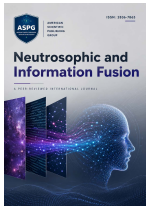
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FULL LENGTH ARTICLE

Fuzzy Logic for the Improving of Handover Decision and the Adaptive Adjustment of Control Parameters in 5G Wireless Networks

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ABSTRACT

Handover process is one of the most important aspects of mobility management in 5G wireless networks. It becomes a hot topic for researchers because it constitutes a guarantee of communication continuity during the user's movement, in addition to being the basic step on which the mobility load balancing process depends to distribute the load between the cells.

The focus on this process is whether by providing solutions to improve the handover decision-making, or by modifying the values of the handover control parameters in a way that it guarantees the reduction of handover problems, because the inaccurate or unnecessary modification of these parameter values will cause a degradation in the quality of service. This paper presents a study targeting two mechanisms to improve handover decision-making and selection of handover control parameters adaptively based on different schemes. The first one is based on a learning model called LIM2 and the second one is based on fuzzy logic and is called RHOT-FLC.

The results show that the RHOT-FLC mechanism, which relies on fuzzy logic and takes into account the user's velocity, provides better performance in terms of average throughput, packet drop rate, average HOPP probability, average HO latency, and HO failure.

Keywords: 5G network ▪ Wireless ▪ Fuzzification ▪ Fuzzy logic ▪ Decision making

1. INTRODUCTION

Mobility management, especially handover management in fifth-generation networks, is critical due to several factors: the use of millimeter waves, the large number of small cells, as well as the high proliferation of connected devices [1, 2].

The handover process uses Handover Control Parameters (HCP), and algorithms to make a handover decision to control the condition of its occurrence, so adjusting these parameters and using an appropriate algorithm to make a decision provides optimal performance for this process, and therefore for the network as a whole [3].

Proceeding from the fact that the determination of the values of the handover control parameters is adaptive, it is necessary to rely on techniques that ensure self-adjustment, as modern algorithms have become necessary to update the values of these parameters in a way that ensures that the quality of the system remains above a certain threshold. As these parameters can contribute positively or negatively to enhancing or deteriorating the performance of the handover process, it is necessary to adapt to different mobility scenarios for users [4]. In addition, they are able to limit the negative impact of the traditional A3 event, which leads to frequent and unnecessary handovers.

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There are a variety of researchers' options to propose intelligent mechanisms that improve the handover operation, and the parameters that are relied on as inputs for these mechanisms also vary, hence the importance of research in evaluating two of these solution mechanisms. They were chosen because they do not depend on a huge data set for a long time of network operation for the training process, and therefore do not increase the execution time of the algorithm, which leads to an increase in the delay of the handover operation. As they depend on various factors for input, it is necessary to determine the most appropriate input to make the decision.

Therefore, the research goal is to identify the most appropriate mechanism to rely on to make the handover decision, achieve better network performance, and reduce handover problems. The research deals with the study of the stages of the handover process and the role of adaptive adjustment of handover control parameters, followed by the study of two mechanisms based on different models for handover timing and adjustment of parameter values. The practical implementation includes testing the most suitable tool for simulating the required network, determining the parameters, building the network and implementing the two algorithms, and then carrying out simulation, analyzing the results and comparison. The research ends with recommendations that determine the future direction of research.

2. MAIN DISCUSSION

2.1 Stages of the Handover Operation

The handover process consists of three stages: triggering, decision, and execution [5]. The handover operation begins with the triggering stage, where the serving base station requests the user equipment to send it measurement reports of the signal strength of the base stations adjacent to this serving station. After receiving the response from the user equipment, decision-making begins at the serving station, in addition to determining the target station based on the reference triggering criteria listed in Table 1, knowing that it is possible for the serving station to request more criteria later. The execution stage begins after the decision-making is over, during which the user equipment breaks off communication with the serving station and establishes communication with the target station.

Table 1. Reference criteria.

Event	Criteria	Explanation
A1	$R_S > \Delta_{A1}$	Serving cell's RSRP is better than a threshold.
A2	$R_S > \Delta_{A2}$	Serving cell's RSRP is worse than a threshold.
A3 (A6)	$R_n > R_S + \Delta_{A3}$	Neighbor cell is better than the serving cell by an offset.
A4 (B1)	$R_n > \Delta_{A4}$	Neighbor cell is better than a threshold.
A5 (B2)	$R_S < \Delta^1_{A5}, R_n > \Delta^2_{A5}$	Serving cell is worse than a threshold, and the neighbor cell is better than a threshold.

2.2 Handover Control Parameters

They are critical and essential parameters for mobility management to judge the handover decision, so they must be determined appropriately to ensure the effectiveness of the operation procedure. The most important of these parameters are HOM and TTT [1], where the handover decision is carried out when the signal strength received from the target station (target RSRP) is greater than in the serving cell, plus the hysteresis margin (HOM), estimated in decibels. The received signal strength should be measured several times in the user equipment (UE) during the TTT (Time To Trigger) interval, estimated in milliseconds.

The user equipment may be subjected to frequent handovers, since the coverage area of the base stations in the fifth generation is less than in the fourth generation. Handover algorithms at that time were based on the A3 event with constant values of the handover control parameters, which led to good system performance. With the fifth generation, the use of fixed values leads to unreliable decisions [6], especially in high-density networks, due to the fact that each mobile phone within one cell moves in a different direction, in a different cell direction, at different speeds, and each mobile phone has a different location, that is, a different signal strength.

This makes it necessary for the handover control parameters to be adapted to different mobility scenarios, so that the same parameter values are not imposed on all mobile phones, but the best values are selected for each equipment based on its own experience to avoid changes that these phones may not need. Also, 5G does not correspond to the constancy of the values of these parameters, as they must be adjustable with time. In the case of a fast user, this avoids delays in the handover operation; in another case, when the signal strength of the serving station is good, a high HOM value can prevent unnecessary handovers or the impact of ping-pong events [7].

2.3 Adaptive Handover Mechanisms

Several mechanisms have been applied to reduce the problems of the handover operation, relying on fuzzy logic or machine-learning techniques of all kinds, including K-means clustering and Q-learning [8]. We discuss two different mechanisms.

2.3.1 Learning-Based Intelligent Mobility Management (LIM2)

The algorithm works at each serving base station independently of the others, where the handover operation is based on the two-part system shown in Figure 1 [5]:

1: **Guess the energy value of the received reference signal based on Kalman-filter-based RSRP estimation (KFE).** To guess the RSRP value, the variation of the received reference signal strength from the base stations (RSRP) and the ambient noise is processed by filtering the ambient noise value, which may come from other radios, from a Wi-Fi network for example, or even from microwave ovens in the surrounding environment.

2: **Handover based on reinforcement-learning-based HO (RLHO).** The input of this section is the output of the filter. In this section, the handover decision is made and the values of the handover control parameters are determined based on reinforcement learning.

Figure 2 shows the stages of system operation.

These stages are summarized as follows [5]:

1. The values of the strength and quality of the received reference signal, RSRP and RSRQ respectively, are derived for all adjacent cells from the measurement reports requested

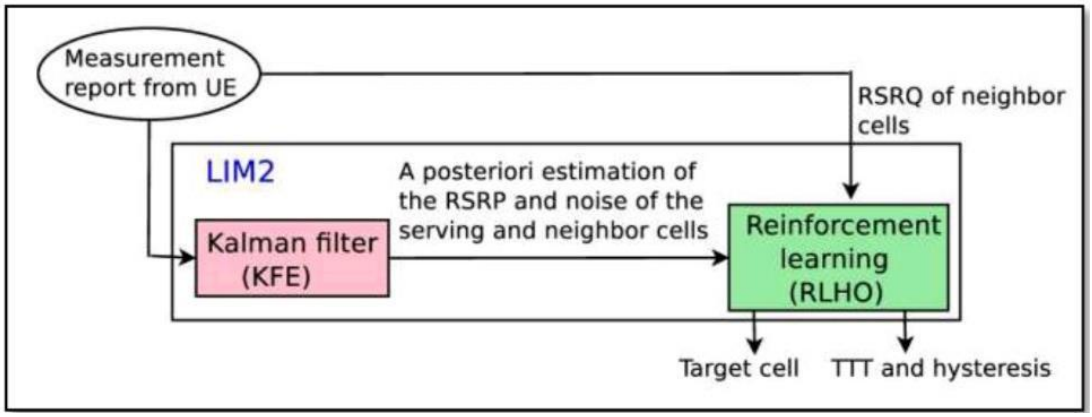


Figure 1. LIM2 system model.

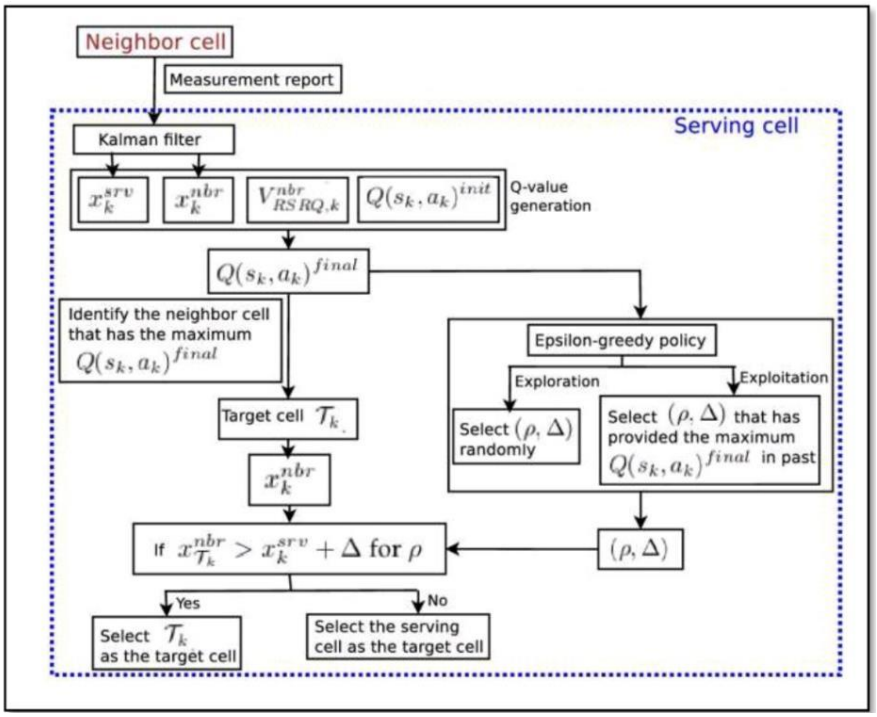


Figure 2. The mechanism of action of the LIM2 system.

by the serving station from the user equipment. These values are considered as inputs to the LIM2 system, as well as the RSRP value of the serving cell.

2. The Kalman filter is designed to calculate the subsequent RSRP values of the serving cell and neighboring cells that are candidates for the user equipment to complete the handover operation to one of them. This filter is used because it relies, when guessing the subsequent value, on the current and previous values only, and does not need measurements for a long time of network operation.

3. Based on the guess, the target cell is identified as the neighboring cell that has the best signal quality in the receiver. The filter calculates the x_k value, which includes the RSRP value and the ambient noise value of both the serving cell and the candidate target cells, denoted by x_k^{srv} and x_k^{nbr}, respectively.

4. Based on the RSRQ obtained from the measurement reports and the x_k values, the final Q value is calculated for all neighboring cells, so that the cell with the highest Q value is considered the target cell. Here, Q is dependent on the action-value function event value and is defined by the following relation [5]:

$$Q(s,a) = \sum_{i=1}^{d} \theta_i \phi_i(s,a), \tag{1}$$

where s is the state of the system, a is the event that causes the system to move from one state to another, and θ is a weight factor that takes values ranging from $0 \leq \theta \leq 1$.

5. The final Q is calculated, which determines the target cell according to the relation [5]:

$$\begin{aligned} Q(s_k,a_k)_{\text{final}} \leftarrow\ & Q(s_k,a_k)_{\text{init}} \\ & + \alpha \left[V_{\text{RSRQ},k}^{\text{nbr}} + \gamma x_k^{\text{nbr}} - x_k^{\text{srv}} \right], \end{aligned} \tag{2}$$

where α is the learning rate, γ is the discount factor, and $V_{\text{RSRQ},k}^{\text{nbr}}$ is the value of the neighboring cell at moment k.

6. Within this algorithm, in the RLHO section, the ε-greedy policy is applied. It is a well-known policy in the field of reinforcement learning for adaptive selection of values for the TTT and HOM parameters. This online learning model explores the possible values of the settings and exploits the best value while taking into account the current state of implementation. It achieves exploration, where a random value is selected for HOM and TTT, denoted by (ρ, Δ), and then exploitation, where the parameter values corresponding to the greatest value of Q are selected.
7. After selecting the target cell and (ρ, Δ), representing the TTT and HOM values respectively, in order to execute the handover decision, the handover triggering criterion is tested by an A3 event according to [5]:

$$x_{\mathcal{T}_k}^{\text{nbr}} > x_k^{\text{srv}} + \Delta \quad \text{for } \rho. \tag{3}$$

If the condition is met during the time period ρ, the handover decision is completed and the target cell becomes the serving cell. If the condition is not met, the handover order is not completed and the current serving cell remains the serving cell.

2.3.2 Robust Handover Optimization Based on a Fuzzy Logic Controller (RHOT-FLC)

An algorithm based on a fuzzy logic controller for making a handover decision is studied, with a dynamic assignment of TTT and HOM values based on the controller's inputs, which include user equipment velocity, RSRP, and RSRQ [6]. Its components are shown in Figure 3.

A fuzzy logic controller (FLC) consists of three stages [4]:

1. **Fuzzification:** at this stage, the numerical values of the system inputs (RSRP, RSRQ, and velocity) are converted into fuzzy-set values by means of membership functions. The most famous is the triangular membership function, used to generate the corresponding fuzzy input values. User navigation speed and RSRQ are divided into four levels, while RSRP is divided into three levels.
2. **Inference engine:** it generates the output according to relations called the 48 rules in this mechanism, where their number results from the number of input levels.
3. **Defuzzification:** the fuzzy values of the output are converted to numerical values to produce the output represented by TTT and HOM.

Figure 4 shows the mechanism of action of the studied controller [6].

The handover decision is made in the following form [6]:

1. The RSRP value is extracted from the measurement reports, arranged, and compared with the RSRP of the target station. If the relationship in Equation (4) is not achieved, the handover decision is not executed:

$$\text{RSRP}_{\text{target}} > \text{RSRP}_{\text{serving}} + \text{HOM}. \tag{4}$$

2. The system inputs are updated, namely the user's navigation speed and the values of both RSRP and RSRQ.
3. The input values are converted to fuzzy sets, and the degree of each membership function is calculated using [6]:

$$f(x) = \begin{cases} 0, & x \le a, \\ \dfrac{x-a}{b-a}, & a \le x \le b, \\ \dfrac{c-x}{c-b}, & b \le x \le c, \\ 0, & c \le x. \end{cases} \tag{5}$$

4. The 48 rules are applied for each membership, where the rules are used to guess the output values depending on the inputs.
5. The TTT and HOM values are updated as outputs of the system depending on the three input parameters, which make up 48 input states.
6. The condition inducing execution of the handover, $\text{RSRP}_{\text{target}} > \text{RSRP}_{\text{serving}} + \text{HOM}$, is checked. If the condition is met for an interval equal to TTT, the handover decision is made.

Table 2 lists the input and output levels.

Table 2. Input and output levels [6].

Input	Degree	Range
Velocity	slow	0 to 30 km/h
	moderate	25 to 70 km/h
	high	65 to 135 km/h
	very high	130 to 160 km/h
RSRP	weak	−160 to −95 dBm
	moderate	−100 to −73 dBm
	strong	−80 to −20 dBm
RSRQ	poor	−60 to −18 dB
	good	−22 to −12 dB
	very good	−14 to −6 dB
	excellent	−10 to +20 dB
Output	**Degree**	**Range**
TTT	very short	0 to 220 ms
	short	210 to 380 ms
	average	370 to 520 ms
	large	510 to 640 ms
HOM	very low	0 to 0.3 dB
	low	0.2 to 0.5 dB
	average	0.4 to 0.8 dB
	high	0.7 to 1 dB

3. PRACTICAL IMPLEMENTATION

The implementation of the practical section was based on MATLAB 2022a, as it supports the policies and models that we rely on to implement the two mechanisms, in addition to supporting fifth-generation networks. It relies on the 5G Toolbox [9], which provides functions compatible with the standards set for these networks and includes reference examples for modeling and simulation, and verification of new radio (NR) 5G communication systems.

The network was built in standalone mode, as this architecture gives better performance for the handover process [10]. The parameters shown in Table 3 were also used; their selection was based on prior studies [6, 5] and 3GPP standards.

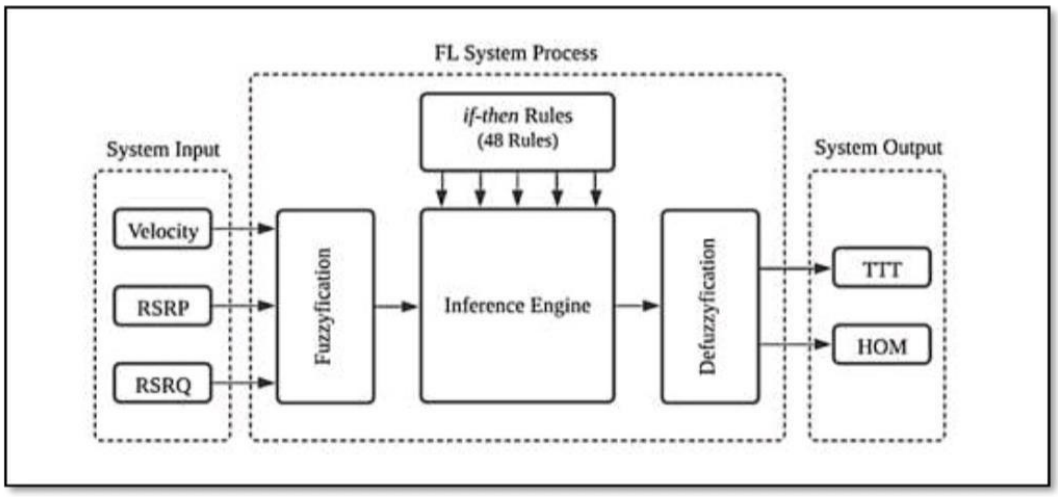


Figure 3. Components of the studied system.

Table 3. Simulation parameters.

Parameter	Value
Number of gNB base stations	50
Cell radius	150 m
Base-station transmission power	46 dBm
User-equipment transmission power	23 dBm
Number of mobile phones covered by the measurement	10 UE
Channel bandwidth	400 MHz
User movement pattern	Constant-velocity mobility model
Carrier frequency f_c	26 GHz
User-equipment navigation speed	Up to 160 km/h
Adaptive TTT	0 to 640 ms
Adaptive HOM	0 to 1 dB
Value of factor α	$\alpha = 0.1$
Value of factor γ	$\gamma = 0.5$
Simulation time	30 seconds

4. RESULTS AND DISCUSSION

The performance of both mechanisms was evaluated in terms of several coefficients. One of them is related to quality of service, and one is related to the performance of the handover operation, as improvement in the performance of the handover operation contributes to improvement of the management of the network as a whole [10].

4.1 Average Throughput

Figure 5 shows a comparison between the two studied mechanisms in terms of average throughput estimated in Mbps, for speed values of 20, 40, 80, 120, and 160 km/h. The results show that the mechanism based on the RHOT-FLC fuzzy controller gives better performance than the algorithm based on the LIM2 learning system, despite the fact that it guesses which cell will give good throughput and which cell provides the best signal quality. The RHOT-FLC mechanism takes into account the speed of user navigation and therefore avoids unnecessary handovers, which generate mutual messages at the expense of user data.

4.2 Packet Loss Rate

As shown in Figure 6, which expresses packet loss as a percentage relative to the user's navigation speed, the RHOT-FLC algorithm gives better performance. It takes into account the user's navigation speed to set the values of the handover control parameters, and therefore takes into account the number of handovers performed per second that will cause a disconnection and thus packet loss. The loss increases by a clearer difference when the user's navigation speed increases using the second mechanism.

4.3 Average HOPP Probability

The RHOT-FLC algorithm gives better performance in terms of the average probability of ping-pong process events, as shown in Figure 7. The assessment of handover operation events is more accurate when studied at low speeds, as it is known that the received signals oscillate more at low speeds [10], so the HOPP rate is clearly visible. At medium and high speeds, the connection between the user equipment and the target station is fast, which leads to a decrease in the HOPP rate, noticeably shown in Figure 7 at speeds of 80, 120, and 160 km/h.

4.4 Average Handover Delay

Figure 8 shows the average delay of the handover operation estimated in milliseconds. This delay includes the three stages of the handover operation. The results show that the RHOT-FLC algorithm gives a lower delay because the stages of implementing the handover decision of the LIM2 mechanism cause a delay in the decision-making stage, which causes a cumulative delay of the handover operation.

4.5 Handover Failure Rate

Figure 9 shows that the lowest failure rate for handovers is achieved by the RHOT-FLC mechanism. Failure occurs due to the inability of the user equipment to connect to the cell, so dependence on the user's navigation speed in adjusting the parameter values contributes to improvement of this criterion. The LIM2 mechanism gives a clear increase in the rate at high speeds, and relying only on the quality and strength of the signal is not enough.

5. CONCLUSIONS AND RECOMMENDATIONS

This research dealt with the study of two mechanisms to improve the handover decision in fifth-generation networks. The mechanisms that rely on mathematical models or machine-learning techniques to provide appropriate solutions vary, and

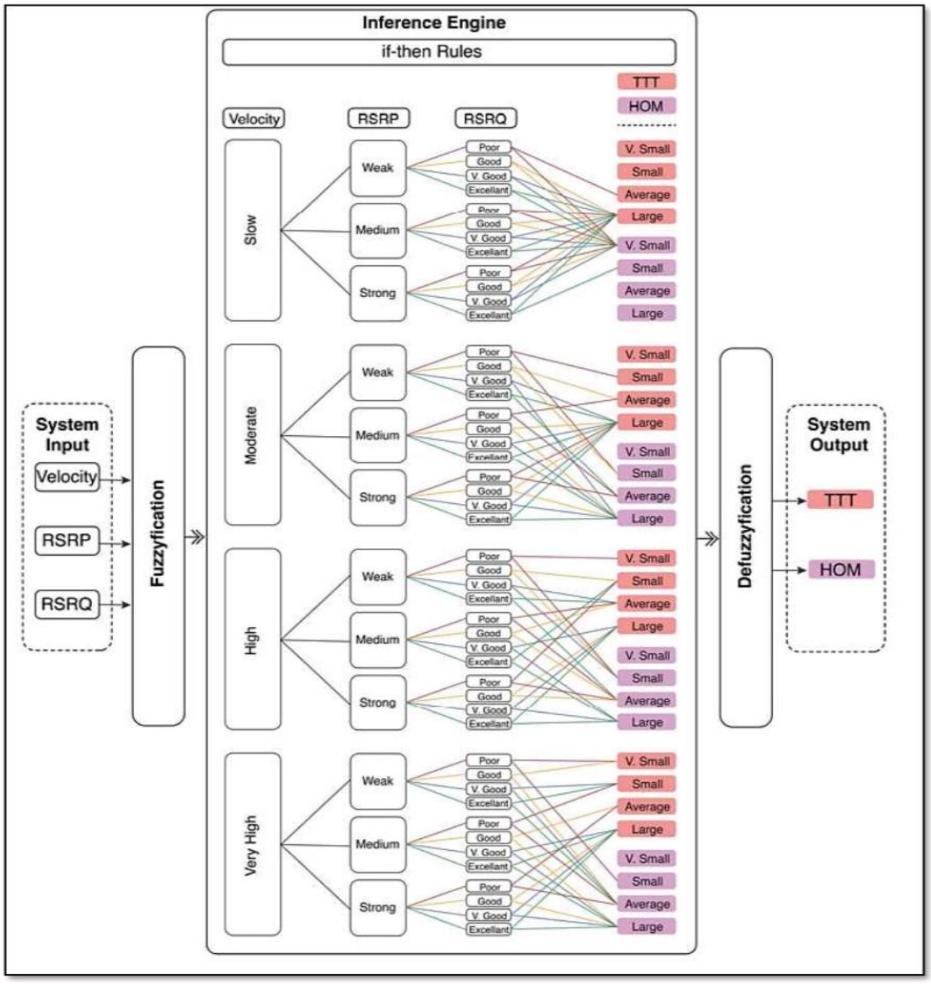


Figure 4. Mechanism of action of the controller.

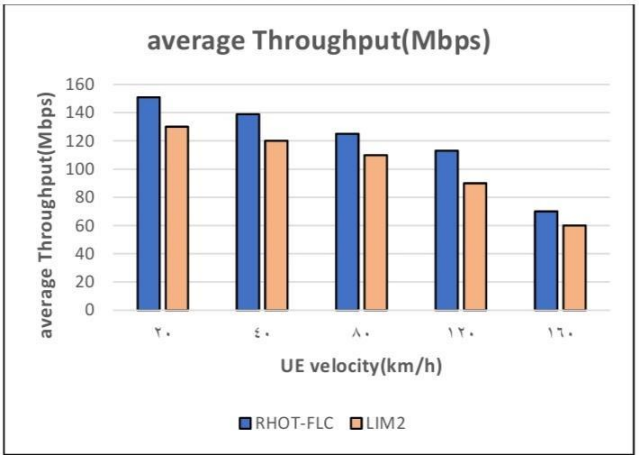


Figure 5. Average productivity.

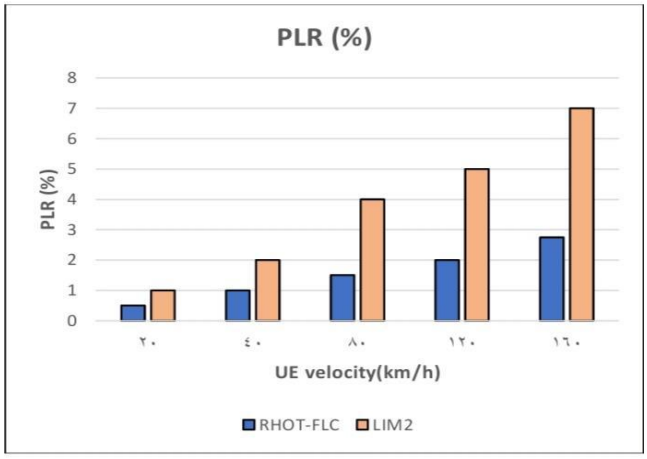


Figure 6. Packet loss rate.

each of these mechanisms depends on different input parameters, so it is necessary to determine the best model and the most appropriate parameters.

The study showed that relying on the user's navigation speed as input to the algorithm gives better results in terms of the studied parameters, and relying on the fuzzy controller gives better performance in the studied network. It is one of the important models in decision-making, with a mechanism that does not cause a large execution time and thus a cumulative delay added to the handover operation, as was the case with the LIM2 model, despite being based on modern learning techniques that contribute to the self-organization of networks.

Therefore, it is necessary to take into account the results obtained when making suggestions to improve the quality of service based on handover management or to improve achievement of the offloading process during load balancing. Reducing unnecessary handovers and delays in the handover operation is one of the most important challenges of mobility management.

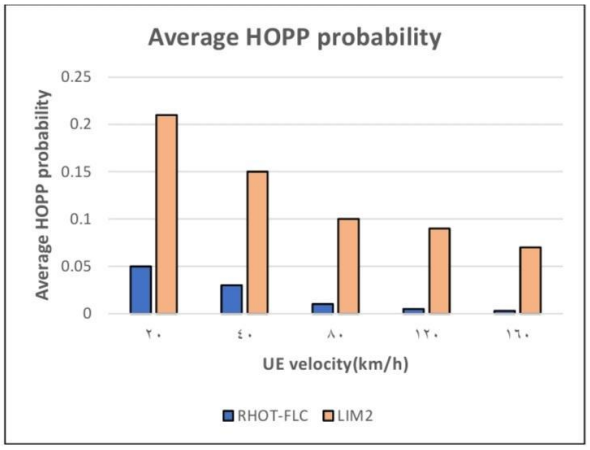


Figure 7. Average probability of ping-pong events.

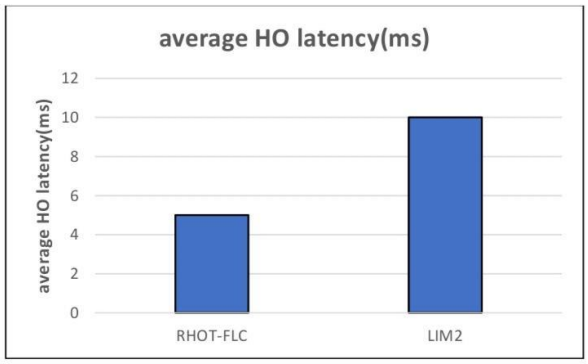


Figure 8. Average handover delay.

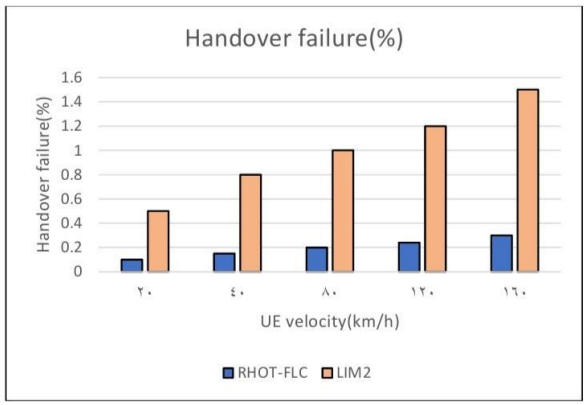


Figure 9. Failure of handovers.

REFERENCES

[1] S. Alraih, R. Nordin, I. Shayea, N. F. Abdullah, A. Abu-Samah, and A. Alhammadi, "Effectiveness of handover control parameters on handover performance in 5g and beyond mobile networks," *Wireless Communications and Mobile Computing*, vol. 2022, pp. 1–18, 2022.

[2] A. Haghrah, M. Pourmohammad Abdollahi, H. Azarhava, and J. Musevi Niya, "A survey on the handover management in 5g-nr cellular networks: Aspects, approaches and challenges," *EURASIP Journal on Wireless Communications and Networking*, vol. 2023, no. 1, p. 52, 2023.

[3] W. Tashan, I. Shayea, S. Aldirmaz-Colak, M. Ergen, M. H. Azmi, and A. Alhammadi, "Mobility robustness optimization in future mobile heterogeneous networks: A survey," *IEEE Access*, vol. 10, pp. 45 522–45 541, 2022.

[4] S. Alraih, R. Nordin, A. Abu-Samah, I. Shayea, N. F. Abdullah, and A. Alhammadi, "Robust handover optimization technique with fuzzy logic controller for beyond 5g mobile networks," *Sensors*, vol. 22, no. 16, p. 6199, 2022.

[5] R. Karmakar, G. Kaddoum, and S. Chattopadhyay, "Mobility management in 5g and beyond: A novel smart handover with adaptive time-to-trigger and hysteresis margin," *IEEE Transactions on Mobile Computing*, pp. 1–16, 2022.

[6] W. S. Hwang, T. Y. Cheng, Y. J. Wu, and M. H. Cheng, "Adaptive handover decision using fuzzy logic for 5g ultra-dense networks," *Electronics*, vol. 11, no. 20, p. 3278, 2022.

[7] W. Tashan, I. Shayea, S. Aldirmaz-Colak, O. A. Aziz, A. Alhammadi, and Y. I. Daradkeh, "Advanced mobility robustness optimization models in future mobile networks based on machine learning solutions," *IEEE Access*, vol. 10, pp. 111 134–111 152, 2022.

[8] P. Ampririt, S. Higashi, E. Qafzezi, M. Ikeda, K. Matsuo, and L. Barolli, "An intelligent fuzzy-based system for handover decision in 5g-iot networks considering network slicing and sdn technologies," *Internet of Things*, vol. 23, p. 100870, 2023.

[9] MathWorks, "5G Toolbox Reference," 2023.

[10] W. K. Saad, I. Shayea, B. J. Hamza, A. Azizan, M. Ergen, and A. Alhammadi, "Performance evaluation of mobility robustness optimization (mro) in 5g network with various mobility speed scenarios," *IEEE Access*, vol. 10, pp. 60 955–60 971, 2022.