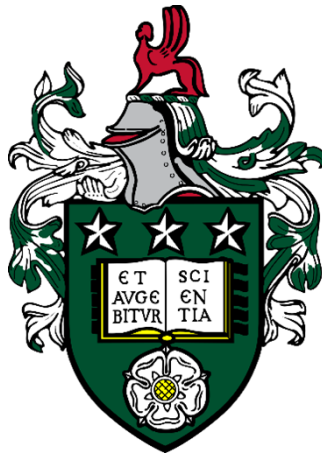

Handover decision-making schemes in UAV communication networks

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ABSTRACT

In recent years, unmanned aerial vehicles (UAVs) have seen increasing application across various industries, including military operations, surveillance, telecommunications, delivery services, and rescue missions. Their ability to maneuver in three-dimensional space with high agility and their ease of deployment makes them highly adaptable for a wide range of tasks. In communication networks, UAVs can serve two primary roles: as aerial user equipment (UE) in cellular networks, known as cellular-connected UAVs, or as aerial base stations (BSs) to provide reliable, cost-effective, and on-demand wireless communication services. When acting as aerial BSs, UAVs enhance the existing terrestrial wireless network by increasing the likelihood of line-of-sight (LoS) communication links to ground UEs, thereby improving connectivity.

However, in both roles, handover (HO) is critical for maintaining connectivity as user associations change. While HO improves the quality of service (QoS) for mobile UEs, frequent HOs can lead to increased signaling overhead and a higher call drop rate. Given that modern terrestrial networks often consist of BSs with various access technologies—particularly in 5G ultra-dense small cell deployments—combined with the fast movement of UAVs and ground UEs, frequent HOs can easily occur. Therefore, reducing the number of HOs is essential to ensure efficient network performance. Additionally, in different scenarios, the purpose of HO goes beyond merely maintaining a high-quality link. For instance, in UAV-aided networks or UAV-aided multi-access edge computing (MEC) networks, other metrics like energy efficiency and computing resource availability play a crucial role in the HO process. By making appropriate HO decisions, these metrics can be optimised to achieve better overall service performance. This thesis proposes various HO decision-making schemes tailored to different UAV network scenarios.

Firstly, for cellular-connected UAVs, they rely on reliable communication links to complete tasks. As aerial UEs in communication network, UAVs suffer high interference and highly frequent unnecessary HO when they are moving and served by the ground communication network system. To address these issues, we proposed an improved Q-Learning (QL) based HO

algorithm. The formation of the action space considers both the Signal-to-Interference-plus-noise ratio (SINR) and the distance between the BSs and UAV with different weights. We defined performance metrics to evaluate the algorithm, which are HO rate, throughput loss rate, and outage rate. The results show the proposed algorithm can further reduce the HO rate by 52.9% with slightly compromising the throughput and the outage rate. Furthermore, the optimal weight combination of ω_{sinr} and ω_d is found to be $\omega_d = 4.75$ and $\omega_{sinr} = 5.25$ are suggested to achieve the best trade-off of the three performance indicators.

Secondly, in the heterogeneous network (HetNet), the deployment of UAV can also cause problems. For example, in UAV-aided HetNet, the number of HO and the number of unnecessary HO will increase because of the dense distribution of small base stations (SBSs) and UAVs. Frequent HO and unnecessary HO can result in interruption, increased overhead and energy consumption, which is not desirable for battery powered UAVs. To solve the problem, a QL based HO decision-making algorithm is proposed with the aim to reduce HO number and improve energy efficiency (EE). In the algorithm, QL can be applied to address decision-making challenges in communication systems widely. However, a large volume of training data can pose challenges and complexities, therefore, in this algorithm, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is utilised to reduce the size of the action space in QL. The proposed hybrid TOPSIS-QL method enhances both the HO performance and the scalability. In this method, SINR, time of stay (ToS) and average EE are taken into account. The simulation results show that the number of HO and unnecessary HO is remarkably reduced by around 48.7% and 69.2% respectively, and the average EE is notably improved by around 46.1% in comparison with the baseline.

Finally, HO decision-making problems also happen in UAV-aided MEC systems. The rapid growth of smart devices and the increasing demand for data computational tasks in 5G-based dense cellular networks result in frequent HO and task migration. This leads to decreased quality of computing and increased energy consumption. A Fuzzy Inference System (FIS)-based HO decision-making scheme for UAV-aided MEC is proposed to address these challenges. Our objectives are to reduce the number of HOs for UEs, decrease energy consumption for BSs, and increase the efficiency of task processing. To achieve this, the FIS is divided into two stages: (i) HO decision and (ii) BS selection. In the HO decision stage, criteria such as the distance between the UE and the serving BS, receive signal strength (RSS), allocated CPU frequency, and task time threshold are considered to determine whether to execute an HO. In the BS selection stage, the system evaluates the distance between the UE and the target BS, the distance between the target BS and the serving BS, the number of connected UEs, the SINR, and the ToS to

select the optimal BS for the UE to connect with. Simulation results demonstrate that the proposed HO scheme achieves better performance in reducing task completion time by 38.6%, increasing the number of successful tasks by 74.1%, and reducing the energy consumption by 95.6%, while also reducing the number of HOs by 84.8% in the comparison with baseline.

NOMENCLATURE

Abbreviations

3D	Three-dimensional
A2A	Air to Air
A2G	Air to Ground
AI	Artificial Intelligence
AP	Access Point
BER	Bit Error Rate
BS	Base Station
CDMA	Code-division Multiple Access
CU	Control Unit
DRL	Deep Reinforcement Learning
EE	Energy Efficiency
ETSI	European Telecommunications Standards Institute
FIS	Fuzzy Inference System
G2G	Ground-to-ground
HAP	High Altitude Platform
HetNet	Heterogeneous Network
HO	Handover
HOM	Handover Margin
IoT	Internet of Things
ISAC	Integrated Sensing and Communication
LAP	Low Altitude Platform
LoS	Line-of-Sight
MARL	Multi-Agent Reinforcement Learning

MCDM Multi-criteria Decision-making
MDP Markov Decision Process
MEC Multi-access Edge Computing
mMTC massive Machine-type Communication
MSB Macro Base Station
NIS Negative Ideal Solution
NLoS None Line-of-Sight
PIS Positive Ideal Solution
PPP Poisson Point Process
QL Q-learning
QoS Quality of Service
RAT Radio Access Technology
RIS Reconfigurable Intelligent Surfaces
RL Reinforcement Learning
RSRP Reference Signal Received Power
RSS Received Signal Strength
RWM Random Waypoint Model
SBS Small Base Station
SD Standard Deviation
SINR Signal to Interference plus Noise Ratio
SIR Signal to Interference Ratio
TOPSIS Technique for Order Preference by Similarity to Idea Solution
ToS Time of Stay
TTT Time-to-trigger
UAV Unmanned Aerial Vehicles
UBS UAv Base Station
UE User Equipment
UMa-AV urban-macro with aerial vehicles
URLLC Ultra-reliable Low-latency Communication
VHO Verticle Handover

VM Virtual Machine

Parameters and Variables

α Learning Rate

α_{LoS} Path Loss Exponent for LoS

α_{NLoS} Path Loss Exponent for NLoS

η_{EE} Energy Efficiency

η_{SE} Spectral Efficiency

γ Discount Rate

κ Scale parameter of Rayleigh Distribution

λ_s Density of SBSs

λ_u Density of UBSs

$\mathbb{R}_{l,i}$ Value of the reward of BS i at waypoint l

$\mathcal{V}_k$ The Number of VMs in the MEC Server at BS k

$\mathcal{V}_k^{mig}$ Number of Tasks need to be Migrated

μ_p Mean of Criterion p

ω_d Weight of Distance

ω_{HO} Measured frequency

ω_{HO} Weight for $I(HO)$

ω_{RSRP} Weight for $RSRP_s'$

ω_{sinr} Weight of SINR

$\omega_A, \omega_B, \omega_C$ Angle between the path of UE and the UE-BS connection

σ_p Standard Deviation of Criterion p

σ_{SF} Deviation of Gaussian Distribution

σ_n Noise Power

τ Migration Time

EE^{norm} Normalized Value of EE

ToS^{norm} Normalized Value of ToS

w_p^{sd} Weight of attribute p based on SD method

θ_1 Horizontal Angle

θ_2 Vertical Angle

θ_{UE}^l	Value of direction
ε -greedy	Epsilon-Greedy policy
ς	Effective Capacitance Switch of the CPU
A^+	Positive Ideal Solution
A^-	Negative Ideal Solution
A_s	Action at State s
$\alpha_{i,p}^{norm}$	Normalized Values of Attributes
B	Bandwidth
$B_m^{k'}$	Allocated Bandwidth of UE i from BS k'
B_{ue}	Channel Bandwidth of UE
C_s	Candidate BSs Set at State s
C_i	Relative Closeness to the Ideal Solution
$C_{m,j}$	Total Number of Required CPU Cycles for Task $U_{m,j}$
$C_{m,j}^{mig}$	Size of Data need to be Migrated
d	Distance between BSs
d_{2D}	Two-dimensional Distance
d_{3d}	3D distance
$d_{k,k'}$	Distance between serving BS k and target BS k'
d_k	Performance Degradation Factor at BS k
d_{l,i_n}	Normalized 3D Distance between way-point l and BS i
$D_{m,j}$	Data Size of the Task $U_{m,j}$
E_k	Consumed Energy of BS k
E_k^{exe}	Energy Consumed in Task Execution
E_k^{mig}	Energy Consumption in Task Migration
f_c	Carrier Frequency
$F_{k,m}$	Actual Computing Capability
$f_{k,m}$	Computation Rate of UE m connected to BS k
f_k	CPU Frequency
G_1	Antenna Gains of the BS

G_2	Antenna Gains of UE
g_0	Reference Channel Power Gain
$h_{k,k'}$	Channel Power Gain between Serving BS k and Target BS k'
$h_{m,k}^{los}$	LoS Channel Gain from User m to k in Uplink
$h_{m,k}^{nlos}$	NLoS Channel Gain from User m to k in Uplink
h_{UT}	Height of UAVs
h_U	Height of UAVs
I	Interference
$I(HO)$	HO Indicator
$I(P)$	Performance Indicator
I_s	Interference of SBSs
I_u	Interference of UBSs
$I_m^{k'}$	Interference from BS k' to UE i
K	Number of BSs
K_s	Number of SBSs
K_u	Number of UAVs
L	Number of Waypoints
l_1	Start Point of Trajectory
M	Number of UEs
n	Number of Waypoints
n_0	Noise power Spectral Density
P_s	Coordination of Way-points at the State s
P_c	Receiver Circuit Power
P_k	Transmission Power from Serving BS k
P_{LoS}	Probability of a LoS
P_m	Transmission Power of UE m
P_{th}	Threshold of SINR
P_{tr}	Transmit Power of the BS
PL	Path Loss

PL_{LoS}	Path Loss of LoS Channel
PL_{NLoS}	Probability of a NLoS
$Q(s,a)$	The Q value of action a at state s
R_{BS}	Radius of the BS
R_{HO}	HO rate
r_{ij}	Normalized Performance Score
$r_{k,k'}$	Data Rate from BS k to BS k'
R_{out}	Outage rate
R_{TL}	Throughput Loss Rate
$RSRP_{s'}$	Normalized RSRP at State s'
$RSS_{k,m}$	RSS from BS k to UE m
s	Current State
s'	Next State
S_i^+	Euclidean distance from the PIS
S_i^-	Euclidean distance from the NIS
SF	Shadowing
$sinr_{l,i_n}$	Normalized SINR of BS i
T	Throughput
t	Interval of Waypoints
$T_{baseline}$	Average throughput of SINR based decision strategy
$T_{m,j}^D$	Completing Time of Task $U_{m,j}$
$T_{m,j}^E$	Execution Time of Task $U_{m,j}$
$T_{m,j}^{Tr}$	Transmission Time of Task j from UE m to BS k
$Th_{m,j}$	Time Threshold for Task $U_{m,j}$
ToS	Value of ToS
$U_{m,j}$	j th Task generated by UE m
V	Speed of UAVs
v_{ij}	Weighted Normalized Value
V_{max}	Maximum Speed

v_{UAV}	Velocity of UAVs
v_{UE}	Velocity of UEs
w_j	Weight of the j -the Criterion
X	Decision Matrix

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DECLARATION

I declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

Details of my publications as first author which has been used in this thesis are as following:

- In Chapter 3: J. Zhong, L. Zhang, J. Serugunda, P. R. Gautam and S. Mugala, "An Improved Q-Learning Based Handover Scheme in Cellular-Connected UAV Network," 2022 25th International Symposium on Wireless Personal Multimedia Communications (WPMC), Herning, Denmark, 2022, pp. 520-525.

As the lead author, the candidate developed the decision-making strategy and simulation as well as wrote the paper.

Dr. Li Zhang, my main supervisor, supervised the work, provided excellent technical advice, modified and proof-read the draft of the paper.

Dr. Jonathan Serugunda and Miss Sheila Mugala improved the ideas and the simulation.

Dr. Prabhat Raj Gautam modified the draft of the paper.

- In Chapter 4: J. Zhong, L. Zhang, M. Alhabo, J. Serugunda and S. N. Mugala, "A Hybrid Scheme Using TOPSIS and Q-Learning for Handover Decision Making in UAV Assisted Heterogeneous Network," in IEEE Access, vol. 12, pp. 31422-31430, 2024, doi: 10.1109/ACCESS.2024.3368916.

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- In Chapter 5: "Fuzzy Inference System Based Handover Scheme with Task Migration in UAV-assisted MEC," Submitted to *IEEE transactions on vehicular technology*. Co-author: Li Zhang.

As the lead author, the candidate developed the decision-making framework and simulation as well as wrote the paper.

Dr. Li Zhang, my main supervisor, supervised the work, provided technical advice, modified and proof-read the draft of the paper.

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INTRODUCTION

1.1 Background

1.1.1 UAV Communication Network

Unmanned aerial vehicles (UAV), commonly known as drones, are aircraft systems that operate without a human pilot on board. They can be remotely controlled or fly autonomously based on pre-programmed flight paths or more complex dynamic automation systems. UAVs have become increasingly popular due to their versatility, ease of deployment, and ability to perform tasks that would be difficult, dangerous, or expensive for human-piloted aircraft [1]. Normally, UAVs are equipped with several instruments for different purposes, such as cameras, sensors, radars etc.

The integration of UAVs in 5G and beyond networks emerges as a promising technology. According to [2], UAVs are increasingly adopted in 4G, 5G and future networks for both commercial and military applications. Cellular-connected UAVs and their supporting communications infrastructure are developing rapidly as evidenced by efforts of 3GPP and other industry initiatives. Many use cases that are already in place or will become reality soon, indicate the need for the further development of the ecosystem [3].

UAVs in communication network can be essential in providing low-latency communication, extended coverage, and high throughput by acting as flying base stations (BSs) or relay nodes in areas with insufficient ground infrastructure.

Specifically, in UAV communication networks, UAVs can serve as aerial BSs, relaying signals to ground users or providing communication services in remote or inaccessible areas. Also, UAV networks rely on both air to ground (A2G) channels (communication between UAVs and ground stations) and air to air (A2A) channels (communication between UAVs). However, there are many challenges faced in UAV communications, which will be described below.

1.1.1.1 Introduction

UAV networks refer to the interconnected system of UAVs that communicate with each other and ground stations to perform coordinated tasks. These networks enable UAVs to collaborate in complex missions such as surveillance, disaster relief, search and rescue, and environmental monitoring.

UAVs can also assist the current ground communication networks to enhance the performance, which is an integral part of modern wireless communication systems, especially in situations where traditional infrastructure is lacking or compromised. UAVs as aerial BSs can provide cost-effective and reliable wireless communication for cellular networks, be supported by the connectivity of the existing terrestrial cellular networks. In contrast to the terrestrial BSs, UAVs aerial BSs can adjust their altitude, avoiding obstacles and thereby improving line-of-sight (LoS) communication links with the ground users. Due to their flexibility, mobility, and adaptive altitude, UAVs aerial BS can efficiently enhance the existing cellular systems by extending the network coverage to rural areas, and providing additional capacity in high-demand hotspot locations [4].

According to [5], UAV networks often consist of multiple layers, where UAVs function as both user equipment (UE) and BSs. The A2G and A2A channels help UAVs maintain connectivity, avoid collisions, and exchange mission-critical data in real time. Meanwhile, UAVs are increasingly being used in MEC scenarios, where computational tasks are

processed closer to the data source rather than relying on distant cloud servers. In such networks, UAVs can process data in real-time, reducing latency and improving performance in time-sensitive tasks such as disaster recovery and surveillance.

1.1.1.2 Challenges of UAV Network

However, there are several challenges that arise in both cellular-connected UAV network and UAV-aided network [6, 7]. Firstly, since UAVs operate at varying altitudes and distances, managing signal interference and ensuring optimal spectrum usage is a critical challenge. Secondly, the deployment of UAVs is also a challenge, as selecting the suitable position and altitude is essential to achieve the maximum coverage and better channel quality. In addition, path planning is crucial for UAVs because appropriate path planning can help avoid collisions while meeting the service demand or energy constraints at the same time. Also, resource management is another challenge as it is necessary to obtain the optimal benefit and maintain the fairness of links. Resources such as bandwidth, coverage, space, power, etc. should be allocated reasonably to maximize benefits. Meanwhile, as the movement of UAVs and UEs, handover (HO) management are crucial to maintaining uninterrupted service. Surveys and the 3GPP releases highlight issues like HO management, security protocols, and reliable communication for both control and data links in UAV communication [8–11]. Throughout the thesis, we focus on the HO challenges in UAV communication network. Efficient HO mechanisms are required to ensure smooth transitions between different coverage areas and minimize data loss or disconnection. Furthermore, as UAVs have limited battery life, and transmitting large volumes of data between UAVs and ground stations can drain energy quickly, minimising energy consumption is important.

1.1.1.3 Scenarios of UAV Networks

UAV networks are increasingly being integrated into various communication and computing systems. The three main UAV network scenarios mentioned in the thesis are introduced below:

- **Cellular-Connected UAV Networks**

In cellular-connected UAV networks, UAVs are treated as aerial UEs within existing cellular infrastructures, such as 4G LTE or 5G networks. This enables UAVs to communicate with the cellular network, maintaining seamless connectivity as they move across different coverage areas. In this scenario, UAVs can be controlled remotely, and real-time data (such as video, sensor data) can be transmitted back to the ground. In this case, UAVs connect directly to terrestrial BSs, and they leverage existing communication protocols for both uplink and downlink transmission. Therefore, applications like surveillance and delivery services can be supported in the scenario [12].

- **UAV-Aided Communication Networks**

In UAV-aided communication networks, UAVs are not just users but serve as flying BSs or relay nodes to assist in providing communication services to ground users. These networks are essential in situations where traditional infrastructure is unavailable, damaged, or insufficient to meet user demand, such as during natural disasters, in remote areas or in mass events with large traffic demand. In this case, UAVs can provide mobile network services to areas without sufficient terrestrial coverage. UAVs can be deployed quickly in areas with limited or no communication infrastructure, making them ideal for emergency communications [13].

- **UAV-Aided Multi-access Edge Computing Networks**

In UAV-aided MEC networks, UAVs are used as mobile edge nodes to perform computation tasks closer to the data source, reducing latency and bandwidth requirements. This setup integrates UAVs into the MEC architecture, enabling them to offer adaptive coverage, enhanced LoS channels, localised computation and flexibility, thereby improving real-time performance for applications such as video analytics, IoT, and autonomous navigation, which are important for applications like rescue operations, disaster response coordination, ad-hoc communication and so on. In this case, users or devices can offload computational tasks, such as

image processing, to UAVs, which process the data locally and return the results. Meanwhile, dynamical allocation of the computational resources in the system depends on the network demand, with some tasks processed locally and others forwarded to ground-based servers [13].

Overall, UAV communication networks are a key enabler for a wide range of commercial, industrial, and defense applications. The continuous development of 5G, AI, and edge computing will further expand their capabilities, making UAV networks an essential component of future wireless communication systems.

1.1.2 Handover

As shown in Fig. 1.1, HO in wireless communication networks refers to the process of transferring an ongoing connection from one BS or access point (AP) to another. It is crucial for maintaining continuous service as mobile devices, such as smartphones or UAVs, move across coverage areas. HO ensures seamless communication without dropped calls or data loss when a user moves out of the coverage area of one BS into another [14].

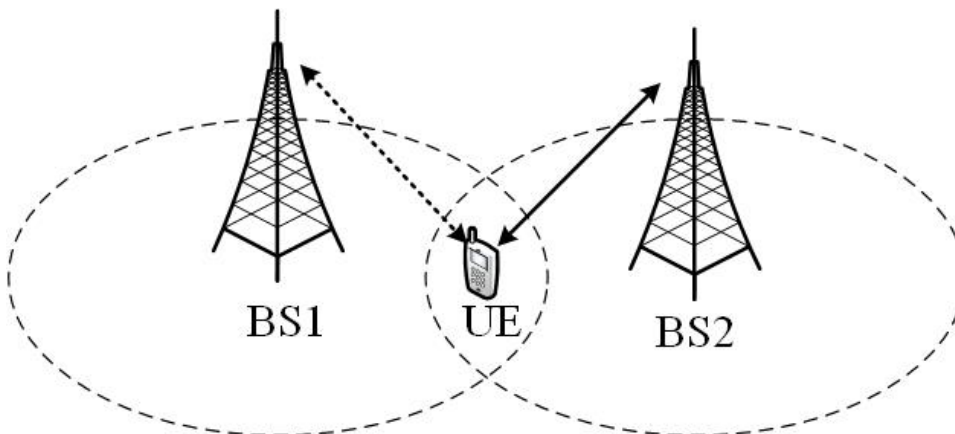


Figure 1.1: HO in wireless communication network

1.1.2.1 Types of Handover

HO can be categorized into horizontal HOs and vertical HOs based on the access technologies involved. When a mobile device switches between cells within the same technology (e.g., from one 4G cell to another 4G cell), the HO is a horizontal HO. It's a common process in cellular networks to maintain connectivity as the user moves [15]. In a cellular network, there are two types of horizontal HO: intra-cell HOs and inter-cell HOs. Intra-cell HOs only change radio channels within a cell in order to minimize the inter-channel interference. Inter-cell HOs change all the connections from the serving BS to the target BS when the UE moves between two adjacent cells [16].

Conversely, vertical HO refers to switching between different types of networks, such as from a 4G network to a Wi-Fi network or between 4G and 5G. This type of HO is essential for supporting seamless connectivity in HetNet [15]. From the network perspective, vertical handoffs can efficiently utilize the bandwidths and balance the network loads [17].

Based on the process of breaking the channels and establishing new ones, HOs can be categorized as hard HO (Break-before-make) and soft HO (Make-before-break). The difference between them is illustrated in Fig. 1.2. Hard HO is when the connection to the current BS is broken before a new connection is established with the next BS. It is common in technologies such as GSM. Though simpler to implement, it can result in brief disruptions during the switch. In this procedure, only one traffic channel is activated. There is a short disconnection on the radio channel in order to achieve the conversion of carrier frequencies. Therefore, hard HO scheme is more likely to cause call drops [16].

On the other hand, in soft HOs, a device is connected to multiple BSs simultaneously before switching entirely to a new one. This process reduces the likelihood of call drops and ensures smoother transitions, as seen in code-division multiple access (CDMA) and 3G networks. In this way, the communication service quality is greatly improved. However, soft HOs can only be applied to the same carrier frequency [16].

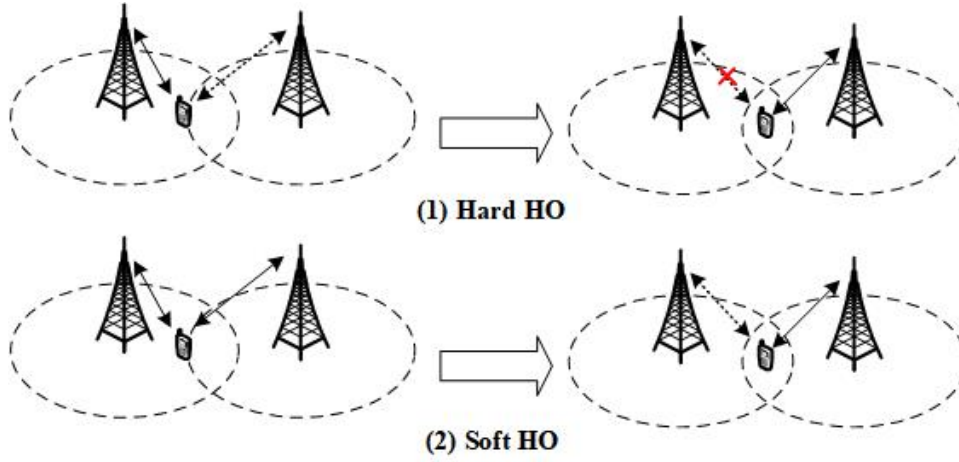


Figure 1.2: Hard and soft HOs in wireless communication network

1.1.2.2 Handover Procedure

A classical HO procedure mainly consists of the following steps [16]:

Initiation: The UE measures channel qualities, such as Received Signal Strength (RSS), Signal to Interference Ratio (SIR), distance, and Bit Error Rate (BER), etc., of different BSs. Then UE sends the report back to the serving BS.

Network selection: The serving BS forwards the measurement report to the control unit (CU), which then considers the resource availability and network load to determine the most suitable BS to maintain the connection. The HO decision-making process can be either centralized or decentralized, depending on where the decision is executed. If a HO is deemed necessary, the CU notifies the target BS to prepare for the connection and instructs the serving BS to issue HO commands to the UE.

Execution: The UE starts to set up a connection with the target BS using additional resources by operations such as authentication, synchronization, network reconfiguration, etc. Finally, the UE sends a signal to the target BS indicating the completion of the HO.

1.1.2.3 Handover Events

According to 3GPP TS 36.331 and 38.331, in cellular networks like LTE and 5G, HO events are used to manage the transition of a UE connection from a BS or cell to another. These events are standardized by the 3GPP. It is crucial to acquire proper events to

ensure smooth transitions, optimal signal quality, and minimal service disruption during HOs. The events are triggered based on signal quality measurements, such as RSRP, and they help decide when and how HO should occur [18]. In this subsection, it is an overview of the key handover events.

- **Event A1: Serving Cell becomes better than a threshold**

This event is triggered when the signal quality of the serving cell exceeds a pre-defined threshold. This event typically represents that the connection with the current serving cell is strong, and further measurements for HO are unnecessary. Thus, it helps reduce unnecessary HO measurements and stop HO procedures when the current signal strength is adequate.

- **Event A2: Serving cell becomes worse than a threshold**

This event happens when the signal quality of the serving cell falls below a certain threshold. It indicates a degradation in the current connection, prompting the system to start measuring neighboring cells to prepare for a potential HO. Additionally, it initiates HO measurements when the connection is weak, ensuring the UE does not experience a significant quality drop.

- **Event A3: Neighbor becomes better than serving cell by an offset**

This event is triggered when the signal strength of a neighboring cell exceeds that of the serving cell by a specific offset. The A3 event is often the primary HO trigger in LTE and 5G networks. It indicates that a neighboring cell offers better signal quality than the current cell, prompting the HO process. Therefore, it is used to ensure the UE moves to a stronger signal source.

- **Event A4: Neighbor becomes better than a threshold**

This event is triggered when the signal quality of a neighboring cell exceeds a certain threshold. It is used to monitor potential HO targets. If a neighboring cell's signal becomes strong enough, it is considered as a potential target cell. Thus, it

allows the system to identify suitable HO candidates even if the current connection is still acceptable.

- **Event A5: Serving cell becomes worse than one threshold, and neighbor becomes better than another threshold**

This event is triggered when the signal strength of the serving cell falls below a lower threshold while a neighboring cell's signal rises above a higher threshold. A5 event is more restrictive than A3, and it is used to ensure that HOs only occur when both the serving cell's signal is poor, and a neighboring cell offers significantly better signal quality. Usually, it is used in more aggressive HO scenarios to ensure that HOs are beneficial and only occur when there's a significant difference in signal quality between the serving and neighboring cells.

- **Event B1: Inter-RAT neighbor becomes better than a threshold**

This event is triggered when the signal quality of a neighboring cell from a different Radio Access Technology (RAT), such as Wi-Fi or 2G/3G, becomes better than a threshold. B1 event supports inter-RAT HOs, where the UE switches between different types of networks (e.g., from LTE to 3G or from LTE to Wi-Fi). Therefore, it is useful for HOs between different types of network technologies, ensuring that the UE can maintain a connection even when it moves outside the coverage area of the current RAT.

- **Event B2: Serving becomes worse than a threshold, and inter-RAT neighbor becomes better than another threshold**

This event is triggered when the signal of the serving cell falls below a threshold, and a neighboring cell from another RAT exceeds a higher threshold. It helps manage inter-RAT HOs when the current serving cell's signal is getting worse, and a neighboring cell from a different RAT provides better connectivity. Thus, it is also used for inter-RAT HOs, ensuring that the UE seamlessly switches between different network technologies when the current cell becomes weak.

1.1.2.4 Measurement Parameters for HO Decisions

Here are some criteria can be considered listed in this section [17].

- **Reference Signal Received Power (RSRP):** RSRP is the average power of Resource Elements that carry cell specific Reference Signals over the entire bandwidth. It can measure the signal power from a specific sector well.
- **Signal to Interference plus Noise Ratio (SINR):** It is a value to judge the communication quality of channel. It involves not only the RSS, but the interference from other links and the background noise.
- **UE speed and UE direction:** UE speed and direction can be used to measure the sojourn time in a cell. If the speed is so fast and the direction is away from target cell, then these two variables can affect the HO decision and avoid some unnecessary HOs.
- **Load of Cells:** HO decision should be affected if the serving BS or the target BS is overloaded.

1.1.2.5 Handover Parameters

For the HO management in cellular networks, Handover Margin (HOM) and Time-to-Trigger (TTT) are critical parameters to decide when a HO is initiated. Both HOM and TTT are essential in balancing the trade-off between HO frequency and connection quality. A high HOM and long TTT will result in fewer HOs but might cause the UE to stay connected to a weaker BS for longer. Conversely, a low HOM and short TTT will result in faster HOs but might lead to more frequent and potentially unnecessary HOs, increasing signaling overhead. Fig. 1.3 is the illustration of HOM and TTT in HO triggering, and the introduction of these parameters is below.

- The HOM is a threshold or offset used to compare the signal strength of the serving BS and a neighboring BS. It ensures that the neighboring BS's signal is sufficiently stronger than the current serving BS before a HO is triggered. HOM can help

prevent ping-pong HOs, where a UE rapidly switches back and forth between two BSs due to the fluctuations in RSS. By adding an offset to the comparison, it requires the signal from the neighboring BS to be significantly better before initiating a HO, thus avoiding unnecessary HOs [19].

- TTT is a time threshold that specifies how long a certain condition must maintain before a HO is triggered. TTT helps to prevent unnecessary HOs by ensuring that the signal strength conditions are stable over a specific period. If the condition, such as a neighboring BS's signal is stronger, holds for the entire duration of the TTT, the HO is initiated. If the condition fluctuates or changes during the TTT period, the timer resets and no HO occurs [19].

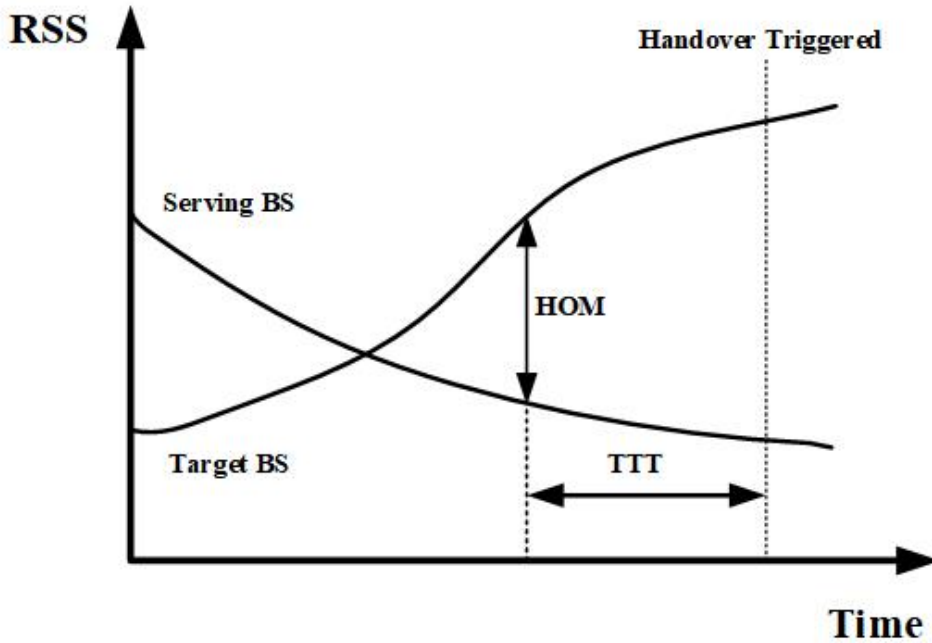


Figure 1.3: HOM and TTT in HO triggering

1.1.3 Handover Decision-Making Process

HO decision-making is a fundamental process to determine the target BS and when and where to trigger HO. It is crucial for managing user mobility and maintaining consistent

and reliable network service. Various HO events, criteria and parameters mentioned above are combined into the HO decision-making process. For instance, modern HO decision-making often does not rely solely on one parameter, where parameters like RSRP, SINR, and even resource load are considered together. Moreover, thresholds and hysteresis margins are set to avoid unnecessary HOs (ping-pong effects). Due to the high mobility and dynamic topology changes, dynamic and context-aware HO decision-making strategies are necessary.

The primary goal of HO decision-making is to maintain a continuous connection for users as they move through different network coverage areas. A well-timed HO ensures that users experience no noticeable interruptions in ongoing calls, data sessions, or other services, providing a seamless communication experience [20].

QoS can be maintained through effective HO decisions. Maintaining high QoS is essential in modern communication networks. Poor HO decisions can result in dropped calls, data packet loss, or degraded service quality. By making intelligent and timely HO decisions based on factors like RSS, SINR, and network load, the network can deliver optimal QoS, ensuring that users receive consistent and reliable service [11].

Additionally, HO decision-making plays a crucial role in resource allocation and network load balancing. By intelligently selecting the target BS or AP, the network can distribute traffic more evenly, preventing congestion in heavily loaded cells and optimizing the use of available resources. This leads to better network performance and more efficient use of spectrum and infrastructure [21].

Furthermore, in densely populated networks, interference from neighboring cells or BSs can significantly impact communication quality. Effective HO strategies help in minimizing interference by selecting the best possible target BS with the least interference, thereby improving the overall network throughput [22].

Also, in scenarios involving high mobility, such as users in vehicles or UAVs, frequent HOs are inevitable. Proper HO decision-making ensures that these transitions are managed efficiently, minimizing the risk of disconnections or degraded performance. This is especially important in applications like autonomous vehicles, UAV networks, and

high-speed rail systems, where reliable connectivity is crucial [23].

HO decisions can also be important in HetNets, where different types of cells (macro, micro, femto, and UAVs) coexist, and HOs are usually vertical HO. In this case, HO decision-making becomes even more complex. Intelligent HO mechanisms are required to manage transitions between different network layers, ensuring seamless connectivity and optimal resource utilization across diverse network architectures [11, 17, 20].

Meanwhile, energy efficiency (EE) can be also considered in HO decisions, as in mobile and UAV networks, power consumption is a significant concern. Frequent and unnecessary HOs can lead to increased signaling overhead and energy consumption. Intelligent HO decision-making can reduce the number of HOs, thereby conserving energy for both the network and the UE [11].

Therefore, HO decision-making is critical to the performance and reliability of modern communication networks. It directly impacts user experience, network efficiency, and overall service quality. As networks become more complex with the integration of technologies like 5G, internet of things (IoT), and UAVs, the importance of advanced HO decision-making algorithms continues to grow. These algorithms must account for various factors such as signal quality, user mobility, network load, and computing resource to provide seamless, high-quality connectivity in an network landscape.

1.2 Handover challenges in UAV networks

In UAV networks, HO is critical to maintaining seamless communication in both cellular-connected UAV scenarios and UAV-aided MEC deployments. However, compared to terrestrial networks, HO in UAV networks introduces additional unique challenges due to high mobility, dynamic topology, and 3D movement. To present these, the challenges can be categorised into common HO challenges and UAV additional challenges. Here is some common HO challenges below.

- **Frequent Handover:** High-speed mobility and densely distributed cells lead to more frequent HO events. UAVs rapidly transit across the coverage areas of

different BSs, increasing the probability of HO failures, service interruptions, and higher signalling overhead [24].

- **Latency and Handover Delay:** HO procedures introduce signalling and execution delays. For UAVs engaged in real-time tasks, minimizing HO-induced latency is crucial to maintaining QoS and operational integrity [25].
- **Handover Decision Criteria:** Conventional HO decisions based primarily on RSS are insufficient. UAVs require multi-metric HO decision-making (e.g., considering SINR, user load, distance to BS, and predicted trajectory) to ensure connectivity in various environments.
- **Interference Management:** Interference from neighbouring BSs, terrestrial UEs, and other UAVs can degrade signal quality, leading to unnecessary or failed HOs. Effective interference-aware HO strategies are essential, particularly in dense urban or emergency deployments [26].
- **Energy Constraints:** Frequent HOs increase signalling energy consumption, reducing the limited operational endurance of UAVs, especially when they simultaneously perform edge computing or relay tasks [27].

There are also some additional challenges for UAV networks:

- **Limited Coverage of Ground Base Stations:**

Ground BSs are typically optimised for serving terrestrial users, meaning their antennas are often tilted downwards. UAVs flying at higher altitudes may only be served by the side lobes of these antennas, which provide weaker signals compared to the main lobe. Additionally, the weak coverage from the side lobes may cause unnecessary or premature HOs as the UAV switches between BSs with suboptimal signal strength [28].

- **Line-of-Sight Dominance and Interference:**

In UAV networks, the A2G communication channel often experiences a high probability of LoS due to the altitude of the UAVs and the absence of obstacles. While LoS is usually beneficial for strong signal quality, it also leads to increased interference from neighbouring BSs and other UAVs, especially in dense environments. LoS dominance can cause UAVs to receive strong signals from multiple BSs, which may lead to confusion in HO decisions and potentially result in ping-pong effects, where the UAV frequently switches back and forth between BSs [24, 26].

- **Vertical Handover in Heterogeneous Networks:** UAVs frequently operate across heterogeneous network environments, involving transitions between macro cells (MBSs), small cells (SBSs), and UAV-mounted BSs (UBSs). Managing vertical HOs across layers with differing backhaul capabilities, coverage radii, and latency characteristics adds further complexity [29].
- **Three-Dimensional Mobility and Dynamic Topology:** UAVs' movement is not limited to a two-dimensional plane, leading to highly dynamic and unpredictable topology changes. Existing terrestrial HO algorithms are poorly suited to account for 3D mobility patterns, complicating the maintenance of stable links.

Overall, HO in UAV communication networks is a more complex and dynamic process than in terrestrial networks, primarily due to the mobility, altitude, and coverage challenges caused by UAVs. To address these challenges, advanced HO decision-making algorithms that incorporate AI, predictive modelling, and edge computing are being explored to optimize HO decisions and improve communication reliability in UAV networks.

1.3 Literature Review

Proper HO decisions can enhance the performance in various UAV networks. In this subsection, the related works that proposing the HO decision-making schemes for cellular-connected UAV networks, UAV aided HetNet, and UAV aided MEC are reviewed.

- **Existing Works in Cellular-connected UAV Networks**

HO decision-making in cellular-connected UAV networks involves the process of transitioning UAVs between different BSs as they move through various coverage areas within a cellular network. Given the high mobility and unique characteristics of UAVs, this process is more complex than in traditional ground UE scenarios. Effective HO decision-making is crucial for maintaining reliable connectivity, optimizing network resources, and ensuring the QoS for UAV operations. Some schemes defined the conditions of HO trigger, such as the authors of [30] proposed an enhanced HO scheme for cellular-connected UAVs. Specifically, this scheme considers the unnecessary HOs occur as the UAV can detect multiple cells with the comparable RSRP levels, and both the UAV navigating at a certain altitude and taking off are involved. In the scheme, the HO event trigger parameters are dynamically adjusted to avoid a UAV to HO from a cell to another cell with a comparable RSRP level. Furthermore, the author exploited the flight path or trajectory information to design an enhanced mobility management scheme to support reliable drone communication in [31]. They proposed a route-aware HO algorithm for drones, where the network will trigger HO based on the flight path information and estimate of the wireless signal environment to minimize HO failure rate and reduce unnecessary HO. Moreover, the authors of [32] proposed a flight direction-based HO scheme to reduce the HO rate. When the A3 event triggering condition is met during TTT, the LSTM network is adopted to predict the future values of the RSRP. Then, the change rate in RSRP and the RSRP threshold, which reflect the flight direction, are used to make the HO decision. Meanwhile, there are also some HO decision-making schemes based on reinforcement learning (RL) proposed in works. A RL based HO optimization mechanism for a cellular-connected UAVs system is proposed in [33]. In the algorithm, the state is the combination of current position and current serving BS, the action consists of the list of potential target BSs, and the reward equation is related to the RSRP and HO cost indicator $I(HO)$. A complete Q table for a specific trajectory is generated after sufficient iterations, which

can make HO decisions that lead to a reduced number of HO. In addition, a deep RL (DRL) driven UAV HO decision scheme for seamless communication in a 3D environment is proposed in [34]. In particular, the proposed DRL framework with a Proximal Policy Optimization algorithm successfully achieved a tradeoff between signal strength and HO frequency. In [35], the authors have used Q-learning (QL) algorithm for HO decision making mechanism to achieve robust UAV connectivity in a cellular-connected UAV network. They take into account the impact of cells deployment for Rural, Semi-rural and Urban scenarios. Also, the impact of the decision distance, where the drone has the choice to make a switching decision on the number of HOs, is considered in the scheme.

From the reviewed works, RL-based schemes can optimise the HO decision-making in cellular-connected UAV networks. However, interference, which is suffered more seriously in UAV networks, is not incorporated in these RL-based schemes. Additionally, HO rate can be further reduced by improving the existed schemes.

- **Existing Works in UAV-aided HetNet**

HO decision-making in UAV-aided HetNets involves managing the transition of communication and services between different types of network layers, such as MBS, small BSs, and UAV BSs. In these complex environments, UAVs act as flexible network nodes that provide additional coverage, capacity, which helps to address the limitations of traditional ground-based networks. Proper HO decision-making in this context is crucial for ensuring seamless connectivity, optimal resource utilization, and enhanced QoS. In [36], an optimization method is proposed to achieve efficient SDN-based network management and fast HOs in UAV networks. The main goal of this article is to present a hybrid UAV selection scheme designed with game theory method for verticle HO (VHO) management based on UAV-aided wireless communications. In this work, the network selection mechanism during VHO process is determined as the multiobjective optimization problem to enhance the communication of the heterogeneous wireless networks. In [37], the

author proposed a UAV-aided network model that considers the advantages and disadvantages of HO procedures. The study concluded that UAVs should employ directive antenna systems, fly at low altitudes, and maintain slower speeds.

However, there is limited research focusing on optimizing HO decision-making in UAV-aided HetNets. Overall, as UAVs are widely used in HetNets and limited works about HO decision-making problems in UAV-aided HetNet, it is necessary to propose a proper HO decision-making scheme for it. Specifically, frequent HO brought by dense cells and mobility UAVs is crucial to be optimised.

- **Existing Works in UAV-aided MEC Networks**

HO decision-making in UAV-aided MEC is a complex process that integrates the unique characteristics of UAV networks with the edge computing paradigm. This integration is crucial in scenarios where UAVs serve as mobile edge nodes, providing computing resources and maintaining communication links for ground UE. In such networks, efficient HO decision-making is essential to ensure seamless connectivity, optimized computing resource allocation, and improved QoS. However, there are few research works about HO decision-making schemes in UAV-aided MEC networks. So only some HO decisions related works for MEC are reviewed below. A HO decision algorithm is proposed in [38] to improve the successful rate of offloading and reduce the HO failure rate and migration cost. This algorithm addresses both mobility management and radio congestion while considering user priority. Additionally, [39] studied the issue of MEC HO in 5G and proposed a HO algorithm considering both network signal strength and MEC server load. The results illustrated the improvement of the end-to-end delay in MEC scenarios. Furthermore, to maximize the long-term utility accounting for users' QoS and cost in MEC networks, a distributed mobility management approach is proposed in [40]. In this approach, game theory and user-oriented deep reinforcement learning are adopted. Moreover, the authors of [41] proposed HO-enabled double deep Q-learning algorithm to minimize the average offloading cost which consists of energy

consumption, transmission delay, and processing delay. In addition, in [42], the authors study the problem of optimal joint migration-and-HO in a multi-user multi-cell MEC system based on virtualization. The optimization problem aims at maximizing the weighted sum offloading rates of all the users while minimizing the incurred migration cost as much as possible by controlling the migration/HO decisions. Also, in [43], the authors implement and fine-tune the Parameterized Deep Q Network algorithm to optimize power consumption for edge computing and BS selection by trade-off between current SINR and HO cost. They take into account the mobility of UE among various BS coverage, the stochastic task arrival, and the channel condition uncertainty produced by the MIMO channel interference, in which parameterized action space-based DRL is suggested for optimizing the allocated power and HO for MEC.

However, few works focus on the HO decision-making problems in UAV-aided MEC. Moreover, the existed RL-based works for MEC scenarios, which are not suitable for the UAV-aided MEC with multiple UEs. Therefore, it is essential to optimise the HO decision-making for multiple UEs to handle the multiple conflicting factors, such as signal quality, task delay, and energy, must be managed simultaneously in UAV-aided MEC.

1.4 Contributions

In this thesis, the research focuses on the HO decision-making schemes for different UAV communication network scenarios. The contributions are outlined below.

- An improved RL based HO decision-making scheme for cellular-connected UAV network is proposed. The scheme is inspired by the work [33]. This work utilizes SINR as the HO criterion to identify potential target BSs. To minimize interference. To enhance the action space of the proposed QL method, we incorporated both the SINR and the distance between BSs and the UE, assigning weights to each factor to select the 10 most suitable BSs. In this way, proposed algorithm can further

reduce the HO rate by 52.9% with slightly compromising the throughput and the outage rate. Furthermore, the optimal weight combination of ω_{sinr} and ω_d is found to be $\omega_d = 4.75$ and $\omega_{sinr} = 5.25$ are suggested to achieve the best trade-off of the three performance indicators.

- To address the HO issue in ultra-dense UAV-aided HetNets, we develop a novel hybrid framework combining the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) with Q-learning (QL). TOPSIS is used to reduce the action space dimensionality by pre-selecting candidate BSs based on multi-criteria ranking (e.g., SINR, distance, load), before applying QL to optimize HO decisions. This hybrid approach has the potential to improve both performance. Thus, the number of HO and unnecessary HO is remarkably reduced by around 48.7% and 69.2% respectively, and the average EE is notably improved by around 46.1% in comparison with the baseline.
- For UAV-aided MEC, we proposed a fuzzy inference system (FIS) based algorithm for HO decision and BS selection for ground UEs. In the HO decision-making process, four criteria related to both the communication and edge computing are considered to determine when a HO should be triggered. Another two-layer FIS system is proposed to select the target BSs for UEs if the HOs are triggered. The modules of first layer can obtain the fuzzy results to rank BSs in the second layer by considering five criteria. Furthermore, task migration is incorporated into the BS selection algorithm in the second layer by evaluating the distance between the serving BS and the target BS after HOs are triggered to improve the performance of edge computing services. Thus, the proposed HO scheme reduces task completion time by 38.6%, increases the number of successful tasks by 74.1%, and reduces the energy consumption by 95.6%, while also reduces the number of HOs by 84.8% in the comparison with baseline.

1.5 Thesis structure

The thesis is focused on HO decision-making problem in UAV networks. In line with this theme, the content of each chapter is listed below.

- Chapter 1 provides an overview of UAVs and HO, outlines the challenges associated with HO in UAV networks, and discusses the research problem along with an literature review. Finally, the main research contributions of the thesis are presented.
- Chapter 2 introduces the methodologies for HO decision-making discussed in the thesis, specifically TOPSIS, QL, and FIS.
- Chapter 3 proposes an improved RL based HO decision-making scheme which is proposed to decrease the HO rate and achieve the optimal trade-off among the performance of HO rate, outage rate and throughput.
- Chapter 4 focuses on the HO decision-making problem in UAV-aided HetNet. A hybrid scheme adopting TOPSIS and QL is proposed with the aims to reduce number of HO and improve energy efficiency.
- Chapter 5 investigates the problem of HO decision-making considering both communication services and edge computing services in UAV-aided MEC. An FIS based algorithm for HO decision and BS selection involving task migration is proposed in this chapter.
- Chapter 6 concludes the thesis. The main findings and contributions are summarised in this chapter. Additionally, the reflections and suggestions for future work are provided.

1.6 List of Publications

- J. Zhong, L. Zhang, J. Serugunda, P. R. Gautam and S. Mugala, "An Improved Q-Learning Based Handover Scheme in Cellular-Connected UAV Network," 2022

25th International Symposium on Wireless Personal Multimedia Communications (WPMC), Herning, Denmark, 2022, pp. 520-525.

- J. Zhong, L. Zhang, M. Alhabo, J. Serugunda and S. N. Mugala, "A Hybrid Scheme Using TOPSIS and Q-Learning for Handover Decision Making in UAV Assisted Heterogeneous Network," in IEEE Access, vol. 12, pp. 31422-31430, 2024, doi: 10.1109/ACCESS.2024.3368916.
- J. Zhong and L. Zhang, "Fuzzy Inference System Based Handover Scheme in UAV-Assisted MEC Network," 2024 11th International Conference on Wireless Networks and Mobile Communications (WINCOM), Leeds, United Kingdom, 2024, pp. 1-6.
- J. Zhong and L. Zhang, "Fuzzy Inference System Based Handover Scheme with Task Migration in UAV-assisted MEC," IEEE transactions on vehicular technology (Submitted).

FUNDAMENTALS OF APPLIED METHODOLOGIES

As introduced in chapter 1, the HO decision-making is the main research problem in this thesis. TOPSIS is first applied to efficiently rank candidate base stations by aggregating multiple conflicting criteria such as RSS, interference, and load, thereby reducing the complexity of the decision space. Q-learning is then used to adaptively optimise HO decisions based on long-term communication quality and system performance, enabling the UAVs to learn from dynamic environments. To further enhance HO decisions strategies under uncertain and imprecise network conditions, an FIS is employed to model uncertainties and support flexible decision-making. In this chapter, these three methods, which are applied in the proposed HO decision-making schemes in various UAV network scenarios, are introduced.

2.1 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

Multi-criteria decision-making (MCDM) is concerned with structuring and solving decision and planning problems involving multiple criteria [44]. TOPSIS is an MCDM method used to identify the best option among a set of alternatives. It was originally

developed by Hwang and Yoon in 1981 [45], based on the concept that the optimal choice should have the shortest distance from the positive ideal solution (PIS) and the farthest distance from the negative ideal solution (NIS). TOPSIS is widely applied in various fields such as engineering, economics, and resource management, where decision-makers need to evaluate and rank alternatives based on multiple, often conflicting criteria.

There are some common characteristics in MCDM problems, such as the presence of multiple non-commensurable and conflicting criteria, different units of measurement among the criteria, and the presence of disparate alternatives. All of the criteria in an MCDM problem can be classified into two categories. Criteria that are to be maximized are benefit criteria. In contrast, criteria that are to be minimized fall into the cost criteria category [46]. Here are the steps of TOPSIS [47]:

- **Construct the Decision Matrix:**

Formulate a decision matrix X with alternatives as rows and criteria as columns. Each cell represents the performance score of an alternative under a specific criterion.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (2.1)$$

In this matrix, m and n is the maximum number of alternatives and criteria respectively, and the x represents a specific criterion value of a specific alternative.

- **Normalize the Decision Matrix:**

Normalize the decision matrix to transform different criteria into a comparable scale. This is typically done using vector normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}}, i = 1, \dots, m; j = 1, \dots, n, \quad (2.2)$$

2.1. TECHNIQUE FOR ORDER PREFERENCE BY SIMILARITY TO IDEAL SOLUTION (TOPSIS)

where r_{ij} is the normalized performance score of x_{ij} , and x_{ij} is j -th criterion value of i -th alternative.

- **Calculate the Weighted Normalized Decision Matrix:**

Assign weights to each criterion based on their relative importance. Multiply each element of the normalized decision matrix by the corresponding criterion weight to obtain the weighted normalized matrix:

$$v_{ij} = w_j \times r_{ij} \quad (2.3)$$

where v_{ij} is the weighted normalized value of j -th criterion of i -th alternative, and w_j is the weight of the j -th criterion.

- **Determine the positive ideal solution (PIS) and negative ideal solution (NIS):**

The PIS is a hypothetical solution that has the best performance in every criterion. It represents an ideal scenario where each criterion achieves its maximum or minimum possible value, which depends on whether the criterion is benefit or cost, considering the decision-maker's objectives. In mathematical terms, PIS is composed of the maximum values for benefit criteria and minimum values for cost criteria. The NIS, on the other hand, is a hypothetical solution that has the worst performance in every criterion. It represents an undesirable scenario where each criterion achieves its minimum possible value. NIS consists of the minimum values for benefit criteria and maximum values for cost criteria. Here identifies the PIS A^+ and NIS A^- :

$$A^+ = \{\max(v_{ij})|j \in J_1; \min(v_{ij})|j \in J_2\} \quad (2.4)$$

$$A^- = \{\min(v_{ij})|j \in J_1; \max(v_{ij})|j \in J_2\} \quad (2.5)$$

where J_1 and J_2 are sets of benefit and cost criteria, respectively.

- **Calculate the Euclidean Distance:**

TOPSIS measures the Euclidean distance of each alternative from both the PIS and the NIS. The alternative closest to the PIS and farthest from the NIS is considered the most preferred option. The distance calculation helps to understand how each alternative performs relative to the best and worst possible scenarios. Compute the Euclidean distance of each alternative from the PIS and NIS:

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - A_j^+)^2} \quad (2.6)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - A_j^-)^2} \quad (2.7)$$

- **Calculate the Relative Closeness to the Ideal Solution:**

Determine the relative closeness C_i of each alternative to the PIS:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (2.8)$$

The value of C_i ranges between 0 and 1. The alternative with the highest C_i value is considered the best choice.

- **Rank the Alternatives:**

Rank the alternatives based on their C_i values in descending order. The alternative with the highest relative closeness to the ideal solution is the most preferred option.

TOPSIS is straightforward to understand and apply, making it accessible for decision-makers without advanced mathematical knowledge. Moreover, TOPSIS can handle both benefit and cost criteria and is applicable to a wide range of decision-making problems [48]. Therefore, by considering both the best and worst possible scenarios, TOPSIS provides a balanced evaluation of alternatives.

2.2 Reinforcement Learning

2.2.1 Introduction

RL is a learning algorithm that focuses on solving various sequential decision-making problems. It operates based on a trial-and-error procedure [49]. This approach can be described using a Markov Decision Process (MDP) characterized by the tuple (S, A, P, R) [33]. MDP problems can be effectively addressed by RL, offering low complexity solutions without requiring prior information [50]. The key components of reinforcement learning are outlined below:

- **Agent:** Main subject of the system, and it selects actions according to the state following the policy.
- **State (S):** A set of the description of the environment.
- **Action (A):** A set of options that agents can select in every state.
- **Environment:** Obey a certain law to give feedback to the agent.
- **Probability (P):** A set of probabilities of an agent that takes an action in any state to move to another state.
- **Reward (R):** Given by the environment after the subject takes a certain action in a certain state and transfers to another state.

Fig 2.1 illustrates the relationship between these elements. As shown in the figure, the RL procedure involves an agent taking actions to alter its state based on received rewards while interacting with the environment. Through trial and error, RL algorithms can solve problems such as optimal control by maximizing a specific performance index associated with the behavior of the controlled system.

Policies guide the agent in selecting actions in a given state. A policy serves as a recommendation for the agent to take the most suitable action [51]. Each decision involves a trade-off between exploration and exploitation. During exploration, the agent

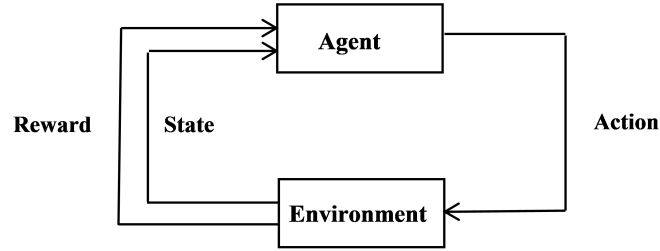


Figure 2.1: The interaction between one single agent and the environment

improves its estimation of action values, leading to more informed decisions in future exploitation phases. In contrast, exploitation involves choosing the action with the highest estimated reward based on current knowledge. This balance is known as the exploration-exploitation dilemma. An effective policy is designed to find the appropriate ratio between exploration and exploitation [51].

One commonly used policy is the Epsilon-Greedy (ε -greedy) policy. It provides a straightforward method to balance exploration and exploitation by making decisions at random [52]. Here, ε represents a probability: the agent chooses to explore with probability ε and chooses to exploit with probability $1 - \varepsilon$. However, maintaining a fixed ε throughout the learning process cannot be optimal, as excessive exploration in later stages may prevent convergence, while insufficient exploration early on can cause the agent to miss better policies. To enhance the policy, a time-varying ε -greedy policy is proposed, where ε decreases gradually over time. Typically, ε is initialized at a relatively high value (e.g., $\varepsilon_0 = 1$) and decays according to a predefined schedule. A common model is the exponential decay:

$$\varepsilon(t) = \varepsilon_0 \times \gamma^t, \quad (2.9)$$

where ε_0 is the initial exploration rate, $\gamma^t \in (0, 1)$ is the decay factor, and t denotes the learning episode or time step. The main idea is to explore more during the early stages and to exploit more in later stages. Therefore, as learning progresses and the agent gains more reliable estimates of action values, ε is progressively reduced, more exploitation of the learned optimal policy, which improving convergence speed and final policy quality.

2.2.2 Discrete Multi-step Decision Algorithm

For multi-step decision problems, the main thing to do is to estimate and calculate the pros and cons of the actions that can be selected in the state corresponding to each step of the decision. The estimate results will be saved in state-action value function space (Q table). Initially, the agent generates an estimate of the Q table, and then in the following process of training, Q table is updated according to the previous result until the optimal Q table is obtained.

QL is a type of model-free RL algorithm. It obtains the optimal Q table for the given MDP. Model-free algorithm can solve the problem when mathematical model does not exist [50]. In QL, an agent selects an action at the current state (s) following a certain policy, then it moves to the next state (s'). After this, the reward of s' and the optimal action value function are acquired to update the Q value of s . The algorithm is depicted in Algorithm 2.1. The new Q value is calculated by the optimal action value function, which is Bellman's Equation [50]:

$$Q(s, a) \leftarrow Q(s, a) + \alpha \left[r + \gamma \max_{a'} Q(s', a') - Q(s, a) \right] \quad (2.10)$$

where α is the learning rate and γ is the discount rate. The action of s' is selected randomly, which means it does not follow the policy, therefore, QL is a kind of off-policy algorithm.

2.3 Fuzzy Inference System

2.3.1 Introduction

In decision-making processes, FIS is applied for the applications that involve uncertainty and imprecision. It helps in aggregating various criteria to reach a decision. A FIS is a computational framework that utilizes fuzzy logic to model complex systems where uncertainty, ambiguity, and imprecision are present. Unlike traditional binary logic, which requires precise inputs, fuzzy logic allows for reasoning with approximate values,

Algorithm 2.1 Q-learning

```

1: Initialize Q-values  $Q(s, a)$  arbitrarily for all states  $s \in S$  and actions  $a \in A$ 
2: Set the learning rate  $\alpha \in (0, 1)$ 
3: Set the discount factor  $\gamma \in (0, 1)$ 
4: Set exploration rate  $\epsilon \in (0, 1)$ 
5: for each episode do
6:   Initialize the starting state  $s$ 
7:   while state  $s$  is not terminal do
8:     Choose action  $a$  from state  $s$  using  $\epsilon$ -greedy policy:
9:       With probability  $\epsilon$ , select a random action
10:      Otherwise, select  $a = \arg\max_a Q(s, a)$ 
11:      Take action  $a$  and observe reward  $r$  and next state  $s'$ 
12:      Update Q-value using the update rule:
13:         $Q(s, a) \leftarrow Q(s, a) + \alpha [r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$ 
14:      Set  $s \leftarrow s'$ 
15:   end while
16: end for

```

making FIS especially useful in scenarios where human decision-making and natural language processing are involved [53]. FIS is widely used in various fields such as control systems, decision-making, pattern recognition, and AI.

There are two types of FIS: Mamdani and Sugeno [54]. The most commonly used FIS is Mamdani, especially in control systems. It uses fuzzy sets for both inputs and outputs and applies fuzzy operations (AND, OR) on the rules to generate a fuzzy output, which is then defuzzified to obtain a crisp result. Mamdani FIS is intuitive and easy to understand, making it suitable for applications that require interpretability. On the other hand, in the Sugeno method, the output of each rule is a linear function of the input variables rather than a fuzzy set. The final output is a weighted average of each rule's output. Sugeno FIS is computationally efficient and well-suited for optimization and adaptive control scenarios.

However, there are some limitations of FIS. Firstly, as the number of inputs increases, the number of fuzzy rules can grow exponentially, making the system complex and difficult to manage. Then, the defuzzification could be sensitive. The choice of defuzzification method can significantly impact the output, and selecting the appropriate method may require domain-specific knowledge. Finally, tuning and optimization are difficult.

Designing and tuning membership functions and fuzzy rules require expert knowledge and may involve trial and error.

2.3.2 FIS process

The FIS process involves evaluating the input values against the fuzzy rules to derive an output. This process typically involves several steps [55]:

- **Fuzzification:**

In fuzzy logic, variables are described using fuzzy sets, which represent ranges of values rather than precise points. FIS uses linguistic variables to describe inputs and outputs in human-readable terms. For example, a temperature variable might have fuzzy sets like "cold," "warm," and "hot," each associated with a membership function. Each element in a fuzzy set has a degree of membership, typically ranging from 0 (not a member) to 1 (full member). Additionally, degree of membership, which is also membership value, is generated by mapping the input values in membership functions. Common shapes of the functions include triangular, trapezoidal, and Gaussian functions.

In this step, crisp input values are converted into fuzzy values using membership functions. The fuzzy values are the elements of a fuzzy set.

- **Rule Evaluation:**

The core of an FIS consists of a set of fuzzy IF-THEN rules that describe the relationship between inputs and outputs. Each rule has the form:

IF < condition > THEN < conclusion >

For example, a simple rule might be: *IF* temperature is "hot" *THEN* fan speed is "high". When there are more than one conditions, the operator between the conditions can be "and", "or", and "not", etc.. These rules are combined to form the rule base of the FIS.

In this step, fuzzy rules are applied to the fuzzified inputs to assess the degree of satisfaction for each rule. Subsequently, the results of all rules are combined to produce a fuzzy output.

- **Defuzzification:**

Convert the fuzzy output back into a crisp value with the output membership function, often using methods like the centroid or maximum membership method.

FIS offers a powerful tool for modeling complex systems where traditional binary logic fails to capture the nuances of human reasoning and decision-making. By handling uncertainty and imprecision, FIS provides a flexible and intuitive approach to solving problems across various domains, including control systems, decision-making, and AI. Its ability to incorporate human-like reasoning makes it particularly valuable in applications where interpretability and adaptability are essential.

2.4 Summary

In this chapter, three methods that are adopted in the HO decision-making in UAV networks in this thesis are described, which are TOPSIS, QL and FIS. Specifically, TOPSIS is a widely used MCDM method that helps decision-makers rank alternatives based on their proximity to an ideal solution. By considering both the best and worst possible scenarios, TOPSIS provides a holistic approach to decision-making, making it applicable to various fields and complex decision problems. Moreover, QL is a fundamental reinforcement learning algorithm that offers a simple yet powerful approach to solving sequential decision-making problems. By leveraging a trial-and-error learning process, QL enables an agent to interact with an environment, explore various actions, and learn an optimal policy that maximizes cumulative rewards over time. The use of Q-table to store and update the expected utility of state-action pairs allows it to handle complex problems without requiring a model of the environment. Furthermore, with its intuitive nature and its closeness to the natural languages, FIS offers significant advantages over

conventional approaches in the design, development, and implementation of various systems and applications. Fuzzy logic can not only reduce development time, but also optimize efficiency and performance in Non-linear systems, time-variant systems, expert systems, systems that are difficult to model, human interface systems are examples of systems [55].

AN IMPROVED Q-LEARNING BASED HANDOVER SCHEME IN CELLULAR-CONNECTED UAV NETWORK

3.1 Introduction

As discussed in Chapter 1, UAVs are increasingly employed across various industries, such as surveillance and delivery services, due to their high agility and ability to maneuver quickly in three-dimensional space with adjustable altitude [56]. These capabilities make UAVs suitable for enhancing service performance in direct ground-to-UAV communication, particularly when connected to cellular networks as cellular-connected UAVs. Cellular-connected UAVs provide a promising solution for integrating UAVs as aerial UEs into existing cellular networks, enabling a wide range of applications [57].

During flight, UAVs experience HOs to maintain connectivity, transferring connections from one BS to the next. HO failures can lead to interruptions and data packet loss, underscoring the need for effective HO technology. However, HO in cellular-connected UAVs presents unique challenges due to their three-dimensional mobility. Unlike ground-based UEs, UAVs are often served by the side lobes of BSs, which have lower transmission

power, as the main lobes are angled downward for ground UEs. Furthermore, UAV connections with ground BSs can experience both line-of-sight (LoS) and none line-of-sight (NLoS) air-to-ground (A2G) channels, though LoS is the main channel given the lack of obstacles at higher altitudes.

As a result, cellular-connected UAVs are easily affected by interference in both uplink and downlink communications, as they may detect strong signals from other UEs and BSs. Additionally, the high mobility of UAVs can cause frequent and potentially unnecessary HOs, increasing the risk of interruptions and packet loss. Therefore, minimizing the number of HOs while maintaining sufficient link quality is essential for ensuring stable connectivity in cellular-connected UAV networks [24].

3.1.1 Related Works and Motivations

In order to reduce the unnecessary HO, it is important to make an appropriate decision so that the UAVs can always connect to the suitable BS. This problem has attracted some attention.

In [58], the authors addresses the problem of frequent and unreliable HOs in cellular-connected UAV communications, where UAVs often rely on weak BS side lobes due to down-tilted antenna configurations, leading to degraded connectivity. To tackle this, the authors propose a fuzzy logic-based handover scheme under multi-connectivity, which allows UAVs to be simultaneously connected to multiple BSs. Unlike traditional schemes that rely solely on RSRP, this method incorporates three criteria, which are average RSRP, the rate of RSRP change, and BS load, to evaluate each BS using a fuzzy inference system and dynamically update the UAV's serving BS set. By accounting for both link quality and stability, the proposed scheme reduces HO frequency, improves link robustness, and achieves higher throughput compared to RSRP-based and load-based benchmarks, especially under practical antenna and mobility constraints. Simulations confirm its effectiveness with up to 76.7% throughput improvement and lower outage and failure rates.

Additionally, [] addresses the challenge of excessive and unnecessary HOs in cellular-

connected UAV communications, which arise due to UAVs frequently associating with weak sidelobes of down-tilted base station antennas, especially under 3D mobility. Traditional RSRP-based HO methods, such as LTE A3 events, are inadequate because they do not consider the UAV's flight direction, resulting in frequent ping-pong effects and short-lived connections. To overcome this, the authors propose a flight direction-based HO scheme that leverages the rate of change in RSRP as a proxy for UAV movement relative to BS beams. When HO is triggered, a Long Short-Term Memory (LSTM) neural network is used to predict future RSRP values of both serving and target BSs. The HO decision is then refined by comparing predicted RSRP changes and applying a threshold to suppress unnecessary HOs. Simulation results show that this approach significantly reduces HO rates by up to 91% compared to LTE, especially in dense networks and with larger antenna arrays, while sacrificing only a small amount of RSRP gain. This demonstrates the method's effectiveness in improving connectivity stability for UAVs in practical deployments.

As the HO of UAV is affected by the flight height, BS antenna gain pattern and the velocity of UAV, the BS providing the highest SINR for a UAV may not be the nearest one from the UAV; the number of detectable cells in the air is much larger than that at the ground; the high flying speed of the UAV causes the sojourn time in each cell would be very small. In [59], the author implement the experiments for UAVs HO in the LTE network, and then propose a HO trigger event parameter dynamically adjusting scheme to reduce the number of unnecessary HOs. This scheme specifically adjust the hysteresis parameter and HOM dynamically. Their experiments show that the proposed scheme can significantly reduce the number of unnecessary HOs and improve the network throughput. However, how to select the most appropriate target BS is also important, which would be their future research direction.

Apart from the interference and frequent HO brought by high mobility, UAVs in general are battery-limited, which restricts their operational lifetime. As the energy consumption of UAV remarkably depends on its velocity, the speed of UAV needs to be optimised. Meanwhile, the speed of UAV considerably influences the connectivity time

and HO rate. Therefore, RL method is used in [60], where the authors proposed a novel learning-based strategy to dynamically adjust the speed of UAVs. As a result, the strategy achieves a balance between time of mission accomplishment, energy consumption, connectivity time and HO rate.

Motivated by the growing demand for reliable and efficient mobility support for cellular-connected drones, which face distinct challenges compared to terrestrial users due to 3D mobility, frequent signal fluctuations, and coverage gaps caused by down-tilted base station antennas, another RL based HO optimization mechanism for a cellular-connected UAVs system is proposed in [33]. Traditional HO mechanisms that rely on associating with the strongest signal often result in frequent and unnecessary HOs, leading to excessive signalling overhead and potential link failures. In the algorithm of [33], the state is the combination of current position and current serving BS, the action consists of the list of potential target BSs, and the reward equation is related to the RSRP and HO cost indicator $I(HO)$. A complete Q table for a certain trajectory is generated after enough iteration, which can make HO decisions leading to reduced HO number. The simulation results have shown that the proposed approach can significantly reduce the number of HOs at the cost of decreased quality of service of the communication link.

However, interference is a more significant challenge in cellular-connected UAV networks due to the altitude factor, which was not addressed in [33]. Therefore, unlike [33], this chapter uses SINR as the primary criterion for HO to identify potential target BSs. To further reduce interference, the classic reuse-3 frequency reuse scheme is implemented. Additionally, the distance between BSs and the UE is considered to refine the action space of the algorithm, thereby reducing the number of HOs effectively. Moreover, the optimal weighting combination of SINR and distance is also suggested. Results indicate that the proposed algorithm successfully lowers the HO rate and achieves an optimal balance among HO rate, outage rate, and throughput when a suitable weighting of distance is applied to a specific trajectory.

3.1.2 Chapter Organisation

The rest of this chapter is organised as follows. System model is described in Section 3.2. The framework of the proposed RL method is introduced in Section 3.3. Section 3.4 presents the simulation results. Conclusion of this chapter is given in section 3.5.

3.2 System Model

In urban environments, it is common for antennas to be installed above rooftop levels, making the urban-macro with aerial vehicles (UMa-AV) scenario relevant here [61]. In this scenario, a UAV is assumed to travel along a predetermined trajectory in three-dimensional space within a defined area. This trajectory is generated randomly to simulate realistic movement. K BSs serving UEs are deployed at a fixed distance d from each other, which can cause interference to the UAV. Three carrier frequencies, f_{c1} , f_{c2} , f_{c3} , are utilized, with adjacent BSs operating on different frequencies to minimize interference.

As the UAV moves, it passes through the coverage areas of the K ground BSs, requiring connection HOs to maintain a reliable network link. To ensure continuous connectivity, the UAV must HO to the optimal BS as it moves. For simulation purposes, the UAV's path is discretised into multiple waypoints, each separated by a time interval t . At each waypoint, the UAV evaluates whether a HO should be triggered and selects the optimal target BS.

3.2.1 Trajectory

A fixed trajectory is applied in the proposed learning scheme, which is generated randomly. The key parameters that decide the trajectory are the start point l_1 and n waypoints along the trajectory. l_1 is generated randomly in the area, and the direction and speed of UAV are randomly picked within a certain range. The direction is decided by the horizontal angle θ_1 and the vertical angle θ_2 , where $\theta_1 \in [0, 360)$ and $\theta_2 \in [-90, 90]$. The maximum speed is V_{max} , so the speed V is randomly generated between 0 and

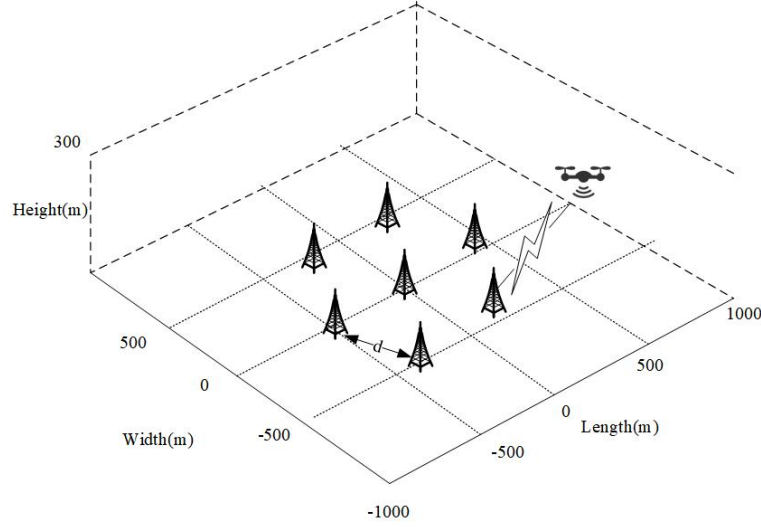


Figure 3.1: Simulation scenario.

V_{max} . After a specific interval time t , a new waypoint is generated, and all the related parameters are generated again until the waypoint l_n .

3.2.2 Propagation Model

In this chapter we only consider A2G channels, therefore the propagation is different with the conventional two-dimensional channel. As mentioned above, A2G channel could be LoS and NLoS, which have different propagation models. The probability of a LoS channel of UAV in 3D scenario at the altitude between 22.5m to 300m in UMa-AV is defined in [8]:

$$P_{LoS} = \begin{cases} 1 & d_{2D} \leq d_1 \\ \frac{d_1}{d_{2D}} + e^{\frac{-d_{2D}}{P_1}} \left(1 - \frac{d_1}{d_{2D}}\right) & d_{2D} > d_1 \end{cases}, \quad (3.1)$$

$$P_1 = 4300 \times \log_{10}(h_{UT}) - 3800, \quad (3.2)$$

$$d_1 = \max(460 \times \log_{10}(h_{UT}) - 700, 18), \quad (3.3)$$

where d_{2D} is the two-dimensional distance between the UE and the BS, $h_{UT} \in (22.5, 100]$ is the height of the current position of the UE, P_1 is the fixed baseline LoS probability when the UAV is at a very close distance ($d \leq d_1$) to the BS, and d_1 is the distance threshold between the UAV and the BS.

According to [8], if the channel is LoS, the path loss between the UE and the BS is defined as:

$$PL_{LoS} = 28.0 + 22 \times \log_{10}(d_{3d}) + 20 \times \log_{10}(f_c), \quad (3.4)$$

where d_{3d} is the 3D distance between the UE and the BS, and f_c is the carrier frequency. On the contrary, when the channel is NLoS, its path loss to BS is calculated as

$$PL_{NLoS} = -17.5 + (46 - 7 \times \log_{10}(h_{UT})) \times \log_{10}(d_{3d}) + 20 \times \log_{10}\left(\frac{40\pi f_c}{3}\right). \quad (3.5)$$

SINR is the metric used in HO decision making. To calculate the SINR, downlink interference from other BSs and RSS between UE and serving BSs should be calculated. The RSS in dBm is calculated as follows

$$RSS = P_{tr} + G_1 + G_2 - PL - SF, \quad (3.6)$$

where P_{tr} is the transmit power of the BS, G_1 and G_2 are the antenna gains of the BS and UE respectively which are both 0 in dB in this chapter, PL is the path loss, and SF is the shadowing between a BS and a UE. SF is Gaussian distribution with mean 0 and deviation σ_{SF} :

$$SF = \mathcal{N}(0, \sigma_{SF}). \quad (3.7)$$

For the LoS channel, σ_{SF} is calculated as

$$\sigma_{SF} = \max\left(4.64 \times e^{-0.0066h_{UT}}, 2\right), \quad (3.8)$$

and for NLoS channel, $\sigma_{SF} = 6$. When the UE is served by the BS i , the interference received by the UE from other BSs is expressed as

$$I = \sum_{j=1, j \neq i}^{k-1} RSS_j, \quad (3.9)$$

where $k - 1$ is the total number of interfering BSs, j represents a certain BS, and the unit of RSS_j is mW. The SINR measured when UE is served by BS i can be obtained as

$$SINR = \frac{RSS_i}{I + \sigma_n^2}, \quad (3.10)$$

where σ_n is the noise power, the calculation of σ_n in dBm is

$$\sigma_n = -174 + 10 \times \log_{10}(B), \quad (3.11)$$

where B is the bandwidth. Combining 3.10 and 3.11, the SINR calculation is represented as

$$SINR = \frac{RSS_i}{\sum_{j=1, j \neq i}^{j=k-1} RSS_j + \sigma_n^2}. \quad (3.12)$$

Throughput is a crucial indicator of the quality of link and can be expressed as

$$T = B \times \log_2(1 + SINR). \quad (3.13)$$

3.3 Improved RL-based HO Scheme

This section presents an improved RL-based HO scheme. RL is a model-free learning algorithm in which an agent takes actions to change its state based on rewards from interactions with the environment [62]. Operating on a Markov process, RL optimizes decision-making over time without requiring a predefined model of the environment. The objective of the proposed scheme is to make HO decisions at each waypoint along the UAV's trajectory. Unlike the approach in [33], this HO scheme incorporates distance as an additional parameter, enhancing the QoS of candidate BSs within the action space and reducing the overall number of HOs.

3.3.1 Q-learning Algorithm in [38]

3.3.1.1 Definition

- **State:** In the RL framework, the state consists of the UAV's current position and the currently serving BS, denoted as $S = [P_s, c_s]$. Here, P_s represents the coordinates of the UAV's position at state s , and c_s is the identifier of the current serving BS, where $c_s \in C_s$, with C_s representing the set of candidate BSs available at state s .
- **Action:** The action A_s ($A_s \in A$) at each state s is the decision to select the next serving BS for the following state s' . This choice determines the serving BS c_s as

the UAV reaches the next waypoint, and consequently, different actions lead to different subsequent states. In [33], the action space A includes BSs available for the UAV at each waypoint, which can be considered as the candidate list $C_{s'}$ for state s' .

- **Reward:** The reward function evaluates the effectiveness of different actions across various states. In this function, the key HO criterion, the RSRP, as in [33], is incorporated. To further minimize the frequency of HOs, if the current serving BS c_s remains in the candidate list of the next state s' , it increases the likelihood of the UAV staying connected to c_s . The reward equation is defined as:

$$R = -\omega_{HO} \times I(HO) + \omega_{RSRP} \times RSRP_{s'}, \quad (3.14)$$

where ω_{HO} and ω_{RSRP} are the weights for the HO indicator $I(HO)$ and the normalized RSRP of the target BS $RSRP_{s'}$, respectively. $I(HO)$ is the HO indicator, which takes a value of 1 if an HO occurs, and 0 otherwise.

3.3.1.2 Training of the QL method

The algorithm in [33] is as follow. An Q-table is firstly created and represented as Q . After a trajectory generated with L waypoints, Q with state set S and action set A is generated to store the content of Q which is the reward R for each state and action. For every state s , the action space A consists of the BSs that can be selected, which can be represented as candidate BS list. Action of state s denoted as A_s consists of k BSs ($k < K$), which are potential to be the target BS. Therefore, the size of Q is $L \times k \times k$, and the rewards of all the decisions are calculated and stored in Q at every state. After that, it is a phase of renewing the Q-table by calculating the new Q value in each episode. Specifically, Q values of every action in every state are updated by evaluate a specific action in every episode. The options of action for an agent are known as action space. The policy of selecting the action in iteration phase is Epsilon-Greedy (ϵ -greedy) Policy, which is followed in every iteration episode. At every state s , the action with higher Q

value is chosen with the probability of ϵ , and there is $1 - \epsilon$ chance to select an action randomly. Then, the Q value of the action will be updated by Bellman Equation

$$Q(s, a) \leftarrow Q(s, a) + \alpha \times [R + \gamma \times \max_{a'} Q(s', a') - Q(s, a)] \quad (3.15)$$

where α is the learning rate, γ is the discount rate, and $Q(s, a)$ is the Q value of the state s and action a stored in the current Q . After iterations, an updated Q is created, which can be followed by the UAVs to determine the sequence of HO decisions of the trajectory.

3.3.2 Improved Algorithm

As outlined in Section 3.1, interference is a significant issue in cellular-connected UAV networks due to the altitude of UAVs, which increases the likelihood of interference. High interference can degrade the QoS provided by the serving BS to UAVs and raises the probability of HOs. Consequently, the improved algorithm uses SINR instead of RSRP to better capture the impact of interference. The reward equation for the Q -table in the proposed scheme is given by:

$$R = -\omega_{HO} \times I(HO) + \omega_{SINR} \times SINR_{s'}, \quad (3.16)$$

where ω_{SINR} is the weights for $SINR_{s'}$, the normalized SINR of the target BS.

The formation of action space A in the proposed algorithm has been enhanced. In [33], A consists of the k BSs with the highest channel quality based on RSRP. This approach considers only the channel quality of candidate BSs. However, in this work, in order to reduce the number of HO, A is determined by both SINR and the distance between the BS and waypoint l . The inclusion of distance increases the likelihood of maintaining the current BS connection, thereby reducing HOs as the UAV transitions between waypoints.

To balance SINR and distance, a reward parameter $\mathbb{R}$ is introduced to determine which BSs should be included in A . The k BSs with the highest $\mathbb{R}$ are selected for A , where $\mathbb{R}$ is based on both SINR and distance:

$$\mathbb{R}_{l,i} = \omega_{sinr} \times sinr_{l,i_n} - \omega_d \times d_{l,i_n}, \quad (3.17)$$

where $\mathbb{R}_{l,i}$ represents the reward value of BS i at the waypoint l , sinr_{l,i_n} is the normalized SINR of BS i , d_{l,i_n} is the normalized distance in three-dimensional area between waypoint l and BS i , ω_{sinr} and ω_d are the weights of SINR and distance, respectively. Different weight combination of ω_{sinr} and ω_d results in different action space A , influencing each HO decision. The proposed algorithm identifies the optimal weight combination, as outlined in Algorithm 3.1. Once the action space is defined at each waypoint, the Q-value is trained according to Algorithm 3.2.

Algorithm 3.1 Formation of Action Space in improved HO scheme

```

1: Initialize input parameters:
   Waypoints  $L$ ,
   number of BS  $K$ ,
   Action Space  $A$ ,  $A \leftarrow 0_{L \times k}$ 
   Set  $\omega_d, \omega_{\text{sinr}}$ 
2: for  $l$  ( $l \in L$ ) do
3:   for BS  $i \leftarrow 1$  to  $K$  do
4:     get SINR  $\text{sinr}_{l,i}$ ,
5:     get Distance  $d_{l,i}$ 
6:   end for
7:    $\text{sinr}_{l,i}$  = Normalized SINR
8:    $d_{l,i}$  = Normalized Distance
9:   for BS  $i \leftarrow 1$  to  $K$  do
10:    Calculate  $\mathbb{R}_{l,i}$  with Equation (3.17)
11:     $\mathbb{R}_l(i) = \mathbb{R}_{l,i}$ 
12:   end for
13:    $A[l,:] = k$  BSs with best  $\mathbb{R}_{l,i}$ 
14: end for
15: return  $A$ 

```

3.4 Simulation Results

This section presents a comparison of the proposed HO scheme with the method in [33], evaluated in terms of HO rate, HO outage rate, and throughput. The performance metrics are obtained by averaging results over 100 simulations, assuming the UAV follows the same trajectory in each trial. According to [33], the ratio of ω_{HO} and ω_{SINR} influences both the HO rate and QoS. The paper reports that equal weights for ω_{HO} and

Algorithm 3.2 Q value iteration

```

1: Initialize input parameters:
   Waypoints  $L$ , number of BS  $K$ 
   Q table  $Q$ ,  $Q \leftarrow 0_{L \times k \times k}$ 
    $HO(k, k) \leftarrow 0_{k \times k}$ 
   Action Space  $A$  in Algorithm 1
   Set  $\omega_{HO}, \omega_{SINR}, \omega_d, \omega_{sinr}, \lambda, \alpha, \gamma$ 
2: for  $l$  in  $L - 1$  do
3:   for  $x = 1 : k$  do
4:     for  $y = 1 : k$  do
5:       get normalized  $SINR_s$  of  $A(l, :)$ 
6:        $Q(l, x, y) = \omega_{SINR} \times SINR_s(y)$ 
7:       if  $A(l, x) \neq A(l + 1, y)$  then
8:          $HO(x, y) = 0$ 
9:       else
10:         $HO(x, y) = 1$ 
11:      end if
12:    end for
13:  end for
14:   $Q(l, x, y)$  is calculated with equation (3.16)
15:  Reward matrix  $R = Q$ 
16:  while training  $< n$  do
17:     $j = 0$ ;
18:    for  $l$  in  $L$  do
19:      if random value  $i (i \in [0, 1]) < \epsilon$  then
20:        picked BS  $j_{new} \leftarrow \operatorname{argmax} Q(l, j, u) (u \in k)$ 
21:      else
22:         $j_{new} \leftarrow$  randomly picked from  $A(l, 1 : k)$ 
23:      end if
24:      Update  $Q(l, j, j_{new})$  with equation (3.15)
25:    end for
26:     $j = j_{new}$ 
27:  end while
28: end for
29: return  $Q$ 

```

ω_{SINR} minimize the HO rate but lead to the lowest RSRP values. According to [33], the weight ratio of ω_{HO} and ω_{SINR} can affect the results. In order to emphasis the impact of the weight combination of ω_d and ω_{sinr} in the formation of action space A, therefore, in this chapter, the ratio of ω_{HO} and ω_{SINR} in the Q-table reward function is set to $\frac{3}{7}$ to demonstrate the effects of various combinations of ω_{sinr} and ω_d .

To clearly illustrate performance trends with different weight ratios, the x-axis of all performance results represents ω_d values ranging from 0 to 10, with ω_{sinr} defined as $10 - \omega_d$. In the simulation, BSs are assumed to be deployed at intervals of 500m within a $2000m \times 2000m \times 300m$ cubic area. The simulation scenario is shown in Fig. 3.2, where asterisks indicate the ground BS locations, and the randomly generated line represents the UAV's trajectory. Simulation parameters are detailed in Table 3.1.

Table 3.1: Simulation parameters

Parameters	Values
Bandwidth (B)	10 MHz
Transmit Power (P_{tr})	44 dBm
BSs distance (D)	500m
Number of BSs (K)	19
Waypoints (L)	1000
Action Space Size (k)	5
Side length of area	2000 m
Height of area	20 m~300 m
Height of BSs	10 m
Carrier Frequency (f_c)	$f_{c1} = 1990$ MHz $f_{c2} = 2000$ MHz $f_{c3} = 2010$ MHz
Threshold (P_{th})	3 dB
Max speed of UAV (V_{max})	20 m/s

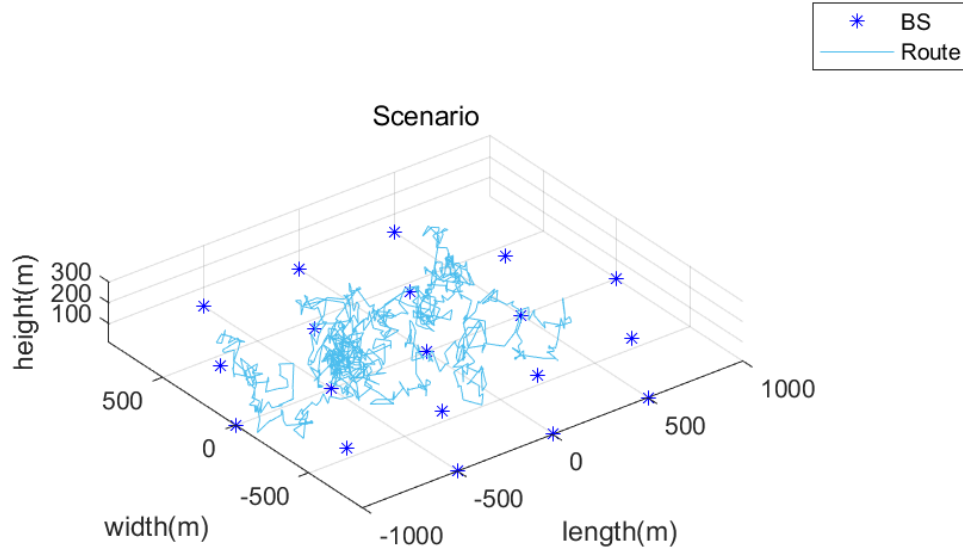


Figure 3.2: Simulation scenario.

3.4.1 Performance Metrics

3.4.1.1 HO Rate

The HO rate, R_{HO} , represents the frequency of handovers occurring along a given trajectory. It is defined as the proportion of waypoints among 1000 waypoints where a HO occurs. A HO is considered to occur at a waypoint if the selected serving BS after the HO decision differs from the previous serving BS.

3.4.1.2 Outage Rate

The outage rate, R_{out} , is defined as the proportion of waypoints at which the SINR of the serving BS falls below a specified threshold, P_{th} , following an HO decision. An outage occurs whenever the SINR of the current serving BS is lower than P_{th} , indicating insufficient signal quality after the HO.

3.4.1.3 Throughput and Throughput Loss Rate

Throughput T is the average throughput achieved at all waypoints along the trajectory after each HO decision. The throughput loss rate, R_{TL} , represents the relative difference

between the average throughput of the proposed scheme and a baseline throughput:

$$R_{TL} = \frac{T_{baseline} - T}{T_{baseline}}, \quad (3.18)$$

where the $T_{baseline}$ is the average throughput when the UAV is always connected to the BS with the highest SINR at each waypoint along the same trajectory. A higher throughput or lower throughput loss rate indicates better communication quality.

3.4.1.4 Performance Indicator

Performance Indicator $I(P)$ is a composite measure incorporating the HO rate, outage rate, and throughput loss rate. It provides an overall assessment of the network's performance with respect to these metrics. The performance indicator is calculated as:

$$I(P) = R_{HO} + R_{out} + R_{TL}, \quad (3.19)$$

where R_{HO} is HO rate, R_{out} is the outage rate, and R_{TL} is the throughput loss rate. A lower value of $I(P)$ corresponds to improved network performance.

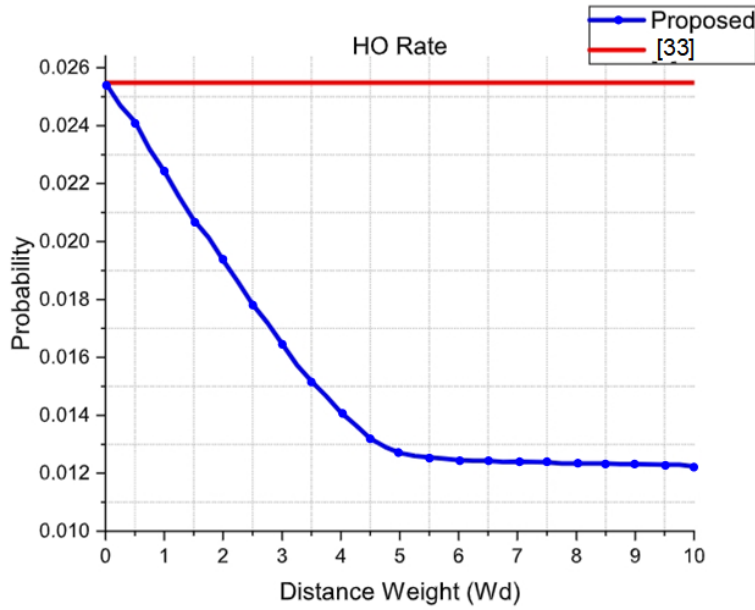


Figure 3.3: HO rate with the increase of ω_d .

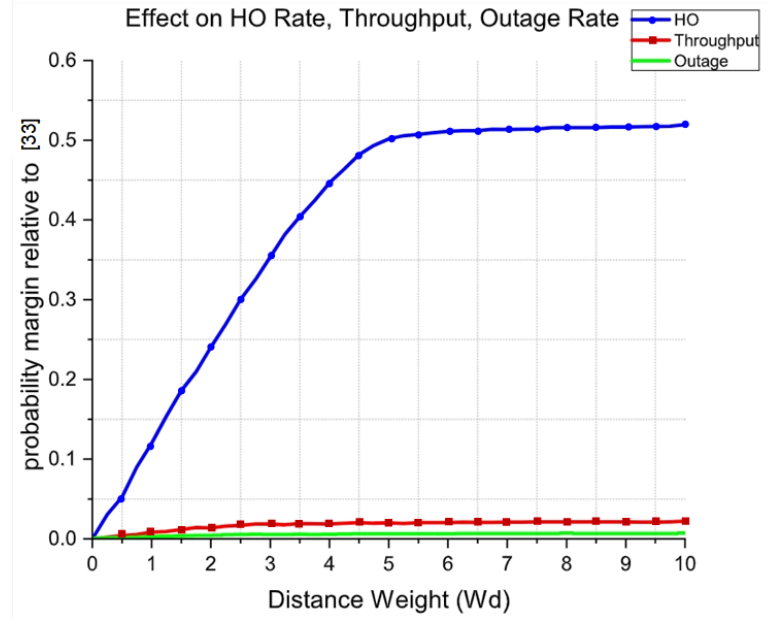


Figure 3.4: Effect on HO rate, throughput, outage rate of different value of ω_d .

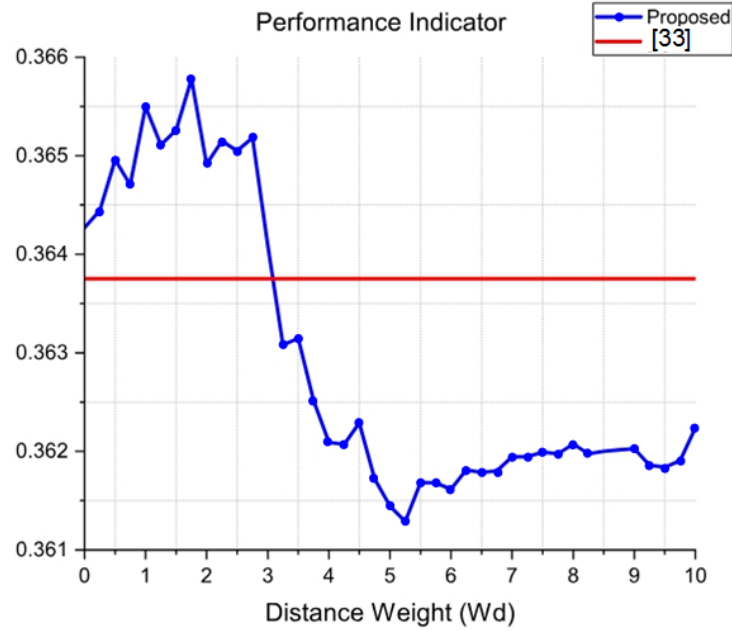


Figure 3.5: Performance indicator of different value of ω_d .

3.4.2 Performance Analysis

Fig. 3.3 illustrates the simulation results for the HO rate across various ratios of ω_d to ω_{sinr} , indicating that distance is not included in the action space, the HO rate mirrors that of [33]. As ω_d increases, the HO rate decreases significantly, demonstrating that incorporating distance effectively reduces the HO rate.

However, increasing ω_d has a negative impact on both throughput and outage rate. Compared to [33], the outage rate increases while throughput decreases. The extent of these effects varies across the three metrics, measured as the difference between the results of the proposed scheme and those of [33]. Fig. 3.4 illustrates these differences for the HO rate, outage rate, and throughput as ω_d increases. The graph shows that the effect of increasing ω_d on reducing the HO rate is significantly greater than its impact on the outage rate and throughput. Consequently, the proposed scheme effectively lowers the HO rate without substantially compromising outage rate or throughput.

To identify the optimal balance between HO rate, outage rate, and throughput, the combined performance indicator $I(P)$, as defined in 3.19, is displayed in Fig. 3.5. As shown in Fig. 3.5, $I(P)$ for the proposed algorithm falls below that of [33] once the weight reaches a certain threshold. Notably, when ω_d is approximately 5.25 and ω_{sinr} equals to 4.75, $I(P)$ achieves its minimum value, indicating the optimal trade-off among HO rate, outage rate, and throughput.

3.5 Summary

In this chapter, we address a scenario where HOs are necessary to maintain a seamless connection between a UAV and ground BSs as it transitions between different BS coverage areas along its trajectory. However, frequent HOs are undesirable due to their potential negative impact on network performance. To mitigate this issue, we propose a RL-based HO decision scheme that enhances an existing algorithm. In the proposed scheme, the action space A is defined not only by RSS or SINR but also by the distance between BSs and waypoints, with adjustable weights applied to each factor. Different

combinations of ω_{sinr} and ω_d result in varying action spaces and performance outcomes. Simulation results indicate that the proposed method significantly reduces the HO rate compared to the existing algorithm, with a marginal increase in outage rate and a slight reduction in throughput. Based on an analysis of the simulation results, the optimal weight combination for ω_{sinr} and ω_d is found to be $\omega_d = 4.75$ and $\omega_{sinr} = 5.25$. This configuration enables the improved algorithm to achieve a substantial reduction in HO rate with minimal impact on HO outage and throughput.

A HYBRID SCHEME USING TOPSIS AND Q-LEARNING FOR HANDOVER DECISION MAKING IN UAV-AIDED HETEROGENEOUS NETWORK

As explained in Chapter 3, QL method is suitable for the sequence HO decision-making problem in cellular-connected UAV network. Similarly, HO decision is also important when UAVs act as BSs in current heterogeneous network (HetNet). This chapter will be focused on applying QL method for HO decision-making problem in UAV-aided HetNet.

4.1 Introduction

To enhance coverage, capacity, and performance by enabling diverse network elements to coexist and operate concurrently, HetNets are widely deployed to provide access services for UE by integrating various access technologies and transmission solutions [63]. HetNet refers to a wireless communication system that combines multiple cell types and access technologies, such as macro cells, small cells, and various radio access technologies. With the growing demand for capacity and coverage, integrating UAVs

into HetNets has become essential due to their flexibility, cost-effectiveness, and rapid deployment capabilities [64–66]. In HetNets, UAVs can function as aerial BSs or relay nodes, utilizing the A2G channel to achieve high-quality communication with ground UEs, largely due to their high probability of line-of-sight LoS connectivity [67]. Their quick deployment, adjustable altitude, and capacity to establish LoS links make UAVs ideal for improving signal quality, minimizing interference, and enhancing network performance in dynamic environments. By offering low propagation delays, reliable communication links, and efficient maintenance, UAV-aided HetNets significantly boost wireless network coverage, capacity, reliability, and energy efficiency, meeting the demands of future communication needs [63]. The inclusion of UAVs adds a versatile, cost-efficient layer to HetNets, supporting a broad spectrum of applications.

Despite these benefits, UAV-aided HetNets also present challenges, particularly related to the need for HOs between different types of BSs [7]. In terrestrial HetNets comprising only macro and small BSs, dense distributions of small BSs frequently lead to both frequent and unnecessary HOs [68]. The addition of UAVs introduces further complexity, as HOs can be triggered by the movement of UAV base stations (UBSs). Furthermore, UEs may connect to UAVs in poor positions, which can result in an increased frequency of HOs [69].

4.1.1 Related Works and Motivations

Several existing studies have addressed HO challenges in UAV wireless networks. In [70], the author proposed a UAV-aided network model that considers the advantages and disadvantages of HO procedures. The study concluded that UAVs should employ directive antenna systems, fly at low altitudes, and maintain slower speeds. In [71], a path-loss-plus-fading model incorporating HO parameters was considered for HO in UAV networks. This study specifically addressed frequent HO problems caused by the transition between LoS and NLoS in UAV networks. A discrete-time Markov chain was employed, and HO failure and ping-pong probabilities were derived by analyzing HO state probabilities during time-to-trigger (TTT). The results revealed a trade-off between HO failure and

ping-pong probabilities through TTT adjustments. Recently, novel reinforcement learning methods have been applied in wireless communications research, such as in [72–74]. Moreover, [75] introduces an adaptive Q-learning framework with multi-criteria decision-making to optimize network rate, HO performance, and probability of identification in urban UAV-assisted HetNets, tackling frequent HOs and resource inefficiencies in dense urban settings. Using real-time feedback, it dynamically optimises HO decisions and resource allocation, reducing HO failures, boosting energy efficiency (up to 30 bps/J), and enhancing POI. Validated against 3GPP and NYM models, the approach achieves superior rates, HO stability, and POI across UAV altitudes, ensuring reliable urban wireless communication. HO decisions are dynamically optimized by applying the proposed algorithm. In [76], a RL-based HO algorithm and mobility control optimization method were proposed for UAV networks. Authors in [77] consider a network consisting of only UBSs, and proposed another intelligent HO method. It introduced a deep learning-based trajectory prediction model and made HO decisions based on predicted channel characteristics. The results showed a higher HO success rate compared to traditional HO methods. In [78], a QL-based HO management solution was proposed between UBSs and static BSs, improving UE capacity. Additionally, as TOPSIS is an effective method in ranking alternatives, it is widely used in many researches. [79] proposed a TOPSIS method to the problem of network selection with a proposed iterative approach to improve the result. In [80], the authors proposed a method to rank BSs based on the weighted attribute for HO optimisation. In this work, authors compared two techniques which are entropy weighting technique and standard deviation weighting technique to scale the importance of the attributes.

From the related works, HO decision-making is widely studied in various UAV networks, with methods such as RL and TOPSIS commonly applied. However, as the demand for HetNets grows, limited research addresses the optimization of HO performance specifically in UAV-aided HetNets. Integrating UAVs within HetNets increases cell density and introduces complex UAV mobility, making HO management increasingly challenging. Motivated by these challenges and building on prior work, this chapter proposes a hybrid

HO decision-making scheme using TOPSIS and QL for UAV-aided HetNets. As discussed in Chapter 3, QL is effective in addressing various decision-making challenges in communication systems. However, in ultra-dense networks with numerous BSs, handling the resulting large datasets can be complex, especially given the potential for noise or errors that can degrade performance. To address this, the proposed method incorporates TOPSIS to reduce the dimensionality of QL's action space, allowing the approach to scale effectively to large scenarios. This hybrid design thereby enhances both performance and scalability, which is essential for efficiently managing the increasing number of BSs in dense environments. In the proposed method, three decision criteria SINR, ToS, and average EE are used across both TOPSIS and QL stages to select the optimal BS at a given location. Additionally, the ToS metric considers the movement of both UAVs and UEs to better align with dynamic conditions. Results demonstrate that the proposed scheme reduces both the number of HOs and unnecessary HOs while achieving higher EE compared to existing methods.

4.1.2 Chapter Organization

The rest of chapter is organized as follows. In Section 4.2, the system model is introduced. The proposed HO scheme is explained in Section 4.3. Section 4.4 presents the simulation results and the analysis. Finally, this chapter is summarised in Section 4.5.

4.2 System Model

4.2.1 UAV-Aided HetNet Model

A three-tier UAV-aided HetNet model is considered in this chapter, as shown in Fig. 4.1. In this model, a round coverage area of a MBS is considered. The MBS is located at the centre of the area, and some SBSs and UBSs are distributed in the area following Poisson Point Process (PPP) distribution with a specific density λ_s and λ_u . In this system, SBSs operate at 5G millimetre wave frequency and UBSs work at a frequency of LTE.

Also, when UAVs are operating, they hover and fly in the air following their own path which is generated randomly. At the same time, a UE moves in the area following a randomly generated trajectory. During the movement of UBSs and the UE, HOs are performed to keep the UE connect to a suitable BS. Usually, since MBS can provide large area and higher transmission power, UEs are easily HO to MBS causing congestion on MBS. Therefore, in this scenario, to minimise the additional impact of congestion, MBS will not be considered as the target BS in any UE HO decisions, and UE will only connect to SBSs and UBSs to offload the traffic from the congested MBS.

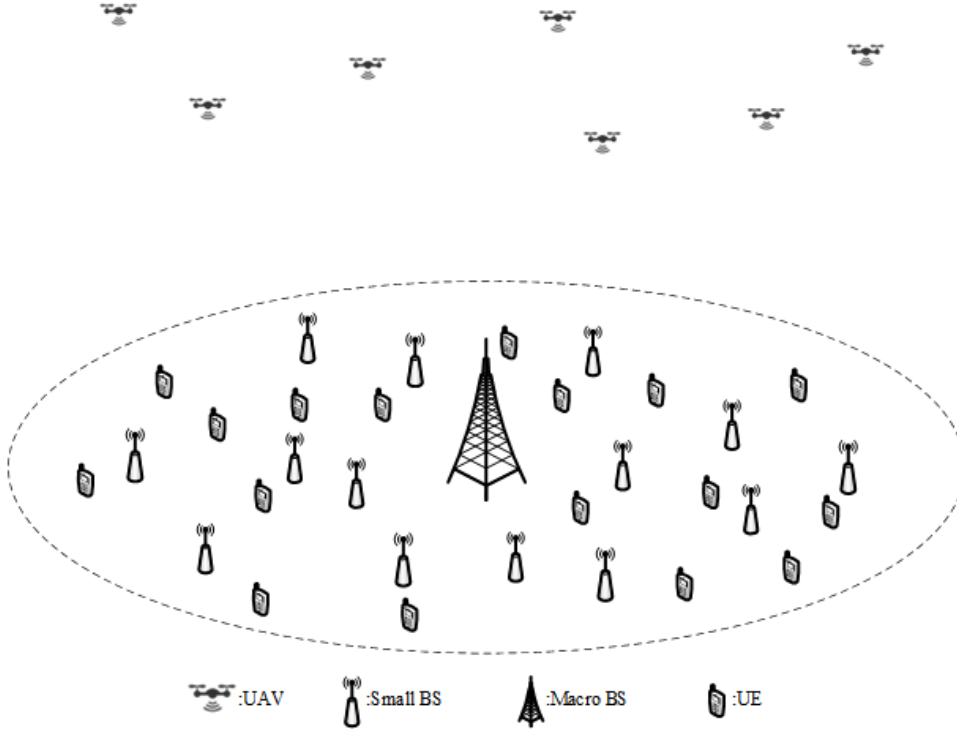


Figure 4.1: UAV-aided three-tier HetNet.

In the model, UAVs and UE are moving at the same time following the trajectories with L waypoints. Every waypoint is generated after UAVs or UE move for a duration of T since the previous waypoint. Each UAV is moving with an unchanged velocity v_{UBS} , but the direction will be changed at every waypoint by randomly generating a moving angle $\theta_{UBS_i}^l$, where i indicates the i th UAV and l ($l \in L$) is the l th waypoint.

The moving model for ground UE is slightly different. The initial point of UE is randomly generated in the area, and UE is moving with a fixed v_{UE} all the time. At every

waypoint l , a new value of direction θ_{UE}^l is randomly selected as $\theta_{UE}^l \in [\theta_{UE}^{l-1} - \frac{\pi}{6}, \theta_{UE}^{l-1} + \frac{\pi}{6}]$, where θ_{UE}^{l-1} is the direction of the UE at the at last waypoint.

4.2.2 Propagation Model

In this work, there are two different types of channels which are ground-to-ground (G2G) and A2G, corresponding to ground and air BSs respectively.

The A2G channel consists of both LoS and NLoS links, and is significantly impacted by obstacles, such as buildings, that lie between UBSs and ground UEs. In this study, for better simulate the channels in dense distribution the LoS condition between a UE and a given BS is determined using a ray-tracing model [81], which is because it models signal propagation based on the physical environment, including reflections, diffractions, and obstructions. Unlike statistical models, it accounts for 3D terrain, building layouts, and UAV altitude, making it especially accurate in complex dynamic scenarios. Specifically, buildings are randomly generated based on a Poisson distribution with density β , while building heights follow a Rayleigh distribution with scale parameter κ . Consequently, when a ground UE connects to a UBS, the channel is classified as LoS if no buildings obstruct the direct path between the UBS and UE; otherwise, it is classified as NLoS.

The path loss for LoS and NLoS links is calculated as follows [8]:

$$PL_{LoS} = 30.9 + 20\log_{10}(f_c) + (22.25 - 0.5\log_{10}(h_U))\log_{10}(d_{3d}), \quad (4.1)$$

$$PL_{NLoS} = 32.4 + 20\log_{10}(f_c) + (43.2 - 7.6\log_{10}(h_U))\log_{10}(d_{3d}), \quad (4.2)$$

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.

In contrast, the LoS probability for G2G channels is low, therefore, it is assumed that G2G channels are assumed to be in NLoS. From [82], the path loss model for G2G channels can be given as:

$$PL_{G2G} = 32.4 + 20\log_{10}(f_c) + 30\log_{10}(d_{3d}), \quad (4.3)$$

In order to improve the quality of communication link, SINR, ToS and EE are measured for HO decision making, as explained in the next section.

4.2.3 HO Decision Criteria

In UAV-assisted HetNets, maintaining reliable connectivity, meeting application-specific demands, and ensuring efficient resource utilization are important. Traditional distance-based approaches are no longer sufficient, as it does not guarantee optimal link quality in complex, dense cells environments with varying antenna patterns and UAV altitudes. Instead, this work adopts a multi-criteria approach centred on three key metrics: SINR, ToS, and EE. SINR provides a direct measure of link reliability by accounting for interference and noise, which are highly variable in dense HetNet deployments. ToS ensures that UEs can avoid low sojourn time, which improves the unnecessary HO. EE addresses the critical constraint of UAV energy consumption, promoting sustainable operation by selecting BSs that minimize power usage while maintaining service quality. Together, these criteria support robust, context-aware HO decisions that are better suited to the dynamic and resource-constrained nature of UAV-aided networks.

4.2.3.1 Downlink SINR for ground UE

SINR is related to the RSRP, interference and noise. The RSRP of both SBSs and UBSs in dBm can be expressed as

$$RSRP = P_t + G_t + G_r - PL + SF, \quad (4.4)$$

where the P_t is the transmit power from the serving BS, G_t and G_r are the antenna gain of transmitter and receiver respectively, PL represents the path loss from the serving BS to ground UE, and SF is the shadowing fading which follows Gaussian distribution with mean 0 and standard deviation σ_{SF}

$$SF \sim \mathcal{N}(0, \sigma_{SF}). \quad (4.5)$$

The values of σ_{SF} for LoS A2G, NLoS A2G and G2G channels are given below [8]:

$$\sigma_{SF}^{LoS} = \max(5 \times e^{(-0.01 \times h_U)}, 2), \quad (4.6)$$

$$\sigma_{SF}^{NLoS} = 8, \quad (4.7)$$

$$\sigma_{SF}^{G2G} = 7.8. \quad (4.8)$$

Downlink interference is caused by other BSs. It is assumed that there are K_s SBSs and K_u UBSs deployed in the area. Then, when the UE is served by BS i , which could be SBSs or UBSs, the interference in mW can be expressed as:

$$I_s = \sum_{j=1, j \neq i}^{K_s} RSRP_j, \quad (4.9)$$

$$I_u = \sum_{j=1, j \neq i}^{K_u} RSRP_j, \quad (4.10)$$

where j represents a BS. Interference is the sum of $RSRP$ from all BSs operating in the same frequency except the serving BS i . Therefore, SINR is given by:

$$SINR = \frac{RSRP_i}{I + \sigma_n^2}, \quad (4.11)$$

where I represents the sum of interference I_s and I_u , and σ_n is noise power, which is calculated in Watt as:

$$\sigma_n = 10^{-3} \times 10^{(-174 + 10 \times \log_{10} B)/10}, \quad (4.12)$$

where B is the bandwidth.

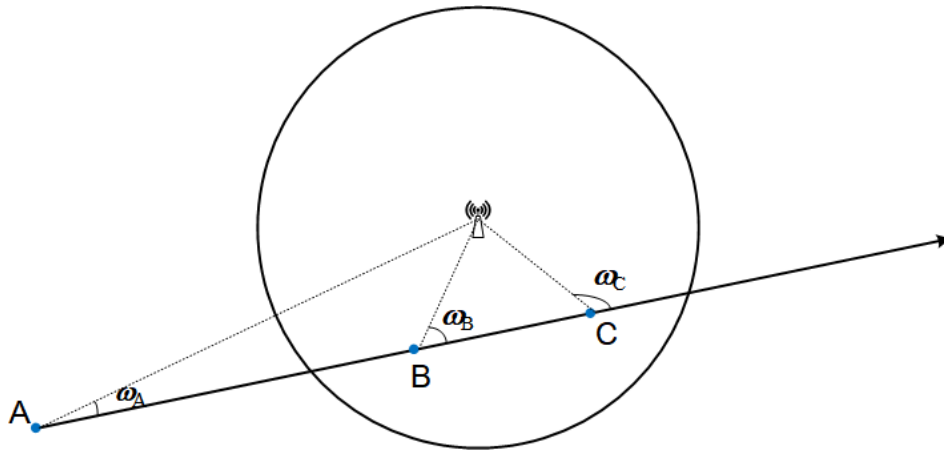


Figure 4.2: UE is moving through a BS coverage.

4.2.3.2 Time of Stay

Time of stay (ToS) is the sojourn time of the UE in a BS. Unnecessary HO is related to ToS. If the ToS of the target BS is lower than a time threshold T_{th} after a HO completes, then the HO is an unnecessary HO. As Fig.2 shows, the position could be at A, B and C when a UE is passing a BS. The corresponding ToS is expressed respectively as

$$ToS_A = \frac{2 \times R_{BS} \times \sqrt{1 - (\frac{d_{2d} \times \sin(\omega_A)}{R_{BS}})^2}}{v_{UE}}, \quad (4.13)$$

$$ToS_B = \frac{d_{2d} \times \cos(\omega_B) + \sqrt{(d_{2d} \times \sin(\omega_B))^2 - R_{BS}^2}}{v_{UE}}, \quad (4.14)$$

$$ToS_C = \frac{\sqrt{R_{BS}^2 - (d_{2d} \times \sin(180 - \Omega_C))^2} - d_{2d} \times \cos(180 - \omega_C)}{v_{UE}} \quad (4.15)$$

where R_{BS} is the radius of the BS, d_{2d} is the distance between the UE and the BS in 2-dimension environment, and the ω_A , ω_B , ω_C are the angles between the path of UE and the connection between UE and the BS in degree.

Additionally, when the target BS is a UBS, the calculation of ToS must also consider the movement of the UBS, including both the velocity and the direction. This is achieved by measuring ToS using relative velocity, which is calculated using vector representation as illustrated in Fig. 4.3, where A and B are the objective movement of UE and UAV. Assuming UAV is static, in relative to the UAV, the UE's path is modified from A to C, and ToS will be measured using the relative velocity.

4.2.3.3 Spectral Efficiency

Spectral efficiency refers to the amount of information (in bits) that can be transmitted over a given bandwidth (in Hz) within a communication channel, typically measured in bits/s/Hz. It reflects how effectively the available frequency spectrum is utilized to deliver data and is a key performance metric in wireless networks [83]. The spectral efficiency of the UE η_{SE} can be calculated as:

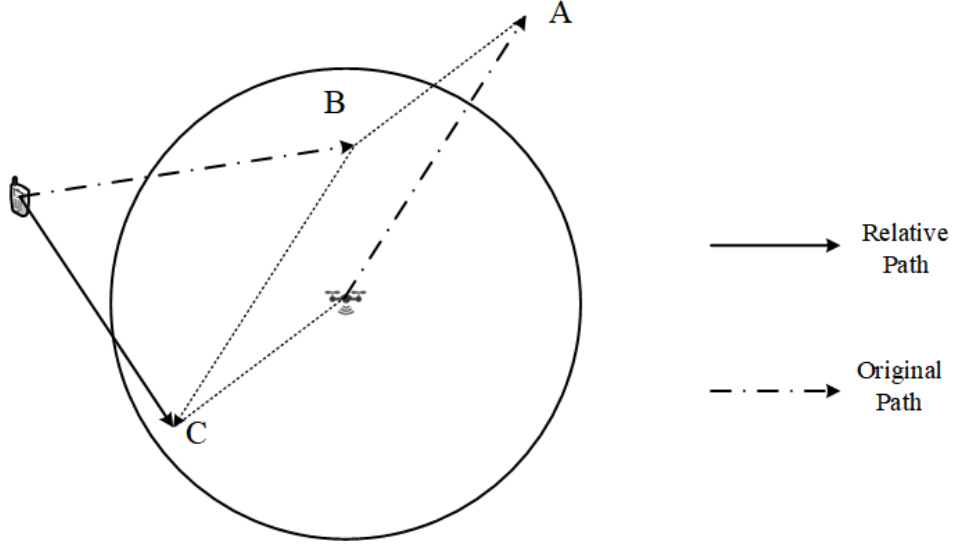


Figure 4.3: Relative velocity of UE.

$$\eta_{SE} = \log_2(1 + SINR), \quad (4.16)$$

4.2.3.4 Energy Efficiency

Considering the limited life time of the UAV battery, it is critical to improve the EE of UAVs at every HO decision making. According to [83], EE in wireless communication systems is typically defined as the ratio of spectral efficiency to power consumption, expressed in units such as bits/Joule. EE is defined as the ratio of the spectral efficiency to power consumption.

$$\eta_{EE} = \frac{\eta_{SE}}{P_t + P_c}, \quad (4.17)$$

where P_t and P_c is the transmit power and receiver's circuit power consumption respectively. This formulation captures how effectively a system transmits data per unit of energy consumed. Spectral efficiency reflects the system's ability to utilize bandwidth efficiently, while power consumption accounts for the energy cost of maintaining that transmission. By taking the ratio, EE quantifies how much useful data (per Hz) is delivered per unit of energy spent.

4.3 Proposed TOPSIS-QL Handover Scheme

In UAV-aided HetNets, managing HO decisions becomes increasingly complex due to high mobility, dense BS deployment, and dynamic service requirements. Traditional HO strategies are often not suitable in such environments, as they typically rely on single-parameter decisions and do not scale well with network density or mobility. To address this, a hybrid decision-making framework combining the TOPSIS with QL is proposed.

TOPSIS is employed to pre-select a subset of promising BS candidates by evaluating SINR, ToS, and EE, thereby reducing the dimensionality and complexity of the action space for the subsequent QL phase. These criteria are specifically chosen to capture key aspects of aerial network performance. For instance, SINR reflects instantaneous link quality; ToS accounts for the expected connection duration based on UAV trajectory and mobility; and EE promotes sustainable operation critical to battery-limited UAVs.

The QL component then dynamically learns the optimal HO policy by considering long-term performance across flight paths. This hybrid approach is not only suitable for UAV-aided HetNets but is also highly applicable to cellular-connected UAV scenarios in Chapter 3, where similar challenges such as high mobility, interference.

However, for the cellular-connected UAV scenarios, where UAVs are the aerial UEs with less ground BSs, the energy constraints demand are not the priority comparing with SINR.

The proposed hybrid method is illustrated in Algorithm 4.1, which shows the HO decision process aims to select an optimal target BS at each waypoint to improve network performance as the UE moves through the coverage area.

Algorithm 4.1 TOPSIS-QL Handover Scheme

```

1: Initialize input parameters:
   Waypoints  $L$ , number of both SBSs and UBSs  $K$ 
   Q table( $L \times 10 \times 10$ )
2: for  $l(l \in L)$  do
3:   for  $BS_i = i : K$  do
4:     get  $SINR_{l,i}$ ,  $ToS_{l,i}$ ,  $EE_{l,i}$ 
5:   end for
6:   Cell List  $CL(l, :) \leftarrow$  Top 10 ranked by TOPSIS
7: end for
8: QL initialize:
9: for  $l(l \in L)$  do
10:  for  $x \in CL(l-1, :)$  do
11:    for  $y \in CL(l, :)$  do
12:      get  $Q(l, x, y)$  according to equation (4.21)
13:    end for
14:  end for
15: end for
16: while training  $\leq 2000$  do
17:    $j = 0$ 
18:   for  $l$  in  $L$  do
19:     if random value  $i(i \in [0, 1]) \leq \epsilon$  then
20:       picked BS  $j_{new} \leftarrow \operatorname{argmax} Q(l, j, u)(u \in 10)$ 
21:     else
22:        $j_{new} \leftarrow$  randomly picked from  $A(l, 1 : k)$ 
23:     end if
24:     Update  $Q(l, j, j_{new})$  with equation (4.22)
25:   end for
26:    $j = j_{new}$ ;
27: end while
28: Return Q table

```

4.3.1 TOPSIS

As introduced in Section 2.1, TOPSIS is a MCDM technique used to rank alternatives based on multiple criteria. In this method, the best and worst criterion values from different alternatives are identified to establish a set of positive ideal solutions and a set of negative ideal solutions. The core idea of TOPSIS is to find the alternative that is closest to the positive ideal solution and farthest from the negative ideal solution

by calculating the Euclidean distance of each alternative from these solutions, using weighted criteria [47].

To determine appropriate weights for each criterion, a standard deviation (SD) weighting technique is applied. This method assigns weights to each criterion based on its standard deviation, reflecting the relative importance of each in the decision-making process [84]. Criteria with less variability among alternatives receive smaller weights, while criteria with larger variances are assigned higher weights. Let P represent the total number of attributes, with m values per attribute p ($p \in P$). The standard deviation of any criterion can be calculated as follows:

$$\mu_p = \frac{1}{m} \sum_{i=1}^m a_{i,p}^{norm}, \quad (4.18)$$

$$\sigma_p = \sqrt{\frac{1}{m} \sum_{i=1}^m (a_{i,p}^{norm} - \mu_p)^2}, \quad (4.19)$$

where $a_{i,p}^{norm}$ denotes the normalized values of different attributes, and i represents a specific value within an attribute. Here, σ_p and μ_p are the standard deviation and mean of the p th attribute, respectively. The weight for attribute p is then given by:

$$w_p^{sd} = \frac{\sigma_p}{\sum_{j=1}^P \sigma_j}, \quad (4.20)$$

where j represents different attributes.

Thus, criteria with higher standard deviations are assigned greater weights, indicating their increased importance.

In the proposed method, SINR, ToS, and EE are the three criteria utilized in the TOPSIS phase. With the weighted criteria, TOPSIS ranks all BS candidates for each waypoint based on their Euclidean distance to both positive and negative ideal solutions. However, as TOPSIS only considers the current waypoint, it does not account for conditions at subsequent waypoints, limiting its ability to optimize the overall HO rate. To further improve HO performance, we introduce a hybrid scheme in which TOPSIS selects the 10 most suitable BSs to form an action space for the QL phase, which is then used to make HO decisions at each waypoint.

4.3.2 Q-Learning

As introduced in section 2.2, QL is a model-free reinforcement learning method. Usually, Markov decision process (MDP) is employed. It can be described as $\{S, A, P, R\}$, where S is the state, A is the possible actions, P is the transition probability for states, and R is the reward from the environment. The process of QL is the agent takes action to change the state based on the reward and interaction with the environment [33]. In the training phase, the agent optimises decision-making by iteratively balancing exploitation and exploration. During exploitation, the agent selects actions that produce the highest immediate reward based on its current knowledge. In contrast, exploration involves selecting actions randomly, enabling the agent to identify alternatives that may initially offer lower rewards but could lead to greater long-term gains. This balance allows the agent to refine its strategy over time, ultimately maximizing overall performance. Consequently, the QL method enables the agent to achieve optimal returns over a sequence of decisions.

State (S): In this study, the ground UE serves as the agent, and its state includes the UE's coordinates and the current serving BS. The UE's position influences channel conditions, while the currently connected BS affects the choice of the next BS.

Action (A): Actions represent the potential target BSs. At each waypoint, the UE decides which BS to connect to in order to optimize performance. Since selecting all BSs within the area as actions would be complex and impractical, the candidate list generated by the TOPSIS method is used as the action space for QL, restricting the agent's choices to BSs in the candidate list. Considering BS density, the action space size is fixed.

Reward (R): The reward function in the algorithm is defined as follows, incorporating SINR, ToS, and EE:

$$R = \text{SINR}^{\text{norm}} \cdot w_{\text{sinr}} + \text{ToS}^{\text{norm}} \cdot w_{\text{tos}} + \text{EE}^{\text{norm}} \cdot w_{\text{ee}} - I(HO), \quad (4.21)$$

where $\text{SINR}^{\text{norm}}$, ToS^{norm} and EE^{norm} represent the normalized values of SINR, ToS, and EE, respectively. $I(HO)$ is the HO indicator, set to 1 if a handover occurs and 0

otherwise. The weights w_{sinr} , w_{tos} and w_{ee} are determined using the standard deviation weighting technique described above.

In the beginning of QL, a Q-table is created containing the states and the corresponding actions of every state. In dense network deployments, where a UAV may simultaneously receive measurable signals from dozens of BSs due to strong LoS conditions, considering all possible BSs in the learning process would result in a prohibitively large action space, increasing training time and risking policy instability. By limiting the action space to the top 10 BSs, which are typically selected using TOPSIS, the agent focuses on a manageable set of high-quality options, improving convergence speed without significantly sacrificing optimality. This fixed-but-flexible approach thus supports scalability across varying network densities, maintaining consistent learning performance while avoiding excessive complexity in ultra-dense UAV-aided HetNets. Therefore, all the BSs are ranked by TOPSIS, and the action space will consist of the top 10 BSs.

As the size of action space of Q-learning is preliminarily reduced by TOPSIS, the proposed hybrid method can achieve more efficient learning and enhanced scalability, which is crucial in efficiently handling an increasing number of BSs. Since there are L waypoints and the length of candidate list is 10, the size of Q-table is $L \times 10 \times 10$. At the training stage, the agent makes decisions for exploitation and exploration according to ϵ -greedy policy at every waypoint iteratively. Following the policy, the agent decides to exploit with the probability of ϵ , and there is $1 - \epsilon$ chance to explore [85]. After every decision, a new reward of the action at a specific waypoint will be calculated to replace the previous value by equation (4.21). Then, Bellman equation is applied to renew the previous Q value after getting the new value [50]:

$$Q(s, a) \leftarrow Q(s, a) + \alpha \times [R + \gamma \times \max_{a'} Q(s', a') - Q(s, a)], \quad (4.22)$$

where α is the learning rate, γ is the discount rate, and $Q(s, a)$ is the Q value of the certain state s and action a stored in the current Q-table. In this research work, the learning rate α and discount rate γ in training stage are fixed at 0.5 and 0.3 respectively according to [33]. The above procedure is repeated until a trained Q-table is generated.

Following the Q-table, a sequence of HO decisions can be made by choosing the best Q value.

4.4 Performance and results analysis

The performance of the hybrid HO scheme is evaluated in terms of the number of HO, number of unnecessary HO and energy efficiency. The performance of the proposed method is compared with that of the conventional method, TOPSIS-only and QL-only methods. For the conventional method, A3 event is used to trigger HO, thus, HO will take place when the RSRP of the target BS is higher than the serving BS. For TOPSIS-only method, we used the same criteria as explained before, and the top ranked BS will be selected as the target BS. For the QL-only method, the action space is also formed by all BSs. The simulation parameters are given in the table 4.1.

4.4.1 Number of HO

The number of HOs for the four methods versus the UE velocity is shown in Fig. 4.4. The density of SBSs and density of UAV are fixed at $60 \times 10^{-6}/m^2$ and $40 \times 10^{-6}/m^2$ respectively, and the velocity of UE increases from $5m/s$ to $55m/s$. It is obvious that the numbers of HOs increases with the increase of UE velocity for all methods. This is because with the increase of velocity, it is more likely for the UE to cross cell boundaries at the next waypoint, resulting in a higher probability of HO. Fig. 4.4 clearly shows that the proposed TOPSIS-QL method, labelled as the TOPSIS-QL, requires the lowest number of HOs, and reduces number of HO by 48.7% in the comparison of conventional method (when the velocity is $25m/s$). The conventional method has the highest number of HO as the UE only connect to the BSs with the best RSRP. However, in the TOPSIS-only method, the number of HOs increases slightly slower than that of the conventional method as it avoids some unnecessary HOs. Although QL-only method considers multiple criteria and future decisions, it is less efficient because its action space includes all available BSs, making the size large, which will lead to long training time. In contrast, the proposed

Table 4.1: Simulation parameters

Parameters	Values
Bandwidth (B)	$B_{SBS} = 500 \text{ MHz}$ $B_{UBS} = 20 \text{ MHz}$
Transmit Power (P_t)	$P_t^{SBS} = 35 \text{ dBm}$ $P_t^{UBS} = 20 \text{ dBm}$
Carrier Frequency (CF)	$f_c^{SBS} = 28 \text{ GHz}$ $f_c^{UBS} = 2 \text{ GHz}$
Density of SBSs (λ_s)	60 ($10^{-6}/m^2$)
Density of Buildings (β)	100 ($10^{-6}/m^2$)
Coverage Radius of BSs (R)	$R_{MBS} = 1000 \text{ m}$ $R_{SBS} = 50 \text{ m}$ $R_{UBS} = 150 \text{ m}$
Number of Waypoints (L)	1000
Height of BSs(h)	$h_{SBS} = 4 \text{ m}$ $h_{UBS} = 100 \text{ m}$
Time Threshold(T_{th})	0.72 s
Receiver Circuit Power (P_c)	0.001 W
Velocity of UAVs (v_{UAV})	10 m/s
Scale Parameter (κ)	20
Learning Rate (α)	0.5
Discount Rate (γ)	0.3

method reduces the action space by incorporating multiple criteria in both TOPSIS and QL phases, including ToS, which helps avoid unnecessary HOs. Additionally, the large number of BSs in the QL-only method slows down learning and results in decisions, while the proposed method improves efficiency and HO performance.

4.4.2 Number of Unnecessary HO

Fig. 4.5 shows the performance of the number of unnecessary HO against distribution density of UAVs from $10 \times 10^{-6}/m^2$ to $100 \times 10^{-6}/m^2$. In addition, the velocity of UE is fixed at 25 m/s. With the increase of the density of UAVs, the number of unnecessary HOs for all

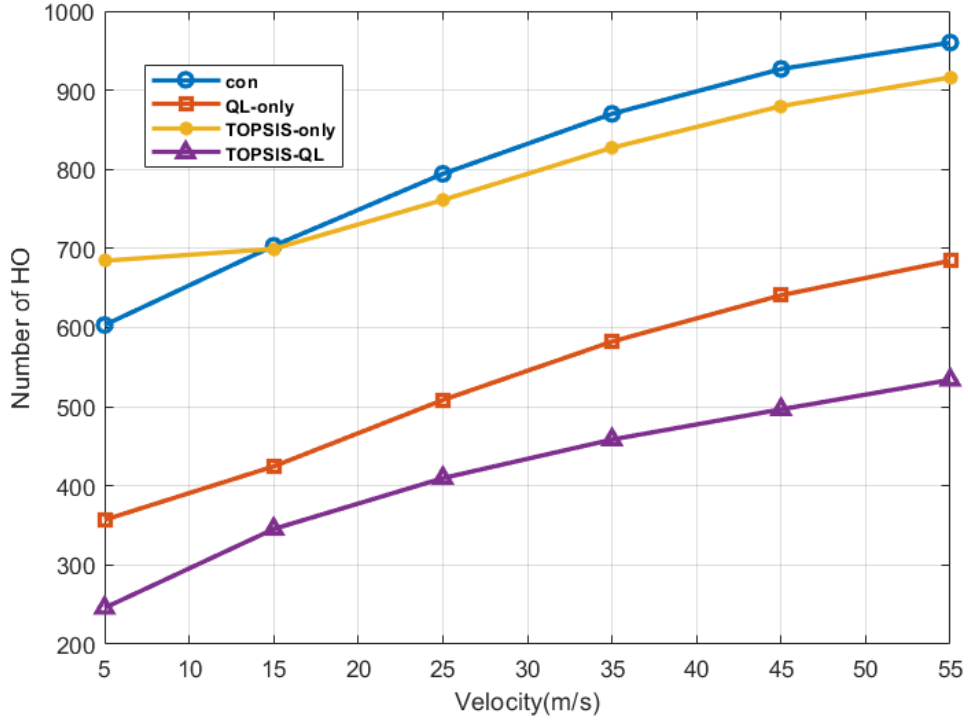


Figure 4.4: Number of HO against UE velocity.

methods decrease. This is because the more UAVs are distributed around UE, it is more likely to choose a BS with higher ToS. It is observed from the figure that the proposed method has the lowest number of unnecessary HOs and the conventional method has the highest number of unnecessary HO for various density of UAVs, specifically, the proposed scheme can reduce the number of unnecessary HO by 69.2% (when the density of UAV is $50 \times 10^{-6}/m^2$). Although both the TOPSIS-only and QL-only methods also use ToS as a criterion, the proposed algorithm performs the best because the ToS is incorporated to both generate the reduced candidate list and select the target BS, while it is only used to select target BS from all potential BSs in the TOPSIS-only and QL-only methods.

4.4.3 Average Energy Efficiency

The average EE is evaluated by averaging the EE cross the UE trajectory. The performance of the average EE against density of UAV is shown in Fig. 4.6. In this simulation, the velocity of ground UE is fixed at 25 m/s. As Fig. 4.6 shows, the average EE of all

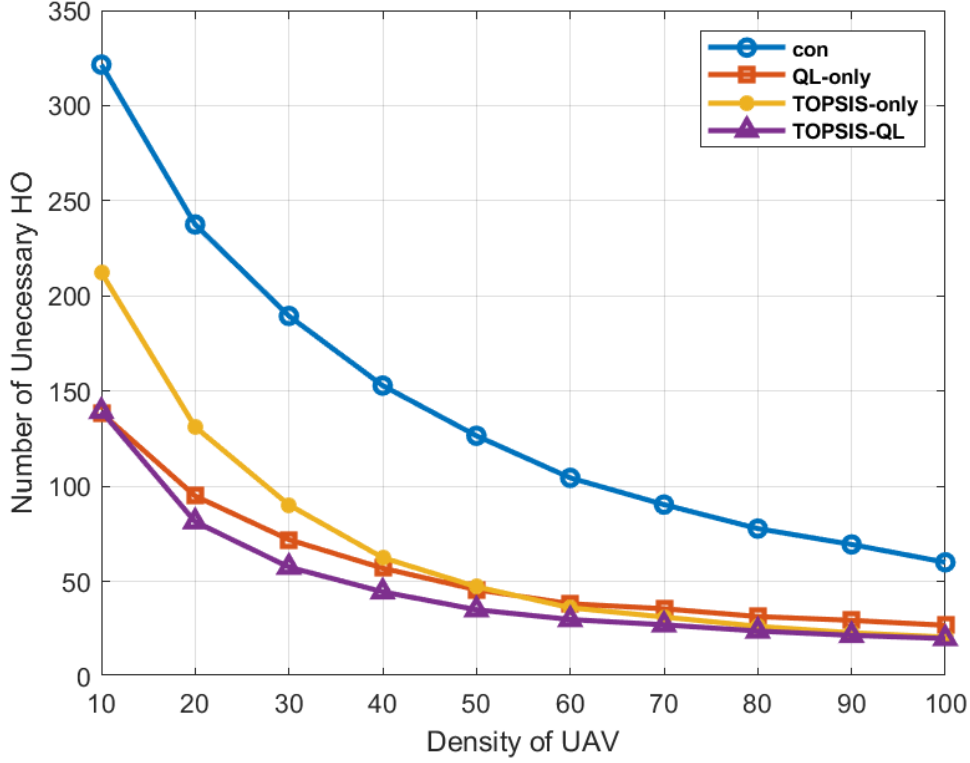


Figure 4.5: Number of Unnecessary HO against density of UAV.

methods are decreasing with the increase of the UAV density. This is because the increase of UAV density leads to higher number of HOs, which cause more transmission interruption, leading to lower EE. Compared to the other three methods, the proposed method can improve the EE by around 46.1% in the comparison of conventional method (when the density of UAV is $50 \times 10^{-6}/m^2$).

4.5 Summary

This chapter proposes a hybrid HO decision-making scheme that combines TOPSIS and QL for UAV-aided three-tier HetNets. Specifically, TOPSIS with a SD weighting technique is employed to reduce the action space dimensionality in QL by selecting candidate BSs that provide enhanced performance. QL then selects the optimal BS from these candidates to maximize overall performance with respect to the number of HOs, unnecessary HOs, and average EE. In the proposed scheme, SINR, ToS, and EE

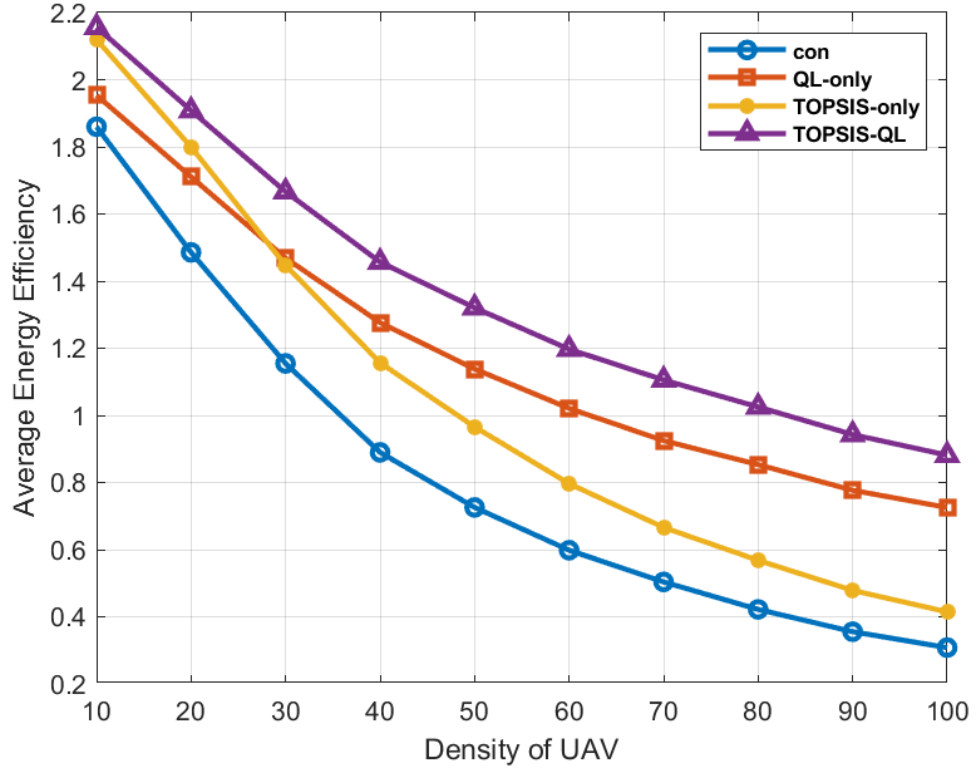


Figure 4.6: Average EE against UAV density.

are adopted as decision criteria. Simulation results demonstrate the effectiveness of the TOPSIS-QL method, outperforming conventional methods, including TOPSIS-only and QL-only approaches, where the number of HO and unnecessary HO is remarkably reduced by around 48.7% and 69.2% respectively, and the average EE is notably improved by around 46.1% in comparison with the baseline.

FUZZY INFERENCE SYSTEM BASED HANDOVER SCHEME WITH TASK MIGRATION IN UAV-AIDED MEC

As introduced in Chapter 3 and Chapter 4, UAVs can act as UEs and BSs in current communication network, and HO decision-making problem also exist in both scenarios. Actually, due to the advanced characteristics of UAVs like agility, ease of deployment, low cost, and etc., UAVs can also aid in MEC networks. Meanwhile, the HO decision-making problem in UAV-aided MEC is different with the communication network due to the involvement of the data processing. Therefore, in this chapter, a HO scheme is proposed for ground UEs in UAV-aided MEC, where UAVs act as both BSs and edge nodes, to improve both communication and edge computing performance.

5.1 Introduction

Recently, with the advancement of 5G technology and the rapid proliferation of smart devices, there has been an increase in mobile applications that demand high computing capacities and low latency, such as augmented reality [86]. Mobile cloud computing

provides an infrastructure for storing and processing data by offloading tasks from mobile devices to cloud servers. However, because cloud servers are typically centralized, data transmission through the core network results in high delays and increased network traffic [87]. To address these challenges, the European Telecommunications Standards Institute (ETSI) has promoted the MEC architecture to reduce service access delay and communication overhead, especially when servers are distant from users [88]. Meanwhile, due to the ease of deployment, low cost, and mobility, UAVs are well-suited to be integrated with MEC to enhance service quality [89]. Usually, in MEC, mobile edge servers are placed at the network edge, such as BSs and APs, which are close to UEs [90]. Therefore, in UAV-aided MEC, UAVs can also act as mobile edge nodes, providing on-the-fly computational resources and LoS connectivity in scenarios where terrestrial infrastructure is lacking or unavailable [91]. This is particularly beneficial for disaster recovery, remote monitoring, and temporary events where rapid deployment and adaptability are critical. Typically, it is necessary for edge servers to serve multiple applications. For security and integrity for multiple applications sharing the same MEC server simultaneously, virtual machine (VM) technology is crucial to ensure resource isolation [92].

As mentioned in Chapter 4, with the advancement of 5G communication technologies, ultra-dense deployments of SBSs have become prevalent in urban HetNets. The environment becomes even more dynamic and complex when mobile UAVs are integrated into the network, leading to frequent HOs as UEs traverse the area [68]. In MEC systems, this complexity is further amplified. Task migration is tightly coupled with HO events, since seamless edge service continuity relies on the UE maintaining a strong connection to both communication and computing resources [42]. Thus, in UAV-aided MEC networks, HO decisions must consider not only wireless link quality but also server load, task delay, and energy consumption. While migrating to a BS with better connectivity and computing availability improves service quality, it can also lead to frequent HOs, increasing signalling overhead, energy consumption, and the risk of task failures [93]. These problems are particularly critical for time-sensitive MEC applica-

tions and energy-limited UAVs [94]. While the TOPSIS–QL approach is effective in UAV-aided HetNets by optimising long-term HO decisions through learning, it is less suitable for MEC scenarios that demand fast, context-aware decisions for seamless task migration with multiple UEs. QL rely on repeated training and predefined trajectories limits its responsiveness in dynamic MEC environments. In contrast, a fuzzy inference system (FIS) offers a lightweight, rule-based solution capable of handling uncertainty and integrating multiple criteria—including SINR, task delay sensitivity, and energy efficiency—without requiring extensive training. This makes FIS particularly well-suited for real-time, low-complexity decision-making in resource-constrained UAV-aided MEC applications.

5.1.1 Related Works and Motivations

Various studies have explored HO decision-making in MEC networks, aiming to improve offloading performance, reduce latency, and minimise task migration overhead. These works can broadly be categorised into three key areas, which are mobility-aware offloading and HO coordination, resource-aware HO decision-making, and learning-based optimisation approaches.

For mobility-aware offloading and HO coordination, the authors in [38] proposed a joint HO and task offloading algorithm to increase the success rate of task completion and reduce HO failure and migration cost. Their method addresses both user mobility and radio congestion, incorporating user priority in the decision-making process. Similarly, Liang et al. [42] developed an efficient joint migration-and-HO algorithm, showing that system performance is constrained by communication capacity under low user density, and by computing load under high user density due to server I/O interference. [39] further extended this perspective in a 5G context by proposing an algorithm that considers both signal quality and MEC server load, demonstrating reduced end-to-end delay in MEC service delivery.

For resource-aware HO decision, [95] introduced a load-balancing framework in a multi-tier UAV-aided MEC system, optimising BS selection, offloading, and resource allo-

cation within overlapping BS coverage zones. This approach highlights the importance of jointly managing user association and task placement to improve system throughput and fairness.

There are also some learning-Based HO and offloading strategies. Guo et al. in [40] proposed a distributed mobility management scheme using game theory and deep reinforcement learning to maximise long-term user utility considering QoS and cost. [41] employed double deep Q-learning to minimize total offloading cost, encompassing energy, transmission, and processing delays. [96] proposed a deep reinforcement learning framework for dynamic server selection and cooperative offloading under network variability. Additionally, [97] investigated the performance impact of HO in uplink and downlink directions, identifying its importance in maximising system throughput.

While several of these methods address HO in MEC, few are tailored for UAV-aided MEC systems, which introduce unique challenges such as 3D mobility, limited energy budgets, dynamic topology, and rapid signal fluctuations. Among the reviewed works, [95] stands out as a promising state-of-the-art benchmark, as it explicitly considers BS selection, load balancing, and offloading in a UAV-assisted MEC context. However, many learning-based schemes assume static or predictable user mobility, which may not generalise well to aerial or fast-moving scenarios. This gap motivates the development of lightweight, real-time decision frameworks, such as the FIS proposed in this work, that are capable of handling uncertainty and integrating multiple metrics like SINR, delay sensitivity, and energy efficiency in UAV-aided MEC networks, making it ideal for managing both HO and task migration in dynamic environments. Therefore, we investigate the problem of HO decision-making considering both communication services and edge computing services in UAV-aided MEC with FIS. The main contributions of the chapter are summarised as follows:

- We proposed a FIS based algorithm for HO decision and BS selection for ground UEs in UAV-aided MEC. In the HO decision, four criteria related to both the communication and edge computing are considered to determine the triggering of HO. Another two-layer FIS system is proposed to select the target BSs for UEs if

the HOs are triggered. In the two-layer FIS system, by considering five criteria, the FIS modules of first layer can get the fuzzy results as the inputs in the second layer where all available BSs are rated. Then, target BS can be selected according to the rates.

- As the task migration costs time and energy, it is necessary to be incorporated into the HO decision-making strategy. Specifically, task migration in the BS selection algorithm considers the distance between serving BS and target BS after HOs are triggered to improve the performance of edge computing service.

5.1.2 Chapter Organisation

The remainder of this chapter is organised as follows. Section 5.2 introduces the system model. The proposed FIS based HO scheme is explained in Section 5.3. In Section 5.4, the simulation results are presented. Finally, Section 5.5 summarised the chapter.

5.2 System Model

5.2.1 UAV-aided MEC

MEC is deployed at the network edge to serve UEs, and the UAVs hovering in the air provides enhanced connectivity. As depicted in Fig. 5.1, this chapter considers a three-tier UAV-aided MEC system, where K BSs and M UEs are randomly distributed, denoted by the set $\mathcal{K} = \{1, \dots, K_s, K_m, K_s + K_m + 1, \dots, K_s + K_m + K_u\}$ and $\mathcal{M} = \{1 \dots M\}$, where K_s , K_m and K_u represent the number of SBSs, MBSs and UAVs respectively, and $K_s + K_m + K_u = K$. Specifically, one MBS ($K_m = 1$) is located at the centre of the area, while the SBSs and UAVs are distributed following a PPP with densities λ_s and λ_u , and UEs and UAVs move following the random waypoint model (RWM). Each BS, irrespective of type, is equipped with a server that provides both communication and edge computing services. For communication services, the MBS and UAVs operate in the LTE frequency band, utilizing licensed spectrum for wide coverage and reliable communications. The SBSs

operate in the millimeter wave frequency band, ensuring high data rates and massive connectivity. For edge computing services, the integrated servers process data if they host the corresponding VMs of the UEs. Dedicated VMs are created for UEs when they connect to the BSs. VMs offer safety, isolation, and resource allocation, containing user profiles and applications to process offloaded tasks. Additionally, VMs can seamlessly migrate between BSs to maintain service continuity as users move [98].

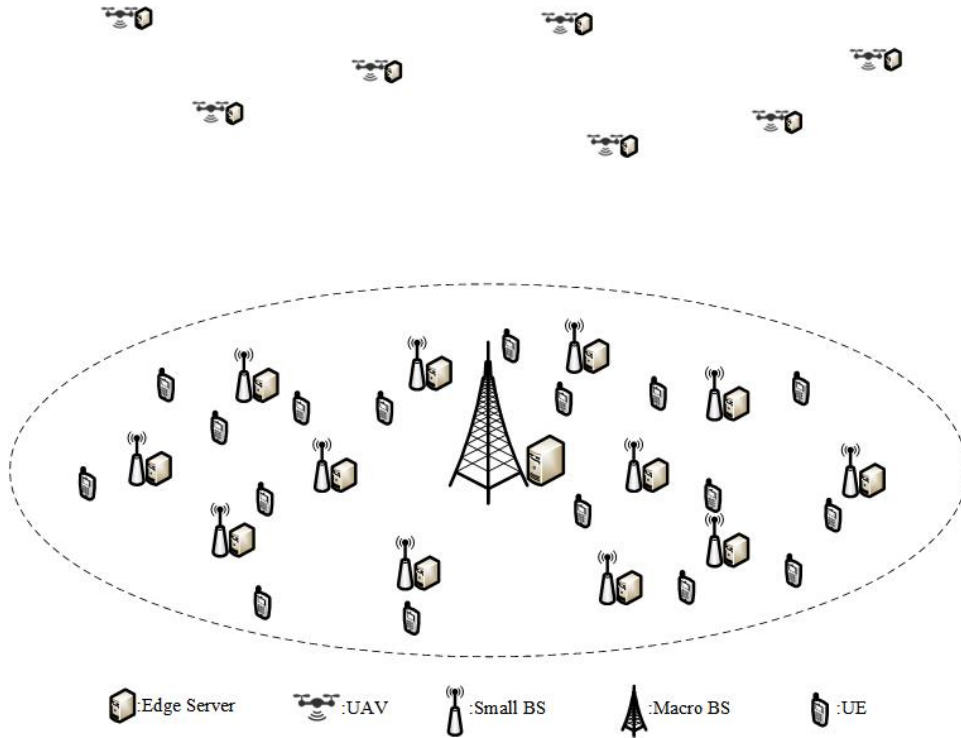


Figure 5.1: Model of three-tier UAV-aided MEC system.

5.2.2 Communication Model

The model considers three types of data transmission: downlink for communication services, uplink for users uploading tasks, and D2D links for task migration. Both ground BSs and UAVs provides downlink services, utilizing G2G and A2G channels. Path loss is a crucial metric for assessing channel quality. For G2G channels, it is assumed that terrestrial obstacles typically block the signals. Therefore, the path loss of G2G

channels between ground BSs and UEs can be modelled as [82]:

$$PL_{G2G} = 32.4 + 20\log_{10}(f_c) + 30\log_{10}(d_{3d}), \quad (5.1)$$

where f_c is the carrier frequency and d_{3d} is the distance between the ground UE and the ground BSs.

For A2G channels, the links can be classified as LoS or NLoS. A ray tracing model is employed to determine the exact type of channels [81]. In this model, obstacles are randomly generated following PPP distribution with density β , and their heights follow a Rayleigh distribution with a scale parameter κ . If no obstacles block the path, the channel is classified as a LoS link; otherwise, it is considered as an NLoS link. The path loss of LoS and NLoS links are given below according to [8]:

$$PL_{LoS} = 30.9 + 20\log_{10}(f_c) + (22.25 - 0.5\log_{10}(h_U))\log_{10}(d_{3d}), \quad (5.2)$$

$$PL_{NLoS} = 32.4 + 20\log_{10}(f_c) + (43.2 - 7.6\log_{10}(h_U))\log_{10}(d_{3d}), \quad (5.3)$$

where the h_U is the height of the UAV. As RSS and SINR are important indicators for the quality of downlink channels. The RSS $RSS_{k,m}$ from BS k to UE m can be calculated by:

$$RSS_{k,m} = P_k + G_t + G_r - PL + SF, \quad (5.4)$$

where P_k represents the transmission power from the serving BS k , 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} :

$$SF \sim \mathcal{N}(0, \sigma_{SF}). \quad (5.5)$$

The values of σ_{SF} for LoS A2G, NLoS A2G and G2G channels are given below[47]:

$$\sigma_{SF}^{LoS} = \max(5 \times e^{(-0.01 \times h_U)}, 2), \quad (5.6)$$

$$\sigma_{SF}^{NLoS} = 8, \quad (5.7)$$

$$\sigma_{SF}^{G2G} = 7.8. \quad (5.8)$$

The quality of links between BSs and UEs is impacted by the interference from neighboring BSs. In the model, SBSs operate on a different carrier frequency compared to the MBS and UAVs. Consequently, when UE m is served by BS k' , which could be any of the MBS, SBSs, or UAVs, the interference of SBSs, UAVs and MBSs, represented as I_m^s , I_m^u , and I_m^m respectively, can be calculated as follows:

$$I_m^s = \sum_{k=1, k \neq k'}^{K_s} RSS_{k,m}, \quad (5.9)$$

$$I_m^u = \sum_{k=1, k \neq k'}^{K_u+K_m} RSS_{k,m}, \quad (5.10)$$

$$I_m^m = \sum_{k=1, k \neq k'}^{K_u+K_m} RSS_{k,m}. \quad (5.11)$$

Therefore, SINR is given by:

$$SINR_m^{k'} = \frac{RSS_m^{k'}}{I_m^{k'} + \sigma_n^2}, \quad (5.12)$$

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

$$\sigma_n = 10^{-3} \times 10^{(-174 + 10 \times \log_{10} B_m^{k'})/10}, \quad (5.13)$$

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

Uplink channel is utilized to upload tasks from UEs. Denote the LoS and NLoS uplink channel gain from user m to k is $h_{m,k}^{los}$ and $h_{m,k}^{nlos}$ respectively. For complex environments with various constructions, uplink channel gain can be characterized by Rayleigh fading model as below [99]:

$$h_{m,k}^{los} = g_0 \times d_{3d}^{-\alpha_{los}}, \quad (5.14)$$

$$h_{m,k}^{nlos} = g_0 \times d_{3d}^{-\alpha_{nlos}} \times \zeta_m, \quad (5.15)$$

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

Thus, the data rate of uplink channel is expressed as [99]:

$$r_{m,k} = B_{ue} \times \log_2 \left(1 + \frac{h_{m,k} P_m}{B_{ue} n_0} \right), \forall m \in \mathcal{M}, \forall k \in \mathcal{K}, \quad (5.16)$$

where B_{ue} denotes the channel bandwidth of UE, P_m denotes transmission power of UE m , n_0 the noise power spectral density and $h_{m,k}$ is the channel power gain, where $h_{m,k} \in \{h_{m,k}^{los}, h_{m,k}^{nlos}\}$.

The D2D channel is built between BSs for task migration. We assume the D2D link shares the channel with a UE which is far away, therefore the interference could be ignored. Thus, the data rate of D2D channels from BS k to k' is calculated by:

$$r_{k,k'} = B_{ue} \times \log_2 \left(1 + \frac{h_{k,k'} P_k}{B_{ue} n_0} \right), \forall k, k' \in \mathcal{K}, \quad (5.17)$$

where P_k denotes the transmission power of the serving BS k , and $h_{k,k'}$ is the channel power gain between the serving BS k and target BS k' . The channel power gain of LoS and NLoS links are given by:

$$h_{k,k'}^{los} = g_0 \times d_{k,k'}^{-\alpha_{los}}, \quad (5.18)$$

$$h_{k,k'}^{nlos} = g_0 \times d_{k,k'}^{-\alpha_{nlos}} \times \zeta_k, \quad (5.19)$$

where $d_{k,k'}$ is the distance between the serving BS k and target BS k' in three dimensions.

5.2.3 Computation Model

In this model, UEs offload their generated tasks to the MEC server to process while they are on the move. At each BS, the MEC server hosts multiple VMs that share physical resources for task processing. However, I/O interference may occur, reducing the computing speed [42]. Therefore, the computing capability is affected by the number VMs. According to [40], the expected computation rate of UE m connected to BS k is $f_{k,m}$, and the performance degradation factor at BS k is defined as d_k ($d_k > 0$). Each BS operates at the same CPU frequency, which is f_k (cycles per second). Thus the expected computation rate can be calculated as [42]:

$$f_{k,m} = \frac{f_k}{V_k}, \forall k \in \mathcal{K}, \quad (5.20)$$

therefore, the actual computing capability $F_{k,m}$ of BS k for user m is

$$F_{k,m} = f_{k,m}(1 + d_k)^{1-\mathcal{V}_k}, \forall k \in \mathcal{K}, \quad (5.21)$$

where $\mathcal{V}_k$ is the number of instantiated VMs in the MEC server at BS k .

To characterize the j_{th} task generated by UE m , we define a 3-tuple $U_{m,j} = (D_{m,j}, C_{m,j}, Th_{m,j})$. Here, $D_{m,j}$ denotes the data size of the task, $C_{m,j}$ represents the total number of CPU cycles required for computation, and $Th_{m,j}$ specifies the time threshold within which the task must be completed. Given that the results of these tasks generally have negligible data sizes, we can disregard the time required to transmit the result back. Consequently, the total task completion time comprises three primary components: the transmission time, the execution time and the migration time. The transmission time of task j from UE m to BS k can be formulated as follows:

$$T_{m,j}^{Tr} = \frac{D_{m,j}}{r_{m,k}}, \forall m \in \mathcal{M}, \forall k \in \mathcal{K}. \quad (5.22)$$

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

$$T_{m,j}^E = \frac{C_{m,j}}{f_{m,k}}, \forall m \in \mathcal{M}, \forall k \in \mathcal{K}. \quad (5.23)$$

In addition, a task migration occurs if the task execution is not completed when a needed HO triggered. Assuming the task migration indicator $i_{m,j}^M$, if a task migration occurs, $i_{m,j}^M = 1$, otherwise it is 0. Then, the task migration time $T_{m,j}^M$ can be expressed as:

$$T_{m,j}^M = \frac{C_{m,j}^M}{r_{k,k'}} \cdot i_{m,j}^M, \forall m \in \mathcal{M}, \forall k \in \mathcal{K}, i_{m,j}^M \in \{0, 1\}, \quad (5.24)$$

where $r_{k,k'}$ is the data rate of migration channel from BS k to BS k' , and $C_{m,j}^M$ is the size of data that need to be migrated. As the task cannot be divided arbitrarily, in our model, we define there are four parts in a task. If a part is not completed when the migration is required, then the part needs to be re-processed after the migration. Thus, the size of data need to be migrated must meet $C_{m,j}^M = \frac{i}{4} C_{m,j}, i \in \{1, 2, 3, 4\}$.

Thus, the task completing time $T_{m,j}^D$ can be denoted by:

$$T_{m,j}^D = T_{m,j}^{Tr} + T_{m,j}^E + T_{m,j}^M, \forall m \in \mathcal{M}, \forall k \in \mathcal{K}. \quad (5.25)$$

5.2.4 Time of Stay Model

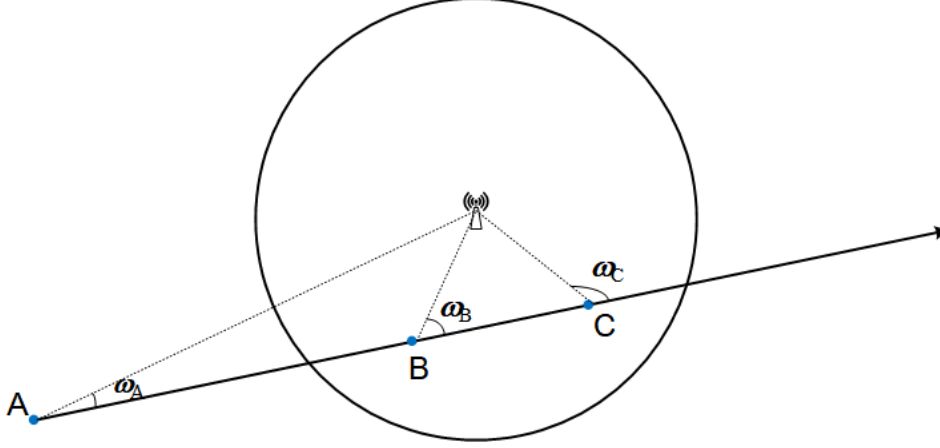


Figure 5.2: UE is moving through a BS coverage.

In the system model, it is essential to calculate the sojourn time of the UE within a BS's coverage area, referred to as ToS. UEs connecting to BSs with a short ToS can lead to frequent HOs and increased task completion time. Both UEs and UAVs are mobile within the area, resulting in relative velocities and directions that can be represented as vectors when UEs connect to UAVs. Same calculation with Section 4.2 is acquired here. Specifically, as illustrated in Fig. 5.2, UEs may occupy positions A , B , and C as they traverse a BS's coverage area. The corresponding ToS can be expressed as follows [100]:

$$ToS_A = \frac{2 \times R_{BS} \times \sqrt{1 - \left(\frac{d_{2d} \times \sin(\omega_A)}{R_{BS}}\right)^2}}{v_{UE}}, \quad (5.26)$$

$$ToS_B = \frac{d_{2d} \times \cos(\omega_B) + \sqrt{(d_{2d} \times \sin(\omega_B))^2 - R_{BS}^2}}{v_{UE}}, \quad (5.27)$$

$$ToS_C = \frac{\sqrt{R_{BS}^2 - (d_{2d} \times \sin(180 - \omega_C))^2} - d_{2d} \times \cos(180 - \omega_C)}{v_{UE}}, \quad (5.28)$$

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.

5.2.5 Energy Consumption Model

In this model, we focus on the the task processing energy consumption in BSs, which encompasses both energy consumed in task execution and task migration. According to [101], there exists a linear relationship between the CPU cycle frequency and energy consumption. Therefore the energy consumed in task execution can be calculated as follows [94]:

$$E_k^{exe} = \sum_{m \in \mathcal{V}_k} \varsigma \cdot (f_{k,m})^2 \cdot D_{m,j}, \quad (5.29)$$

where $\mathcal{V}_k$ is the number of UEs that BS k serves and ς represents the effective capacitance switch of the CPU. For the energy consumption of task migration, assuming there is a task migrated from BS k to BS k' , it can be calculated as:

$$E_k^{mig} = \sum_{m \in \mathcal{V}_k^{mig}} p_k \cdot T_{m,j}^M, \quad (5.30)$$

where p_k is the transmit power of BS k , $\mathcal{V}_k^{mig}$ represents the number of tasks that need to be migrated and $T_{m,j}^M$ denotes the migration time

Therefore, the energy consumed in task processing is expressed:

$$E_k = E_k^{exe} + E_k^{mig}, \forall k \in \mathcal{K}. \quad (5.31)$$

5.3 Proposed Fuzzy Inference System based Handover Scheme

5.3.1 Overview of the proposed method

Based on the system model outlined earlier, UAV-aided MEC networks with dense BS deployments face substantial challenges, including frequent HOs, increased task completion delays, and elevated energy consumption. These issues are exacerbated by the mobility of both UAVs and ground UEs, which makes task migration highly dynamic and delay-sensitive [42]. In contrast to traditional HO schemes that primarily consider radio link quality alone, effective HO decision-making in UAV-aided MEC must jointly

optimize for low latency, computational resource efficiency, energy usage, and service continuity to meet the demands of real-time edge computing applications.

To address these challenges, we propose a HO and BS selection scheme based on a FI), which excels in handling uncertain, non-linear, and multi-dimensional decision problems. Unlike machine learning-based methods such as RL or deep QL, which are commonly used in UAV and HetNet contexts, FIS requires no pre-training, imposes minimal computational overhead, and is inherently interpretable. These features make it highly suitable for real-time deployment on UAVs, where computational capacity and energy are limited.

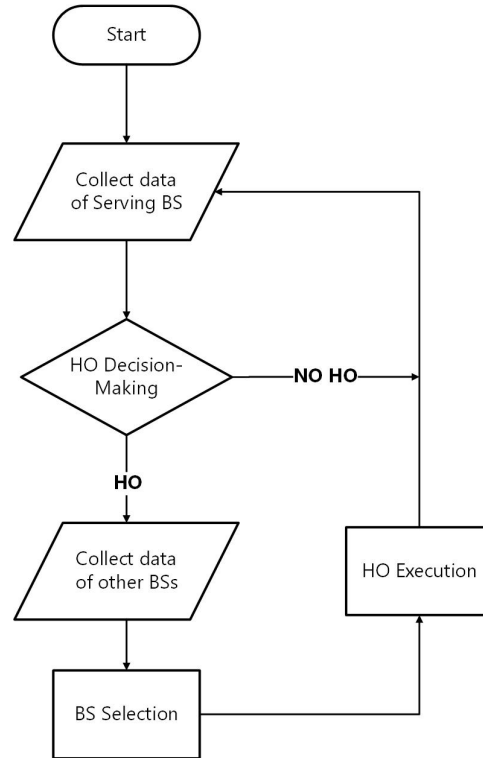


Figure 5.3: Process of the proposed algorithm

Our methodology is structured to two fundamental components: HO decision-making and BS selection. As shown in Fig. ??, the first phase involves collecting data from the current serving BS at each waypoint to determine whether a HO should be triggered. If a HO is required, data from other candidate BSs is subsequently gathered. All collected data then serves as input for the second phase, where the target BS is selected. If

there is no HO is decided, the UE continues to maintain its connection with the current serving BS. Finally, if a HO decision is made, the HO is executed. In the HO decision-making phase, multiple factors are evaluated to determine whether a HO event should be initiated based on the current network quality. A FIS is employed to assess variables including RSS, distance, allocated CPU cycle frequency and task time threshold. The FIS model performs a dynamic analysis of these inputs to produce an output that indicates the tendency of HO triggering, which is a variable from 0 to 1 (1 means absolutely HO). If this output surpasses a predetermined threshold, indicating a potential degradation in connectivity quality, a HO is triggered. The comprehensive procedure is presented in Algorithm 5.1.

Algorithm 5.1 First Stage: HO Decision Making

```

1: Input: RSS, Distance, Users_Number
2: Output: HO_Decision
3: HO_Tendency  $\leftarrow$  FuzzyInference(RSS, Distance, F_CPU, Time_Threshold)
4: return HO_Tendency
5: if HO_Tendency > Threshold then
6:   HO_Occurs  $\leftarrow$  True
7:   BS_Selection()
8: else
9:   HO_Occurs  $\leftarrow$  False
10:  Stay with current BS
11: end if

```

In the BS selection phase, a multi-level FIS is utilized to assess the key criteria for each BS. In the first layer, criteria are categorized into two distinct FIS modules. The first FIS module evaluates criteria related to the quality of links, including SINR, ToS, and the distance between the UE and BSs. The second FIS module focuses on data execution criteria, such as the number of connected UEs and the distance to the serving BS. These two FIS modules operate in parallel, and their outputs are subsequently combined and processed by a higher-level FIS in the next layer. This hierarchical evaluation process ensures a comprehensive and nuanced assessment, culminating in a detailed rating for each candidate BS, which reflects its ability to meet the requirements of the UE. The detailed steps of this process are outlined in Algorithm 5.2.

Algorithm 5.2 Second Stage: BS Selection

```
1: function BS_SELECTION
2:   Input: SINR, ToS, Distance_( $BS \rightarrow UE$ ), Serving_Users, Distance_( $BS \rightarrow BS$ )
3:   Output: Best_BS
4:   FISResult_1  $\leftarrow$  FIS1(SINR, ToS, Distance_( $BS \rightarrow UE$ ))
5:   FISResult_2  $\leftarrow$  FIS2(Distance_( $BS \rightarrow BS$ ), Serving_Users)
6:   Rating  $\leftarrow$  FuzzyInference(FISResult_1, FISResult_2)
7:   Best_BS  $\leftarrow$  ChooseBestBS(Rating)
8:   return Best_BS
9: end function
```

Compared to state-of-the-art learning-based approaches such as those in [40, 41, 96], which aim to optimise HO and task offloading in MEC via deep RL or game-theoretic methods, our FIS-based approach offers greater real-time responsiveness and lower model complexity. Moreover, unlike optimisation-based methods that require global network knowledge or centralised control, FIS can operate in a distributed, self-contained manner with only local observations, making it ideal for decentralised UAV environments. Through this design, the proposed FIS method enables adaptive, low-latency, and energy-aware HO decisions that directly account for task migration needs and network heterogeneity.

5.3.2 Proposed FIS

The primary goal of the FIS process is to optimise both HO decision-making and BS selection, enhancing performance in HO and edge computing. Fuzzy logic theory employs partial membership to describe criteria rather than using fixed thresholds. During both the fuzzification and defuzzification stages, criteria values can partially belong to different categories simultaneously, which is quantified by their degree of membership. These degrees collectively form the membership functions. During the inference stage, fuzzy rules are crucial parameters that incorporate all measurements. Based on these rules, fuzzy inference results are generated from the inputs and membership functions. Subsequently, the center of gravity method is applied for defuzzification, translating the fuzzy output into a precise value.

5.3.2.1 Membership Function

In FIS systems, each input and output for every FIS module is categorized using specific membership functions. Input membership functions are configured as trapezoidal, while output functions are triangular.

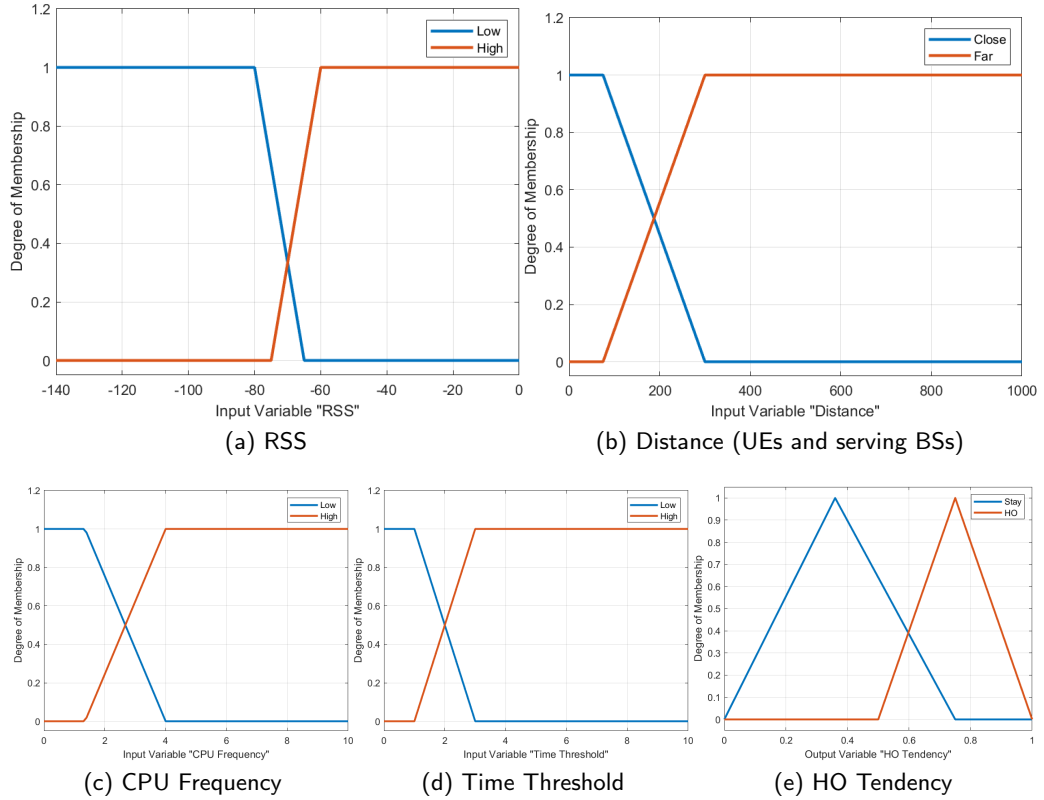


Figure 5.4: Membership functions of HO decision-making FIS

At the HO decision-making stage, inputs include RSS, distance between the BS and the UE, allocated CPU frequency, and task time threshold, and the output is assumed as the HO tendency as the output is positively correlated with the inputs. Fig. 5.4 illustrates corresponding membership functions. For RSS, two categories are defined: “Low” (below $-65dBm$) and “High” (above $-75dBm$). The distance is categorized as “Close” if it is less than $300m$ and “Far” if it exceeds $75m$. Allocated CPU frequency is “Low” below 4×10^9 and “High” above 1.3×10^9 . The task time threshold is “Low” if under $3s$ and “High” if over $1s$. The HO tendency is “Stay” if the value ranges from 0 to 0.75 and “HO” if it

5.3. PROPOSED FUZZY INFERENCE SYSTEM BASED HANDOVER SCHEME

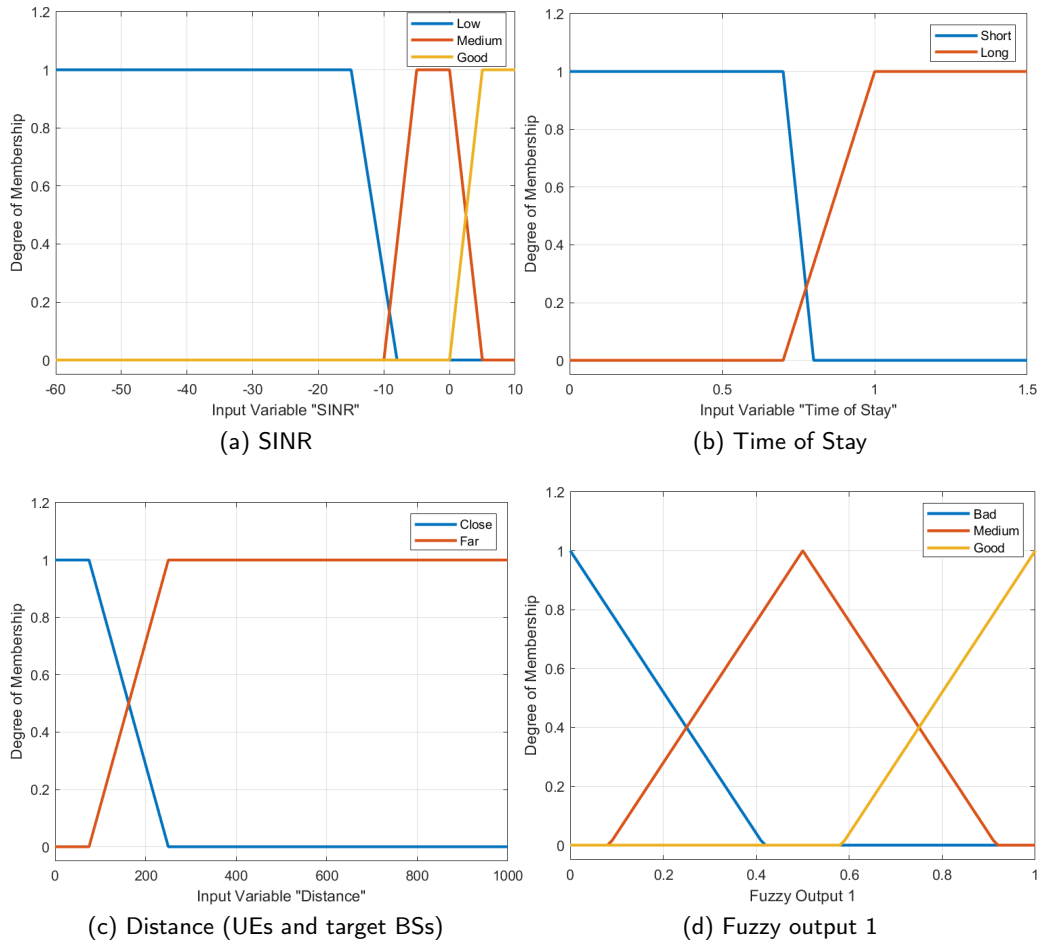


Figure 5.5: Membership functions of communication evaluation FIS in BS selection

exceeds 0.5.

During BS selection, five inputs and three outputs are considered, as shown in Fig. 5.5 and Fig. 5.6. Fig. 5.5 depicts the first layer FIS membership functions for evaluating BSs based on communication criteria. The inputs are SINR, ToS, and the distance between UEs and target BSs. SINR is classified as “Low” below $-8dB$, “Medium” from $-10dB$ to $5dB$, and “Good” above $0dB$. ToS is “Long” if over $0.7s$ and “Short” otherwise. The distance between UEs and target BSs is “Close” if less than $250m$ and “Far” if over $75m$, stricter than the first stage for selecting BSs with better service quality. The output for the communication evaluation FIS is the BS evaluation from a communication perspective: “Bad” below 0.41, “Medium” from 0.08 to 0.91, and “Good” above 0.58.

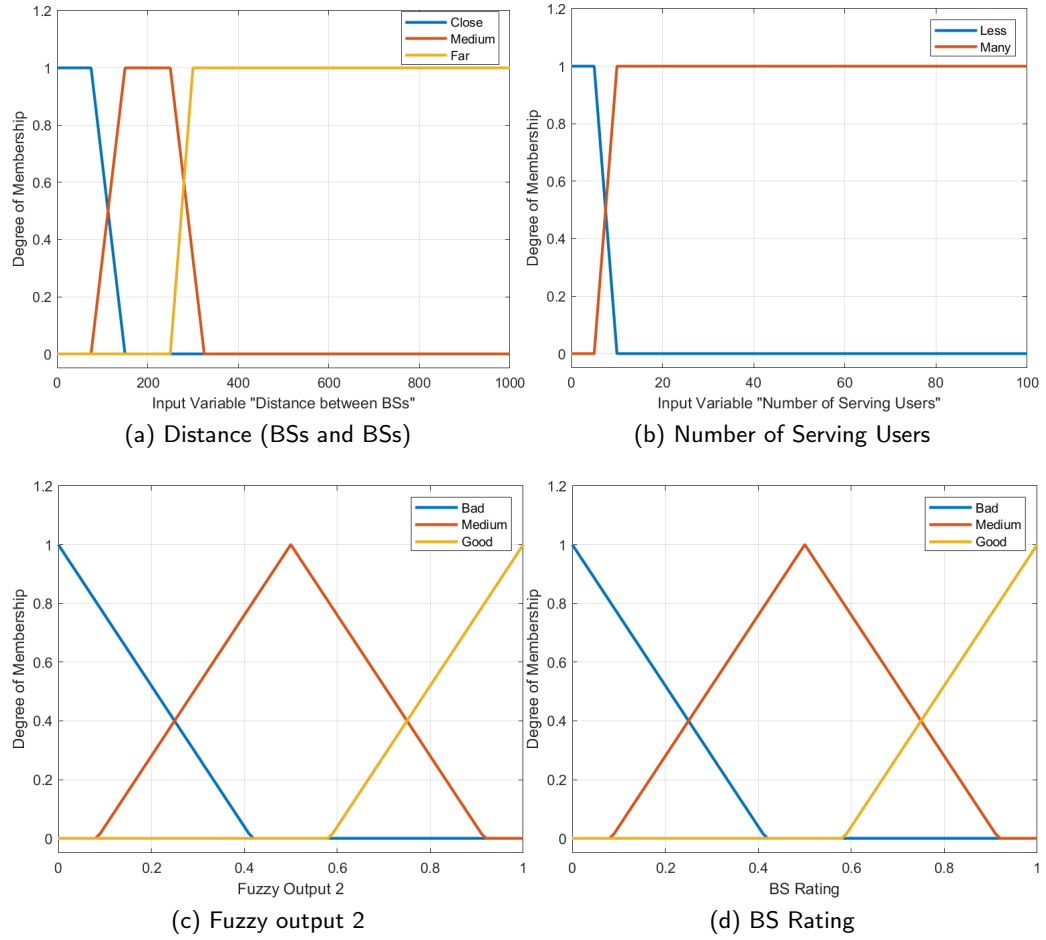


Figure 5.6: Membership functions of edge computing evaluation FIS and BS rating FIS in BS selection

Fig. 5.6 shows the membership function of the edge computing evaluation FIS. This FIS considers the distance between target BSs and the serving BS and the number of current serving users. The distance is “Close” if less than 150m, “Medium” between 75m and 325m, and “Far” above 250m. The categories for serving users are “Less” and “many”. A BS starts to be considered “many” when serving more than 5 users and “Less” when serving fewer than 10 users. The output for the edge computing evaluation FIS is the evaluation of BS from computing perspective, where the output membership function is the same with that of the communication evaluation FIS. Both outputs are then inputs for the BS rating FIS, with membership functions consistent with the previous outputs.

Table 5.1: Rules of HO decision-making FIS

Input					Output
NO.	Distance	RSS	CPU frequency	Time Threshold	HO Tendency
1	Close	Low	Low	Low	Stay
2	Close	Low	Low	High	HO
3	Close	Low	High	Low	Stay
4	Close	Low	High	High	Stay
5	Close	High	Low	Low	Stay
6	Close	High	Low	High	HO
7	Close	High	High	Low	Stay
8	Close	High	High	High	Stay
9	Far	Low	Low	Low	HO
10	Far	Low	Low	High	HO
11	Far	Low	High	Low	Stay
12	Far	Low	High	High	HO
13	Far	High	Low	Low	Stay
14	Far	High	Low	High	HO
15	Far	High	High	Low	Stay
16	Far	High	High	High	Stay

5.3.2.2 Fuzzy Rules

Table 5.1 and 5.2 detail the four FIS modules of the proposed method. The HO decision-making FIS utilizes 16 If-Then rules to map four fuzzy inputs to two fuzzy outputs. In the BS selection FIS, there are three distinct FIS modules, each governed by its own set of rules: 12 If-Then rules, 9 If-Then rules, and 6 If-Then rules, respectively. All rules employ the *and* logical operation, meaning the output category values are determined by the minimum mapping value among the different input categories. Subsequently, the *or* operator combines the same output categories, and *and* operator combines the different output categories from various rules, enabling the defuzzification process via the output membership function. This structured approach ensures a comprehensive and accurate fuzzy logic inference, enhancing the performance of HO decision-making and BS selection.

Table 5.2: Rules of BS selection FIS 1, FIS 2 and FIS 3

Input				Output
NO.	SINR	ToS	Distance(UE and BS)	Fuzzy Result 1
1	Low	Short	Close	Bad
2	Low	Long	Close	Medium
3	Medium	Short	Close	Bad
4	Medium	Long	Close	Good
5	Good	Short	Close	Medium
6	Good	Long	Close	Good
7	Low	Short	Far	Bad
8	Low	Long	Far	Bad
9	Medium	Short	Far	Bad
10	Medium	Long	Far	Medium
11	Good	Short	Far	Bad
12	Good	Long	Far	Medium
Input				Output
NO.	Distance (BS and BS)	Number of Serving UEs		Fuzzy Result 2
1	Close	Less		Good
2	Medium	Less		Good
3	Far	Less		Medium
4	Close	Many		Bad
5	Medium	Many		Bad
6	Far	Many		Bad
Input				Output
NO.	Fuzzy Output 1	Fuzzy Output 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

5.4 Performance and Results Analysis

The efficacy of the FIS-based HO scheme is evaluated using four key metrics: the number of HOs, task completion time, the number of successfully completed tasks, and BS energy consumption. To ensure a comprehensive performance assessment, we compare the proposed method against three alternative schemes: Distance-based, RSS-

based, and TOPSIS-based schemes. Both Distance-based and RSS-based approaches are conventional and widely employed in mobile communication networks, whereas TOPSIS is a popular MCDA method. In the Distance-based scheme, HO events are triggered when the RSS of the current BS falls below a certain threshold, which is A2 event. Under this scheme, UEs select the nearest available BS. In the RSS-based scheme, UEs choose the BS with the highest RSS whenever an A3 event is triggered. The TOPSIS-based scheme uses similar criteria as our proposed method except the impact of tasks migration, and the top-ranked BS is selected for HO.

In our simulations, we utilize a random waypoint model to emulate UE movement patterns, with UE velocities randomly assigned between $1m/s$ to $5m/s$. UAVs also move randomly, with velocities ranging from $5m/s$ to $15m/s$. Tasks are generated by UEs at regular 10-second intervals, with task sizes follows a Gaussian distribution (mean 1×10^7 bits, standard deviation $\sigma_{task} = 1 \times 10^5$). A complete list of simulation parameters is provided in Table 5.3.

5.4.1 Average Number of Handover

Fig. 5.7 presents the average number of HOs experienced by each UE during their movement for FIS-based method, distance-based method, RSS-based method, and TOPSIS-based method over varying durations. As expected, the number of HOs increases with longer movement durations for all methods, as UEs are more likely to cross cell boundaries over time. Notably, the proposed FIS-based method, labeled as “FIS”, demonstrates superior performance in minimizing the number of HOs. Even as the total movement time extends, the FIS method maintains a significantly lower number of HOs compared to the distance-based, RSS-based, and TOPSIS methods. From the figure, when the moving time is 100s, the proposed method reduces the number of HOs by 84.8% in the comparison with RSS-based method. This superior performance indicates that the FIS approach is more efficient in managing connectivity and maintaining stable connections, thereby reducing the frequency of required HOs as users move. This efficiency stems from the use of multiple criteria in the proposed scheme with varying membership degrees to

Table 5.3: Simulation parameters

Parameters	Values
Bandwidth (B)	$B_{SBS} = 500 \text{ MHz}$ $B_{MBS} = 20 \text{ MHz}$ $B_{UBS} = 20 \text{ MHz}$ $B_{ue} = 10 \text{ MHz}$
Transmit Power (P_t)	$P_t^{SBS} = 35 \text{ dBm}$ $P_t^{MBS} = 46 \text{ dBm}$ $P_t^{UBS} = 20 \text{ dBm}$
Transmit Power of UEs(P_{ue})	$P_{ue} = 0.1 \text{ W}$
Carrier Frequency (f_c)	$f_c^{SBS} = 28 \text{ GHz}$ $f_c^{MBS} = 2 \text{ GHz}$ $f_c^{UBS} = 2 \text{ GHz}$
Density of BSs (λ)	$\lambda_s = 50 (10^{-6}/m^2)$ $\lambda_u = 50 (10^{-6}/m^2)$
Density of Buildings (β)	$100 (10^{-6}/m^2)$
Radius of BSs (R)	$R_{SBS} = 50 \text{ m}$ $R_{MBS} = 1000 \text{ m}$ $R_{UBS} = 150 \text{ m}$
UE moving duration (L)	50 to 100 s
Height of BSs(h)	$h_{SBS} = 4 \text{ m}$ $h_{MBS} = 20 \text{ m}$ $h_{UBS} = 100 \text{ m}$
Scale Parameter (κ)	20
Number of UEs (M)	100
CPU Frequency (f_k)	1×10^{10}
Reference Channel Power Gain (g_0)	1.42×10^{-4}
Path Loss Exponent (α)	$\alpha_{LoS} = 2.5$ $\alpha_{NLoS} = 3.5$
Effective Capacitance Switch of CPU (ς)	3×10^{-16}
performance degradation factor (d_k)	0.25

determine the necessity of a HO, rather than relying on a fixed threshold. Using membership degrees can provide greater flexibility, smoother decisions compared to hard fixed thresholds for the multi-criteria environments like UAV-aided MEC networks. In contrast, the distance-based and RSS-based methods depend on a single parameter to make HO decisions, leading to a higher number of HOs. The distance-based method performs better than the RSS-based method since the decision to trigger a HO in distance-based method is based on the A2 event, while HO is triggered once there is a higher-RSS BS in RSS-based method. Furthermore, the TOPSIS-based method, which ranks BSs based on multiple criteria, experiences more frequent changes in the top-ranked BS compared to the distance-based method because it takes more other factors into consideration to rank

the BSs. Consequently, the TOPSIS-based method results in a higher number of HOs than the distance-based method.

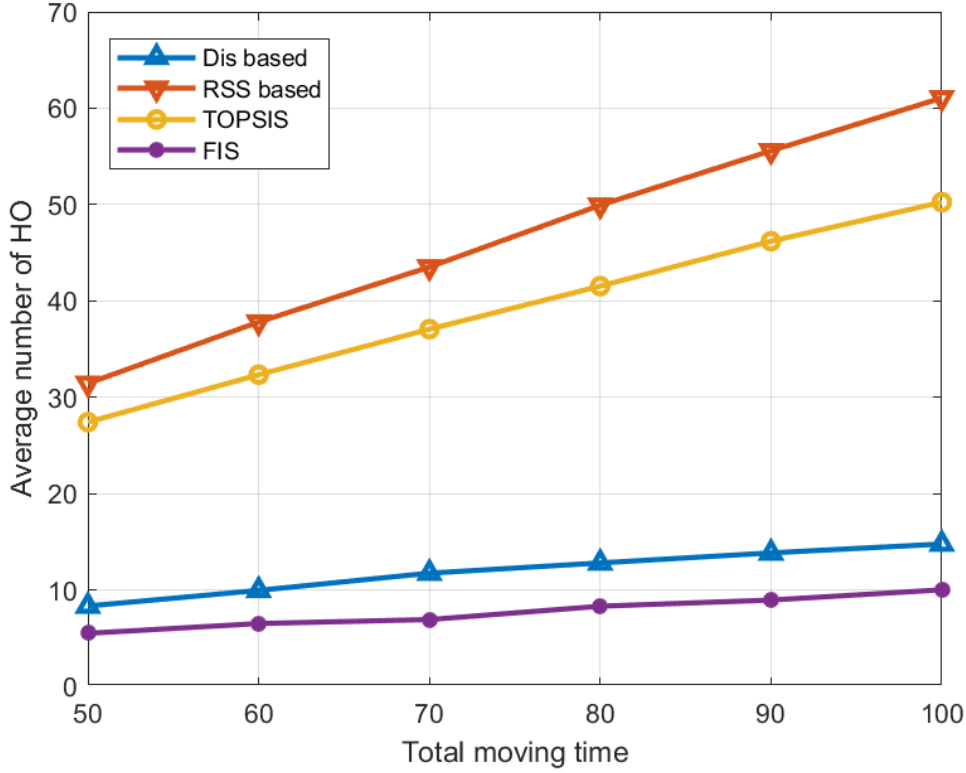


Figure 5.7: Average number of HO against moving time

5.4.2 Average Task Completing Time

The average task completion time consists of both the transmission and execution time of all tasks per UE during their movement period. In this case, transmission time includes the time of task uploading and task migration during HO procedure, and The execution time is defined as the duration of the task processing. Fig. 5.8 illustrates the performance of average task completion time for different methods. As observed, the average task completion time increases over time for all methods, primarily due to the higher task generation rate with extended duration. The proposed FIS-based approach achieves the shortest average task completion time compared to alternative methods. From the figure, the proposed method can reduce task completion time by 38.6% when the moving time is 100s in the comparison with RSS-based method. This superior performance

is attributed to the FIS method's ability to strike an appropriate balance between high-quality service from BSs and HO frequency. Appropriate membership function can generate the membership degree that more accurately describe the input values than other MCDM methods. Therefore, the FIS-based approach optimally manages connectivity and computing resources, thereby reducing the time required to complete tasks. The TOPSIS-based method shows improved performance over the RSS-based method, largely because the TOPSIS approach considers the number of connected users, which helps distribute the load more effectively. The distance-based method performs less completing time than the RSS-based method as well. This is mostly because fewer tasks can be completed in distance-based method. As distance-based method triggered HO less than RSS-based method, the large size tasks are stuck for a longer time once the serving BS is busy. Also, UEs in the distance-based method can generally utilize higher quality uplinks with less path loss to upload tasks. Conversely, the RSS-based approach experiences more HOs, which can help the large size tasks migrate to better BSs, so there are more completed tasks. Meanwhile, increased HO means high migration time, leading to longer average task completion times.

5.4.3 Average Number of Successful Tasks

Fig. 5.9 illustrates the average number of successful tasks as a function of the total movement time for the four evaluated methods. The average number of successful tasks is defined as the average number of tasks generated by each UE that are completed within their respective time thresholds. As depicted in the figure, the number of successful tasks increases with longer UE movement durations. Notably, the proposed FIS-based method and the TOPSIS-based method demonstrate a higher number of tasks that are completed within the time threshold compared to other methods. From the figure, the proposed method can increase the number of successful tasks by 74.1% when the moving time is 100s in the comparison with Dis-based method. This advantage is attributed to joint consideration of both communication and data processing criteria, enabling a more balanced and effective task completion strategy in the proposed method. The

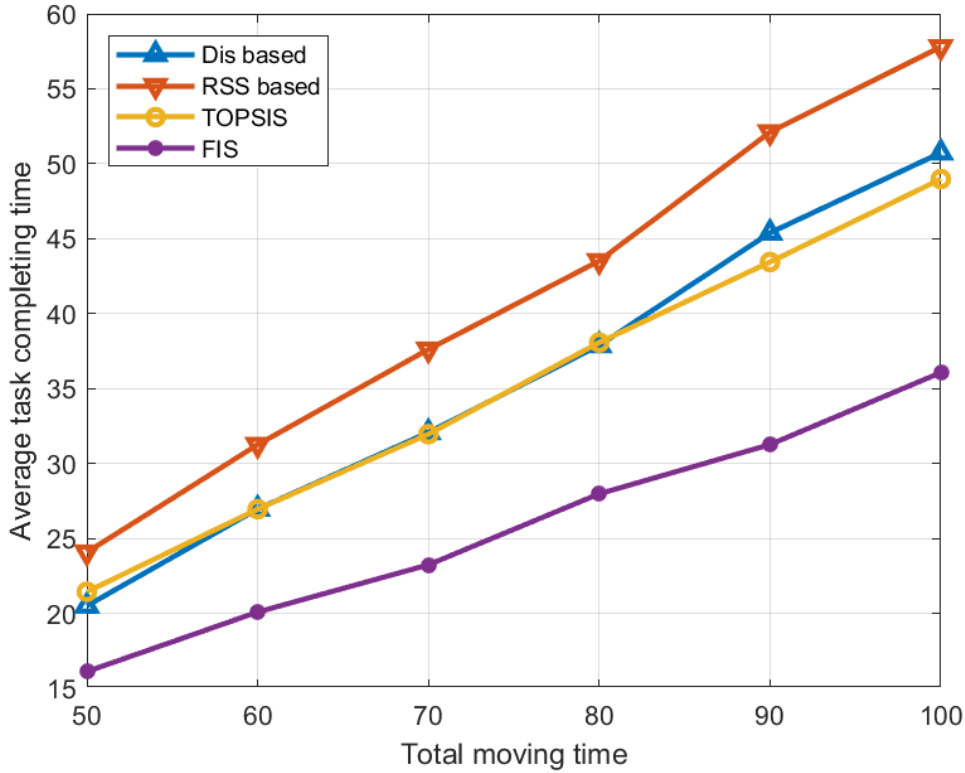


Figure 5.8: Average task completing time against moving time

FIS-based approach, in particular, achieves a greater number of timely task completions as it optimally balances the criteria from both sides, ensuring efficient connectivity and resource allocation. The RSS-based method results in more successful tasks than the distance-based method. This difference arises because tasks must wait for the completion of preceding tasks after they are generated. As the distance-based method tends to maintain the connection with the current BS longer, it happens more frequently than RSS-based method that a large size task is stuck in a BS which can only allocate less computing resource to it, while the following tasks in the waiting list cannot be processed. On the other hand, the RSS-based method, despite not always selecting the optimal BS for CPU allocation, successfully process more tasks because more HO means fewer stuck tasks.

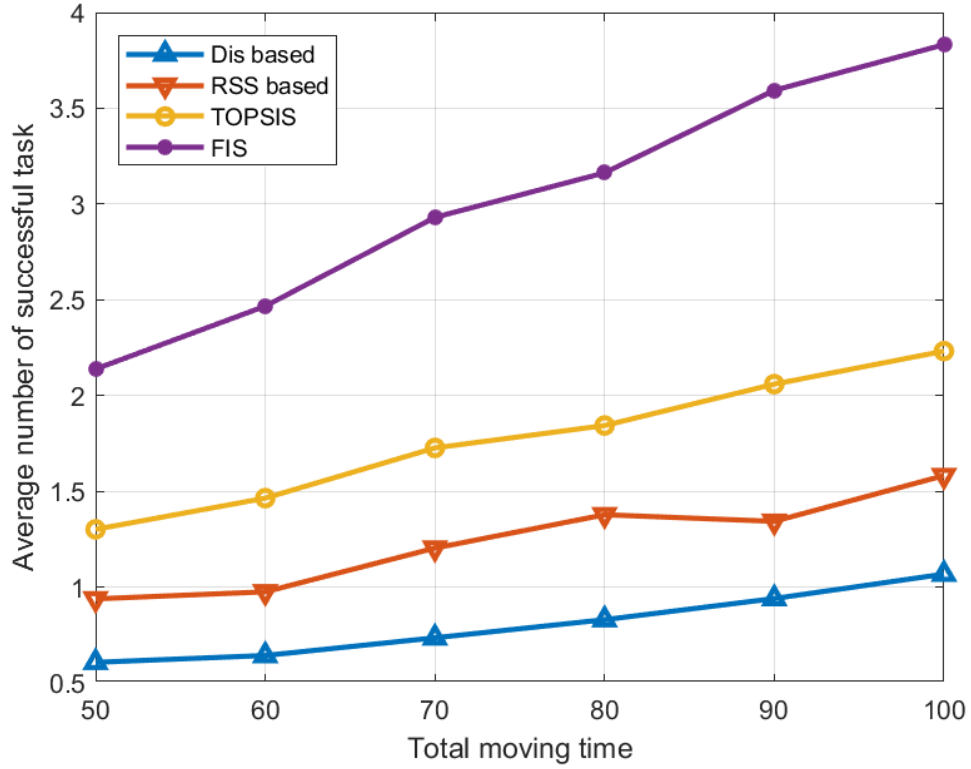


Figure 5.9: Average number of successful task against moving time

5.4.4 Average Energy Consumption

The average energy consumption per BS is a critical metric, particularly for energy-constrained BSs like UAVs. Optimizing energy consumption is essential when these BSs are serving UEs. Energy consumption in BSs comprises both execution energy consumption and migration energy consumption. Fig. 5.10 illustrates that as the UEs move for longer durations, the energy consumption of BSs increases correspondingly. The trends in energy consumption across the four methods closely mirror those observed in the number of HOs. This similarity arises because fewer HOs result in lower energy costs associated with migration, assuming execution energy remains constant. From the figure, the proposed method can reducing the energy consumption by 95.6% when the moving time is 100s in the comparison with RSS-based method. Notably, the energy consumption curve for the TOPSIS-based method is relatively flatter. This is because, despite a high frequency of HOs, the TOPSIS-based method tends to select BSs with fewer connected users as the target BS. Consequently, fewer task migrations occur, leading to a more

efficient energy consumption profile.

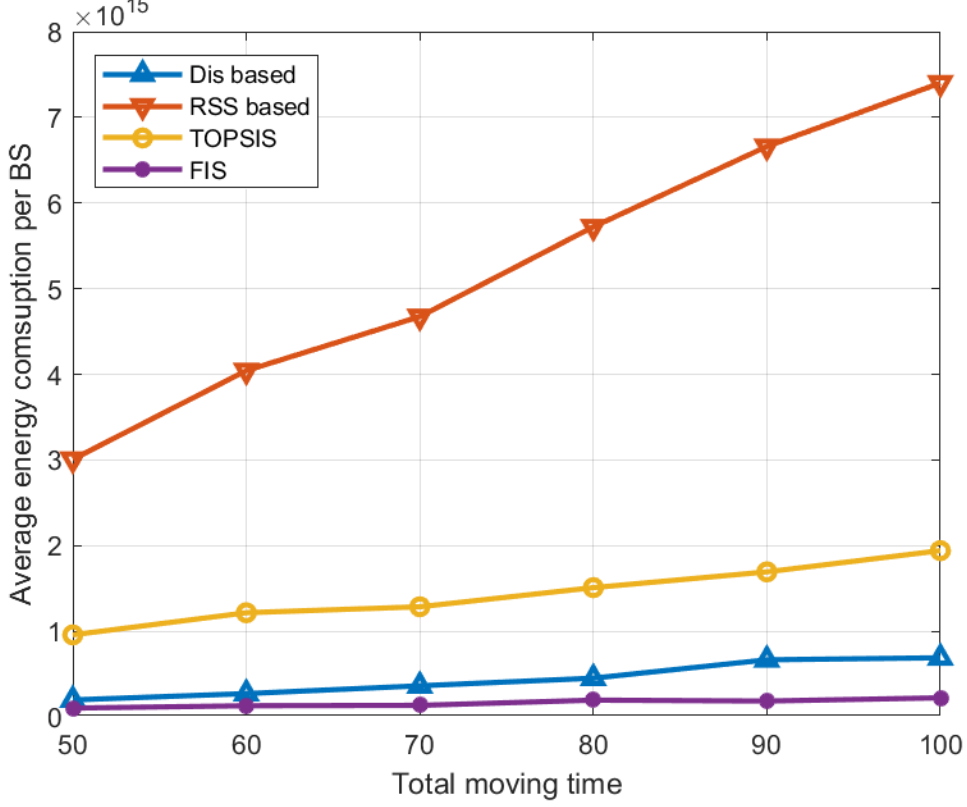


Figure 5.10: Average BS energy consumption against moving time

5.5 Summary

In this chapter, we have explored the HO decision-making challenge within UAV-aided MEC systems. To enhance performance in both communication and edge computing, we introduced a FIS-based HO decision-making scheme aimed at reducing HO frequency and improving computing service quality. The scheme involves two main stages: HO decision-making and BS selection. In the HO decision-making stage, four criteria serve as inputs to a FIS module, which determines the HO tendency. A HO event is triggered if this tendency exceeds a predefined threshold. For the BS selection stage, a hierarchical approach employs three FIS modules across two layers to determine the optimal BS. The first layer focuses on communication-related criteria such as SINR, ToS, and distance

between BSs and UEs. Simultaneously, the second FIS module evaluates the number of connected users and the distance between other BSs and the serving BS, influencing edge computing service quality. The fuzzy outputs from the first layer modules feed into the second layer FIS module, which computes the overall BS rating. Subsequently, the highest-rated BS is selected as the target BS. Simulation results demonstrate that our proposed HO scheme outperforms RSS-based, distance-based, and TOPSIS-based schemes in various metrics. When total moving time is 100s, the proposed HO scheme achieves better performance in reducing task completion time by 38.6%, increasing the number of successful tasks by 74.1%, and reducing the energy consumption by 95.6%, while also reducing the number of HOs by 84.8% in the comparison with baseline.

CONCLUSIONS AND FUTURE WORK

The primary objective of this thesis is to optimize HO decision-making in various UAV networks to improve both HO performance and QoS. Several UAV communication networks are discussed in section 1.1.1.3. In cellular-connected UAV networks, an improved QL-based HO decision-making scheme is researched; for UAV-aided HetNet, a hybrid TOPSIS-QL HO decision-making scheme is proposed to enhance both the HO and energy efficiency performances; an FIS based HO decision-making scheme is proposed for UAV aided MEC to enhance the performances in terms of the number of HO, the cost of task, and the energy consumption. This chapter summarises the key contributions of the thesis and discusses potential areas for future research.

6.1 Concluding Summary

UAVs are widely used in various fields recently. As UEs, UAVs can perform tasks like border patrol, traffic monitoring, and environmental assessments while remaining connected to the cellular network. Meanwhile, companies like Amazon and DHL are exploring UAV delivery services, relying on cellular networks to maintain UAV connectivity and control over long distances. As the aerial BSs, UAVs can provide temporary or supplementary

network services in areas lacking strong network infrastructure and establish communication links in areas where terrestrial infrastructure has been damaged. Moreover, as mobile edge nodes, UAVs can process data in real time without requiring a connection to a central server, eliminating the need to send raw data to distant cloud servers.

Due to the movement of UAVs and UEs, HOs are required to ensure seamless communication without dropped calls or data loss when a user moves out of the coverage area of one BS into another. However, owing to the diverse scenarios in different UAV networks, the requirement for HO decisions have become more complicated. Specifically, stronger interference because of the A2G link and complex resource management also affect the HO decisions in various UAV networks. The conventional single criterion HO strategies are not sufficient to meet the requirements. Therefore, the HO decision-making schemes are investigated in this thesis for various UAV networks to enhance both the HO and QoS performances. This thesis has presented a comprehensive discussions on the following aspects:

Chapter 2 presented a review of the methodologies adopted in the thesis for decision-making problems, which are TOPSIS, QL, and FIS. TOPSIS is a widely used MCDM method that helps decision-makers rank alternatives based on their proximity to an ideal solution. QL is a fundamental reinforcement learning algorithm that offers a simple yet powerful approach to solving sequential decision-making problems. FIS is a flexible and intuitive tool to solve decision-making problems for the systems which are not traditional binary logic.

Chapter 3, Chapter 4, and Chapter 5 proposed HO decision-making schemes in three UAV network scenarios, which are cellular-connected UAV networks, UAV aided HetNet, and UAV aided MEC respectively. In Chapter 3, we address the challenges of HO in cellular-connected UAV networks, where UAVs cause frequent HOs due to their high mobility in three-dimensional space. An improved QL-based HO scheme based on [33] to mitigate these issues is introduced. In the system model, a UAV-UE moves along a predefined trajectory, where it has to HO to maintain connectivity. A unique feature of this scheme is the use of SINR and distance metrics in the action space definition,

enabling for a more informed decision-making process. The reward function in the QL algorithm is designed to balance the HO rate and the quality of service, promoting connections to BSs with better SINR while also considering the distance to reduce unnecessary HOs. Simulation results show that the proposed scheme can significantly reduce the HO rate compared to existing algorithms, although it results in a slight increase in HO outage rate and a reduction in throughput.

In Chapter 4, we focus on a more complex network environment: UAV-aided HetNets. It presents a novel hybrid HO scheme that combines TOPSIS and QL to make HO decisions in a multi-tier network environment consisting of MBSs, SBSs, and UAV BSs. The system model incorporates various criteria like SINR, ToS, and EE to evaluate potential target BSs. The proposed hybrid scheme uses TOPSIS to rank the BSs based on multiple criteria, effectively reducing the scale of action space for the QL algorithm, allowing the proposed scheme to be applied for large scale networks. This integration enables more efficient and accurate HO decision-making by selecting the best target BS from a smaller, high-quality set of candidates. Simulation results indicate that the hybrid TOPSIS-QL scheme significantly reduces the number of HOs and unnecessary HOs, while also enhancing energy efficiency compared to conventional and standalone methods.

FIS provides a flexible and adaptive framework for handling frequent fluctuation of network topology and user mobility. Unlike RL-based method, it allows real-time HO decision-making without massive historical data and long training periods. Therefore, in Chapter 5, we proposed an FIS-based HO scheme with task migration in UAV-aided MEC networks. This scheme addresses the complexities of HO decision-making by considering both communication and edge computing performance. The system aims to reduce HO frequency, task delays, and energy consumption while enhancing the number of successful tasks completed within their time thresholds. The proposed method uses a two-stage process: first, making HO decisions using an FIS that evaluates multiple criteria such as SINR and remaining time before task deadlines; and second, selecting the optimal BS for task migration. Simulation results demonstrate that this FIS-based

scheme outperforms traditional methods by effectively managing the trade-offs between HO frequency, task migration, and overall network performance.

6.2 Recommendations for Future Work

This thesis focused on the HO decision-making in UAV networks through QL, TOPSIS and FIS-based schemes. In this chapter, there are some future research direction recommended in the domains that can be explored.

- **Advanced Machine Learning Techniques**

Extend the QL-based HO schemes by incorporating DRL techniques such as DQN or Actor-Critic methods. These approaches can handle the high-dimensional state and action spaces more effectively, especially in dynamic environments with a large number of UAVs, BSs and positions. It is efficient to train massive data for HO decisions without pre-known trajectory. Another potential method is Multi-Agent Reinforcement Learning (MARL). Considering the scenario where multiple UAVs or UEs operate collaboratively, MARL can be employed to optimize HO decisions in a cooperative manner, improving overall network performance while reducing interference and resource contention among UAVs [102].

- **Handover Decision-Making in 6G and Beyond**

HO decision-making in 6G and beyond networks will be driven by advanced technologies like AI, machine learning, terahertz communication, intelligent surfaces, and edge computing [103]. With the emergence of 6G networks, which promise ultra-reliable low-latency communication (URLLC) and massive machine-type communication (mMTC), future research could focus on adapting HO strategies for these new standards. Investigate how UAV networks can leverage 6G features such as reconfigurable intelligent surfaces (RIS), terahertz communication, AI, and integrated sensing and communication (ISAC) to enhance HO performance. Moreover, UAVs, which are energy limited and flexible, will play a more crucial role

in the next generation networks. Therefore, the key focus of future HO strategies will be on ensuring uninterrupted, high-quality service while managing energy efficiency, network resources, and complex mobility patterns.

- **Handover in UAV Swarm Networks**

If a region for the mission is larger than the coverage of a single UAV, it cannot work effectively. In order to improve the performance of a single UAV in tasks such as border security, surveillance, cargo delivery, and visual shows, UAV swarms are employed. UAV swarms can fulfill intensive tasks more efficiently. While fulfilling a task, the UAVs in the swarm may act autonomously or communicate with each other, and the number of UAVs in a swarm can be high depending on the assigned duty [104]. Therefore, it is necessary to investigate HO decision-making in UAV swarm networks, where multiple UAVs operate in a coordinated manner. This includes exploring how swarming behavior can be leveraged to optimize HO processes, improve coverage, and enhance communication reliability considering the role of UAVs as both network users and communication service providers.

DERIVATION OF TIME OF STAY IN CHAPTER 4

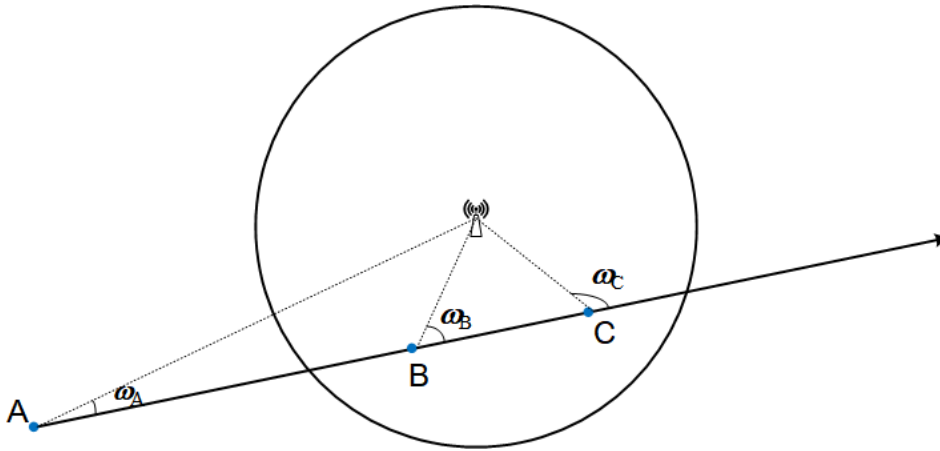


Figure A.1: UE is moving through a BS coverage.

- When a UE is at position A , as the Fig. A.2 shows, the ToS of the UE is the sojourn time in the cell, and the path of the UE in cell will be the red line, therefore the

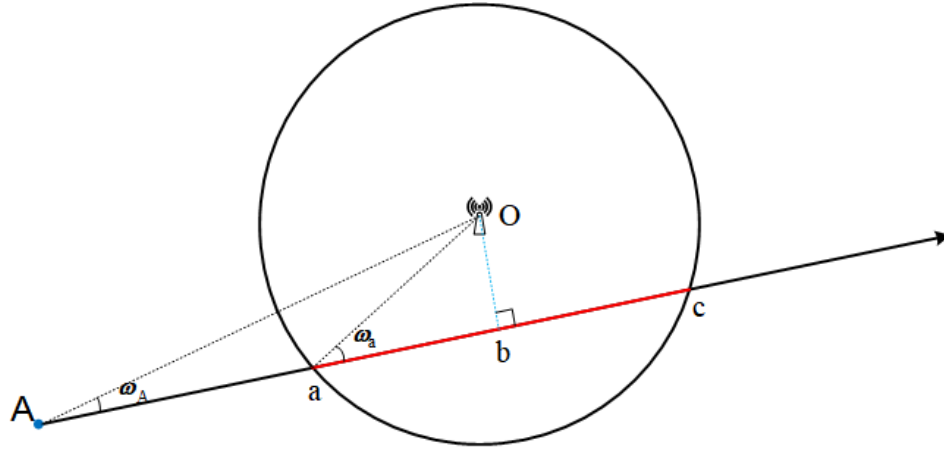


Figure A.2: Path of UE A in cell.

derivation of ToS at position A is below:

$$\begin{aligned}
 ToS_A &= \frac{\overline{ac}}{v_{UE}} \\
 &= \frac{2 \times \overline{ab}}{v_{UE}} \\
 &= \frac{2 \times \overline{Oa} \times \cos(\omega_a)}{v_{UE}} \\
 &= \frac{2 \times \overline{Oa} \times \sqrt{1 - (\frac{\overline{Ob}}{\overline{Oa}})^2}}{v_{UE}} \\
 &= \frac{2 \times \overline{Oa} \times \sqrt{1 - (\frac{\overline{OA} \times \sin(\omega_A)}{\overline{Oa}})^2}}{v_{UE}}
 \end{aligned} \tag{A.1}$$

where $\overline{Oa}$ is the radius of BS R_{BS} and $\overline{OA}$ is the distance d_{2d} between the BS and position A in 2D, therefore the ToS of position A can be calculated as:

$$ToS_A = \frac{2 \times R_{BS} \times \sqrt{1 - (\frac{d_{2d} \times \sin(\omega_A)}{R_{BS}})^2}}{v_{UE}} \tag{A.2}$$

- When a UE is at position B, as the Fig. A.3 shows, the UE is in the cell and has not passed over the BS. In the case, the path of the UE will be the red line in Fig. A.3,

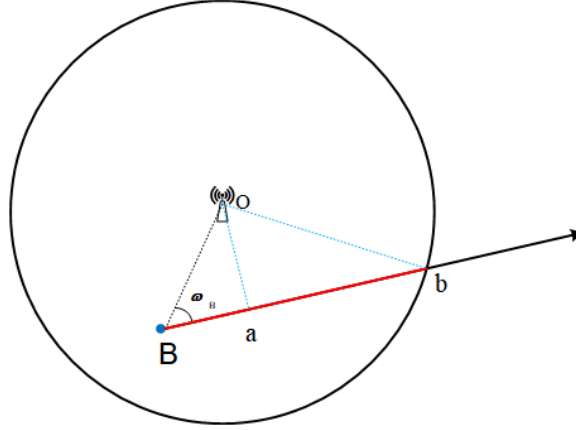


Figure A.3: Path of UE B in cell.

therefore the derivation of ToS at position B is below:

$$\begin{aligned}
 ToS_B &= \frac{\overline{Bb}}{v_{UE}} \\
 &= \frac{\overline{Ba} + \overline{ab}}{v_{UE}} \\
 &= \frac{\overline{OB} \times \cos(\omega_B) + \sqrt{\overline{Ob}^2 - \overline{Oa}^2}}{v_{UE}} \\
 &= \frac{\overline{OB} \times \cos(\omega_B) + \sqrt{(\overline{OB} \times \sin(\omega_B))^2 - \overline{Oa}^2}}{v_{UE}}
 \end{aligned} \tag{A.3}$$

where $\overline{Oa}$ is the radius of BS R_{BS} and $\overline{OB}$ is the distance d_{2d} between the BS and position B in 2D, therefore the ToS of position B can be calculated as:

$$ToS_B = \frac{d_{2d} \times \cos(\omega_B) + \sqrt{(d_{2d} \times \sin(\omega_B))^2 - R_{BS}^2}}{v_{UE}} \tag{A.4}$$

- When a UE is at position C , as the figure in A.4 shows, the UE is in the cell and has passed over the BS. In the case, the path of the UE will be the red line in

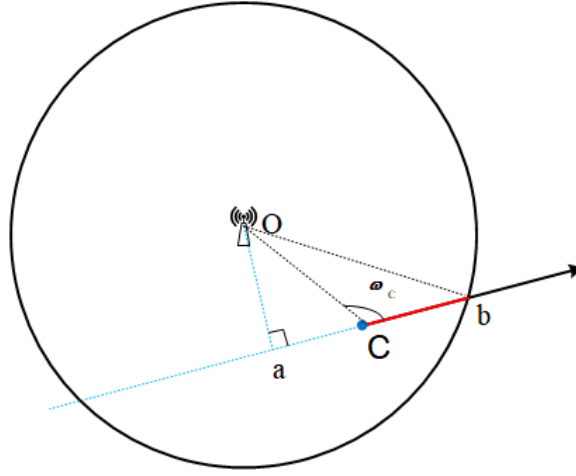

 Figure A.4: Path of UE C in cell.

Fig. A.4, therefore the derivation of ToS at position C is below:

$$\begin{aligned}
 ToS_C &= \frac{\overline{Cb}}{v_{UE}} \\
 &= \frac{\overline{ab} - \overline{ac}}{v_{UE}} \\
 &= \frac{\sqrt{\overline{Ob}^2 - \overline{Oa}^2} - \overline{OC} \times \cos(180 - \omega_C)}{v_{UE}} \\
 &= \frac{\sqrt{\overline{Ob}^2 - (\overline{OC} \times \sin(180 - \omega_C))^2} - \overline{OC} \times \cos(180 - \omega_C)}{v_{UE}}
 \end{aligned} \tag{A.5}$$

where $\overline{Ob}$ is the radius of BS R_{BS} and $\overline{OC}$ is the distance d_{2d} between the BS and position C in 2D, therefore the ToS of position C can be expressed as:

$$ToS_C = \frac{\sqrt{R_{BS}^2 - (d_{2d} \times \sin(180 - \omega_C))^2} - d_{2d} \times \cos(180 - \omega_C)}{v_{UE}} \tag{A.6}$$

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