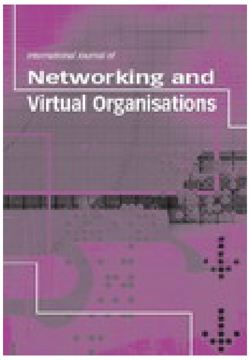

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Efficient call admission control in LTE networks with cascade feed forward network

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Abstract: This research proposes a cascade feed forward network (Cascade FFN) for the optimal call admission control (CAC) over networks. Initially, the long-term evolution (LTE) network is simulated and the incoming call is recognised as a new call or else handoff call. Likewise, the handoff call is identified by various channel parameters. Finally, the CAC is performed using the Cascade FFN, which is obtained by incorporating the deep feed forward network (DFN) and cascaded deep neuro-fuzzy network (DNFN). After the admission of the new user, number of active users in the individual cell is updated. The simulation is performed based on various parameters and the proposed model has gained throughput of 444058 bps, cell power of 54.267 dBm, delay of 0.081 s, user call drop of 940, call blocking probabilities of handoff and new user as 0.693, and 0.677; and the call dropping probabilities of handoff and new user is 0.733, and 0.740.

Keywords: long term evolution (LTE) networks; CAC; call admission control; QoS; quality-of-service; DL; deep learning; FFN; feed forward network.

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1 Introduction

In future generations, wireless telecommunication will enlarge its network by providing services by integrating audio, information, and compact disks with a decreased amount of power and low-cost mobile computing devices across the wireless medium (Shafi et al., 1997). The QoS is necessary to support various network-incorporated services by rectifying the major challenges that occur from resource provisioning. One of the specific provisioning approaches is CAC. The CAC is utilised for resolving congestion and call-dropping issues by restricting the enormous amount of call connections into the network. The call connection dropping may occur because of the movement of the users; this is considered another important branch in mobile communication networks (Fang and Zhang, 2002). Usually, the CAC approach diminishes the possible occurrence of traffic and holds a provident function by serving the QoS. The assured QoS is provided by effectively avoiding traffic congestion through the utilisation of CAC techniques. The implemented algorithm enables one to make an accurate decision on whether the call is connected or dropped. A well-organised CAC approach can enhance the blocked call or dropped call possibilities and the overall system utilisation (Deshmukh and Deshmukh, 2013; Asuquo et al., 2014; Al-Maitah et al., 2018). In the view of fourth-generation (4G) wireless communication networks, developing multimedia applications through various QoS in the appearance of diversified access to wireless technologies (Yarrabothu et al., 2020; Zhang and Li, 2021) is the most difficult problem. This kind of network depends on the network requirements like bandwidth, mobility, and application necessities, and the user mobility across the network in an imbalanced manner.

In heterogeneous models based on wireless systems for supporting a multiple variety of implementations is mostly based on two components, such as effective radio resource control and CAC strategies. In CAC-based schemes, it gradually maintain the QoS delivery to different users based on the objective level by preventing the amount of current calls in the network structure. However, in early voice-enabled circuit-switch based mobile cellular networks, the development of 4G network is based on packet switching technique at the wireless medium and the operations are implemented by the utilisation of IP-based network architectures. For this kind of network function, the packet level performance metrics like the probability of packet dropping, and delay occurring on packet transmission from wireless and wired mediums are considered along with the call level performance metrics for the development of the CAC model (Niyato and Hossain, 2005). In cellular networks, the CAC plays an essential part in providing an assured QoS. In contrast, the prior models on CAC are engaged only on the tradeoff in both call blocking and handoff probabilities and it was not limited to the issues created based on wireless network congestions. A novel reformation of cores and physical layer models based on LTE (Pradeep and Lakshminarasimman, 2020; Rao Challagundla et al., 2020) provides essential improvements in early-designed technologies such as universal mobile telecommunication models and high-speed packet access approaches. The process handover or handoff is defined as a processing of call transferring between one cell to another cells. The call transfer from one communication medium to another medium is operated based on time slots, utilised frequency bands or code for the newly developed base station (BS) (Tekinay and Jabbari, 1991; Pollini, 1996; Marichamy et al., 1999).

The transfer function is performed in the latest ground control station; if it has empty cells then the call is initiated to the corresponding channel as the hand-off call. Dropping the call and call delay are the most important possible occurrences while all the channels are utilised at the time of handoff instance. Various handoff approaches were developed for the implementation and evaluation of the probabilities of forced termination and blocking of the call. The forced extinction possibility is derived based on the prospect of the falling of a connected call because of the failure in handoff. The call blocking probability is termed the blocking probability of the new call request (Tekinay and Jabbari, 1992; Iera et al., 2002). Presently, handoff schemes are implemented to diminish the probability of forced termination without affecting the cal-blocking abilities (Ekiz et al., 2005). For the efficient construction of mobile communication in the future a network machinist, seller, access supplier, service contributor, software developer, content supplier, and client-included flexible network is necessary. It is anticipated that the LTE-based system models will be cross-connected in large quantities and supply an enlarged coverage of the marketplace. Furthermore, the procedure for access and transmission-based approaches is widely developed in terms of required transmission bandwidth and QoS of the mobile communication mediums. The customer's expectations on coverage and QoS increase continuously. Thus, it is important to construct a superior LTE network from the early stage of their deployment (Jadhav and Kolekar, 2019).

The principle propose of this research is to implement an effectual CAC in LTE networks namely, Cascade FFN. This is devised by the combination of DFN (Zhao et al., 2018) and DNFN (Hu et al., 2017). Initially the LTE network is simulated. The incoming call is recognised as fresh or handoff calls. The determination of a fresh call is derived based on user parameters and cell parameters. Subsequently, the handoff call recognised based on channel parameters. Finally the CAC is performed using proposed Cascade FFN.

The major contribution is highlighted as follows,

- **Proposed Cascade FFN for optimal CAC in LTE networks:** This investigation implemented a successful model for call admission control (CAC) in LTE networks by developing a fuzzy network model, named as Cascade FFN.

The remaining part of this research is prepared as follows: Section 1 illustrates the basic concept of the paper. In Section 2, the literature survey of the work is deliberated with various issues of the existing works. Section 3 shows the system model of the utilised network; Section 4 explains the proposed cascade FFN approach for CAC. The result of the Cascade FFN technique is illustrated in Section 5. In Section 6, the conclusion of the developed model is presented with its future scope.

2 Motivation

The CAC offers a satisfied QoS and network-based user requirements in wireless communication. Various CAC-based approaches are designed and their evaluation results do not satisfy some assumptions and user needs in respect to the probability of call-blocking due to the mobility of user. This situation occurred when the holding time of the channel and new and handoff calls were not balanced.

2.1 Literature survey

Zarai et al. (2014) developed an RBR-CAC approach for LTE networks the devised model, which attained call admission as handoff and new call situations while the residual resources. The initiated resources block the incoming handoff call from the neighbour directly this is held as a new call. However, this approach failed to expand the protocol for assuring the QoS in the states of call blocking and professed size of the call in the wireless heterogeneous network. Vulpe et al. (2017) employed M-CAC for CAC for multi-carrier systems. This model utilised multiple accumulation of LTE components and the user radio circumstances and QoS to enhance the throughput of the user. However, this model did not introduce numerous QoS segments for users and also did not develop a most favourable energy allotment procedure. Kim et al. (2015) implemented aP-CAC for serving video streaming control over LTE networks. The devised model obtained improved QoE and the network consumption in a cell via scene freezing period, throughput, and the amount of admitted UEs. However, this approach failed to analyse the effects of system parameters and did not examine their standards systematically. Zhang and Zhang (2017) designed a T-CAC in heterogeneous networks. This system enhanced the residual power resource with scarce channel resources; this enabled the two joint power and channel reservation schemes in the real system. Moreover, this model was further enhanced by improving the user experience, reducing costs, and efficient resource utilisation in multi-network syncretic mobile communication.

Umar et al. (2021) devised an enhanced adaptive call admission control (EA-CAC) for LTE networks. This model effectively diminished the bandwidth wastage. In addition, it increased throughput range. However, this model failed to combine bandwidth alteration approaches to ensure bandwidth is unconfined via calls utilised to connect afresh call requests. Evelyn et al. (2022) presented a fuzzy logic-based call admission concept for mobility management in LTE networks. The Queuing technique was derived to control the new and handoff calls through a queuing model. However, this approach failed to ensure the QoS as per the user requirements. Suresh and Kumaratharan (2021) implemented an Artificial Fish Swarm Algorithm Fuzzy Inference System (FIS-AFSA) for cloud radio access networks. The employed optimisation approach effectively reduced the traffic congestions occurred on the 5G networks. Also, various external calls were condensed because of the diminution of resource utilisation in personal cloud communications. However, this model failed to be deployed in other networks for decision-making. Zreikat (2022) developed an intelligent multi-cell CACA for load balancing in 5G networks. This scheme limited the user admittance based on a threshold value, a large space from the base control station, along with the utmost amount of energetic users obtained in the specific cell. However, this method failed to incorporate various traffic scenarios to reduce the homogeneous traffic over all cells.

Goyal et al. (2018) presented a fuzzy logic-based optimisation algorithm for enhancing mobility robustness and load balancing in LTE/4G networks. They incorporated optimisation techniques to fine-tune the fuzzy logic system for enhancing the performance of mobility robustness and load balancing. This method improved the robustness of mobility, reduced the frequency of unnecessary handovers and thereby enhanced user experience. However, the performance of the fuzzy logic system heavily depends on the selection of input parameters and membership functions, which may require extensive tuning and expertise.

2.2 Challenges

The issues handled by various prior models implemented for the CAC in LTE networks are explained in the following portion.

- The model developed in Zarai et al. (2014), for the efficient mobility control and assures QoS in wireless mobile networks. However, in this approach the resource allocated in the neighbouring cell is utilised by few handoff call thus the allocated resources are wasted, it attained poor resource utilisation.
- The developed model in Kim et al. (2015) attained improved information rates. Furthermore, it is a challenging task while it turn in respect to the varied data service achieved and enhanced the quality across the wireless mobile network.

- The employed model in Evelyn et al. (2022), for the efficient mobility control in LTE networks. In this strategy, the acquired calls were not beat the queue volume in the base control station. The approach was developed to drop incoming call in an automatic manner, through conjunction occurred in the queued handoff calls and this diminished the effectiveness of the network.
- In Zreikat (2022), implemented an intelligent multi-cell CACA approach assisted for 5G networks. This approach failed to analyse and incorporate different propagation architectures, such as urban, sub-urban, and rustic environments for the computation of capacity of practical environments.
- The CAC is employed for maintaining the equalisation among handoff call and initiated call blocking and the possibility of handoff call blocking is efficient than the possibility of new call jamming. Therefore developing a handoff call priority based model deployed in wireless network is an important measure in this era.

3 System model

In wireless telecommunication, the LTE network (Jadhav and Kolekar, 2019) has several cells with a limited amount of channels and offers high-speed services to mobile users. The cell reservation is the process that is reported to its adjacent cells frequently. The lifetime of the call depends on the maintenance of distribution through the call. The direction factor is utilised for selecting the desired cell for the hand-off call.

3.1 Network traffic modelling

The call admission of the time-varying channel depends on the position. Some channel parameters, like channel state, location, queued status, and application layer requirements are considered for the development of QoS-based dynamic system. Here, the communication period is initiated and the corresponding channel is cultivated into segments based on resources. At first, the status of all the channel parameters is analysed by the scheduler before block allocation which assists in computing the power consumption and obtained throughput of individual cells. The mobile users are separated into the following three classes with unique characteristics. These classes are explained as.

3.1.1 Video-streaming users

It represented high-definition resolution videos by utilising the Best Effort (BE) Queuing characteristics. The on-time service delivery and traffic control approaches give a service assurance requested by the user. The service delivery depends on traffic class-based prioritisation schemes.

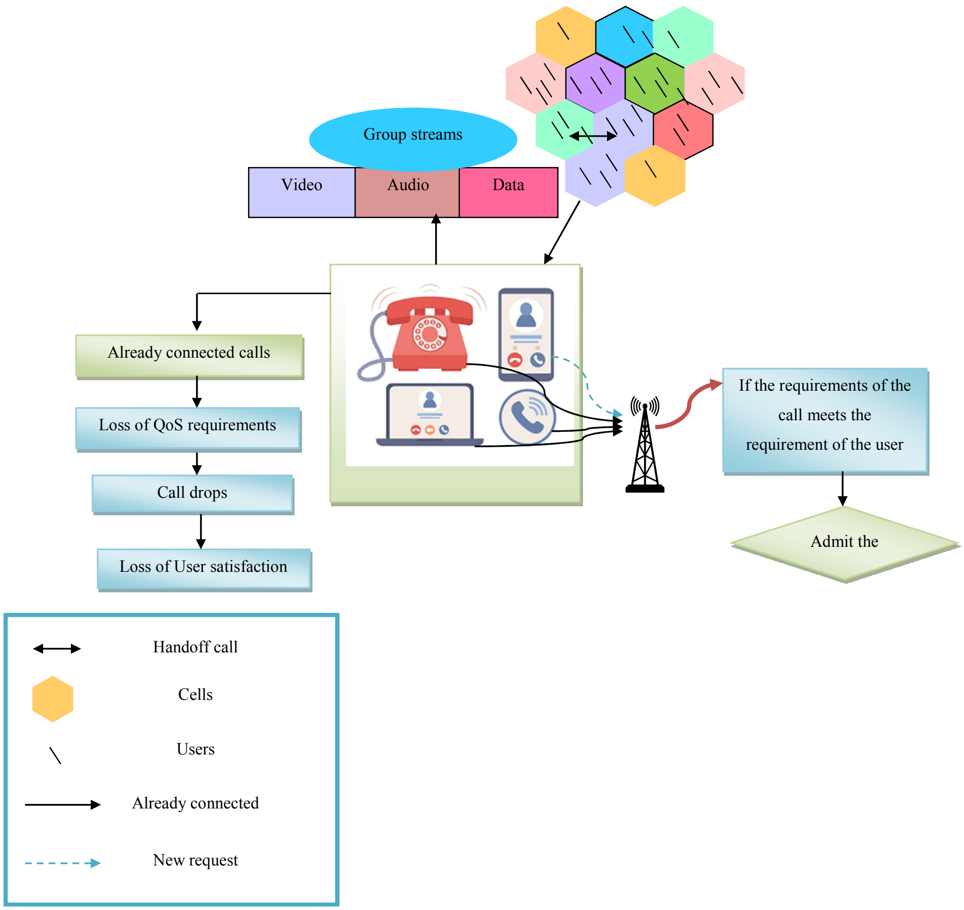
3.1.2 VoIP conversational users

The variable bit rate (VBR) is the kind of characteristic of a queue. The QoS obtained on behalf of the visual users is continually underprivileged and the network congestion with moderate bit rate level is still insensible to QoS.

3.1.3 Document streaming users

The property of the stack is distinct as the constant bit rate (CBR) Queue. The streamed file transformation utilises the queuing strategies. Figure 1 shows the system design of the LTE network.

Figure 1 System design of the LTE network (see online version for colours)

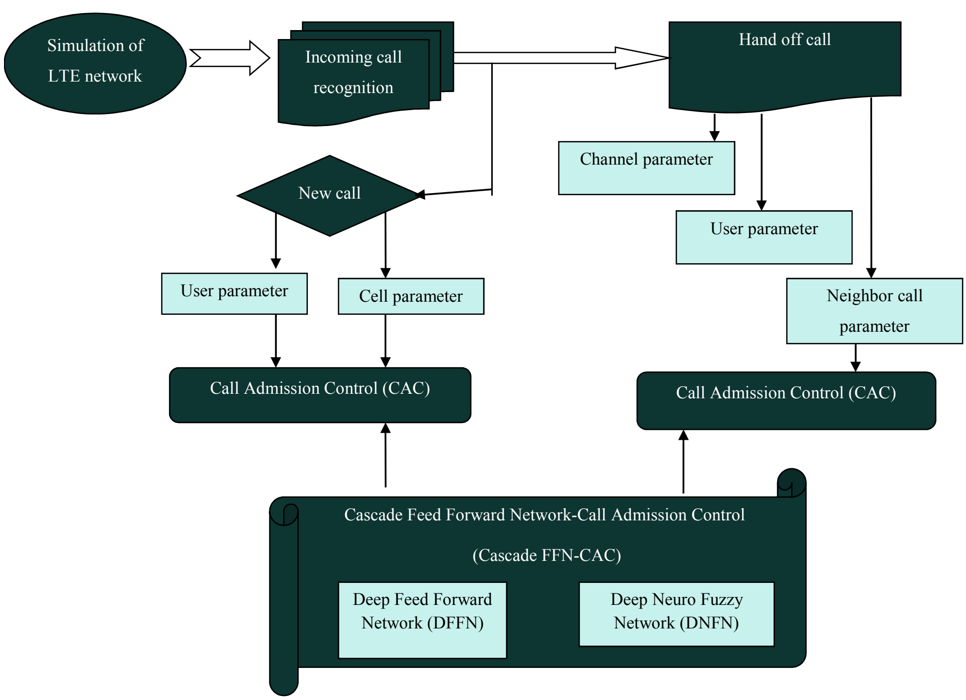


4 Proposed cascade FFN model for call admission control

The LTE is the intelligible network that provides user-demand services and the implementation of LTE is exponentially growing because of its on-demand services with assured QoS. The CAC approach has major issues for assuring the QoS. The activation of efficient QoS guaranteed the connection without dropping and handoff issues (Jadhav and Kolekar, 2019). At present, reservation and bandwidth degradation-based schemes are implemented for the effective utilisation of the network and provide assured QoS for call admission. However, regardless of various requirements, they remain unsuccessful.

To ensure the essential QoS by means of the obtainable capitals in the deployed network, this work develop Cascade FFN for CAC in the LTE networks. Effective CAC helps in managing network resources efficiently, ensuring that the network can handle new and handoff calls without degrading performance. The proposed model enhances the overall network performance by reducing call drop and blocking probabilities, increasing throughput, and minimising delays. Initially, the LTE network is simulated. After that, the incoming calls are recognised as either new calls or handoffs. For finding new calls, there are two parameters like the user required parameters and specific cell parameters are considered. The user parameters considered are path loss of the user, signal to interference noise ratio (SINR), throughput of the user, reference signal received power (RSRP), and delay of the user. The cell parameters including the power of the cell, number of users, subcarrier power, throughput of the cell, and cell coverage are considered (Zreikat, 2022). On the other hand, for finding a handoff call, the channel parameters such as channel bandwidth and channel holding time, the user parameters, and the neighbour cell features are considered. Thereafter, CAC is performed using the Cascade FFN, which is obtained by the combination of deep feed forward network (DFN) (Zhao et al., 2018) and deep neuro fuzzy network (DNFN) (Hu et al., 2017). After connecting the new user, the amount of active users in each cell is modified. Figure 2 illustrates the block diagram of Cascade FFN for CAC in LTE networks.

Figure 2 Block diagram of cascade FFN for CAC in LTE networks (see online version for colours)



4.1 Incoming call recognition

The incoming call is acknowledged via a fresh or handoff calls. The determination of a fresh call is derived based on user parameters and cell parameters. The user parameters are grouped based on the path loss, SINR, RSRP, throughput and delay of the user. In addition, the power of the cell, number of users, subcarrier power, throughput of the cell, and cell coverage are taken as cell parameters. Subsequently, the identification of the handoff call is based on channel parameters, like channel bandwidth and channel holding time, the user parameters, and the neighbour cell parameters.

4.1.1 User parameter

The reorganisation of new and handoff calls depends on the following user parameters.

a *Path loss of the user*

The path loss is termed as a degradation or defect of electromagnetic signals during the transmission. This degrades the quality of the transmitted signal at the receiver end. It is measured by the evaluation of the energy of the transmitted signal, gain from the antenna, frequency, and distance of the utilised communication medium.

$$P_l = m + n * \log_{10} d_{BS} \tag{1}$$

where, d_{BS} represents the distance between the user and the base control station, and m, n represents the consumer constraints.

b *SINR*

The SINR is considered to compute the strength of the transmitted data by comparing the necessary signal to the redundant intrusions and noisy parameters.

$$S_{\text{int}} = \left[10^{\left(-\frac{1}{n}\right)} \right] * \frac{E_c}{\sum_{a=1}^{\phi} 10^{\left[\frac{-l^{out}}{n}\right]} \times E_c} \tag{2}$$

Here, S_{int} represents the ratio of signal to interference, n denotes a constant, E_c indicates the cell power, and l^{out} represents the outdoor power loss.

c *RSRP*

The reference signal is an un-modulated signal containing the resource parameters, and the received power from the reference signal is computed based on the power received by the communication network.

$$RXP = E_{sc} + A_g + U_{pl} \tag{3}$$

where E_{sc} represents the sub-carrier power, A_g indicates antenna gain, U_{pl} denotes the user path loss.

d *Throughput of the user*

The throughput is measured through the evaluation of effectively transmitted and acknowledged information at various instances of time.

$$P_T = \min\left[\Delta, \Delta_{\max}\right] * X * Y * \log_2\left(1 + \lambda * I_{SN}\right) \quad (4)$$

where X indicated as constant, Y represents the symbol per bit, Δ is calculated by $\Delta = B_R * K * S$, here, S denotes the total amount of users, B_R indicates the resource block. $\lambda = \frac{-1.5}{\log(5\times\alpha)}$, here α is a constant, and $\Delta_{\max}$ represents the maximum amount of utilised resource power.

e *Delay of the user*

The delay that occurs in the communication medium is denoted as the time consumed by the data transformation over the network.

$$\delta = \frac{G}{H} \quad (5)$$

where δ is the user delay, G represents the total amount of bits, H indicates the added buffer.

4.1.2 Cell parameter

The considered cell parameters such as the power of the cell, subcarrier, throughput, and coverage are described as follows,

a *Power of the cell*

The cells are the distributed space like radio, cellular, and mobile network which is linked with a specific base control station. It cell is computed by using the following expression,

$$C_p = \max\left[\min\left(\left(x * \max\left[P_{crs}\right] + w * \log_{10} \kappa_{\max}\right) + y, \rho_{\max}^{\Omega}\right), \rho_{\min}^{\Omega}\right] \quad (6)$$

where P_{crs} is developed $P_{crs} = C_{sub} + J_{sub} - D_{out}$ here, C_{sub} represents the power of the sub-carrier cell, J_{sub} represents the gain, $\rho_{\max}^{\Omega}$ represents the maximum energy of the Ω cells.

b *Subcarrier power*

A subcarrier is a reconstructed signal generated by modifying the frequency to transmit additional information. This is computed as follows,

$$\varphi = n * \log_{10}\left[10^{\left[\left(\frac{E_c}{n}\right) \Big/ \left(\frac{\tau}{f}\right)\right]} * 1000\right] \quad (7)$$

where f represents a constant and φ denotes the power of subcarrier.

c *Throughput of the cell*

The throughput is the rate measured in terms of the effective packet delivery of the cells. The throughput of the cell is formulated as,

$$c_t = \sum_{g=1}^{\beta} C_u^v \tag{8}$$

where, C_u^v represents the throughput of the v^{th} user.

d *Cell coverage*

The parameter cell coverage is obtained as the percentage of space that has received a transmitted signal at a minimum rate of power. The cell coverage is computed as,

$$\theta_{\max}(l) = \left(\left(Q - \frac{\chi \cdot (4\pi r)^2}{\varpi \cdot (\pi)^2} \right) \cdot \psi \right) + 1 \tag{9}$$

4.1.3 Channel parameter

The channel parameters like holding time and channel bandwidth are considered for call recognition that is elaborated in the following section.

a *Channel holding time*

It is measured by the duration taken by cell to designate and utilise a channel before handoff. This is computed by considering the holding time and the location of the cell.

$$h(T) = \min\{\mu, v\} \tag{10}$$

where μ represents call residency time and v denotes residual lifetime of call holding time.

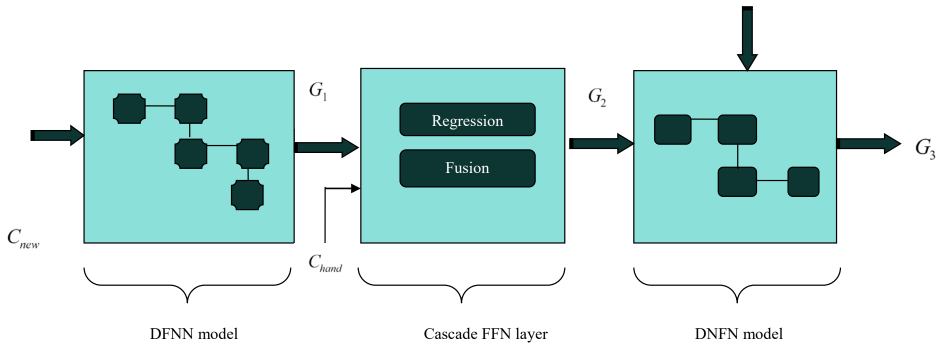
b *Channel bandwidth*

The optimal bandwidth coupled with the frequency reuse factor is the bandwidth. The optimal bandwidth was selected through the ratio of uplink and downlink parameters.

4.2 Call admission control

Here, a Cascade FFN model is urbanised for CAC. The call admission is recognised as either a fresh or a handoff call. The input C_{new} is given to the DFNN which is taken as a user and cell parameters of the new call. Here, the data is progressed and obtained the outcome is indicated as G_1, which is subjected to the Cascade FFN layer along with the hand-off parameters. The Cascade FFN layer has regression and fusion sections. The regression node examines the similarity among the target and the selected parameters. The fusion is performed on the separated features and the fused output from the cascade FFN layer G_2 is given to the DNFN model the detected end result is G_3. The network structure of Cascade FFN is designed in Figure 3.

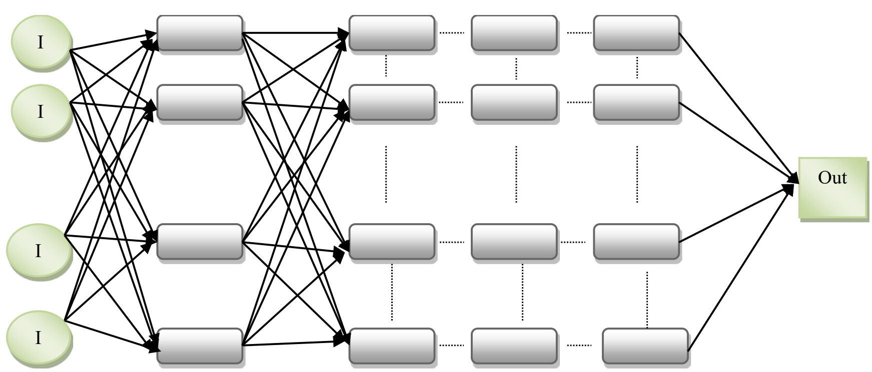
Figure 3 Network design of cascade FFN (see online version for colours)



4.2.1 DFNN model

The mathematical design of DFNN (Luo et al., 2020) was developed by imitating the human brain process details. In general, these DFNN approaches contain three specific segments, such as input, hidden, and output layer. The amount of hidden layers shows the deep architecture of the implemented model. The hidden layer with an increased quantity of neurons in DFNN provides a dataset with various levels of identification. Figure 4 shows the architecture diagram of the DFNN.

Figure 4 Architecture diagram of the DFNN model (see online version for colours)



Let us consider the training dataset developed via the traditional historical data having input database $T = \{T_t | t = 1, 2, 3, \ldots, S_{in}\}$ and output data as $V = \{V_v | v = 1, 2, 3, \ldots, j\}$. The variables available in the input are defined as A at R total trained samples. Assume that each kind of input variants had the same sample time, the input database becomes,

$$V_R = \{r_{t,v} | v = 1, 2, 3, \ldots, T\} \tag{11}$$

The v^{th} training sample, the obtained first hidden layer of the i^{th} neuron is computed as follows,

$$V_{1,t_1} = k\left(\sum_{t=1}^{t=S_{in}} \left(H_{in.,t,1,i_1}\right)\right) \tag{12}$$

When i_x^{th} neuron presented in the hidden layer is calculated as,

$$V_{x,i_x} = k\left(\sum_{i_{x-1}=1}^{i_{x-1}=S_{hid,x-1}} \left(H_{x-1,i_{x-1},x,i_x} G_{x-1,i_{x-1}}\right)\right) \tag{13}$$

Therefore, the available neuron in the last layer is formulated as,

$$G_1 = k\left(\sum_{i_y=1}^{i_y=S_{hid,y}} \left(H_{y,i_y,P} G_{y,i_y}\right)\right) \tag{14}$$

where, h represents the weighting factor between the neurons, t denotes the volume of neurons in the first layer, x represents the amount of hidden layers, i_x indicates the neurons presented in the second layer, and k indicates the creation function.

a *Activation function*

The activation function is tested for achieving the better prediction performance by considering the following activation functions,

Sigmoid function, $f(X) = \dfrac{1}{1+e^X}$ (15)

Hyperbolic tangent function $f(X) = \tanh(X)$ (16)

Rectified Linear unit function $f(X) = \begin{cases} 0 & for \quad X < 0 \\ X & for \quad X \geq 0 \end{cases}$ (17)

Exponential Linear function $f(X) = \begin{cases} e & for \quad X < 0 \\ X & for \quad X \geq 0 \end{cases}$ (18)

b *Learning approach*

The learning approaches are utilised in DFNN is to reduce the mean absolute error percentage among desired outcome V and formed $\hat{V}$ by varying the weight factors. The combined weight factor is expressed as follows,

$$\begin{aligned} H = &\left\{H_{in,t,1,i_1} \middle| S_{in} \geq t \geq 1, S_{hid,1} \geq i_1 \geq 1\right\} \cup \left\{H_{x-1,i_{x-1},x,i_x} \middle| y \geq x \geq 2, S_{hid,x-1} \geq i_x \geq 1\right\} \\ &\cup \left\{H_{y,i_y,P} \middle| S_{hid,y} \geq i_y \geq 1\right\} \end{aligned} \tag{19}$$

4.2.2 Cascade FFN model

The output from the DFNN model and the handoff call parameters are fed into the input for cascade FFN model. In DFNN, the input is taken as follows,

$$V = \sum_{b=1}^{z} K_b * N_b \tag{20}$$

Utilising the fractional concept, the G_2 becomes,

$$G_2 = \chi * V + \frac{1}{2} * \chi * G_1 \quad (21)$$

Here, V represents the outcome from the l^{th} interval and V_1 represents the output from $(l-1)^{th}$ interval.

The G_2 represents the output of the Cascade FFN layer, which is derived as,

$$G_2 = \chi * \sum_{b=1}^{z} K_b * N_b + \frac{1}{2} * \chi * G_1 \quad (22)$$

4.2.3 DNFN model

A customised practice was implemented for training the CAC systems (Bodyanskiy and Tyshchenko, 2019). The new procedures are incorporated for the optimisation of neurons in a pool is considered for modelling by utilising the new methodology of the constructed nodes beside with innovative learning models. Initially, the vector function is expressed as,

$$p(q) = \left(p_1(q), \ldots, p_m(q) \cdots p_y(q)\right)^W \in \Re^c \quad (23)$$

where, $q = 1, 2, 3, \ldots.$ represents the present sampling time obtained from the model's sympathetic layer.

This information is fed into the input to each node of DNFN, and comprehensive fuzzy neurons are utilised as nodes and categorised by enhanced validation measures when divergent to conventional neurons. The DNFN contains conjunctions of additional complicated character that develop it to possibly function in arbitrary functions.

Here d represents the amount presented layers and its quantities are modified during learning state. The output $\hat{z}_c^{[d]}(q)$, which develops an ensemble and executed in the generalised nodes. This integrates the optimal possible output $\hat{z}_c^{*[d]}(q)$ of an ensemble and each layer is weighted using linear combinations. The input layer volume of the second layer is derived as,

$$p^{[2]}(q) = \left(p^W(q), \hat{z}^{*[1]}(q)\right)^W \in \Re^{c+1} \quad (24)$$

Similarly, for third layer the above expression becomes,

$$p^{[3]}(q) = \left(p^W(q), \hat{z}^{*[1]}(q), \hat{z}^{*[2]}(q)\right)^W \in \Re^{c+2} \quad (25)$$

The general equation for the d^{th} hidden layer is formulated as,

$$p^{[d]}(q) = \left(p^W(q), \hat{z}^{*[1]}(q), \hat{z}^{*[2]}(q), \cdots, \hat{z}^{*[d-1]}(q)\right)^W \in \Re^{c+d-1} \quad (26)$$

At the instance, all the layers are trained through the online mode successively as a data obtained at the final process of the prior model.

The fuzzy neuron is termed as a training structure having nonlinear action with varied appearance of signals and an Individual output value to carried out as follows,

$$\hat{\omega} = \sum_{\sigma=1}^{v} g_{\sigma}\left(s_{\sigma}\right) \tag{27}$$

where, s_{σ} represents the module, $\hat{\omega}$ indicates the scalar output of the network. The entry of σ^{th} element is derived as,

$$g_{\sigma}\left(s_{\sigma}\right) = \sum_{\eta=1}^{v} \beta_{\mu\sigma}\omega_{\eta\sigma}\left(s_{\sigma}\right) \tag{28}$$

where $\beta_{\eta\sigma}$ indicates the weight of the nonlinear synapse, $\omega_{\eta\sigma}\left(s_{\sigma}\right)$ represents the membership relation. The reduced conversion performance is formulated as,

$$\hat{\mu} = \sum_{\sigma=1}^{v}\sum_{\eta=1}^{v} \beta_{\mu\sigma}\omega_{\eta\sigma}\left(s_{\sigma}\right) \tag{29}$$

Inside the neo-fuzzy neuron this modelling offers triangular membership construction through the activation functions. This attains several improvements for the simulation via differentiable smooth connections. Through the triangular membership the segment wise linear filtering approach may liable for the reduction of accuracy rate obtained from the output. The growing amount of user's defined functions opposed these negative properties. At last, it terminates the improvement of the weight parameters and examines the system complexity and employing with the demands on learning times. The obtained flaws are neglected by using the cubic splines technique and it is derived as follows,

$$\omega_{ab}\left(s_{\sigma}\right) = \begin{cases} 0.25\left(2 + 3\dfrac{2a_{\sigma} - o_{ab} - o_{a,b-1}}{o_{ab} - o_{a,b-1}}\right) - \left(\dfrac{2a_{\sigma} - o_{ab} - o_{a,b-1}}{o_{ab} - o_{a,b-1}}\right)^{3}, & s_{\sigma} \in \left[o_{a,b-1}; o_{ab}\right] \\ 0.25\left(2 + 3\dfrac{2a_{\sigma} - o_{ab} - o_{a,b+1}}{o_{ab} - o_{a,b+1}}\right) + \left(\dfrac{2a_{\sigma} - o_{ab} - o_{a,b+1}}{o_{ab} - o_{a,b+1}}\right)^{3}, & s_{\sigma} \in \left[o_{a,b+1}; o_{ab}\right] \end{cases} \tag{30}$$

The input measure causes two operational relations at a certain instance of time. However, the implemented functions failed to attain the desired conditions used in the Ruspini partition. The cubic splines approach provide an action of smooth polynomial fitting through the replacement for element wise approximation and enhance the opportunity of integration of high level simulations on non-linear signal. Figure 5 explains the architecture of DNFN model.

The σ^{th} component of the term s_{σ} offers two active neighbouring functionalities, and their summation is one, it is expressed as follow,

$$\omega_{\eta\sigma}\left(s_{\sigma}\right) + \omega_{\eta+1,\sigma}\left(s_{\sigma}\right) = 1 \tag{31}$$

$$g_{\sigma}\left(s_{\sigma}\right) = \beta_{\mu\sigma}\omega_{\eta\sigma}\left(s_{\sigma}\right) + \beta_{\mu+1,\sigma}\omega_{\eta+1,\sigma}\left(s_{\sigma}\right) \tag{32}$$

Scrutinising additional variables, the above expression becomes,

$$\varphi_{\eta\sigma}\left(s_{\sigma}\right) = \omega_{\eta\sigma}\left(s_{\sigma}\right)\left(\beta_{\eta\sigma}^{0} + \beta_{\eta\sigma}^{1}s_{\sigma} + \beta_{\eta\sigma}^{2}s_{\sigma}^{2} + \cdots + \beta_{\eta\sigma}^{f}s_{\sigma}^{f}\right) \tag{33}$$

$$g_{\sigma}\left(s_{\sigma}\right) = \sum_{\eta=1}^{v} \omega_{\eta\sigma}\left(s_{\sigma}\right)\left(\beta_{\eta\sigma}^{0} + \beta_{\eta\sigma}^{1}s_{\sigma} + \beta_{\eta\sigma}^{2}s_{\sigma}^{2} + \cdots + \beta_{\eta\sigma}^{f}s_{\sigma}^{f}\right) \tag{34}$$

$$\beta_\sigma = \left(\beta_{1\sigma}^0, \beta_{1\sigma}^1, \ldots, \beta_{1\sigma}^f, \beta_{2\sigma}^0, \ldots, \beta_{2\sigma}^f, \ldots, \beta_{\eta\sigma}^f\right)^W \tag{35}$$

$$\tilde{\omega}_\sigma(s_\sigma) = \left(\omega_{1\sigma}(s_\sigma), s_\sigma\omega_{1\sigma}(s_\sigma), \ldots, s_\sigma^f\omega_{1\sigma}(s_\sigma), s_\sigma\omega_{2\sigma}(s_\sigma), \ldots, s_\sigma^f\omega_{2\sigma}(s_\sigma), \ldots, s_\sigma^f\omega_{\mu\sigma}(s_\sigma)\right)^W \tag{36}$$

The above equation is written as,

$$g_\sigma(s_\sigma) = \beta_\sigma^W \tilde{\omega}_\sigma(s_\sigma) \tag{37}$$

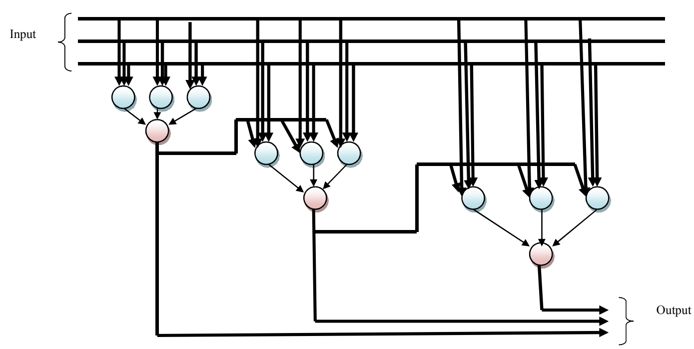
$$\hat{\mu} = \sum_{\sigma=1}^{\nu} g_\sigma(s_\sigma) = \sum_{\sigma=1}^{\nu} \beta_\sigma^W \tilde{\omega}_\sigma(s_\sigma) = \tilde{\beta}^W \tilde{\omega}(\sigma) \tag{38}$$

If s_σ is $s_{\eta\sigma}$, then the output G_3 is taken as,

$$G_3 = \beta_{\eta\sigma}^0 + \beta_{\eta\sigma}^1 s_\sigma + \cdots + \beta_{\eta\sigma}^f s_\sigma^f, \quad \eta = 1, 2, 3, \ldots, \nu \tag{39}$$

where, $\beta_{\eta\sigma}$ represents the output of the previous layer (G_2).

Figure 5 Architecture of DNFN model (see online version for colours)



The result from the DNFN is denotes as G_3. It is compared with the threshold If G_2 exceeds the threshold then, the call is admitted. In contrast, if G_2 lies below the threshold then the call will be blocked.

$$\Gamma = \begin{cases} \textit{admit the call}; & \textit{if } G_3 < \textit{threshold} \\ \textit{block the call}; & \textit{Otherwise} \end{cases} \tag{40}$$

4.3 Upgrade the term of the cell and the amount of users

The amount of the active users in the separate cells is modified, after the admission or blocking of the fresh call utilisation in the cell.

4.4 Termination

This process is continued until clearing the all queued requests. Based on the appearance of user service requests, the users may categorised as audio, video, and information stream users. The incoming call gets identified whether it is new call or handoff call and its pattern is explained by the Poisson distribution. If new call is identified, the corresponding cell and user constraints are derived for obtaining the efficient decision using fuzzy strategies. For the duration of call admission more channels are initiated to the user and the corresponding throughput is estimated for the satisfaction of requested service. The channel status is defined the wireless connection among the user and base control station. The call admission is depended based on the fuzzy outputs if the output lies under the threshold value then the call get admitted, if not the call get blocked. Likewise, for handoff calls the channel and user parameter is estimated and it is checked with the essential conditions. Once the condition gets satisfied the call may continue otherwise the call will be ended up.

5 Result and discussion

In this section, the obtained results of the cascade FFN approach is evaluated through the implementation system and its assessments are conducted with existing schemes.

5.1 Experimental setup

The newly deployed approach namely Cascade FFN is effectively evaluated using the MATLAB tool in PC with Windows 10 OS. The simulation parameters of proposed Cascade FFN-CAC are given in Table 1.

5.2 Performance metrics

The essential performance parameters deployed for the implementation of Cascade FFN are delay, throughput, cell power, and user call dropping and blocking possibility of the hand off user and the call blocking and dropping possibility of new user. These metrics are computed using equations (1)–(10).

5.3 Comparative methods

In this section, the traditional approaches of cascade FFN namely, RBR-CAC (Zarai et al., 2014), M-CAC (Vulpe et al., 2017), P-CAC (Kim et al., 2015), T-CAC (Zhang and Zhang, 2017), fuzzy-CAC are employed to validate the effectiveness of the proposed model.

Table 1 Simulation parameters

Parameters	*Values*
Bandwidth of the system	10 MHz
Number of subcarriers	60
Bandwidth of the subcarrier	375 kHz
Frequency of the carrier	2000 MHz
Radius of the cell	1000 m
Distance of the correlation	40 m

Table 1 Simulation parameters (continued)

Parameters	*Values*
Channel model	Typical urban
Maximum transmit power	20 dBm
Minimum transmit power	0 dBm
Speed of the users	3 km/h
Gain of antenna	14 dBi
Path loss	231 dB
Number of priority groups	3
Transmit power of the BS	43 dBm

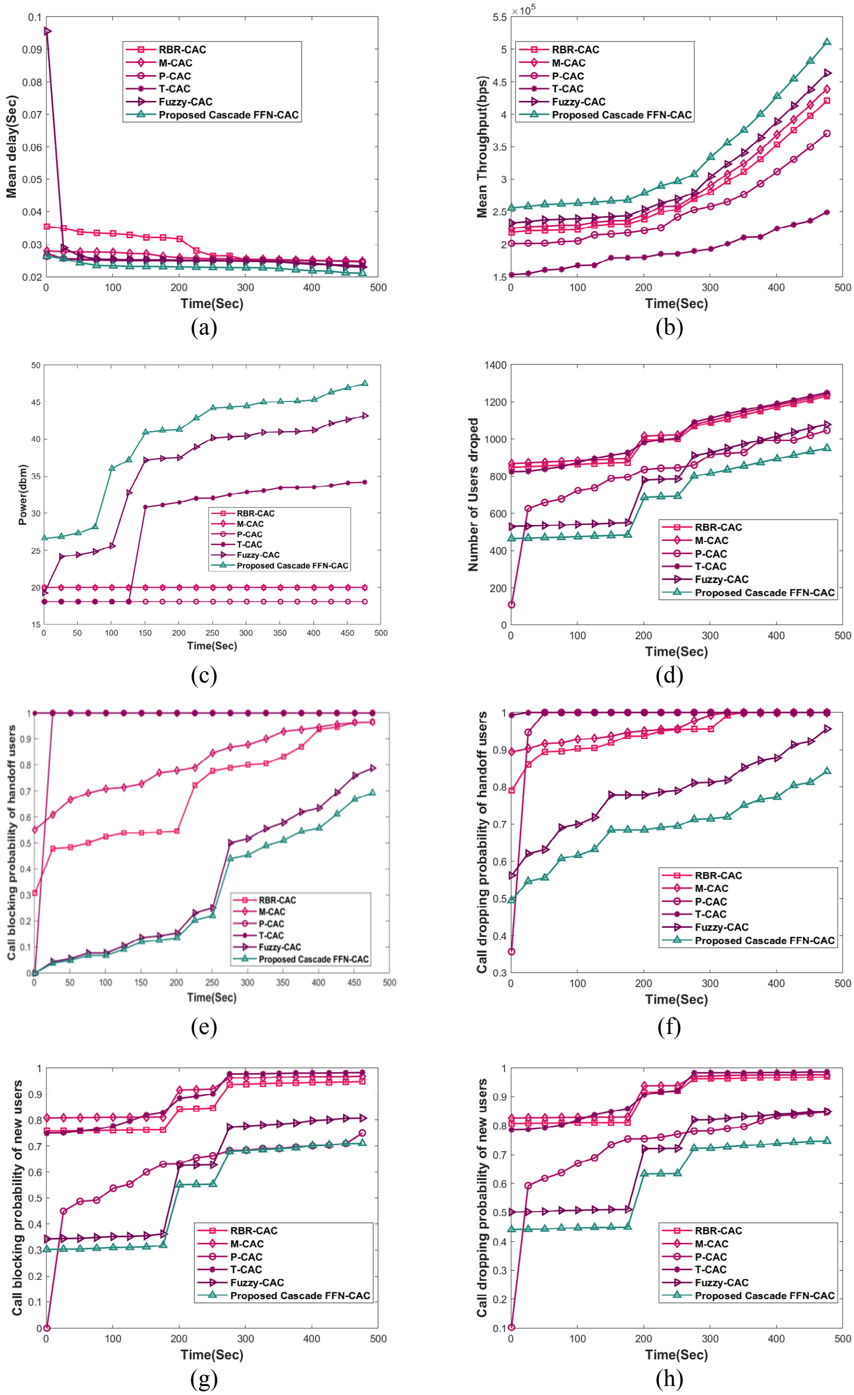
5.3.1 Comparative analysis

The Cascade FFN assessment is done with the traditional scheme by adapting the performance measures. It is computed in two scenarios: analysis based on cell size as (5×5) and the cell size as (10×10). The comparative analysis of the proposed model based on the cell size with prior models is revealed in the beneath portion.

a *Assessment with cell size* 5×5

Figure 6 illustrates the assessment based on the performance parameters using cell size (5×5) by varying the time. Figure 6(a)) shows the analysis based on delay. At time = 476 s, the delay of the Cascade FFN attained as 0.021 s and the traditional models achieved as 0.025 s, 0.025 s, 0.025 s, 0.023 s, 0.023 s. Figure 6(b)) illustrates the analysis based on throughput. The Cascade FFN-CAC achieved throughput as 510431 bps, whereas the traditional models accomplished throughput as 420930 bps, 439263 bps, 370428 bps, 249392 bps, and 464028 bps with time 476 s, respectively. The assessment based on cell power is illustrated in Figure 6(c)). When time = 476 s, the cell power attained as 47.464 dBm for Cascade FFN-CAC and for early models the power accomplished as 20 dBm for RBR-CAC, 20 dBm for M-CAC,18.065 dBm for P-CAC, 34.193 dBm for T-CAC and 43.149 dBm for fuzzy-CAC. Figure 6(d)) illustrates the analysis based on the amount of user call drops. The user call drop attained for the Cascade FFN-CAC is 950, and the traditional approaches obtained call drop as 1232, 1242, 1047, 1251, and 1079 respectively. The assessment on call blocking probability of the handoff user is illustrated in Figure 6(e)). The call blocking probability of the hand off user with existing models and the Cascade FFN-CAC achieved as 1, 1, 1, 1, 0.913, and 0.803 respectively. Figure 6(f)) establishes the evaluation based on call dropping probability of the hand off user. When time=476 s, the call blocking probability of the hand off user gained 0.842 for devised Cascade FFN-CAC model and the prior models accomplished as 1, 1, 1, 1, and 0.957 respectively. Figure 6(g)) leverages the call blocking probability of the new user. At time = 476 s, the call dropping probability of the new user accomplished as 0.710 for Cascade FNN-CAC, and the traditional models achieved as 0.948, 0.970, 0.750, 0.983, 0.807 correspondingly. Figure 6(h)) leverages the call dropping probability of the new user. The cascade FFN-CAC obtained reduced dropping probability as 0.748 and the early devised models achieved as 0.970, 0.978, 0.849, 0.987, and 0.850 at the time of 476 s.

Figure 6 Comparative analysis using cell size (5×5) : (a) delay; (b) throughput; (c) cell power; (d) user call drops; (e) call blocking probability of handoff users; (f) call dropping probability of handoff users; (g) call blocking probability of new users and (h) call dropping probability of new users (see online version for colours)



b *Assessment with cell size 10×10*

Figure 7 illustrates the evaluation of Cascade FFN with cell size (10x10) by varying the time. Figure 7(a)) shows the assessment founded on delay. At time = 476 s, the delay of the Cascade FFN attained as 0.081 s and the traditional models achieved delay as 0.093 s, 0.092 s, 0.092 s, 0.092 s, 0.092 s. Figure 7(b)) explains the assessment based on throughput. At time = 476 s, the Cascade FFN reached throughput as 444058 bps, whereas the traditional models accomplished throughput as 361537 bps, 339248 bps, 310692 bps, 223556 bps, and 403689 bps with time 476 s independently. The evaluation based on cell power is explained in Figure 7(c)). When time = 476 s the cell power attained 54.267 dBm for Cascade FFN-CAC model and for early models power accomplished as 20 dBm for RBR-CAC, 14.286 dBm for M-CAC, 8.738 dBm for P-CAC, 39.014 dBm for T-CAC and 49.334 dBm for fuzzy-CAC. Figure 7(d)) shows the assessment based on the amount of user call drops. The user call drop obtained for the Cascade FFN-CAC as 940, and the traditional approaches attained user call drops as 1246, 1247, 1033, 1255, and 1068. The evaluation on call blocking probability of the handoff user is illustrated in Figure 7(e)). The call blocking probability of the hand off user using RBR-CAC, M-CAC, P-CAC, T-CAC, fuzzy-CAC and the Cascade FFN-CAC achieved as 0.966, 0.966, 1, 1, 0.787, and 0.693. Figure 7(f)) leverages the call dropping probability of the handoff user. At time = 476 s, the call dropping probability of the handoff user accomplished as 0.733 for Cascade FNN-CAC, and the traditional models namely, RBR-CAC, M-CAC, P-CAC, T-CAC, and fuzzy-CAC achieved as 0.966, 0.966, 1, 1, and 0.833. Figure 7(g)) establishes the evaluation based on call blocking probability of the new user. When time = 476 s, the call blocking probability of the new user gained as 0.677 for Cascade FFN-CAC model and the prior models accomplished as 0.946, 0.991, 0.785, 0.982, and 0.769 respectively. Figure 7(h)) leverages the call dropping probability of the new user. The cascade FFN-CAC obtained dropping probability as 0.740 and the early devised models achieved as 0.991, 0.992, 0.840, 0.989, and 0.841 at the time of 476 s.

5.4 Comparative discussion

The comparative discussion of Cascade FFN-CAC along with early devised models, like RBR-CAC, M-CAC, P-CAC, T-CAC, fuzzy-CAC to establish the effectiveness of Cascade FFN-CAC is discussed in Table 2. The metrics used for Cascade FFN-CAC are delay, throughput, cell power, and user call dropping and blocking probability of the hand off user and the call blocking and dropping probability of the new user. The proposed model attained a delay of 0.081 s, throughput of 444058 bps, cell power of 54.267 dBm, user call drop of 940, call blocking probabilities of handoff and new user is 0.693, and 0.677, respectively; and the call dropping probabilities of handoff and new user is 0.733, and 0.740 with cell size as 10×10 .

Figure 7 Comparative analysis using cell size (10×10) : (a) delay; (b) throughput; (c) cell power; (d) user call drops; (e) call blocking probability of handoff users; (f) call dropping probability of handoff users; (g) call blocking probability of new users and (h) call dropping probability of new users (see online version for colours)

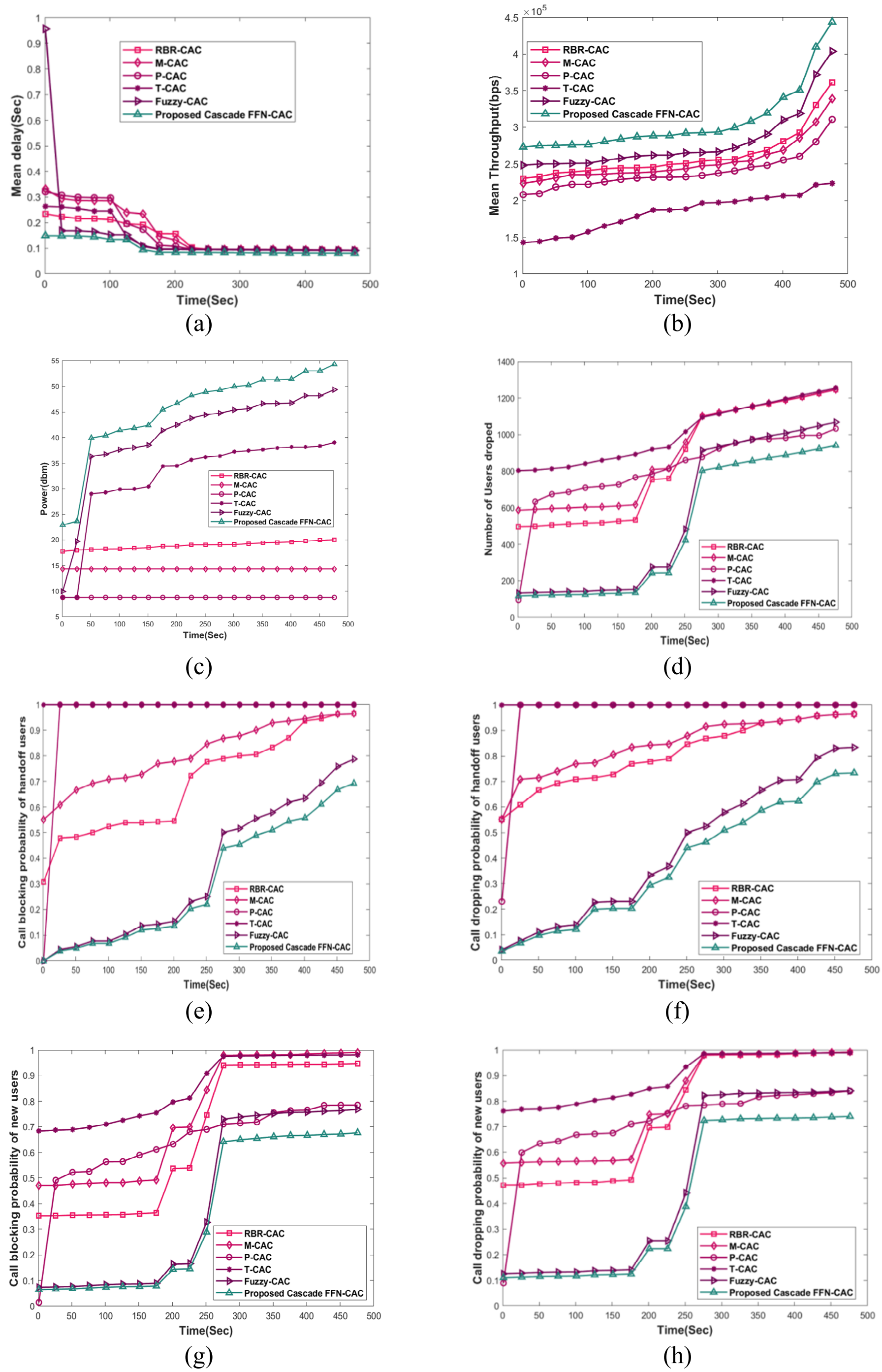


Table 2 Comparative discussion

Dataset	*Metrics/Methods*	*RBR-CAC*	*M-CAC*	*P-CAC*	*T-CAC*	*Fuzzy-CAC*	*Proposed Cascade FFN-CAC*
Cell size 5×5	*Delay* (sec)	0.025	0.025	0.025	0.023	0.023	0.021
	Throughput (bps)	420930	439263	370428	249392	464028	510431
	Cell power (dBm)	20	20	18.065	34.193	43.149	47.464
	User call drops	1232	1242	1047	1251	1079	950
	Call blocking probability of handoff user	1	1	1	1	0.913	0.803
	Call blocking probability of new user	0.948	0.970	0.750	0.983	0.807	0.710
	Call dropping probability of handoff user	1	1	1	1	0.957	0.842
	Call dropping probability of new user	0.970	0.978	0.849	0.987	0.850	0.748
Cell size 10×10	*Delay* (sec)	0.093	0.092	0.092	0.092	0.092	**0.081**
	Throughput (bps)	361537	339248	310692	223556	403689	**444058**
	Cell power (dBm)	20	14.286	8.738	39.014	49.334	**54.267**
	User call drops	1246	1247	1033	1255	1068	**940**
	Call blocking probability of handoff user	0.966	0.966	1	1	0.787	**0.693**
	Call blocking probability of new user	0.946	0.991	0.785	0.982	0.769	**0.677**
	Call dropping probability of handoff user	0.966	0.966	1	1	0.833	**0.733**
	Call dropping probability of new user	0.991	0.992	0.840	0.989	0.841	**0.740**

The proposed method can be applied to improve the performance of LTE and other cellular networks, ensuring better user experiences and service reliability. The Cascade FFN-CAC model achieves an increased throughput of 444058 bps, ensuring that the network can handle large volumes of data efficiently. With a delay reduced to 0.081 s, the model ensures quicker response times, which is essential for real-time applications. The model significantly reduces call drop and blocking probabilities for both new and handoff calls, enhancing user satisfaction and reliability. By effectively distinguishing between new and handoff calls and using channel parameters for decision-making, the model ensures optimal call admission, balancing network load and user demands. With a cell power of 54.267 dBm, the model ensures efficient power usage, which is beneficial for both network operators and users. The model's ability to simulate various parameters and incorporate deep learning techniques makes it adaptable to different network conditions and scalable for future network expansions. The proposed model considers specific parameters for CAC and might not include all the dynamic factors affecting LTE networks, such as varying traffic patterns, mobility of users, and interference levels. In future, the parameters and input features used in the Cascade FFN model will be optimised to enhance accuracy and efficiency in diverse network scenarios. Also, advanced machine learning techniques, such as reinforcement learning and adaptive algorithms will be used to improve the CAC decision-making process dynamically. Moreover, this research will be expanded by computing extreme low and high spectral efficiency of the channels in LTE network.

6 Conclusion

This research proposes a fuzzy based Cascade FFN-CAC for providing assured QoS based CAC in LTE networks. If the QoS requirement of the user and cell is matched, after that the call request is linked in a particular cell in the LTE network. The efficient cell selection is computed by validating the features from the channel and the user. The implementation of the Cascade FFN is initiated from the simulation of the LTE network. The call reorganisation is derived based on new call and the hand off call. The new call is recognised by deriving the corresponding user and cell parameters. Also the handoff call is identified using channel parameters. The CAC is employed using Cascade FFN-CAC. The effectiveness of the Cascade FFN is evaluated based on performance parameters and existing models. Thus the cascade FFN-CAC model gained increased throughput and cell power as 444058 bps and 54.267 dBm than the prior approaches and attained reduced delay as 0.081sec, user call drop as 940, call blocking probabilities of handoff and new user as 0.693, and 0.677, respectively; and the call dropping probabilities of handoff and new user is 0.733, and 0.740.

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