IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 4, December 2024, pp. 4281~4290
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i4.pp4281-4290

Signalling overhead minimization aware handover execution using ensemble learning in next generation wireless networks

Bhavana Srinivas[1], Nadig Vijayendra Uma Reddy[2]
[1]Department of Electronics and Communication Engineering, New Horizon College of Engineering, Bangalore, India
[2]Department of AI and ML, New Horizon College of Engineering, Bangalore, India

Article Info

Article history:

Received Nov 22, 2023
Revised Mar 7, 2024
Accepted Apr 18, 2024

Keywords:

Deep learning
Heterogeneous wireless networks, handover
Machine learning
Quality-of-service
Reinforcement learning

ABSTRACT

Upcoming smart intelligent heterogeneous wireless networks (HWNs) and their uses can greatly benefit from the merging of long-term evolution (LTE) sub-6 GHz along with millimeter wave (mmWave) frequencies by boosting the coverage, bandwidth, reliability, seamless connectivity, and high quality of service (QoS). Nevertheless, because of the inability of directed waves in terms of coverage, it is difficult to locate the appropriate mmWave remote radio units (RRUs). Therefore, it is crucial to lessen the burden of the handover signaling processes. In meeting research requirements this paper presents signaling overhead minimization aware handover execution (SOMAHE) model. The SOMAHE model first introduces a novel handover mechanism between LTE and mmWave is presented in this research, followed by a machine learning (ML)-based autonomous handover execution technique. To estimate the handover success rate, the model introduces a feature ensemble learning (FEL) model built using XGBoost (XGB) model that makes use of sampling windows channel data. To conclude, combining FEL into the SOMAHE model reduces signaling overhead while simultaneously increasing the handover success-rate. Experiment results with varying mobile terminals, demonstrate that the SOMAHE model significantly outperforms the existing standard deep q-networks (DQN)-based handover-execution method.

Corresponding Author:

Bhavana Srinivas
Department of Electronics and Communication Engineering, New Horizon College of Engineering
Bangalore, India
Email: bhavanas_12@rediffmail.com

1. INTRODUCTION

As of the year 2020, it has been observed that the global landscape is intricately intertwined with a staggering number of 25 billion embedded devices, which are seamlessly connected to an equivalent number of individuals. This interconnectedness has resulted in the generation of an immense volume of data, estimated to be approximately 40 trillion gigabytes these statistics, obtained from reputable sources [1], highlight the significant role played by both embedded devices and interconnected individuals in today's world. The wireless internet of things (IoT) is important in the context of future intelligent applications within this environment. However, the integration of a large-scale deployment of mobile terminals presents numerous research complexities and obstacles that require careful consideration [2].

These challenges encompass various aspects including communication, storage capabilities, and networking infrastructure. In addition to the considerations, several additional issues demand attention in the field. These challenges include but are not limited to inter-operability, diversity, as well as information and management of devices [3]. In the context of a heterogenous wireless network environment, it is important to note that the available radio resources are inherently crowded. Consequently, managing the use of these resources poses a significant challenge, particularly in scenarios involving dense networks where numerous smart devices contend for these resources. In the context of this network, its efficiency is contingent upon the efficient allocation of resources, specifically orthogonal codes, frequencies, as well as time slots, in an evolving manner. In addition, it is important to investigate how variations related to stability and the management of peak traffic are addressed to fulfill the quality of service (QoS) requirements of users. The proliferation of new IoT-based applications necessitates the need for low-latency, high bandwidth, throughput, and spectral efficiency, as well as consideration of user's context [4].

The utilization of heterogeneous wireless networks (HWNs) has attracted significant attention within the research community and multiple sectors due to its ability to effectively address handling resource challenges [5]. Radio access technology (RAT) selection and resource allocation is a crucial aspect that greatly influences the efficiency of the two types of network-level along with user-perceived experiences [6]. This is primarily due to the inherent tradeoff involved in the handover operation, allocation, and collective use of resources. Resource sharing is a practice that has been observed to enhance the effectiveness of bandwidth utilization. Nevertheless, it is important to note that this practice can also lead to the occurrence of disruption between adjacent networks. On the contrary, dividing resources serves to decrease use of resources by effectively removing any interference that may arise from adjacent networks [7]. It is anticipated that future HWNs will operate alongside various networks that utilize non-overlapping bands of frequencies. This coexistence will enable other wireless access systems to utilize a single spectrum-band without interference. Considering future developments in HWNs, it is anticipated that a harmonious coexistence of sharing resources and splitting will prevail. Therefore, in the case of general HWNs depicted in Figure 1, it is imperative to investigate and develop effective handover and resource allocation techniques [8].

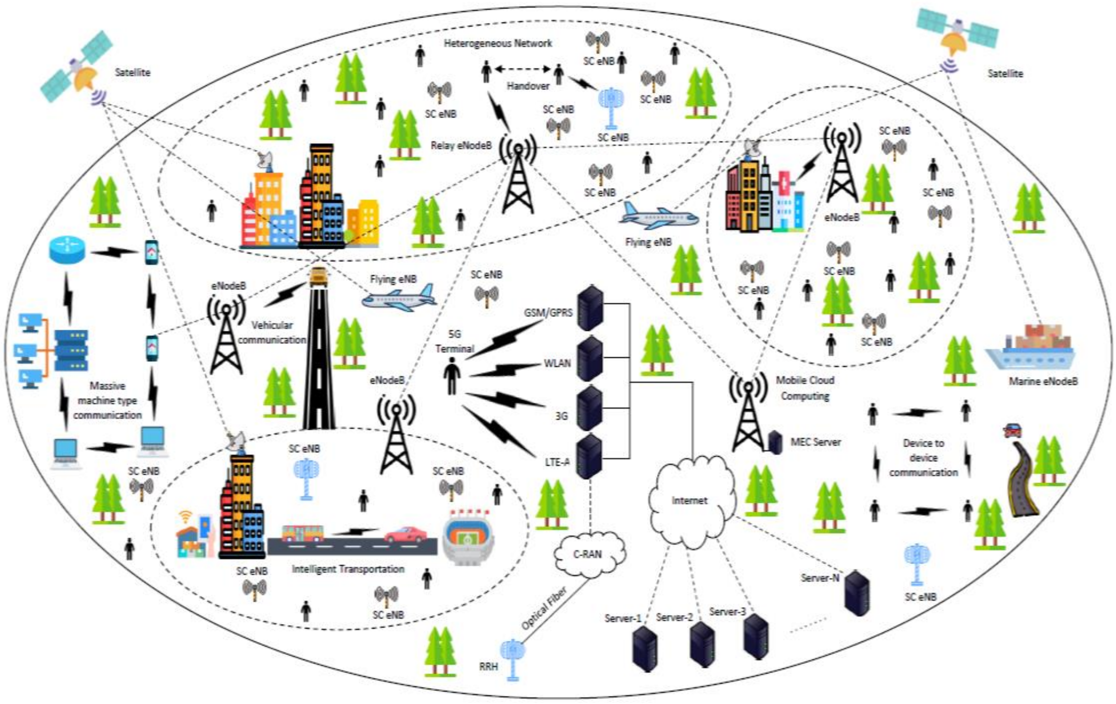

Figure 1. Architecture of heterogenous wireless networks [5]

The research work is aimed at developing an effective handover execution algorithm namely signaling overhead minimization aware handover execution (SOMAHE); recently, machine learning (ML) [7]–[9], reinforcement learning (RL) [10], [11], and deep learning (DL) [12] have been used for handover execution in HWNs with good effects. However, the current method is time consuming and exhibits higher signaling overhead. In addressing the research work introduce feature ensemble learning (FEL) using XGB into SOMAHE to reduce signaling overhead and achieve autonomous handover execution. Once users are handover to new network it causes interference; in addressing the proposed work introduces a novel resource allocation to newly handoff users. The significance of SOMAHE is described as given here.

– The work introduces a novel autonomous handover execution model that reduces signaling overhead.
– The model introduces FEL using XGB for better handover decision-making.
– The SOMAHE improves system throughput, reduces handover failure, and better energy efficiency.

The manuscript organization is discussed as follows: section 2, discusses current state-of-the-art methods of designing effective handover execution and resource allocation model for HWNs. Section 3 discusses the working of proposed methodology in designing effective handover execution with enhanced resource utilization. Section 4 discusses the experiment and result of proposed methodology over existing methodology; section 5, discusses the research novelty and significance and future research direction to enhance the model.

2. LITERATURE SURVEY

This section presents a review of recent research pertaining to the development of an efficient network selection and resources allocation technique for HWNs. In a previous research investigation [13], an approach for handling resources was developed. This approach relies on exact measurements, but it should be noted that the models used in this study require manual optimization of parameters as an additional prerequisite. Recent research has primarily concentrated on addressing QoS parameters at the network level, as evidenced by studies [13], [14]. Additionally, there has been a notable emphasis on satisfying user preference requirements, as indicated by investigations [15]. Nevertheless, it has been observed that these models exhibit a significant energy consumption when attempting to enhance their success-rate. In a prior study [16], the significance of reusing system resources in order to enhance energy conservation was demonstrated. Additionally, the study also highlighted the significance of resource consumption and its impact on overall system performance. In the past few years, there has been a notable utilization of ML approaches in the realm of automatic decision making, as indicated by reference [17]. Pujar *et al.* [17] introduced a handover-execution approach for 5G cellular networks that relies on the k-nearest neighbors (KNN) algorithm. They demonstrated that this approach exhibits an excellent performance in terms of target-discovery, and further highlighted the advantages of employing ML techniques for decision-making processes in this context. The current approach has been developed with a focus on homogeneous networks, but it is important to note that there remains a gap in understanding how ML approaches can be effectively applied to heterogeneous cellular networks [18], [19].

According to Majid *et al.* [20], a novel approach is proposed for predicting handover-execution using an XGBoost-based approach. The primary objective is to mitigate the need for regular measurement updates and improve the general efficiency of next-generation networks. This approach is implemented and evaluated in the context of the experiments. Nevertheless, it has been observed that traditional ML algorithms could be less effective when dealing with datasets that demonstrate imbalanced behavior. Iborra *et al.* [21], it was demonstrated that the current approach in question does not effectively consider both QoS and energy conservation as simultaneous factors. A supervised ML approach was employed to develop an approach for choosing an optimal network configuration that satisfies the real-time requirements of a given application. Cao *et al.* [22], the simultaneous challenges of frequently load-balancing and handover were investigated in the context of a large coverage network. A deep-reinforcement algorithm, specifically deep q-networks (DQNs), was employed in their study to address the issue of signaling-overhead reduction and throughput maximization while minimizing handover-failures [23]. In a recent study [24], the objective was to optimize the number of individuals in a network while minimizing handover-failures, taking into account the mobility patterns of individuals in a densely populated network. An anticipatory technique was introduced by the researchers to determine the location of an individual by leveraging previous positions through the utilization of a learning method.

The challenge of finding the best possible outcome in a game-theory approach [25], [26] is modeled as a predictable issue that is known to be NP-hard. The study conducted by Magoarou [27] aimed to acquire the geographic position of users using an unsupervised learning approach. The primary objective of this research was to address the practical challenges associated with handover as well as allocation of resources, while taking into account the influence of small scale faded appearance. Tong *et al.* [28], the utilization of software defined network (SDN) was explored as a potential solution for tackling mobility along with user allocation of resources challenges in HWNs. The researchers in this study employed a three-phase approach for developing multipath-based communication. The initial step involved utilizing a steady state system for predicting the user's location. In the second stage, an ambiguous analytical centralized procedure was employed for choosing the appropriate network. Lastly, within the third step, a multi-path transmission protocol was utilized to execute the process of handover. This approach was described detail in [29]. In the study conducted by the researchers, various attributes were utilized for training a network of neurons in order to facilitate the execution of handover in the context of HWNs. These attributes encompassed the packet loss and bit-error-rate, signal-to-noise ratio, shifting speed, least delay, and highest transmission rate. The current resource selection process lacks a systematic approach, as it relies on a random method rather than taking into account the consumer's priority requirements. The consideration of efficient load distribution in order to minimize handover failure and maximize utilization of resources has not been addressed in previous studies [5], [8], [11]. The present discourse endeavors to shed light on the study's technique employed in tackling different study difficulties.

3. PROPOSED METHODOLOGY

This section discusses the mathematical model of proposed SOMAHE algorithm. The model discusses the standard handover execution model and proposed handover execution to reduce signaling overhead using novel FEL built with XGB. Finally, an effective resource selection model is introduced to maximize the resource utilization for newly handoff mobile terminals.

3.1. System and radio model

Assume there exists a highly dense heterogenous-wireless communication network (HWCN). In this scenario, let s represent the radius for network overlap among the millimeter wave (mmWave) (5G) and long-term evolution (LTE). Further, it is considered that mobile terminals are mobile, and environment being dynamic; hence, due to which, the HWCN environment has to implement the poisson distribution (PD). Moreover, there are significant differences between the technology and frequency-bands used by the 5G and LTE. Whenever a mobile terminal is connected to a given cellular-network, it sends data associated with the given down-link radio-frequency it has detected to the relevant base stations (BSs). The key distinction lies in the ability of BS to make decisions with respect to the reconfiguration of measurement-gaps in LTE. This capability is facilitated by the utilization of ML approaches, which enable these techniques to recognize the possibility that the mmWave-band may not provide sufficient signal strength to sustain continuous communication. Moreover, it is imperative to note that as the mobile terminal approaches the periphery within the network, it becomes necessary for said device to seamlessly transition its connectivity to an alternative RAT in order to sustain uninterrupted service provision. The anticipated number of mobile terminals which could be effectively managed within a given unit space is characterized by the method μ alongside the level of intensity variable φ. This work discusses the procedural framework μ pertaining to mobile terminal denoted as O, operating within the context of cellular-communication environment X. The data pertaining to mobile terminal is acquired by means of the PD, characterized by a mean value of φX, as expressed by (1).

$$\varphi X = \varphi \pi s^2 \tag{1}$$

The variable s represents the radius of the cellular-network. The precise location of the j^{th} mobile terminal is determined using a continually uniform distribution within the two-dimensional space $\mathbb{S}^2$, employing polar-coordinates (s_j, θ_j). Here, s_j represents the radial distance from the origin, with values ranging from 0 to s. Meanwhile, θ_j represents the angular position, ranging from 0 to 2π. The index j denotes the specific mobile terminal, with j taking values from 1 to O, i.e., $0 \leq s_j \leq s$, $0 \leq \theta_j \leq 2\pi$ and $j = 1,2,3, \dots, O$.

In this work, decisions concerning handoffs are modeled with the help of historical information regarding the effectiveness rate of handoffs for each individual mobile terminal, utilizing an approach called feature ensemble learning XGB (FEL-XGB). To effectively apply FEL-XGB algorithm, it is imperative that the duration of the collection session, denoted as U, does not exceed the channel's-coherence duration (CD). To maintain the validity of the technique, it is imperative that the duration of session U remains within the limits of CD. Given that not all mobile terminals require handoff functioning, the number of samples size obtained must not exceed the sum of all handoff attempts. Each time a mobile terminal is connected to a network using LTE or switched to a different LTE network, a handover implementation algorithm was run within the receiving network to determine how to best handle the connection.

3.2. Objective function for automatic handover generation

To efficiently perform handover operations in dense HWCN environment, the existing work has adopted a KNN, XGB, RL, deep Q-learning, and DL technique. It is hard to handle processing simultaneously at the same time, though, and whenever there exists data imbalance, the accuracy associated with the handover implementation approach is greatly affected. Consequently, the impact on the quality of experience (QoE) for the user is observed. This study employs the FEL-XGB classification algorithm to predict handover executions due to its ability to carry out individual trees in a distributed way. The proposed approach holds promise for addressing the real-time demands of HWNs that operate with distributed BSs. The technique exhibits the potential for scalability as it pertains to input size, allowing for the accommodation of larger datasets. Additionally, it demonstrates the capability to effectively capture and develop strong correlations within the collection of features. The FEL-XGB technique aims to reduce the objective variable by incorporating a distinguishable normalization term along with a convex loss-function. Specifically, it includes an expression $\beta\|x\|_1$, which represents the $L1$ norm of the variable x weighted by the variable's parameter β, while the expression $\frac{1}{2}\varphi\|x\|_2^2$, which represents half the square of the $L2$ norm of x weighted by the variable φ. The overall objective work is formulated as $\beta\|x\|_1 + \frac{1}{2}\varphi\|x\|_2^2 + \varphi^U$. The size of each leaf is represented by the variable U, while the vector x consists of the corresponding weights of the leaves in the specific gradient-boosting tree. The utilization of a normalization term serves to mitigate the issue of over-fitting and enhance the optimization of computation challenges. Applying the subsequent equation, we can characterize the $n \times 0$ matrix that represents the target collection of features.

$$Y = \left[Y_j\right]_{j=1}^{o} \tag{2}$$

The variable o represents the number of feature sets that are taken into consideration for the learning process. On the other hand, Y_j denotes a multi-dimensional feature-vector that is generated for a specific time instance. The supervised-labeled-vector, denoted as y, is a binary variable that represents the execution of handover. Specifically, the value 1 indicates that handover has been carried out, while the value 0 signifies that handover has not been carried out. This work examines an overall of 5 features. These features include the coordinates of mobile terminals, the physical distance between mobile terminals alongside the BS, the reference symbol received power (RSRP) in both mmwave and LTE technologies, the modification of RSRP measurements depending upon the $X1$ interface, alongside the modification of RSRP measurements depending upon the $X2$ interface. The collection of the three remaining parameters is able to be achieved by directly accessing mobile terminals. On the other hand, the initial two features are achievable by analyzing the radio resource control (RRC) messages. This is possible by utilizing the detected arrival time variance or the global navigating structure, as mentioned in reference [26]. The optimization of hyper-parameters involves the utilization of the grid searching methodology, which takes into account k-fold cross validation (K-CV) as a means to enhance the accuracy of handover execution. According to the findings presented in [10], the computational involved in the presented technique can be accurately characterized by (3).

$$C = O\big(mn(e_{\uparrow}F + n\log n)\big) \tag{3}$$

The variable $e_{\uparrow}$ represents the parameter that characterizes the highest possible depth of the boosted trees. While the variable F denotes the parameter that quantifies the total size of the trees. The measurement of computation complexes is conducted in relation with the overall size of mobile terminal encompassed throughout a cellular network, as well as the expressed frequency at which these measurements are taken.

3.3. Handover mechanism

As specified in the LTE protocol specification, the mobile terminal is responsible for measuring the RSRP associated with the LTE network. This RSRP value is compared against the handover quality-specifier in order to initiate the RRC X2 process. The LTE network undergoes a reconfiguration of the RRC protocol, which is primarily driven by the utilization of measurement-gaps. Moreover, it has been observed that mobile terminals exhibit an increased RSRP compared to the handover quality-specifier. This variation in signal strength prompts the initiation of RRC X1 process. When the power of mmWave exceeds the predetermined quality threshold, mobile terminal initiates RRC Y2. Subsequently, it arbitrary chooses a slot within the mmWave channel to facilitate communication, resulting in an efficient handover process. The comprehensive depiction of the conventional and proposed handover procedure for execution is illustrated in Figures 2 and 3. Figures 2 and 3 illustrates that handover attempts are made during phase X, while handover execution occurs during phase Y, when the LTE network chooses to permit handover.

The utilization of the conventional approach may result in a marginal increase in overhead. This work introduces an algorithm for executing handovers using ML techniques. The determination of whether to acknowledge measurements from mobile terminal devices or utilize ML-based handover success rate accuracy levels is accomplished. The receiver operating characteristic (ROC) curve is a widely used tool in predictive modeling research. In this study, we employed the ROC curve to estimate the likelihood of a handover either failing or succeeding. To ensure robustness and accuracy of our predictions, we employed a 10-fold K-CV approach. Additionally, we employed an FEL-XGB, for calculating the ROC curve. In the event that the determined power obtained by the LTE system is found to be below the minimum requirement for handover quality, along with the anticipated obtained power within the mmwave system is determined to be greater than the established handover quality-specifier, the handover algorithm will continue with its normal execution method. In the instance that the projected obtained power of mmWave is lower than the handover quality-specifier, the LTE network is going to block the mobile terminals demand to transition through LTE to mmWave. The utilization of mobile terminals has shown promise in mitigating potential handover failures. The suggested handover execution approach for HWNs making use of a FEL-XGB method is depicted in Figure 3.

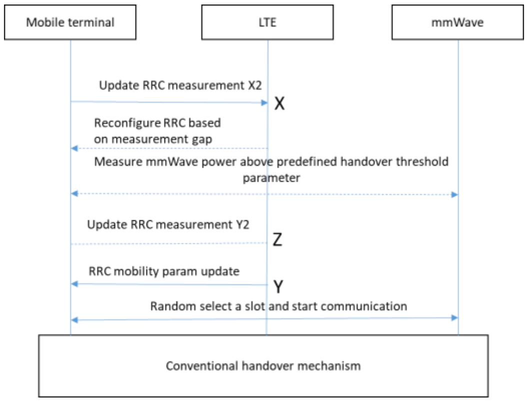

Figure 2. Conventional handover execution approach

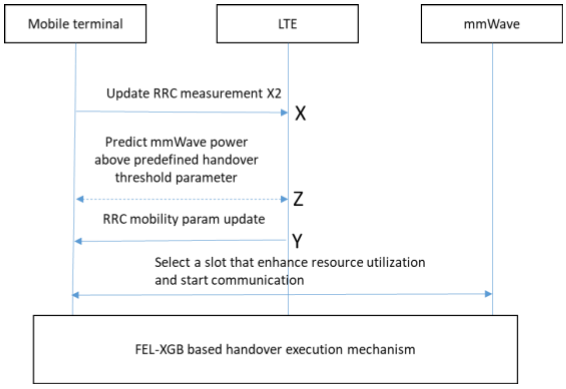

Figure 3. Proposed handover execution approach

3.4. Feature ensemble XGB classifier model

The XGB classifier approach employs a sequential learning system that takes into account the second-order derivatives. In order to effectively adjust to the automated handover-execution techniques, it is necessary to obtain the two-derivatives (in particular, the Hessian and sigmoid) of the loss-function with the aim of prediction. Assume that the variable n is used to represent the size of the sample information being considered, while the variable o is used to represent the size of the feature being considered. The initial predictions, denoted as a_j, are transformed using the sigmoid equation to obtain probability-based predictions, denoted as $\hat{z}_j = \alpha(a_j)$. The sigmoid operation, denoted as $\alpha(\cdot)$, is employed to define the transformation. Additionally, the symbols β along with φ are employed to denote two distinct loss-functions in the context of this study. According to [6], [9], it can be used to derive the additive-learning process as shown in (4).

$$M^{(u)} = \sum_{j-1}^{o} m\left(z_j, a_j^{(u-1)} + g_u(y_j)\right) + \delta(g_u) \tag{4}$$

The variable u denotes the repetition number utilized during the learning process of the automatically handover-execution approach. By employing the Taylor's second-order expanding technique on (4), the resulting equation can be derived as shown in (5). The variable h_j represents the gradient-function, that will be determined by utilizing the given (6). The variable i_j represents hessian-function, that will be determined by utilizing the given (7).

$$M^{(u)} \approx \sum_{j-1}^{o}\left[m\left(z_j, a_j^{(u-1)}\right) + h_j g_u(y_j) + \frac{1}{2} i_j \left(g_j(y_j)\right)^2\right] + \delta(g_u) \tag{5}$$

$$\propto \sum_{j-1}^{o}\left[h_j g_u(y_j) + \frac{1}{2} i_j [g_u y_j]^2\right] + \delta(g_u)$$

$$h_j = \frac{\partial \mathcal{M}}{\partial a_j} \tag{6}$$

$$i_j = \frac{\partial^2 \mathcal{M}}{\partial a_j^2} \tag{7}$$

The scalar parameters h_j along with i_j are utilized within the context of specific boosting trees, which are commonly employed for addressing binary issues. The XGBoost algorithm does not inherently provide automated differences operation capabilities. Therefore, this work introduces a manual approach for calculating the necessary derivatives. The choice of the sigmoid-function to be the activating function during the loss-function can be explained by its derivative, which is explained in (8). In (9) allows for the derivation of a weighed loss-function that is specifically designed for the purpose of handover selection in an HWN.

$$\frac{\partial \hat{z}}{\partial a} = \frac{\partial \alpha(a)}{\partial a} \\ = \alpha(a)\big(1-\alpha(a)\big) \\ = \hat{z}(1-\hat{z}) \tag{8}$$

$$\mathcal{M}_v = -\sum_{j=1}^{n}\big(\beta z_j \log(\hat{z}_j) + (1-z_j)\log(1-\hat{z}_j)\big) \tag{9}$$

The symbol β is used to represent the bias variable, which is employed to characterize imbalanced features. In the event that the value of β exceeds 1, it is vital to incorporate the extra loss variable. This is achieved by categorizing the value of 1 as 0. In the same manner, when the value of β is given here, the optimization of the loss-function size is focused on ensuring that data-features through an identifier of 0 are properly categorized. The evaluation of derivative of first-order is done using the given as (10).

$$\frac{\partial \mathcal{M}_x}{\partial a_j} = -\beta^{z_j}\big(z_j - \hat{z}_j\big) \tag{10}$$

The aforementioned equation bears resemblance to the expression $\frac{\partial \mathcal{M}}{\partial a}$ term commonly employed in the computation of general cross-entropy-loss. A notable distinction in this context is the utilization of the variable β^{z_j} to regulate the current variable. The second-derivative is calculated by taking another derivative with reference to a_j based on (10) in the following manner.

$$\frac{\partial \mathcal{M}_x^2}{\partial^2 a_j} = -\beta^{z_j}\big(1-\hat{z}_j\big)\big(\hat{z}_j\big) \tag{11}$$

3.5. Resource allocation model

In (12) explains how the ratio of average occupied slots to the overall slots within the associated network is calculated to determine V using the standard utilization of resources approach. where D_y is the number of actively being used slots, and N is the number of slots accessible when the steady-state likelihood δ_t is considered. The proposed SOMAHE model is able to reduce the overall time to perform handover with minimal failure and better resource selection i.e., higher throughput as shown in next section.

$$V = \sum_{t\in T}\frac{D_y}{N}\delta_t \tag{12}$$

4. SIMULATION STUDY

In this section, we will analyze the experimental results of the handover efficiency of the proposed SOMAHE and existing technique namely centralized training with decentralized execution deep q-network (CTDE-DQN) [11]. The C#-based SIMITS simulator have been used to conduct simulation and study the performance of SOMAHE and CTDE-DQN. The python XGB-wrapper function have been used into SIMITS simulator for hyperparameter optimization to perform autonomous handover execution. The network parameter used for running the simulation study is given in Table 1 like [11] considering radio propagation model defined in [20]. A study was carried out to assess the performance metrics related to handover operations, specifically the handover failures, overall energy-consumption, and throughput by varying the time-slots size.

Table 1. Network parameter

Network Parameter	Value
Number of BSs (N)	9
Number of MTs (U)	30
Transmit power of the macro BS (P0)	43 dBm
Transmit power of small BSs (P1 to Pn)	23 dBm
Electrical circuit power of BSs (pcircuit)	2 W
Bandwidth for each BS (W)	20 MHz
Network area	[-0.5, 0.5] * [--0.5, 0.5] km^2
Thermal noise power spectral density	- 174 dBm/Hz
Number of bits per packet (V)	100 kbits
Path-loss exponent (y)	3.8
Correlation coefficient of small fading (p)	0.9
Threshold level of available link quality (9th)	-140 dBm
Time slot duration Ts	1 sec
Throughput reuirement Rth	100 kbps

4.1. Results and discussion

In this section the performance of proposed SOMAHE and existing CTDE-DQN is studied in terms of handover failure, energy consumption and throughput performance by varying the time-slots size from 2000 to 8000 μ seconds [t]. Figure 4 shows the handover failure performance experienced using SOMAHE and CTDE-DQN. The results demonstrate that the SOMAHE outperforms CTDE-DQN considering all scenarios in terms of handover failure reduction; thus, an average handover failure reduction of 47.48% is experienced by SOMAHE in comparison with existing CTDE-DQN model.

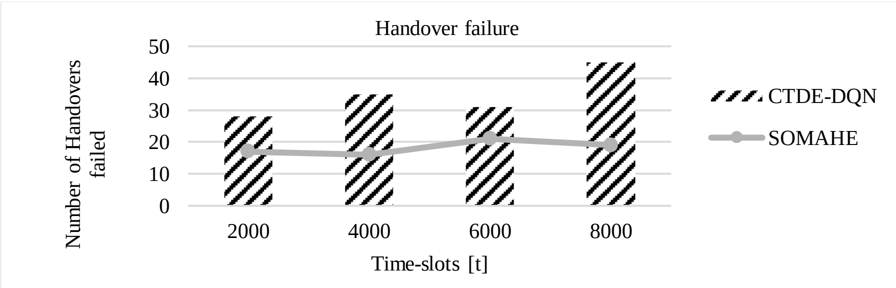

Figure 4. Handover failure performance

Figure 5 shows the energy consumption performance experienced using SOMAHE and CTDE-DQN. The results demonstrate that the SOMAHE outperforms CTDE-DQN considering all scenarios in terms of energy consumption reduction. Thus, an average energy consumption reduction of 10.55% is experienced by SOMAHE in comparison with existing CTDE-DQN model. Figure 6 shows the throughput performance experienced using SOMAHE and CTDE-DQN. The results demonstrate that the SOMAHE outperforms CTDE-DQN considering all scenarios in terms of throughput improvement. Thus, an average throughput improvement of 26.27% is experienced by SOMAHE in comparison with existing CTDE-DQN model.

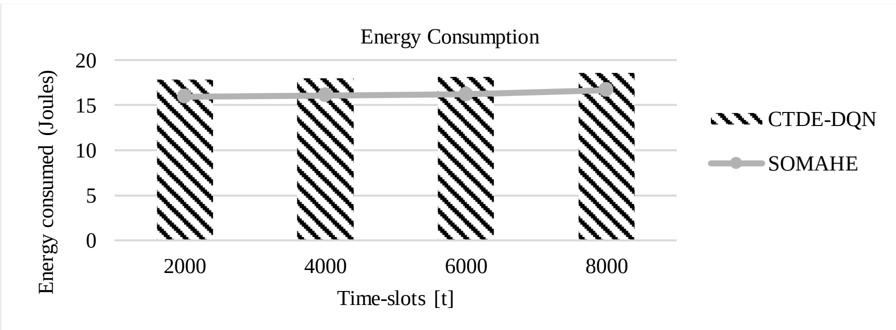

Figure 5. Energy consumption performance

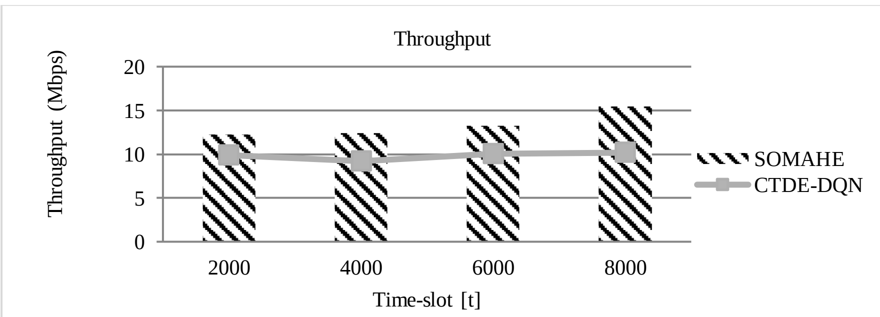

Figure 6. Throughput performance

5. CONCLUSION

The present study initially carried out an extensive investigation of diverse handover mechanisms that are currently in use within HWNs. Based on the findings of the survey, it is evident that the current handover technique has proven to be ineffective in achieving a satisfactory balance among meeting performance requirements and achieving energy reduction objectives. Moreover, the current technique gives rise to energy-overhead due to the presence of further signaling-overhead. The modeling of an automatically handover technique that incorporates ML techniques has been undertaken in order to mitigate the process of signaling overhead. The KNN-based handover technique exhibited a lack of accuracy in its prediction capabilities due to the technique's inability to effectively address feature imbalance concerns. In order to tackle the study's challenges at hand, this paper introduces a novel handover and resource allocation technique that leverages the power of ML, specifically the FEL-XGB algorithm. In this work, an FEL-XGB algorithm is proposed to tackle the issue of better hyperparameter optimization to reduce handover failure with better resource optimization. The handover technique suggested in this study, which relies on FEL-XGB, demonstrates significantly improved accuracies in terms of handover failure reduction in contrast to the handover technique depending on DQN. Experiments are carried out to assess the handover performance by varying the time-slot size. The obtained outcome demonstrates that the handover failure is reduced by 47.48% through the utilization of the FEL-XGB-based SOMAHE handover technique in comparison to the CTDE-DQN-based handover technique. In addition, it has been observed that the implementation of a SOMAHE handover technique based on FEL-XGB demonstrates a significant reduction in energy consumption, specifically by 10.55%, in comparison to a handover technique dependent on CTDE-DQN. The FEL-XGB-based SOMAHE handover technique has been observed to yield an overall throughput improvement of 26.27%, in comparison against the CTDE-DQN-based handover technique. This improvement can be attributed to the decrease in further signaling overhead and better resource optimization strategy. The presented SOMAHE approach demonstrates robustness and scalability, regardless of the varying time-slots size considering larger number of mobile terminals working within a HWNs. Future work would consider assess the performance of proposed model considering more diverse mobility scenarios and radio propagation models; alongside more enhanced resource optimization strategy should be developed considering more diverse scenario to mitigate interference effect under large density mobile terminals.

REFERENCES

[1] A. Haghrah, M. P. Abdollahi, H. Azarhava, and J. M. Niya, "A survey on the handover management in 5G-NR cellular networks: aspects, approaches and challenges," *Eurasip Journal on Wireless Communications and Networking*, vol. 2023, no. 1, Jun. 2023, doi: 10.1186/s13638-023-02261-4.

[2] Y. Ullah, M. B. Roslee, S. M. Mitani, S. A. Khan, and M. H. Jusoh, "A survey on handover and mobility management in 5G hetnets: current state, challenges, and future directions," *Sensors*, vol. 23, no. 11, 2023, doi: 10.3390/s23115081.

[3] M. Emran, V. Thayananthan, M. Umair, I. Kotuliak, M. S. Qureshi, and M. B. Qureshi, "The handover and performance analysis of lte network with traditional and SDN approaches," *Wireless Communications and Mobile Computing*, vol. 2022, pp. 1–9, Apr. 2022, doi: 10.1155/2022/7387737.

[4] A. U. Rehman, M. B. Roslee, and T. J. Jiat, "A survey of handover management in mobile hetnets: current challenges and future directions," *Applied Sciences*, vol. 13, no. 5, Mar. 2023, doi: 10.3390/app13053367.

[5] J. Tanveer, A. Haider, R. Ali, and A. Kim, "An overview of reinforcement learning algorithms for handover management in 5G ultra-dense small cell networks," *Applied Sciences*, vol. 12, no. 1, Jan. 2022, doi: 10.3390/app12010426.

[6] J. Lima, A. Medeiros, E. Aguiar, V. Jr., and T. Guerra, "User-level handover decision making based on machine learning approaches," *Journal of Communication and Information Systems*, vol. 37, no. 1, pp. 104–108, 2022, doi: 10.14209/jcis.2022.11.

[7] M. K. Dahouda, S. Jin, and I. Joe, "Machine learning-based solutions for handover decisions in non-terrestrial networks," *Electronics*, vol. 12, no. 8, Apr. 2023, doi: 10.3390/electronics12081759.

[8] A. Priyanka, P. Gauthamarayathirumal, and C. Chandrasekar, "Machine learning algorithms in proactive decision making for handover management from 5G & beyond 5G," *Egyptian Informatics Journal*, vol. 24, no. 3, 2023, doi: 10.1016/j.eij.2023.100389.

[9] E. Kim and I. Joe, "Handover triggering prediction with the two-step XGBOOST ensemble algorithm for conditional handover in non-terrestrial networks," *Electronics*, vol. 12, no. 16, Aug. 2023, doi: 10.3390/electronics12163435.

[10] S. Khosravi, H. S. Ghadikolaei, J. Zander, and M. Petrova, "Reinforcement learning-based joint handover and beam tracking in millimeter-wave networks," in *IEEE Wireless Communications and Networking Conference, WCNC*, vol. 2023-March, pp. 1–6, Mar. 2023, doi: 10.1109/WCNC55385.2023.10118761.

[11] Y. Song, S. H. Lim, and S. W. Jeon, "Handover decision making for dense HetNets: a reinforcement learning approach," *IEEE Access*, vol. 11, pp. 24737–24751, 2023, doi: 10.1109/ACCESS.2023.3254557.

[12] Y. Jang, S. M. Raza, M. Kim, and H. Choo, "Proactive handover decision for UAVs with deep reinforcement learning," *Sensors*, vol. 22, no. 3, Feb. 2022, doi: 10.3390/s22031200.

[13] M. Ozturk, M. Akram, S. Hussain, and M. A. Imran, "Novel QoS-aware proactive spectrum access techniques for cognitive radio using machine learning," *IEEE Access*, vol. 7, pp. 70811–70827, 2019, doi: 10.1109/ACCESS.2019.2918380.

[14] A. Zhu, S. Guo, B. Liu, M. Ma, J. Yao, and X. Su, "Adaptive multiservice heterogeneous network selection scheme in mobile edge computing," *IEEE Internet of Things Journal*, vol. 6, no. 4, pp. 6862–6875, Aug. 2019, doi: 10.1109/JIOT.2019.2912155.

[15] J. Chen, Y. Wang, Y. Li, and E. Wang, "QoE-aware intelligent vertical handoff scheme over heterogeneous wireless access networks," *IEEE Access*, vol. 6, pp. 38285–38293, 2018, doi: 10.1109/ACCESS.2018.2853730.

[16] S. H. Sreedhara, V. Kumar, and S. Salma, "Efficient big data clustering using adhoc fuzzy c means and auto-encoder CNN," in *Lecture Notes in Networks and Systems*, vol. 563, pp. 353–368, 2023, doi: 10.1007/978-981-19-7402-1_25.

[17] P. Pujar, A. Kumar, and V. Kumar, “Plant leaf detection through machine learning based image classification approach,” *IAES International Journal of Artificial Intelligence*, vol. 13, no. 1, pp. 1139–1148, Mar. 2024, doi: 10.11591/ijai.v13.i1.pp1139-1148.

[18] B. Ma, W. Guo, and J. Zhang, “A survey of online data-driven proactive 5G network optimisation using machine learning,” *IEEE Access*, vol. 8, pp. 35606–35637, 2020, doi: 10.1109/ACCESS.2020.2975004.

[19] L. Yan *et al.*, “Machine learning-based handovers for sub-6 GHz and mmWave integrated vehicular networks,” *IEEE Transactions on Wireless Communications*, vol. 18, no. 10, pp. 4873–4885, Oct. 2019, doi: 10.1109/TWC.2019.2930193.

[20] S. I. Majid, S. W. Shah, S. N. K. Marwat, A. Hafeez, H. Ali, and N. Jan, “Using an efficient technique based on dynamic learning period for improving delay in AI-based handover,” *Mobile Information Systems*, vol. 2021, pp. 1–19, Aug. 2021, doi: 10.1155/2021/2775278.

[21] R. S. -Iborra, L. B.-Escobedo, and J. Santa, “Machine learning-based radio access technology selection in the internet of moving things,” *China Communications*, vol. 18, no. 7, pp. 13–24, Jul. 2021, doi: 10.23919/JCC.2021.07.002.

[22] Y. Cao, S. Y. Lien, Y. C. Liang, K. C. Chen, and X. Shen, “User access control in open radio access networks: a federated deep reinforcement learning approach,” *IEEE Transactions on Wireless Communications*, vol. 21, no. 6, pp. 3721–3736, Jun. 2022, doi: 10.1109/TWC.2021.3123500.

[23] B. Galkin, E. Fonseca, R. Amer, L. A. Dasilva, and I. Dusparic, “REQIBA: regression and deep q-learning for intelligent UAV cellular user to base station association,” *IEEE Transactions on Vehicular Technology*, vol. 71, no. 1, pp. 5–20, Jan. 2022, doi: 10.1109/TVT.2021.3126536.

[24] B. Zhang, S. Liu, J. L. Yu, and Z. Han, “A learning aided long-term user association scheme for ultra-dense networks,” *IEEE Transactions on Vehicular Technology*, vol. 71, no. 1, pp. 820–830, Jan. 2022, doi: 10.1109/TVT.2021.3127367.

[25] J. Chen *et al.*, “Joint task assignment and spectrum allocation in heterogeneous uav communication networks: a coalition formation game-theoretic approach,” *IEEE Transactions on Wireless Communications*, vol. 20, no. 1, pp. 440–452, Jan. 2021, doi: 10.1109/TWC.2020.3025316.

[26] H. Hu, C. Ma, and B. Tang, “Channel allocation scheme for ultra-dense femtocell networks: based on coalition formation game and matching game,” in *2019 IEEE MTT-S International Wireless Symposium, IWS 2019 - Proceedings*, May 2019, pp. 1–3. Doi: 10.1109/IEEE-IWS.2019.8803970.

[27] L. L. Magoarou, “Efficient channel charting via phase-insensitive distance computation,” *IEEE Wireless Communications Letters*, vol. 10, no. 12, pp. 2634–2638, Dec. 2021, doi: 10.1109/LWC.2021.3109295.

[28] H. Tong, T. Wang, Y. Zhu, X. Liu, S. Wang, and C. Yin, “Mobility-aware seamless handover with MPTCP in software-defined hetnets,” *IEEE Transactions on Network and Service Management*, vol. 18, no. 1, pp. 498–510, Mar. 2021, doi: 10.1109/TNSM.2021.3050627.

[29] X. Tan, G. Chen, and H. Sun, “Vertical handover algorithm based on multi-attribute and neural network in heterogeneous integrated network,” *Eurasip Journal on Wireless Communications and Networking*, vol. 2020, no. 1, Dec. 2020, doi: 10.1186/s13638-020-01822-1.

BIOGRAPHIES OF AUTHORS

Bhavana Srinivas earned her Bachelor's of Engineering BE degree in ECE from Nagarjuna College of Engineering & Technology, Bangalore in 2009. She has obtained her master's degree in M.Tech. (ECE) from Dayanandhsagar College of Engineering in 2012 and currently she is a research scholar at New Horizon College of Engineering doing her Ph.D. in Electronics and Communication Engineering. She has attended many workshops and induction programs conducted by various universities. Her areas of interest are communication and machine learning. She can be contacted at email: bhavanas_12@rediffmail.com.

Nadig Vijayendra Uma Reddy is professor and head (AI and ML), New Horizon College of Engineering, Bangalore with an experience of 26 years in Teaching. She is qualified in Bachelor and Master Degrees in Electronics and Communication Engineering, and Ph.D. in mixed mode VLSI design and executive PG degree in AI & ML. Her areas of interest are analog and mixed mode VLSI design, data analytics, machine learning, artificial intelligence, and wireless sensor networks. She can be contacted at email: nvumareddy@gmail.com.