Multi-Level Fuzzy Inference System Based Handover Decision Model for Unmanned Vehicles

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***Abstract*—In coming years, mobile communications systems will have a significant role for Unmanned Aerial Vehicles (UAVs), that will either function as mobile users or as mobile base stations in the sky. No doubt UAVs or drones provide a number of benefits for mobile communications networks and other non-communication services, but they also have a number of drawbacks, particularly when it comes to managing handover (HO). A number of approaches have already been suggested by various authors for making the HO easy and efficient, but only few parameters were considered for making the HO decision. However, with the advancement in technology and continuous rise in users, the handover system's reliance factors continue to grow, which could make the system more complex. As a result, the requirement for creating and implementing a system that can effectively manage system complexity arises. In order to reduce the complexity of the system, a novel method is proposed in this paper in which multi-level fuzzy system is used. The main goal of using the fuzzy system at different levels is to minimize the rule complexity of fuzzy systems at different levels which in turn enhances the performance of handover systems. In addition to this, number of parameters like coverage, speed limit, cost, connection time, security and power consumption were taken into consideration while designing the handover system. The model works in three levels, at the first level coverage, speed limit and cost parameters are processed to generate the first probability output. At the second level, connection time, security and power consumption parameters are considered to get the second probability output. The two outputs obtained thus serves as the input to third level where again they are processed to get the final output as estimation level. The efficacy of the suggested multi-level fuzzy system is analyzed in the MATLAB tool. The experimental results are obtained and compared with the traditional handover systems in terms of various dependency factors to prove its efficiency.**

***Index Terms*—Drones, Unmanned Aerial Vehicles (UAVs), fuzzy systems, handover decisions etc.**

I. Introduction

An Unmanned Aerial Vehicle (UAV) that is often called as Drone is a form of unmanned vehicles which are not driven by the human pilots. A typical UAV system typically includes a UAV, ground based controllers and a communication module in between these controllers. On the basis of whether the UAV is controlled by the human administrator or is working automatically, UAVs can fly a vast distance with different angles [1]. The aerial mobility of these UAVs is sponsored by their four rotors that provide the required lift. These four rotors are often known as Quad-copters that are responsible for performing Vertical Takeoff and Landing (VTOL). Because of its intrinsic dynamic environment, the quadrotor has an edge in maneuverability [2], [3]. In the future generation of mobile networks, integrated UAVs would indeed be extensively used in wide and diverse areas which include targeted deliveries, monitoring systems, army, and defense networks and so on. As a result, it becomes necessary for interconnected drones to transform the idea of monitoring, as well as the methods and ideologies for gathering information. With the advancement in technology, the drones will be utilized by every community like government organizations, corporations, and individuals in the future. In addition to this, by installing the drone technology in cellular network systems, the reliability, efficiency and stability of the communication systems can be improved considerably. Moreover, they will also be responsible for providing good network coverage particularly in high-density locations. They can also provide connectivity in areas where conventional devices fail to connect, as it is difficult to create a network in short time [4]. Even though drones may assist current and upcoming wireless communication networks in a variety of ways, its Handover (HO) management is an essential problem that must be solved quickly.

Handover is considered as an essential mechanism in wireless networks in which a stable connection and effective telecommunications services is ensured while users are moving from one place to another. In an ideal case, the handover technique must be able to seamlessly shift the User Equipment (UE) from one station to other while moving. In other words, handover can also be defined as the process of shifting from one Base Station (BS) to another nearby BS in order to retain its connectivity when the received signal is getting altered at the boundary of coverage of original BS. Nevertheless, instead of just retaining a connectivity, a handover across heterogeneous networks entails a series of choosing the best wireless network at any given time. In such circumstances, there is a need of handover and as well as choosing of radio access methods. HO processes can be caused by a variety of circumstances, including a lack of delivering transmitted signal, load balancing, or high packet error levels. Whenever, there is an undesirable

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increase in any of these factors, the connectivity should be transferred from basic cell site to another nearby cell site, so that a more stable, efficient and reliable communication must be maintained. However, the process gets a bit hectic and difficult when the user equipment is a drone [5], [6]. Due to the characterization of drones, the process of handover becomes more tough and problematic to handle. The flight in drones is dominated by the Line-of-Sight (LoS) paths, however the level of interference from another communication lines is much greater when compared with traditional terrestrial systems. Since, the antennas of the base station are often angled in downward directions which consequently serve in the sky through side lobes. Due to this reason, the likelihood of coverage in UAV-UE is slightly less than the user equipment's that are on the ground. Three crucial stages are followed in a handover.

- Data collection: in this stage, the information about the network which includes the form, status and Received Signal Strength (RSS) is collected. In addition to this, the information about the user like its terminal power consumption, security, user preference and rate are also collected.
- HO Decision stage: once the data is collected, the next step is to make HO decision. In this step, the timing of HO and its target wireless network is chosen.
- HO execution: this is the last step in HO process in which the shifting of new wireless network takes place [7].

In order to maintain the stable and reliable wireless connection for drones, it is important to create robust and stable wireless connections that can be used while communicating, commanding and controlling in real time scenarios. For this the cellular network which is also famous for its widespread coverage and smooth HOs can be used. However, the major drawback of these cellular networks is that they are particularly designed for equipment's that are used by the customer on ground which possess unique issue for aerial user equipment's [8]. In addition to this, because the likelihood of receiving Line of Sight (LoS) penetrating to the surrounding BSs keeps on rising with the increase in height, the wireless channels sandwiched between flying customers and neighboring base stations undergo Free-space fading.

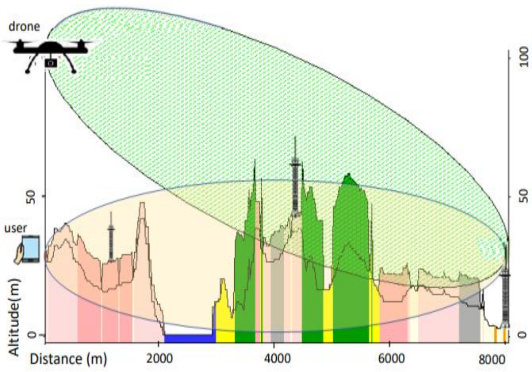


Fig. 1. Drone and terrestrial communications.

As a result of this, there may occur a huge interference in drone communication during uplink direction of terrestrial user equipment's. While as, in the downward communications the drone communication is more prone to undergo through severe interferences from the nearby base station. Furthermore, the customers on the ground frequently receive powerful signals from the neighboring base stations which the connectivity between user and BS less complex when compared with drone connectivity, in which LoS signals are acquired from various surrounding BSs, as represented in Fig. 1 [9].

These issues can lead to low signal quality, frequent handovers, and greater Handover Failures (HOF) rate in drones while communicating in cellular architecture. Recently, a study was conducted by the 3GPP (third generation partnership projects) on improved Long-Term Evolution (LTE) support for UAVs which concluded that aerial user equipment's can downgrade the SINR (signal to noise ratio) and also lead to significant HOF when compared with the terrestrial UE. One of the major factors that is responsible for triggering the frequent HO in drones is their speed that must be controlled.

Nevertheless, the UAVs can operate as the hotspot for communication and relays in heterogenous type of network architecture to overcome issues like frequent HO, HOF owing to Doppler frequency shift and fewer throughputs because of the fast fading and multipath loss. Therefore, it is extremely important to improve the HO management in drones so that its implementations are anticipated by the future 5G and 6G network systems [10]. Over the years, a large number of researchers have been done on how to deploy UAVs in dynamic network, intermittent connectivity, and high flexibility with smooth HO. The scientific community is increasingly focused on developing one of most efficient routing systems. Nonetheless, in order to effectively achieve the HO that is caused by the movement and varying location of UAVs, the issues related to them are analyzed and studied by considering the best possible Quality of Service (QoS) parameters under different scenarios. However, with the advancement in technology and growing number of users, the dependency factors of handover system keep on increasing which may increase the system complexity. Hence, the need for developing and adopting such system arises that can handle the system complexities in an effective way. Therefore, in this paper an effective and efficient HO mechanism is provided specifically for drones. The major contribution of our study is:

- We will be analyzing different parameters of drones at different levels for making a handover decision easy and effective.
- A multi-level based fuzzy system will be designed for analyzing these parameters at different stages.
- On the basis of the fuzzy output, the probability of the handover is determined that decides whether HO should take place at this point or not.
- Finally, the performance of suggested approach will be analyzed in MATLAB software.

The remaining section of the paper are categorized as; Section II reviews some of the recent technologies employed by many researchers for making HO decisions, followed by problem formulation. Section III discusses proposed work and its working mechanism. Section IV discusses results obtained for the proposed work and finally conclusion is written in Section V.

II. LITERTAURE REVIEW

Over the years, a significant number of methods have been suggested by various researchers for seamless HO decisions, some of them are discussed here. Kirshna *et al*. [11] proposed a drone assisted distributed routing model wherein main focus was given to QoS in Drone Internet of Things (D-IoT). The mobility and parameters of aerial drones were stochastically modelled, with an emphasis on the environments of highly dynamic flying ad-hoc networks. Moreover, in order to develop a fully distributed routing architecture, the authors used these drone-centric modelling techniques. Along with this, they also utilized a neuro-fuzzy interference system has made route selection more accurate and effective. Results showcased that suggested D-IoT model attains best results than standard models in context of various network metrics. Similarly, Manoj *et al*. [12] integrated fuzzy system along with chicken swarm optimization and Genetic Algorithm (GA) to develop a Hybrid Intelligent Optimization Algorithm (HIOA) model for lowering the energy consumption in an Internet of Things (IoT) network. Furthermore, it has also been analyzed that significant number of researchers are working on HO decision in drones, however, not much work has been done in clustering and classification process. Keeping this in mind, Mahmoud *et al*. in [13] proposed Metaheuristics with Adaptive Neuro-Fuzzy Inference System Decision Making (MANFIS-DM) model that was based on metaheuristic algorithm and Adaptive Neuro-Fuzzy Interface System (ANFIS) for decision making process. The authors used Quantum Different Evolution-based Clustering (QDE-C) for evaluating the fitness function using average distance, distance to UAV and degree. While as, classification module comprises of sub-processes like feature extraction by Dense Convolutional Network (DenseNet), hyper-parameter tuning by Adadelta: An Adaptive Learning Rate Method and classification by ANFIS. The suggested technique achieved an accuracy of 99.13%. Likewise, Sayed *et al*. [14] proposed a Quantum Neural Network based Multi-Labeled Aerial Image Classification (QNN-MLAIC) approach that consisted of various stages like image acquisition, preprocessing, detecting objects, Feature Extraction (FE) and finally classification. The authors utilized the beetle antenna search algorithm for optimizing the parameters of Quantum Neural Network (QNN) classifier. The efficacy of the system was analyzed on UC Merced aerial database under varying conditions.

In addition to this, it is important to analyze the mobility parameters in other wireless techniques like Vehicular ad hoc networks (VANETS), Wireless Local-Area Network (WLAN), Mobile ad hoc networks (MANETS), etc., to have better understanding of handovers. Therefore, we have reviewed some of the latest HO techniques along with their QoS parameters in below mentioned literatures.

Azzali *et al*. [15] suggested a method for making the HO decisions that was based on Fuzzy logic in order to enhance the QoS efficacy in heterogenous VANETS. The parameters that were used by the authors in this method were, HO rate, Received Signal Strength (RSS), throughput, packet loss ratio, Noise Signal Ratio (NSR), Signal to Interference Ratio (SIR), Carrier-to-Interference Ratio (CIR), Bit Error Rate (BER), position, distance, status of battery, speed and cost for selecting the optimal network architecture. Abdullah *et al*. [16] proposed an algorithm for making the vertical HO decision easy and effective in heterogenous networks by incorporating various parameters in wireless systems. The three vertical HO algorithms suggested were mobile weight, weight of network and equal weight. In addition to this, the authors of this paper also introduced three interfaces, those are, Worldwide Interoperability for Microwave Access (WiMAX), Wireless Local-Area Network (WLAN) and LTE. Subramani *et al*. [17] suggested a two -levelled Fuzzy based vertical handover system for selecting the best QoS parameters for making the HO decision. Here, data rate, latency and RSS were taken as three inputs for FL system. Sunita *et al*. [18] proposed a method for making the HO decisions that was based on fuzzy systems in order to select the best network for HO in between WLAN, WWAN and cellular networks. In this work, the authors considered received signal strength, bandwidth, delay, cost, mobile station velocity (MS-velocity), user preference, security and total number of users. In addition to this, to minimize the complexity of rules and system 4-levlled fuzzy controller is utilized. Chen *et al*. [19] proposed a deep Q-learning algorithm by utilizing the deep reinforcement learning tools in order to make the HO decisions more effectively so that stable drone connectivity can be ensured. By doing so, Ho rate is minimized with little loss in the signal strength. In order to choose the appropriate unmanned aerial vehicle during HO, Goudarzi *et al*. [20] developed a unique method that was based on cooperative game theory. The major theory was to reduce the end to end delay, HO latency and signaling overheads. Furthermore, SDN (software defined network) and MIH (media independent HO) were utilized as the forwarding switches for maintaining the effective mobility. Sonika Singh *et al*. [21] suggested a model Fuzzy Logics (FL) based HO decision model in which coverage, speed limit, cost, connection time and security were taken as the five inputs of fuzzy system which were processed by 160 rules to generate Ho probability. Kumar *et al*. [22] introduced a new method for providing the stable and robust aerial connectivity, namely, quality of service provisioning framework for UAVs (QSPU). Park *et al*. [23] suggested a seamless HO mechanism for UAVs in 3D space by adjusting the height of drone and distance among drones. Moreover, the authors used the HO success likelihood and fake HO initiation likelihood for computing the coverage decision algorithm. Mathonsi *et al*. [24] proposed a smart intersystem HO (IH) method in which four intelligent algorithms: Grey Prediction Theory (GPT), Multiple-Attribute Decision Making (MADM), Fuzzy Analytic Hierarchy Process (FAHP) and Principal Component Analysis (PCA) were incorporated for reducing the delay in HO.

From the literature survey conducted, it is analyzed that over the years a significant number of methods have been proposed by researchers for making the decision of handover effectively. After analyzing literature, it was observed that majority of the researchers considered limited parameters while developing a handover decision system. However, with the advancement in technology and growing number of users, the dependency factors of handover system keep on increasing which may increase the system complexity. Hence, the need for developing and adopting such system arises that can handle the system complexities in an effective way. For this, the researchers recommended fuzzy system for handling such complexities because the users can easily define rules as per the requirements and is cost effective. Although the FIS are able to generate good results with limited parameters but as soon as the number of parameters utilized in the system are increased, the rule complexity and time consumption of fuzzy system also increases which in turn enhances the complexity of entire system and ultimately affects its performance. Inspired from these findings, a novel and unique method will be developed in this paper that will consider number of important parameters for making the handover decision with reduced complexity and time consumption.

III. Overview of Proposed Scheme

After analyzing the literature review in the prior section, we have observed that current HO decision technique has complexity and low accuracy issues that degrade their performance. Keeping this in mid, a new HO decision system is proposed in this manuscript that is based on soft computing methods. In the proposed work, a multi-level fuzzy system is proposed in which various parameters are considered as inputs at different level so that complexity of the overall system is reduced. The main objective of the proposed model is to reduce the complexity of HO system while also increasing its accuracy for effective HO. To combat this task, a multi-level fuzzy system HO model is designed wherein different parameters of drones are analyzed at different levels for making the HO decision easy and accurate. As mentioned earlier, that traditional HO system analyzes only few parameters for making the HO decision, however, after analyzing literature survey we analyzed that number of parameters must be considered for making the HO efficient. Therefore, in proposed work we considered parameters like coverage, speed limit, and cost at first fuzzy level and at second fuzzy level factors like connection time, security and power consumption were evaluated. The output generated by two fuzzy system in the form of probability, serves as input to the third fuzzy system that evaluates these two inputs and generates output "estimation level" that determines whether HO should take place or not. The novelty of this work is that we have considered various important HO parameters at different levels for increasing the accuracy of HO. Moreover, we also analyzed that complexity of fuzzy systems arises by increasing the evaluating parameters, therefore, to reduce this complexity we evaluated HO factors of drones at three different fuzzy levels. The flowchart of the proposed multi-level fuzzy system is depicted in Fig. 2. In addition to this, an algorithm is also given for the proposed work. (Algorithm 1)

Algorithm 1: proposed HO decision model

Initialize the network parameter for handoff decision
Generate random location drone and define Base Station location
Initial Calculate parameter for handoff decision i.e. Coverage C_d, Speed S_d, Cost CS_d, Connection time CT_d, Security ST_d, Power consumption PS_d.
For no of Simulation n,

a. Calculate Euclidean distance between BS and drone using formula :
$$\text{Euclidean Distance}= \sqrt{(x1-x2)^{2}+(y1-y2)^{2}}$$
b. Calculation of Coverage C_d using Euclidean distance and then Speed S_d, Cost CS_d, Connection time CT_d, Security ST_d, Power consumption PS_d.
c. Calculate handoff decision of fuzzy 1 as follows:
d_1=evalfis([C_d, S_d, CS_d],fis1)
d. Calculate handoff decision of fuzzy 2 as follows:
d_2=evalfis([CT_d, ST_d, PS_d],fis2)
e. Calculate final handoff decision of fuzzy 3 as follows:
d_3=evalfis([d_1, d_2],fis3)
f. Generate final handoff decision with fuzzy 3 system

End
Evaluate performance parameter

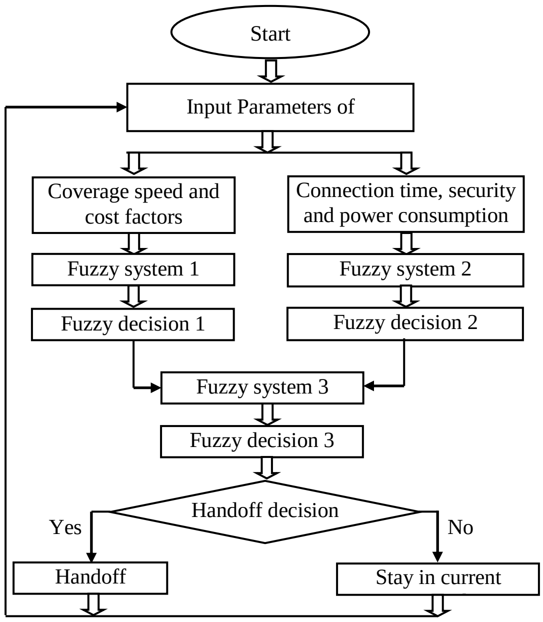


Fig. 2. Proposed handover system.

A fuzzy inference technique in which multiple attributes are examined to decide the handover is the heart of the smart handover decision systems. The specific range of every attribute specifies the criteria for determining the estimation level which allows the handover appropriately. Fig. 2, represents the block diagram of the proposed handover system in which three inputs are served to the first fuzzy system which upon processing generates the first output as F_{1out}. Similarly, another different set of parameters are taken into consideration for the second fuzzy system to generate the second output as F_{2out}. The outputs of the first and second fuzzy system then serves as the input to the third FIS which again is processed by the defined set of rules to get the estimation level as the final output. This output specifies whether handover should take place or not.

The main motive of using the multi-level fuzzy system in the proposed scheme is to reduce rule complexity at each level which in turn reduces the overall system complexity and delay and improves the throughput. The suggested scheme works by utilizing the same computing approaches that were used in traditional systems but in an advanced way just to make the handover decision more effective. By doing so, the proposed system will have the ability to minimize the time and complexity with effective decision strength.

The detailed block diagram of the fuzzy system that is used at the first level is given in Fig. 3. Fig. 3 given above consists of three layers, the input layer where all the input is taken, and the rule layer where the inputs are processed as per the rules defined and the output layer where the output generated from the fuzzy system is provided. In this case, three parameters namely, coverage, speed limit and cost serve as input at the input layer. The coverage is the critical factor in handover system which is inversely related to the strength of reception signal. Mathematically drone coverage for handover can be evaluated by using the equation given as

$$\text{coverage} = \pi d^2 = \pi\left(R^2 - A^2\right) \tag{1}$$

where R represents the radius of BS, A represents the altitude of drone and d represents the radius of BS coverage in 3D space.

Also, we know that if handover occurs too quickly I the system it can lead to delays, packet loss and high-power consumption. To mitigate this issue, the speed limit factor is introduced in the system that can be evaluated by

$$\text{Speed Limit}\left(\propto\right) = S\left(\omega/\delta\right) \tag{2}$$

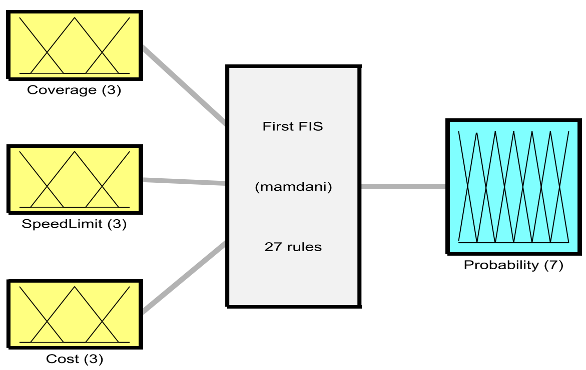


Fig. 3. Proposed first level fuzzy model.

The third parameter used in the first fuzzy system is cost which must be low. Every variable at the input contains three membership functions whose diagrams are shown in Fig. 4 (a), Fig. 4 (b) and Fig. 4 (c).

Fig. 4 represents the diagram of the three membership variable along with their three membership functions. The input variable coverage has three membership function those are, low, average and high whose value are normalized between 0 and 1. Similarly, the membership variable speed limit and cost also consists of three functions namely, low, medium and high whose values are also normalized between 0 and 1. The value of each variable along with its normalized and linguistic variables is recorded in Table I.

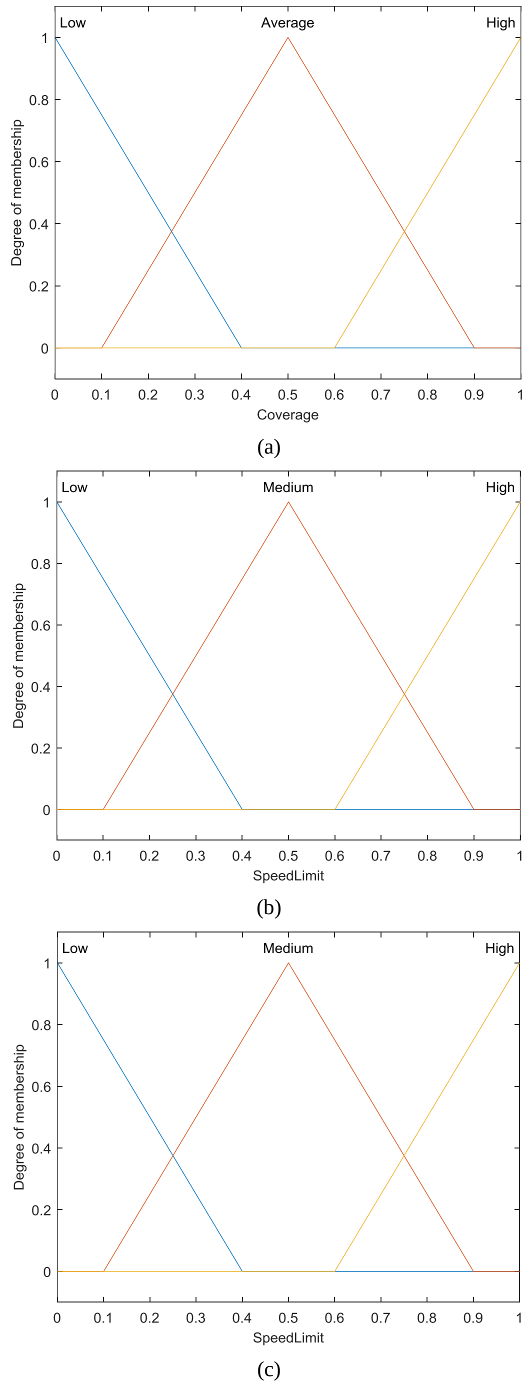


Fig. 4. Input variables of first fuzzy model.

TABLE I: VALUES OF INPUT MEMBERSHIP VARIABLES AND FUNCTIONS

Fuzzy input variables	Normalized range	Linguistic variable
Coverage	*x* is greater than 0 but less or equal to 0.4 *x* greater 0.1 but less or equal to 0.9 *x* greater than 0.6 but less or equal to 1	Low Average High
Speed limit	*x* is greater than 0 but less or equal to 0.4 *x* greater 0.1 but less or equal to 0.9 *x* greater than 0.6 but less or equal to 1	Low Medium High
Cost	*x* is greater than 0 but less or equal to 0.4 *x* greater 0.1 but less or equal to 0.9 *x* greater than 0.6 but less or equal to 1	Low Medium High

At the second layer i.e., rule layer, the three inputs are processed as per the rules defined in it to generate a single output probability at the final layer of the fuzzy system. The graph obtained for the output is depicted in Fig. 5. The final stage of the model is defuzzification where the fuzzy inputs values are transformed into crisp values which help in handover decisions. The output probability is generated along with its seven membership functions those are, VL, ML, L, M, H, MH, VH whose values are normalized within the range 0 and 1. This output is then stored and later on used as an input on third level. The normalized values and linguistic variables of the output are mentioned in Table II.

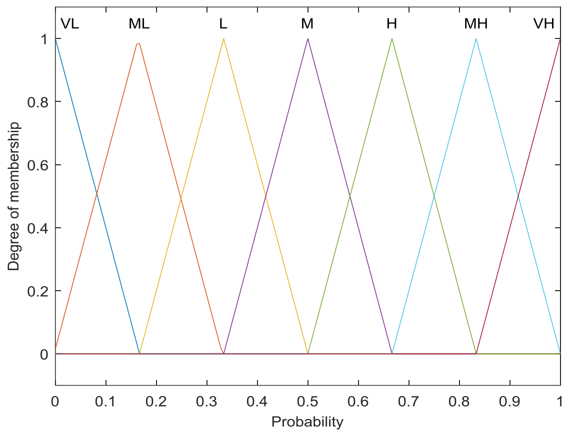


Fig. 5. Output generated by proposed model.

TABLE II: VALUES OF OUTPUT MEMBERSHIP VARIABLE

Fuzzy output variable	Normalized range	Linguistic variable
Probability	*x* greater than zero but less or equal to 0.16 *x* greater than zero but less or equal to 0.33 *x* greater than 0.16 but less or equal to 0.5 *x* greater than 0.33 but less or equal to 0.6 *x* greater than 0.5 but less or equal to 0.83 *x* greater than 0.6 but less or equal to 1 *x* greater than 0.83 but less or equal to 1	Very low Medium low Low Medium High Medium high Very high

As already mentioned that the proposed model utilizes number of parameters at different fuzzy level to make the handover decision effectively. Once the output "probability" is generated by the first fuzzy system, another set of three parameters those are, connection time, security and power consumption are utilized as inputs for the second fuzzy system along with their three membership functions. These variables are processed by the 27 rules that are defined in the Mamdani type of fuzzy system to generate another single output as "probability" in the end. The systematic diagram of the second fuzzy inference system is shown in Fig. 6. The connection time and power consumption of the system should be low so that handover takes place timely with less power consumption. Also, the security should be high so that data is protected from hackers. Each of the three variables again is divided into three membership functions with their respective range. The graph obtained for each variable is illustrated in Fig. 7 (a), Fig. 7 (b) and Fig. 7 (c).

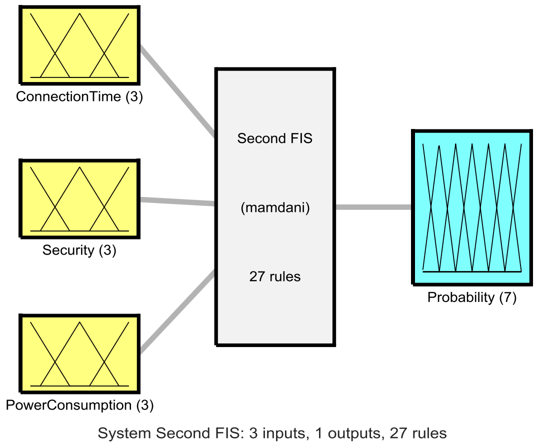


Fig. 6. Second fuzzy system.

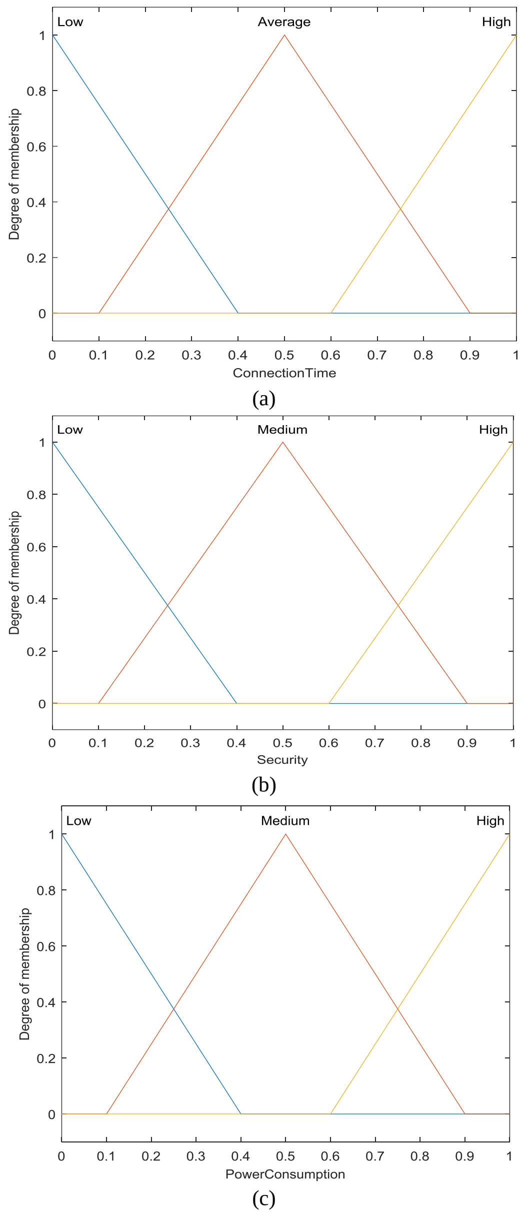


Fig. 7. Input variables for second fuzzy system.

Fig. 7 illustrates the graphs of three input variables i.e. connection time in (a), security in (b) and power consumption in (c). After analyzing the graphs, we observed that Low, average and high are three membership function of connection time whose values are normalized between 0 and 1. While as, the other two variables i.e. security and power consumption contains low, medium and high as their membership functions whose values are gain normalized between 0 and 1. The specific range of every variable along with its normalized and linguistic variables are shown in Table III.

TABLE III: SPECIFIC VALUE OF VARIABLE FOR SECOND FIS

Fuzzy input variables	Normalized range	Linguistic variable
Connection time	*x* is greater than 0 but less or equal to 0.4	Low
	x greater 0.1 but less or equal to 0.9	Average
	x greater than 0.6 but less or equal to 1	High
Security	*x* is greater than 0 but less or equal to 0.4	Low
	x greater 0.1 but less or equal to 0.9	Medium
	x greater than 0.6 but less or equal to 1	High
Power consumption	*x* is greater than 0 but less or equal to 0.4	Low
	x greater 0.1 but less or equal to 0.9	Medium
	x greater than 0.6 but less or equal to 1	High

The three inputs are then processed by the rules that are already defined in the fuzzy system in order to generate a single output probability. This output is generated by using the different set of attributes that is processed by the fuzzy system to determine the probability of handover. The final output is divided into seven membership functions and is shown in Fig. 8.

As shown in Fig. 8, the output generated by the second fuzzy system contains seven membership functions namely, VL, ML, L, M, H, MH and VH. The value of these functions is normalized within the range from 0 to 1. In addition to this, the exact range of each functions along with its linguistic variable is represented in Table IV.

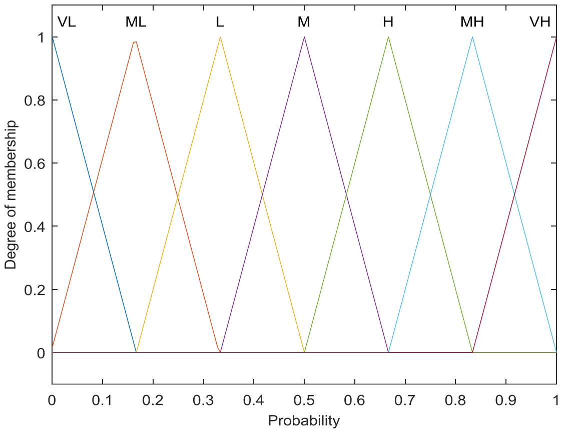


Fig. 8. Output generated by second FIS.

TABLE IV: RANGE OF OUTPUT GENERATED BY SECOND FIS

Fuzzy output variable	Normalized range	Linguistic variable
Probability	*x* greater than zero but less or equal to 0.16	Very low
	x greater than zero but less or equal to 0.33	Medium low
	x greater than 0.16 but less or equal to 0.5	Low
	x greater than 0.33 but less or equal to 0.6	Medium
	x greater than 0.5 but less or equal to 0.83	High
	x greater than 0.6 but less or equal to 1	Medium high
	x greater than 0.83 but less or equal to 1	Very high

At the third and final stage of proposed handover system, the two outputs generated by the first and second fuzzy system serve as the input to third fuzzy system used. The layout of the third fuzzy system is shown in Fig. 9.

Fig. 9 illustrates the block diagram of the third fuzzy system that is used in the proposed work. The three systems are again divided into three sections those are, fuzzification, rule evaluation and defuzzification. At the fuzzification stage, the outputs obtained from previous two fuzzy system serve as inputs that are later on evaluated by the rules defined in the rule layer and finally generate results on the basis of these rules. The two inputs variables are represented by FIS_1 and FIS_2 and are again sub-categorized into three membership functions, as illustrated in Fig. 10 (a) and Fig. 10 (b).

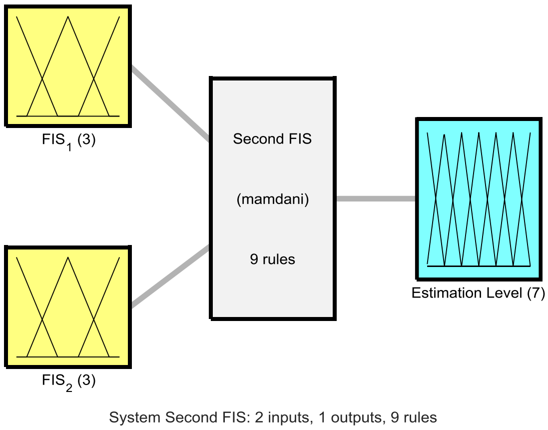
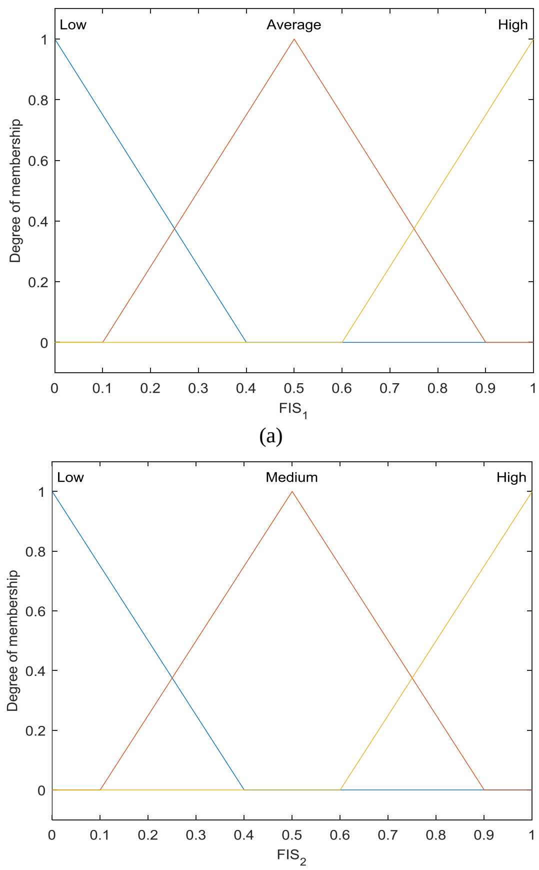


Fig. 9. Third fuzzy module.



(a)

(b)

Fig. 10. Input variable for third fuzzy system.

TABLE V: INPUT VARIABLE RANGE FOR THIRD FIS

Fuzzy input variables	Normalized range	Linguistic variable
FIS_1	x is greater than 0 but less or equal to 0.4	Low
	x greater 0.1 but less or equal to 0.9	Average
	x greater than 0.6 but less or equal to 1	High
FIS_2	x is greater than 0 but less or equal to 0.4	Low
	x greater 0.1 but less or equal to 0.9	Medium
	x greater than 0.6 but less or equal to 1	High

The graphs of the two inputs variables i.e. FIS_1 and FIS_2 of third and final fuzzy system are illustrated in Fig. 10 (a) and (b) respectively. Each variable is divided into three membership functions those are Low, average, high for FIS_1 and low, medium, high for FIS_2. The values of each variable are normalized between 0 and 1. Table V represents the normalized range and linguistic variables of two inputs.

Finally, the two inputs are processed by the given set of rules to produce a single output as estimation level which determines whether the handover should take place or not. The final outcome of the proposed multi-level handover system is estimation level that is shown in Fig. 11.

As depicted in the above figure, the final output "estimation level" contains seven membership functions as, VL, ML, L, M, H, MH and VH. The range of normalizing is between 0 and 1. The final output is obtained by defuzzification process that converts the fuzzy inputs into crisp values which assist in making the handover decision. The range of normalization and linguistic variables are given in Table VI.

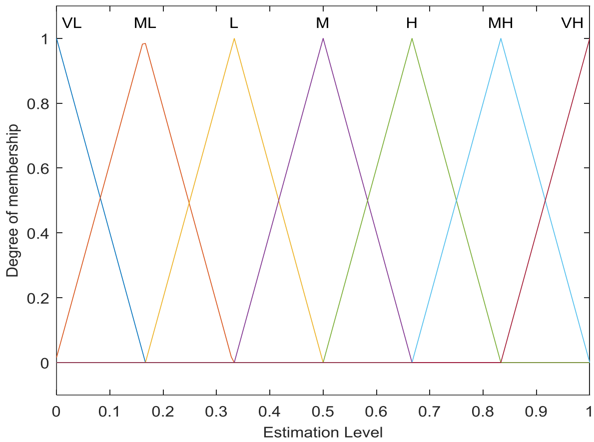


Fig. 11. Final output of the proposed Handover system.

TABLE VI: NORMALIZED RANGE AND LINGUISTIC VARIABLES FOR FINAL OUTPUT

Fuzzy output variable	Normalized range	Linguistic variable
Estimation level	x greater than zero but less or equal to 0.16	Very low
	x greater than zero but less or equal to 0.33	Medium low
	x greater than 0.16 but less or equal to 0.5	Low
	x greater than 0.33 but less or equal to 0.6	Medium
	x greater than 0.5 but less or equal to 0.83	High
	x greater than 0.6 but less or equal to 1	Medium high
	x greater than 0.83 but less or equal to 1	Very high

IV. SIMULATION RESULTS AND DISCUSSIONS

This section discusses the results that are attained by the proposed multi-level fuzzy system with increased performance factors. The entire system is designed and simulated in the MATLAB environment by using the MATLAB's in-built fuzzy toolbox. Moreover, the performance of the proposed multi-level fuzzy system is also compared with the conventional fuzzy models in terms of various performance metrics which include, estimation level, PDR, packet loss, throughput and delay to prove its efficacy.

Initially, the performance of the proposed handover system is evaluated and compared with traditional handover models in terms of their estimation level while moving in two directions i.e. random and straight. The graph obtained for the same is given in Fig. 12.

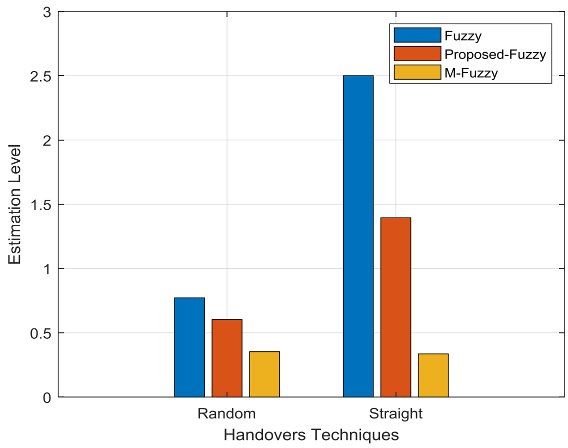


Fig. 12. Comparison for estimation level.

Fig. 12 illustrates the comparison graph for estimation level in random and straight directions. The performance of proposed multi-level fuzzy system is depicted by the yellow colored bar whereas, the blue and orange colored bar illustrates the performance of conventional fuzzy and proposed fuzzy handover schemes. From the graph, it is observed that the value of estimation level attained by the traditional fuzzy and proposed fuzzy model is 0.7717 and 0.6035 while moving randomly and 2.5000 and 1.3934 while moving in straight direction. On the other hand, the estimation level in proposed multi-level fuzzy approach came out to be lowest of all with 0.3534 and 0.3359 while moving randomly and straight respectively.

Also, the efficacy of the suggested multi-level fuzzy handover system is also assessed and compared with the previous handover systems in terms of their packet delivery ratio (PDR) and is shown in Fig. 13.

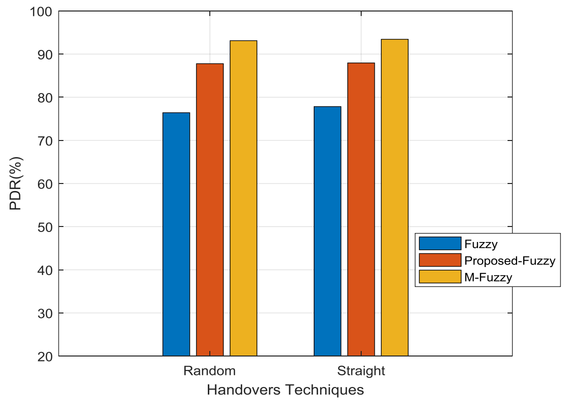


Fig. 13. Comparison for PDR.

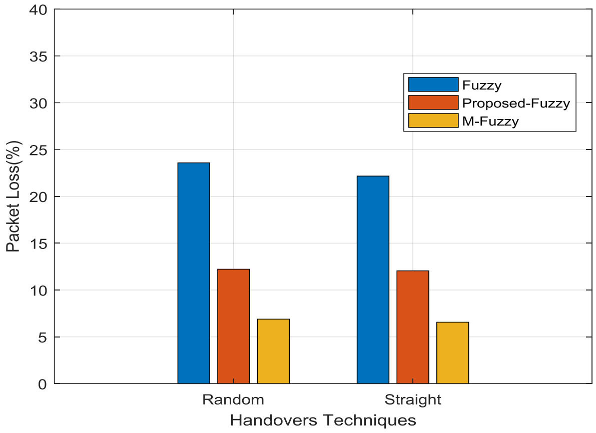


Fig. 14. Comparison for packet loss.

After analyzing the graph closely, it is observed that the PDR percentage achieved by the proposed handover system while moving in random direction is 93.1104 and 93.4375 while moving straightly. While as, in conventional fuzzy the PDR value came out to be just 76.4160 in random direction and 77.8320 in straight direction. Moreover, the value of PDR in proposed fuzzy system is mounted to 87.8320 and 87.6563 in random and straight directions. These values prove that the proposed multi-level fuzzy system has highest PD ratio and hence is more effective.

Likewise, the performance of the proposed handover system is also analyzed and later on compared with the standard fuzzy and proposed fuzzy systems in terms of packet loss. Fig. 14 illustrates the graph obtained for the same. From the graph, it is observed that in standard fuzzy system that a lot of packets gets lost during handover i.e. 23.5840 and 22.1680 while moving in random and straight directions. This is followed up by the proposed fuzzy model whose packet loss ratio is 12.2217 and 12.0508 in random and straight directions. In contrast, when the performance of the proposed multi-level fuzzy system is analyzed, its packet loss percentage came out to be just 6.8896 and 6.5625 while moving in random and straight directions.

In addition to this, the effectiveness of the proposed multi-level fuzzy model is analyzed and also compared with the prior fuzzy and proposed fuzzy handover systems in terms of throughput while moving randomly and straightly and is shown in Fig. 15 above. The blue and orange bars represent the performance of fuzzy and proposed fuzzy system whereas, the yellow bar represent the performance of proposed handover system. After analyzing the graphs closely, it is observed that the throughput value in fuzzy system is 77.057% when its moves randomly and 62.312 when moving in straight direction. This throughput value is enhanced by the proposed fuzzy system with 89.940% and 89.760% while moving in random and straight directions respectively. However, when we talk about the throughput value generated by the suggested Multi-level fuzzy system, it came out to be 95.3450% in random direction and 95.6800% in straight direction. Thus, proving the robustness of the model.

Finally, the efficiency of the suggested m-fuzzy system is evaluated and assessed in terms of the delay. The comparison graph is demonstrated in Fig. 16.

From the above graph (see Fig. 16), it is observed that among all the handover system, the delay is lowest in the suggested multi -level fuzzy system with just 9.562E-05 and 0.000138 values while moving in random and straight directions. While as, in traditional fuzzy and proposed fuzzy system the value of delay is 23.5840 and 12.2217 while moving in random direction and 22.1680 and 12.0508 while moving in straight direction. These values prove that the proposed multi-level fuzzy handover system is able to make handover decision more effectively and efficiently. The specific values of each parameter are also recorded in Table VII.

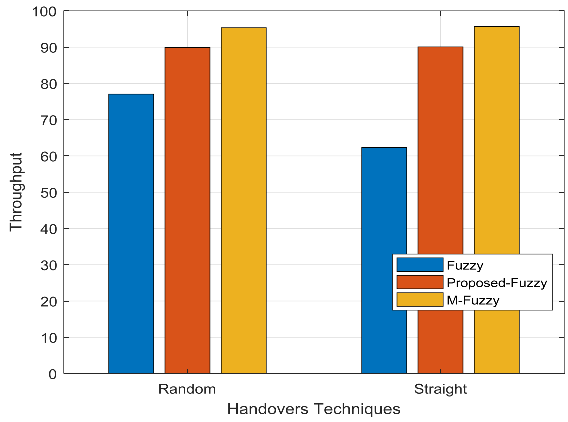


Fig. 15. Comparison for throughput.

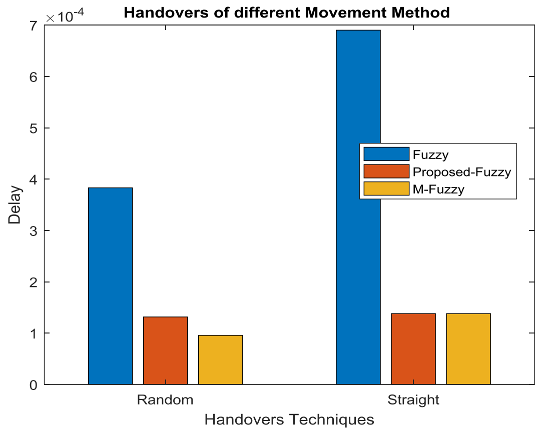


Fig. 16. Comparison graph for delay.

TABLE VII: SPECIFIC VALUE OF PERFORMANCE PARAMETERS

Parameter	Traditional (Random movement)	Traditional (Straight movement)	Proposed Fuzzy System (Random movement)	Proposed Fuzzy System (Straight movement)	M-Fuzzy System (Random movement)	M-Fuzzy System (Straight movement)
Estimation Level	0.7717	2.5000	0.6035	1.3946	0.3534	0.3359
PDR (%age)	76.4160	77.8320	87.8320	87.6563	93.1104	93.4375
Throughput (%age)	77.057	62.312	89.940	89.760	95.3450	95.6800
Delay	0.000383	0.000690	0.00017	0.000138	9.562E-05	0.000138
Packet Loss	23.5840	22.1680	12.2217	12.0508	6.8896	6.5625

V. CONCLUSION

In this paper, a new and unique multi-level fuzzy based approach is proposed for making handover decisions more effectively and easily. The whole model is simulated in the MATLAB software. The simulation outcomes were obtained and later on compared with the traditional fuzzy and proposed fuzzy handover systems in terms of various performance metrics which include, estimation level, PDR, throughput, delay and packet loss. After analyzing the results closely, it is clear that the proposed multi-level fuzzy system is providing optimal results for each parameter. The value of estimation level came out to be 0.3534 and 0.3359 in multi-level fuzzy system when moving in random and straight directions while as it came out to be 0.7717 and 2.5000 in fuzzy system and 0.6035 and 1.3946 in proposed fuzzy model. Also, the value of PDR in traditional fuzzy and proposed model came out to be just 76.41% and 87.83% in random direction and 77.83% and 87.65% in straight directions, while as it was mounted to 93.11 and 93.43% in multi-level fuzzy based approach. Moreover, the proposed multi-level fuzzy based approach outperforms the traditional models in terms of delay also whose value came out to be just 9.562E-05 and 0.000138 while moving in random and straight directions. In addition to this, the packet loss in proposed multi-level fuzzy system was least with values 6.8896 and 6.5625 when moved randomly and straightly. After analyzing all results, it was found that the multi-level fuzzy based approach is more effective, reliable and efficient in making the handover decisions.

In future more, work can be done on selecting more appropriate mobility parameters in drones that make the HO decision easy. Moreover, advanced ML or DL technique along with optimization algorithms for making HO decision easy is yet explored.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Theoretical formalism was created, analytical calculations were made, and numerical simulations were carried out by Sonika Singh. The final draught of the manuscript was written by Sonika Singh and Mandeep Kaur Sandhu. The study was overseen by Mandeep Kaur Sandhu.

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