



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 parameters 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, 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 term of average throughput, packet drop rate, average HOPP probability, average HO latency, 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].

The handover process uses Handover Control Parameters (HCP), and algorithms to make a delivery 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 [2].

Proceeding from the fact that the determination of the values of the delivery 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 [3], in addition, they are able to limit the negative impact of the traditional A3 event, which leads to frequent and unnecessary deliveries.

There are a variety of researchers' options to propose intelligent mechanisms that improve the handover operation, and the parameters that are relied on as income for these mechanisms also vary, hence the importance of research in evaluating two of these solutions mechanisms, as 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 income. Therefore, it is necessary to determine the most appropriate income to make the decision. Therefore, to achieve the research goal of identifying the most appropriate mechanism to rely on to make the handover decision to achieve better network performance, and reduce handover problems.

The research deals with the study of the stages of the delivery process, the role of adaptive adjustment of delivery control parameters, followed by the study of two mechanisms based on different models for delivery timing and adjustment of parameter values, followed by practical implementation, which 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, and we end the research with recommendations that determine the future direction of research.

2. Main Discussion

1- Stages of the Handover operation (HO):

The delivery process consists of three stages as shown in Figure (1): triggering, decision, and Execution [4].

The handover operation begins with the triggering stage, where the served base station requests the user to send it measurement reports of the signal strength of the base stations adjacent to this service station. After receiving the response from the user processing, decision-making begins at the service station, in addition to determining the target station based on the reference induction criteria built in Table (1), knowing that it is possible for the service station to request more criteria later. The execution stage begins after the decision-making is over, during which the user's processing breaks off communication with the served terminal and establishes communication with the target terminal.

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 Serving cell with a offset
A4 (B1)	$R_n > \Delta_{A4}$	Neighbor cell is better than a thresh-old
A5 (B2)	$R_S < \Delta_{A5}^1,$ $R_n > \Delta_{A5}^2$	Serving cell is worse than a thresh- old value, and neighbor cell is better than a threshold

2- Handover Control Parameters (HCP):

They are critical and essential parameters for the mobility department 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 serviced cell, plus the hysteresis margin (HOM) (estimated in decibels), since the received signal strength should be measured several times in the user UE (user equipment) processing during the TTT (Time To Trigger) interval (estimated in milliseconds).

The user's processing may be subjected to frequent deliveries, since the coverage area of the base stations in the fifth generation is less than in the fourth generation, since the 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. Whereas with the fifth generation, the use of fixed values leads to unreliable resolution [5], 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 made 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, or in time, so in the case of a fast user to avoid delays in the handover operation, and in another case when the signal strength of the service station is good, a high Hom value can prevent unnecessary handovers or the impact of ping-pong events [6].

3- Mechanisms for improving handover decision-making and adjusting the values of handover control parameters adaptively:

Several mechanisms have been applied to reduce the problems of the handover operation, relying on fuzzy logic or machine learning techniques of all kinds, both K-means and Q-learning cluster algorithms. We will discuss in this case two different mechanisms:

- Learning-based Intelligent Mobility Management (LIM2)

The algorithm works at each serviced base station independently of the other, where the handover operation is based on a two-part System [4] as shown in Figure (3):

1: Guess the energy value of the received reference signal based on the 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 the WiFi network for example or even from microwave ovens in the surrounding environment.

2: Handover based on (RHO) reinforcement learning-based HO: reinforcement learning

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.

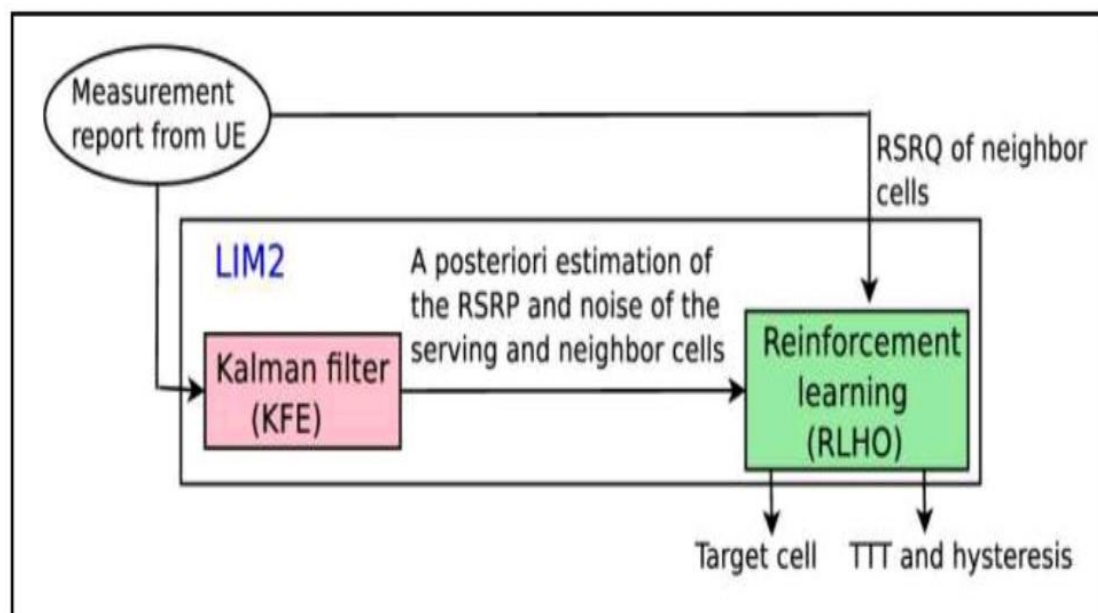


Figure 1. LIM2 system model.

Figure (4) shows the stages of the system operation:

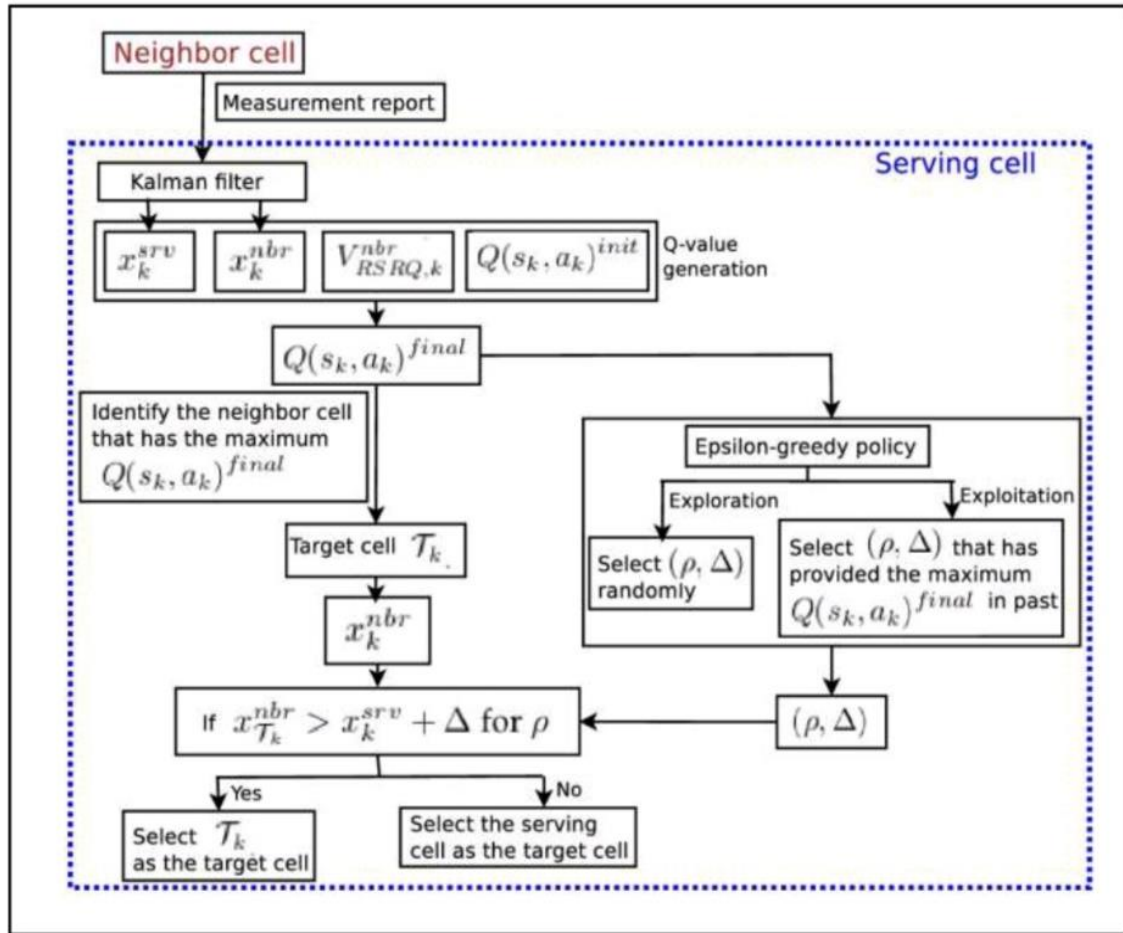


Figure 2. The mechanism of action of the LIM2 system.

These stages are summarized as follows [4]:

1. The values of the strength and quality of the received reference signal RSRP, RSRQ, are derived respectively for all adjacent cells from the measurement reports requested by the service station from the user's processing, these values are considered as input to the system LIM2, as well as the RSRP value of the served cell.
2. The Kalman filter is designed to calculate the subsequent RSRP values of the served cell and neighboring cells, being a candidate that the user's processing completes the handover operation to one of them, and this filter has been used because it relies in guessing the subsequent value on the current and previous value only, and does not need measurements for a long time of network operation.
3. Based on the guess, the target cell identifies as the neighboring cell that has the best signal quality in the receiver, where the filter calculates the x_k value, it includes the RSRP value and the ambient noise value of both the serving cell and the candidate cells to be the target, and they are denoted respectively x_k^{nbr} and x_k^{srv} .
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. Where Q is a dependent of the action-value function event value and is defined by the following relation [4]:

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

Where: s : the state of the system.

a : the event that causes the system to move from one state to another.

θ : weight factor and takes values ranging from $0 \leq \theta \leq 1$

5. The final Q is calculated, which determines the target cell according to the relation [4]:

$$Q(s_k, a_k)^{final} \leftarrow Q(s_k, a_k)^{init} + \alpha [V_{RSRQ,k}^{nbr} + \gamma x_k^{nbr} - x_k^{srv}] \quad (2)$$

Where α is the learning rate.

γ : discount factor.

$V_{RSRQ,k}^{nbr}$: value of the neighboring cell at moment k.

6. Within this algorithm, in the RLHO section, the greedy policy is applied, which is a well-known policy in the field of reinforcement learning for adaptive selection of values for TTT parameters, HOM, which is an online learning model, explores the possible values of the settings, and invests the best value taking into account the current state of implementation, it achieves exploration, where a random value is selected for HOM and TTT, which is denoted by (ρ, Δ) , and then investment (exploitation), where the value of the parameters is chosen, which corresponds to the greatest value of Q.

7. After selecting the target terminal and (ρ, Δ) representing the TTT and HOM value respectively in order to execute the handover decision, the delivery handover induction criterion is tested by an A3 event, according to the gradient [4]:

$$x_{J_k}^{nbr} > x_k^{srv} + \Delta \quad \text{for } \rho \quad (3)$$

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

– **improved delivery based on the fuzzy logic microcontroller ((RHOT-FLC)):**

An algorithm based on a fuzzy logic microcontroller for making a handover decision will be studied, with a dynamic assignment of TTT & HOM values based on values for the controller's input, the user navigation speed includes UE velocity, RSRP and RSRQ [5].

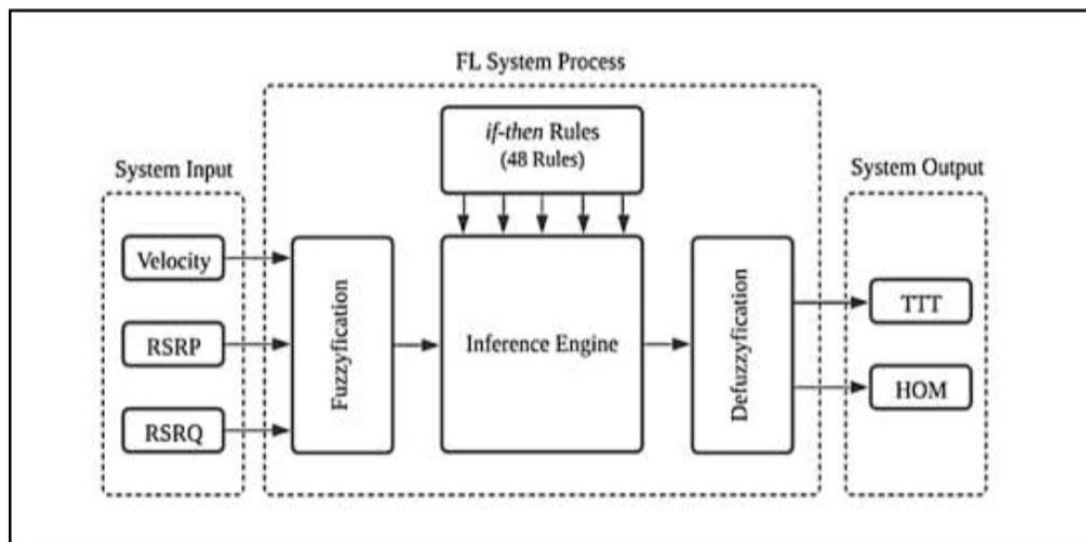


Figure 3. Components of the studied system.

A fuzzy logic controller (FLC) consists of three stages [3] according to figure (5):

1. Fuzzification: at this stage, the numerical values of the system income (RSRP, RSRQ, Velocity) are converted into fuzzy set cloud values or fuzzy set cloud values by means of membership functions dependencies, the most famous of which is the triangular MF dependency to generate the corresponding fuzzy income values, the user navigation speed and RSRQ were divided into 4 levels while RSRP was divided into three levels.

2. **Inference Engine:** which generates the output according to Relations called the 48 rules in this mechanism, where their number results from the number of income levels.
3. **Defuzzification:** where the fuzzy values of the output are converted to numerical values to produce the output represented by TTT and HOM.

Figure (6) shows the mechanism of action of the controller of the studied mechanism [5]:

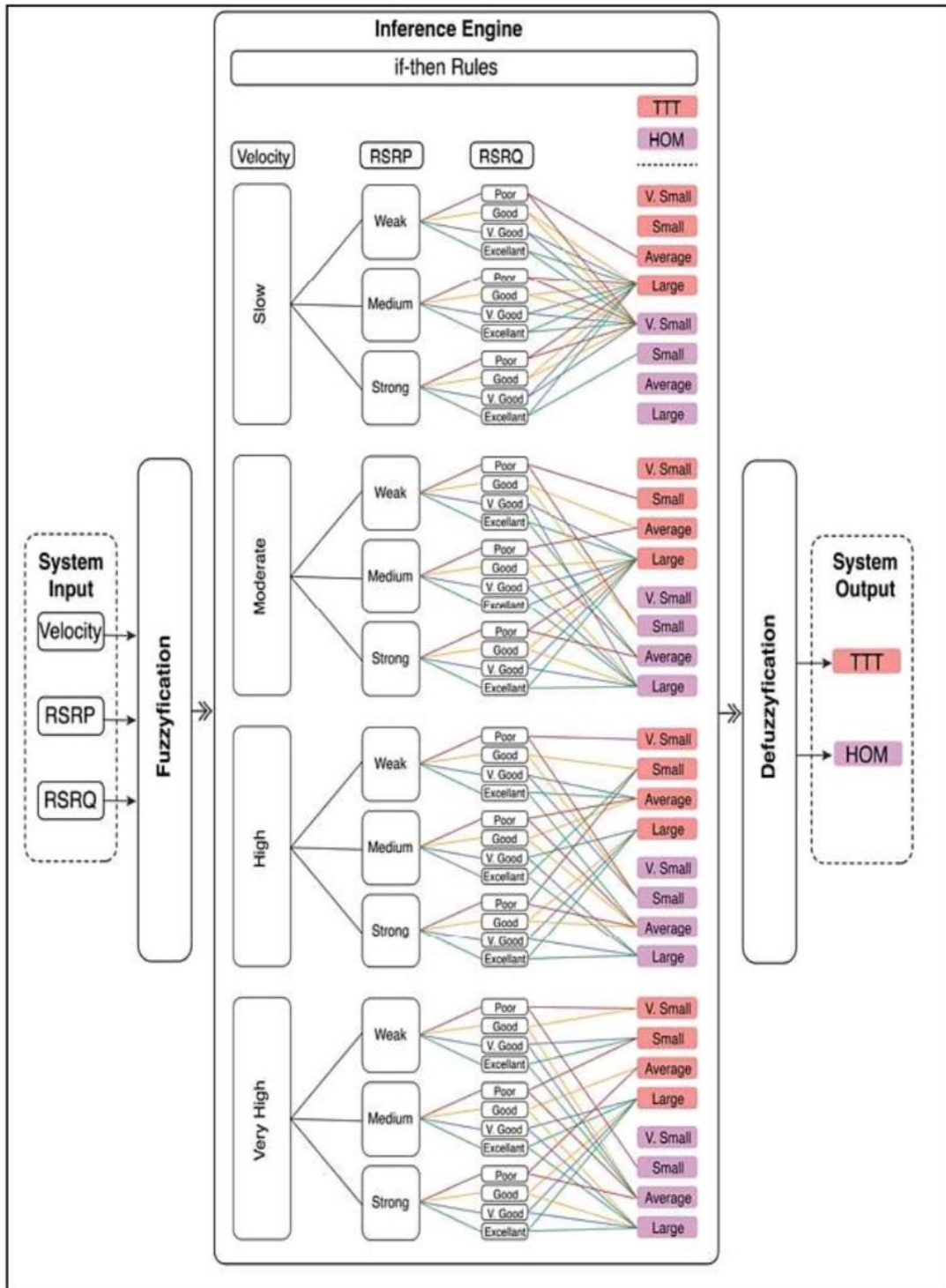


Figure 4. Mechanism of action of the controller.

The decision to extradite is made in the following Form [5]:

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

$$RSRP_{target} > RSRP_{serving} + HOM \quad (4)$$

- 2- The system inputs are updated namely: the speed of user navigation, the value of both RSRP and RSRQ.
- 3- Converting income values to Fuzzy sets, calculating the degree of each dependent (membership function) by relation (5) [5]:

$$f(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0, & c \leq x \end{cases} \quad (5)$$

- 4- Apply the 48 rules for each membership, where the rules are used to guess the output values depending on the income.
- 5- The TTT, HOM values are updated as an output of the system depending on the three income parameters, which make up 48 income states.
- 6- Checking the condition of inducing the execution of the handover according to the drawdown:

$$RSRP_{target} > RSRP_{serving} + HOM$$

If the trailing condition is met for an interval amount equal to TTT, the handover decision is made. Table (2) also shows the income and output levels.

Table 2: Income and output levels [5]

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 will rely on to implement the two mechanisms, in addition to supporting fifth-generation networks, relying on [9,8,7] 5g toolbox, which provides functions compatible with the standards set for these networks, includes reference examples for modeling and simulation, and verification of new radio (NR) 5G communication systems. The network was built from the Standalone style, as this architecture gives better performance for the handover process [10], and the parameters shown in Table (3) were also relied on, the choice of which was based on [5,4], relying on 3gpp standards.

Table 3: Simulation parameters

Parameter value	Parameter
Number of gnb base stations	50
Cell radius	150 m
Transmission power of the base station	46 dbm
User processing transmission power	23 dbm
The number of mobile phones covered by the measurement	10 UE
Channel package width	400 MHZ
User movement pattern	Constatnt velocity mobility model
Carrier frequency f_c	26 GHZ
The user processing navigation speed	Up to 160 km/h
Adaptive TTT	range from 0 ms to 640 ms
Adaptive HOM	domain from 0 db to 1 db
The value of the factor α	$\alpha = 0.1$
The value of the 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 the quality of Service, and one of them is related to the performance of the handover operation, as the improvement in the performance of the handover operation contributes to the improvement of the management of the network as a whole [11].

– **First: in terms of average productivity:**

Figure (7) shows a comparison between the two studied mechanisms in terms of average throughput estimated in Mbps, for the values of speeds (20,40,80,120,160) km/h, where the results showed 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 guesses which cell provides the best signal quality, but the RHOT-FLC mechanism takes into account the speed of user navigation, therefore it avoids unnecessary deliveries, which generates mutual messages at the expense of user data.

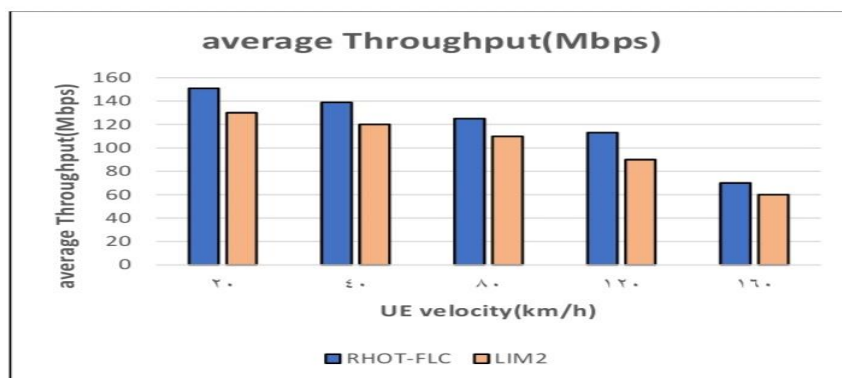


Figure 5. Average productivity.

- **Second: in terms of packet loss rate:**

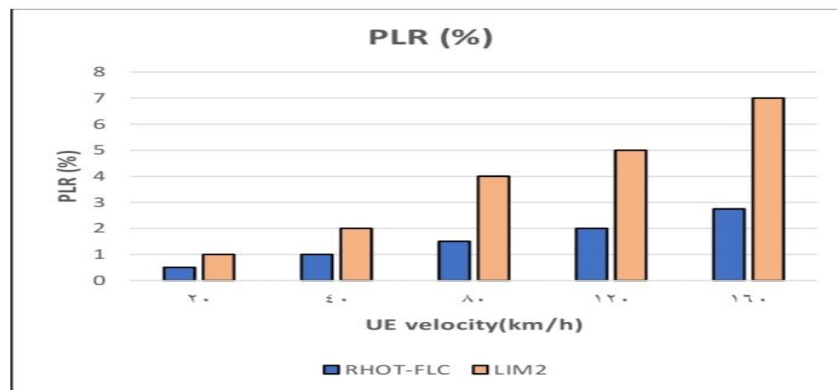


Figure 6. Packet loss rate.

As shown in Figure (8), which expresses the packet loss (as a percentage) relative to the user's navigation speed, the RHOT-FLC algorithm gives better performance, as 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, while the loss increases by a clearer difference by increasing the user's navigation speed when using the second mechanism.

- **Third: in terms of the average probability of happening HOPP**

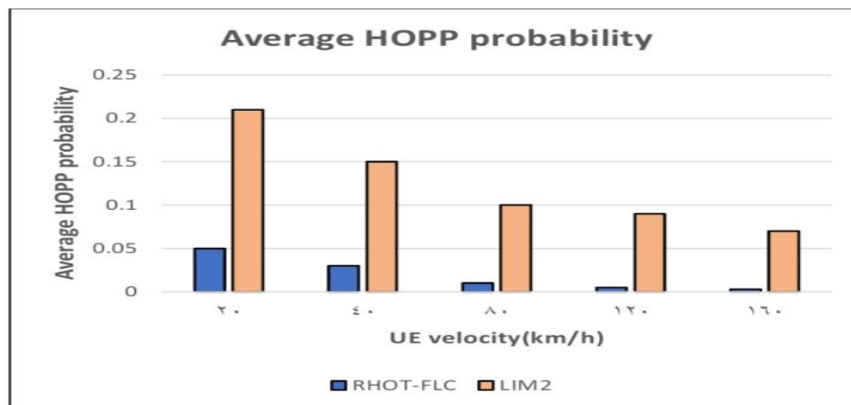


Figure 7. Average probability of ping pong events.

The RHOT-FLC algorithm gave better performance in terms of the average probability of pp process events as shown in Figure (7), and 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 [11], so the HOPP rate is clearly visible, while at medium and high speeds the connection between the user's processing and the target station is fast, which leads to a decrease in the HOPP rate, which is noticeably shown in Figure (7) at speeds 160 & 120 & 80.

- **Fourth: in terms of the average delay of the handover operation:**

Figure (10) shows the average delay of the handover operation estimated in milliseconds, and this delay includes the three stages of the handover operation, where the results showed that the RHOT-FLC algorithm gave 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.

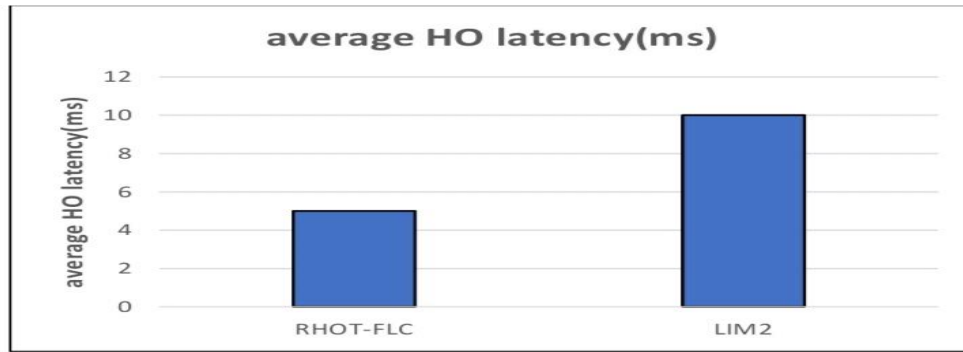


Figure 8. Average handover delay.

- **Fifth: in terms of the failure rate of the handover operation:**

Figure (9) shows that the lowest failure rate for deliveries is achieved by the RHOT-FLC mechanism, the failure occurs due to the inability of the user's processing to link to the cell, so the dependence on the user's navigation speed in adjusting the parameter values contributed to the improvement of this criterion, while the LIM2 mechanism gave a clear increase in the rate for high speeds, and it was not enough to rely only on the quality and strength of the signal.

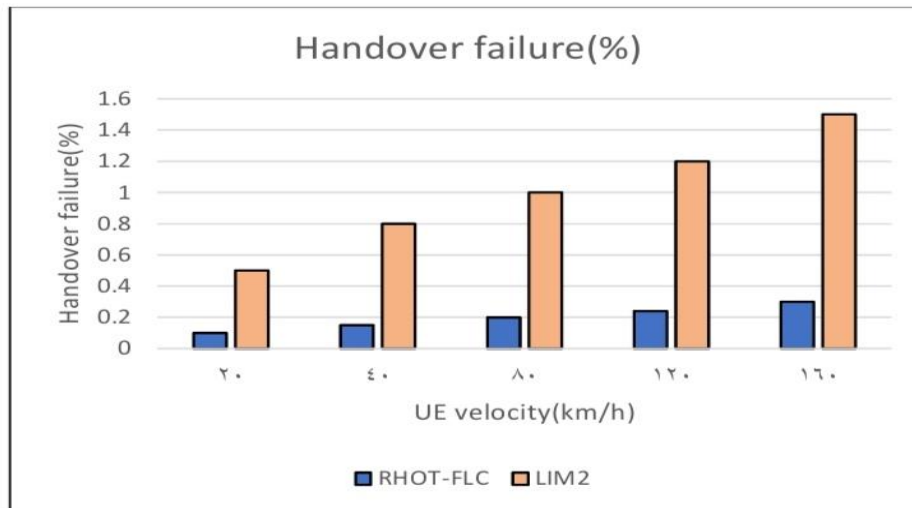


Figure 9. Failure of handovers.

5. Conclusions and recommendations

This research dealt with the study of two mechanisms to improve the handover decision in fifth generation networks, where the mechanisms that rely on mathematical models or machine learning techniques to provide appropriate solutions vary, and each of these mechanisms depends on different income parameters, so it is necessary to determine the best model and the most appropriate parameters. As it turned out through the study 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 as 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, and 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 the achievement of the emptying process offloading during Load balancing the fact that reducing unnecessary deliveries and delays in the handover operation is one of the most important challenges of mobility management.

References

- [1] Alraih S, Nordin R, Shayea I, Abdullah NF, Abu-Samah A, Alhammadi A. Effectiveness of Handover Control Parameters on Handover Performance in 5G and beyond Mobile Networks. Elfergani I, editor. *Wireless Communications and Mobile Computing*. 2022 Mar 29; 2022:1-18.
- [2] Tashan W, Shayea I, Aldirmaz-Colak S, Ergen M, Azmi MH, Alhammadi A. Mobility Robustness Optimization in Future Mobile Heterogeneous Networks: A Survey. *IEEE Access*. 2022; 10:45522–41.
- [3] Alraih S, Nordin R, Abu-Samah A, Shayea I, Abdullah NF, Alhammadi A. Robust Handover Optimization Technique with Fuzzy Logic Controller for Beyond 5G Mobile Networks. *Sensors*. 2022 Aug 18; 22(16):6199.
- [4] Karmakar R, Kaddoum G, Chattopadhyay S. Mobility Management in 5G and Beyond: A Novel Smart Handover with Adaptive Time-to-Trigger and Hysteresis Margin. *IEEE Transactions on Mobile Computing*. 2022; 1–16.
- [5] Hwang WS, Cheng TY, Wu YJ, Cheng MH. Adaptive Handover Decision Using Fuzzy Logic for 5G Ultra-Dense Networks. *Electronics*. 2022 Oct 12; 11(20):3278.
- [6] Tashan W, Shayea I, Aldirmaz-Colak S, Aziz OA, Alhammadi A, Daradkeh YI. Advanced Mobility Robustness Optimization Models in Future Mobile Networks Based on Machine Learning Solutions. *IEEE Access*. 2022; 10:111134–52.
- [7] 5G Toolbox User's Guide. available at: https://www.mathworks.com/help/pdf_doc/5g/index.html.
- [8] 5G Toolbox Getting Started Guide. Available at: https://www.mathworks.com/help/pdf_doc/5g/index.html.
- [9] 5G Toolbox Reference .available at: https://www.mathworks.com/help/pdf_doc/5g/index.html.
- [10] Saad WK, Shayea I, Hamza BJ, Azizan A, Ergen M, Alhammadi A. Performance Evaluation of Mobility Robustness Optimization (MRO) in 5G Network With Various Mobility Speed Scenarios. *IEEE Access*. 2022; 10:60955–71.