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CASE STUDY

Predictive handover mechanism for seamless mobility in 5G and beyond networks

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Abstract

Scalability is one of the important parameters for mobile communication networks of the present generation and further to the future 5G and beyond networks. When a user is in motion transferring from one cell site to another, then the handover procedure becomes important in the sense that it ensures that a user gets consistent connection without interruption. Nevertheless, the classic handover process in cellular networks has some sort of drawback like causing service interruptions, affecting packet transmission, and increased latency which is highly uncongenial to the evolving applications which have stringent requirement to latency. To overcome these challenges and improve the mobile handover in 5G and future mobile networks, this article puts forth a predictive handover mechanism using reinforcement learning algorithm. The RL algorithm outperforms the ML algorithm in several aspects. Compared to ML, RL has a higher handover success rate (∼95% vs. ∼90%), lower latency (∼30 ms vs. ∼40 ms), reduced failure rate (∼5% vs. ∼10%), and shorter disconnection time (∼50 ms vs. ∼70 ms). This demonstrates the RL algorithm's superior ability to adapt to dynamic network conditions.

1 | INTRODUCTION

Handover is an important process that determines the quality of mobile communication networks that are in place today because they enable users to maintain constant and highly effective communication throughout the available communication cells in their operating network. Previous schemes in handover management in cellular networks, for instance, the 4G LTE systems, normally employ distinct signal strength-based reactive actions [1]. This can lead to unusual delay in handover decision and is not effective in high user mobility or complex network structure.

An overview of how handovers in 5G networks are managed is presented in this article [2], using various approaches and challenges of user mobility, along with providing evaluations against key performance indicators, which are crucial in ensuring seamless connectivity in high-density environments. One of the strategies to overcome constraints is based on the applied machine learning algorithms to predict the mobility of the user and future handover events [3].

This survey [4] focuses on the challenges in handover and mobility management inside HetNets at 5G. It investigates the impact of increased user density and proposes solutions that maintain QoS and QoE during handovers. Through predicting the user's movement, the network proactively optimizes the target cell and its resources which helps to avoid interruption of the service during handover. Other related works have explored the use of context, for instance, the user location, velocity, and the current network conditions to aid decision-making for handover [5].

Various issues concerning mobility management in 5G and beyond networks, among which are predictive handover mechanisms are addressed in this review [6]. It reviews network flattening and distributed mobility management as a means for improving the user experience and reducing latency during handovers.

A predictive handover mechanism using machine learning techniques to improve the performance of 5G networks handovers is proposed in this article [7]. The proposed approach will be intended for minimizing latency by predicting user mobility and enhancing user experience.

The evolution of mobile networks has introduced significant requirements for handover mechanisms, particularly in the context of 5G and beyond. Predictive handover mechanisms enhance the network efficiency by reducing latency and maintaining connectivity.

As users move between different cells in a mobile network, handover mechanisms are essential for maintaining seamless connectivity. Traditional handover techniques often suffer from delays and dropped connections, especially in high-speed context. Predictive handover mechanisms use machine learning and data analytics to anticipate user movement and optimize handover processes. Device-to-device (D2D) communication and its impact on handover in 5G systems, highlighting new strategies to optimize mobility management, are investigated in [8]. A new handover scheme using prediction of user behaviour in order to optimize handover decisions in 5G networks is proposed in this article [9], therefore reducing the latency of handovers and enhancing the overall performance of the network.

Recent studies have focused on various predictive approaches to enhance handover efficiency in 5G networks:

- **Machine learning techniques**: A machine-learning-based predictive handover framework is proposed by Zhang et al. (2021) [10]. The user mobility data is utilized to forecast the next cell a user is likely to connect to. This model demonstrated a significant reduction in handover latency, improving user experience in dense urban environments [10].
- **Context-aware handover**: A context-aware predictive handover mechanism was introduced by Liu et al. (2022) [11], which integrates real-time network conditions, user behaviour, and environmental factors. The user movement prediction accuracy was improved by this approach, which leads to optimized resource allocation during handovers [11].
- **Deep learning models**: In 2023, a deep learning model was developed by Chen et al. for predictive handover that utilized recurrent neural networks (RNNs) to analyse user trajectory patterns [12]. Their results indicated enhanced prediction accuracy and reduced interruption times during handovers [12].

While predictive handover mechanisms offer promising solutions, several challenges remain such as:

- **Data privacy**: The user privacy and data security should be considered during collection and analysis of mobility. Privacy-preserving techniques that can be integrated into predictive handover algorithms to safeguard user information while maintaining performance are studied by Wang et al. [13].
- **Real-time processing**: The network resources are utilized by the real-time data processing. To address this issue, a decentralized architecture that distributes the computational load across edge devices, enabling faster decision-making during handover events is proposed by Kumar et al. [14]. To enhance connectivity and reduce latency, innovative hybrid predictive handover mechanisims are produced for Beyond 5G networks. Multiple prediction techniques are integrated to improve performance in dynamic network environments [15].
- **Integration with beyond 5G networks**: As networks evolve towards 6G, utilization of predictive handover mechanisms with emerging technologies such as the Internet of Things (IoT) and artificial intelligence (AI) is required. The importance of interoperability is highlighted by Zhao et al., suggesting that future networks should incorporate hybrid models that leverage both predictive analytics and traditional methods [10].

From the previously presented papers in this section, we noticed that Zhang et al. [10] have used AI in 5G handover improvement. The article discussed the implementation of several machine learning algorithms, such as decision trees and support vector machines, for predicting handover events. The performance of these algorithms is evaluated based on prediction accuracy and latency [10]. On the other hand, in this work, another algorithm (reinforcement learning) is going to be explored and compared with support vector machines. It has been proven that reinforcement learning algorithm overcame the support vector machines in many mobile network contexts.

The future of predictive handover mechanisms in 5G and beyond is to integrate advanced technologies such as AI, edge computing, and blockchain. Continued research is needed to refine predictive algorithms, enhance privacy measures, and ensure scalability in diverse network environments.

Predictive handover mechanisms represent a significant enhancement in mobile network technology, particularly in the context of 5G and future generations. Using machine learning and real-time data analytics, these mechanisms can significantly enhance user experience and network efficiency. However, addressing challenges related to privacy, real-time processing, and integration with emerging technologies will be crucial for the successful deployment of these solutions.

1.1 | Seamless mobility in the 5G era: Advancements in handover mechanisms

5G is the evolving mobile communication technology that promises high-speed broadband connections and capability to the added billions of connected devices. Nevertheless, one of the main pre-requisites that are deemed necessary in the actualization of 5G is the ability to maintain continuity for users while moving between adjacent cell sites or distinct network domains. This level of mobility can only be realized depending on the efficiency of the handover processes that are in 5G and beyond networks.

Multi-connectivity or the ability of a user equipment (UE) to maintain multiple connections with the cells or the network domains concurrently has also been postulated as a viable solution to increase the resilience of handovers and achieving seamless mobility [16]. Through simultaneous connections, the UE manages to create a smoother transition during the handover reducing the chances of a discontinuity in service. Reference [17] throws light on challenges associated with seamless handover in 5G networks. It discusses various solutions that may facilitate the efficiency of handovers, considering the importance of predictive algorithms in handling mobility effectively.

Thus as 5G and other next generation networks are developed, it becomes very significant to support the requirement for service continuity control (SCC) and mobility as users require fast and uninterrupted service while on the move. The innovations in handover methods with predictive methods, contextual decision-making methods, and multi-connectivity provide the hope for increased levels of mobility and user satisfaction in the 5G and the future network generations.

2 | MOTIVATION AND OBJECTIVES

Usual handover strategies applied in cellular networks currently are generally organized around using information measured in real time, and decision-making which is reactive. This hopefully can lead to delayed handover decisions and also suboptimal performance especially when there is a lot of mobility of the user or the network architecture is complicated. The rationale for this study stems from the need to design a proactive handover mechanism that would enable the prediction of future handovers so as to mitigate on the interruptions in the Continuity of Service for users who are on the move. The first of those is the development of a promising handover prediction algorithm suitable for integration into the future 5G and beyond networks.

2.1 | The key contributions of this work include

1. Machine learning algorithms simulation comparison and selection to predict user mobility pattern as well as predicting handover occurrences using previous mobility pattern, user context, and network information in 5G mobile networks.
2. Exploring an accurate prediction-based handover decision-making system that can initiate the configuration of the target cell and provide resources, with the help of which a particular mobile user can be easily handed over.
3. Real time updates of the predictive handover algorithm as well as the feedback mechanisms employed throughout the network will also have to be incorporated into the overall framework.
4. Testing of the solution and the assessment of its efficiency, precision and speed, as well as of issues related to the solution's realization.
5. Proving that the application of the predictive handover mechanism (RL) can enhance the mobility management in 5G and beyond networks, decreasing a failure rate of handovers and handover time compared to the reactive approach.

3 | PREDICTION AND ARTIFICIAL INTELLIGENCE IN COMMUNICATIONS

Artificial Intelligence or AI can be defined as an enhanced procedure or a way of thinking that is changing the relation between man and his environment. But what AI can do best of all is to predict, and predict is what lies at the heart of many uses of AI and capacity to predict the future.

As for the total skill of prognosis, there is no doubt; in fact, it has been the driving force of diversified human initiatives for several decades. As for the sense of expectation of the future events in the most general sense, and as for such purposes as weather forecasts, expectations and predictions of economical state of affairs, expecting the future is one of the most basic and most congenital of human instincts. However, here AI has taken it to the next level using tens of thousands of data inputs, complex calculations and state-of-the-art computers to provide much better predictions that humans could ever think of.

Their biggest strength when applied to the process of prediction is their capability to identify concealed correlations in data that are not discernible by the human intellect. This is so empowered with the ability to analyse and compute massive amounts of information and unearth obscure phenomena as well as the capability of predicting with effects that are mostly monumental. For instance, in the sphere of medicine, artificial intelligence algorithms can study patients' records, patients' genetics, patients' environment, and further calculate a person's probability of receiving diseases on the basis of early diagnostic and individualized therapy. Similarly, in the financial fields, the AI models are capable of identifying the trends in the stock price movements, investment options, and associated risks depending on the market movements, consumers' behaviour, other economic factors etc.

Beyond these depressing careers, it is making routine predictable through AI's predictive processing. Recommendation systems hence which are derived by AI are in a position to discover several products, or even a piece of content or even services that will be the most fascinating or useful to us. It would be easier if smart personal agents could forecast our needs and present us with the necessary information or suggestions.

Nevertheless, the ability to use employing AI to predict the capability of the system has advantages and disadvantages in addition to ethical considerations. The use of AI system in influencing important decisions also poses a worry especially on matters concerning bias included, infringement of privacy, and influence of the decisions made by the AI systems. It has become a new focal area for researchers, policymakers and stakeholders, AI enthusiasts to make sure that predictions made by AI systems are understandable, explainable and unbiased.

Yet, it must be noted that the prospect of using AI in the prediction of events is huge. It is the only approach to reconciling with the fact that the complexity is growing rapidly, and we must learn to cope with it; it is not about the automation of work processes but rather about making sound decisions, planning, and searching for new business opportunities.

As we continue to progress down the road of progressing into artificial intelligence then foresight is going to be one of the most beneficial and crucial resources that have ever been invented. AI prediction might be revealing other opportunities as a way of making the world a better one in the respect that it becomes responsive to our needs, sustainable and in a position to build and bring into existence what we as humanity, want to see in our life.

In this work, a new predictive handover mechanism is incorporated into the machine learning algorithms to predict the user's mobility behaviour and probable handovers.

Handover target cell as well as the time for the handover to occur can be predicted by the mobility data that can be derived from past usage history, user related factors and network circumstances all of which are gathered and analysed by the implementable AI algorithm. This information is then used to set up the target cell and every resource required to use to make the transition smooth for 5G mobile user. And feedback mechanism incorporation and real time adjustments are thought to be capable of capturing these changes in the network environment.

4 | HANDOVER IN MOBILE NETWORKS

In a typical mobile network, the average latency due to handover can vary depending on several factors, including the type of handover (intra-frequency, inter-frequency, or inter-RAT), the technology in use (e.g. 4G LTE, 5G), and the network's configuration.

1. Latency due to handover:
   - 4G LTE Networks: It is takes approximately 50 to 150 ms of handover latency in normal circumstances. This embraces the time taken to detect the need to perform the handover, the time taken to communicate with adjacent cells for handover and the time taken to switch to the new cell.
   - 5G Networks: Latency can even go well below 10 ms for instance; 10 ms below in the best scenario owing to hand over processes and network design.
2. Disconnection during handover:
   - 4G LTE Networks: Latency and interruption during handover are negligible and are hardly noticeable in well-optimized network. However, such problems as bad connection signal, or too many people using the network might lead to brief interruptions.
   - 5G Networks: To this extent, handover is one of the key features of 5G, which is created in a way that makes it very tough for the connection to be dropped. As shown with the use of some of the technologies like Dual Connectivity, the transition is often smoother than in the 4G networks.

On the whole the time delay that occurs during a hand over is averaged to range between 10 and 150 ms and hand over drops are very rare and may not be felt by the users at all. Performance is relative and therefore depends on the specific network optimization, the technology applied and the environment.

In 5G system there are usually impacts from handover failure and operators usually assess them based on metrics and simulations.

For instance, the handover success rate and failure rate such as the Key Performance Indicators (KPIs) are mostly examined in the studies. These outcomes are often illustrated in simulations where various factors which include the TTT (Timer To Trigger) and the gNB density are varied to exemplify how they influence the performance of handover. For instance, in cases of ultra-dense networks, Failure ratio could be experienced when TTT values are set to very low values that lead to early handovers.

Actual operator data might show graphs where handover success rates decline sharply with increased user speed or poor signal quality. A typical graph might plot the number of handovers versus user speed or SINR (Signal-to-Interference-plus-Noise Ratio), with an evident spike in failures as these factors worsen. Some operators use techniques like "conditional handover" to reduce these failures, which are illustrated through comparison graphs showing reduced failure rates when these methods are applied.

Actual results of 5G handover failures are typically presented including metrics like handover success rates, latency, packet loss, and specific failure rates in different scenarios (e.g. urban vs. rural, different frequency bands) as shown in Table 1.

TABLE 1 Handover performance metrics in 5G network.

Metric	Scenario 1 (urban, high mobility)	Scenario 2 (urban, low mobility)	Scenario 3 (rural)
Handover success rate (%)	95.2%	98.7%	93.5%
Handover latency (ms)	15 ms	10 ms	20 ms
Handover failure rate (%)	4.8%	1.3%	6.5%
Average disconnection time (ms)	50 ms	30 ms	70 ms
Packet loss during handover (%)	0.3%	0.1%	0.5%

5 | 5G HANDOVER PROCESS IMPROVEMENT USING AI ALGORITHMS

Based on the literature survey, some AI algorithms are as follows since they can support the enhancement of the 5G handover procedure in decision-making, failure prediction and management of the network resources. The following are some of the best AI algorithms suited for this purpose:

5.1 | Reinforcement learning (RL)

- Algorithm: Classes of reinforcement learning methods include Q-Learning, Deep Q-Networks (DQN), … and Proximal Policy Optimization (PPO).
- Application: The other basing RL algorithms can adjust handover parameters such as TTT and HOM (Handover Margin) through practical interactions within a network environment. They assist in reducing the handover failure and therefore are useful in enhancing the performance of handover process.
- Advantages: They help the network to have the real-time control of the factors such as user speed, signal strength and cell load resulting in an enhanced handover process.

5.1.1 | Key Components of RL

Agent: It can be called the learner or decision-maker.

Environment: The external system that interacts with the agent.

State (s): It shows the current situation of the agent in the environment.

DATE (a): Agent's choices based on the agent's action that might affect the state.

REWARD (r): Feedback from the environment with respect to its action; hence it is either positive or negative.

5.1.2 | RL mechanism workflow

1. Initialization: This is the initial state of the agent.
2. Action Selection: The agent chooses an action according to some policy, strategy for selecting actions.
3. State Transition: The agent executes an action and ends up in a new state in the environment.
4. Reward Signal: The environment produces a reward signal depending on the action taken.
5. Policy Update: An agent then updates its policy to maximize the cumulative rewards it gets over time.

5.1.3 | Key algorithms

a. Q-learning is model-free. It learns an action-value function using Bellman equation updates. It keeps an estimate of expected return in a Q-table for every state or state-action pair after receiving a reward.
b. Deep Q-networks: Combine Q-learning with deep neural networks for approximations of the Q-value function, which allows them to work in high-dimensional state spaces.
c. Policy gradient methods: Direct optimization of the policy by altering its parameters according to rewards obtained. Typical methods include REINFORCE and Actor-Critic methods.

Machine learning (ML) mechanisms:

On the other hand, machine learning (ML) consists of various algorithms, which can be further categorized into supervised, unsupervised, and semi-supervised learning.

Major varieties of ML algorithms are:

1. Supervised learning: Algorithms learn from labelled data. The model is trained on input–output pairs.

   These are some examples of the supervised learning algorithms:

   A. Linear regression: Continuous outcome prediction.
   B. Support vector machines: SVM classifies data by finding a separating hyperplane.
   C. Decision trees: Decision Trees use a tree-like model for making decisions.
2. Unsupervised learning: There are no labelled outputs for algorithms to learn patterns in data.

   Examples:

   A. K-means clustering: It groups similar data points.
   B. Principal component analysis (PCA): Reduces the dimensionality while preserving the useful variance.
3. Semi-supervised learning:

   This involves a mix of a small amount of labelled data and a large amount of unlabelled data.

   Example: Very often used in scenarios where labelling is expensive or time-consuming, such as image classification.

ML mechanism components:

- Data pre-processing: Cleaning and preparing data for training. Examples include normalization and handling missing values.
- Feature extraction: The identification of relevant features that contribute to the outcome.
- Model training: The process of adjusting model parameters on a training dataset.
- Evaluation: The process of drawing inferences about model performance based on metrics that include but are not limited to accuracy, precision, recall, and F1 score.
- Prediction: The process of making inferences from new data based on the trained model.

Applications in networks:

- Traffic prediction: This involves the use of flow history for the forecast of network flow with the objective of optimizing resource allocation.
- Anomaly detection: This helps in the detection of unusual behaviour that may depict security threats or failures in any system.
- Quality of service management: It is aimed at predicting and managing metrics related to network performance.

Block representations for both RL and ML are shown in Figures 1a and b, respectively.

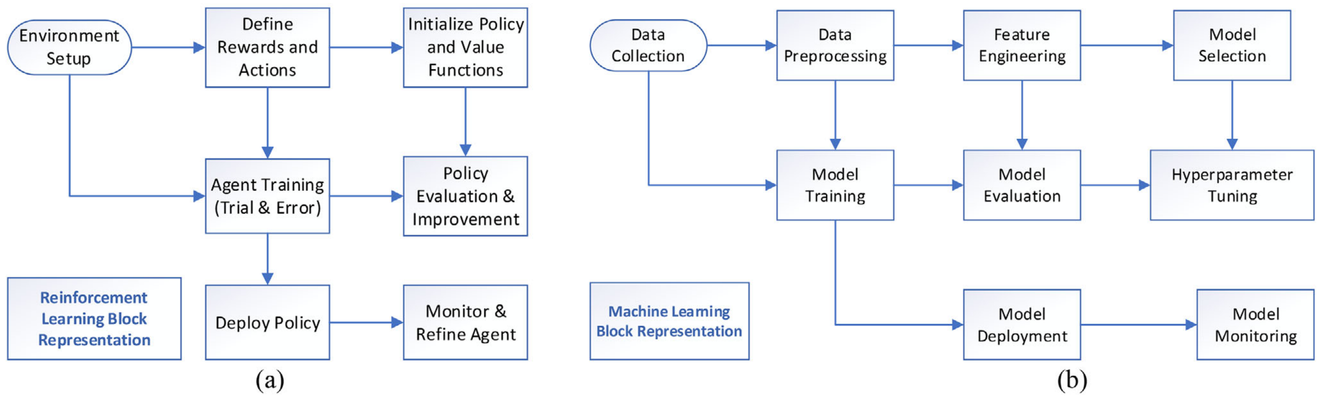

FIGURE 1 Block representation: (a) Reinforcement learning and (b) machine learning.

5.2 | Supervised learning

- Algorithm: Support Vector Machine (SVM), Decision Trees, and Random Forests are some of the important algorithms in performing dependable binary classification, even when there are a large number of instances and comparatively fewer features available.
- Application: Such algorithms are capable of forecasting outcomes of handover based on statistical information. Drawing from user mobility and network condition, they assist in decision making on the right time and location to initiate handovers.
- Advantages: A high level of accuracy in the forecasts besides its ability to work even when there exist threshold conditions and non-linear interdependencies between input data.

5.3 | Unsupervised learning

- Algorithm: The tools which were used in the research carried out are K-Means Clustering and Principal Component Analysis (PCA).
- Application: In unsupervised learning, anomaly detectors are employed for the identification of anomalies and similar handover events are grouped. It can also assist in determining conditions that could potentially lead to handover failures and therefore handover pre-emptive measures be made.
- Advantages: These methods are helpful in recognizing new patterns in unlabelled data sets which can be paramount in identifying new handover behaviour on the field.

5.4 | Deep learning

- Algorithm: 'Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) Networks.
- Application: CNNs can be used to analyse spatial aspects of the network environment and LSTMs work well when they are to predict the temporal sequence of the environment wherein the user is present thus helping to predict the user trajectory and thereby identify the best time for handing over the user to another base station.
- Advantages: High capability to accommodate complex patterns and dependencies over the time intervals necessary for the exact prediction of users' movements and other network conditions' shifts.

5.5 | Federated learning

- Algorithm: Federated averaging.
- Application: This algorithm enables multiple edge devices to cooperate for learning the same prediction model, without transferring any training data to other devices. It is especially helpful in 5G to perform optimization of handover procedures without a negative impact on users' privacy.
- Advantages: Supplements the model with the data of different origins, without the re-collection of the data, and maintains confidentiality while increasing the effectiveness of the model.

5.6 | Genetic algorithms

- Application: Due to the dynamic nature of the system there could be evolution of the framework to decide on the best handover decision rules out of a possible very large number of combinations.
- Advantages: Optimisation can be used and are efficient in identifying global optima in large problem spaces and this may be particularly suitable for multi-objective problems in handovers.

5.7 | Fuzzy logic systems

- Application: Handover decisions can also be made with fuzzy logic when some of the input variables such as signal strength are not well defined or are fuzzy. It assists in coming up with more versatile and sound handover decisions.

- Advantages: Flexibility with regard to any vagueness and ambiguity so that more accurately can be configured corresponding with the real-world conditions during the handover or shift.

5.8 | Transfer learning

- Application: Transfer learning is the use of models learnt in one environment (e.g. a particular city or situation) for application in another environment helping to speed up optimization process for making appropriate handover decisions in other unknown or less learnt environment.
- Advantages: Reduces the amount of labelled data that is required at a specific moment, thus making implementation faster, and more effective.

Among these algorithms including RL, deep learning algorithms, genetic algorithms, federated learning etc., they are helpful in enhancing the 5G handover process. They assist in more accurate handover decisions; avoidance of failures in handover; and delivery of excellent user experience particularly during the worst network conditions. Moreover, it is possible to incorporate these algorithms into self-organizing networks as well as they are being implemented by more and more telecom operators to increase the reliability and performance of 5G networks.

6 | AI ALGORITHMS TO HANDLE HANDOVER PROCESS IN 5G AND BEYOND NETWORKS

This is a comparison of two AI algorithms that can improve the 5G and beyond handover process: Reinforcement learning (RL) and the support vector machines (SVM).

6.1 | Reinforcement learning (RL)

Reinforcement learning is a type of machine learning mechanism wherein the agent learns to make decisions through interaction with the environment. Based on its actions, it receives rewards or penalties to lead toward the optimization of its strategy over time.

6.1.1 | Advantages

- Dynamic adaptation: RL is always tuned to network conditions and user behaviours, making it appropriate to deal with dynamic nature in 5G environments.
- Long-term optimization: The RL will optimize the policy for long-term cumulative rewards, which would pay off definitely with respect to the minimization of handover failure and latency for long-term performance.
- Exploration-exploitation trade-off: The RL strikes a balance between the exploration of new policies and the exploitation of the policies already known to be good, thereby making decisions enhanced through trial-and-error.

6.1.2 | Challenges

Complexity in training: RL generally involves large amounts of data and time for training, which could be its disadvantage in rapidly changing environments.

Convergence problems: Ensuring convergence of the RL algorithm to an optimal policy may sometimes be very problematic in a complex state space.

6.2 | Support vector machines (SVM)

Support vector machines represent the supervised learning models for performing classification and regression tasks. Support vector machines perform their function by finding the hyperplane that best separates different classes in feature space.

6.2.1 | Advantages

- High accuracy: SVMs are often highly effective in classification problems and thus very efficient in the forecasting of Handover based on past trends of data.
- Robustness to overfitting: If proper kernel functions and regularization are introduced, SVMs can perform well with high-dimensional data without overfitting.
- Easy interpretation: SVM yields transparent decision boundaries that may help in analysing various other factors influencing the handover decisions.

6.2.2 | Challenges

- Static nature: SVMs are relatively less adaptable to dynamic changes than RL; every time the conditions vary, they need to be re-trained with new data to adapt to those changes.
- Computationally expensive: Training in SVMs for larger datasets may be computationally expensive and might take up much time.

This is compared in Table 2 by explaining that the benefits in terms of improvement regarding the 5G handover procedure of both reinforcement learning and support vector machines are again based on the use case and the environment of the network. For example:

- Reinforcement Learning is more applicable to dynamic, high-mobility environments with fast-changing conditions; that's because it keeps learning and will adapt continuously with any new knowledge for further optimization of the handover decisions.

TABLE 2 Comparison Summary.

Feature	Reinforcement Learning	Support Vector Machines
Adaptability	Highly adaptive to dynamic environments	Less adaptive; requires retraining
Training Complexity	High; requires extensive interaction	Moderate; requires labelled data
Long-Term Optimization	Focuses on cumulative rewards	Generally optimized for immediate classification
Accuracy	Can be high with sufficient data	Known for high accuracy in classification
Interpretability	Less interpretable	More interpretable with clear boundaries
Computational Resources	Can be resource-intensive during training	Can be computationally intensive, especially with large datasets
Performance in Dynamic Environments	Excellent (Learns and adapts to changing conditions)	Limited (Static once trained, needs updates)
Training Requirements	High (Requires dynamic exploration and feedback)	Medium (Trains on labelled historical data)
Best Use Cases	High-mobility scenarios, dynamic environments	Stable environments, predictable patterns
Computational Demand	High (Requires continuous learning)	Lower (Training can be done offline)

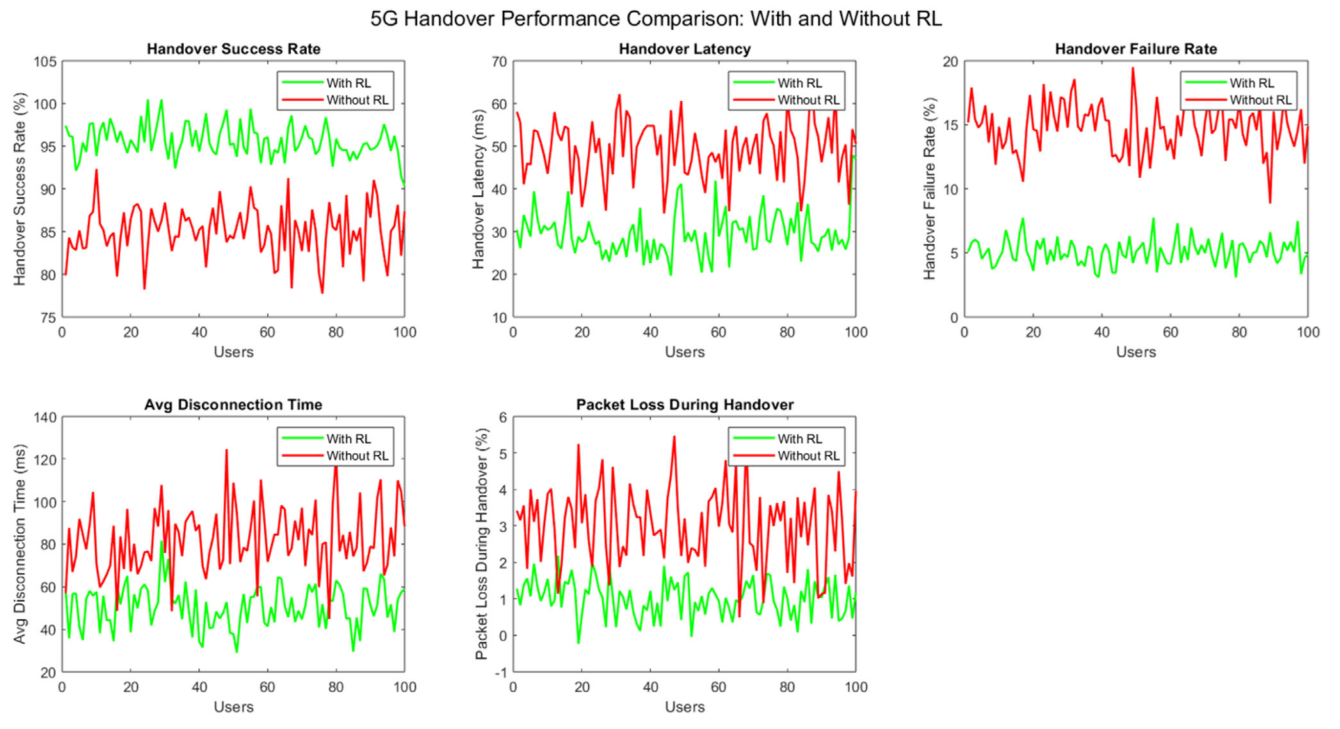

FIGURE 2 Handover performance based on RL.

- Supervised Learning is suitable for certain environments which change very slowly and the conditions within the network can be predicted. It is simpler to implement but less capable than RL in handling sudden changes

7 | HANDOVER SIMULATION RESULTS ANALYSIS (WITH AND WITHOUT RL ALGORITHM)

As shown in Figure 2, MATLAB is used to compare 5G handover performance with and without a Reinforcement Learning (RL) algorithm. In simulation, 5 Cells and 100 mobile users are used. The following is a brief prestation of results per each parameter:

7.1 | Handover success rate (%)

- With RL, the success rate is comparatively higher, averaging around 95%, and with fewer fluctuations. This therefore shows that reinforcement learning algorithms optimize handover decision making, hence giving a higher rate of successful handovers.

- Without RL, the success rate is comparatively lower, averaging about 85% but with a higher variability. Thus, this indicates that classic handover mechanisms lack good decision-making during dynamic conditions.

RL learns optimum policies depending on network conditions to enhance the success rate of handovers in mobile 5G networks. It is essential in 5G networks where high-speed movement and dense user environments are well-known.

7.2 | Handover latency (ms)

- With RL: The latency of handover is ∼30 ms, variance reduced, which means execution of a faster handover.
- Without RL: The latency is higher with larger fluctuations. This is likely due to the more frequent suboptimal handover decisions.

RL-based algorithms are much better at predicting when a handover in mobile networks will be needed. Consequently, the process is smoother and latency much lower. In 5G and beyond, there is a need to minimize latency to enable real time applications, for instance virtual reality and autonomous driving.

7.3 | Handover failure rate percentage

- RL: The failure rate is low, at around 5%, with very little variance. It is most probable that the RL algorithm foresees poor handover conditions and acts to prevent this or chooses better options.
- No RL: Much higher failure rate at about 15% points out that without RL, there are more failed attempts at handover.

Handover failures result in service interruption in mobile networks, which exacerbates the user experience, especially for critical services. As this work has demonstrated, RL decreases failure rates by learning from the historical data and real-time condition which cells are better targets.

7.4 | Average disconnection time (ms)

- With RL: The disconnection time is shorter, almost 50 ms, with less fluctuation. This may be indicative that RL optimizes the process of reconnecting users during handovers.
- No RL: longer disconnection times (close to 80 ms)—this could be either due to delayed actions or poorly chosen target cells.

Disconnection time reduction during handovers is of critical importance for applications relying on continuous connectivity in mobile networks, including video calls or IoT. As the results have just shown, simulation results show how RL minimizes disconnection by learning to predict and prevent any event resulting in disconnections.

7.5 | Packet loss during handover percentage

- RL: Packet loss is low at about 1%, implying that in the case of RL, selected conditions reduce disturbances and maintain data integrity during the handover.
- Without RL: Higher packet loss, about 3%, which shows the usual handover procedures are less reliable to hold the data transmission during the handovers.

The data-intensive service for 5G should guarantee the quality of experience of the applications with video streaming or online gaming by reducing packet loss. The RL is going to reduce packet loss by making decisions in real time on which congestions or weak cells to avoid.

Graphs in Figure 3 prove that reinforcement learning significantly enhances all the handover performance metrics of 5G networks: reduces latency and packet loss, enhances success rates, while times of disconnection and failures are minimized, which is shown by simulation results. Therefore, it can be assumed that in 5G networks, RL will be a very important approach since these networks require high reliability with low latency and seamless user experience, especially in dynamic and high-mobility environments.

8 | AI BASED HO (RL VS. ML) COMPARISON AND RESULTS DISCUSSION

MATLAB simulation tool is used to test and compare the handover performance based on two algorithms: Reinforcement learning (RL) and machine learning (ML) algorithms in a 5G network with 5 cells and 100 users. As shown in Figure 3, comparison graphs are generated for the following metrics:

- Handover success rate percentage
- Handover latency (ms)
- Handover failure rate percentage
- Average disconnection time (ms)
- Packet loss during handover percentage

8.1 | The results analysis and discussion

Below are the main observations about the graphs results as shown in Figure 3.

1. Handover success rate percentage

- RL algorithm: The success rate is higher (∼95%), with relatively small variations. This demonstrates that the RL algorithm learns and adapts to changing network conditions

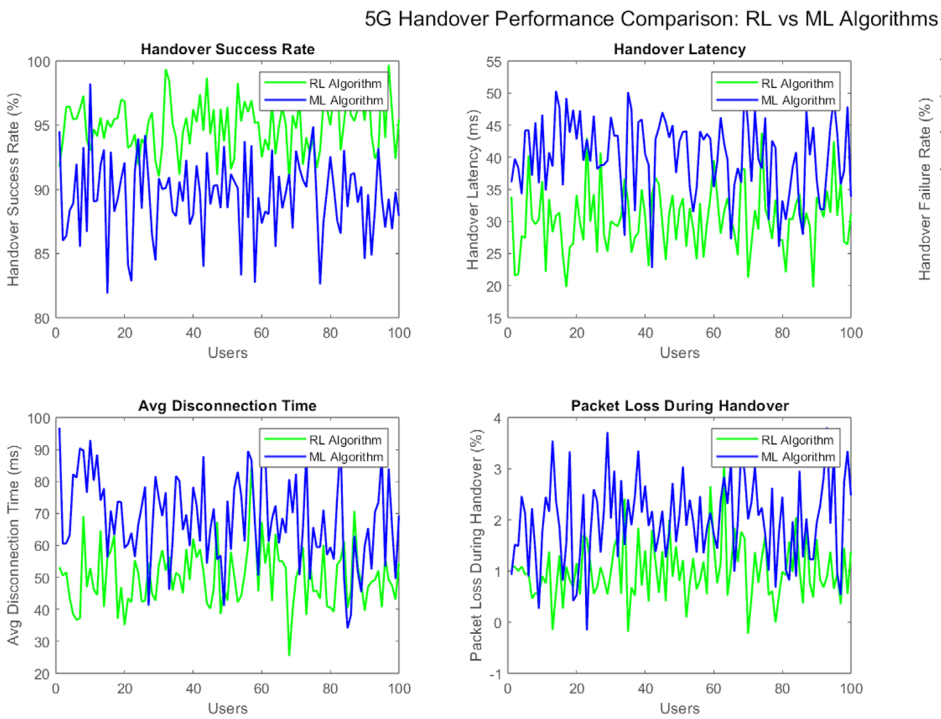

FIGURE 3 5G handover performance RL vs ML algorithms.

more effectively comparing with ML algorithm, ensuring smoother handovers.

- ML algorithm: The success rate is slightly lower (∼90%), and there is more variability. This reflects that the ML algorithm may not learn as effectively as the RL algorithm in dynamic environments.
- The algorithms designed for reinforcement learning learn optimal policies through interaction with the environment and may achieve higher success rates against their traditional or supervised machine learning-based competitors. This is particularly useful in 5G and beyond wireless networks, where user mobility and network conditions are fluctuating on a very fast scale.

2. Handover latency (ms)

- RL algorithm: Lower latency (∼30 ms), which signifies faster handover decision and execution.
- ML algorithm: Higher latency (∼40 ms). This may indicate that the ML-based algorithm takes a little longer to react, or is less effective at predicting the optimum time for handover.

This therefore means that lower latency in the decision-making of RL-based algorithms for handovers will go a long way in 5G and beyond networks, which are to support even real-time applications like autonomous driving or virtual reality. In fact, the RL algorithm learned to minimize latency by improving on the ML algorithm through better prediction.

3. Handover failure rate percentage

- RL algorithm: Compared with ML, it has a much lower failure rate (∼5%). It shows that RL works well in reducing the failure rate of handovers.
- ML algorithm: More failures (∼10%), which means ML-based handover decisions are more prone to failures.

In any mobile network, the handover failure rate is a vital factor to be reduced in order to maintain connectivity uninterrupted, particularly for cases of high speed and mobility. The RL algorithm can better avoid the occurrence of handovers at sub-optimal conditions, hence reducing the failure rate compared to the ML algorithms.

4. Average disconnection time (ms)

- RL algorithm: The disconnection time is much lesser (∼50 ms), which shows that RL is far better in the continuity of the connection during the handover.
- ML algorithm: Longer disconnection time (∼70 ms) means ML is not as efficient in minimizing service interruptions while compared with the RL algorithm.

In 5G and beyond mobile networks, services like online gaming or video calls require seamless connectivity. The capability of the RL algorithm in minimizing disconnection time proves its superiority to handle fast and seamless handovers compared to the ML algorithm.

5. Packet loss during handover (%)

- RL algorithm: Low packet loss (~1%) reflects that data integrity is maintained by the reinforcement learning-based handover mechanism during a handover.
- Packet loss is more significant with the ML algorithm, about 2%, which is to mean that packet loss cannot be prevented efficiently by only using the ML algorithm.

Due to the emergence of high-data demanding applications in mobile communication, such as video streaming and cloud gaming, a low packet loss is very important. This means that the RL algorithm is more capable of efficient handovers, as it gives better performance in light of packet loss.

The results developed across the five parameters in the brief presentation show that, overall, RL outperforms ML algorithms in 5G handovers. Evidence includes key metrics such as:

- Handover success rate: The ability of RL algorithms to learn and adapt better against network changes will ensure higher success rates.
- Handover latency: Better and faster decision-making in RL reduces latency.
- Handover failure rate: RL minimizes handover failure by making better predictions on when to initiate or avoid a handover.
- Disconnected time: RL reduces the disconnection time of users in any handovers.
- Packet loss: RL-based handovers result in fewer packet losses in order to retain data integrity.

It has already been derived that RL is highly suitable for dynamic and unpredictable environments, such as 5G networks, where the mobility of users is high and network conditions may change in a very short time. ML algorithms work toward solving this by offering various decision-making algorithms; however, they are not as adaptive in real time as their RL counterparts, hence recording lower performances across key handover metrics.

These are very valuable insights that support the fact that RL-based algorithms will surely meet the complexity of 5G handovers since speed and accuracy are the main concerns.

8.2 | Overview and key insights

From the comparative analysis, it is evident that RL algorithms outperform ML algorithms along all handover performance metrics in a 5G network. The reason, of course, is due to the capability of RL for adaptability and real-time decisions, thus making it very suitable in a 5G environment characterized by high mobility, high speed, and unpredictability. The main insights that can be derived from this comparative analysis are as follows:

Higher success rate: The RL algorithms provide higher handover success rates through continuous learning and adaptation-critical in ensuring reliable service in the dynamic 5G environment.

Lower latency: Fast decision-making in real time leads to low latency due to RL, something crucial for applications in real time that require seamless transitions over networks.

Lower rates of failure: RL's predict-and-avoid capability with respect to suboptimal conditions in handovers means fewer failures to knit together connectivity and user experience.

Minimum disconnection time: RL minimizes the disconnection time of users during handover; hence, applications which require continuous connectivity, like gaming and video calls, may be supported through it.

Less packet loss: Effective handover management in RL assures minimum packet loss during transitions, thus assuring data integrity.

The gist of the analysis is that RL algorithms have huge potential in handling 5G handover because of the learning-based methodology; thus, this produces real-time continuous optimization for the decisions of handovers. Further, it places RL as a robust solution toward handling the numerous complexities associated with 5G networks, specifically on use cases that require high speed with low latency, such as autonomous vehicles, augmented reality, and smart city applications. Even ML algorithms, while offering some improvements in performance compared with traditional methods, are only bounded by their inept nature for dynamic 5G environments. This also underlines the suitability of RL-based algorithms for meeting such performance requirements related to next-generation wireless networks for improved handover efficiency, reduced latency, and greater continuity of services.

8.3 | The limits of the proposed approach and validity of experimental results

The assessment of reinforcement learning as an approach compared to the traditional machine learning algorithm in improving handover performance in 5G networks does present relevant information. However, to comprehensively obtain the applicability of this method in field operation, considerations of limitations with respect to the current approach and experimental results have to be considered with due care.

8.3.1 | Limitations of the proposed approach

Model assumptions: Simplified network model: The simulation was performed in an artificial environment with a fixed network configuration - 5 cells and 100 users. Actually, the structure of a 5G network is much more complex, having different user densities, a different mobility pattern, and many other environmental factors not taken into account by the modeling.

Static parameters: This often means that the parameters that are used in RL and ML models do not have direct similarities to reflecting the real live conditions. For instance, interference level, flexibility of user behaviour, and the amount of network load could differ significantly under the given conditions which may have an effect on the algorithms.

8.3.2 | Training and convergence

Training requirements: RL methods converge to optimal policies after considerable amounts of training. When applied in real life, this may mean heavy investment in time and resources into training, instead of the implementation of the RL method in itself, which may get quite delayed. Convergence Issues: RL algorithms do not always converge to a satisfying solution in highly volatile environments. Regarding this aspect, performance may be poorer compared with other classical ML techniques.

8.3.3 | Computational complexity

Resource intensive: Many of the RL algorithms are computational expensive, especially when deep learning strategies are used. This could be an issue anytime a system must operate on limited IoT devices or have to make decisions in real-time.

Latency in decision-making: It may demonstrate near-real time latency when applied in simulation form, an implementation of RL may prove to be high latency when used in real-time learning and real time adaptability required to make decisions.

Generalization may be poor: The results that have been obtained from the various simulations may not be very good in terms of generalizing to so many other real-life problems. There are large-scale changes in algorithm performance depending on user behavior, mobility, and environment variations. »

Testbed environment: Lack of a testbed environment that is critical in terms of validating the results obtained from the simulations restricts confidence in the proposed approach. Real-world conditions may pose unexpected challenges that were not considered during the simulations.

8.4 | Validity of experimental results

8.4.1 | Reproducibility

Simulation-based results: The results here are based on simulations done using MATLAB. Although this helps in controlled experimentation, much has to be done in order to ensure the parameters of simulation and its configuration are reproducible to verify the findings.

Independent verification: This needs independently to be checked by further simulations or experiments in different scenarios to enhance the credibility of the results.

8.4.2 | Benchmarking against established methods

Baseline algorithm comparison: The proposed RL goes well against the ML algorithms. Still, it may be considered a more complete work by comparison with other known algorithms or hybrid approaches. Performance Metrics: The metrics chosen are indeed relevant, namely handover success rate, latency, failure rate, time of disconnection, packet loss; several other metrics could give more wholeness to the view, in relation to energy consumption and user experience.

8.4.3 | Statistical analysis

Statistical significance: The report has to contain the calculations of the statistical tests to show if the differential of the performance metrics is significant or may be caused by pure chance, with multiple trials with statistically valid tests may be necessary here.

While the proposed RL approach here demonstrates very promising results for the performance improvement of handovers in 5G networks, several limitations do need to be identified. These experimental results are only valid with regards to model assumptions, complexity of real-world conditions, and further testing and validation. Only when the limitations of the proposed approach are addressed by comprehensive real-world evaluations and benchmarks against established methods will it be more reliable and have wider applicability. Therefore, the future direction of research should be towards these, so that overcoming these challenges will pave the way for effectively integrating RL algorithms into next-generation wireless networks.

9 | REAL-WORLD DEPLOYMENT SCENARIOS

Deploying RL in handover management for high-speed vehicular networks and ultra-dense urban environments in 5G and beyond mobile networks presents new opportunities with unique challenges. Two real deployment scenarios are discussed next, along with ways in which RL mechanisms can handle handovers in such contexts with efficiency:

A. High-speed vehicular networks

Scenario: High-speed vehicle communications, for example, over the highways, require a faster and more efficient handover to maintain the connectivity intact. Since the location is changing rapidly, quick decisions are to be made to avoid dropped calls.

Dynamic state monitoring: These RL algorithms will continuously monitor the speed at which the vehicle is moving, its direction, and also the quality of the signal it is receiving at every instant of time to dynamically estimate the most opportune moment for handover.

Predictive models: The learned traffic patterns and vehicle trajectories through RL can be used to predict when a vehicle is going to enter into the coverage area of a new base station, thus triggering proactive handovers.

Cooperative decision: RL can enable vehicles to exchange information about network conditions with other vehicles; this may create a cooperative environment and improve the overall performance of the network.

Load balancing: It will dynamically change the thresholds in the handover based on the real-time network load. It will ensure that base stations are not overloaded without affecting user connectivity.

Following are some of the parameters that the RL agent may consider: Signal strength, Latency, User's Velocity and Trajectory, Network load and congestion, Distance towards the nearest base stations.

The learned policy by the RL mechanism can select among various actions like: Trigger a handover to one base station, Delay a handover, Change transmission power, and Change communication channels.

The reward signal for the RL agent could be designed in various ways to represent desired objectives of rewarding successful completion of a handover without unnecessary interruptions, reducing handover delay, and using network resources efficiently without overloading any particular base station.

9.1 | Challenges for the approach

Challenges and considerations for this approach are:

A. Environment dynamics

Fast-moving environments: High-speed environments and city environments have rapidly changing conditions to which the RL algorithms must be robust and adapt to.

Training in varied conditions: The RL models need to be trained on simulations that can represent real-world conditions operating under variable traffic flow and user behaviors.

B. Scalability

Scaling up: The RL approach shall be able to scale up efficiently for thousands of vehicles and base stations in ultra-dense urban areas; techniques such as distributed RL or hierarchical models may be used.

C. Integration with existing systems

Legacy systems: Any integration of the RL mechanisms to the existing network management systems shall be carefully planned so as to ensure that compatibility is retained, together with seamless operations.

Reinforcement learning for handover management in high-speed vehicular networks and ultra-dense urban environments opens up new vistas that help in reinforcing connectivity and improving user experience. Since it employs dynamic state monitoring, predictive modeling, and collaborative decision making, RL effectively copes with the unique challenges arising within the context of such complicated environments. As 5G and beyond continue to evolve, integration with reinforcement learning mechanisms will very much remain a cornerstone for top-notch network performance to ensure seamless connectivity for mobile users.

10 | COMPUTATIONAL REQUIREMENTS

Different computational requirements for the use of reinforcement learning to enhance handover prediction in real-time and considerations of feasibility within a 5G mobile network are manifold. This section explores these aspects in detail, including insight into how the solution will scale with increased network complexity.

A. Processing power

Real-time decision making and latency sensitivity: The decision of handovers provided in 5G networks should be within milliseconds or less for service continuity. High-power computing resources such as CPUs and GPUs are essential to big volumes and high-speed processing.

Algorithmic complexity: The advanced RL algorithms, with deep learning (Deep Reinforcement Learning-DRL), especially have great demand in computational power both in training and inference phases.

B. Data handling capabilities

Real-time data ingestion: Continuous streams of data from different sources, such as user devices and environmental sensors should be processed by the system. These range from signal strength, user speed, to network load.

High throughput: Architecture has to support high throughput for processing incoming data coming from several vehicles and devices at the same time.

C. Training requirements

Simulation environments and complex simulations: Most of the training of RL models requires sophisticated simulations, which actually should emulate real-world scenarios of 5G networks. These kinds of simulations, in order to create more realistic scenarios, can actually be computationally intensive and demanding in terms of large resources.

Online learning: To implement the capability for online learning, the updates to the RL model have to be continuous concerning arriving data. Regular computational resources are required to process and learn from newer experiences.

10.1 | Feasibility of implementation

A. Infrastructure considerations

Localized processing: The utilization of RL algorithms on edge devices such as Roadside Units or small cells contributes significantly to a drastic reduction of latency, since computations are done closer to the source. In this case, only minimal information needs to be transmitted back to the centralized servers to reduce latency bottlenecks.

Scalable training: During training phases, scalable processing resources are provided by cloud computing to handle the computational load by allocating resources dynamically.

B. Network latency and reliability

Execution latency: The time from data collection to executing the decision should be minimized for timely prediction of handover. Delays in processing may lead to interruption of service, which is particularly important in high-speed vehicular environments.

Fault tolerance: The design of the system should be on a redundant basis so that any failure in real time is handled to ensure continuous operation without any failure in hardware or software.

10.2 | Scalability w.r.t increasing network complexity

A. Hierarchical RL approaches

Hierarchical models: Hierarchical RL can decompose the problem into smaller task, while the network complexity is increased. For example, agents localized within specific areas or sectors of the network make decisions, and then a global agent coordinates the overall network performance.

Modular learning frameworks: Independent learning is enabled at each individual agent, though sharing of strategies allows scalability without overloading any one agent.

B. Distributed RL frameworks

Parallel learning: Many agents may learn in parallel with lower computational loads using Distributed RL methods. For example, simultaneous learning of multiple vehicles or base stations can result in faster learning speeds.

Collaborative learning: Without actually sharing data, devices can collaboratively learn from the local data at some advantage to privacy and bandwidth. Agents update their models based on local experiences and share only model updates.

C. Adaptive resource allocation

Dynamic adjustments: Bandwidth, processing power, and other resources dynamically scale up (to keep performance at an optimum), when complexity increases, (increasing number of users and volume of traffic).

Load balancing: The decisions regarding handovers may be optimally done by the RL mechanisms so that the load on each base station depends precisely on the occupancy such that no single base station acts as a bottleneck.

Given adequate computational resources and infrastructures, the implementation of Reinforcement Learning for handover prediction can be materialized in 5G mobile networks. With edge computing, hierarchical RL, and distributed learning frameworks, massive real-time processing and handling will definitely be required to scale up most of these approaches. These approaches will automatically handle resource management and performance optimization when network complexity rises in order to enable seamless connectivity and enhanced user experience in high-speed and ultra-dense environments.

11 | RAPIDLY CHANGING NETWORK CONDITIONS ADAPTION

Adaptability in the system ensures that in case of sudden shifts in network conditions, such as bursts in traffic or changes in user mobility, reinforcement learning will make handover predictions suitable for 5G mobile networks. The objectives are to ensure seamless connectivity, hence optimally assuring network performance. It is contingent upon the following described conditions: Each system adaptation towards optimization can be carried out as follows:

11.1 | Dynamic state representation

A. Real-time monitoring

Continuous state updates: The system continuously monitors key network parameters, such as signal strength and quality, for instance, RSSI (received signal strength indicator) and SINR (signal to interference plus noise ratio).

- User mobility patterns: Speed and direction
- Network load: The number of active users and bandwidth utilization
- Environmental factors: For example, weather conditions, physical obstacles
- Feature Engineering: The RL agent may also use some derived features, like historical trends of the traffic flow, peak hour usage, and location history of users, for better understanding of the current state.

11.2 | Adaptive action selection

A. Context-aware decision-making

Flexibility in action space: The action space of the RL agent may vary w.r.t. prevailing context. For example: The agent will perform handovers during peak hours to less congested base stations. In a high-mobility scenario, it could use proactive handovers to avoid latency.

B. Policy adaptation

Online learning: The agent follows online learning methods for updating the policy at runtime. When a stream of new data arrives, it updates knowledge about the environment and revises the decision-making strategy.

Exploration vs. exploitation: The RL system creates a balance in exploring new actions and exploits the previous profit-making ones. For example, an unplanned traffic spike: the agent will explore new handover strategies hardly ever used previously.

11.3 | Robustness to traffic spikes

A. Predictive modeling

Traffic prediction: Increases in traffic prediction is learnt by the RL agent from the historical data. It learns to identify patterns related to user behavior, and prepare accordingly for an increase in demand.

Anomaly detection: It can be designed to host several anomaly detection algorithms that would compute spikes in traffic that happen without prior knowledge and adapt to rapidly changing conditions.

B. Load balancing strategies

Dynamic resource allocation: The RL agent may, upon detecting spikes in traffic, dynamically allocate resources by threshold tuning for handover will be performed to ensure the users are shifted to the least congested base stations.

Load balancing: Any load, if at all, will have to be distributed across the neighbors such that no base station gets overloaded.

Multi-agent coordination: Deploying multiple RL agents, for example, multiple base stations can share the information of the surge in traffic and respond accordingly for good overall performance of the network.

11.4 | Adaptation to user mobility

A. Trajectory prediction

User behavior modeling: The RL system will learn from the historical data to have the predictive pattern about user mobility. For example, if users often travel through certain routes, the RL system could initiate a handover when the users approach the coverage area boarder of a cell.

B. Contextual awareness

Adaptation to changes of environment: RL will be enabled to adapt to changes in the environment, that is, any mobility factor such as road construction, detours, or routes introduced. This may allow for handover strategies timely adaptations.

11.5 | Feedback mechanisms

A. Reward structuring

Dynamic reward signals: The reward function can be designed to reflect real-time network conditions. During peak times or when low latency is required this mechanism could be applied. In such cases, higher rewards for successful handovers could be given.

B. Continuous improvement

Feedback loop: The result of the handover will be feedback to the RL agent for decision-making in the future. If any handover results in degraded network performance, then the agent will learn from that to make an alternative decision.

The adaptability of the RL-enhanced handover prediction system in 5G mobile networks depends upon continuous real-time monitoring, dynamic state representation, and robustness of decision-making. Predictive modeling, anomaly detection, and coordinated multi-agent strategies are shared to address rapid network changes for ensuring seamless connectivity in the midst of unexpected spikes or shifting traffic and user mobility. This flexibility lends considerable robustness to the approach and is well-placed for application to the modern mobile network with its complexity and dynamics.

12 | CONCLUSIONS AND FUTURE WORK

A novel RL AI based handover mechanism is introduced in this work to enhance seamless mobility in 5G and beyond mobile communication networks. The proposed solution uses machine learning techniques (Reinforcement Learning algorithm) to minimize service disruptions and maintain high-quality connectivity for mobile networks. A significant improvement has been proven comparing with other machine learning (ML) mechanisms in this research. Future research is to improve 6G networks using predictive handover mechanism such as context-aware resource management, multi-connectivity, and network slicing, to further improve the overall mobility and quality of experience in next-generation mobile networks.

AUTHOR CONTRIBUTIONS

All authors contributed significantly to the research and development of this manuscript. **Thafer H. Sulaiman**: Literature review; methodology; writing the original draft; data collection; analysis; interpretation of results. **Hamed S. Al-Raweshidy**: Reviewing; editing the manuscript; providing technical support and supervision. All authors have read and approved the final version of the manuscript and agree with the order of authorship.

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest regarding the publication of this article in IET.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request. The datasets generated during and/or analyzed during the current study are not publicly available due to reasons such as privacy concerns, proprietary restrictions etc., but may be available from the corresponding author upon request.

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