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INTELLIGENT VERTICAL HANDOVER DECISION FRAMEWORK FOR 5G NETWORKS VIA DATA MINING

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Abstract
Seamless vertical handover (VHO) is essential for ensuring continuous connectivity and high Quality of Service (QoS) in 5G heterogeneous networks. However, variations in network behaviors and protocols complicate VHO decision-making, often resulting in higher latency and service disruptions. This paper proposes a data mining-based VHO decision framework for 5G networks that leverages historical handover data to optimize mobility management. Using multivariate regression and Analysis of Variance (ANOVA), the framework identifies critical parameters such as signal strength, bandwidth, jitter, latency, packet loss, and coverage. Simulations conducted in the NetNeuman environment demonstrate that the proposed approach outperforms baseline algorithms by reducing latency, improving handover success rates, and enhancing overall network performance. Real-time decision-making, supported by historical insights, enables the framework to better meet user demands, thereby improving both reliability and user experience. The study also highlights the potential of integrating advanced machine learning methods for adaptive and predictive mobility management in future 6G networks. This work contributes to the development of intelligent, data-driven handover mechanisms vital for achieving ultra-reliable low-latency communication and seamless mobility in next-generation wireless systems.

1. INTRODUCTION

The advent of fifth-generation (5G) wireless systems is expected to support ultra-reliable low-latency communication (URLLC), enhance mobile broadband (eMBB), and enable massive machine-type communication (mMTC) for use in self-driving cars, virtual reality applications, and smart cities [1], [2]. To maintain uninterrupted access in such heterogeneous network scenarios, vertical handover (VHO) algorithms need to be robust and automated [3]. VHO is defined as the seamless transition of the connection of a mobile device from one network technology to another, e.g., shifting from Wi-Fi to 5G LTE while keeping services active [4], as illustrated in the Figure. 1. Unlike horizontal handovers, which are confined to one network technology, VHOs are multisourced with diverse access technologies with varying levels of complexity in the decision-making process [5]. Received signal strength (RSS), bandwidth, jitter, latency, packet loss, network coverage, user mobility, among others, must be managed at the same time for optimal handover decision to be achieved [6].

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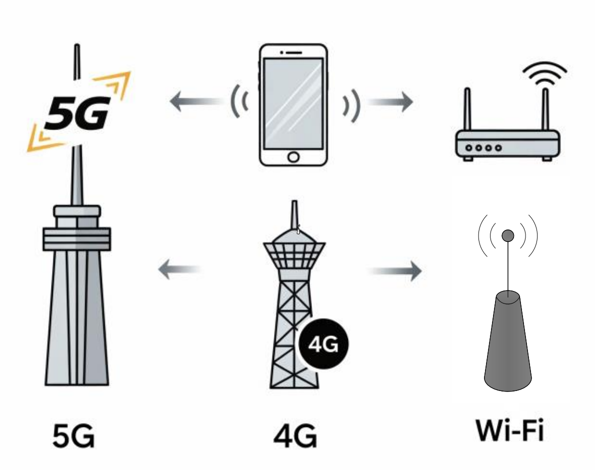

Figure. 1. Vertical Handover

Conventional handover decision algorithms like RSS-based or cost-function-based procedures are not able to handle the complexity of heterogeneous networks and lead to sub-optimal decision-making, higher latency, or loss of services [7]. Machine learning-based techniques for improving handover performance using machine learning from network data have been explored in recent times [8]. However, the application of data mining techniques, particularly sequence-based analysis of historical handover data, remains underexplored for VHO decision-making in 5G networks.

As the 5G networks evolve, intelligent and adaptive VHO protocols are an absolute necessity to deal with network heterogeneity and mobility. Real-time optimization in such a scenario cannot be addressed by manual or uninformed decision-making processes [9]. Where current research lacks is the availability of a data-driven VHO system that can draw insightful patterns from mobility handover data to make optimal target network selections.

This paper introduces a data mining sequence-based VHO decision model for 5G networks. Contributions are:

- Formulation of a new data mining-based VHO model with the use of multivariate regression analysis and ANOVA to determine major network parameters having an impact on handover decisions.
- Extraction of past handover tendencies to predict the most suitable target network for best VHO, based on RSS, bandwidth, jitter, latency, packet loss, and coverage.
- Large-scale testing with realistic simulation data in the NetNeuman environment to demonstrate gains in handover success rate, latency, and network performance compared to baseline techniques.

2. Related Work

2.1 Vertical Handover in HetNets

Vertical handover (VHO) guarantees seamless mobility between heterogeneous wireless networks by supporting user equipment (UE) to keep ongoing sessions uninterrupted in the process of handovers among various technologies like Wi-Fi, LTE, and 5G NR [10]. Nevertheless, these mechanisms tend to yield sub-optimal decisions, such as ping-pong and excessive handovers under varying channel conditions, compromising Quality of Service (QoS) [11]. To counter these limitations, cost-function-based methods have been introduced with various parameters like bandwidth, latency, jitter, energy consumption, and cost [12]. These solutions rank candidate networks through weighted sums of normalized parameters. Optimal weight assignments are nevertheless still subjective and difficult to determine, constraining adaptability under dynamic network environments [13].

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2.2 Multi-Attribute Decision Making (MADM) Techniques

MADM techniques, including the Analytic Hierarchy Process (AHP) [14], the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)) [15], and Grey Relational Analysis (GRA) [16], have been extensively applied in VHO decision-making, to handle various parameters at the same time. While AHP computes the relative weights on the basis of pairwise comparisons, TOPSIS ranks the alternatives based on their distance from the ideal solution, and GRA evaluates the relational closeness to that ideal performance. Their structured methodologies outperform those based on the simple cost function. However, MADMs are subject to scalability issues as the number of parameters and alternatives increase [17]. Additionally, the dependence on the expert-defined weights of the technique, autonomy is constrained. Moreover, they also do not provide forecasts to predict future conditions of the network for proactive handover decision-making.

2.3 Machine Learning-Based VHO Decision Approaches

Some of the recent studies focus on adaptive and predictive VHO decisions using machine learning (ML)-based approaches [18]. For instance, SVM, Random Forests, and ANN can classify optimal target networks depending on network parameters. Reinforcement Learning (RL) has also developed in VHO [19], through which an optimal policy of handover is learned by environmental interaction [20]. RL-based techniques dynamically adapt to several network conditions and are thus aligned with the self-optimizing characteristics envisioned for 5G and further [21]. However, supervised learning models require large amounts of labeled data, which is often not feasible, while RL incurs costs for exploration and delays for convergence.

2.4 Data Mining Applications in Mobility Management

Data mining has been extensively applied in wireless networks for the detection of anomalies, prediction of traffic, and optimization of resource allocation. With frequent pattern mining, mechanisms have been developed to derive user behavior and mobility patterns that are beneficial for resource management before the event takes place [22]. In the application of data mining under VHO, clustered network parameter data using data mining for handover decisions showing increased decision accuracy. However, the application of multivariate regression-based data mining to extract historical parameter impact patterns for informed real-time VHO decision-making in heterogeneous 5G networks remains underexplored.

2.5 Research Gaps

Thus far, works have made meaningful advancements in VHO decision making drawing from MADM and ML approaches. However, a couple of notable gaps still exist:

- There is a lack of interpretable data-driven models quantifying the impacts of parameters on handover success, which should be a basis for autonomous network management and optimization.
- Regression data mining frameworks have yet to find serious application for extracting historical decision patterns to aid real-time VHO in heterogeneous and ultra dense 5G environments.

This research fills these gaps by putting forward data mining-based VHO decision-making, based on multivariate regression analysis and ANOVA, to extract important network parameters, determine predictive decision rules, and improve handover performance in 5G networks.

3. Proposed Data Mining Based VHO Framework

This section presents the proposed data mining-based VHO decision-making framework for 5G networks that utilizes multivariate regression analysis to find key parameters in handover decisions and develop an optimal decision model, block diagram shown in Figure 2.

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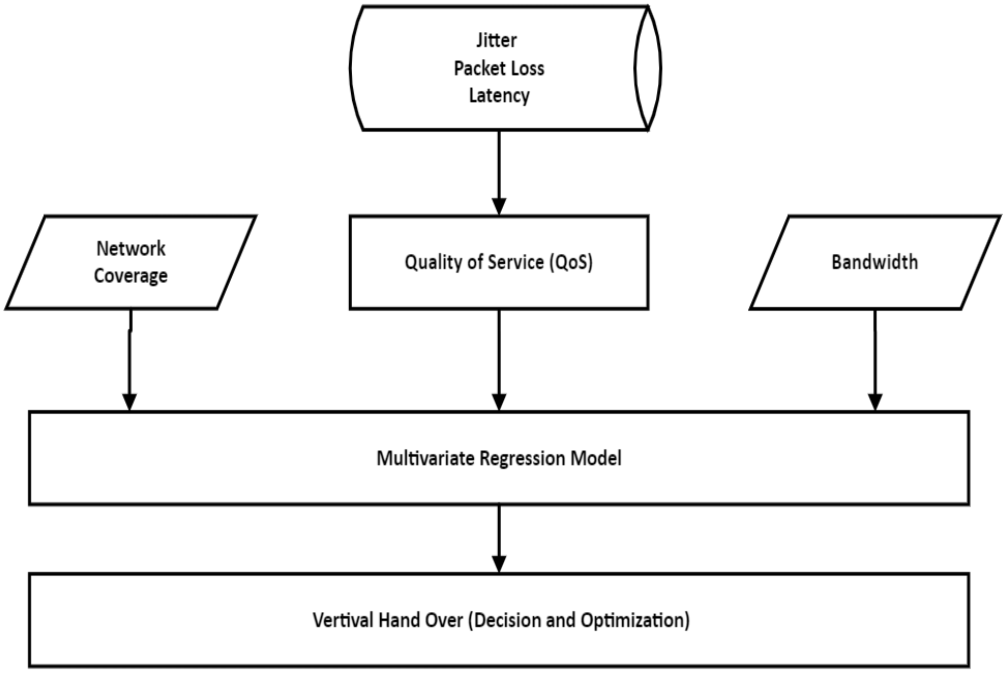

Figure 2. Data Mining based VHO Mechanism

3.1 Data Collection

Data collection has been done in both simulated and actual heterogeneous network scenarios, measuring parameters such as Received Signal Strength (RSS), bandwidth, jitter, latency, packet loss, and network coverage throughout the handover procedures. Measurements were configured to 3GPP standards through RRC Reconfiguration and RRC Resume signaling procedures. The data sets included numerous observations of inter-RAT handovers, i.e., between WiMAX and 5G NR (L3500) technologies.

3.3 Sampling

A straightforward random sampling with replacement (SRSWR) method was used to extract representative data subsets while maintaining original data characteristics. The merged data set was then split into Technology Mode switches with a Decision HO characteristic as a binary variable to denote VHO instances. This allowed easy model training process and allowed efficient tracing of pre- and post-handover parameter dynamics.

3.4 Proposed Algorithm Workflow

The proposed VHO decision-making algorithm comprises the following steps. Detailed flow chart is shown in the Figure 3.

1. **Data Analysis:** Analyze gathered data to derive patterns and correlations among network parameters and effective handover decisions.
2. **Rule Generation**: Derive decision rules in "if-then" formats from the observed patterns to make future VHO decisions.
3. **Decision Making:** Incorporate the rules to make decisions on the best handover target based on real-time network conditions. In cases where there are more than one suitable rules, a conflict resolution procedure selects the best alternative.
4. **Continuous Improvement:** Dynamic revision of decision rules from newly acquired data to improve decision accuracy and promptness.

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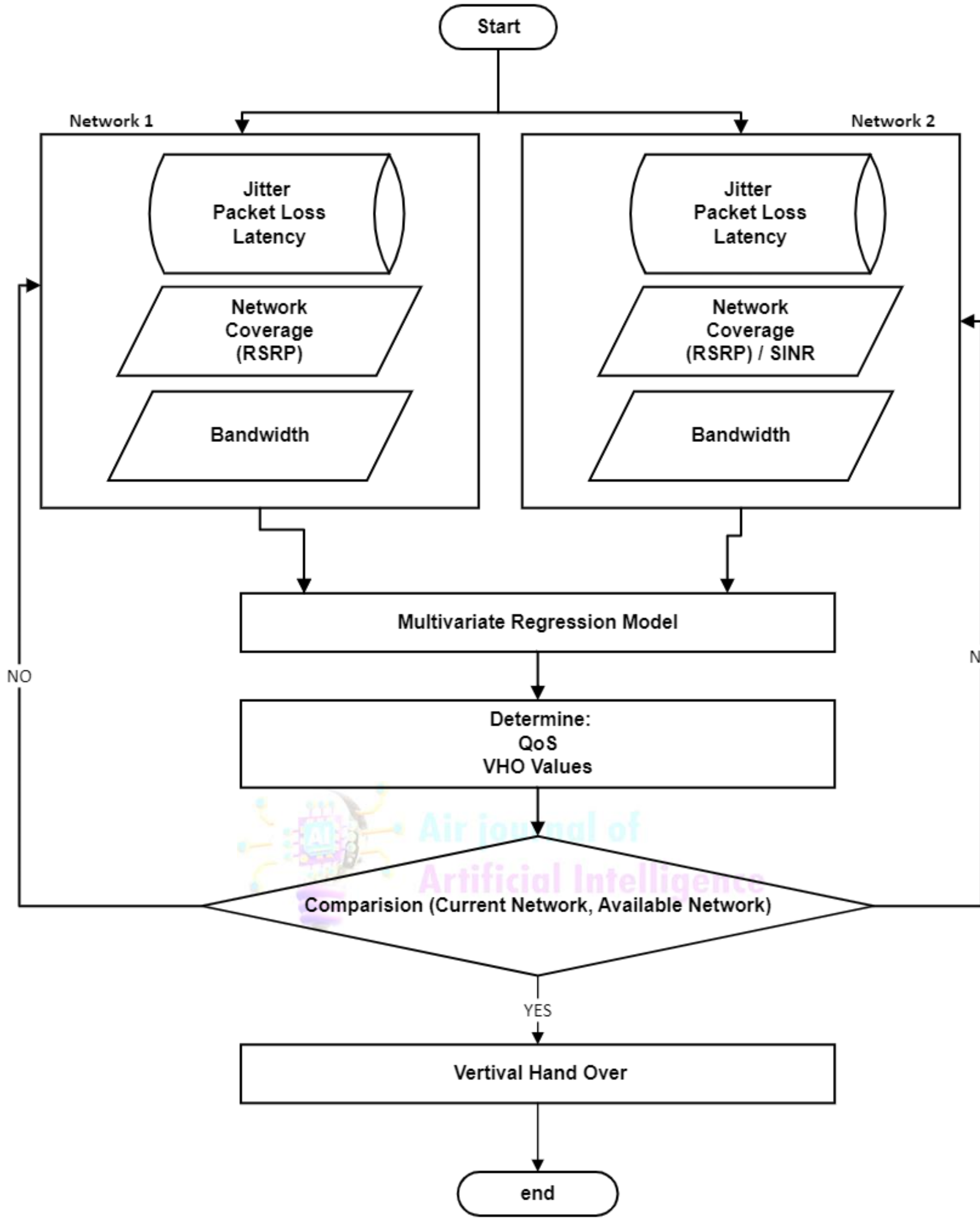

Figure 3. Detailed flow chart of the DM based VHO algorithm.

3.5 Multivariate Regression Analysis

Multivariate regression was employed to model the correlation between the success of handover (dependent variable, Y) and a number of independent network parameters (x). The general equation for regression is:

$$Y = \beta_0 + \beta_1 x + \varepsilon \quad (1)$$

Where β_0 and β_1 are the intercept regression coefficients, and ε is the error term. The Ordinary Least Squares (OLS) method was used to estimate coefficients:

$$\beta = \frac{X'Y}{X'X} \quad (2)$$

where X is the design matrix, X' its transpose, and Y the dependent variable vector.

Regression Analysis Steps:

1. Data Preparation: Cleaning, missing values handling, and variable transformations.
2. Design Matrix Generation: Generation of a design matrix of n observations and p independent variables with an extra column of ones for the intercept.

3. Estimation of Coefficients: Matrix algebra used to obtain β values.
4. Interpretation: All the coefficients indicate the change in Y expected for a one-unit change in the corresponding X, keeping the others constant.

3.6 Analysis of Variance (ANOVA)

ANOVA was used to test the statistical significance of every parameter in reaching VHO decisions. It tests significant differences in the means between parameter groups and gives hints towards contributory features for building the model. The ANOVA F-statistic is calculated as:

$$F = \frac{MST}{MSE} \tag{3}$$

where MST is the mean square treatment and MSE is the mean square error. A higher F-value indicates greater significance of the independent variable on the dependent outcome.

3.7 Model Formulation

The proposed framework integrates data mining, multivariate regression, and ANOVA analysis to build an interpretable and adaptive VHO decision-making model for heterogenous 5G networks to ensure better mobility management and network performance

4. Experiments and Results

4.1 Simulation Setup

Simulations were conducted using the NetNeuman simulator to evaluate the proposed data mining-based VHO decision framework. The simulation parameters are summarized in

Table 1. Simulation Parameters

Parameter	Value
Number of UEs	100
Simulation Duration	1800 seconds
Network Technologies	5G NR (L3500), Wi-Fi
Mobility Models	Random Waypoint, Gauss-Markov
Baseline Algorithms	RSS-based, Cost-function-based, AHP-TOPSIS

The evaluation considered the following key performance indicators:

- **Handover Success Rate** (%) – Ratio of successful handovers to total attempted handovers.
- **Average Latency (ms)** – Mean time taken to complete a handover.
- **Packet Loss** (%) – Percentage of packets lost during handover events.
- **User Throughput (Mbps)** – Average user data rate post-handover.

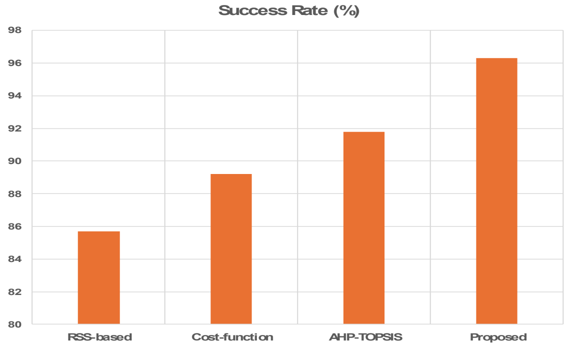

Figure 4. Success Rate Comparison

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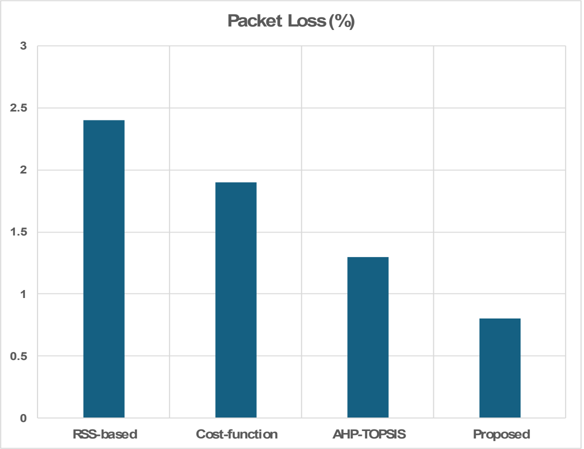

Figure 5. Packet Loss Comparison

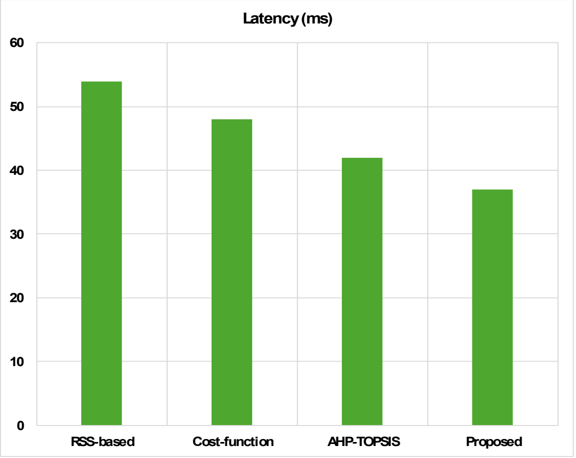

Figure 6. Latency Comparison

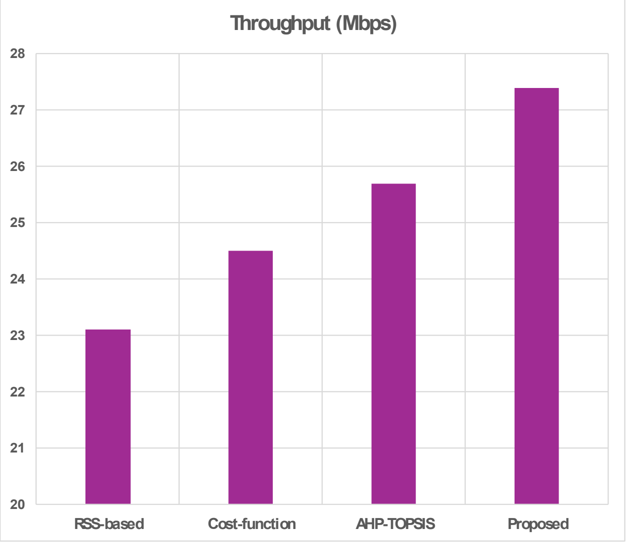

Figure 7. Throughput (MbpS) Comparison

4.2 Results and Discussions

Performance comparison among the proposed model and baseline algorithms is shown in this section. The simulation results show that the new data mining-based VHO decision model performs better than classic algorithms for all metrics of evaluation. Namely, it recorded a handover success rate of 96.3% as revealed in the Figure. 4, which is around 4.5% better than AHP-TOPSIS and far better than RSS based methods. This enhancement owes to the regression model's capacity to measure the effect of various parameters, which makes more accurate decisions possible. Moreover, the suggested approach minimized the average handover latency to 37 ms, improving the quality of user experience, especially for delay-sensitive services as depicted in Figure. 5. The packet loss during the handover was minimized to 0.8%, signifying improved reliability and uninterrupted service continuity as depicted in the Figure. 6. The throughput of the user also increased to 27.4 Mbps, evidencing improved utilization of resources and network performance as depicted in the Figure. 7.

5. Conclusion and Future work

This article presented a data mining sequence-based vertical handover decision model for 5G networks, leveraging multivariate regression and ANOVA to derive patterns of historical handover for real-time decision-making. Simulation results show enhancements in handover success rate, latency, packet loss, and throughput over conventional methods. The futu re work will involve integrating with AI-based models to achieve intelligent mobility management in 6G networks.

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