by a Poisson process with a mean arrival rate of λ calls/sec. The call hold times were evenly distributed. The performance was tested for three types of calls: VOIP, video streaming, and data on demand. The random walk mobility model is considered for devices. The data created by this code can be used to determine node density, connectivity, moving area graphs, and any other necessary data that can be obtained from the main generated data. This code simulates random mobility models, random waypoints, random directions, and random walks. The simulation configuration is given in Table 2.

Performances of solutions under proposition solution are evaluated by probabilities of droppings of calls for each of the services, QoS violation rate, revenue, delay, and jitter. The performance is compared against the revenue-maximizing RAT selection strategy proposed by the joint admission control solution proposed by Khan et al. [10], Khloussy et al. [12], and the multi-RAT framework proposed by Vimal et al. [13].

Probabilities of blocking calls are compared through the variance of the rates of arrival for data on-demand services with results presented in Table 3.

With the rise in rates of arrivals, the blocking of call probabilities rise, but the drop rate is lower in the proposed solution compared to Khan et al., Khloussy et al., and Vimal et al. The average call drop probability is 0.082 in the proposed solution compared to 0.17 in Khan et al., 0.18 in Khloussy et al., and 0.2 in Vimal et al. The call drop probability is lower in the proposed solution due to two modes of bandwidth adjustment to accommodate calls and provision to maximally use the waiting time of the calls.

Probabilities of blocking calls are compared through the variance of the rates of arrival for data on VOIP services with results presented in Table 4.

With the increase in arrival rate, the average call-blocking probability increases but the value is lower in the

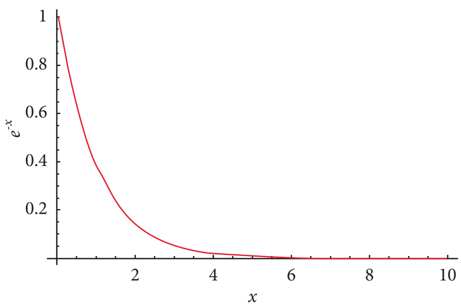

Figure 2: Bandwidth factor degradation.

Table 2: Simulation configuration.

Parameter	Values
LTE bandwidth	20 MHz (100 RB; 180 kHz per 1 RB)
WLAN bandwidth	100 Mbps
VOIP call	Bandwidth max = 1 RB Bandwidth requested = 1 RB Bandwidth minimum = 1 RB Wait time: 300 ms Average call hold time: 3 min
Video streaming	Bandwidth max = 2 RB Bandwidth requested = 1 RB Bandwidth minimum = 1 RB Wait time: 1500 ms Average call hold time: 5 min
Data on demand	Bandwidth max = 3 RB Bandwidth requested = 2 RB Bandwidth minimum = 1 RB Wait time: 10000 ms Average call hold time: 9 min
Revenue	Data on demand: 1 Voice: 2 Video streaming: 3
Simulation time	30 min

Table 3: Call blocking probability for data services.

Arrival rate	Proposed	Khan et al.	Khloussy et al.	Vimal et al.
5	0	0	0	0
10	0.02	0.17	0.19	0.20
15	0.12	0.23	0.25	0.27
20	0.19	0.28	0.30	0.33
Average	**0.0825**	**0.17**	**0.18**	**0.2**

proposed solution compared to existing works. The average call-blocking probability is 0.04 in the proposed solution but it is 0.18 in Khan et al., 0.20 in Khloussy et al., and 0, 22 in Vimal et al. The call drop probability is lower in the proposed solution due to active learning-based admission control based on revenue maximization.

Probabilities of blocking calls are compared through the variance of the rates of arrival for data on video streaming services with results presented in Table 5.

The call drop probability increases with an increase in arrival rate, but the increase is lower in the proposed solution compared to existing works. The average call drop probability in the proposed solution is 0.02 but it is 0, 15 by Khan et al., 0.17 by Khloussy et al., and 0.21 by Vimal et al. The QoS violation rate is measured at the end of the simulation for different types of services and the result is given in Figure 2. The QoS violation rate is marginally higher in the proposed solution at 0.32 compared to 0.25 at Khan et al., 0.26 at Khloussy et al., and 0.28 at Vimal et al. This higher value in the proposed solution is due to a reduction in QoS violation at 0.26 at the proposed solution for VOIP call and 0.24 for video streaming. Khan et al. have 0.28, Khloussy et al. have 0.33, and Vimal et al. have 0.35 for VOIP call which is higher compared to the proposed solution. Khan et al. have 0.32, Khloussy et al. have 0.36, and Vimal et al. have 0.37 for video streaming calls which are higher compared to the proposed solution. The proposed solution has reduced the QoS violation rate due to effective bandwidth allocation for the calls. Figure 3 shows a comparison of QoS violation rate.

Table 4: Call blocking probability for VOIP services.

Arrival rate	Proposed	Khan et al.	Khloussy et al.	Vimal et al.
5	0	0.12	0.13	0.15
10	0.02	0.15	0.16	0.17
15	0.06	0.21	0.24	0.26
20	0.09	0.24	0.27	0.30
Average	**0.04**	**0.18**	**0.20**	**0.22**

Table 5: Call blocking probability for video streaming services.

Arrival rate	Proposed	Khan et al.	Khloussy et al.	Vimal et al.
5	0	0.11	0.12	0.13
10	0.01	0.13	0.15	0.16
15	0.03	0.17	0.18	0.26
20	0.06	0.20	0.22	0.30
Average	**0.02**	**0.15**	**0.17**	**0.21**

The total revenue at end of simulation times is under measurement toward the solutions and results are given in Figure 4. The proposed solution has 9.24% higher revenue compared to Khan et al. 9.04% higher revenue in comparison to Khloussy and others, and 8.56% larger revenue in comparison to Vimal and others. The revenue has increased in solutions under the proposition for framing of training set based on revenue maximization and making call admission decisions based on the training set.

The average delay and jitter are measured for VOIP calls and video streaming calls at end of simulation time and the result is given in Table 6. The average delay for VOIP calls is at least 34% lower compared to Khan and others, 35.6% lower compared to Khloussy and others, and 67% lower compared to Vimal et al. The average delay for video streaming calls is at least 34% lower compared to Khan and others, 65.89% lower compared to Khloussy and others, and 66.56% lower compared to Vimal et al. The average delay is reduced due to the provision of sufficient bandwidth and degradation based on multicriteria factors when need to accept new/handover calls. The average jitter for VOIP calls is at least 3.9% lower compared to Khan and others, 6.93% lower in comparison with Khloussy and others, and 98% lower in comparison with Vimal and others. These average jitters for video streaming calls are at least 22.42% lower

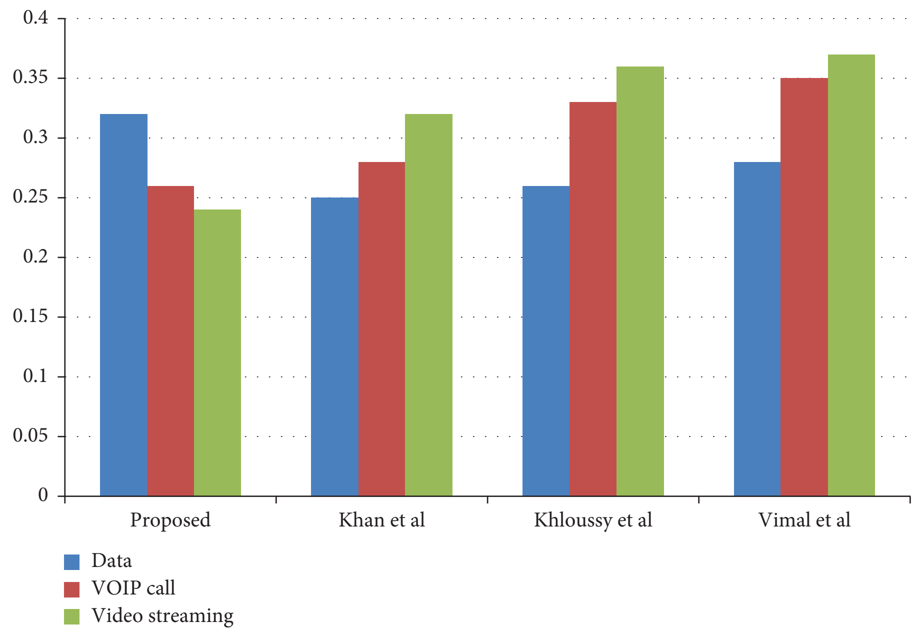

FIGURE 3: Comparison of QoS violation rate.

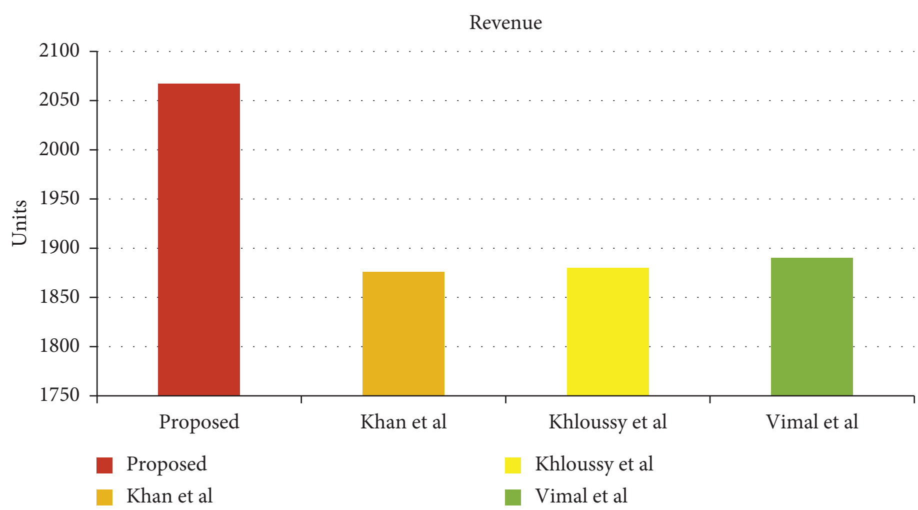

FIGURE 4: Comparison of revenue.

TABLE 6: Comparison of delay and jitter.

	Delay (ms)			
Service	Proposed	Khan et al.	Khloussy et al.	Vimal et al.
VOIP	30	40.2	40.7	50.1
Video streaming	30.2	40.5	50.1	50.3
	Jitter (ms)			
VOIP	10.1	10.5	10.8	20
Video streaming	10.7	13.1	17.4	18.7

compared to Khan et al. 62.6% lower compared to Khloussy and others with 74.7% lower compared to Vimal and others. Jitters have reduced inside the solutions under proposition as provision for sufficient bandwidth for VOIP and video streaming calls due to their higher revenue.

5. Conclusion

Active learning-assisted call admission and bandwidth management solution is proposed in these works. The call admission is on basis of multiple factors of priority, service, network situation, and load conditions with the ultimate goal of revenue maximization. The call admission control logic can be easily adapted by modifying the training dataset. Bandwidth adjustment proposed in this solution has two modes aggressive and nonaggressive which have high adaptability to dynamic load characteristics. This higher value in the suggested solution is caused by a decrease in QoS violation, which is 0.26 for VoIP calls and 0.24 for video streaming in the suggested solution. Due to excellent bandwidth allocation for the calls, the suggested method has reduced the rate of QoS violations. The total revenue after the simulation is measured against the solutions. The proposed approach has higher revenue which is 9.24%, 9.04%, and 8.56%. Under the proposal for framing the training set based on revenue maximization and basing call admission decisions on the training set, revenue has increased in solutions. The proposed solutions are capable of achieving reduce the call block probability up to 0.08 for data on-demand services, up to 0.04 for VOIP services, and 0.02 for video streaming services. The proposed solution is also able to reduce the delay by 34% and jitter by 3.9% for VOIP services, reduce the jitter by 3.9%, and jitter by 22.42% for video streaming services compared to existing works.

Data Availability

The datasets used and/or analyzed during the current study can be obtained from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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