Efficient Handover Execution Mechanism For Heterogenous Wireless Network Based On Machine Learning

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Abstract
The incorporation of mmWave along with LTE sub-6 delivers advantages to enhance the reliability, optimized coverage and bandwidth of the smart network along with its significant applications. However, the identification of the right mmWave remote radio units (RRU) is one of the main challenges and this occurs due to the blindness coverage of the directional beams. Moreover, the mmWave network depend on the edge of cloud deployment that to satisfy the low latency of the smart applications. Furthermore, due to limited battery resource within IoT devices the consumption of energy should be minimized for the handover. Hence, it is very much essential to reduce the signal overhead for the handover process. In the first phase of this research, the work focuses for the efficient handover mechanism within the LTE and mmWave. Later, an automated handover execution technique is developed within LTE and mmWave by utilizing XGBoost classification algorithm. The XGBoost classification algorithm is applied for the prediction of handover success rate via channel information that is based on sampling window. Finally, the XGBoost based mechanism for handover along with the performance evaluation will be carried out through several IoT devices and then result obtained displays the XGBoost-based handover established that it is better than the existing model of KNN-based handover execution algorithm.

Keywords: - HWN (Heterogeneous wireless network), XGBoost algorithm, RAT (Radio access Technology), Machine Learning

1 INTRODUCTION
In upcoming future, for building smart ecosystem several huge-scale technologies are implemented such as sensor needed and IoT. These technologies will evolve over the time. Same as smart robots and self-driving vehicle that gathered wide attention globally and enhance data communication [1]. [2] Furthermore, in past few years self-driven cars like as google car [3] is been developed by
considering several cognitive framework. These frameworks comprises of several data that is gathered from various types of sensors as well as artificial intelligence (AI) models established in those cars. Sub-domain of AI that is deep learning (DL) and machine learning (ML) for the smart manoeuvring of vehicle along with other vehicles. Further, by implementing the several transporting model that comprises of several effective network as well as computer capabilities, we can improvise the efficiency of vehicle. Here the safety of the vehicle is estimated through the low latency and reliable environment for the effective transmission of control packets (CP) due to sensor constraints [4]. Moreover, to achieve a self-sustainable model for avoiding the high level of maintenance for the smart cities along with IoT is developed. A substantial amount of energy is saved as all the above-mentioned phenomena develops less energy consumable devices.

![Architecture of Heterogeneous wireless communication network.](image)

IoT is one of the huge model that display the vision of large-scale infrastructure and it establishes the flexible computing ecosystem [5]. Iot is defined as global network, which consists of infrastructure as well as possesses by self-configuration capabilities [6]. Iot is a human designed intellect network model that connects through several models via internet and this involves various communication technologies such as Ethernet, ZigBee, wireless sensor network (WSN), Wi-Fi, LTE. Some other protocols are such as IPV6, it comes over the personal network that is also referred as 6LoWPAN, next is low power WAN form LoRA alliance (LoRaWAN) as well as mmWave, narrowband IoT (NB-IoT) and machine type LTE communication (LTE-MTC). All these types of models led to the rapid transformation of the IoT technology towards a highly heterogeneous environment and that led to interoperability within various devices, Fig 1 shows this. Furthermore, here several objects that are interconnected can sense the knowledge as well as information that leads to exchange of data along with physical phenomena. Moreover, the energy plays a very significant role in all the battery-powered devices those comprises with communication, processing as sensing capabilities.

In this research, here we majorly focus on the handover approach of Iot devices through the LTE to mmWave technologies (referred as 5G) [7-8]. Performance metrics consider several features that are robust connectivity, low energy dissipation as well as good availability and high quality streaming...
along with very low latency with high throughput. Moreover, novel algorithm are been modelled for meeting the requirement [9]. The very first step is to utilize the density for enhancing the frequencies of spatial mmWave [10]. Further, this develops an obstacle for the handover management [11]. Later on, the data gets very much closer to the user so it reduces the latency through the mobile edge cloud (MEC) adoption [9]. Further, the automated decision making approach through the machine learning as well as SDN is utilized which leads towards the complexity in the handover mechanism for a given cellular network. Although, the application of the AI (Artificial Intelligence) is to carry the automated decision method for a cellular network is been modelled for the optimization of resource allocation [12] for Efficient RAT selection along with handover mechanism [13]. Furthermore, the huge amount of data is collected for feature analysis of the HWN [14].

In the recent years, various handover algorithms are architecture, which requires the measurement in absolute manner [16]. Although we have to manually optimize the few models as it is not possible to be absolute within HWNs. Further, they have implemented restrictions on several models for real time applications [15]. By considering QoS of networks several existing methodologies have been developed [16], [17], [18], [19]. Whereas, only restricted amount of studies are been focused for the RAT approach by considering the user preferences within HWN [20], [21], [22]. Furthermore, the existing methodologies did not do tradeoffs within success rate as well as energy optimization. [23] A changeover model based on the KNN technique was developed for the 5G cellular network with acceptable performance, and it has been demonstrated that the ML approach aids in decision-making [24]. Moreover, it has been noted that research has not yet integrated an effective ML approach into the HWN [24]. This research project focuses on handover execution mechanisms for the heterogeneous network using a machine learning technique in order to address this problem. This study focuses on a modified XGBoost classification strategy to deal with the issue of data imbalance that impacts prediction accuracy; the suggested XGBoost handover approach reduces signal overhead in heterogeneous cellular networks.

Research contribution are as follows:

- Efficient handover execution approach by utilizing XGBoost machine learning algorithm is presented.
- Better handover success rate and reduced handover failures is achieved those results in energy efficient network.

2 PROPOSED METHODOLOGY

The handover execution technique for diverse wireless communication environments is presented in this section. Firstly, the system model used to execute handover operations is provided. Second, a handover execution model based on machine learning is proposed to reduce handover failure and signaling overhead.
Fig. 2. Heterogeneous communication network composed of LTE and mmWave.

(a) **Heterogeneous communication network:**

Let us consider the HWN model that is dense as well as its mmWave and LTE co-exist along with each other by considering the radius $s$ as displayed in the figure 2. Further, the IoT devices, which are placed by a random manner through a HWN model. This follows the Poisson distribution [25]. Here the LTE and mmWave operates with several technologies along with bands, all the IoT devices are connected with cellular network and it reports the measurement of all the downlinks radio frequencies to the given base station (BS). The BS decides the measurement gap within the long-term evolution and this is considered as the major changes. As the implementation of ML techniques, this aids the model along with that might be not possessed for the feasible signal that to maintain the communication Evolution. Furthermore, the IoT devices reaches near to the network edges and the IoT devices are given to the different RAT technologies for the continuation of the service. Further, the expected count of IoT devices will be denoted by the intensity parameter $\phi$ along with process $\mu$. This research focuses by describing the process $\mu$ for the IoT devices within the environment $X$. Henceforth the Poisson distribution is utilized for obtaining the information for the IoT devices. Here the Poisson distribution with the mean that is represented through the $\phi X$ as given through the below equation.

$$\phi X = \phi \pi s^2$$

Here $s$ denotes the cellular network radius. The $j^{th}$ denotes the device location that is gathered through the continuous distribution in uniform way in $S^2$ that is applied for the polar coordinates $(s_j, \theta_j)$, where $0 \leq s_j \leq s$, $0 \leq \theta_j \leq 2\pi$ and $j = 1,2,3,\ldots,0$.

Using past data on the likelihood that a handover will be successful for a particular IoT device, the XGBoost classification model is utilized to override handover decision making. The collection session $U$ cannot exceed the channel coherence time in order to use ML models. The session $U$ cannot last longer than the channel coherence time for the model to be considered valid. Additionally, because not all IoT devices required handover operation, the sample size gathered could not exceed the total number of handover attempts. Every time a new IoT device entered an LTE network or switched to a
new LTE network, the LTE network conducted the HO execution algorithm for the corresponding IoT device.

(b) Machine Learning based handover execution algorithm:

For efficient handover operations in a complex heterogeneous wireless communication environment, the current model makes use of a KNN machine-learning model. The accuracy of their handover approach for execution will be greatly harmed when there is data imbalance because processing them in parallel is challenging. Thus, this has an impact on the user experience. In order to forecast how a handover will be handled, this paper uses the XGBoost classification technique because each tree can be executed concurrently using parallel computing platforms. Thus, it can be used for distributed BSs' real-time HWN requirement.

Reference symbol established for power (RSRP) in LTE along with mmwave, distance between IoT devices and the base station (BS), coordinate of the IoT device, RSRP measurement update based on X1, and RSRP measurement update based on X2 are all features that are taken into consideration in this work. The first two features are gathered by RRC (radio resource control) messages utilizing observed arrival time difference or a global positioning system, while the final three parameters can be received directly from IoT devices [26].

The IoT device measures the RSRP of the LTE network, which is less than the handover quality specifier for initializing RRC X2, as defined in the LTE standard [27]. The RRC is then reconfigured by the LTE network based on the measurement gap. Moreover, an IoT device initializes RRC X1 after measuring an RSRP higher than the handover quality specifier. If the mmWave power exceeds the
predetermined quality specifier, the IoT device initializes RRC Y2, chooses a random mmWave channel slot for communication, and successfully completes HO. Fig. 3 depicts the full conventional handover execution process in its entirety. Figure 3 shows that the handover attempt is made in phase X and the actual handover is made in phase Y, which is when the LTE network opted to permit the HO.

![Diagram](image.png)

Fig. 4. Machine learning based handover execution methodology.

Employing the conventional model will result in a small overhead. Thus, this study presents a handover execution technique based on machine learning. Fig. 4 depicts the algorithm for the suggested machine learning-based handover execution strategy for HWNs. Using Fig. 4, the choice of accepting IoT device measurement or employing machine learning-based handover success rate accuracy is made. The updated XGBoost method is used to generate the ROC curve, which is used to determine if HO will succeed or fail. The HO algorithm will then continue with its usual execution process if the measured LTE received power is less than the specified handover quality specifier is and the anticipated mmWave received power is greater than the handover quality specifier is. Alternatively, the LTE network prevents the IoT device request from being switched from LTE to mmWave if anticipated mmWave received power is less than the handover quality specifier. Help the IoT device overcome potential handover difficulties by doing so. The suggested handover execution model employing machine-learning method for HWNs is shown in Fig. 4 along with the handover execution process. The XGBoost algorithm-based machine learning handover execution model helps minimize handover failures and lower signaling overhead for carrying out handover. Hence, as demonstrated experimentally below, help in obtaining improved handover success rate performance with reduced energy use.

3 EXPERIMENT RESULT AND ANALYSIS
The experiment analysis of the proposed enhanced XGBoost-based model for handover execution compared to the current KNN-based model for handover execution is shown in this part. The Python framework is used to implement both models in order to perform simulation. These are descriptions of the simulation parameters taken into account. 2.1 GHz frequency is set for the LTE center along with that 5G center frequency is fixed to 28GHz. Further, LTE bandwidth is established to 20 MHz, on the other hand the 5G bandwidth is fixed to 100MHz. Here COST 231 is utilized for the modelling of LTE propagation paradigm. The entire model presented [1], [2] is applied as 5G propagation paradigm. Here simulation time is established to 50 millisecond as well as the cell radius is set for 350 meters. Further, LTE 46 dBm is set for the LTE BS power along with 5G BS power will be established to 46dBm. RRC even X1, X2, and Y2 is set to -125 dBm, -130 dBm, and -95 dBm respectively. IoT device size is varied in this experiment, ranging from 50 to 400, and performance is evaluated in terms of the handover success rate as well as the handover failures, and overall energy usage for carrying out handover operations. The proposed model XGBoost-based HO results are compared with those of the existing model KNN-based HO.

![Handover execution success rate](image)

**Fig. 5.** Handover execution success rate performance.

Figure 5 displays the handover execution model success rate obtained using the KNN-based HO and XGBoost-based HO models while taking into account various IoT devices. According to the results, the XGBoost algorithm raises the handover success rate for a variety of IoT devices by 1.54%. Additionally, it is noted that the XGBoost-based HO model for execution model is effective when considered through high-density communication ecosystem.

The handover failure results are obtained by the KNN-based HO as well as XGBoost-based HO models while considering various IoT devices. This is displayed in Fig. 6. According to the results, the XGBoost model decreases handover failures significantly by 43.84% while considering various IoT devices. Adoption of HO execution algorithm based on machine learning is responsible for the notable decrease in handover failure reduction.
Figure 7 illustrates the energy efficiency results obtained using the KNN-based HO and XGBoost-based HO models while considering various IoT devices. From the results, it is evident that the XGBoost model minimizes energy usage by 0.65% considering various IoT devices. Due to the reduction of signal overhead, the energy is also reduced.

4  CONCLUSION

This research established that the signal overhead affects the handover execution as it results in handover failure. This affects the performance of the packet transmission and along with that; it increases the energy consumption through the IoT devices. To address this issue we present a machine learning based model for handover execution utilizing XGBoost algorithm. The Proposed model for
handover execution enhance the handover success rate value by 1.54% while comparing it to existing KNN-based Handover mechanism. Further, the XGBoost-based mechanism for handover reduces the failure of handover by 43.84% while comparing with KNN-based mechanism for handover. Further, the XGBoost-based mechanism for handover reduces the energy consumption by the value of 0.65% while comparing it with KNN-based mechanism for handover. Overall result that we achieved establishes that proposed handover execution paradigm is robust as well as scalable irrespective to the size of IoT device that is operating within a heterogeneous network. Future research would be considered as performance evaluation of the model along with RAT selection by considering diverse QoS constraint in the heterogeneous cellular network.

References


