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Vaidehi Bakshi[1],
Dr. Rakesh Kumar[2]

A Review on Machine Learning Assisted Handover Mechanisms for Future Generation IoT Networks

Abstract: - Machine Learning and Deep Learning Algorithms have been explored widely to identify potential avenues to optimize future generation IoT networks. One such area happens to be a data driven model for initiating handover among multiple access techniques such as FDM, OFDM, OTFS and NOMA. The amount of data which is generated for variable channel conditions typically in IoT applications is enormously large and hence conventional rule based mechanisms do not render high accuracy in handover problems in IoT and wireless Ad-Hoc networks. With the increasing data handling ability of machine learning and deep learning models, handover based on various channel metrics such as fading factor, received SNR and error rates can be implemented. This rules out the need for conventional handover mechanisms for software defined networks. Multiple machine learning and deep learning models have been explored thus far for initiating handovers for IoT applications, which are explored and discussed in this paper. The salient features of each of the approaches has been highlighted along with identifying potential research gaps, thereby paving the path for future research the domain.

Keywords: Internet of Things (IoT), Machine Learning, Handover, Quality of Service, Future Generation Wireless Systems, Bit Error Rate.

1. INTRODUCTION

The Internet of Things (IoT) represents a transformative paradigm that connects physical devices, sensors, and systems to the internet, enabling seamless data exchange and automation. IoT networks comprise diverse devices such as smart home appliances, wearables, industrial sensors, and connected vehicles. These devices communicate using wireless technologies like Wi-Fi, Zigbee, LoRaWAN, and 5G, supporting applications in healthcare, transportation, agriculture, and smart cities. The growing integration of IoT devices into daily life has led to a significant increase in the complexity of network architectures. As devices move between different locations, ensuring continuous connectivity becomes a critical challenge, particularly in dynamic environments like smart cities or vehicular networks [1].

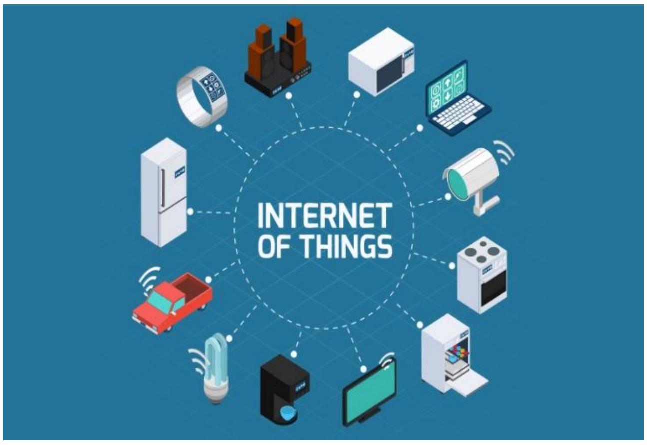

Fig.1 The IoT Framework

[1] Department of Computer Science and Engineering1,2
Rabindranath Tagore University, Raisen, India1,2
Corresponding Author: Vaidehi Bakshi
vaidehibakshi35@gmail.com1
rakeshmittan@gmail.com2

Figure 1 depicts the IoT framework. Data transmission is the cornerstone of IoT networks, enabling devices to exchange information with each other and centralized systems. IoT devices collect vast amounts of data through sensors, which are then transmitted to cloud servers or edge devices for processing and analysis [2]. The efficiency and reliability of data transmission directly impact the performance of IoT applications, from real-time monitoring in healthcare to predictive analytics in smart factories. This process involves a combination of wired and wireless communication protocols designed to meet the specific requirements of IoT systems, such as low power consumption, minimal latency, and secure data handling [3].

IoT networks rely on various communication technologies, each suited to specific applications and environments. Short-range protocols like Bluetooth, Zigbee, and Wi-Fi are commonly used for home automation and wearable devices, providing high-speed data transfer over limited distances. On the other hand, long-range protocols like LoRaWAN, Sigfox, and cellular networks (e.g., 4G, 5G) cater to industrial IoT and smart city applications, where devices are distributed over wide areas. The choice of technology depends on factors such as data rate, power efficiency, range, and network scalability [4]. For instance, low-power wide-area networks (LPWANs) are ideal for battery-operated devices that require infrequent data transmission over long distances. IoT data transmission faces several challenges due to the diverse and dynamic nature of IoT ecosystems. Bandwidth limitations, signal interference, and network congestion can hinder the smooth flow of data, especially in environments with a high density of devices. Power constraints in IoT devices also necessitate the use of energy-efficient transmission techniques, as frequent data communication can drain batteries quickly [5]. Furthermore, ensuring data integrity, confidentiality, and availability during transmission is critical to addressing security threats such as eavesdropping, data tampering, and denial-of-service attacks. These challenges demand robust transmission protocols and adaptive network management strategies [6].

2. DATA OPTIMIZATION AND HANDOVER

Typically, wireless channels in IoT networks exhibit a frequency dependent nature depicted in figure 2.

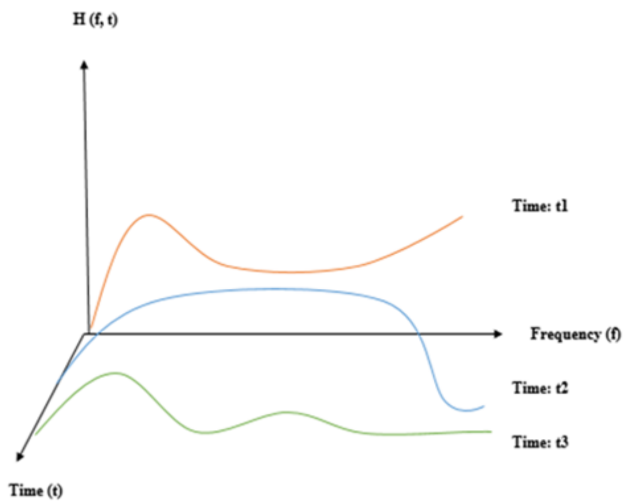

Fig.2 Frequency dependent nature of wireless channels.

The nature of wireless channels can be represented as [7]:

$$\boldsymbol{H = g(f,t)} \quad \textbf{(1)}$$

Here,

H denotes the frequency response of the channel

g denotes the governing function

t denotes the time variable.

f denotes the frequency variable.

Due to the frequency ad temporal variations, the signal strength received at the IoT gateway may often be extremely fluctuating as depicted in figure 3.

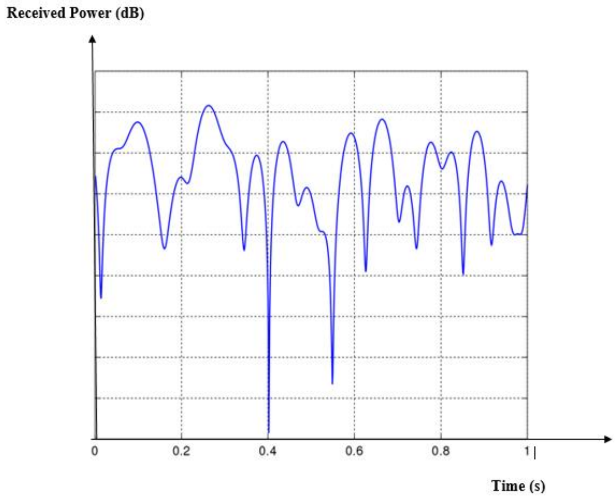

Fig.3 Typical received signal strength at the IoT gateway

Due to the variability in the signal strength, the quality of service (QoS) degraded making is necessary to employ handover among multiple access techniques Handover, also known as handoff, refers to the process of transferring an ongoing network connection from one access point or base station to another without interruption. In IoT networks, handover ensures that devices maintain seamless communication as they move across network boundaries [8]. Unlike traditional cellular networks, IoT devices exhibit unique challenges due to their varying power constraints, diverse protocols, and differing data transfer requirements. Efficient handover mechanisms are essential to guarantee low latency, minimize packet loss, and support uninterrupted services in scenarios such as connected cars transitioning between cell towers or wearable health monitors moving across Wi-Fi zones [9]. As IoT networks expand, the demand for reliable and efficient handover mechanisms becomes increasingly critical. Inefficient handovers can result in service disruptions, increased energy consumption, and degraded user experiences, particularly in latency-sensitive applications like remote surgery or autonomous driving. Additionally, the heterogeneous nature of IoT networks necessitates advanced algorithms capable of handling transitions across different wireless technologies. Factors such as network load, signal strength, and device mobility patterns must be considered to optimize handover processes. Addressing these challenges ensures not only the reliability of IoT services but also enhances their scalability and user acceptance [11].

The ongoing development of IoT networks highlights the need for innovative handover solutions tailored to the specific requirements of IoT applications. Emerging technologies like artificial intelligence (AI), edge computing, and 5G are pivotal in shaping advanced handover strategies. AI-driven predictive models can anticipate mobility patterns and optimize network resource allocation, while edge computing can reduce latency by processing data closer to the device. However, challenges such as security vulnerabilities, interoperability issues, and the integration of sustainable energy-efficient methods remain areas for further research. Solving these challenges will pave the way for robust, future-proof IoT networks capable of supporting the evolving digital ecosystem [12]. Advancements in communication technologies and network optimization techniques are helping to overcome data transmission challenges in IoT networks. Adaptive data compression, intelligent routing algorithms, and edge computing solutions are being implemented to enhance transmission efficiency and reduce latency. For instance, edge devices can preprocess data locally, transmitting only relevant information to the cloud, thereby reducing the load on communication channels. Additionally, emerging technologies such as 5G and 6G promise higher bandwidth and lower latency, enabling seamless data transmission for mission-critical applications [13]. Integrating artificial intelligence (AI) and machine learning (ML) into network management can further optimize data flow, predict traffic patterns, and ensure efficient resource allocation. While several handover protocols can be implemented for IoT Networks, yet the most common ones can be [14]:

Between multiple access techniques (NOMA, OFDM, OTFS etc.)

Between (device to device: D2D) and Cellular modes

Between Wifi and WiMax etc.

The choice of the handover needs to be application specific and the features should be chosen accordingly.

3. MODELS FOR IMPLEMENTING HANDOVER

The future of IoT data transmission lies in the convergence of advanced technologies such as AI, blockchain, and quantum computing. AI-based algorithms can predict network conditions and optimize transmission paths, while blockchain ensures secure and decentralized data exchange [15]. As IoT devices proliferate, the development of standardized protocols and interoperable systems will become increasingly vital. These innovations will enable IoT networks to handle massive data volumes efficiently, unlocking their full potential across diverse industries. The most commonly used data driven machine learning models for IoT handover are presented next [16]:

Machine learning models can be trained using vast amounts of network data, such as user mobility patterns, historical handover events, and network conditions [17]. By analyzing this data, ML algorithms can learn to predict when a handover is necessary and which target cell would provide the best service quality. Supervised learning techniques, such as decision trees, random forests, and neural networks, can be employed to classify the optimal handover timing and target base station. Reinforcement learning, on the other hand, can be used to develop intelligent agents that make handover decisions based on real-time network conditions, optimizing long-term network performance [18].

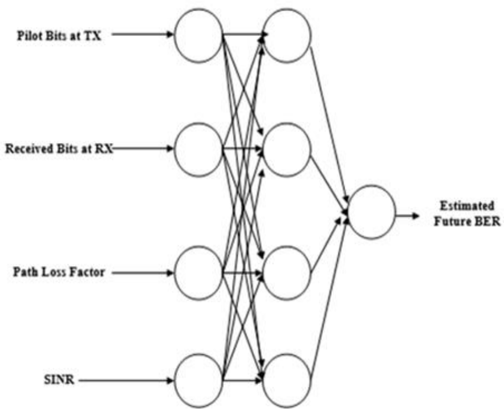

Fig.4 Machine Learning Assisted Model for Handover

Figure 4 depicts a generic machine learning neural model for handover. In this model, the Bit Error Rate (BER) is to be estimated by the model based on channel metrics. Several types of machine learning techniques have been applied to optimize handover in wireless networks [19]. Supervised learning methods such as support vector machines (SVMs) and decision trees are commonly used to predict the optimal handover time based on labeled training data [20]. Unsupervised learning techniques, such as clustering algorithms, help in identifying patterns in user mobility and network usage, enabling more efficient handover decisions. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can process more complex datasets, including time-series data, and improve handover prediction accuracy in rapidly changing environments [21]. Additionally, reinforcement learning has gained attention for its ability to optimize handover strategies by learning from real-time interactions with the network environment [22].

For instance, if the handover is to be initiated between multiple access techniques such as OFDM and NOMA, the following condition can be employed:

$if\ (BER_{NOMA} < BER_{OFDM})$

{

Choose NOMA as the transmission technique

$else$

{

Fall back to OFDM

}

In this case, the multiple access technique NOMA has been chosen as the primary access techniques while OFDM has been chosen to be the automatic fall back option.

4. PREVIOUS WORK

This section presents the most recent research in the domain with the identified research gaps to bolster future research.

Pranato et al. [23] proposed that by utilizing a Radio Intelligent Controller (RIC), Open Radio Access Network (O-RAN) offers a way to integrate machine learning into cellular networks. This allows for the modular improvement of numerous RAN features without altering any existing RAN network element. This work replaced the vector autoregression approach with a neural network and improved it so that it takes the movement of the User Equipment (UE) into account.

Abdulkarem et al. [24] proposed that purpose of implementing a handover mechanism is to minimize the time required for the cellular network to execute. By analyzing the 5G cellular network's resource allocation and handover mechanism, we can determine how well the suggested simulation model performs. Because of this change, both the time it takes to prepare for and carry out a handover are decreasing..

Haghrah et al. [25] proposed that depending on the quality of the received signal, critical performance measures like the handover ratio, the frequency of handover failures, and the frequency of radio link failures are used to assess the handover procedure.

Nyangaresi [26] proposed that several attacks that can exploit handover protocol include man-in-the-middle attacks, DOS attacks, impersonation attacks, jamming attacks, and packet replays. Furthermore, it does not provide hig fohrward key secrecy. This research presents a method for selecting a target monitoring area that makes use of Self-Organizing Maps (SOMs). The handoff entities are further authenticated using a mechanism that relies on elliptic curve cryptography. There has been a marked decrease in ping-pong and unsuccessful handoffs, according to the data collected.

Khan et al. [27] proposed that the complexity of the radio environment makes it difficult to solve these problems using analytical models since they may not characterize the wireless channel. In this study, we suggest ML techniques that are driven by data to effectively address these issues in WLAN networks. Authors compare the outcomes of the suggested strategies to those of more conventional methods of addressing the aforementioned issues.

Liu et al. [28] proposed that may encounter the edge of coverage more often as a result of the densification of small base stations, which could bring about significantly higher inter-cell interference. This study presented a new handover method that combines the benefits of fuzzy logic with multiple attributes decision algorithms (MADM). This study uses historical data to define the ideal membership functions within the fuzzy system, which further enhances the performance of the suggested scheme. It also incorporates the subtractive clustering technique.

Alhabo et al. [29] proposed that the deployment of ultra-dense tiny cells can lead to severe interference, a high number of frequent needless handovers, and/or handover failure. As a result, excessive power consumption is anticipated. To improve the network's energy efficiency, it's a good idea to put some small cells into idle mode, as long as this doesn't reduce service quality. To lessen the load on dense small cell networks, we offer a game-theoretic approach in this study.

Research Gaps

The research gaps identified based the study of existing work in the domain and in general suggests that most of the research frameworks do not identify techniques which exhibit co-existence or mutual coherence of metrics. Although condition checking isn't always required, it's worth thinking about because wireless and IoT networks can have different receiver sensitivities, which can increase the likelihood of errors. Equalization is not incorporated into the handover procedure in current research. Equalization for the handover procedure, which can lower the mistake rate and improve the system's quality of service, is not included in the current research.

1. Typically, the above research gaps can be addressed by analyzing the error rate characteristics under variable SNR.
2. Employing an iterative equalization mechanism.

The equalization mechanism is depicted in figure 5.

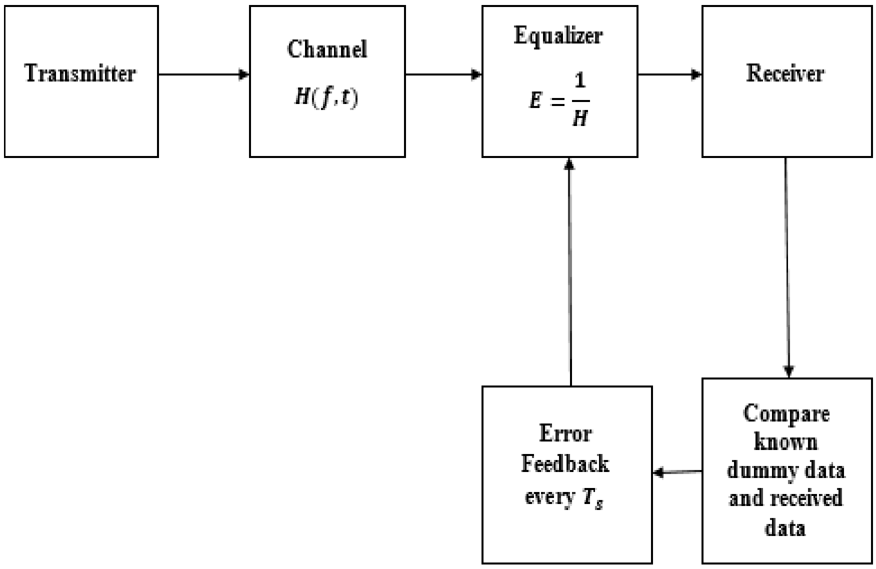

Fig.5 Channel Equalization

Channel equalization can be performed by iteratively sensing the channel and employing it to invert the characteristics [30].

$$E(f,t) = \frac{1}{\sum_{i=1}^{n} H(f,t-Ti)} \quad (2)$$

Here,

$E(f,t)$ denotes equalizer response.

n are samples.

T denotes sampling time

To estimate the channel,

Compute the error in time domain as [31]:

$$\boldsymbol{e(t) = y(t) - d(t)} \text{ at the receiving end} \quad \textbf{(3)}$$

Obtain h(t) as:

$$\boldsymbol{h(t) - y(t) = e(t)} \quad \textbf{(4)}$$

This process can be applied iteratively for samples over a period 'T'.

5. SOCIAL RELEVANCE

The social relevance of the research can be attributed to the need for seamless connectivity among users under stationary or mobile conditions under diverse geographical and topographical scenarios. In addition to their technical importance, these processes have significant social relevance and influence, affecting multiple facets of everyday life, economic activities, and society progress. An efficient handover process plays a crucial role in improving connectivity, facilitating economic development, providing essential services, and closing the gap in digital access. Some practical applications bolster the concept [32].

Enhanced Connectivity and QoS: The continuous connectivity is essential for maintaining social relationships, enabling real-time communication, and supporting mobile lifestyles. Whether it's a business call on the move or accessing information while traveling, effective handover mechanisms keep individuals connected, enhancing their social interactions and productivity [33].

Enhancing Economic Growth: By ensuring seamless connectivity, handover mechanisms contribute to economic efficiency, enabling businesses to leverage mobile technologies and digital platforms. This, in turn, drives innovation, creates jobs, and boosts economic growth [34].

Supporting Critical Services: The role of handover mechanisms extends to critical services such as healthcare, emergency response, and public safety. Telemedicine, for instance, relies on stable and continuous connections to provide remote consultations and monitor patients' health in real-time. Similarly, emergency services depend on reliable communication networks to coordinate responses and manage crises effectively. Efficient handover mechanisms ensure that these critical services are not disrupted, thereby enhancing public safety and health outcomes. The reliability of these networks can be life-saving, particularly in emergency situations where every second counts [35].

Improving Conditions in Socially Backward Areas: Handover mechanisms also play a role in bridging the digital divide, ensuring that connectivity is not just a privilege of urban areas but extends to rural and underserved regions. As wireless networks expand, effective handover management is crucial for providing consistent service across diverse geographical areas. This helps in reducing the gap between urban and rural populations in terms of access to information, educational resources, and economic opportunities. By facilitating broader access to mobile and internet services, handover mechanisms promote inclusivity and support socio-economic development in less connected regions in areas such as [36]:

- Education.
- Healthcare.
- Local Business
- Small finances.
- Information exchange etc.

CONCLUSION

It can be concluded from previous discussions that machine learning offers a transformative approach to optimizing handover processes in wireless networks. By enabling more intelligent, data-driven decisions, ML-based handover mechanisms can significantly improve network performance, enhance user experience, and ensure the efficient use of network resources. As wireless networks continue to evolve with the deployment future generation technologies, machine learning will play an increasingly critical role in managing the complexities of modern communication systems, paving the way for more adaptive and resilient handover strategies. This paper presents a holistic review of the existing work in the domain, existing challenges and future directions of research.

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