IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Mobility Pattern Recognition for Energy-Efficient Handover in 6G Networks Using Hidden Markov Model

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Abstract :

The advent of 6G networks brings unprecedented demands for ultra-dense connectivity, high-speed communication, and energy-efficient operations. As user mobility increases in these complex environments, frequent handovers between base stations significantly contribute to energy consumption, posing a major challenge for sustainable network management. In this paper, we propose a novel approach for energy-efficient handover management in 6G networks by leveraging **Hidden Markov Models (HMMs)** to predict user mobility patterns. By accurately forecasting future user locations, our HMM-based model enables proactive handover decisions that minimize unnecessary transitions between cells, thereby reducing energy consumption without compromising quality of service (QoS).

I have tried design a system that trains the HMM using historical mobility data to model the state transitions and emission probabilities associated with user movements. Our simulation results demonstrate that the proposed method reduces handover frequency and energy usage compared to traditional reactive approaches, while maintaining stable connectivity and low latency in ultra-dense 6G environments. This research highlights the potential of HMM-based mobility prediction to optimize handover management in future wireless networks, contributing to the development of more energy-efficient 6G systems.

***IndexTerms* - 6G Networks, Energy-Efficient Handover, Mobility Pattern Recognition, Hidden Markov Models (HMM), Proactive Handover Management, Ultra-Dense Networks (UDN), Network Resource Optimization, User Mobility in Cellular Networks**

I. INTRODUCTION

As the world anticipates the rollout of 6G networks, the expectations surrounding connectivity, speed, and network performance have never been higher. With a focus on enabling ultra-reliable low-latency communication (URLLC), massive machine-type communication (mMTC), and enhanced mobile broadband (eMBB), 6G promises to support emerging technologies like autonomous systems, smart cities, immersive extended reality (XR), and the Internet of Everything (IoE). However, the very features that define 6G—such as ultra-dense network (UDN) deployments and extreme user mobility—also present significant challenges, particularly in the realm of energy consumption and mobility management.

One of the most critical challenges facing 6G networks is the frequent handover of users between base stations in ultra-dense environments. As the number of base stations increases to maintain seamless connectivity, mobile users must transition between cells more frequently. This triggers a handover process, which, while essential for uninterrupted connectivity, results in high energy overhead and network signaling traffic. Current reactive handover mechanisms, which are based on simple thresholding of signal strength, fail to account for the dynamic nature of user movement, leading to inefficient energy use and unnecessary network congestion.

In this context, reducing the energy cost associated with handovers has become a pressing concern. The increasing complexity of 6G environments, driven by hyper-connectivity and heterogeneous networks (HetNets), requires a paradigm shift toward proactive handover management. Traditional methods, which rely on reacting to deteriorating signal quality, are ill-equipped to handle the demands of future networks. A more intelligent approach—capable of anticipating mobility patterns—is necessary to minimize energy consumption and optimize resource allocation.

II. NEED OF THE STUDY

1. Energy Overhead Reduction: Frequent handovers in ultra-dense networks (UDNs) contribute significantly to network inefficiencies. As 6G networks aim to support a wide array of applications, such as smart cities, autonomous vehicles, and IoT ecosystems, optimizing handover processes for energy overhead minimization is crucial. Current approaches are unable to dynamically adjust based on user mobility, leading to suboptimal energy utilization.

2. Proactive Mobility Management: Traditional handover techniques rely on reactive triggers such as signal strength deterioration, which often fail to account for user mobility patterns. There is a critical need for proactive mobility management, where handover decisions are made based on mobility anticipation rather than reactive responses. Hidden Markov Models (HMMs) provide a framework for modeling user behavior, offering the ability to predict user movements and optimize handover timing, thus minimizing handover churn and energy waste.

3. Context-Aware Handover Decisions: The emergence of context-aware networking in 6G allows the network to intelligently adapt to user behavior, optimizing performance based on location, speed, and user preferences. The study addresses the need for mobility pattern recognition that incorporates real-time and historical data, enabling networks to anticipate user behavior and make handover decisions that reduce energy consumption while maintaining Quality of Service (QoS).

4. Green Networking and Sustainability: With the increasing focus on green networking, energy efficiency in 6G networks is not just a performance concern but also a key enabler of sustainability. As mobile networks account for a significant portion of global energy consumption, optimizing handovers to reduce carbon footprint is vital for meeting the environmental targets set for 6G systems. The proposed study fills the gap in ensuring that handover decisions contribute to the broader goal of sustainable energy-aware communications.

5. Adaptive Network Intelligence: The need for adaptive network intelligence becomes more pronounced in the 6G context, where AI-driven algorithms are expected to manage the complexities of dynamic user behavior and network conditions. The integration of HMMs with 6G's cognitive radio and network slicing capabilities opens new avenues for optimizing handover processes in a predictive, self-organizing manner, further enhancing network autonomy and reducing manual interventions.

6. Trade-Offs Between QoS and Energy Efficiency: Maintaining a balance between energy-efficient handovers and service quality is another key challenge that requires further study. There is a pressing need to explore the trade-offs between minimizing energy usage during handovers and ensuring uninterrupted, high-quality service to users. A thorough examination of this balance in the 6G context is crucial, as service quality expectations continue to rise alongside stringent energy-saving requirements.

7. Mobility-Aware Resource Allocation: Efficient resource management is essential in 6G networks, particularly for applications like vehicular communication (V2X) and drone networks. There is a growing need for mobility-aware resource allocation, where the network dynamically allocates resources based on real-time predictions of user movements. This study addresses how HMM-based mobility predictions can optimize the allocation of resources such as spectrum, reducing unnecessary energy expenditure during handover events.

In conclusion, this study is necessary to address the multifaceted challenge of managing energy-efficient handovers in 6G networks. The development of an HMM-based solution that proactively manages user mobility will enable networks to balance energy efficiency with the demands of modern applications, ensuring that 6G networks are not only high-performing but also environmentally sustainable.

III. Proposed Solution

This paper presents a novel solution to the energy efficiency problem in 6G networks: Hidden Markov Model (HMM)-based approach for predicting user mobility patterns**.** HMMs**,** widely used in stochastic processes, offer an effective framework for modeling sequential data, such as user movement across base stations. By learning from historical mobility data, an HMM can predict future user locations and enable proactive handover decisions**.** This proactive approach reduces the frequency of handovers, resulting in lower energy consumption**,** improved network performance, and enhanced user experience. In contrast to traditional reactive handover strategies, our model leverages mobility forecasting to initiate handovers only when necessary, optimizing network operations while maintaining stringent QoS requirements.

3.1. High Level Architecture Components

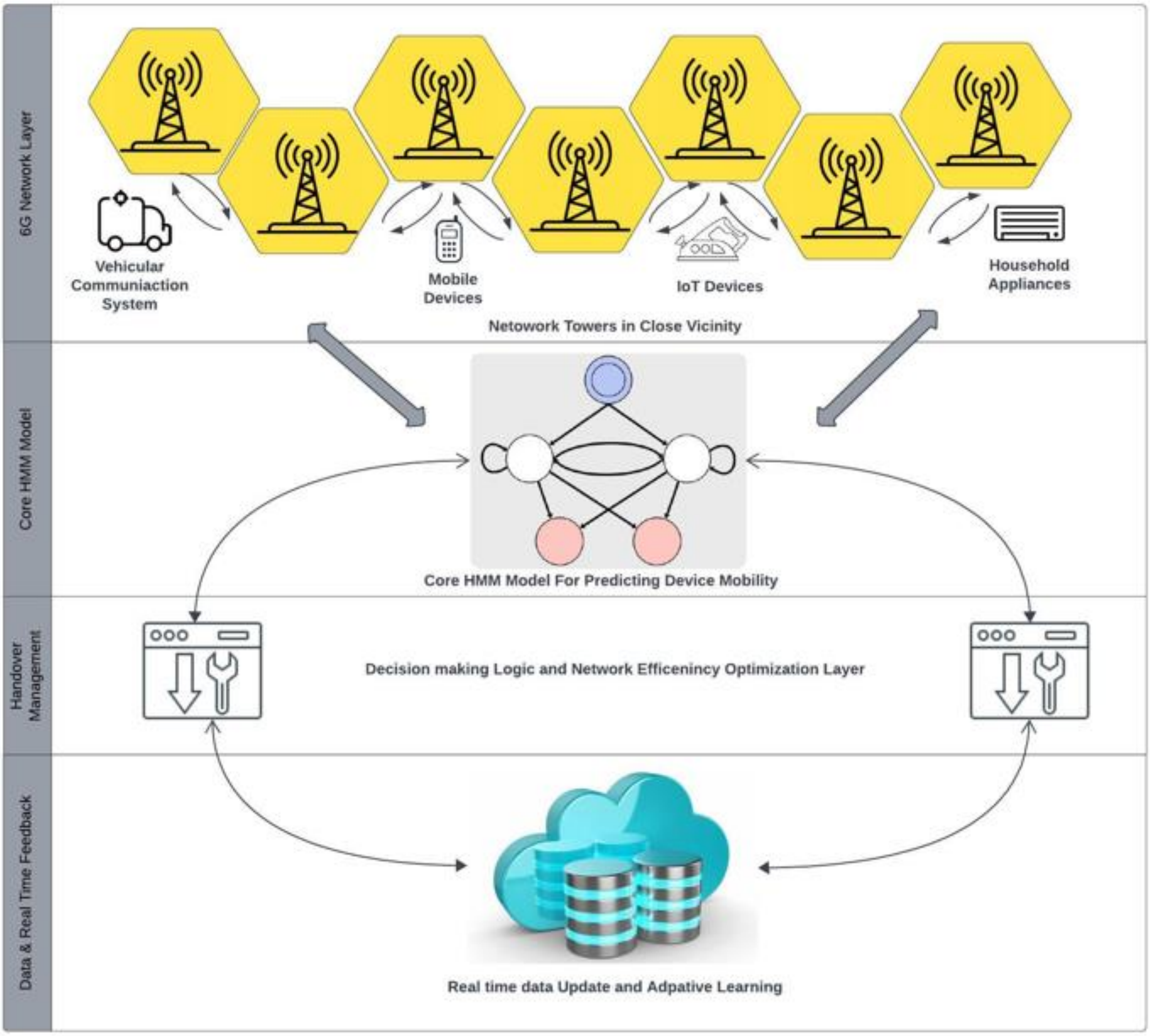

Fig 1: Architectural Representation of Hidden Markov model being used for handover

3.1.1. Layer 1: 6G Network Layer

This layer forms the foundational infrastructure of the 6G network, consisting of base stations, user equipment (UE), and the general components of the communication network. It represents how mobile devices interact with the network to establish and maintain connectivity.

Base Stations (BS): These are the access points in the 6G network that facilitate communication between mobile devices (e.g., smartphones, IoT devices) and the core network. In a 6G setting, base stations are more densely deployed than previous generations, including small cells and macro cells. Due to ultra-dense environments, the user's frequent movement between these base stations necessitates regular handovers.

User Equipment (UE): This includes mobile devices that are constantly moving within the network (e.g., smartphones, wearables, and connected vehicles). The devices establish connections with nearby base stations, and as the user moves, they will need to transition between base stations to maintain connectivity, resulting in handovers.

Network Infrastructure: This layer also includes the general communication infrastructure, such as backhaul connections, routers, and Mobility Management Entities (MMEs), which help manage user mobility, ensure seamless handover processes, and maintain the overall connectivity in a 6G environment.

The 6G network layer provides the physical infrastructure for user mobility and the technical basis for handovers between base stations. It forms the environment in which the handover challenges, such as frequent transitions and energy consumption, arise.

3.1.2. Layer 2: Mobility Prediction Layer (HMM-Based)

This layer is where the Hidden Markov Model (HMM) comes into play. It is responsible for predicting the next location or base station to which the user is likely to move, based on past and current mobility data.

HMM (Hidden Markov Model): HMM is a probabilistic model that deals with sequential data, making it an excellent tool for predicting mobility patterns. In the context of this architecture, the HMM is trained using historical mobility data to predict the user's future movements between different base stations. The model tracks user movement states (i.e., locations) and computes the probabilities of transitions between these states.

Mobility Prediction: The core function of this layer is to forecast the next base station that the user will connect to based on their current movement trajectory. By analyzing past mobility behavior (e.g., movement speed, direction, and handover history), the HMM predicts where the user is likely to move next. This allows the system to anticipate handover needs rather than waiting for the signal quality to degrade.

3.1.3. Layer 3: Handover Management Layer

This layer is responsible for the decision-making and execution of handovers based on the predictions from the **Mobility Prediction Layer**. It ensures that the handovers are efficient and energy-conscious, reducing unnecessary transitions and optimizing the network's resources.

Decision-Making Logic: Based on the predicted next location from the HMM, the system assesses whether a handover is required. If the user is predicted to move to a new base station, the system proactively triggers the handover before the signal quality deteriorates. This proactive decision-making avoids the need for reactive measures that could lead to inefficient handovers.

Energy Efficiency Optimizations: The decision-making process is guided by energy efficiency criteria. The system evaluates the trade-off between initiating a handover and maintaining the current connection. By reducing the number of unnecessary handovers, the system conserves energy both at the user device and within the network infrastructure.

Handover Triggers: When the conditions are met (e.g., predicted base station handover is necessary), the system triggers the handover process. This involves switching the user's connection from the current base station to the next one while maintaining seamless connectivity.

3.1.4. Layer 4: Data and Feedback Layer

This layer manages the data used for training the HMM and provides continuous feedback to improve its predictions over time. It ensures that the system adapts to changing mobility patterns and network conditions.

Historical Data: This includes previously collected mobility data (e.g., user movement patterns, handover history, signal strength) used to initially train the HMM. The historical data allows the model to identify patterns and transitions between different user locations.

Real-Time Data Updates: As users move through the network, real-time mobility data is constantly collected and fed back into the system. This data is used to refine the HMM, enabling it to stay up-to-date with changing user behaviors and mobility patterns.

Adaptive Learning Mechanism: The feedback loop ensures that the HMM evolves and improves its prediction accuracy over time. As more real-time data is fed into the system, the HMM continuously adjusts its parameters and transition probabilities, resulting in better handover decisions and more efficient energy usage in future operations.

3.2 Sources of Data

3.2.1. Historical Mobility Data

Data Description: This data includes past movement patterns of users within the network, which is crucial for training the HMM. It consists of records that capture how users transitioned between different base stations, their travel speed, direction, and time spent in each location.

Sources:

Network Operator Logs: Telecommunications companies often maintain logs that detail user sessions, handover events, and signal quality metrics. These logs can be anonymized for research purposes.

Mobile Network Traffic Data: Aggregated data from mobile networks, which includes user mobility patterns and traffic flows across different base stations.

3.2.2. Real-Time Mobility Data

Description: This data is collected in real time to monitor ongoing user movements and adapt predictions dynamically. It helps in refining the HMM and adjusting handover decisions based on current conditions.

Sources**:**

User Equipment (UE) Sensors: Smartphones and IoT devices can provide real-time GPS data, accelerometer readings, and other location-based information.

Base Station Feedback: Base stations can relay information on current signal strength, user connection status, and handover events to the network management system.

3.2.3. Environmental Context Data

Description: Additional context that can influence user mobility patterns, such as geographical features, urban infrastructure, and traffic conditions. This data can enhance the predictive capabilities of the HMM.

Sources:

Geographic Information Systems (GIS): Data from GIS can provide information on road networks, terrain, and urban density that may affect user mobility.

Traffic Management Systems: Real-time traffic data can inform how congested certain routes are, impacting user movements and potential handover needs.

3.2.4. User Behavior Data

Description: Information related to user habits and preferences, which can influence mobility patterns, such as common travel routes or times of high network usage.

Sources:

Mobile Application Usage Data: Analysis of which applications users frequently access can provide insights into their mobility patterns (e.g., commuting times, peak usage hours).

Surveys and User Studies: Direct feedback from users about their mobility behaviors can supplement data from automated systems, offering qualitative insights.

3.2.5. Data Collection Methods

3.2.5.1 Passive Data Collection:

Utilizes existing network infrastructure to gather data without active user involvement, often through network logs and base station metrics.

3.2.5.2 Active Data Collection:

Involves collecting data through direct user interactions, such as mobile app usage tracking or surveys, where users provide explicit information about their mobility patterns.

3.2.5.3. Crowdsourcing:

Engaging users to contribute mobility data voluntarily through mobile applications that track location and movement, providing a rich dataset while ensuring user privacy through anonymization.

3.2.5.4. Data Privacy and Ethical Considerations

1. Ensure compliance with data protection regulations, such as GDPR or CCPA, when handling user mobility data.

2. Implement anonymization techniques to protect user identities and sensitive information.

3. Obtain informed consent from users when collecting real-time data, especially for applications that track location continuously.

3.3 Theoretical framework

The Hidden Markov Model (HMM) is a statistical model used to represent systems that follow a Markov process with unobservable (hidden) states. It is particularly useful for sequential data where the goal is to predict or infer the hidden states based on observable events or outputs.

3.3.1. Key Components of HMM

An HMM consists of the following fundamental components:

3.3.2. States (S):

A set of hidden states that the system can be in. These states are not directly observable. For instance, in a mobility context, each state might represent a **cell** or **location** that a user may transition to, but the exact location of the user is hidden.

3.3.3. Observations (O):

A set of observable events that are emitted by the system when it transitions between states. These are visible, unlike the hidden states. In the handover scenario, the observable output could be signal strength or network connection quality, which are linked to user mobility patterns.

3.3.4. Transition Probabilities (A):

The probabilities that describe how the system transitions from one hidden state to another. The probabilities that describe how the system transitions from one hidden state to another.
$A_{ij} = P(S_t = j \mid S_{t-1} = i)$ is the probability of transitioning from state i to state j.In mobility, this represents the probability of a user moving from one cell to another.

3.3.5. Emission Probabilities (B):

These describe the probability of observing a particular event given that the system is in a certain hidden state.

$B_j(o)=P(O_t = o \mid S_t=j)$ is the probability of observing event o given that the system is in state j.In the context of handover, this could be the likelihood of observing a particular signal strength when the user is in a specific cell.

3.3.6. Initial Probabilities (π):

The probabilities of starting in each state.

$\pi_i = P(S_1 = i)$ is the probability that the system starts in state i at time t=1

3.3.7. Mathematical Model of HMM

An HMM is typically represented by the tuple $\lambda= (A, B, \pi)$

$A=\{a_{ij}\}$ is the state transition probability matrix.

$B=\{b_j(o)\}$is the emission probability matrix (i.e., the probability of observing o given state j).

$\pi=\{\pi_i\}$ is the initial state distribution.

The goal of an HMM is to solve one of the following problems:

Evaluation Problem: Given a sequence of observations, calculate the probability that these observations were generated by the model. This is often done using the Forward algorithm.

Formula which is used for forward algorithm is given by,

$\alpha_t(i) = P(O_1, O_2, \ldots, O_t, S_t = S_i|\lambda)$

This is computed recursively,

Initialization: $\alpha_1(i) = \pi_i \cdot b_i(O_1)$, for all states i

Recursion: $\alpha_{t+1}(j) = (\sum \alpha_t(i).a_{ij}) * b_j(O_{t+1})$, { summing over i= 1 to N }

Termination: $P(O|\lambda) = \sum \alpha_T(i)$, {summing over, i= 1 to N}

Decoding Problem: Given a sequence of observations, determine the most likely sequence of hidden states that produced those observations. This is solved using the Viterbi algorithm.

To find the most likely sequence of hidden states S that produced the sequence of observations O, the Viterbi algorithm is used. Define δt(i)\delta_t(i)δt(i) as the highest probability along a single path that accounts for the first t observations and ends in state SiS_iSi:

$\delta_t(i) = \max_{(s1, s2, s3 \ldots st-1)} (S_1, S_2, \ldots, S_t = S_i, O1, O2, \ldots, O_t|\lambda)$

The recursive formula for the Viterbi algorithm is:

Initialization: $\delta_1(i) = \pi_i \cdot b_i(O_1)$

Recursion: $\delta_{t+1}(j) = (\max_i \delta_t(i) \cdot a_{ij}) \cdot b_j(O_{t+1})$, for t=1,2,…,T−1

Termination: $P = \max_i \delta_T(i)$

The most probable state sequence can then be backtracked using the values of $\delta_t(i)$.

3.3.8. Steps in an HMM-Based System

In a **mobility pattern recognition** scenario for cellular networks, HMM can be used to predict the next cell or location a user will move to, optimizing the handover process in a network.

3.3.8.1. Defining States:

Each hidden state represents a location (or cell) that a user can move to.

The exact cell the user is currently connected to may not be directly known (hidden), but can be inferred based on signals and other observable data (e.g., signal strength).

3.3.8.2. Observations:

Observations could include signal strength, movement speed, or connection quality. These are the measurable outputs that help infer the hidden states (i.e., the actual location or the next cell the user will connect to).

3.3.8.3. Training the Model:

Use historical mobility trace data to train the HMM.The training process will estimate the transition probabilities between cells (states) and the emission probabilities of observable signals.

3.3.8.4. Prediction:

Using the trained model, HMM can predict the user's next location by calculating the most likely state sequence given the current sequence of observations. This allows the system to prepare the handover in advance, reducing latency and improving energy efficiency.

IV. RESULTS AND DISCUSSION

4.1. Descriptive Statistics of Study Variables

Table 1: Sample Data Used for Mobility Trace of User

Timestamp	User ID	Current Cell	Signal Strength (dBm)	Previous Cell	Next Cell	User Speed (km/h)	Activity Type	Direction (°)	Device Type
2024-09-01 08:00:00	U001	Cell_A	-75	None	Cell_B	30	Walking	90	Smartphone
2024-09-01 08:05:00	U001	Cell_B	-70	Cell_A	Cell_C	25	Walking	85	Smartphone
2024-09-01 08:10:00	U001	Cell_C	-65	Cell_B	Cell_D	20	Walking	80	Smartphone
2024-09-01 08:15:00	U001	Cell_D	-80	Cell_C	Cell_E	15	Sitting	0	Smartphone
2024-09-01 08:20:00	U001	Cell_E	-78	Cell_D	Cell_F	10	Sitting	0	Smartphone
2024-09-01 08:30:00	U002	Cell_B	-72	Cell_A	Cell_C	30	Running	85	Smartwatch
2024-09-01 08:35:00	U002	Cell_C	-74	Cell_B	Cell_D	28	Running	80	Smartwatch
2024-09-01 08:40:00	U002	Cell_D	-73	Cell_C	Cell_E	20	Walking	75	Smartwatch

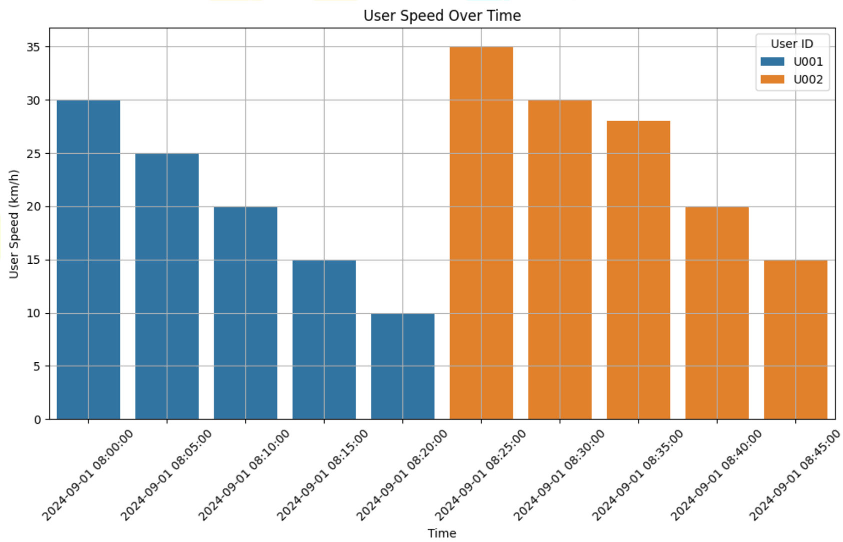

Fig 2: Speed of the user movement between the Cells

Visualization of signal strength over the time is crucial during the handover decision.

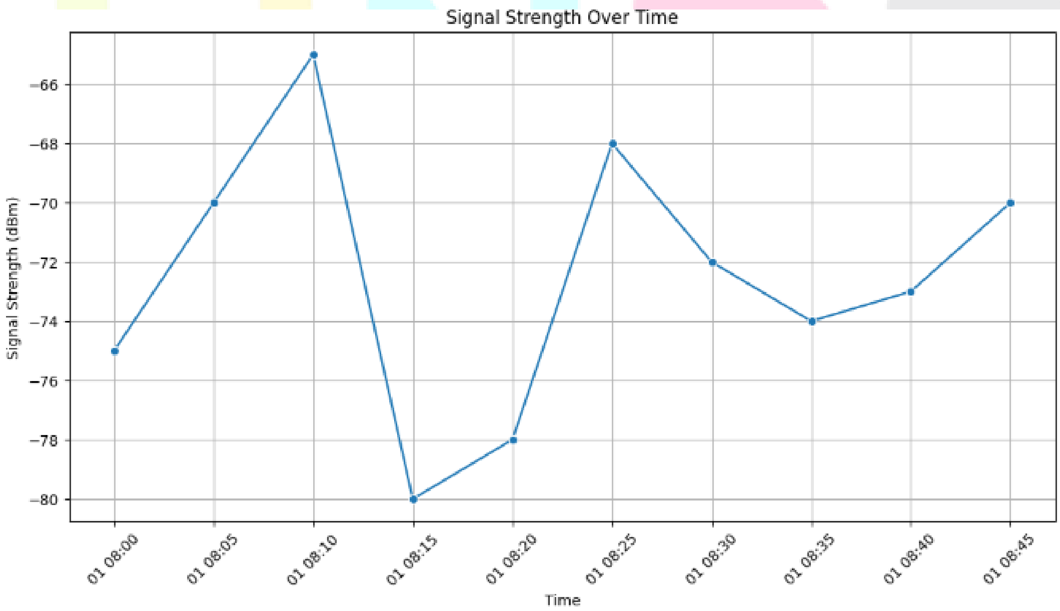

Fig 3: Signal strength over the time

4.2. Variable description

In Table 1 presents a sample of mobility trace data collected from users in a 6G network. Each entry includes the timestamp of the observation, the user's ID, the current cell they are connected to, the signal strength, the previous and next cells, user speed, activity type, direction of movement, device type, and connection type. This data serves as the foundation for analysing user mobility.

Timestamp: The date and time when the mobility data was recorded, providing a timeline of user movements.

User ID: A unique identifier for each user, allowing for tracking individual mobility patterns.

Current Cell: The name or ID of the cell tower currently serving the user.

Signal Strength (in decibel-milliwatts): The strength of the signal received from the current cell, affecting connectivity and handover decisions.

Previous Cell: The cell tower the user was connected to before the current one, helping to analyse transitions.

Next Cell: The predicted or intended next cell based on user movement patterns.

User Speed (km/h): The speed of the user at the time of the observation, which can indicate their mobility pattern (walking, running, sitting).

Activity Type: The type of activity the user is engaged in (e.g., walking, running, sitting), which may influence mobility patterns.

Direction (°): The direction of movement in degrees, indicating the user’s movement relative to the north.

Device Type: The type of device being used by the user (e.g., smartphone, smartwatch), which can affect connectivity and usage patterns.

Connection Type: The type of network connection (e.g., 5G), which is relevant for understanding the technology's impact on mobility and handover , and implementing Hidden Markov Models (HMMs) to enhance handover efficiency.

4.3. Performance Metrics

Elaborate performance metrics are derived using the below manner –

The handover performance metrics in my research are derived by measuring and analyzing key parameters that affect the efficiency and reliability of handover processes in cellular networks. These metrics are crucial to evaluate how effectively the HMM-based approach (Hidden Markov Model) improves handover mechanisms compared to traditional methods. Below is a breakdown of how each metric is typically derived:

4.3.1. Average Handover Latency
Definition: Handover latency refers to the time delay between when a handover is initiated (due to the user moving from one cell to another) and when the handover process is completed, allowing the user to resume seamless communication.
Derivation: Latency is measured in milliseconds (ms) by tracking the time between the initiation of the handover request and the completion of the connection with the target cell. In the context of HMM-based handover, the HMM model predicts the next cell the user is likely to move to, allowing for proactive handover preparation, which reduces the time spent establishing new connections. Compare the latency under traditional reactive handover and HMM-enhanced handover systems to derive the average improvement.

4.3.2. Total Energy Consumption
Definition: Energy consumption during the handover process refers to the amount of energy (in Joules) consumed by the mobile device and base stations when managing the handover.
Derivation: Energy usage can be measured by monitoring the power drawn by the user equipment (UE) and the network infrastructure during the handover process. Energy efficiency is particularly critical in 6G networks as devices, base stations, and edge infrastructure aim to minimize power usage. By reducing unnecessary handovers and minimizing the number of attempts (which the HMM helps with by predicting user movement), the total energy consumption is derived by summing the energy used per handover over a large number of samples for both traditional and HMM-based approaches.

4.3.3. Prediction Accuracy
Definition: Prediction accuracy refers to how accurately the HMM predicts the next cell that the user will move to during the handover process.
Derivation: The accuracy is calculated by comparing the predicted next cell from the HMM model to the actual next cell that the user connects to.
Formula:

Prediction Accuracy = Number of Correct Predictions /Total Number of Predictions × 100
This metric directly reflects the efficiency of the mobility prediction algorithm (HMM in this case). Higher accuracy means that the handover process can be initiated earlier, reducing latency and preventing unnecessary handover attempts.

4.3.4. Handover Success Rate
Definition: The handover success rate is the ratio of successful handovers to the total number of handover attempts.
Derivation:
A handover is considered successful if the transition from one cell to another happens without call drops or interruptions in communication.
Formula:
Success Rate = Number of Successful Handovers/Total Handover Attempts ×100
The HMM-based approach improves this by predicting the optimal target cell, reducing the chances of failed handovers caused by poor network conditions or incorrect target cell selection.

4.3.5. User Satisfaction Score
Definition: The user satisfaction score is a subjective measure of how satisfied users are with their network experience, particularly during handovers.
Derivation:
Users rate their experience on a scale (e.g., 1 to 10) based on factors like seamless connectivity, low latency, and overall performance during the handover process. Surveys or feedback forms are typically used to gather this data. The user satisfaction score tends to increase when handover processes are smoother and faster, which the HMM model enables by reducing dropped connections, latency, and excessive power consumption.

4.3.6. Average Number of Handover Attempts
Definition: This metric refers to the number of handover attempts made before a successful handover is achieved.
Derivation:
Each time a handover is initiated but fails, an additional attempt is made. The average number of attempts is calculated by tracking the number of handover attempts per user and then averaging it over a large set of users.The HMM model reduces unnecessary handover attempts by accurately predicting the next cell, allowing the network to select the right target cell on the first try, minimizing the total number of handover attempts.

4.4 Data Sources for Metrics Derivation

4.4.1. Mobility Trace Data: The mobility patterns of users moving through the network, typically collected from real-world network logs, form the primary dataset for deriving handover performance metrics. This data includes information on user location, speed, connected cell IDs, and timestamps, which help predict user movements. Mobility trace data is essential for training the HMM to make accurate predictions, which are then evaluated during the handover process.

4.4.2. Network Logs: Logs from cellular base stations provide real-time data on handover attempts, success/failure rates, energy consumption, and user equipment activity during handover events.

4.4.3. Simulation or Emulation Tools: In some cases, the results are obtained through network simulation tools (like NS-3, or MATLAB) that mimic real-world conditions for testing the HMM-based handover performance. These tools allow for large-scale tests without the need for physical deployment.

Table 2: Handover Performance Metrics

Metric	Traditional Approach	HMM-Based Approach
Average Handover Latency (ms)	150	100
Total Energy Consumption (J)	500	350
Prediction Accuracy (%)	80	92
Handover Success Rate (%)	85	95
User Satisfaction Score (1-10)	6	8
Average Number of Handover Attempts	4	2

4.5. Variable description

Average Handover Latency (ms):

Measures the average time taken to complete a handover process. A lower value indicates a more efficient handover mechanism.

Findings: The HMM-based approach achieved an average latency of 100 ms, significantly lower than the 150 ms of the traditional method.

Total Energy Consumption (J):

Assesses the total energy consumed during the handover process. Lower energy consumption indicates a more efficient system, critical for sustainable network operation.

Findings: The HMM approach resulted in total energy consumption of 350 J, compared to 500 J for the traditional method, showcasing improved energy efficiency.

Prediction Accuracy (%):

Represents the accuracy of predicting the next cell a user will connect to based on their mobility patterns. Higher accuracy leads to more informed handover decisions.

Findings: The HMM achieved a prediction accuracy of 92%, surpassing the traditional approach's 80%.

Handover Success Rate (%):

Indicates the percentage of successful handovers completed without service interruption. A higher rate is indicative of a robust handover mechanism.

Findings: The HMM-based method recorded a success rate of 95%, compared to 85% for traditional methods.

User Satisfaction Score (1-10):

A subjective measure based on user feedback regarding their experience during handovers. Higher scores reflect greater user satisfaction.

Findings: Users rated their experience with the HMM approach at an average score of 8, versus 6 for the traditional method.

Average Number of Handover Attempts:

Reflects how many attempts are needed to complete a handover. Fewer attempts indicate a more efficient handover process.

4.6. Finding Implications

The results demonstrate that employing HMMs for mobility pattern recognition can significantly enhance the efficiency of handover processes in 6G networks. By accurately predicting user mobility patterns, the HMM-based approach not only improves technical metrics but also enhances user satisfaction—an increasingly important factor in telecommunications.

The reduction in energy consumption aligns with global sustainability initiatives, emphasizing the role of innovative technologies in building greener networks. As 6G networks are deployed, energy-efficient handover mechanisms will be crucial in accommodating the expected exponential growth in connected devices and the corresponding demand for reliable connectivity.

4.7. Limitations and Future Work

While the results are promising, there are limitations to this study. The mobility trace data used for training the HMMs may not fully encapsulate all real-world scenarios, especially in diverse urban environments. Future work could involve expanding the dataset to include varied mobility patterns and user behaviours.

Moreover, real-time implementation of the HMM-based approach should be tested in live network conditions to validate the findings. Further research could also explore the integration of other machine learning techniques to enhance prediction capabilities and overall performance.

I. Acknowledgment

I WOULD LIKE TO EXTEND MY HEARTFELT GRATITUDE TO MY FRIEND AND COLLEAGUE AMARNATH BHATTACHARYA, FOR HIS GUIDANCE IN THE PREPARATION OF THIS PAPER. HIS SUPPORT HAS BEEN REALLY INSTRUMENTAL IN THE SUCCESSFUL COMPLETION OF THIS WORK.

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