

Adaptive Pine Cone Optimization-based Bayesian Multi-head Attention Encoder-Decoder Neural Network for Call Admission Control in LTE

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Abstract: Call Admission Control in Long-Term Evolution (LTE) networks plays a crucial role in resource management by deciding whether to accept incoming call requests without compromising the Quality of Service (QoS) for existing users. However, traditional methods face challenges, like inefficient resource utilization, increased call blocking, and reduced user satisfaction. These limitations are further amplified under high-traffic scenarios and dynamic mobility patterns, which are common in modern wireless environments. To tackle these issues, an efficient model named Adaptive Pine Cone Optimization-based Bayesian Multi-head Attention Encoder-Decoder Neural Network (APCO_BMAE-Net) is proposed for Call Admission Control in the LTE network. Here, the incoming call recognition phase categorizes the call as either a new or a handoff call. New calls are recognized based on user and cell parameters, while handoff calls are identified using user, neighboring cell, and channel parameters. This classification helps tailor the decision-making process based on the type and urgency of the call request, particularly prioritizing handoff calls to prevent dropouts. These parameters from new calls and handoff calls are provided to the corresponding Call Admission Control, which decides whether to admit or reject the call. The decision-making process in Call Admission Control is accomplished by the proposed APCO_BMAE-Net, where the Bayesian Multi-head Attention Encoder-Decoder Neural Network (BMAE-Net) is fine-tuned using APCO. Moreover, APCO is the incorporation of the Adaptive concept with the Pine Cone Optimization Algorithm (PCOA). Furthermore, APCO_BMAE-Net has attained the Cell power of 66.868 dbm, the Call blocking probability of handoff calls as 0.798, and the Call blocking probability of new calls as 0.864.

Keywords: LTE Network, New Calls, Handoff Calls, Call Admission Control, Bayesian Multi-Head Attention Encoder-Decoder Neural Network.

Nomenclature

Abbreviation	Description
LTE	Long Term Evolution
QoS	Quality of Service
CAC	Call Admission Control
APCO	Adaptive Pine Cone Optimization
BMAE-Net	Bayesian Multi-head Attention Encoder-Decoder Neural Network
PCOA	Pine Cone Optimization Algorithm
ML	Machine Learning
GoS	Grade of Service
BS	Base Station

1. Introduction

The rapid advancement of cellular technologies has led to the emergence of LTE as a key innovation to meet growing network demands. LTE utilizes sophisticated techniques such as Orthogonal Frequency Division Multiple Access (OFDMA) and Multi-user Multiple-Input Multiple-Output (MU-MIMO) to enhance data transmission rates, extend coverage areas, and improve spectral efficiency [1]. However, even with these technological improvements, effectively managing limited wireless resources remains a major concern. Dynamic user mobility and bursty traffic patterns often exacerbate resource contention and hinder service continuity. Hence, Call Admission Control has been introduced as a crucial mechanism for efficient resource allocation [2]. Call Admission Control ensures that only those calls that the network can support without degrading service quality are allowed, thereby upholding the required Quality of Service

(QoS), preventing network congestion, and maintaining system stability [3]. This control is essential for both managing handoff calls and initiating new calls and ongoing connections are transferred between cells as users move. Particularly, handoff calls are more sensitive to resource allocation decisions, since a dropped handoff can result in abrupt session termination. The primary aim is to prevent call drops while preserving QoS standards [4]. As a fundamental aspect of Radio Resource Management (RRM), Call Admission Control plays a key role in ensuring smooth and reliable communication, enabling mobile networks to meet user expectations and perform efficiently under varying traffic and mobility conditions [5] [1].

To meet user QoS requirements, Call Admission Control schemes manage handoff calls by monitoring current bandwidth availability. Typically, a portion of bandwidth is reserved for incoming handoff calls, while the remaining resources are allocated to new call requests. This bandwidth partitioning must be dynamic and context-aware to efficiently adapt to unpredictable traffic loads. An effective Call Admission Control strategy must balance optimal resource utilization to maintain improved QoS for all admitted users [1]. Various Call Admission Control techniques have been developed for LTE networks to address these needs. Threshold-based methods admit calls based on fixed resource limits, while guard channel schemes reserve bandwidth exclusively for handoff calls, minimizing dropped connections during mobility [6]. Utility-based Call Admission Control approaches evaluate the overall network impact of admitting new calls without degrading ongoing sessions [7]. More advanced techniques use Machine Learning (ML) and fuzzy logic to adapt decisions dynamically based on real-time traffic and network conditions. Optimization models are also employed to minimize call blocking while satisfying QoS constraints [8]. Grade of Service (GoS) metrics, such as call blocking and dropping rates, are critical for network operators because they directly affect call accessibility and retention, serving as indicators of network capacity and performance [9]. Despite these developments, existing Call Admission Control methods often struggle to adapt to fluctuating traffic conditions. Thus, there is a growing need for intelligent, scalable, and adaptive models that can autonomously manage resources in highly dynamic LTE environments.

The major intention is to develop a novel method for Call Admission Control, namely APCO_BMAE-Net. Initially, LTE network simulation is performed, which is followed by incoming call recognition. Here, incoming calls are categorized as handoff calls and new calls. New calls are evaluated based on cell and user parameters. Moreover, handoff calls are identified using channel parameters, user parameters, and neighboring cell parameters. This classification enables context-specific decision-making, reducing the risk of unnecessary call drops or inefficient bandwidth allocation. These parameters are provided to the Call Admission Control to choose whether to reject or admit the call. In Call Admission Control, the decision-making process is performed by utilizing APCO_BMAE-Net, where the BMAE-Net is trained using APCO. Moreover, APCO incorporates the adaptive concept with PCOA.

The main contribution of this work is delineated below.

- **Proposed APCO_BMAE-Net for Call Admission Control in LTE:** In an LTE network, the decision-making in Call Admission Control is performed by a potent model, namely APCO_BMAE-Net. Here, BMAE-Net is trained using APCO, which incorporates the adaptive concept with PCOA. This enables the model to effectively navigate high-dimensional decision spaces and maintain robust performance under uncertain traffic conditions.

Structure of the remaining parts: Section 2 details the literature survey by highlighting the advantages and drawbacks of existing approaches based on Call Admission Control in LTE networks; Section 3 discusses the system model of developed APCO_BMAE-Net method; Section 4 provides strategies and algorithms of APCO_BMAE-Net; Section 5 demonstrates the evaluation of APCO_BMAE-Net; Section 6 concludes the work with summary and future scope.

2. Motivation

Call admission control mechanisms face challenges in handling diverse traffic types and dynamic network conditions resulting in increased call drops and blocking rates. This inefficiency impacts user experience and network performance. In real-world LTE environments, fluctuating bandwidth, user mobility, and varying QoS demands complicate resource management and disrupt service continuity. Therefore, there is a need for a more adaptive Call admission control model that can effectively manage resources and prioritize calls. Such a model should be capable of distinguishing between new and handoff, calls assessing real-time system parameters, and responding to traffic bursts or congestion with minimal latency. Hence, developing such a model is crucial to improving QoS and optimization of network utilization.

2.1 Literature Survey

V. S. Jadhav, *et al.* [10] developed a method for call admission control, namely Fuzzy-based Call Admission Control in LTE networks. Even though this method dynamically adapted to changing network loads to

maintain QoS, minimize call drops, and improve resource efficiency, it faced increased computational complexity that affected the practical performance in densely populated network environments. The fuzzy rule base also became difficult to scale with increasing network size and traffic diversity. E. E. Evelyn, *et al.* [3] introduced the Efficient Call Admission Control method for call admission control. Although this scheme improved the network quality of service by reducing interference and easing buffer congestion, it struggled with additional delays that affected time-sensitive communications. This latency limited its suitability for real-time services such as VoIP or video streaming, where fast admission decisions are essential. A. Gautam, *et al.* [11] presented Joint Call Admission Control for effective management of calls in LTE networks. This strategy enhanced call management in LTE networks and led to better network performance and more efficient handling of calls. However, it failed to integrate Phase Type distribution for service without increasing model complexity and computational overhead, which hindered the practical processing of bursty network traffic. As a result, the approach struggles to maintain low call-blocking rates under sudden traffic spikes. R. H. Puspita, *et al.* [12] designed Fuzzy Q-learning for call admission control in LTE networks. This strategy integrated fuzzy logic and Fuzzy Q-Learning to reduce complexity by discretizing state and action spaces for more efficient processing. However, it possessed a lack of consideration for additional parameters, such as call acceptance ratio comparison. This omission reduced the granularity of decision-making, especially in networks with heterogeneous user demands.

2.2 Challenges

- While Fuzzy-based CAC developed in [10] for LTE networks improved decision-making under uncertain conditions, it faced challenges due to high computational demands during practical operations. The increased processing load made it less suitable for real-time deployment in high-density or latency-sensitive environments.
- In [3], the introduced method improved resource utilization and reduced call blocking, but struggled to adapt quickly to highly dynamic network conditions. Its inability to respond swiftly to rapid fluctuations in traffic and user mobility reduced its effectiveness under real-time constraints.
- In LTE networks, real-time challenges arise from the necessity to rapidly analyze large volumes of data and promptly make decisions to uphold service quality. Any delay or processing slowdown can result in call drops, higher latency, and reduced user satisfaction. Traditional CAC models lack the flexibility to learn from evolving network behavior, which limits their adaptability and scalability. Thus, there is a need for the effective management of call admission control in LTE networks.

3. System Model

LTE enables high-speed wireless communication for mobile users through a network composed of multiple cells [10]. In which, each cell contains a limited number of channels. Each cell is denoted as α and each channel as β . These cells work together to ensure continuous coverage, enabling seamless mobility for users across different geographical regions. Moreover, incoming calls arrive according to a Poisson process and are assigned to a single channel. This modeling reflects the randomness of call arrivals, which is suitable for real-world behavior in mobile networks. Each user initiates a call with an exponentially distributed duration. Such a distribution realistically captures the variability in call lengths experienced in voice and data services. Depending on whether users are moving at high or low speeds, the dwell time in a cell varies which influences the probability of a handoff. A handoff is triggered if the dwell time is shorter than the call's duration and the success is determined by the residual lifetime and the directional movement of the user. Efficient handoff prediction and handling are critical in maintaining ongoing sessions without interruption, especially in high-mobility scenarios such as vehicles or fast-moving users. Moreover, the system model of call admission control in the LTE network is displayed in Fig. 1.

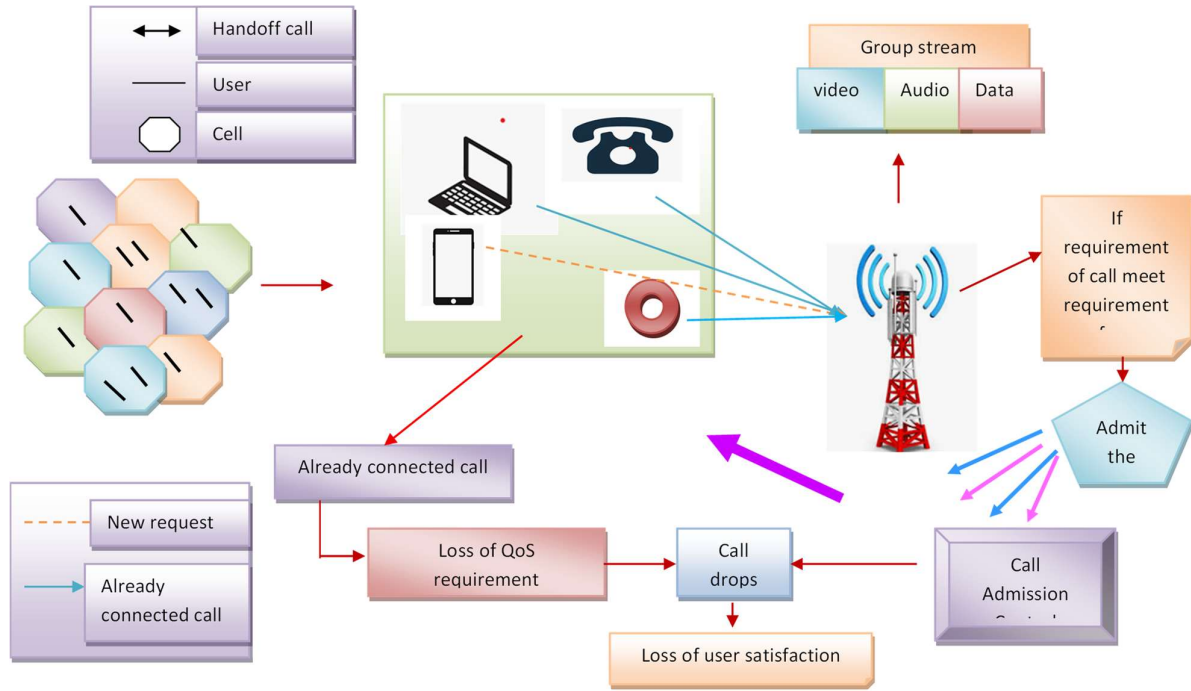


Fig. 1. System model of Call admission control in LTE network

4. Proposed Adaptive Pine Cone Optimization-based Bayesian Multi-head Attention Encoder-Decoder Neural Network for Call Admission Control in LTE network

In LTE networks, call admission control is responsible for evaluating whether new call requests can be granted access without compromising the QoS for active users. Several conventional Call Admission Control approaches struggle to adjust to fluctuating network conditions resulting in inefficient resource use and higher chances of call drops or rejections. These limitations arise from their static thresholds, lack of predictive capabilities, and inability to process multidimensional context-aware inputs. Hence, APCO_BMAE-Net is developed for Call Admission Control in LTE networks. LTE network simulation is performed initially. Then, incoming call recognition takes place. Here, incoming calls are classified as new calls or handoff calls. This classification enables the network to prioritize critical handoff requests while managing new call admissions based on the current network load and user context. New calls are assigned based on user and cell parameters. These parameters are provided to the Call Admission Control to decide whether to admit or reject the call. Moreover, handoff calls are processed using channel parameters, user parameters, and neighboring cell parameters, and the corresponding parameters are fed to Call Admission Control. This multi-parameter framework supports more accurate and context-driven decision-making that adapts to the real-time behavior of the network. Here, the decision-making in Call Admission Control is performed by utilizing BMAE-Net, where the BMAE-Net is trained using APCO. Moreover, APCO is devised by merging the Adaptive concept with PCOA. Additionally, the structure of APCO_BMAE-Net for call admission control in LTE networks is illustrated in Fig. 2.

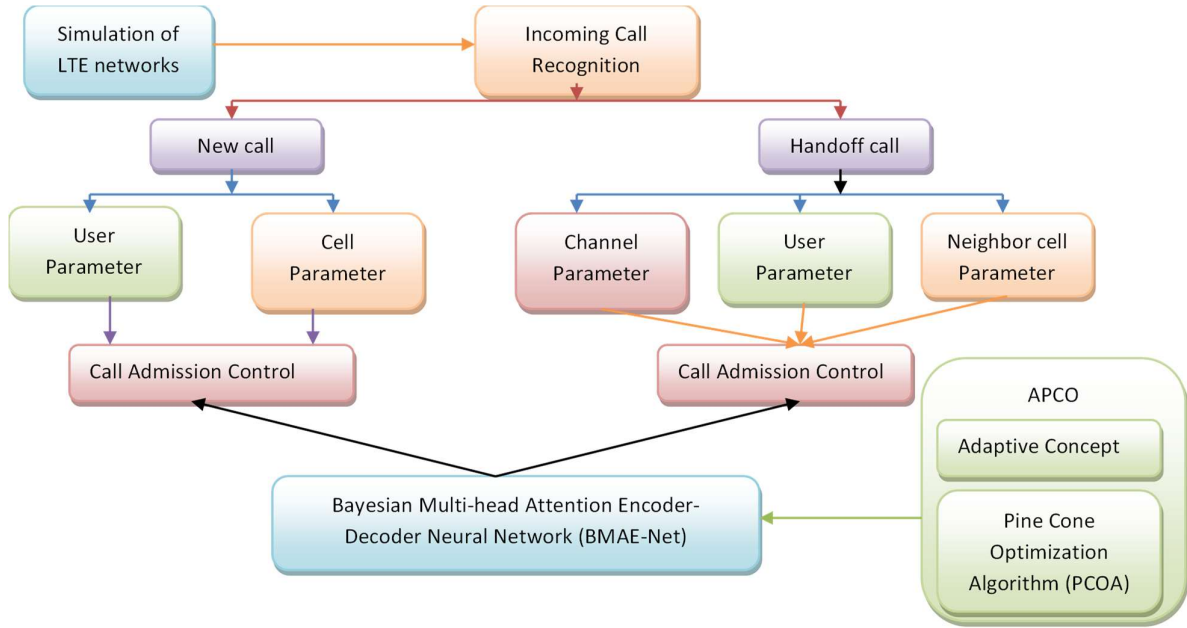


Fig. 2. Structure of APCO_BMAE-Net for Call Admission Control in LTE network

4.1 Incoming Call Recognition

Incoming Call Recognition is the process of detecting and categorizing calls by analyzing specific network and user-related factors. In this phase, incoming calls are classified as new calls or handoff calls. This distinction is essential for prioritizing ongoing sessions over new connections, especially in high-mobility or resource-constrained environments. User and cell parameters are used to recognize the new calls. These parameters reflect the user's current network conditions and the cell's capacity to serve additional users without compromising QoS. Handoff calls are identified by evaluating parameters, such as neighbor cell parameters, channel parameters, and user parameters. The inclusion of neighboring cell context allows the system to anticipate and prepare for user migration between coverage areas. Specifically, user parameters include factors like the path loss of the user and the delay of the user, while cell parameters encompass the power of the cell and the cell coverage. Furthermore, channel parameters include channel bandwidth. By leveraging this comprehensive multi-parameter input, the system ensures accurate classification and resource-aware routing of incoming calls.

4.1.1 User Parameter

User parameters involve parameters like path loss of the user and the delay of the user that influence call admission decisions, and it is expressed as,

$$Up = \{F, A\} \quad (1)$$

Where F implies path loss of the user, and A represents the delay of the user.

a) Path loss of the user: It [10] refers to the service that should be provided to users immediately by minimizing any delays, and it is measured based on the distance between the user and the Base Station (BS). Here, the path loss of the user F is expressed as,

$$F = g + h \times \log_{10} Z_{qr} \quad (2)$$

where the distance between the user and BS is represented as Z_{qr} . Moreover, g and h are constants.

b) Delay of the user: The user's delay [10] is calculated based on the data held in both the base transceiver buffer and the user buffer, expressed as follows.

$$A = \frac{M^\sigma}{g^M} \quad (3)$$

where the branch trace store buffer is represented as M^σ and the user buffer is indicated as g^M .

4.1.2 Cell Parameter

Cell parameters include the power of the cell and cell coverage that influence call admission decisions, like admit or block. Moreover, the Cell parameter can be expressed as follows.

$$Cp = \{E, B\} \quad (4)$$

Here, the power of the cell is indicated by E , and cell coverage is denoted by B .

a) Power of the cell: It is determined by considering several factors, including the number of resource blocks, the maximum and minimum power levels of femtocells, subcarrier power, outdoor path loss, and the antenna gain of the cell [10]. The power of the cell E is expressed as,

$$E = \max \left[\min \left(\left(s \times \max \left[R(\phi) \right] + u * \log_{10} \mathbb{R}_{\max} \right) + l, E_{\max}^{femto} \right), E_{\min}^{femto} \right] \quad (5)$$

$$R(\phi) = E_V^Z + J_V^Z - W^{dr} \quad (6)$$

Here, the subcarrier power of the cell is indicated as E_V^Z , the antenna gain of each cell is implied as J_V^Z , the maximum power of the femtocell is indicated as $E_{\max}^{femto}$ minimum power of femtocell is specified as $E_{\min}^{femto}$. Additionally, constant parameters of cells are s , u and l .

b) Cell coverage: In Cell coverage [13], the maximum number of active users within the cell can be evaluated by considering the radius as a . It is given as,

$$B(a) = \left\lceil \left(\frac{Y - \gamma_0 \cdot (4\pi a)^2}{V_{Y_{\max}} \cdot (C)^2} \right) \varphi \right\rceil + 1 \quad (7)$$

Here, the wavelength is signified as C , maximum power of transmission is denoted as $V_{Y_{\max}}$, thermal noise is represented as γ_0 , spreading factor is represented as V , and interference factor is denoted by φ .

4.1.3 Channel Parameters

Channel parameters include attributes like channel bandwidth, which affect call admission decisions.

a) Channel Bandwidth: It represents the spectrum range assigned for transmitting data over a communication channel. Channel bandwidth is denoted as C_b

4.2 Call Admission Control

Call Admission Control is a system utilized in networks to choose if incoming call requests can be accommodated based on available resources. It aims to optimize resource allocation while preserving the QoS for ongoing connections. Here, the decision-making process in call admission control is performed by employing BMAE-Net.

In call admission control, new calls are recognized based on the user parameter Up and cell parameters Cp , and is expressed below.

$$NC = \{Up, Cp\} \quad (8)$$

Handoff calls are identified by evaluating parameters such as channel parameters, user parameters, and neighbor cell parameters. It is formulated as,

$$HC = \{Us, Cs, Ns\} \quad (9)$$

Where the channel parameter is indicated as Cs , the user parameter is denoted as Us , and the neighbor cell parameters are represented as Ns .

Then, the handoff call HC and new call NC is fed as input to the BMAE-Net to perform call admission control.

4.2.1 Call admission control using BMAE-Net

In this work, the call admission control is performed by employing BMAE-Net. The Bayesian multi-head attention module replaces standard linear layers with Bayesian linear layers to capture uncertainty and retain critical information. It is particularly suited for dynamically changing LTE environments where uncertainty and variability are prominent. This allows the model to not only focus on relevant features through attention but also quantify uncertainty, leading to more informed and confident admission decisions. This approach enhances prediction across intervals and strengthens the model's feature extraction capabilities by leveraging probabilistic inference within attention mechanisms [14]. The attention mechanism dynamically weighs feature importance, ensuring the network emphasizes the most relevant parameters for call acceptance. Moreover, BMAE-Net is designed to overcome issues like information loss and reduced model performance. It improves generalization, handles noisy or incomplete inputs, and adapts well to fluctuating traffic patterns and user behavior. It is mathematically expressed as,

$$Q = \text{attention}(NC, HC) = s \max \left(\frac{NC \cdot HC^{\aleph}}{\sqrt{m}} \right) \quad (10)$$

Where Q represents the call admission control output, the input new call is denoted as NC , and input handoff call is indicated as HC , and $\aleph$ indicates the length of the call.

4.2.2 Tuning of BMAE-Net using APCO

BMAE-Net is tuned by using APCO, and hybrid optimization is the integration of the adaptive concept and PCOA [15]. This combination enhances the optimizer's ability to adjust search behavior dynamically based on the evolving performance of candidate solutions. PCOA is a bio-inspired method that mimics the way pine cones disperse seeds and enables effective exploration and exploitation of the solution space in optimization tasks. This nature-inspired mechanism helps avoid premature convergence and ensures a better balance between global search and local refinement.

-Solution encoding: Solution encoding defines candidate solutions within the search space. Each encoded solution corresponds to a possible configuration of BMAE-Net, influencing how the model processes admission decisions.

Fitness Evaluation: Fitness evaluation helps identify the most effective choice in the decision-making process based on certain criteria. In this context, fitness may be assessed based on call blocking probability, throughput, or QoS satisfaction rate. This initial diversity promotes a broad search of the solution landscape in the early phase. Each cone acts as a local search agent, while each tree serves as a guidepost for convergence, forming a dual-level population structure for enhanced optimization efficiency.

Step 1: Initialization of population

PCOA utilizes two types of populations: pine trees and their surrounding cones. The solution space is evenly partitioned into segments with a tree positioned at the center. During initialization at each segment, several cones are distributed around each tree. The population initialization is expressed as,

$$Po_{x,y} = lb_y + \overline{rand}_{1 \times \dim} \times (rand \times Ub_y - rand \times lb_y) \quad (11)$$

where the position of the pine cone is represented as Po , the random vector between 0 to 1 normal distribution is denoted as $\overline{rand}_{1 \times \dim}$, the random number between 0 to 1 normal distribution is indicated as $rand$, the pine tree index is represented as y , and the pine cone index is signified as x . Here, $rand$ is made adaptive and it is expressed as,

$$rand = \frac{\eta_1}{\pi} \times \frac{(Ub - Lb)}{pc} \quad (12)$$

where, the lower bound is represented as Lb , the upper bound is denoted as Ub , random number with Levy flight distribution is indicated as η_1 and pc signifies the pollination cycle.

Step 2: Exploitation phase

As pine cones mature and fall due to gravity their dispersion is limited to areas near the tree. To mimic this, the search space is divided into super-cubes. Each super-cube with a tree at its center, around which multiple solutions are generated using a specific dispersion operator.

Step 3: Exploration Phase

In pine tree pollination, agents originate from male cones and move toward female cones either between different trees or within the same tree.

Step 4: Dispersal Phase

Animals such as squirrels, birds, bears, and rodents consume pine cones and help to disperse their seeds throughout the environment.

Step 5: Fitness re-evaluation

The fitness function is iterated continuously until the optimal solution is attained.

Step 6: Termination

The algorithm will terminate after the best solution is attained.

4.3 Update users of cell and Number of users

Once a new user is admitted or blocked in a cell, the count of active users in each cell is updated accordingly. This dynamic update ensures that the system maintains an accurate view of the current load, which is essential for future call admission decisions. It also helps in load balancing, predicting resource exhaustion, and supporting mobility management strategies by enabling efficient handoff planning.

4.4 Termination

The admission control method in LTE categorizes incoming user requests as data, video, or voice, identifies them as handoff calls or new calls, and follows a Poisson arrival pattern. This traffic model closely reflects real-world arrival characteristics in wireless systems, where call requests are stochastic and time-sensitive. For new calls, fuzzy logic evaluates user and cell parameters to decide if the call should be admitted based on throughput and channel availability. This ensures service continuity for active sessions, which is critical for maintaining user satisfaction and reducing call drop rates. For Handoff calls, similar parameter checks are performed and calls are continued only if sufficient resources are available. The

algorithm terminates after all incoming requests within the simulation period have been processed, or when optimal allocation is achieved as per APCO's convergence criteria.

5. Results and Discussion

The result of the devised APCO_BMAE-Net for Call admission control is detailed in this part.

5.1 Experimental Setup

APCO_BMAE-Net for Call admission control is implemented in the PYTHON tool.

5.2 Comparative Methods

Fuzzy-based CAC [10], ECAC [3], JCAC [11], and Fuzzy Q-learning [12] are the traditional approaches utilized for analyzing the performance of APCO_BMAE-Net for Call admission control.

5.3 Comparative Analysis

The performance of APCO_BMAE-Net is compared with traditional methods by varying time based on various cell sizes, is discussed in this part.

5.3.1 Assessment of APCO_BMAE-Net based on cell size (15×5)

The comparative assessment of APCO_BMAE-Net based on cell size (15×5) by varying time is illustrated in Fig. 3. Moreover, the time of 450 sec is considered for further analysis. This evaluation highlights how APCO_BMAE-Net performs under varying cell configurations, which reflects real-world deployment scenarios in urban and suburban LTE networks. The assessment of APCO_BMAE-Net with respect to cell power is depicted in Fig. 3 a). The APCO_BMAE-Net has reached the cell power of 66.868 dbm, whereas the conventional methods have reached cell power of 40.515 dbm, 43.879 dbm, 52.370 dbm, and 58.390 dbm. This indicates a superior signal transmission capability and broader coverage offered by APCO_BMAE-Net, ensuring better connectivity and fewer dropped calls. Fig. 3 b) shows the analysis of APCO_BMAE-Net for call blocking probability of handoff calls. Here, existing methods have attained the call-blocking probability of handoff calls as 0.936, 0.923, 0.875, and 0.832. However, APCO_BMAE-Net has reached the probability of 0.798. this reduction demonstrates improved handling of mobility-related transitions and more efficient resource management for ongoing connections. Fig. 3 c) portrays the evaluation of APCO_BMAE-Net for the call blocking probability of new calls. APCO_BMAE-Net has attained the call blocking probability of new calls as 0.864, whereas conventional approaches have attained the probability of 0.966, 0.934, 0.914, and 0.889. This highlights APCO_BMAE-Net's ability to accommodate new traffic requests more effectively without compromising QoS, even under limited resource availability.

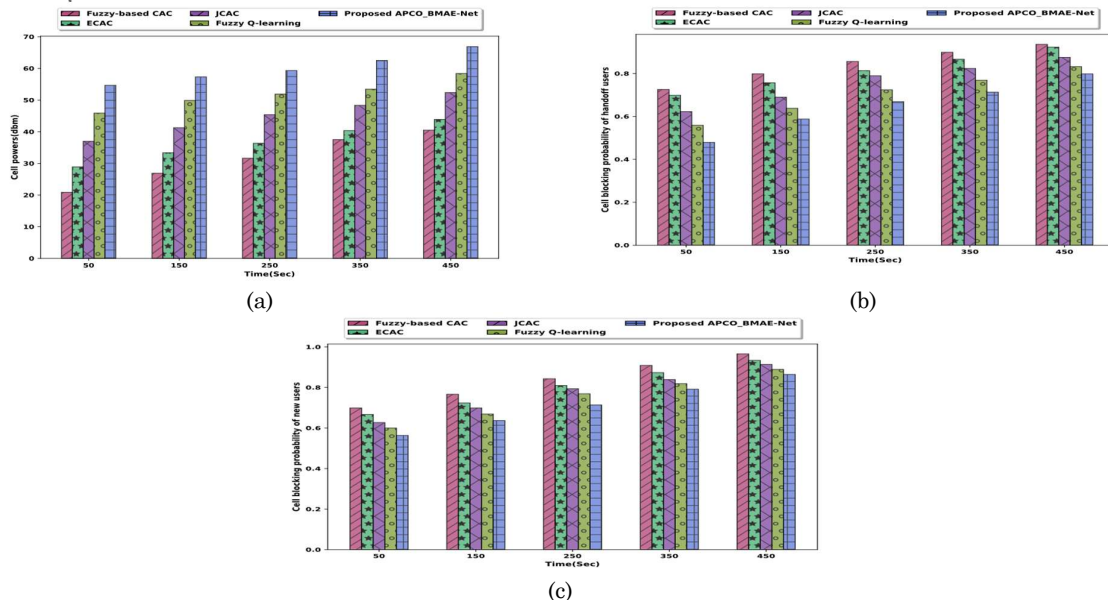


Fig. 3. Assessment of APCO_BMAE-Net based on cell size (15×5) by varying time, a) cell power, b) Call blocking probability of handoff calls, c) Call blocking probability of new calls

5.3.2 Assessment of APCO_BMAE-Net based on (10×10) cell size

Fig. 4 portrays the comparative assessment of APCO_BMAE-Net based on cell size (10×10) by varying time. For the subsequent analysis, the time of 450 sec is considered. This second set of evaluations provides further validation of APCO_BMAE-Net's robustness across different time intervals and network configurations. The assessment of APCO_BMAE-Net with respect to cell power is illustrated in Fig. 4 a). Here, APCO_BMAE-Net has reached the cell power of 67.112 dbm, however, the traditional strategies have attained cell power of 41.688 dbm, 44.549 dbm, 53.565 dbm, and 58.799 dbm. This confirms PCO_BMAE-Net's ability to achieve higher signal strength, enabling better coverage and link stability in high-demand environments. The analysis of APCO_BMAE-Net for call blocking probability of handoff calls is represented in Fig. 4 b). Existing methods have reached the call-blocking probability of handoff calls as 0.942, 0.913, 0.862, and 0.822. However, APCO_BMAE-Net has reached the probability of 0.806. This improvement indicates a more efficient accommodation of ongoing user sessions, which is essential for maintaining service continuity during mobility. Fig. 4 c) demonstrates the assessment of APCO_BMAE-Net for call blocking probability of new calls. APCO_BMAE-Net has attained the call blocking probability of new calls as 0.885, while traditional approaches have attained the probability of 0.956, 0.924, 0.912, and 0.900. These results further highlight the effectiveness of APCO_BMAE-Net in managing network load while preserving QoS, making it suitable for real-time LTE applications.

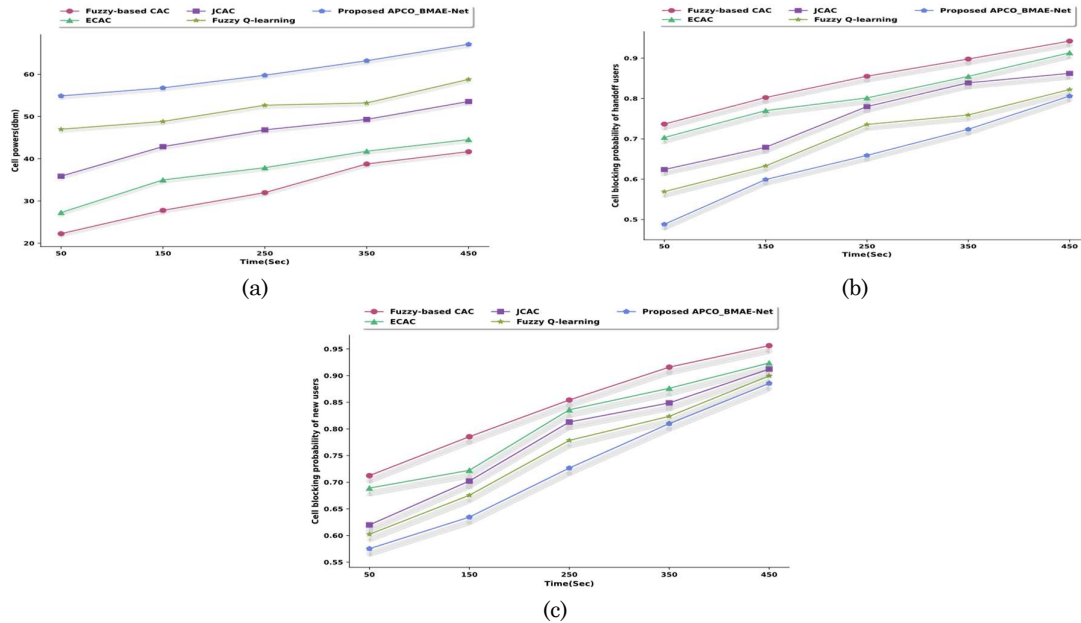


Fig. 4. Evaluation of APCO_BMAE-Net based on cell size (10×10) by varying time, a) cell power, b) Call blocking probability of handoff calls, c) Call blocking probability of new calls

5.4 Comparative Discussion

Table 1 describes an assessment of APCO_BMAE-Net with existing approaches. Here, APCO_BMAE-Net has reached the cell power of 66.868 dbm. This high signal strength reflects a stronger transmission capability, translating into broader coverage, reduced link failures, and enhanced signal quality for end users. This high cell power indicates strong signal transmission capability and improved network coverage of the developed method. In terms of the call blocking probability of handoff calls, APCO_BMAE-Net has reached the probability of 0.798. This low value demonstrates the model's ability to sustain ongoing sessions effectively, particularly for mobile users transitioning between cells. This demonstrates efficient resource allocation and enhanced continuity of ongoing communications. In addition to this, APCO_BMAE-Net has attained the call-blocking probability of new calls as 0.864. This improvement indicates better handling of incoming traffic, particularly during peak load situations, ensuring a higher rate of call acceptances without compromising ongoing services. This highlights the improved network accessibility and effective handling of incoming traffic of the model. Thus, APCO_BMAE-Net has the potential to significantly improve network reliability and user experience by minimizing call drops and optimizing resource utilization.

Table 1. Comparative discussion of APCO_BMAE-Net

Variation	Metrics	Fuzzy-based CAC	ECAC	JCAC	Fuzzy learning	Q-Proposed APCO_BMAE-Net
Cell size (15×5) by varying time	Cell power (dbm)	40.515	43.879	52.370	58.390	66.868
	Call blocking probability of handoff calls	0.936	0.923	0.875	0.832	0.798
	Call blocking probability of new calls	0.966	0.934	0.914	0.889	0.864
Cell size (10×10) by varying time	Cell power (dbm)	41.688	44.549	53.565	58.799	67.112
	Call blocking probability of handoff calls	0.942	0.913	0.862	0.822	0.806
	Call blocking probability of new calls	0.956	0.924	0.912	0.900	0.885

6. Conclusion

Efficient resource allocation in LTE networks is crucial to maintaining high QoS among fluctuating traffic demands and user mobility. Traditional Call Admission Control approaches often depend on static thresholds and struggle to adapt to dynamic network conditions. It leads to suboptimal resource use, increased call drops, and lower user satisfaction during congestion periods. These limitations underscore the need for intelligent, adaptive mechanisms that can make context-aware decisions in real-time. To address these challenges, this work proposes a novel model called APCO_BMAE-Net for dynamic Call Admission Control. At first, LTE network simulation takes place. Then, the categorization of incoming calls into handoff calls and new calls occurs in the incoming call recognition phase. New calls are evaluated based on cell and user parameters, whereas handoff calls are analyzed by considering channel, user, and neighboring cell parameters. These inputs are fed into the Call Admission Control, which utilizes the APCO_BMAE-Net. BMAE-Net introduces uncertainty-aware attention mechanisms, while APCO ensures adaptive optimization by integrating the PCOA with an adaptive concept. Additionally, APCO_BMAE-Net has attained a Cell power of 66.868 dbm, the Call blocking probability of handoff calls as 0.798, and the Call blocking probability of new calls as 0.864. These outcomes validate the potential of APCO_BMAE-Net to enhance network performance, reduce call drops, and support high QoS standards in LTE environments. Moreover, APCO is designed by integrating PCOA with an adaptive concept. Future work is to incorporate adaptive, intelligent, and privacy-aware resource management for improved network performance and user experience.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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