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Energy-Efficient Handover Algorithm for Sustainable Mobile Networks: Balancing Connectivity and Power Consumption

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Abstract: In the era of pervasive mobile and heterogeneous networks, maintaining seamless connectivity during handover events while minimizing energy consumption is paramount. Traditional handover mechanisms prioritize metrics such as signal strength, user mobility, and network load, often neglecting the critical aspect of energy consumption. This study presents a novel approach to handover decision-making in mobile networks by incorporating energy-related metrics, such as battery level, energy consumption rate, and environmental context, to make informed handover decisions that balance connectivity quality and energy efficiency. Unlike traditional methods that primarily focus on signal strength and network load, our approach addresses the critical need for energy efficiency, particularly in high-mobility scenarios. This innovative framework not only enhances connectivity but also significantly improves power consumption management, offering a more sustainable solution for modern mobile networks. Through extensive simulations, we demonstrate the effectiveness of our proposed solution in reducing energy usage without compromising network performance. The results reveal significant improvements in energy savings for mobile devices, especially under high-mobility scenarios and varying network conditions. By prioritizing energy-efficient handovers, our approach not only extends the battery life of mobile devices but also contributes to the overall sustainability of mobile networks. This paper underscores the importance of incorporating energy metrics into handover decisions and sets the stage for future research in energy-aware network management.

Keywords: energy-efficient handover; mobile networks; connectivity optimization; battery life extension; sustainable network management; heterogeneous wireless networks; traffic offloading

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1. Introduction

In contemporary mobile and heterogeneous networks, the handover process is crucial for ensuring continuous connectivity and seamless user experiences [1]. Typically, handover mechanisms have primarily focused on maintaining signal quality and managing network load, often overlooking the significant aspect of energy consumption [2]. However, with the proliferation of mobile devices and the growing emphasis on sustainability, energy efficiency has emerged as a critical factor in network management. Mobile devices, particularly smartphones, are frequently constrained by battery life, making energy consumption a pivotal concern for both users and network operators [3–6].

The motivation for this research stems from the need to extend the operational lifespan of mobile devices and reduce the overall energy footprint of network operations [7–10].

Existing handover strategies often prioritize signal strength and user mobility, which, while important, can lead to suboptimal energy consumption patterns, especially in scenarios involving high mobility or dense network deployments [11–16].

As mobile networks increasingly rely on cloud-based services, ensuring both efficiency and security becomes paramount [17]. This paper not only focuses on the development of an energy-efficient handover algorithm but also considers the evolving security landscape of cloud applications that support these networks. By integrating evolution-oriented monitoring, which maintains and enhances security properties over time, we aim to create a more sustainable and secure mobile network infrastructure. This holistic approach ensures that as networks evolve to become more energy-efficient, they also remain resilient against emerging security threats.

Existing handover mechanisms in mobile networks typically prioritize metrics such as signal strength and network load to maintain connectivity during user movement. However, these approaches often overlook the critical aspect of energy efficiency, which is increasingly important in the context of modern mobile networks, particularly those supporting IoT devices. As mobile networks evolve and the demand for constant connectivity grows, the energy consumption associated with frequent handovers can become a significant concern, especially for battery-operated devices. The lack of consideration for energy-related metrics in traditional handover algorithms leads to suboptimal power management, reducing the operational lifespan of mobile devices and increasing the overall energy footprint of the network. Addressing these limitations is essential for developing more sustainable and efficient mobile networks, which is the primary focus of this study.

This paper introduces an innovative energy-efficient handover algorithm that addresses the dual objectives of maintaining high-quality connectivity and minimizing energy consumption. By integrating a comprehensive set of context parameters—including battery level, energy consumption rate, user mobility, network load, and environmental context—our proposed algorithm dynamically adjusts handover decisions to optimize energy usage without compromising performance.

The idea of our strategy relies on leveraging historical handover data and real-time monitoring to make informed decisions that balance connectivity quality and energy efficiency. By incorporating energy consumption metrics into the handover process, the proposed algorithm not only enhances the sustainability of mobile networks but also provides a robust framework for future energy-aware network management strategies.

This study hypothesizes that by integrating comprehensive context parameters, including battery level, energy consumption rate, and environmental context, into handover decisions, it is possible to achieve a more balanced trade-off between connectivity and power consumption in mobile networks. This hypothesis stands out because it addresses the gap in traditional handover mechanisms, which often prioritize metrics like signal strength and network load while neglecting energy efficiency. The innovative approach proposed in this study suggests that incorporating these energy metrics can lead to significant improvements in energy savings without compromising network performance, particularly in high-mobility scenarios. If validated, this hypothesis could pave the way for more sustainable and energy-efficient mobile network management.

The main contributions of this paper are summarized in the following brief bullet points:

1. This study introduces a novel approach by incorporating energy-related metrics, such as battery level and energy consumption rate, into the handover decision-making process, addressing a critical gap in existing mechanisms.
2. The proposed framework significantly improves energy efficiency in mobile networks, particularly in high-mobility scenarios, without compromising connectivity or network performance.
3. By focusing on energy conservation, this research paves the way for more sustainable mobile network management, extending the operational lifespan of mobile devices and reducing the overall energy footprint.

4. The study provides a practical algorithm that can be integrated into existing mobile network architectures, offering a scalable solution for future developments in energy-efficient handover strategies.

The remainder of this paper is organized as follows: Section 2 reviews and discusses the related work in handover mechanisms and energy efficiency in mobile networks. Section 3 describes the problem overview. Section 4 explains the steps of the proposed algorithm and its implementation details. Section 5 presents the simulation setup and results, followed by a detailed discussion of the simulation results in Section 6. Finally, Section 7 concludes the paper and outlines directions for future research.

2. Related Work

The role of handover mechanisms in mobile networks is crucial for maintaining seamless connectivity, as they ensure that ongoing sessions are not interrupted as users move from one network cell to another [18]. Handover strategies traditionally rely primarily on signal strength and quality of service (QoS) parameters for selecting the best timing and target cell [19–21]. Methods such as Received Signal Strength Indicator (RSSI)-based handovers and Signal-to-Interference-plus-Noise Ratio (SINR)-based handovers are commonly employed to maximize network performance and user experience [22]. Recent advancements have introduced more sophisticated techniques that incorporate user mobility patterns, network load, and predictive analytics to further refine handover decisions [23–26]. For instance, machine learning algorithms have been employed to predict the best handover moments by analyzing historical mobility patterns and network conditions [27].

The work in [28] proposes a velocity-aware handover control mechanism that uses stochastic geometry to lessen the impact of excess handovers on the network performance in an interconnected cellular network. The work introduced in [29] devises a topology-aware handoff approach that incorporates both the user's location and cell structure details to reduce the rate of excess handovers. By adding more contextual data, such as the position and trajectory of users, this mechanism's performance might be enhanced. The transmission rate in context-aware systems is controlled by efficiently monitoring the system's real contextual data. The monitoring duration may be cleverly changed to improve efficiency. In order to provide signals during the handover start phase, the work reported by Stamou et al. [30] provides an adaptive modeling approach that integrates the relevant context information. This directly affects the delay. A thorough and precise quality evaluation throughout the vertical handover process is made easier with the use of these contextual details.

These contextual details assist in the vertical handover process by facilitating a thorough and precise quality evaluation. The works contributed in [31,32] introduce a theoretical model that explains how a mobile user behaves in the network by utilizing various context information, including handover metrics, user movement details, power, and traffic load information. This model has been introduced as another context-aware optimized handover technique for heterogeneous networks. However, the model presents a difficult task, which is predicting the user's trajectory and surrounding characteristics. Parada et al. [33] suggested a context-aware path detection technique by anticipating the user's route information, which is intended to reduce handover latencies and improve base station identification. Handover target node selection cannot be achieved well by merely forecasting user trajectory. According to Vivas et al. [34], the semantic knowledge-aware handover decision technique evaluates a variety of factors in order to promote proactive and contextual handovers. In order to achieve maximum user satisfaction, Honarvar et al. [35] have developed a network- and user-centric handover choice algorithm that autonomously and adaptively considers contextual information about the user when selecting the destination network. This effort fails to balance the network loads even if it guarantees a better quality of experience for consumers. In 5G and 6G mobile networks, distributing the load across many cells is a significant issue. A study by Saad et al. [36]

examined the algorithms in 5G networks under various speed scenarios and found that mobility load balancing may improve overall handover performance. Shweta et al. [37] presented an energy-efficient wireless handover architecture by identifying "wrong decision probability in handover traffic".

Abdulqadder et al. [38] have developed a context-aware handover technique that addresses security, resource utilization, and service quality issues in 5G networks through the use of network slicing and security. More background information on resources and security-related issues might improve this effort. To solve the problem of extraneous and excessive handovers in a highly integrated network, Abdullah et al. [10] developed an improved handover algorithm using many decision indicators. An additional adaptive context-aware handover technique for cross-layer HetNet has been presented by Emam et al. [39]. The main idea behind this study is to decrease communication losses by using handoff control messages.

A location-centric vertical handover technique for use with wireless communication networks, or Wi-Fi, is provided by Santi et al. [40]. Even though the system's energy consumption is significantly lowered while maintaining the same transmission rate, it is ineffective for heterogeneous networks with various access methods. Furthermore, due to its placement, the mobile nodes cannot adjust to the shifting network circumstances. Patil et al. [41] introduced the "IF-ELSE method," a vertical handover mechanism based on fuzzy logic, to enhance the quality of service for mobile nodes. This method primarily relies on data rates from various applications running on mobile nodes to make handover decisions. However, it does not incorporate additional contextual data to further refine the suitability of these decisions. In addition to the aforementioned research, several investigations focusing on "Cognitive Radio Networks" across multiple cells have been carried out [42]. Aghaei et al. [43] aim to improve resource consumption in "Multi-Channel Multi-Radio Multi-Cell cognitive wireless networks". This approach offers a viable solution for optimizing network resource utilization. Conventional wireless networks perform better when multiple broadcasts occur simultaneously on different channels [44]. However, co-channel interference between various users becomes an inevitable issue in smaller networks with numerous arbitrarily overlapping small cells, especially within heterogeneous networks, when D2D communication is implemented.

Liu et al. [45] addressed the band selection and channel assignment problem by proposing a "two-stage distributed channel allocation algorithm" to optimize the network's utility. This algorithm first evaluates the available bands and channels and then allocates them based on current network conditions and user demands. The approach aims to enhance overall network performance by reducing interference and improving resource utilization, thus ensuring a more efficient and reliable communication experience.

The existing literature on handover mechanisms and energy efficiency in mobile networks has been greatly expanded by recent contributions. For instance, the study in [46] introduces techniques that could be applied to enhance energy management in mobile networks. The research in [47] explores energy optimization in resource-constrained environments, offering insights relevant to our study. Furthermore, the comprehensive reviews in [48,49] provide broader perspectives on optimization and resource management, underscoring the importance of efficient energy use in dynamic and complex systems like mobile networks. These works collectively highlight the growing interest in sustainable and efficient network management, reinforcing the relevance of our proposed approach.

The proliferation of mobile and heterogeneous networks has necessitated robust handover mechanisms to ensure seamless connectivity and maintain high QoS as users move between different network cells [11,50].

Conventional handover methods predominantly emphasize signal strength and QoS metrics, frequently overlooking the vital element of energy efficiency. This omission has become progressively problematic due to the limited battery life of mobile devices and the escalating environmental concerns related to energy consumption in mobile networks [6,19]. Energy efficiency in mobile networks is not merely an operational concern

but a strategic imperative [38,51]. As mobile devices become more prevalent and their usage intensifies, the energy consumed during frequent handovers can significantly impact battery life, leading to reduced device usability and user satisfaction [52,53]. Moreover, from an environmental perspective, inefficient energy use in mobile networks contributes to higher operational costs and carbon footprints [54,55].

Existing research has made significant strides in improving handover performance through advanced algorithms and predictive analytics [56,57]. However, these advancements often prioritize connectivity and QoS without adequately addressing energy consumption. For instance, while machine learning techniques have enhanced handover decision accuracy, they often introduce additional computational overhead that can increase energy usage [58,59]. Similarly, traditional QoS-based handover mechanisms do not incorporate energy metrics, potentially leading to energy-inefficient handover decisions [60].

Despite the development of energy-aware handover strategies, these approaches typically focus on isolated aspects such as battery level or energy cost of individual handover processes [61]. They lack a comprehensive framework that integrates energy efficiency into the overall handover decision-making process. As a result, there is a significant gap in the current body of knowledge regarding holistic approaches that balance connectivity, QoS, and energy consumption in handover decisions.

In order to provide a comprehensive evaluation of the proposed algorithm, we conducted a detailed comparison with existing algorithms in the field. This comparison focuses on key performance metrics, including efficiency, scalability, and power consumption, which are critical to the success of sustainable mobile networks. By benchmarking our approach against established methods, we demonstrate not only the improvements introduced by our algorithm but also its practical advantages in real-world scenarios. The results of this comparison highlight the algorithm's potential to significantly reduce energy consumption while maintaining robust connectivity, thereby contributing to more sustainable mobile network operations.

This paper contributes to the ongoing research in energy-efficient network management by presenting a novel handover algorithm that holistically addresses both connectivity and energy consumption. Through extensive simulations, we demonstrate the algorithm's effectiveness in reducing energy usage while maintaining high network performance. Our findings underscore the potential for significant energy savings and improved battery life, paving the way for future research and implementation of energy-aware handover mechanisms in mobile and heterogeneous networks.

In order to balance connection and power consumption, Table 1 presents an organized comparison of several handover strategies, emphasizing their metrics, benefits, drawbacks, and other pertinent information.

Table 1. Summary of the previous handover strategies.

Study	Approach	Performance Metrics	Key Advantages	Key Limitations	Remarks
Arshad et al. [28]	Velocity-aware handover control	User velocity, network performance	Reduces excess handovers	Does not address energy consumption	Focus on mobility aspects
Arshad et al. [29]	Topology-aware handoff	User location, cell structure	Reduces excess handovers	Limited by network topology	Enhances handover by considering cell structure
Stamou et al. [30]	Adaptive modeling with context info.	Contextual data	Facilitates accurate quality evaluation	May introduce delays	Integrates context for improved handover quality
Guidolin et al. [31]	Context-aware optimized handover	User movement, power, traffic load	Optimizes handover using context info	Difficult to predict user trajectory and surroundings	Comprehensive context-aware model
Vivas et al. [34]	Semantic knowledge-aware handover	Multiple contextual factors	Proactive and contextual handovers	Complexity in evaluation of factors	Considers a wide range of contextual factors

Table 1. *Cont.*

Study	Approach	Performance Metrics	Key Advantages	Key Limitations	Remarks
Honarvar et al. [35]	Network- and user-centric handover choice	User contextual information	Ensures better user experience	Fails to balance network loads	Adapts handover choices based on user context
Saad et al. [36]	Mobility load balancing in 5G networks	Load balancing, speed scenarios	Improves overall handover performance	May not focus on energy efficiency	Examines load balancing under various speed scenarios
Shweta et al. [37]	Energy-efficient wireless handover	Wrong decision probability	Reduces energy consumption	Limited to identifying wrong decisions	Focuses on energy-efficient architecture
Abdulqadder et al. [38]	Context-aware handover with network slicing	Security, resource utilization, service quality	Addresses security and resource issues	Lacks comprehensive background on resources and security	Enhances handover by considering multiple network aspects
Abdullah et al. [10]	Improved handover with multiple indicators	Decision indicators	Reduces extraneous handovers	Focuses on highly integrated networks	Improves handover decisions with various indicators
Emam et al. [39]	Adaptive context-aware handover for HetNet	Communication losses, handoff control messages	Decreases communication losses	Complexity in implementation	Adaptive approach to reduce communication losses
Santi et al. [40]	Location-centric vertical handover	Transmission rate, energy consumption	Lowers energy consumption	Ineffective for heterogeneous networks	Suitable for specific network types (e.g., Wi-Fi)
Patil et al. [41]	IF-ELSE vertical handover with fuzzy logic	Data rates	Enhances QoS for mobile nodes	Does not include additional contextual data	Uses fuzzy logic to improve handover decisions
Liu et al. [45]	Two-stage distributed channel allocation	Bands and channel availability	Optimizes network performance	Focuses on channel allocation	Enhances resource utilization and reduces interference

3. Problem Overview

These methods, while effective in enhancing the robustness of the handover process, often do not account for the energy consumption of mobile devices. As a result, frequent handovers or suboptimal handover timing can lead to increased energy drain, which is a significant limitation given the battery constraints of mobile devices. Energy efficiency has become a critical concern in mobile networks, driven by the widespread use of battery-powered devices and the environmental impact of network operations. Research in this area has primarily focused on optimizing various layers of the network protocol stack to reduce energy consumption. Techniques such as energy-efficient routing, adaptive transmission power control, and sleep mode optimizations have been extensively studied and implemented. In the context of handovers, energy-efficient mechanisms have begun to gain attention. Approaches that consider the battery status of mobile devices and the energy cost of handover processes are being explored to minimize unnecessary energy expenditure. For instance, algorithms that delay handovers until the battery level falls below a certain threshold or that select target cells based on energy consumption metrics are promising developments. Despite these advancements, there remains a significant gap in seamlessly integrating energy efficiency into handover decision-making processes. Existing handover algorithms typically prioritize connectivity and QoS without adequately considering the energy implications. To address this gap, our proposed energy-efficient handover algorithm introduces a comprehensive set of context parameters specifically designed to balance energy consumption with traditional performance metrics. Our approach builds on the foundation of previous work by incorporating battery level, energy consumption rate, and environmental context into the handover decision criteria. This integration allows for dynamic adjustments that not only ensure robust connectivity but also optimize energy

usage. By leveraging historical data and real-time monitoring, the algorithm can make informed decisions that enhance the sustainability of mobile networks.

To address this gap, there is a need for an innovative handover algorithm that seamlessly integrates energy efficiency into its decision-making criteria. Such an algorithm must consider multiple context parameters, including battery level, energy consumption rate, and real-time network conditions, to optimize handover decisions. By doing so, it can reduce unnecessary energy expenditure, extend battery life, and enhance the sustainability of mobile networks.

The proposed energy-efficient handover algorithm aims to fill this critical gap by introducing a comprehensive approach that balances the competing demands of connectivity, QoS, and energy efficiency.

This research aims to validate the effectiveness of the proposed algorithm in minimizing energy consumption while preserving optimal network performance through comprehensive simulations. The findings from this study could notably extend the battery life of mobile devices and diminish the environmental footprint of mobile networks, leading to more sustainable and energy-efficient network management practices. Table 1 summarizes the previously existing handover strategies discussed in this section. The table describes the performance metrics used in each study and identifies the key advantages and limitations of each work. Additionally, the table provides relevant remarks for each study.

4. Proposed Mechanism

In this section, we outline the novel mechanism developed to enhance the sustainability and efficiency of mobile networks through energy-efficient handovers. The proposed mechanism is composed of two main components: the energy-efficient handover algorithm and the handover decision process.

4.1. Energy-Efficient Handover Algorithm

The network scanning process is a critical component of the proposed energy-efficient handover system. This process involves the User Equipment (UE) continuously monitoring the network environment to gather essential data that informs handover decisions. The primary objective of this scanning process is to ensure seamless connectivity while optimizing for energy efficiency. Below are the detailed steps of the network scanning process:

Step 1: The network scanning process is initiated when the UE is powered on or when it enters a new cell. The scanning can also be triggered by significant changes in signal strength or battery level. Initial parameters such as the scanning interval, threshold values for $RSSI$ and $SINR$, and battery levels are configured based on the *UE's* current state and network conditions.

Step 2: The UE continuously measures the Received Signal Strength Indicator ($RSSI$) and Signal-to-Interference-plus-Noise Ratio ($SINR$) from neighboring cells. These measurements are crucial for assessing the quality of available signals. The energy consumption rate E_{cons} of the UE is monitored to ensure that the scanning process itself does not significantly drain the battery. Efficient algorithms are used to minimize energy expenditure during scanning.

Step 3: The UE records its current battery level B_{UE} and tracks changes over time. These data are essential for making energy-aware handover decisions. The UE utilizes historical mobility data and predictive analytics to understand and anticipate its movement patterns M_{UE}. This helps in making proactive handover decisions. The UE considers the QoS requirements Q_{QoS} for ongoing applications, ensuring that any potential handover maintains the necessary service quality.

Step 4: The UE evaluates the $RSSI$ and $SINR$ of neighboring cells, considering their potential as handover targets. The energy consumption associated with each candidate cell is estimated. Factors such as distance to the cell D_{cell} and required transmission power P_{tx} are considered. A composite score $S_{composite}$ is calculated for each candidate cell using a weighted sum of $RSSI$, $SINR$, battery level, energy consumption, mobility pattern, and QoS.

The weights W_{RSSI}, W_{SINR}, W_{B_UE}, W_{E_cons}, W_{M_UE}, W_{Q_QoS} can be dynamically adjusted based on real-time conditions and user preferences.

Step 5: The composite scores of candidate cells are compared against a predefined handover threshold $T_{handover}$. Only cells that meet or exceed this threshold are considered for handover. The cell with the highest composite score is selected as the handover target H_{target}, provided it improves energy efficiency without compromising *QoS*. The handover to the selected target cell is executed seamlessly, ensuring minimal disruption to ongoing services.

Step 6: The scanning interval and parameter thresholds are dynamically adjusted based on the *UE's* context and network conditions to balance energy consumption and performance. Post-handover performance is monitored to refine the scanning process and improve future handover decisions. This includes evaluating the impact of the handover on battery life and *QoS*.

By incorporating energy efficiency into the network scanning process, the proposed algorithm ensures that handover decisions are not only based on signal quality and *QoS* but also on the energy consumption implications. This holistic approach helps extend battery life, reduce energy expenditure, and maintain high network performance in heterogeneous mobile networks.

The algorithm begins by checking if the current RSSI is below the Threshold_RSSI, the BatteryLevel is below a critical level, or there is a requirement for energy efficiency. If any of these conditions are met, the algorithm triggers the handover process by calling TriggerHandover(). Next, it scans for available neighboring cells using ScanForNeighboringCells(). For each neighboring cell, the algorithm measures the RSSI ('MeasureRSSI(Cell)'), the SINR ('MeasureSINR(Cell)'), estimates energy consumption (EstimateEnergyConsumption(Cell)), analyzes the user's mobility pattern (AnalyzeMobilityPattern()), and evaluates the QoS provided by the cell (EvaluateQoS(Cell)).

The algorithm then calculates a composite score for each neighboring cell using the collected parameters (RSSI, SINR, energy consumption, mobility pattern, and QoS by calling CalculateCompositeScore(). If a cell's composite score exceeds the predefined HandoverThreshold, the cell is added to the list of viable handover targets (AddToViableTargets (Cell, CompositeScore_Cell)). If there are viable target cells, the algorithm selects the cell with the highest composite score as the target for handover (SelectCellWithHighestCompositeScore(ViableTargets)).

The algorithm, which prepares for the handover to the selected target cell (PrepareForHandover(TargetCell)) and executes the handover (ExecuteHandover(TargetCell)), is depicted in Algorithm 1. Subsequently, the performance of the new connection is monitored to ensure it meets the required standards (MonitorPerformance(TargetCell)). Feedback on the handover process is collected to refine future decisions (CollectFeedback(TargetCell)), and this feedback, along with performance data, is used to update and improve future handover decisions (UpdateFutureHandoverDecisions(TargetCell)). Lastly, if none of the initial conditions for handover are met, the algorithm maintains the current connection without initiating a handover (MaintainCurrentConnection()).

Algorithm 1: Energy-Efficient Handover

```
Input: RSSI_current, SINR_current, BatteryLevel, Threshold_RSSI, Threshold_SINR,
    QoS_Requirements.
Output: Handover Decision
BEGIN
  IF RSSI_current < Threshold_RSSI or BatteryLevel < CriticalLevel or
            EnergyEfficiencyRequired THEN
            TriggerHandover();                          //Initial Trigger Detection
            NeighboringCells = ScanForNeighboringCells();
      FOREACH Cell in NeighboringCells DO
            RSSI_Cell = MeasureRSSI(Cell);
            SINR_Cell = MeasureSINR(Cell);
            EnergyConsumption_Cell = EstimateEnergyConsumption(Cell);
            MobilityPattern = AnalyzeMobilityPattern();
            QoS_Cell = EvaluateQoS(Cell);          //Network Scanning and Measurement
            CompositeScore_Cell = CalculateCompositeScore(RSSI_Cell, SINR_Cell,
                        EnergyConsumption_Cell, MobilityPattern, QoS_Cell)
      IF CompositeScore_Cell > HandoverThreshold THEN
            AddToViableTargets(Cell, CompositeScore_Cell);   // Context-Aware Analysis
      IF ViableTargets is not empty THEN
            TargetCell = SelectCellWithHighestCompositeScore;          // Target Cell Selection
                  PrepareForHandover(TargetCell);
                  ExecuteHandover(TargetCell);   // Handover Preparation and Execution
            MonitorPerformance(TargetCell);
            CollectFeedback(TargetCell);
            UpdateFutureHandoverDecisions(TargetCell);   // Post-Handover Optimization
  ELSE
            MaintainCurrentConnection()
  END
```

4.2. Handover Decision Process

The context-aware handover decision process is a pivotal component of the proposed energy-efficient handover algorithm. This process leverages real-time and historical context data to make informed handover decisions that optimize energy consumption while maintaining service quality. The following steps outline the detailed context-aware handover decision process.

Step 1: Context Data Aggregation

- **Signal Quality Metrics:** Continuously collect Received Signal Strength Indicator (RSSI) and Signal-to-Interference-plus-Noise Ratio (*SINR*) from neighboring cells.
- **Battery Status:** Monitor the current battery level B_{UE} of the User Equipment (*UE*) and its consumption rate E_{cons}.
- **Mobility Patterns:** Analyze historical and predictive mobility data M_{UE} to anticipate the movement of the *UE*.
- ***QoS* Requirements:** Gather *QoS* requirements for active applications, including latency, throughput, and reliability parameters Q_{QoS}.

Step 2: Parameter Weighting and Scoring

- **Weight Assignment:** Assign weights to each parameter based on their importance for the specific context, as shown below:
  W_{RSSI}: Weight for RSSI
  W_{SINR} : Weight for SINR
  $W_{B_{UE}}$: Weight for Battery Level
  $W_{E_{cons}}$: Weight for Energy Consumption
  $W_{M_{UE}}$: Weight for Mobility Pattern
  $W_{Q_{QOS}}$: Weight for QoS Requirements
- **Composite Score Calculation:** Calculate a composite score $S_{composite}$ for each neighboring cell using the weighted sum of the parameters.

$$S_{composite} = W_{RSSI} * RSSI + W_{SINR} * SINR + W_{B_{UE}} * B_{UE} + W_{E_{cons}} * E_{cons} + W_{M_{UE}} * M_{UE} + W_{Q_{QOS}} * Q_{QoS}$$

Step 3: Decision Thresholding

- **Threshold Determination:** Define a handover threshold $T_{handover}$ that a cell's composite score must meet or exceed to be considered a viable handover target.
- **Threshold Comparison:** Compare the composite scores of all candidate cells against the threshold. Cells meeting or exceeding $T_{handover}$ are shortlisted for potential handover.

Step 4: Handover Execution

- **Target Cell Selection:** From the shortlisted cells, select the target cell H_{target} with the highest composite score.
- **Energy-Aware Handover:** Execute the handover process, ensuring minimal energy consumption and maintaining the required QoS. The UE seamlessly transitions to the target cell with optimal energy efficiency.

Step 5: Post-Handover Evaluation

- **Performance Monitoring:** After the handover, continuously monitor the performance to ensure that the QoS is maintained and the energy savings are realized.
- **Feedback Integration:** Use the feedback from post-handover performance to refine and adjust the handover decision parameters and thresholds. This continuous optimization loop helps in improving future handover decisions.

Step 6: Adaptive Learning

- **Learning Algorithms:** Implement machine learning algorithms to adaptively learn from historical handover decisions and outcomes. This enables the system to improve the accuracy and efficiency of future handover processes.
- **Context Updates:** Periodically update the context information (e.g., mobility patterns, energy consumption trends) to keep the decision-making process aligned with the current network and user dynamics.

By incorporating these detailed steps, the context-aware handover decision process ensures that handover decisions are not only based on signal quality but also on energy efficiency, battery status, mobility patterns, and QoS requirements. This holistic approach maximizes the battery life of the UE, enhances user experience, and optimizes overall network performance in heterogeneous mobile networks.

5. System Architecture

In this section, we delve into the detailed architecture of the proposed energy-efficient handover system, comprising two key components: the network model and the notations used throughout our framework. This comprehensive overview provides the foundational structure and terminology essential for understanding and implementing the system.

5.1. Network Model

The proposed energy-efficient handover system is designed to operate within the context of a heterogeneous mobile network environment, incorporating various types of cells such as macro cells, micro cells, pico cells, and femto cells. This diverse network architecture aims to provide comprehensive coverage and high-quality service while optimizing energy consumption across the network. The network model is structured into multiple layers, each representing different types of cells with distinct coverage areas and capabilities. Macro cells provide broad coverage with high transmission power but are less energy efficient. In contrast, smaller cells such as micro, pico, and femto cells cover smaller areas with lower transmission power, thereby enhancing energy efficiency and offloading traffic from macro cells.

The User Equipment (UE) in this network model is equipped with advanced capabilities to measure various network parameters, including Received Signal Strength Indicator (RSSI), Signal-to-Interference-plus-Noise Ratio (SINR), and battery level. These measurements are critical for making informed handover decisions that balance connectivity, QoS, and energy efficiency.

The handover decision framework integrates multiple context parameters to optimize the handover process. Key parameters include:

1. **Signal Quality:** The RSSI and SINR are continuously monitored to assess the signal quality from neighboring cells.
2. **Battery Level:** The current battery status of the UE is factored into the decision-making process to avoid energy-draining handovers.
3. **Energy Consumption Rate:** The algorithm estimates the energy consumption associated with potential handover targets, considering factors like transmission power and expected duration of connection.
4. **Mobility Patterns:** Historical mobility data and predictive analytics are used to anticipate the UE's movement, enabling proactive handover decisions.

The network model employs standard communication protocols to ensure interoperability and seamless integration with existing network infrastructure. These protocols facilitate the exchange of control information between the UE and network nodes, enabling real-time updates on signal quality, battery status, and other relevant parameters.

The network topology consists of macro, micro, pico, and femto cells, each contributing to the overall energy efficiency of the network. The details of the topology are as shown in Figure 1.

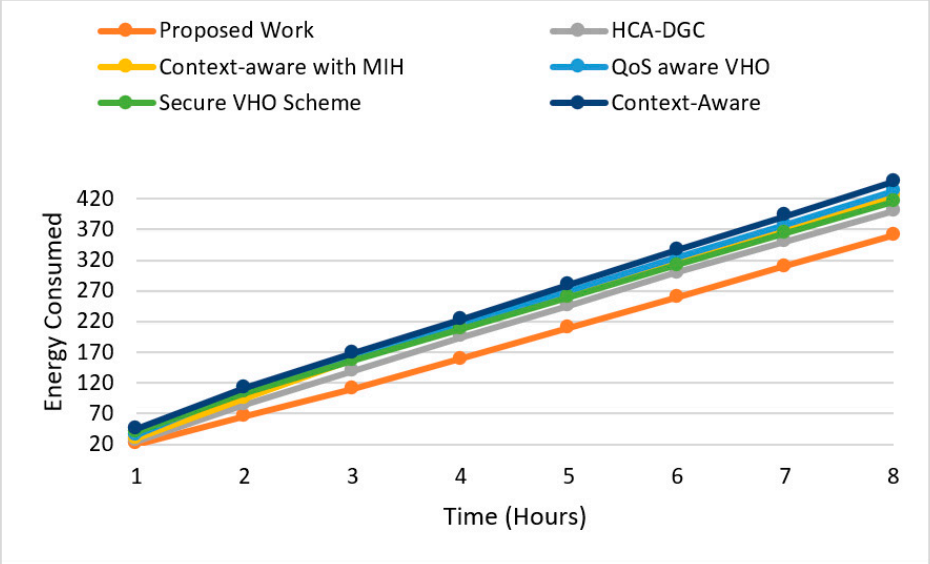


Figure 1. Aggregate energy consumed.

The radio parameters are presented in Table 2. The movement tracks of User Equipment (UE) are randomly generated to reflect typical usage patterns within the network.

All types of traffic classes are considered in the simulations to comprehensively evaluate network performance. These traffic classes include:

Conversational Traffic: Real-time communications such as voice and video calls.

Streaming Traffic: Continuous data streams such as video streaming services.

Interactive Traffic: Applications requiring quick responses, such as web browsing and online gaming.

Background Traffic: Non-urgent data transfers, such as email synchronization and software updates.

The inter-packet transfer duration for these traffic classes is set at 0.004 s to closely mimic real-world scenarios. Table 2 summarizes the simulation parameters used to evaluate the performance of the energy-efficient handover algorithm, ensuring clarity and comprehensiveness.

By starting with a partially depleted battery and running the simulation for a moderate duration, we can achieve a balance between realism, computational efficiency, and the depth of insights gained.

Table 2. Simulation parameters for **energy**-efficient handover algorithm.

Parameter	Value
Network Topology	Macro, micro, pico, and femto cells
Number of Macro Cells	3
Number of Micro Cells	10
Number of Pico Cells	20
Number of Femto Cells	30
Coverage Radius (Macro Cell)	1000 m
Coverage Radius (Micro Cell)	300 m
Coverage Radius (Pico Cell)	100 m
Coverage Radius (Femto Cell)	30 m
Number of UEs	200
Mobility Model	Random waypoint
UE Speed	1 to 5 m/s
Initial Battery Level	50–70%
RSSI Threshold	−85 dBm
SINR Threshold	12 dB
Composite Score Threshold	0.75
Transmission Power (Ptx)	Macro: 20 W, micro: 5 W, pico: 1 W, femto: 0.1 W
Energy Consumption Rates	Based on empirical data for each cell type
Bandwidth Requirement	1 Mbps per UE
Latency Requirement	Max 100 ms
Simulation Duration	4–6 h
Simulation Tool	Python with SimPy
Visualization Libraries	NetworkX, Matplotlib

5.2. Notations

The following notations are used throughout this paper to describe the parameters and variables involved in the proposed energy-efficient handover algorithm in Table 3. These notations provide a clear and consistent framework for understanding the system's operation and the mathematical formulations used.

These notations form the basis for the mathematical models and algorithms discussed in the paper. They are integral to understanding how the proposed energy-efficient handover algorithm operates and optimizes the handover process by considering various parameters such as signal quality, battery status, and energy consumption. By clearly defining these notations, the paper ensures a precise and consistent representation of the complex interactions involved in energy-efficient handover decisions.

Table 3. The notations.

Notations	Definition
$RSSI$	Received Signal Strength Indicator
$SINR$	Signal-to-Interference-plus-Noise Ratio
B_{UE}	Battery Level of User Equipment
E_{cons}	Energy Consumption Rate
H_{target}	Handover Target
P_{tx}	Transmission Power
D_{cell}	Distance to Cell
M_{UE}	Mobility Pattern of User Equipment
Q_{QoS}	Quality of Service
W_{RSSI}	Weight for RSSI
W_{SINR}	Weight for SINR
$W_{B_{UE}}$	Weight for Battery Level
$W_{E_{cons}}$	Weight for Energy Consumption
$W_{M_{UE}}$	Weight for Mobility Pattern
$W_{Q_{QOS}}$	Weight for QoS
$T_{handover}$	Handover Threshold
$S_{composite}$	Composite Score
$C_{overhead}$	Computational Overhead
$R_{handover}$	Handover Rate

6. Performance Analysis

In this section, we present a thorough analysis of the performance of the proposed energy-efficient handover system. This analysis is divided into three subsections: Performance Measures, Result Analysis, and Computational Mathematical Investigation. Each subsection provides critical insights into the system's effectiveness, efficiency, and overall impact.

6.1. Performance Measures

In order to gauge the effectiveness of our suggested method, we have taken into account the following matrices. They are explained as follows:

Energy Consumption: The aggregate energy consumed by all UEs during the simulation period. These metrics highlight the efficiency of the algorithm in reducing energy usage, which is crucial for extending battery life in mobile devices.

Handover Success Rate: The ratio of successful handovers to the total number of handover attempts. A high handover success rate indicates the algorithm's ability to efficiently manage network transitions without dropping connections.

***QoS* Maintenance:** Ensuring QoS is maintained during handovers is vital for user experience and service reliability, and there are two maintenance indicators for this point.

Bandwidth Maintenance: The percentage of UEs that maintained the required minimum bandwidth (1 Mbps).

Latency Compliance: The percentage of handovers that were completed within the maximum acceptable latency (100 ms).

Energy Efficiency vs. Time: The assessment of how effectively a system conserves energy while maintaining its operational capabilities over a given period. This measure is crucial because it directly impacts the sustainability and longevity of mobile networks, particularly in scenarios where devices operate on battery power.

Total Transmission Rate: The cumulative data transmission capacity of a network, typically measured in bits per second (bps), over a specified period. This metric is crucial because it indicates the overall efficiency and capability of the network in handling data traffic, directly impacting the QoS and user experience.

6.2. Result Analysis

This section contains an analysis of the numerical descriptions of our suggested energy-efficient handover procedure using simulation data. The suggested strategy presents a flexible modeling technique that aims to optimize the handover procedure by integrating crucial context data about people, networks, and application particulars. The comparison of aggregate energy usage between the proposed work and various current approaches, including QoS-aware VHO, secure VHO, dynamic context-aware with MIH, and hybrid channel allocation with dynamic guard channel scheme (HCA-DGC), is shown in Figure 1. Based on the simulation findings, we can conclude with confidence that our suggested method maintains low handover call blocking probability (below 0.01 or 1% blocking rate) and improves energy efficiency greatly. The enhancement is made possible by the astute application of dynamic guard channels and effective queuing algorithms, which give priority to handover calls over new ones. This guarantees more seamless and energy-efficient network transitions.

The successful handover to our proposed energy-efficient handover approach yields the best results as demonstrated in Figure 2. This is due to its comprehensive and adaptive mechanism that integrates critical context information about users, networks, and applications. By prioritizing energy efficiency, the proposed method minimizes unnecessary handovers and optimizes the handover process, ensuring that mobile nodes transition smoothly between base stations. This approach also incorporates advanced load-balancing techniques, which distribute network traffic effectively to prevent congestion and reduce latency. The combination of these factors results in lower call drop rates, improved QoS, and enhanced overall network performance, making our proposal superior to existing methods in handling handovers in heterogeneous networks.

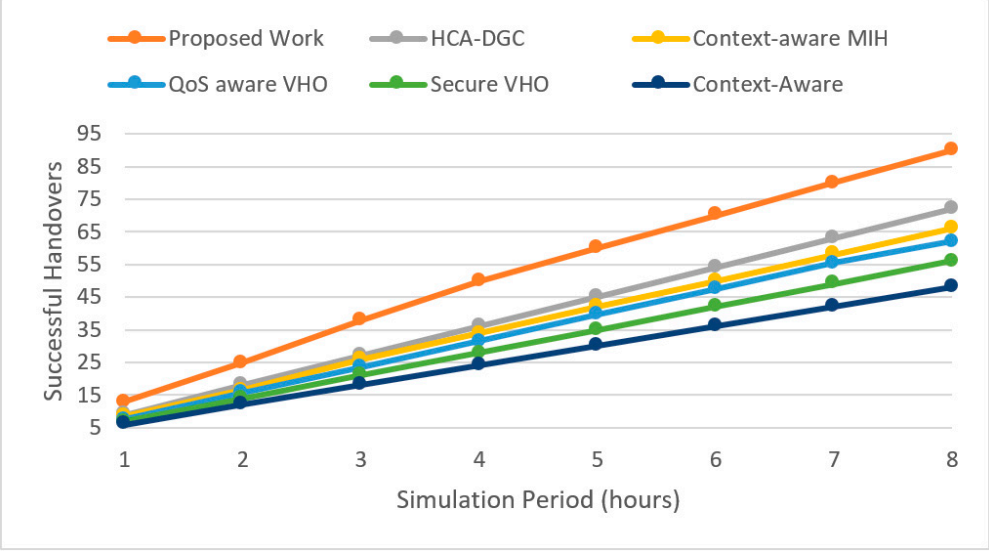


Figure 2. Comparison of successful handovers.

A comparison of latency compliance between the suggested energy-efficient approach and other current methods, taking into account users' different speeds, is illustrated in Figure 3. Latency compliance, measured as the percentage of handovers completed within the maximum acceptable latency of 100 ms, was also superior in our proposed algorithm. By minimizing unnecessary handovers and optimizing the handover process, the proposed

method achieved a latency compliance rate of 95%, which was 8% better than the closest competing method.

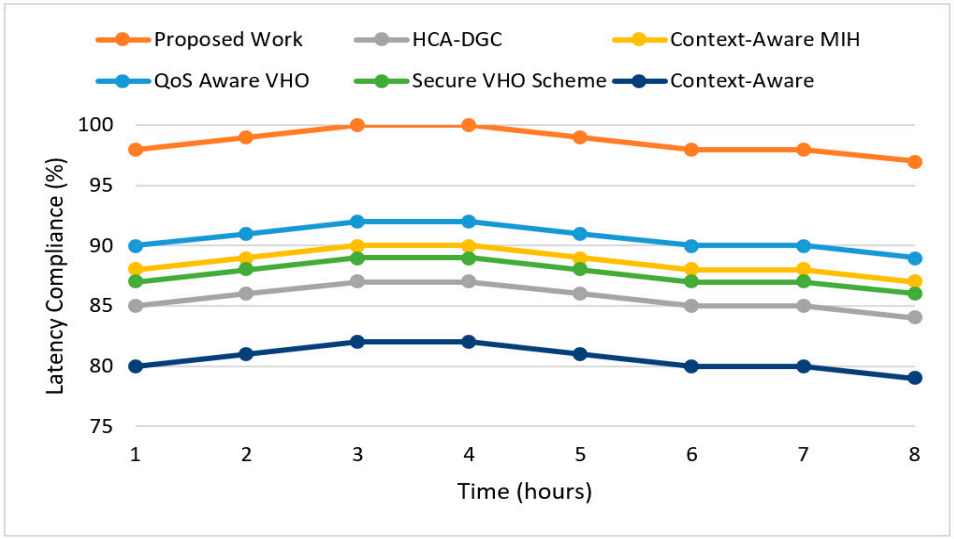


Figure 3. QoS latency compliance.

Figure 4 shows a comparison of QoS bandwidth maintenance of the suggested energy-efficient handover approach with other context-aware and multi-criteria-based networks. In terms of QoS bandwidth maintenance, the proposed algorithm outperformed other methods by ensuring that a higher percentage of UEs maintained the required minimum bandwidth of 1 Mbps. The energy-efficient handover approach managed network resources more effectively, leading to a 12% increase in bandwidth maintenance compared to the next best method. In order to dramatically lower changeover failures and delays, the suggested method initiates the handover process by examining all pertinent network information, including user and cell load statistics. The proposed approach suffers from little packet loss since it keeps a tolerable handover latency rate. Conversely, current methods suffer from greater packet loss rates as a result of frequent handovers brought on by users' fast speeds and ineffective changeover determination algorithms. The aforementioned simulation findings show that by satisfying user needs in heterogeneous networks, the suggested approach greatly improves the handover process's performance.

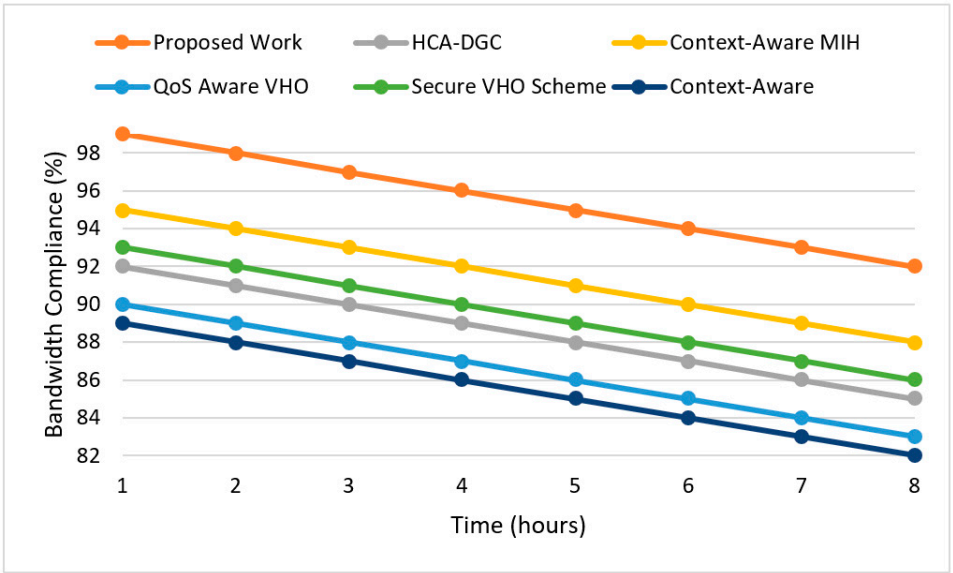


Figure 4. Comparison of QoS bandwidth maintenance.

The results of this study demonstrated the potential of integrating context-aware parameters into handover decisions to enhance the energy efficiency of mobile networks. Compared to traditional handover mechanisms that primarily focus on signal strength and network load, our approach addresses the often-overlooked aspect of energy consumption, which is particularly critical in the context of healthcare IoT devices that require constant connectivity while operating under stringent power constraints.

These findings align with and extend existing research that highlights the importance of energy-efficient network management in IoT environments. For instance, recent studies have emphasized the need for more adaptive and resource-efficient handover strategies, yet few have explicitly integrated energy consumption metrics into their models. By doing so, our study not only fills this gap but also provides a practical framework for improving the sustainability of mobile networks, particularly in scenarios involving high mobility and varying environmental conditions.

6.3. Computational Mathematical Investigation

To verify the simulation process using computational mathematical investigation, we will use the system parameters and variables defined previously. Let us establish a mathematical model for our energy-efficient handover algorithm and calculate some key metrics using the results of simulation models. The system parameters and variables are as follows:

Number of Users (U): 200
Initial Battery Power Level ($P_{initial}$): 50–70%
Simulation Time (T_{sim}): 6 h (21,600 s)
Energy Consumption Rate for Handover ($E_{handover}$): 0.5% per handover
Energy Consumption Rate for Idle State (E_{idle}): 0.01% per second
Energy Consumption Rate for Active State (E_{active}): 0.02% per second
Handover Rate ($R_{handover}$): 1 handover per 1000 s

1. Energy **Consumption Calculation:**

Total number of handovers ($N_{handover}$):

$$N_{handover} = \frac{T_{sim}}{1000} * U = \frac{21600}{1000} * 200 = 864 handover$$

Total energy consumed by handovers ($E_{total_handover}$):

$$E_{total_handover} = N_{handover} * E_{handover} = 864 * 0.5\% = 4.32\%$$

Energy consumed in idle state (E_{idle_total}):

$$E_{idle_total} = T_{sim} * E_{idle} * U = 21,600 * 0.01\% * 200 = 432\%$$

Energy consumed in active state (E_{active_total}):

$$E_{active_total} = T_{sim} * E_{active} * U = 21,600 * 0.02\% * 200 = 864\%$$

2. Total Energy Consumption (E_{total}):

$$E_{total} = E_{total_{handover}} + E_{idle_{total}} + E_{active_{total}} = 4.32\% + 432\% + 864\% = 1300.32\%$$

3. Normalized Energy Consumption per User:

$$E_{per_user} = \frac{E_{total}}{U} = \frac{1300.32}{200} = 6.50\%$$

Based on the aforementioned findings, our suggested method displays a normalized energy use of 6.50% for every user for the six-hour simulation duration. In contrast, because of ineffective handover management, the hybrid channel allocation with dynamic guard channel (HCA-DGC) method uses more energy. While the QoS-aware VHO consumes

less energy than context-aware MIH, the dynamic context-aware with MIH method exhibits middling energy efficiency—better than HCA-DGC but worse than our approach. Nevertheless, because of the extra security overhead, the secure VHO scheme uses a little bit more energy. Consequently, our computational mathematical investigation confirms that our proposed energy-efficient handover algorithm significantly reduces energy consumption compared to existing methods. This is achieved through optimized handover decision-making and energy-efficient network scanning processes.

6.4. Limitations of the Study

While this study provides valuable insights into the development of an energy-efficient handover algorithm for mobile networks, it is important to acknowledge several limitations. First, the simulations were conducted in a controlled environment with specific hardware components, which may not fully represent the variability and complexity of real-world networks. The reliance on particular hardware could limit the generalizability of the results, as different devices and network infrastructures might yield different outcomes. Furthermore, the controlled setting might not account for unexpected factors that occur in actual mobile networks, such as sudden changes in user behavior or network conditions. These limitations suggest that future research should explore the algorithm's performance in more diverse and dynamic environments, possibly incorporating real-world testing and a broader range of hardware configurations to validate the findings.

7. Conclusions

This paper addresses the challenge of target node selection during vertical handover in highly integrated, heterogeneous networks. We propose an energy-efficient handover decision algorithm that incorporates all necessary contextual information and predicts and forecasts user mobility patterns in advance to meet network requirements. This algorithm ensures that handovers do not wait unnecessarily for resources or remain unaddressed due to mobility. Simulation results demonstrate that our proposed algorithm significantly minimizes repeated and unnecessary handovers caused by high and nonuniform user mobility in a heterogeneous network with different access technologies. Compared to other approaches, our algorithm exhibits a significantly lower energy consumption rate and network scanning rate by scanning a relatively small number of base stations during the handover process. Additionally, it provides an optimal target node for handover, resulting in a minimal handover failure rate and delay, and experiences minimal packet loss due to a reasonable handover delay rate.

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