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Fuzzy Inference System Based Handover Scheme in UAV-Assisted MEC Network

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***Abstract*—Due to the rapid growth of smart devices and 5G technology increase the requirement of computational tasks, unmanned aerial vehicles (UAVs) assisted Mobile Edge Computing (MEC) networks are designed to improve the task processing by reducing latency. Considering the necessity to complete the task quickly, the UE must seamlessly handover (HO) to the optimal BS, which may lead to frequent HO. This paper introduces a Fuzzy Inference System (FIS) based HO decision-making scheme for UAV-assisted Mobile Edge Computing (MEC) networks, addressing the increasing demand for computational tasks. At first, the proposed method optimizes HO decisions using RSS, distance, and number of serving users. Then, it employs a two-layer FIS to select the target base station (BS), considering SINR, time of stay (ToS), distance, and user connectivity. Simulation results demonstrate the FIS-based method can achieve less HO frequency and task delay compared to RSS-based and TOPSIS-based schemes.**

***Index Terms*—UAV, mobile edge computing, fuzzy inference system, handover, task delay**

I. Introduction

The rapid growth of smart devices and the evolution of 5G technology increase the demand for computationally intensive services, burdening mobile service providers [1]. Traditional cloud data processing faces challenges due to increasing real-time tasks, prompting the adoption of Mobile Edge Computing (MEC) to reduce latency [2]. In MEC, mobile edge nodes, typically situated at base stations (BSs), offer proximity to user equipment (UEs) in Heterogeneous Networks (HetNets) [2]. Unmanned aerial vehicles (UAVs) are integrated into HetNets to enhance communication services cost-effectively, leveraging air-to-ground (A2G) channels for line-of-sight (LoS) links with ground UEs [3]. UAVs are enabled to handle processing and storage tasks, promoting the appearance of UAV-assisted MEC networks [3].

MEC can be used to meet the requirement of faster and efficient data processing responses. There are several existing studies about optimising the task offloading in UAV-assisted edge computing network. [4] addresses task delay minimization in UAV-aided MEC networks through user association and UAV deployment optimization. Additionally, [5] presents a framework for minimizing total task delay and proposes joint computing offloading and resource allocation, considering varying BS computing capacities. Furthermore, [6] proposes a game-theoretic approach to minimize energy consumption and time latency, achieving optimal computation offloading decisions with minimal system costs.

The existing literature emphasizes task processing performance. Yet with the integration of edge servers into BSs, the BSs assume dual roles as communication nodes and edge server. Consequently, selecting the target BS entails considerations beyond task response delay, encompassing communication quality while UEs are in motion. The link quality between UEs and BSs is affected by the motion of UEs, and the allocated CPU cycles are fluctuated over time, therefore, UEs may need to initiate handovers (HO) to connect to better BSs. Given the importance for swift task completion, UEs must seamlessly HO to an optimal BS, potentially increasing the number of HOs. HO involves transferring an ongoing call or data session from a serving BS to a target BS without degrading service quality. However, frequent HOs pose challenges such as increased signaling overhead, elevated call drop rates, and packet loss. Hence, finding a balance between short task response times with less number of HOs is essential.

Motivated by the observation of HO issues above, this paper presents an fuzzy inference system (FIS) based HO decision-making scheme to tackle this issue. The method employs a FIS to optimize HO decisions based on three criteria: Received Signal Strength (RSS), distance, and the number of serving users. Upon HO triggering, a two-layer FIS is deployed to select the appropriate target BS considering candidate BS criteria such as Signal-to-Interference-plus-Noise Ratio (SINR), distance, Time of Stay (ToS), and the number of connected users. This approach aims to reduce both the number of HOs and task delays effectively.

The rest of paper is organized as follows. Section II presents the system model, and in Section III, the proposed scheme is introduced. Section IV shows the performance and the results analysis. Finally, the paper is concluded in Section V.

II. System Model

A. UAV assisted mobile edge computing system

Usually, MEC is deployed close to the users. In rural, the different BSs are suitable to integrate edge servers, and UAVs are hovering beyond the terrestrial facilities to assist the network [4]. As shown in Fig. 1, this paper investigates a three-tier UAV-assisted MEC system with K BSs, including small BSs (SBSs) distributed within the coverage area of an macro BSs (MBS), and UAVs deployed above. The MBS is located at the centre of the area, and the SBSs and UAVs are distributed following the Poisson Point Process (PPP) with a specific density λ_s and λ_u. These BSs, irrespective of their type, are equipped with communication and edge computing capabilities for data transmission and local data processing. Both MBS and UAVs operate within the LTE band to ensure wide-area coverage, while SBSs utilise millimeter wave frequencies to support high data rates and massive connectivity. Each BS is equipped with a central processing unit (CPU) for edge computing tasks. Also, there are M Ground UEs randomly distributed and offload computing tasks to BSs.

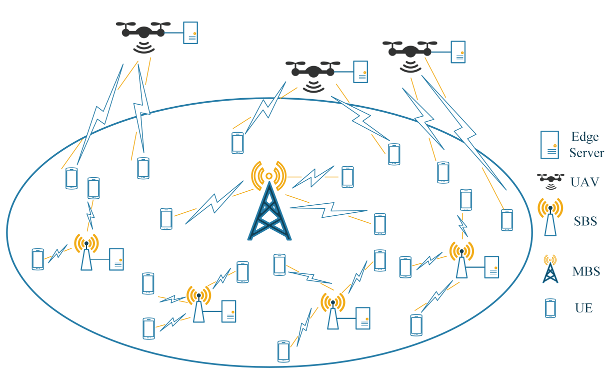


Fig. 1. Model of three-tier UAV assisted MEC system.

B. Propagation model

In this model, two types of data transmission are considered: downlink for communication service and uplink for edge computing. The network integrates ground BSs and UAVs, using both ground-to-ground (G2G) and air-to-ground (A2G) channels. A2G channels consist of line-of-sight (LoS) and non-line-of-sight (NLoS) links, determined using a ray tracing model [7]. Obstacles are randomly generated following a Poisson distribution with density β, and building heights follow a Rayleigh distribution with scale parameter κ. A link is LoS if there are no obstacles blocking the path; otherwise, it is NLoS.

Path loss is a crucial metric to measure the quality of a channel. According to [8], the calculation of the path loss of the LoS and NLoS links are given below:

$$\begin{aligned} PL_{LoS} &= 30.9 + 20\log_{10}(f_c) \\ &+ (22.25 - 0.5\log_{10}(h_U))\log_{10}(d_{3d}), \end{aligned} \tag{1}$$

$$\begin{aligned} PL_{NLoS} &= 32.4 + 20\log_{10}(f_c) + \\ &(43.2 - 7.6\log_{10}(h_U))\log_{10}(d_{3d}), \end{aligned} \tag{2}$$

where f_c is the carrier frequency, h_U is the height of the UAV and d_{3d} is the distance between the ground UE and the UAV in 3D environment.

However, the G2G path are usually blocked by terrestrial obstacles, therefore, it is assumed that G2G channels are NLoS. From [9], the path loss model of G2G channels for SBSs and MBSs can be given as:

$$PL_{G2G} = 32.4 + 20\log_{10}(f_c) + 30\log_{10}(d_{3d}). \tag{3}$$

C. Task Model

In this model, all tasks are generated by ground UEs and offloaded to BSs for processing, and each task can only be transmitted and processed in its entirety. We assume the CPU in each BS has the same operating frequency, which is f_m cycles per second. For a specific BS, the computation capacity for each offloaded task is equally distributed. To describe a specific j_{th} task U_{ij} of UE i, we define a 2-tuple as $U_{ij} = (D_{ij}, C_{ij})$, where D_{ij} represents the data size and C_{ij} is the total number of the CPU cycles.

Task delay consists of transmission time and execution time. The task data is transmitted via uplink channel. Thus, the data rate of uplink channel is expressed as [10]:

$$\begin{aligned} r_{ik} =& B_i \times log_2\left(1 + \frac{h_i P_i}{B_i n_0}\right), \\ & \forall i = \{1, 2, ..., M\}, \forall k = \{1, 2, ..., K\}, \end{aligned} \tag{4}$$

where B_i denotes the channel bandwidth of UE i, P_i denotes transmission power of UE i, h_i is the channel power gain and n_0 the noise power spectral density. For complex environments with various obstructions, h_i is described using Rayleigh fading model as below. When the channel is LoS, the channel power gain is denoted by [10]:

$$h_i^{los} = g_0 \times {d_{3d}}^{-\alpha_{los}}, \tag{5}$$

and the channel power gain for NLoS channel is represented as:

$$h_i^{nlos} = g_0 \times {d_{3d}}^{-\alpha_{nlos}} \times \zeta_i, \tag{6}$$

where g_0 denotes the reference channel power, ζ_i denotes the Rayleigh fading coefficient, and α_{los} and α_{nlos} are the path loss exponent for LoS link and NLoS link respectively.

Then, the transmission time of task j from UE i to BS k can calculated as:

$$T_{ij}^{Tr} = \frac{D_{ij}}{r_{ik}}, \forall i = \{1, 2, ..., M\}, \forall \{k = 1, 2, ..., K\}, \tag{7}$$

After the transmission, the data is executed by a BS k. The execution time of task U_{ij} can be calculated as:

$$T_{ij}^{E} = \frac{C_{ij}}{\frac{f_m}{N_k}}, \forall i = \{1, 2, ..., M\}, \forall k = \{1, 2, ..., K\}, \tag{8}$$

where N_k is the number of connected UEs of the BS k, and f_m is the CPU operating frequency. Thus, the task delay T_{ij}^D can be denoted by:

$$T_{ij}^D = T_{ij}^{Tr} + T_{ij}^E, \forall i = \{1, 2, ..., M\}, \forall k = \{1, 2, ..., K\}, \quad (9)$$

D. HO decision criterion

1) Downlink RSS and SINR: RSS and SINR are the important indicators to measure the quality of channels. The RSS in dBm can be calculated by:

$$RSS = P_t + G_t + G_r - PL + SF, \quad (10)$$

where P_t represents the transmission power from the serving BS, G_t and G_r denote the antenna gains of the transmitter and receiver respectively. Additionally, PL stands for the path loss as described previously, while SF signifies the shadow fading, which follows Gaussian distribution with a mean of 0 and a standard deviation denoted by σ_{SF}:

$$SF \sim \mathcal{N}(0, \sigma_{SF}). \quad (11)$$

The values of σ_{SF} for LoS A2G, NLoS A2G and G2G channels are given below [11]:

$$\sigma_{SF}^{LoS} = \max(5 \times e^{(-0.01 \times h_U)}, 2), \quad (12)$$

$$\sigma_{SF}^{NLoS} = 8, \quad (13)$$

$$\sigma_{SF}^{G2G} = 7.8. \quad (14)$$

Downlink interference arises from neighboring BSs. In our system model, there exists one MBS, K_s SBSs, and K_u UAVs. When user equipment (UE) i is served by BS k', which could be any of the MBS, SBSs, or UAVs, and given that the carrier frequency of SBSs differs from that of the MBS and UAVs, the interference of SBSs, UAVs and MBSs, which are denoted as I_i^s, I_i^u, and I_i^m respectively, can be expressed as follows:

$$I_i^s = \sum_{k=1, k \neq k'}^{K_s} RSS_i^k, \quad (15)$$

$$I_i^u = \sum_{k=1, k \neq k'}^{K_u + K_m} RSS_i^k, \quad (16)$$

$$I_i^m = \sum_{k=1, k \neq k'}^{K_u + K_m} RSS_i^k, \quad (17)$$

where K_m is the number of MBS, which equals to 1, k represents a BS. Therefore, SINR is given by:

$$SINR_i^{k'} = \frac{RSS_i^{k'}}{I_i^{k'} + {\sigma_n}^2}, \quad (18)$$

where $I_i^{k'}$ represents the interference of the path from BS k' to UE i, and σ_n is noise power, which can be calculated as:

$$\sigma_n = 10^{-3} \times 10^{(-174 + 10 \times log_{10}{}^{B_i^{k'}})/10}, \quad (19)$$

where $B_i^{k'}$ is the allocated bandwidth of UE i from BS k'.

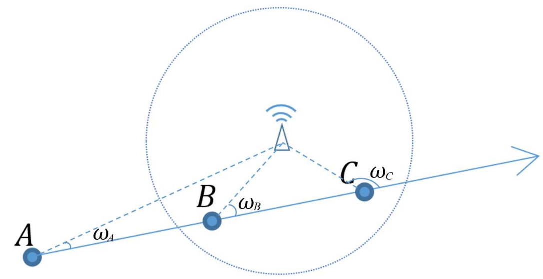


Fig. 2. UE is moving through a BS coverage.

2) Time of Stay: The ToS denotes the duration for which a UE remains connected to a BS. If the ToS of the target BS is insufficient or even zero, it will potentially result in task failures as UEs cannot receive task outcomes. As depicted in Fig 2, a UE can be positioned at A, B, or C while traversing a BS. The respective ToS at each position is represented as follows:

$$ToS_A = \frac{2 \times R_{BS} \times \sqrt{1 - (\frac{d_{2d} \times \sin(\omega_A)}{R_{BS}})}}{v_{UE}}, \quad (20)$$

$$ToS_B = \frac{\sqrt{{R_{BS}}^2 - (d_{2d} \times \sin(\omega_B)^2)} + d_{2d} \times \cos(\omega_B))}{v_{UE}}, \quad (21)$$

$$ToS_C = \frac{\sqrt{{R_{BS}}^2 - (d_{2d} \times \sin(180 - \omega_C)^2)}}{v_{UE}} - \frac{d_{2d} \times \cos(180 - \omega_C))}{v_{UE}}, \quad (22)$$

where R_{BS} represents the radius of the BS, d_{2d} denotes the distance between the UE and the BS in a two-dimensional environment, while ω_A, ω_B, and ω_C signify the angles formed between the trajectory of the UE and the connection line between the UE and the BS, measured in degrees.

III. Proposed Fuzzy Inference Based Handover Scheme

A. Overview of the proposed method

In the context of UAV-assisted MEC systems, we propose a HO decision-making scheme based on FIS principles. At first, all inputs of FIS will be mapped into a fuzzy set, which is a set of degree descriptions, according to the membership function. Then, Using the If-Then rules in Knowledge base, it performs reasoning by producing a fuzzy output. At last, it converts the fuzzy output given by the output membership function to produce a real-valued output [12]. The primary aim of our method is to address the dual challenge of reducing the frequency of HO events while minimizing task delay, thereby enhancing the efficiency of both HO management and edge computing operations. Fig. 3 illustrate the process of the proposed algorithem.

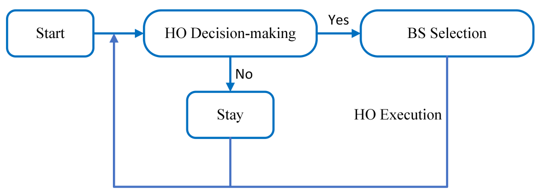
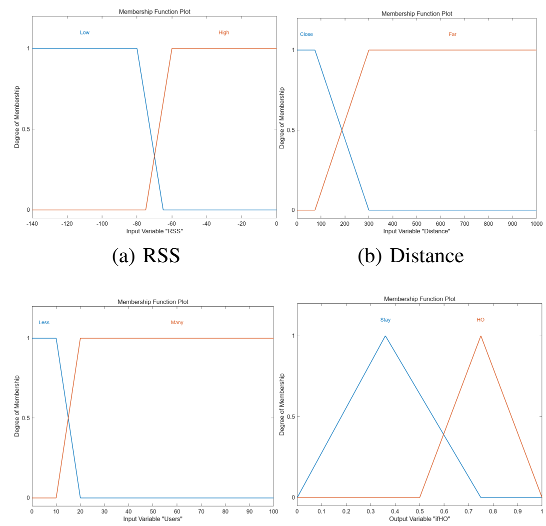


Fig. 3. Process of the proposed algorithm



(a) RSS (b) Distance

(c) Number of Serving Users (d) HO Tendency

Fig. 4. Membership function of HO decision-making FIS

Our method comprises two main components: HO decision-making and BS selection. In the HO decision-making stage, various factors are considered to determine whether a HO event should be initiated based on the quality of the network. A FIS evaluates factors including RSS, distance, and the number of serving users to determine whether HO should take place. Through an FIS model, these input variables are dynamically analysed to produce an output representing the tendency for HO. If the FIS output surpasses a threshold, indicating potential degradation of connectivity, HO is activated. Algorithm 1 outlines this process.

Algorithm 1 First Stage: HO Decision Making

```
Input: RSS, Distance, Users_Number
Output: HO_Decision
HO_Tendency ← FuzzyInference(RSS, Distance, Users_Number)
return HO_Tendency
if HO_Tendency > Threshold then
    HO_Occurs ← True
    BS_Selection()
else
    HO_Occurs ← False
    Stay with current BS
end if
```

In the BS selection phase, a multi-level FIS evaluates key criteria including SINR, ToS, distance, and user connectivity at each BS. Two FIS modules in the first layer operate in parallel, with their outputs aggregated and fed into a higher-level FIS in the second layer. This comprehensive assessment generates a rating for each candidate BS, indicating its suitability to meet the UE's needs. Algorithm 2 illustrates this process.

Algorithm 2 Second Stage: BS Selection

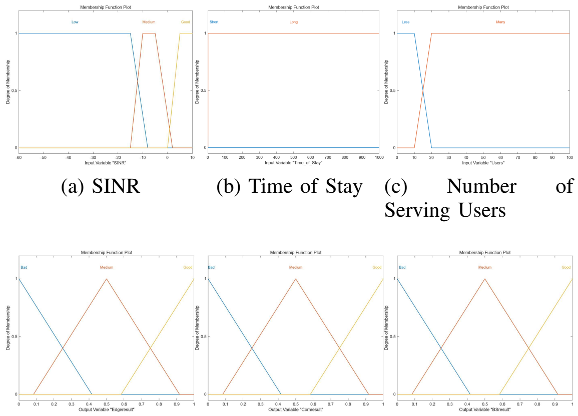
```
function BS_SELECTION
    Input: SINR, ToS, Distance, Serving_Users
    Output: Best_BS
    Criteria_1 ← FIS1(SINR, ToS)
    Criteria_2 ← FIS2(Distance, Serving_Users)
    Rating ← FuzzyInference(Criteria_1, Criteria_2)
    Best_BS ← ChooseBestBS(Rating)
    return Best_BS
end function
```

B. FIS details

1) membership function: In the FIS, the goal is to enhance both HO decision making and BS selection performance simultaneously. Fuzzy logic employs partial membership to categorize criteria instead of strict thresholds. In this approach, criteria values are assigned membership degrees, which allow them to belong to multiple categories to varying extends. These membership degrees are then used to define the membership function.

At the HO decision-making stage, inputs include RSS, distance, and number of serving users, and the output is the HO tendency. Fig. 4 displays corresponding membership functions. For RSS, "Low" is assumed below -65 dBm, transitioning to "High" beyond -75 dBm. Distance is assumed to be "Close" if it is less than 300m and "Far" when it longer than 75m, while for number of users, "Less" signifies a value below 20, and "Many" indicates a value exceeding 10. During BS selection, four inputs and three outputs are considered, depicted by Fig. 5. The SINR is categorized as "Low" when its value falls below -8 dB, "Medium" if it ranges from -15 dB to 2 dB, and "Good" if it exceeds 0 dB. ToS is classified as "Long" if it exceeds 0.7 seconds; otherwise it is considered "Short". Regarding the number of users and Distance, the membership functions remain consistent with those of the first stage. All output memberships are configured as triangular.

2) Fuzzy Rules: Fuzzy rules are proposed to take account of all those key measurements. All the rules are defined with IF-Then logical operation. Following the rules, the fuzzy inference results can be generated by the inputs and the membership function. After that, centre of gravity method is used for defuzzification. Table I, Table II illustrate the four FIS in the proposed method respectively.



(a) SINR (b) Time of Stay (c) Number of Serving Users

(d) Fuzzy Result 1 (e) Fuzzy Result 2 (f) BS Rating

Fig. 5. Membership function of BS selection FIS

TABLE I
RULES OF HO DECISION-MAKING FIS

	Input			Output
NO.	**Distance**	**RSS**	**Users Number**	**HO Tendency**
1	Close	High	Many	Stay
2	Close	High	Less	Stay
4	Close	Low	Many	HO
5	Close	Low	Less	Stay
7	Far	High	Many	Stay
8	Far	High	Less	Stay
9	Far	Low	Many	HO
10	Far	Low	Less	HO

TABLE II
RULES OF BS SELECTION FIS 1, FIS 2 AND FIS 3

	Input		Output
NO.	**SINR**	**ToS**	**Fuzzy Result 1**
1	Low	Short	Bad
2	Low	Long	Medium
3	Medium	Short	Bad
4	Medium	Long	Medium
5	Good	Short	Bad
6	Good	Long	Good
	Input		**Output**
NO.	**Distance**	**User Number**	**Fuzzy Result 2**
1	Close	Less	Good
2	Close	Many	Medium
3	Far	Less	Medium
4	Far	Many	Bad
	Input		**Output**
NO.	**Fuzzy Result 1**	**Fuzzy Result 2**	**BS rating**
1	Bad	Bad	Bad
2	Bad	Medium	Bad
3	Bad	Good	Bad
4	Medium	Bad	Bad
5	Medium	Medium	Medium
6	Medium	Good	Good
7	Good	Bad	Bad
8	Good	Medium	Good
9	Good	Good	Good

IV. PERFORMANCE AND RESULTS ANALYSIS

We evaluate the performance of FIS-based HO scheme by comparing it with two alternatives: a RSS-based scheme and a TOPSIS-based scheme. RSS-based approach is a conventional scheme and widely used in mobile communication network, while TOPSIS is a popular method for decision-making problems with multiple criteria. In the RSS-based approach, HO occurs when there is a BS with better RSS. In the TOPSIS-based method, similar criteria are used, but the top-ranked BS is chosen for HO. Simulations use a random waypoint model for UE movement, with velocities ranging from $1m/s$ to $5m/s$. Tasks are generated every 10 seconds, and their sizes follow a Gaussian distribution with mean 10×10^5 and standard deviation $\sigma_{task} = 1 \times 10^6$. Additional simulation parameters are listed in Table III.

TABLE III
SIMULATION PARAMETERS

Parameters	**Values**
Bandwidth (B)	B_{SBS} = 500 MHz B_{MBS} = 20 MHz B_{UBS} = 20 MHz B_{ue} = 10 MHz
Transmit Power (P_t)	P_t^{SBS} = 35 dBm P_t^{MBS} = 46 dBm P_t^{UBS} = 20 dBm
Transmit Power of UEs(P_{ue})	P_{ue} = 0.1 W
Carrier Frequency (CF)	CF_{SBS} = 28 GHz CF_{MBS} = 2 GHz CF_{UBS} = 2 GHz
Density of BSs (λ)	$\lambda_s = 10\ (10^{-6}/m^2)$ $\lambda_u = 10\ (10^{-6}/m^2)$
Density of Buildings (β)	100 $(10^{-6}/m^2)$
Radius of BSs (R)	R_{SBS} = 50 m R_{MBS} = 1000 m R_{UBS} = 150 m
UE moving duration (L)	50 to 100 s
Height of BSs(h)	h_{SBS} = 4 m h_{MBS} = 20 m h_{UBS} = 100 m
Scale Parameter (κ)	20
Number of UEs (M)	100
CPU Frequency (f_m)	1×10^{10}
Reference Channel Power Gain (g_0)	1.42×10^{-4}
path loss exponent (α)	α_{LoS} = 2.5 m α_{NLoS} = 3.5 m

A. Average Number of Handover

The average number of HOs of the three methods over varying duration time is depicted in Fig. 6. This metric represents the average count of HOs experienced by each UE during their movement period. It's evident that the number of HOs increases over time for all methods. This is because UEs are more likely to pass through cell boundaries with longer movement. Fig. 6 illustrates the proposed FIS-based method, denoted as "FIS", experienced minimal HOs. It is due to the various membership degrees of multiple criteria that determine whether HO or not instead of a fixed threshold. Conversely, because the TOPSIS-based method ranks BSs with multiple criteria, the top-ranked BS changes more frequently than RSS-based method, TOPSIS-based method causes the higher number of HOs than RSS-based method.

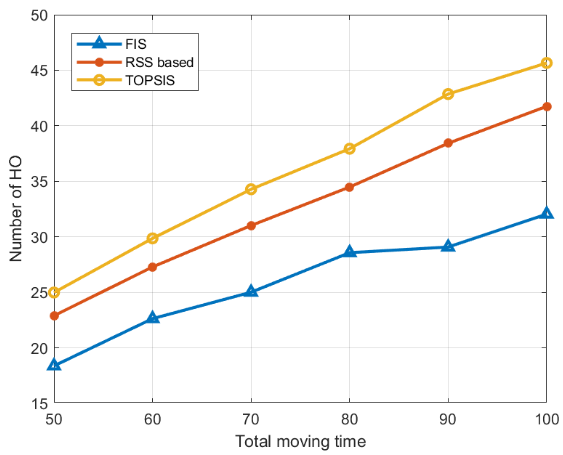


Fig. 6. Average number of HO against moving time

B. Average Task Delay

The average task delay is measured by transmission and execution time of all tasks per UE during their movement period. The performance of average task delay is illustrated in Fig. 7. As shown, the average task delay increases over time for all methods. This is attributed to the higher task generation rate over extended duration. As the proposed method can find an appropriate balance between high quality service from BSs and HO frequency, in comparison to alternative methods, the proposed FIS-based approach achieves the shortest average task delay. The TOPSIS-based method exhibits improved performance over the RSS-based method, primarily due to the consideration of multiple criteria in the TOPSIS-based approach.

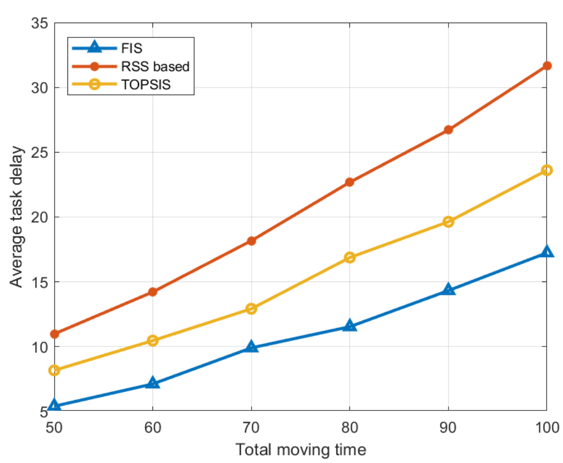


Fig. 7. Average task delay against moving time

V. Conclusion

This paper proposes an FIS-based HO decision-making scheme for a UAV-assisted three-tier MEC system, consisting of two stages: HO decision-making and BS selection. The HO decision-making stage employs an FIS with three criteria inputs to determine the HO tendency. The BS selection stage employs three FIS modules in two layers. The first FIS involves SINR and ToS, while the second FIS evaluates distance and number of connected users. These fuzzy results are then used as inputs for the third FIS to calculate the BS rating, then the highest-rated BS is selected as the target BS. Simulation results demonstrate the superiority of the proposed FIS-based method in average number of HO and task delay compared to RSS-based and TOPSIS-based methods. However, although the method can achieve the good performance, the design of it is mainly based on experience. More accurate and detailed designs are required to optimise the results.

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