PLACEMENT OF AERIAL BASE STATIONS FOR 5G AND BEYOND

CHIN YONG HAO

UNIVERSITI TUNKU ABDUL RAHMAN

PLACEMENT OF AERIAL BASE STATIONS FOR 5G AND BEYOND

CHIN YONG HAO

A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering (Honours) Electronic and Communications Engineering

Lee Kong Chian Faculty of Engineering and Science
Universiti Tunku Abdul Rahman

April 2024

DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions .

Signature	:	Chin
Name	:	CHIN YONG HAO
ID No.	:	1904976
Date	:	28 April 2024

APPROVAL FOR SUBMISSION

I certify that this project report entitled **"PLACEMENT OF AERIAL BASE STATIONS FOR 5G AND BEYOND"** was prepared by **CHIN YONG HAO** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Engineering (Honours) Electronic and Communications Engineering at Universiti Tunku Abdul Rahman.

Approved by,

Signature : ________________________

Supervisor : ________________________

Date : ________________________

Signature : ________________________

Co-Supervisor : ________________________

Date : ________________________

ACKNOWLEDGEMENTS

I would like to thank everyone who had contributed to the successful completion of this project. I would like to express my gratitude to my research supervisor, Dr. Lee Ying Loong for his invaluable advice, guidance and his constant supervision throughout the completing of the project.

In addition, I would also like to express my gratitude to my loving parents and friends who had helped and given me encouragement throughout my study in pursuing Bachelor’s Degree in University Tunku Abdul Rahman. Last but not least, thanks to every lecturer for their patience in teaching and guiding me during my study.

ABSTRACT

The significant increase in the global traffic demands has impelled the rising in request for small cell base stations. The market size for 5G Base Station is experienced rapid growth since 2020 and expected to keep increasing at a compound annual growth rate (CAGR) of 72.5% within 2023 and 2030. This upcoming trend of increment due to high demands in 5G applications, such as Internet of Things (IoT) devices, high-speed data transmission, massive connections between machines in automative and manufacturing, and low-latency communications. To overcome the issues of overwhelming numbers of 5G devices, application of unmanned aerial vehicle-mounted aerial base station (UAV-ABS) appears promising to strengthen the capacity and coverage of 5G networks and beyond. However, the optimal positions of ABSs require consideration of quality of service (QoS), network coverage, interference management and collision avoidance. This project presents a three-dimensional multi-ABS placement scheme based on the whale optimization algorithm (WOA). A joint multi-objective ABS placement problem is formulated with objectives to simultaneously maximise α -fairness utility function and throughput under the constraints of user data rate requirement and collision avoidance. Simulation results show that the proposed scheme surpasses other schemes in the aspects of Jain's fairness index, loss rate and perform well in total data rate, either under different numbers of user or user data rate requirements. Overall, the proposed scheme is a promising method that can be adopted in solving the ABS placement problem. Data rate requirements can be fulfilled while minimising loss rate and guaranteeing minimum loss rate. Further improvement on the performance metrics can be attained through implementation of hybrid optimisation scheme to avoid early convergence and overcome the drawbacks of WOA.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF SYMBOLS / ABBREVIATIONS

A	set of ABSs
$\mathcal{A}_u$	data rate requirement of user, $(\mathrm{b} \cdot \mathrm{s}^{-1}) \cdot \mathrm{Hz}^{-1}$
$\boldsymbol{A}$	algorithm coefficient vector
a	environmental parameter
ABC	artificial bee colony
ABS	aerial base station
AHA	artificial hummingbird algorithm
ACO	ant colony optimisation
b	environmental parameter
BS	base station
$\mathcal{B}$	constant parameter of logarithmic spiral shape
$c_{s,u}$	user association state of user with base station
$\boldsymbol{C}$	algorithm coefficient vector
$d_{s,u}$	distance between base station and user, m
d_{safe}	safe distance between base station and user, m
D	dimension of optimisation problem
$\boldsymbol{D}$	distance between prey and whale, m
$\boldsymbol{D'}$	distance between best-obtained solution and search agent, m
f_c	carrier frequency, Hz
f_α	α-fairness
f_T	sum of α-fairness value
f_{jain}	Jain's fairness index
f_{loss}	loss rate
f_{tot}	total data rate of all users
$\boldsymbol{F}$	fitness function
$\boldsymbol{F_p}$	penalty function
GA	genetic algorithm
GBS	ground base station
GSA	gravitational search algorithm
GWO	grey wolf optimisation
$\mathcal{G}_{s,u}$	channel gain

$\gamma_{s,u}$	SINR between user and base station
$L_{s,u}$	total path loss, dB
$L_{s,u}^{LoS}$	path loss of LoS link, dB
$L_{s,u}^{NLoS}$	path loss of NLoS link, dB
LoS	line-of-sight
$l_{i,j}$	horizontal distance between two ABSs
l	random number within [-1,1]
λ	large integer
n_s	load of BS s
η_{LoS}	additional mean losses due to the LoS links, dB
η_{NLoS}	additional mean losses due to the NLoS links, dB
n_{max}	set of BSs with maximum sum of α-fairness value
$NLoS$	non-line-of-sight
$\boldsymbol{N}$	set of search agents
$\boldsymbol{N}_s$	number of users served by BS s
$\boldsymbol{N}_s^{max}$	maximum user capacity of BS s
σ^2	additive white Gaussian noise (AWGN) power, dBm
PSO	particle swarm optimisation
P	objective function
$P_{s,u}$	probability of line-of-sight (LoS)
p_s	maximum transmission power from base station, dBm
p	random number within [0,1]
$\phi_{s,u}$	angle of LoS between user and base station (°)
Φ_s	utility function of BS s
QoS	quality of service
$R_{s,u}$	data rate received by user, $(\mathrm{b} \cdot \mathrm{s}^{-1}) \cdot \mathrm{Hz}^{-1}$
r	random value within [0,1]
r_1, r_2	penalty parameters
SINR	signal-to-interference-plus-noise ratio
SI	swarm intelligence
$\boldsymbol{S}$	set of base stations
t	current iteration number
t_{max}	maximum iteration

UAV	unmanned aerial vehicles
$\boldsymbol{U}$	set of users
υ_c	speed of light, m s^{-1}
WOA	whale optimisation algorithm
ω	number within [0,2]
$\mathbf{X}_k^t$	position vector of search agents
$\mathbf{X}^{*t}$	position vector of best-obtained solution

INTRODUCTION

1.1 General Introduction

Due to the continuous increase in traffic demands around the world, requests for small cells are increasing from day to day. A study done by Ericsson in December 2023 shows that the worldwide average usage of mobile data per month was expected to reach 21 GB by 2023 and estimated to reach 56 GB in 2029, close to triple of it in 2023. Following the migration from 4G to 5G, the average mobile data traffic per devices is predicted to rise by a factor of three (Ericsson, 2023). Compared to large and medium-sized cells, small cells are able to support a higher capacity of mobile users, which are the impact of the growing number of users and mobile network infrastructure. The installation of airborne communication stations, such as aerial base station (ABS), is a crucial alternative for providing service to regions with a temporary surge in data usage. Different with terrestrial base station, ABSs have the benefit of being able to align with the traffic demand and to add more capacity to the existing ground infrastructure. Since their proximity to the mobile stations is comparatively smaller, path loss is facilitated, thereby facilitating the provision of extensive services (Andryeyev & Mitschele-Thiel, 2019).

Unmanned aerial vehicles (UAV), also known as remotely piloted planes (RPA) has high mobility. Since the first usage of UAV in the military field in 1849, the application of UAV has been expanded to other fields, especially in telecommunications. In the 1970s through the 1990s, computer technology advanced, resulting in increasingly advanced drones with more sophisticated functions (Alley-Young, 2023). In the 21st century, rapid development of artificial intelligence (AI) has seen the potential of UAV-ABSs in telecommunication systems. In 5G and beyond, the promising performance of ABS, can improve capacity and bit rate even when the variation of user density and service coverage area are unpredictable. To provide guaranteed quality of service (QoS), optimise bit rate and maximise the number of users per station, the placement of the ABS in a three-dimensional space needs to be studied.

In the past few years, lots of research and studies on the optimisation of the placement of ABS had been completed. Among the optimisation methods applied in their solutions, metaheuristic optimisation is the most used in this scenario. Examples of metaheuristic optimisation algorithm are genetic algorithm (GA), grey wolf optimisation (GWO), particle swarm optimisation (PSO) and whale optimisation algorithm (WOA).

1.2 Importance of the Study

This project provides insights into the feasibility and performance of the proposed multi-ABS placement scheme in solving multi-objective ABS placement problem with presence of the ground base station (GBS), which could help with future implementation in the real world. The formulation of the constraints which limit the placement of the ABS, and those related issues that affect the QoS of ABSs are figured out, may provide guidelines for future implementation of the scheme in the society. On top of that, this study is crucial to provide a scalable and high adaptability optimisation solution to a multi-objective ABS placement problem under interference from the GBS with varying numbers of ABSs and users, as placing the ABSs manually is impractical.

1.3 Problem Statement

In this project, a system model consisting of a single GBS and multiple ABSs is assumed to service an area. Therefore, the placement of ABSs needs to consider a variety of factors, including network coverage, user capacity enhancement, energy efficiency, interference management and mobility and dynamic optimisation. The placement of ABSs must keep a safe distance between any two ABSs to avoid collision while not overlapping with each other to maximise the user capacity per ABS. Apart from that, the system should ensure that each user is assigned to a single ABS. The maximum number of users assigned to each ABS should be balanced among the ABSs. To achieve better QoS and signal-to-interference-plus-noise ratio (SINR), path loss and interference caused by other ABSs and the base station must be taken into consideration. The performance of the scheme to be decided by maximising the α-fairness utility function. Figure 2.1 displays a network model with multiple ABSs and a single GBS.

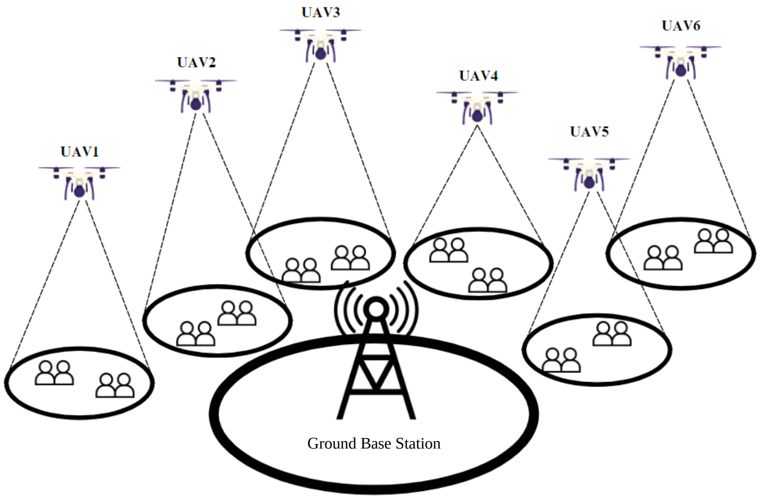

Figure 2.1: Multi-ABS and Single-GBS Network Model

In order to fulfil the requirements, the system model must be handled by an ABS placement mechanism based on the requirement and environmental factors. Some of the previous studies discovered the challenge of ABS placement in 3-Dimension (3D). The effect of the ABS altitude on the network performance was covered in order to maximise QoS and optimise user-ABS association. Centralized optimisation theory, optimal transport theory and stochastic geometry were applied in this research. Other than that, some other papers worked on the ABS placement through trajectory optimisation and channel modelling by implementing machine learning and probabilistic models respectively. The issues of energy-efficient trajectory optimisation, path loss and probabilities of LoS and NLoS were covered by these papers (Chaalal, Senouci and Reynaud, 2022). Nevertheless, those studies completed in the past rarely recognise interference from and load balancing as one of the issues when modelling ABS placement schemes. Another key problem is the complexity of joint maximisation due to the multi-objective ABS placement problem. There is a trade-off between load balancing and data rate, which could be another major issue in this project.

1.4 Aim and Objectives

In this study, the main objective is to formulate an optimisation algorithm to model the positioning of ABSs to maximise the performance of the ABS network. This algorithm will be used for beyond-5G networks to optimise mobile coverage while ensuring achievements of maximum data rate, zero collision and load balance between ABSs. The specific objectives of this project are:

- To formulate the multi-objective ABS placement problem for cellular networks with ground base station (GBS) under multiple constraints.
- To develop the optimisation scheme that solves the formulated multi-objective ABS placement problem.
- To evaluate the fairness and data rate performance of the proposed optimisation scheme under different scenarios.

1.5 Scope and Limitation of the Study

Firstly, a mathematical model for ABS networks was constructed with the proper equations, which include the calculation of path loss, probability of line of sight (LoS) and signal-to-interference-plus-noise ratio (SINR). Next, a multi-objective ABS placement algorithm is developed by implementing a metaheuristic algorithm to optimise the network link data rate and other parameters. Finally, the efficiency of the applied algorithm in solving the ABS placement problem is evaluated through MATLAB simulations. The observations were compared with other proposed optimisation methods. One of the difficulties of solving the problem using metaheuristic optimisation is that the currently available metaheuristic algorithm is limited to single-objective optimisation problems. Some modifications on the proposed objective functions are required to ensure the problem is compatible with the metaheuristic algorithm chosen. Other than that, the proposed network environment includes the interference from the ground base station and its effect to the performance of the ABSs should be considered. Moreover, the hardware limitation of the project due to expensive ABS and time consuming in real-world testing, which can be costly. Therefore, the complex ABS placement problem can only be simulated through software.

1.6 Contribution of the Study

In this study, the proposed optimisation algorithm can be used to improve the efficiency of ABSs' performance in 5G-and-beyond networks, while the existing GBS does not affect much the performance of ABSs. A joint multi-objective ABS placement and user association problem with the aims to maximise α-fairness utility function and link data rate, subjected to fulfilment of user requirements and ABS collision avoidance constraints. To solve this problem, a modified whale optimisation algorithm (WOA) is proposed, by implementing a greedy algorithm and α-fairness-based user association. The observation on the outcomes of the proposed optimisation algorithm shows that it surpasses the performance of the artificial hummingbird algorithm (AHA)-based ABS placement algorithm and the random-based placement scheme in terms of loss rate, Jain's fairness index and data rate.

1.7 Outline of the Report

This report outlines the project as follows. This Chapter 1 briefs the idea of the ABS placement problem, issues related, and its importance of the study and contribution. The aims of this project are mentioned clearly in this chapter. The literature review on the proposed ABS placement optimisation methods in the past and study on various metaheuristic optimisations is presented in Chapter 2. These proposed methods are analysed and reviewed from different resources, including articles and journals. Chapter 3 describes the problem formulation and the proposed WOA-based ABS placement optimisation scheme, software used and procedures to model the problem and scheme in coding. Chapter 4 shows the evaluation of the proposed scheme and discussion on the results and comparison through graphical method. The conclusion and summary of the study on ABS placement schemes and future improvement recommended are presented in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The main focus of this literature review is to study the mathematical modelling of ABS networks and optimisation solutions that have been developed and applied by other researchers. The keywords used to search for the reference journals or articles are UAV, ABS placement, and optimisation. The journals or articles to be discussed in this section were published within three years from now.

2.2 ABS Positioning Models

The importance of a ABS positioning model to maintain their formation of flight by adjusting their location. One of the research papers proposed a polar coordinate system to maintain the position of the ABS receivers using polar coordinate system and pure azimuthal passive positioning. This proposed method is used to solve for positioning of passive ABSs, which receive signal from other fixed position ABSs. A trigonometric function model for ABSs is introduced, which is based on the relative position between any two ABSs. The positions of the free ABSs are adjusted based on the coordinates and angle of signals received from the transmitting ABSs (Yang et al., 2023).

Other than ABS positioning through coordinates and angles, another proposed algorithm applied reinforcement learning (RL) and a deep Q-network (DQN). In this proposed method, the position and power transmitted of ABS are optimised to enhance the channel capacity of the user terminal as well as increase confidentiality, even though the exact location of the eavesdropper is unknown. The algorithm shows fast convergence speed and higher confidentiality compared to conventional Q-networks. The deep Q-network aids in optimising the legitimate capacity by positioning and maximising transmission power (Abdalla, Behfarnia and Marojevic, 2022).

Viet and Romero (2022) provided a comprehensive study on the challenges encountered when come to the problem related to ABS placement. The authors reviewed diverse technologies of ABS positioning to service user terminals under regions where terrestrial base station is absent. Apart from that, this paper also analysed the challenges those cause the problem to be complicated, either in 2D or 3D space. Part of the discovered challenges are location suitability, quality of channel and dynamic environment with manipulating user terminals' position and environmental metrics. Some of the existing approaches includes fixed ABS height position, positioning in 3D space and adaptive placement algorithms. Firstly, based on the fixed height approach, the authors concluded that a lower altitude implies that the blocking probability between ABS and user terminals is higher. Under free space, the altitude is to be fixed at an adequately large value. Under the fixed height approach, a few other placement methods based on K-mean clustering, sparse-recovery optimisation and virtual forces. While considering placement in the 3D space, the ABS altitude is also enhanced apart from the horizontal position. For example, channel-agnostic placement associates user with ABSs as the channel condition is favourable. However, the main drawback of this method is challenging to position ABS at the close to optima during the initial stage, prior to actual placement. Besides that, this method implies low exploration and simply falls on local optima. The ABS placement algorithms described above mostly are non-adaptive and focus on optimizing a single key performance metric only.

The ABS positioning methods proposed are based on different theorems and algorithms. Metaheuristic algorithms, such as the particle swarm algorithm (PSO) and ant colony optimisation (ACO), have advantages over the approaches mentioned above. Due to the algorithm's flexibility and adaptability, metaheuristic algorithms are highly flexible and applicable to problems with different complexity levels. Moreover, a bundle of modified and improved versions has been introduced to further improve the optimisation performance and feasibility of the algorithms.

2.3 Metaheuristic Optimisation

The metaheuristic algorithm is one of the optimisation algorithms applied in solving optimisation problems in mathematics and engineering. This algorithm is a good solution to a complex and difficult optimisation problem that needs to be solved optimally. It is critical to determine an optimum solution from an imperfect search space in this real-world environment. The development of metaheuristic optimisation, which is based on metaheuristic algorithms, is one of the outstanding achievements in solving optimisation problems. From the perspective of different authors, different metaheuristic algorithms are proposed, which have a vast variety of applications to solve non-linear optimisation problems. Metaheuristic optimisation is also able to solve NP-hard (non-deterministic polynomial-time hard) problems, problems for which no efficient algorithm exists. Hence, metaheuristics use less computational effort than other algorithms to obtain an optimal solution. The fact that most of the optimisation problems in nature are multi-objective functions with non-linear constraints.

In engineering, the majority of highly non-linear problems require solutions to multi-objective problems, and it is problematic to formulate these problems, especially those related to artificial intelligence (AI) and machine learning. Therefore, metaheuristic algorithms play an important role in solving real-world problems that are difficult to solve using ordinary optimisation methods. The metaheuristic algorithms are categorised based on their searching strategies: either nature-inspired or non-nature-inspired, population-based or non-population-based search and more (Informs, n.d.).

2.3.1 Swarm Intelligence (SI)

Swarm intelligence (SI) is one of the disciplines under the population-based metaheuristic algorithms. A population-based algorithm executes the optimisation with a random initial population, which advances towards optimality over the iteration. Compared with the algorithms with a single solution, population-based algorithms have more pros than cons. Multiple search agents provide solutions that assist each other and stay away from local optima. In addition, population-based algorithms typically come with better exploration than exploitation (Mirjalili, Mirjalili and Lewis, 2014). It deals with both natural and artificial systems, which are composed of many individuals that coordinate using distributed control and self-organisation. The swarm intelligence is mostly interested in the group behaviours that arise from the natural interactions of the individuals with one another and their surroundings. Some examples of prominent natural systems mimicked by swarm intelligence are ant colonies, bird flocks, fish schools and bacterial foraging. As a consequence, natural swarm intelligence research, where the biological systems above are studied, generates other metaheuristic optimisation solutions, including ant colony optimisation (ACO), particle swarm optimisation (PSO), whale optimisation algorithm (WOA) and gorilla troop optimizer (GTO) algorithms.

2.3.2 Particle Swarm Optimisation (PSO)

Among the swarm intelligence (SI) algorithms, particle swarm optimisation (PSO) is the most proposed algorithm for solving optimisation problems related to ABS placement. As suggested by its name, PSO is based on the group behaviour of animals in nature. Each single individual's behaviour depends on its own and also on the group's behaviour. In this algorithm, any optimum point discovered by one particle will lead the swarm towards that point. In solving multivariable optimisation, the swarm is pretended to have a fixed number of particles that are initially placed randomly in a multidimensional space. Each particle explores the space and remembers the discovered optimum point. The exchange of information between particles facilitates the repositioning of particles towards the group optimum point (Qawqzeh et. al., 2021). As a result, the particles progressively approach the optimal state over certain iterations. The iteration of the algorithm keeps repeating whenever the convergence criterion is not fulfilled and not all particles converge to the same optima. The issue with this algorithm is early convergence and the maximum of the objective function is skipped.

2.3.2.1 Applications of PSO in the Placement of ABS

In a research conducted by Yuwei Long and Nan Cen from Missouri University of Science and Technology, a PSO algorithm was proposed to optimise the sum-rate of visible-light-band ABS networks. The drones' locations and orientations in real time are the parameters to be optimised to resolve the optimisation problem. According to the simulation results, the proposed algorithm is capable of convergently enhancing overall performance by 24% within 10 to 20 iterations. This algorithm's performance surpasses that of the heuristic optimisation algorithm. The aim of this algorithm is to maximise the channel capacity of each user by considering the angles between the ABS and photodetector (PD) at the end user within a three-dimensional search space. The altitudes of ABSs are taken into consideration since they affect the field measurements, which depend on the ABSs' height. A total of 100 particles are used in the simulation, with the channel capacity as the fitness function. With a bandwidth of 20 MHz per user, the performance of PSO is compared with a heuristic algorithm (centroid-based method). The comparison results prove that the proposed algorithm outperforms the heuristic-based method for all scenarios tested. The proposed algorithm converges faster towards the global maximum while producing higher sum throughput for different numbers of users (Long and Cen, 2022). The drawback of this research is the limited number of terminal users. The simulation is tested on a scenario with a maximum of ten users, instead of a high population area in the real-world environment. Besides, this research overlooks the safety distance between ABSs to avoid collisions.

Another study on the application of PSO in ABS placement was conducted, which considered an ultra-dense service area with no accessibility to the global positioning system (GPS). Instead of directly applying the conventional PSO algorithm, hierarchical PSO (HPSO), RPSO-I and RPSO-II are proposed. The hierarchical PSO (HPSO) was introduced to reduce the complexity of PSO by decreasing the particle number used in the overall process and reducing the search space at the end. In RPSO-I, the particle update criteria were modified, which initially depended on the particle number. When lacking particles, the update criteria are designed by searching for the best reference solution. Conversely, when sufficient particle numbers were available, RPSO-II was introduced. The performance of the proposed algorithm was examined based on particle efficiency (PE) and localisation error, which resulted in better performance than conventional PSO (Zhang and Zhang, 2022).

2.3.3 Grey Wolf Optimization (GWO)

Another new metaheuristic optimisation solution proposed by S. Miralili, S.M. Mirjalili and A. Lewis is grey wolf optimisation (GWO). This work was motivated by a species of grey wolf called Canis lupus. Like PSO, the GWO algorithm simulates the social structure and hunting tactics of grey wolves in the wild. In general, the hierarchy of the grey wolf is categorised into four layers, including alpha, beta, delta and omega. The three primary steps in hunting are looking for prey, encircling and attacking. The work also used to be assessed with 29 standard benchmarks and compared with other well-known algorithms such as PSO and the gravitational search algorithm (GSA). Each hierarchy layer mentioned above plays a distinct role in the simulation. The alpha is responsible for leading the group and making decisions during hunting. Therefore, the alpha is considered as the best solution. Hence, the second and third best solutions are given by beta and delta. The rest of the solutions are named as omega. The mathematical algorithm represents each grey wolf and prey with different position vectors. The position vector of each wolf is updated based on the alpha (fittest solution). The exploration and exploitation phases are controlled by two main variables (a and C). Based on the benchmark testing, four groups of minimisation functions are used: unimodal, multimodal, fixed-dimension modal and composition functions. The exploitation analysis, referring to the results of unimodal functions, demonstrates the excellent performance of GWO in exploiting the search space due to its exploitation operators. On the other hand, the multimodal function outputs show the exploration ability of GWO to surpass other algorithms, especially PSO and GSA. In consequence, GWO has merit in both exploitation and exploration while showing a good balance between both and avoiding local optima (Mirjalili, Mirjalili and Lewis, 2014).

2.3.3.1 Application of Grey Wolf Optimisation (GWO) in the Placement of ABS

Research was done regarding load balancing for aerial base stations (ABS), which applied a modified GWO algorithm to optimise the placement of ABS. In this research, the optimisation algorithm aims to maximise the objective function (utility functions) in terms of its ability to fulfil the delay QoS requirement and avoid ABS collisions. Due to the limitations of the original GWO algorithm, which is inadequate to deal with continuous and binary variables, a modified version of the GWO algorithm was introduced. The simulation results, which involved the probability of blocking, total achievable edge computing (EC) and Jain’s fairness index, were tested under two conditions. The convergence performance for different numbers of users with a minimum data rate of 6 kbps per user is better than the other optimisation schemes, such as random ABS placement and user association (RnD) and geographical partitioning-based ABS deployment and user association (PD). Apart from that, the convergence performance under the same user number but different EC requirements per user is also superior to other schemes. Hence, the proposed modified GWO algorithm attains higher load balancing, a lower blocking percentage and a higher EC compared to the other scheme under different scenarios. The proposed algorithm converges after 80 iterations, which is fairly fast and stable (Jiang et al., 2023).

2.3.4 Whale Optimisation Algorithm (WOA)

According to a journal paper published in 2023, a review of the whale optimisation algorithm had been done since the algorithm had gained the attention of researchers. As a consequence, more than 100 variations have been proposed for solving optimisation problems, including more than 116 WOA variants. In general, this algorithm is also one of the Swarm Intelligence (SI), similar to PSO and GWO, that successfully solve NP-hard problems with the minimum objective function required. With high adaptability and reliability, WOA has been developed to solve both continuous and binary optimisation problems. However, at the same time, WOA also suffers from imperfect search strategies, early convergence, unbalance issues and falling into local optima instead of global optima. Consequently, improved and hybrid variants of WOA are typically applied to strengthen the performance of conventional WOA. As per discussed by the authors, the WOA algorithm is based on three main searching strategies: the encircling prey strategy, looking for prey, and spiral bubble-net attacking. Mathematical models are proposed to simulate the strategies mentioned, with two main parameters to control the flow of the algorithm. Due to the easy-to-understand search mechanisms, the conventional algorithm is improved by modifying those three search strategies, which has a great impact on its performance. The conventional algorithm was tested using the Congress on Evolutionary Computation (CEC) 2018 test suite to access the performance of WOA in exploitation, exploration, avoiding local optima and balancing between exploration and exploitation. Referring to the testing results, conventional WOA faces issues of low performance of exploitation and exploration, and easily falls into local optima. In addition, the conventional WOA is unable to achieve balance between exploitation and exploration, converges too early and has lesser population diversity (Nadimi-Shahraki et al., 2023).

2.3.4.1 Applications of the Improved and Hybrid Whale Optimisation Algorithm (WOA)

Instead of applying WOA independently to solve optimisation problems, many researchers preferred to implement either an improved version or a hybrid version of WOA. According to the statistic, out of the 57 hybrid variants of WOA reviewed, 58% of the papers proposed hybridising with swarm intelligence algorithms, followed by evolutionary algorithms. Among the improved versions of WOA, 49 were proposed to solve continuous problems through some techniques, such as Lévy flight optimisation, chaotic maps and mutation strategies (Nadimi-Shahraki et al., 2023).

In 2021, an improved WOA (IWOA) was proposed to solve the problem of flight path planning for UAVs in battlefield environments. Adaptive weights were added to the WOA algorithm and the linear convergence factor was replaced by a nonlinear one. This modification alleviates the unbalanced issue of exploiting and exploring. An adaptive inertia is added to the position updating functions in the exploitation phase. In addition to that, a nonlinear adjustment strategy was introduced to speed up the convergence without modifying the existing convergence factor. The simulation results provide a smoother path and shorter path length as compared to PSO, conventional PSO and the Artificial Bee Colony (ABC) algorithm. Anyhow, this research considers only two-dimensional path planning and the lack of an altitude parameter (Liu et al., 2021).

A hybrid algorithm, based on the Whale Optimisation Algorithm (WOA) and the Particle Swarm Algorithm (PSO), was suggested to complement the drawbacks of WOA. The PSO algorithm with its feature of communication within particles, is able to strengthen the optimisation performance of WOA. The newly developed algorithm has the advantage of jumping out of local optima by triggering another search. Not only that, but the inertia weight was also applied to balance exploration and exploitation. This approach was also applied to the research papers reviewed in the previous part. The novel hybrid algorithm WOAPSO was tested with 30 CEC 2017 objective functions and compared with WOA and PSO. The comparison obviously shows that the WOAPSO algorithm has improvements in both convergence speed and accuracy and the capability to search for the global optimum. Nonetheless, the proposed algorithm falls into local optimum after multiple iterations due to random global search instead of exploring the discovered optimum space (Yuan et al., 2021).

2.4 Summary

Based on the reviewed research papers and journals, metaheuristic optimisation is one of the optimum solutions to solve optimisation problems in engineering. Each of these algorithms has its own pros and cons, which can be countered by proposing an improved version or hybridisation with other algorithms as well. After reviewing the papers and journals, it can be concluded that the application of metaheuristic optimisation in ABS placement is widely used, but the majority of the research targeted on path planning and placement for UAV without taking into account the collision issue, interference management and load balance among the ABS. Despite some of the existing research papers considered channel capacity as one of the objective functions to be optimised, the issues of load balancing and interference from terrestrial base stations are still overlooked. Application of metaheuristic algorithms in solving multi-objective problem is rarely seen due to its complexity of application and trade-off issue. Most of the proposed schemes focused only on single objective, either load balancing or data rate or other objective. However, this sounds impractical in the real-life implementation.

CHAPTER 3

METHODOLOGY AND WORK PLAN

3.1 Introduction

In this project, the placement of the ABS is planned to be optimised through the application of whale optimisation algorithm (WOA). Software MATLAB was used to simulate the algorithm. This algorithm is preferred due to its flexibility in solving the multi-objective and multi-constraint ABS placement problem. The WOA algorithm is selected since so far there is no proposed solution using WOA in solving the ABS placement problem, which is constrained by maximum data rate, interference, safety distance between ABSs and load balancing. The workplan for this project is shown in Figure 3.1.

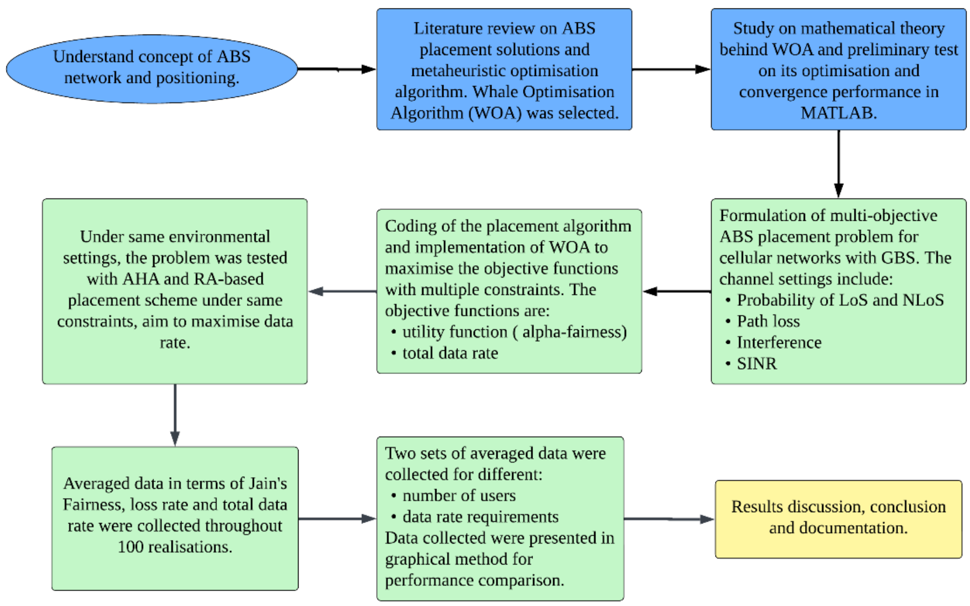

Figure 3.1: Project Workplan

3.2 Project Gantt Chart

Figures 3.2 and 3.3 show the Gantt Charts of this project.

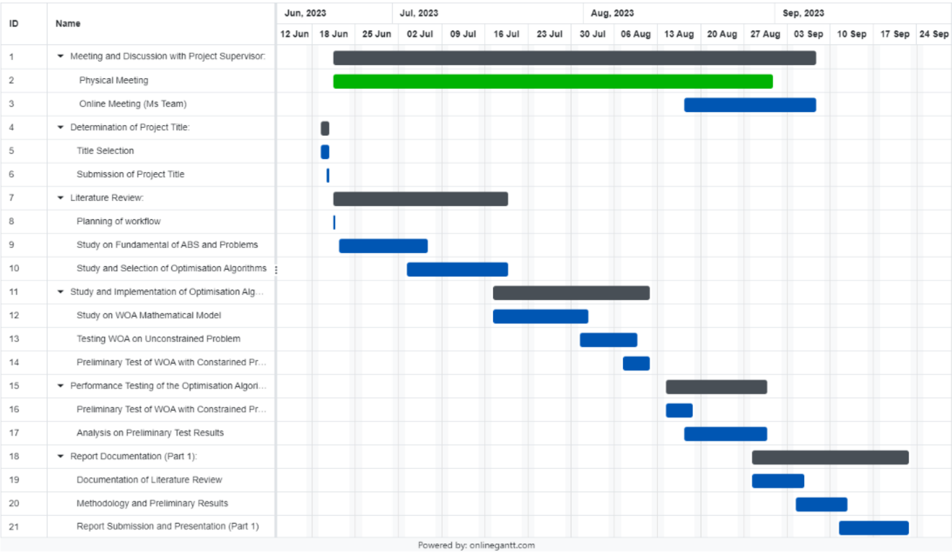

Figure 3.2: Part 1 Project Gantt Chart

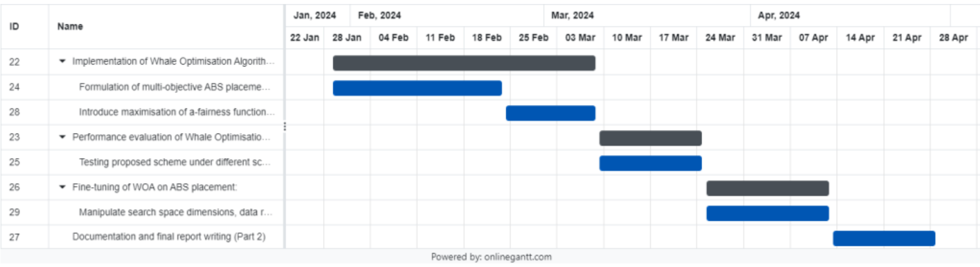

Figure 3.3: Part 2 Project Gantt Chart

3.3 Network Environment Formulation

For the simulation of the ABS placement using whale optimisation algorithm (WOA), a program is coded using MATLAB software. Firstly, a system model is formulated with a GBS and multiple ABSs to provide network service to users. $\boldsymbol{U}$ denotes the set of users, A denotes the set of ABSs and the set of all base stations is denoted as $\boldsymbol{S} = \{1, A\}$, where base station $s = 1$ denotes the GBS. The 3D Cartesian positions of base station $s \in \boldsymbol{S}$ and user $u \in \boldsymbol{U}$ are denoted by (x_s, y_s, z_s) and $(x_u, y_u, z_u = 0)$ respectively. For all users $u \in \boldsymbol{U}$ and base stations $s \in \boldsymbol{S}$, the distance (in metre) between user u and base station s is calculated with equation (3.1).

$$d_{s,u} = \sqrt{(x_s - x_u)^2 + (y_s - y_u)^2 + z_s^2} \tag{3.1}$$

The probability of line-of-sight (LoS) between base station s and user u, which is affected by the environment and locations of base stations and users, is calculated in equation (3.2). Fig. 3.4 shows the dimension of the proposed search space.

$$P_{s,u} = \frac{1}{1+ae^{-b(\phi_{s,u}-a)}} \tag{3.2}$$

where

a, b are environmental parameters and

$$\phi_{s,u} = \sin^{-1}\left(\frac{z_s}{d_{s,u}}\right) \tag{3.3}$$

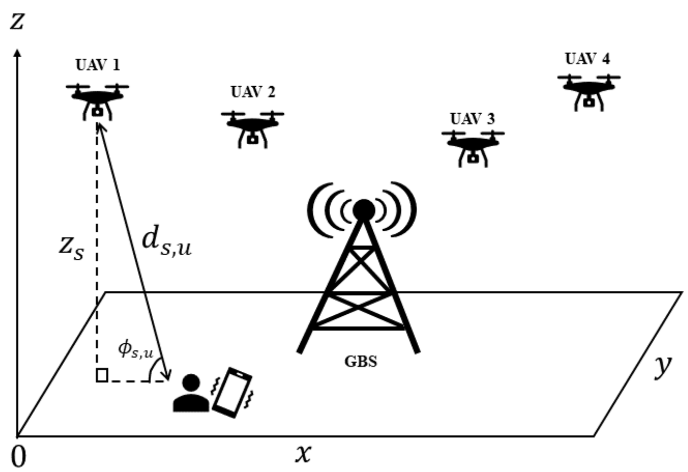

Figure 3.4: Proposed Search Space Dimension

From equation (3.2), it is noticed that when the angle $\phi_{s,u}$ increases, which is the elevation angle between base station s and user u, the probability of LoS increases. Then, the path loss (in dB) of the LoS link and the non-line-of-sight (NLoS) link can be expressed in equations (3.4) and (3.5) (Shakoor et al., 2021):

$$L_{s,u}^{LOS} = 20\log\left(\frac{4\pi f_c d_{s,u}}{\upsilon_c}\right) + \eta_{LoS}, \tag{3.4}$$

$$L_{s,u}^{NLoS} = 20\log\left(\frac{4\pi f_c d_{s,u}}{\upsilon_c}\right) + \eta_{NLoS}, \tag{3.5}$$

where

η_{LoS} = additional mean losses due to the LoS links, dB

η_{NLoS} = additional mean losses due to the NLoS links, dB

f_c = carrier frequency, Hz

υ_c = speed of light (3×10^8 m s^{-1})

Including the path loss due to the LoS and NLoS links, the path loss (in dB) between base station s and user u can be calculated using equation (3.6):

$$L_{s,u} = P_{s,u}L_{s,u}^{LoS} + \left(1 - P_{s,u}\right)L_{s,u}^{NLoS}. \tag{3.6}$$

The data rate (b · s^{-1} · Hz^{-1}) per user u is provided by base station s is modelled by Shannon's capacity in equation (3.7):

$$R_{s,u} = \log_2(1 + \gamma_{s,u}), \tag{3.7}$$

where $\gamma_{s,u}$ is the signal-to-interference-plus-noise ratio (SINR) between user u and base station s provided by equation (3.8):

$$\gamma_{s,u} = \frac{p_s \mathcal{G}_{s,u}}{\sum_{j\in\mathcal{S}\setminus\{s\}} p_j \mathcal{G}_{j,u} + \sigma^2}, \tag{3.8}$$

where

p_S = maximum transmission power from base station

$\mathcal{G}_{s,u}$ = channel gain between base station s and user u

σ^2 = additive white Gaussian noise (AWGN) power, dBm

The channel gain is calculated using path loss provided by equation (3.6) as below.

$$\mathcal{G}_{s,u} = 10^{-\frac{L_{s,u}}{10}} \tag{3.9}$$

3.4 Optimisation Problem Formulation

After the ABS network model has been designed, a set of problems and constraints to be formulated, which are to be optimised using the WOA-based placement scheme.

3.4.1 ABS Placement

The placement of ABS in a heterogeneous network with ranges being shown in equations (3.10), (3.11) and (3.12). For the GBS, its coordinate is fixed at the centre of the search space at altitude $z = 0$ m.

$$x_{min} \le x_i \le x_{max} \quad \forall i \in A \tag{3.10}$$

$$y_{min} \le y_i \le y_{max} \quad \forall i \in A \tag{3.11}$$

$$z_{min} \le z_i \le z_{max} \quad \forall i \in A \tag{3.12}$$

In equations (3.10)3.10 , (3.11) and (3.12), the variables x_{min} , y_{min} and z_{min} represent the minimum boundaries of the search space, and x_{max} , y_{max} and z_{max} are the maximum boundaries.

To avoid collision between ABSs, a safety distance of d_{safe} in metres between any two ABSs to be maintained at the horizontal dimensions as formulated in equation (3.13).

$$l_{i,j} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} > d_{safe} \quad \forall i,j \in A \;\&\; i \neq j \tag{3.13}$$

By implementing equation (3.13), collisions between any two ABSs can be avoided, regardless of the different altitudes of the ABSs. Besides, this constraint also reduces the probability of overlapping between any two ABSs in the horizontal direction, which overlapping might reduce the coverage area.

3.4.2 User Association

User association is a process to determine which ABS should serve specific user. This is crucial to optimise the network performance and provide good QoS to users. To assure that each of the user u is associated with one base station s only, the constraints below are be fulfilled:

$$\sum_{s \in \boldsymbol{S}} c_{s,u} \leq 1 \quad \forall u \in \boldsymbol{U}, \tag{3.14}$$

$$\sum_{s \in \boldsymbol{S}} c_{s,u} R_{s,u} \geq \mathcal{A}_u \quad \forall u \in \boldsymbol{U}, \tag{3.15}$$

where

$c_{s,u}$ = user association state of user u with base station s

$\mathcal{A}_u$ = data rate requirement of user u, $\mathrm{b \cdot s^{-1} \cdot Hz^{-1}}$

When $c_{s,u} = 1$, user u is associated with base station s, else $c_{s,u} = 0$ which means that the user u is not assigned to any base station yet. Based on the constraint stated in (3.14), it ensures that each user can only be assigned to maximum one base station. The constraint in (3.15)3.14 suggests that the data rate provided by the assigned base station s must be meet the data rate requirement of user u.

3.4.3 Load of Base Stations

The maximum number of users per base station s and current user number served by base station s is denoted by $\boldsymbol{N}_s^{max}$ and $\boldsymbol{N}_s$ respectively. The load of the base station s is calculated by the ratio of the number of users served by the base station to its maximum user capacity in equation (3.16).

$$\eta_s = \frac{\boldsymbol{N}_s}{\boldsymbol{N}_s^{max}} \quad \forall s \in S \tag{3.16}$$

where

$$\boldsymbol{N}_s = \sum_{u \in \boldsymbol{U}} c_{s,u} \quad \forall s \in \boldsymbol{S}$$

To ensure the base station s is not overloaded, $\boldsymbol{N}_s < \boldsymbol{N}_s^{max}$ and hence

$$0 \leq n_s \leq 1 \tag{3.17}$$

3.4.4 Utility Function and α-Fairness

The α-fairness concept is an introduced generic fairness concept, which is used to make decisions about where to place objects to optimise certain thing. In term of ABS placement, α-fairness also referred to as allocation fairness, a metric to ensure that resources are distributed fairly among all users to avoid resource monopolisation. The utility function is generally used to examine the performance of the placement option based on specific constraints. The utility function typically considers a few factors, such as resource utilisation, latency and channel capacity. Maximising the utility function is one of the goals in optimising the placement of ABSs. The utility function Φ_s of base station s is formulated in equation (3.18):

$$\Phi_s = f_\alpha(\boldsymbol{N}_s), \tag{3.18}$$

where $f_\alpha(\cdot)$ is denoted as the α-fairness function expressed in equation (3.19).

$$f_\alpha(x) = \begin{cases} \frac{x^{1-\alpha}}{1-\alpha} & \alpha \geq 0 \\ \ln(x) & \alpha = 1 \end{cases} \tag{3.19}$$

The variable α generally denotes the alpha parameter in the utility function. Its values range from zero to infinite, which determines the degree of fairness. For example, $\alpha = 1$ can attain proportional fairness, $\alpha = 0$ can achieve maximum throughput and $\alpha = \infty$ results in max-min fairness (Jin, Zhang and Hanzo, 2015).

3.4.5 Objective Functions

The aim to optimise the ABS placement by maximising the utility function in equation (3.18) and overall data rate while maintaining load balance, safety distance and QoS per user. Based on the formulated problems, the overall optimisation problems for the multi-ABS network are shown in equation (3.20).

$$\mathbf{P}: \max_{\mathrm{c}} \textstyle\sum_{s\in\boldsymbol{S}} \Phi_s, \quad \max_{\mathrm{x,y,z,c}} \textstyle\sum_{u\in\boldsymbol{U}} \sum_{i\in\boldsymbol{A}} c_{i,u} R_{i,u} \tag{3.20}$$

subject to the constraints in 3.10, (3.11), (3.12), (3.13), (3.14), (3.15) and (3.17). The term 'max' represents the maximisation operator. The first objective function is designated to maximise the sum utility function for any possible configuration of the user association. The second objective function is aimed to maximize total data rate.

3.5 Whale Optimisation Algorithm

The WOA algorithm is proposed by Mirjalili and Lewis in 2016, which is inspirited by the natural hunting behaviour of humpback whales. This kind of whale hunting is typically done in groups by targeting groups of prey. The WOA mimics the three main hunting strategies of humpback whales: encircling and searching for prey and spiral bubble-net attacking. This algorithm eases the modelling of the optimisation scheme, which involves complex multidimensional search space. Furthermore, WOA is flexible to be adopted in solving the proposed problem. First and foremost, the initialised position vector of k th search agent or whale for $k \in \boldsymbol{N}$ at t th iteration can be represented in equation (3.21):

$$\mathbf{X}_k^t = \{x_{k,1}^t, x_{k,2}^t, \dots, x_{k,D}^t\} \quad \forall k \in \boldsymbol{N}, \tag{3.21}$$

where

$\boldsymbol{N} =$ set of whales or search agents

$D =$ dimension of optimisation problem

The variable D denotes the dimension of the problem based on the number of variables to be optimised. Since a three-dimensional ABS coordinate is considered, $D = 3|A|$ where A is the set of ABSs.

3.5.1 Encircling Prey Strategy

This strategy is applied to search and encircle the optimum target prey. While the other search agents approach the optimum agent by updating their position using equations (3.22) and (3.23):

$$\mathbf{X}_k^{t+1} = \mathbf{X}^{*t} - \boldsymbol{A} \times \boldsymbol{D} \quad \forall k \in \boldsymbol{N}, \tag{3.22}$$

$$\boldsymbol{D} = |\boldsymbol{C} \times \mathbf{X}^{*t} - \mathbf{X}_k^t| \quad \forall k \in \boldsymbol{N}, \tag{3.23}$$

$$\boldsymbol{A} = 2 \times \omega \times r - \omega, \tag{3.24}$$

$$\boldsymbol{C} = 2 \times r, \tag{3.25}$$

$$\omega = 2 - t \times \left(\frac{2}{t_{max}}\right), \tag{3.26}$$

where

$\mathbf{X}_k^t$ = position vector of k th search agent at current iteration t

$\mathbf{X}^{*t}$ = position vector of best-obtained solution at iteration t

$\boldsymbol{D}$ = distance between the prey $\mathbf{X}^{*t}$ and the search agent $\mathbf{X}_k^t$

$\boldsymbol{A}$ = algorithm coefficient vector

$\boldsymbol{C}$ = algorithm coefficient vector

ω = number within [0,2]

r = random value within [0,1]

t_{max} = maximum iteration

From equations (3.22) to (3.26), the value of ω reduces from two to zero linearly over iteration t. As a result, the value of $\boldsymbol{A}$ reduces linearly with α and drives the position vector of k th search agent towards the optimal location. Hence, we can conclude that the value of $\boldsymbol{A}$ is within [-ω, ω].

3.5.2 Spiral Bubble-Net Attacking (Exploitation Phase)

During the hunting process, the whales release bubble net to encircle and surround small fish and prawn. This strategy can be formulated through two ways: shrinking encircling and spiral updating position. These hunting strategies are formulated as the exploitation phase in the WOA algorithm, where the search agents update towards the optimum solution. The former strategy is similar to the encircling prey strategy as described in equations (3.22) to (3.26). The latter is discussed in section below.

3.5.2.1 Spiral Updating Position Method

Through this mechanism, the distance between current optimum solution $\mathbf{X}^{*t}$ and search agent $\mathbf{X}_{\mathrm{k}}^{t}$ is calculated in equation (3.27). The position updating in spiral motion towards the solution is computed in equation (3.28):

$$\boldsymbol{D}' = |\mathbf{X}^{*t} - \mathbf{X}_k^t| \quad \forall k \in \boldsymbol{N}, \tag{3.27}$$

$$\mathbf{X}_k^{t+1} = \boldsymbol{D}' \times e^{\mathcal{B}l} \times \cos(2\pi l) + \mathbf{X}^{*t} \quad \forall k \in \boldsymbol{N}, \tag{3.28}$$

where

$\boldsymbol{D}' =$ distance between best-obtained solution and search agent

$\mathcal{B} =$ constant parameter of logarithmic spiral shape

$l =$ random number within [-1, 1]

In this algorithm, the humpback whales surround the targets in contracted pattern and encircling them. There is a 50 % probability that either one of the spiral encircling methods will be chosen to update the location of the search agents. This model is defined in equation (3.29):

$$\mathbf{X}_k^{t+1} = \begin{cases} \mathbf{X}^{*t} - \boldsymbol{A} \times \boldsymbol{D} & if\ p < 0.5 \\ \boldsymbol{D}' \times e^{\mathcal{B}l} \times \cos(2\pi l) + \mathbf{X}^{*t} & if\ p \geq 0.5 \end{cases}, \tag{3.29}$$

where

$p =$ random number within [0,1]

3.5.3 Searching for Prey Strategy (Exploration Phase)

In this strategy, the search agents (whales) search in the problem space to determine the undiscovered region. The position vector of a randomly selected search agent $\mathbf{X}_{\text{rand}}$ is used to update the position of each search agent in the population. This position update is computed in equation (3.30):

$$\mathbf{X}_k^{t+1} = \mathbf{X}_{\text{rand}} - \boldsymbol{A} \times \boldsymbol{D} \quad \forall k \in \boldsymbol{N}, \tag{3.30}$$

$$\boldsymbol{D} = |\boldsymbol{C} \times \mathbf{X}_{\text{rand}} - \mathbf{X}_k^t|, \tag{3.31}$$

where

$\mathbf{X}_{\text{rand}}$ = position vector of a randomly selected search agent

The parameters $\boldsymbol{A}$ and $\boldsymbol{C}$ are calculated using equations (3.24) and (3.25) respectively. The parameter $\boldsymbol{A}$ is applied to keep the search agents away from the random search agent $\mathbf{X}_{\text{rand}}$ to promote exploration and avoid convergent to local optimum.

3.5.4 Flow of the WOA algorithm

The flowchart of the WOA is showed in Figure 3.1. A total of $\boldsymbol{N}$ humpback whales or search agents are randomly distributed in a three-dimensional space. The initial values of the objective functions are calculated for each search agent. Then, the initial values of control parameters $\boldsymbol{A}$, $\boldsymbol{C}$, l and p are updated and the optimisation process starts. The value of p is investigated, whether less than or higher than 0.5. If $p \geq 0.5$, the spiral updating position method in equation (3.28) is implemented. While $p < 0.5$, the position vector is updated through searching for prey strategy formulated in equation (3.30) for $|\boldsymbol{A}| \geq 1$, and the encircling prey strategy defined in equation (3.22) is used when $|\boldsymbol{A}| < 1$. Hence, the parameter $|\boldsymbol{A}|$ controls the exploration and exploitation of the algorithm, while the parameters p determines the position updating method. After each iteration, a set of new values are calculated from the objective functions for each new position. The best solution value is updated and replaced the current best solution. The position vector with respect to the best search agent is then shown. Finally, the optimisation is ended after fulfilling the maximum iteration t_{max}.

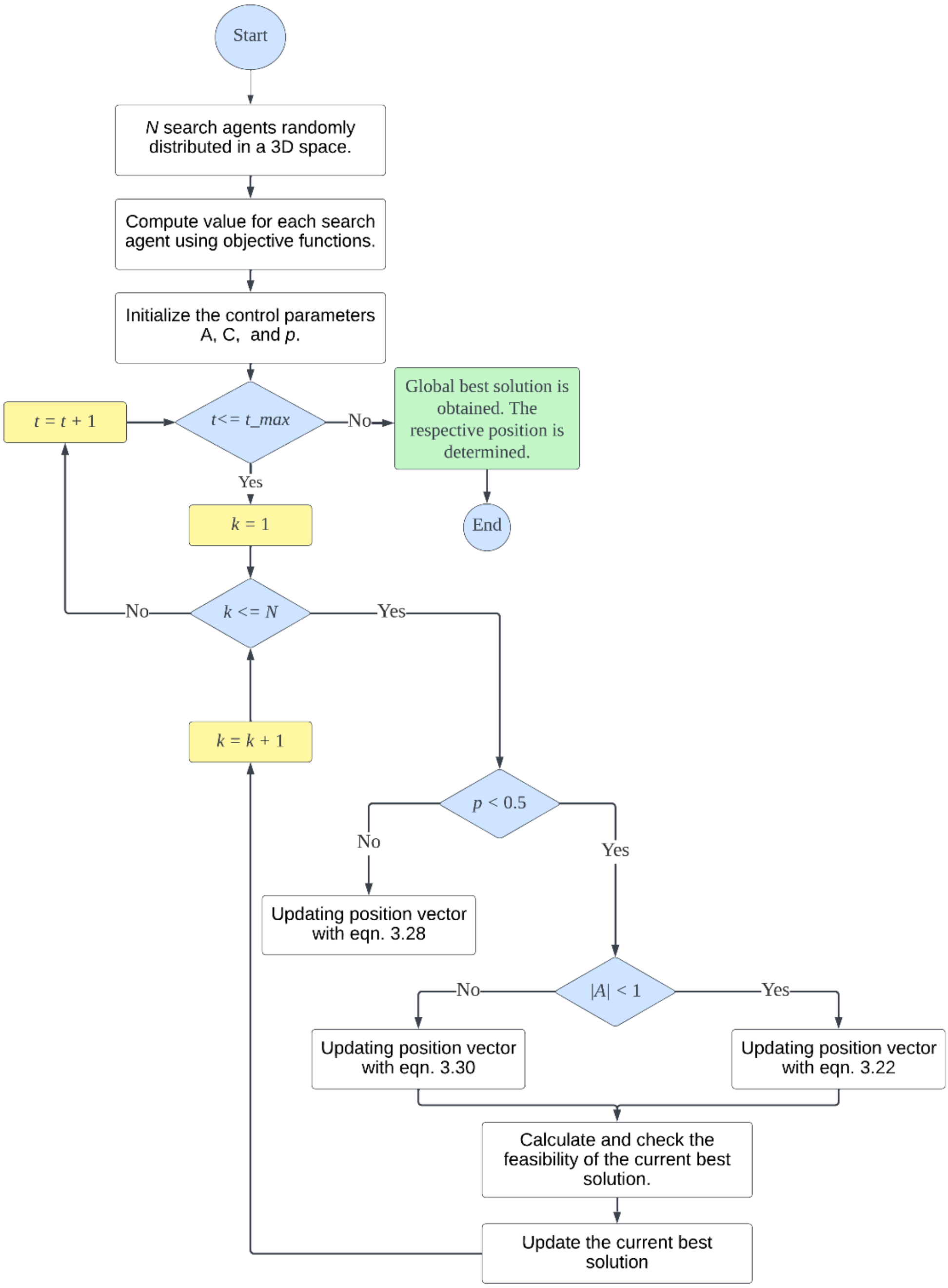

Figure 3.5: The Flowchart of WOA

3.6 Proposed Greedy Algorithm

Due to the ability of the WOA to solve single objective function instead of multi-objective functions as shown in equation (3.20), a greedy algorithm is chosen as another approach other than the penalty function and weighted sum methods as proposed before. The greedy algorithm makes the optimal choice at every iteration and attempts to locate the global optima. To solve the multi-objective placement problem, application of the greedy algorithm is proposed to maximise the first objective function in equation (3.19). Considering the parameter to be applied in the equation (3.19), which is the load or the number of users associated with base stations, $\boldsymbol{N}_s$, there is possibility that the value of f_α approaches $-\infty$ during the initial stage of optimisation process, where no user is associated with any ABS yet. In order to overcome this issue, equation (3.32) is utilised.

$$f_\alpha(x) = \begin{cases} f_\alpha(x) & x \neq 0 \\ -\lambda & x = 0 \end{cases} \tag{3.32}$$

where λ denotes a large integer. As in equation (3.32), when the input argument x of the function $f_\alpha(x)$ is a nonzero, equation (3.19) is referred. Else, a large negative value is assigned to the function due to undefined natural logarithm of zero.

The greedy algorithm is summarised in as Algorithm 1.The greedy algorithm is started by initialising user association $c_{s,u}$ equals to zero. The variable $f_T(m)$ denotes a set of sums of $f_\alpha(n)$ for base station $m, n \in \boldsymbol{S}$, where $f_\alpha(n)$ denotes the α-fairness value for each base station $n \in \boldsymbol{S}$ when computing value of $f_T(m)$ for base station m. Next, in order to fulfil the constraint in equation (3.15), the data rate calculated in equation (3.7) for each base station including the GBS is verified at the fifth line of Algorithm 1. By default, if none of the base stations fulfil the requirement of user u, $c_{s,u}$ for that user is zero which means that no base station is associated with user u. For each of the base stations which fulfils the constraint, the respective total α-fairness value $f_T(m)$ is calculated. Considering the value of user association is set to one for one of the fulfilled base stations and zero for others, the total α-fairness value for the respective base station is computed by summing up α-fairness values according to equation (3.32) for all base stations, and then the value its $c_{s,u}$ is reset to zero. The algorithm is repeated for other fulfilled base stations. Then, the base station with the maximum α-fairness value is associated with user u. The variable n_{max} at line 16 of the algorithm is a set of base stations with maximum total α-fairness value f_{max}. In some cases, where there is possibility to have more than one base station with same f_{max}. A randomly chosen base station $s \in n_{max}$ is associated with user u.

As a result of this algorithm, each user u is assured to be connected to base station s with the maximum total α-fairness value for all possible user association $c_{s,u}$ configurations. Consequently, the first objective function in equation (3.20) is optimised through Algorithm 1. After user association is done, the load of each BS $s \in \boldsymbol{S}$ is checked using equation (3.16) to ensure that the constraint equation (3.17) is fulfilled.

Algorithm 1: Greedy algorithm for α-fairness-based user association

Initialise $c_{s,u} = 0 \quad \forall s \in \boldsymbol{S}$ and $u \in \boldsymbol{U}$
For $u \in \boldsymbol{U}$
  Initialise $f_T(m) = 0, f_\alpha(n) = 0$
  For $s \in S$
    If $R_{s,u} \geq \mathcal{A}_u$
      For $m \in \boldsymbol{S}$
        Set $c_{m,u} = 1$
        For $n \in \boldsymbol{S}$
          $\boldsymbol{N_s}(n) = \sum_{u \in \boldsymbol{U}} c_{n,u}$
          Obtain $f_\alpha(n)$ using $\boldsymbol{N}_s(n)$ and equation 3.19
        End for
        $f_T(m) = \sum_{n \in S} f_\alpha(n) \quad \forall n \in \boldsymbol{S}$
        Set $c_{m,u} = 0$
      End for
      $f_{max} = \max\left(f_T(m)\right) \quad \forall m \in \boldsymbol{S}$
      $n_{max} = \{m \in \boldsymbol{S}: f_T(m) = f_{max}\}$
      If $|n_{max}| > 1$
        Set $c_{m,u} = 1$ if $f_T(m) = f_{\max}$ for a random $m \in n_{max}$
      Else
        Set $c_{m,u} = 1$ where $f_T(m) = f_{\max}$
      End if
    End if
  End for
End for

3.7 Optimisation of Fitness Function Using WOA

As discussed in Section 3.6, the objective to maximise the utility function is achieved through implementation of the greedy algorithm. For another objective function as mentioned in equation (3.20), its aims to optimise QoS performance through maximisation of the sum data rate for all user $u \in \boldsymbol{U}$. To optimise this objective, a weighted sum approach is implemented. A fitness function for each search agent (whale) with a penalty function is formulated as in equation (3.33).

$$\boldsymbol{F} = \sum_{u \in \boldsymbol{U}} \sum_{i \in A} c_{i,u} R_{i,u} + \boldsymbol{F_p} \tag{3.33}$$

where $\boldsymbol{F_p}$ is penalty function formulated in equation (3.34):

$$\boldsymbol{F_p} = \sum(l_{i,j} - d_{safe}) \quad \forall i,j \in A \ \& \ i \neq j \tag{3.34}$$

The penalty coefficient is considered to be one since the ABSs distance constraint in equation (3.13) is equally important with the objective function. The fitness function of the problem is applied in the WOA algorithm to maximise the total data rate received by all associated users while considering the safety distance as the constraint affecting the fitness value. The details of the proposed WOA-based multi-ABS placement algorithm is summarised in Algorithm 2.

Algorithm 2: WOA Algorithm

1. Initialise $F_{leader} = -\infty$ and $\mathbf{X}_{leader} = \{0\}$.
2. **For** $t \leq t_{max}$
3. **For** $k \in \boldsymbol{N}$
4. Perform **Algorithm 1**.
5. Evaluate fitness function $\boldsymbol{F}$ in (3.33).
6. **If** $\boldsymbol{F} > F_{leader}$
7. Update F_{leader}.
8. $\mathbf{X}_{leader} = \mathbf{X}_k^t$
9. **End if**
10. **End for**
11. Generate random r and p value between 0 and 1.
12. Compute value $\boldsymbol{A}$ and $\boldsymbol{C}$ in (3.24) and (3.25) respectively.
13. **If** $p < 0.5$
14. **If** $\text{abs}(\boldsymbol{A}) \geq 1$
15. Perform **searching for prey strategy** in (3.30).
16. Update $\mathbf{X}_k^t$.
17. **Else if** $\text{abs}(\boldsymbol{A}) < 1$
18. Perform **encircling prey strategy** in (3.22).
19. Update $\mathbf{X}_k^t$.
20. **End if**
21. **Else if** $p \geq 0.5$
22. Perform **spiral updating position method** in (3.28).
23. Update $\mathbf{X}_k^t$.
24. **End if**
25. Set $t = t + 1$.
26. **End for**

From Algorithm 2, the fitness function in equation (3.33) for each whale $k \in \boldsymbol{N}$ is evaluated after the user association with the maximum α-fairness value is completed in Algorithm 1. At each iteration t, the leader fitness function is determined by comparing the fitness value of search agent k and the best historical fitness value F_{leader} obtained. The optimum positions of ABS $i \in A$ are decided by $\mathbf{X}_{leader}$, which are the whale positions with the best fitness value F_{leader}. After obtaining the best positions, the positions of all search agents are updated via a randomly chosen position updating methods mentioned in line 11 to 24 of Algorithm 2. Algorithm 2 is repeated until t_{max} iterations to evaluate the fitness function for the updated search agents' positions after each iteration.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Simulation Parameters

The proposed placement scheme is evaluated under a search space of 4000×4000 m^2 and height boundary between 100 m and 1000 m. Therefore, the search space boundaries were formulated as $x_{min} = 0$ m, $x_{max} = 4000$ m, $y_{min} = 0$ m, $y_{max} = 4000$ m, $z_{min} = 100$ m and $z_{max} = 1000$ m. The number of ABSs, $|A| = 4$ and one GBS are considered. The number of search agents $|\boldsymbol{N}| = 20$ and $t_{max} = 100$ are set. Besides, the network is assumed to be in an urban area with environmental parameters $a = 0.6$, $b = 0.11$, and additional mean losses caused by LoS and NLoS links are 1 dB and 20 dB respectively (Niu, Zhao and Li, 2021). The carrier frequency of the signal, $f_c =$ 2 GHz and transmit power p_s of all ABSs and the GBS are 30 dBm (1 W) respectively. The AWGN power σ^2 = -110 dBm (10^{-14} W) and the safety distance between ABSs is restricted to minimum at 25 m.

4.2 Performance Metrics Evaluation

The performance of the proposed scheme is tested under the designated simulation parameters in terms of Jain's fairness index, loss rate and total data rate of the network. In addition, the proposed scheme is compared with the Artificial Hummingbird Algorithm (AHA)-based ABS placement scheme and the Random ABS placement algorithm (RA) under same performance metrics. Both of these algorithms are multi-ABS placement scheme with single objective function to maximise a sum utility function related to fair QoS provisioning (Lim et al., 2023). User association in both schemes is done according to the highest data rate between the user and the ABS.

Jain's fairness index is utilised to show the degree of balance and fairness in resources allocation. The equation to compute Jain's fairness index is shown in equation (3.35):

$$f_{jain} = \frac{(\sum_{i \in A} n_i)^2}{|A|(\sum_{i \in A} n_i^2)}, \tag{3.35}$$

where n_i is the load of ABS $i \in A$.

The loss rate of the network is calculated in equation (3.36):

$$f_{loss} = \frac{|\boldsymbol{U}| - \sum_{u \in \boldsymbol{U}} \sum_{s \in \boldsymbol{S}} c_{s,u}}{|\boldsymbol{U}|}, \tag{3.36}$$

where $\boldsymbol{U}$ and $\boldsymbol{S}$ are the sets of users and base stations respectively. The loss rate indicates the percentage of users without any connection. The final performance metric is the total data rate of all users as shown in equation (3.37):

$$\sum_{i \in \boldsymbol{A}} \sum_{u \in \boldsymbol{U}} c_{i,u} R_{i,u} \tag{3.37}$$

where $c_{i,u}$ is the user association state of ABS i and user u.

The results for each performance metric are collected and averaged for all the placement schemes under 100 sets of environment settings. Figure 4.1 displays the comparisons of the convergence rate for different proposed placement schemes under 100 realisations with the same environmental settings and $|\boldsymbol{U}| = 200$. The simulation result demonstrates that the convergence rate of the proposed WOA-based multi-ABS placement scheme outperforms the other two schemes, which is on average less than 10 iterations. This differs from the other two schemes, where the AHA-based placement scheme does not converge within 100 iterations and the RA-based placement scheme starts to converge at around 20 iterations. It appears that the proposed WOA-based placement scheme achieves more promising performance in convergence rate. The comparisons of the performance metrics under two conditions.

i) Different numbers of users $|\boldsymbol{U}| = 50, 100, 150, 200, 250$ and 300.

ii) Different data rate requirements per user $\mathcal{A}_u = 8,9,10$ and 11 bits $\cdot$ $\mathrm{s}^{-1} \cdot$ Hz.

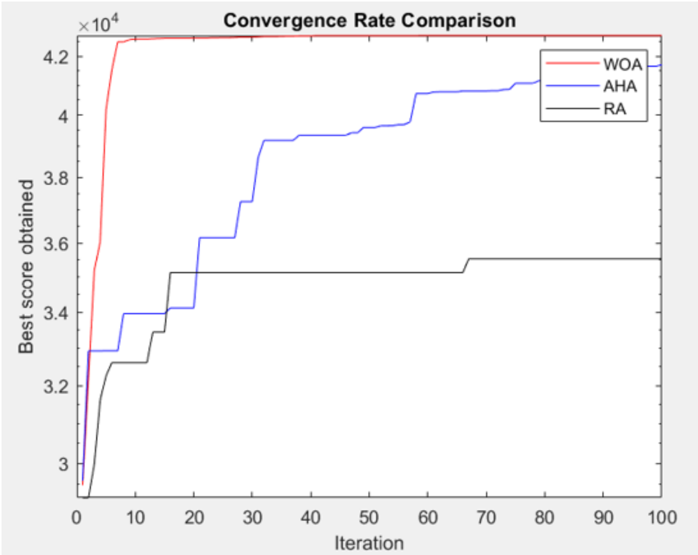

Figure 4.1: Comparison of Convergence Rate

4.2.1 Results Comparison Under Condition (i)

Figures 4.2, 4.3 and 4.4 illustrate the comparisons of Jain’s fairness index, loss rate and total data rate respectively under condition (i) with the data rate requirements being set to $\mathcal{A}_u = 10\ \text{bits} \cdot \text{s}^{-1} \cdot \text{Hz}^{-1}$.

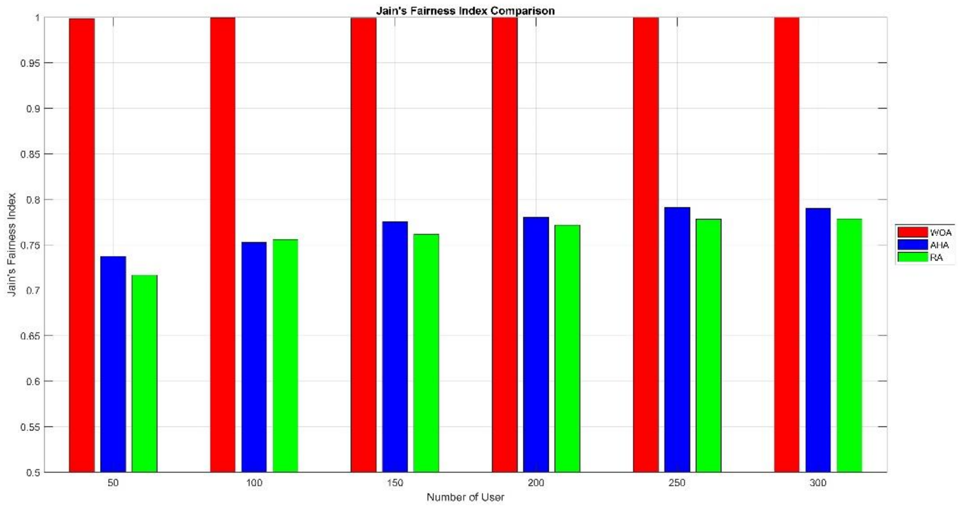

Figure 4.2: Jain’s Fairness Index Comparison Under Condition (i)

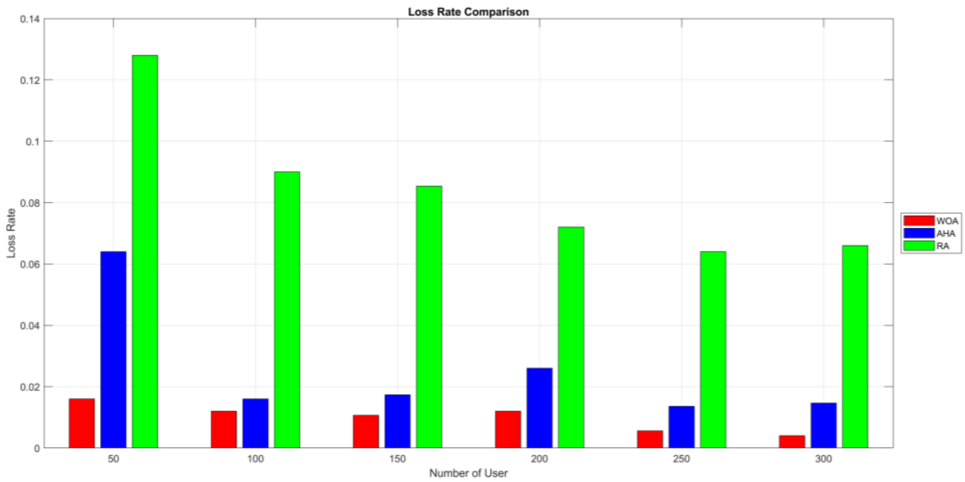

Figure 4.3: Loss Rate Comparison Under Condition (i)

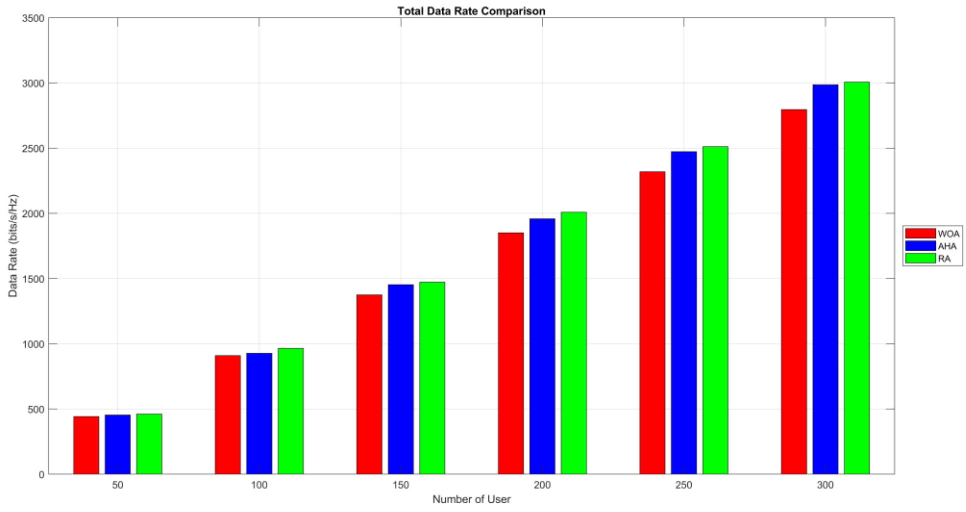

Figure 4.4: Total Data Rate Comparison Under Condition (i)

The results in Figure 4.2 indicate that averaged Jain's fairness index of the WOA-based placement scheme is higher than 0.9 for all numbers of users. The averaged Jain's fairness index of the proposed WOA-based placement scheme is significantly higher than the other two schemes and closer to one, which means more balanced resource allocation among users. This performance closely related to user association through maximisation of the α-fairness value as discussed in Algorithm 1 in Section 3.6. As the value of α = 1 in equation (3.19), proportional fairness is achieved and it balances the performance between the resource allocation efficiency and fairness. Through the greedy algorithm, the α -fairness value is maximised among all possible user association configurations. As compared to the AHA-based and RA-based placement schemes, both schemes only maximise the proportional fairness after each user is associated with an ABS. Therefore, the proposed WOA-based placement scheme contributes to fairer resources distribution and notably higher Jain's fairness value with difference of more than 0.2 with other schemes.

On the other hand, the results in Figure 4.3 illustrates that loss rate of the proposed WOA-based scheme is lower than those of the AHA-based and RA-based placement schemes. The loss rate of the WOA-based scheme is less than that of the RA-based scheme by approximately 85 %, and less than that of the AHA-based scheme by approximately 67 % when $|\boldsymbol{U}|$ = 50. The loss rate difference keeps increasing until more than 92 % lower for the WOA-based scheme, compared to RA-based scheme. However, its difference compared to the AHA-based scheme is much smaller, that is between 25 % to 70 % lower for the WOA-based scheme. Thus, it is worth noting that the proposed WOA-based scheme is able to cope with the poor network coverage and provide fair connection for each ABS while complying with the data rate requirement. In contrast, the AHA-based and RA-based schemes lead to higher loss rates, especially the RA-based scheme. Due to the user association based on maximization of data rate, these two schemes not able to provide fair allocation of resources by withdrawing users with lower data rate. However, the overall loss rate for all schemes is low.

In Figure 4.4, it seems that the total data rate attained by the proposed WOA-based scheme is slightly lower than the other schemes. While the achieved total data rate of the AHA-based is close to the result from the RA-based scheme. These results imply that the total data rate is collectively increasing with the number of users $|\boldsymbol{U}|$. The proposed WOA-based scheme does not outperform the other schemes due to the consideration of proportional fairness and maximisation of data rates, causing a trade-off between fairness and maximum throughput. Besides, another issue related to the GBS, is that some users are associated with the GBS, which greatly affects the maximisation of the α-fairness function. Since the total data rate of users associated with the ABS is taken into account in the proposed algorithm, this might lead to lower total data rate.

4.2.2 Results Comparison Under Condition (ii)

Figures 4.5, 4.6 and 4.7 display the comparisons of the performance metrics among all schemes under condition (ii) with the number of users being set to $|\boldsymbol{U}| = 200$.

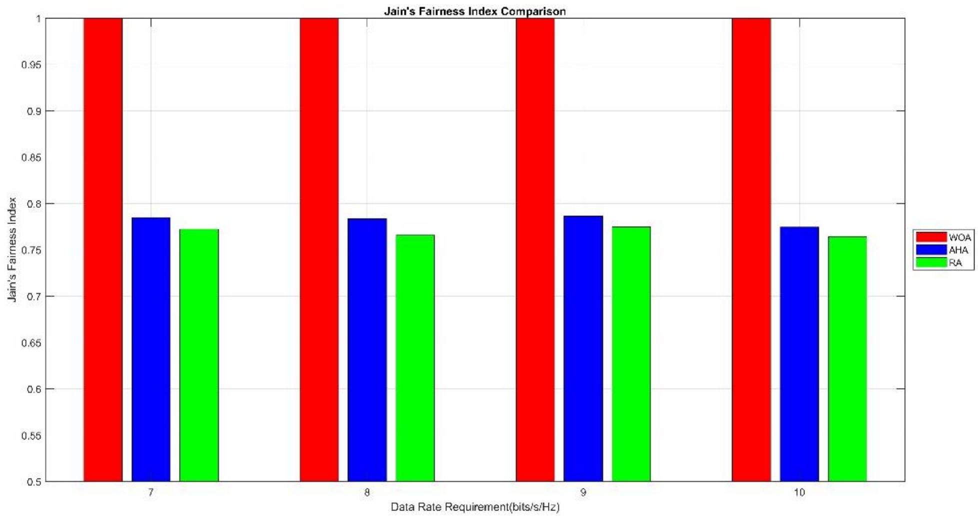

Figure 4.5: Jain's Fairness Index Comparison Under Condition (ii)

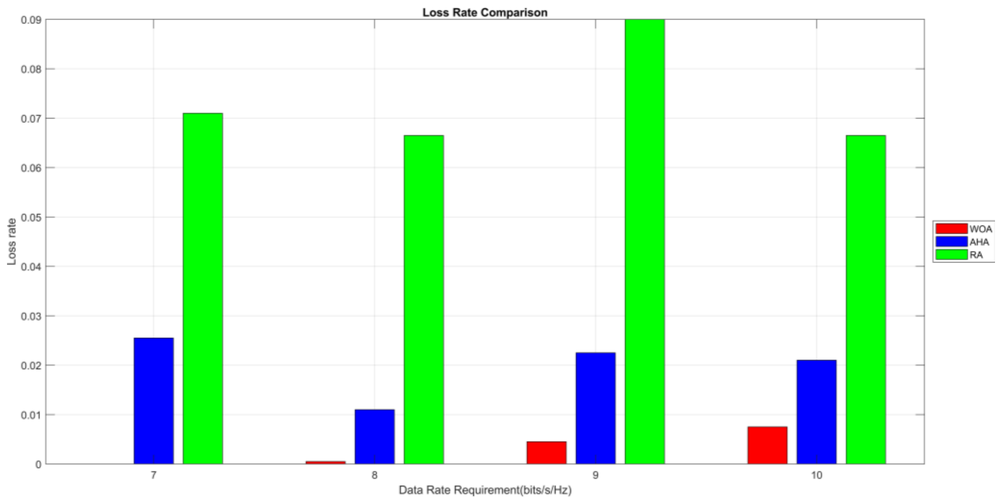

Figure 4.6: Loss Rate Comparison Under Condition (ii)

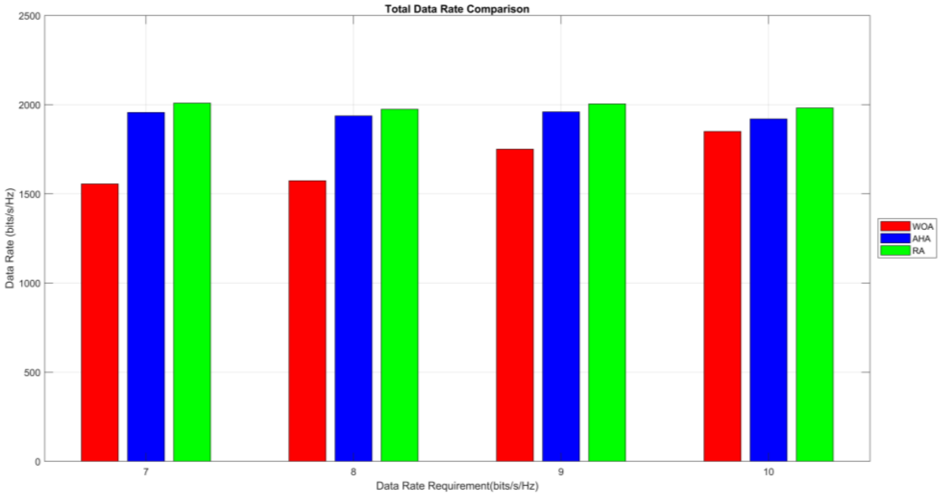

Figure 4.7: Total Data Rate Comparison Under Condition (ii)

Based on the results in Figures 4.5, 4.6 and 4.7, the discussions for comparisons of Jain’s fairness index, loss rate and total data rate are similar with the discussions in Section 4.2.2. In the aspect of loss rate, as the user data rate requirement increases, the average loss rate of the proposed WOA-based scheme increases slightly from close to zero loss rate to 0.8 % of loss rate. This observation is mostly caused by the increase in the number of users who fail to fulfil the increasing data rate requirement. Overall, the proposed scheme surpasses the other schemes in terms of Jain’s fairness index and loss rate.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

Throughout this project, a WOA-based multi-ABS placement scheme was developed to solve the multi-objective ABS placement problem formulated for multi-ABS network with the presence of a GBS. The developed placement optimisation scheme has successfully solved the optimisation problem with two objective functions and constrained by multiple requirements including an existing GBS, load balancing and collision avoidance. From this study, it is found that the proposed WOA-based placement scheme has a remarkable performance in terms of Jain's fairness index and loss rate compared to the other placement schemes. Through maximisation of the α-fairness function and data rate, the network resources can be utilised efficiently while ensuring load balancing. Due to the trade-off between fairness and data rate, the total data rate does not surpass the other two schemes but close to them. It is also found that the difficulties in developing a multi-ABS placement scheme with multiple objective functions using a metaheuristic algorithm, which is more often applied in single-objective ABS placement problems. This project has also provided conclusive evidence that metaheuristics such as WOA is applicable in solving multi-objective ABS placement problems with the presence of a GBS. The flexibility of the algorithm allows it to be integrated into or with other algorithms whenever required to solve problems beyond its limit. The findings of the developed scheme provide another important study in the complexity of joint maximisation using the metaheuristic algorithm.

5.2 Recommendations

While the success of the proposed scheme in solving the complex multi-objective ABS placement problem, better performance can be achieved through utilizing its benefit of flexibility. Hybridization of the WOA algorithm with other optimisation algorithms, such as Grey Wolf Optimisation (GWO) and Particle Swarm Optimisation (PSO) can aid in overcoming the shortcoming of WOA in its exploration strategy.

CHAPTER 6

REFERENCES

Ericsson, 2023. *Mobile data traffic outlook, Mobile Data Traffic Forecast Mobility Report - Ericsson*. [online] Available at: <https://www.ericsson.com/en/reports-and-papers/mobility-report/dataforecasts/mobile-traffic-forecast> [Accessed 06 April 2024].

Andryeyev, O. and Mitschele-Thiel, A., 2019. *Efficiency vs. Accuracy of Aerial Base Station Placement*. In: IEEE (Institute of Electrical and Electronics Engineers), 2019 International Conference on Networked Systems (NetSys). Munich, Germany, 18-21 March 2019. New York: IEEE.

Alley-Young, G., PhD, 2023. Drone (Unmanned aerial vehicle). *Salem Press Encyclopedia* [Preprint]. Available at: <https://research-ebsco-com.libezp2.utar.edu.my/linkprocessor/plink?id=069fa8e7-75aa-3234-95be-e98a691b37b5> [Accessed 1 September 2023].

Chaalal, E., Senouci, S.M. and Reynaud, L., 2022. A New Framework for Multi-Hop ABS-Assisted 5G-Networks With Users' Mobility Prediction. *IEEE Transactions on Vehicular Technology*, [e-journal] 71(4), pp.4412–4427. https://doi.org/10.1109/TVT.2022.3149711.

Yang, Z., Wang, Y., Zhang, B., Bai, Y. and Feng, Y., 2023. The Research of UAV Cluster Flight Positioning Model Based on Polar Coordinate System. *2023 IEEE 3rd International Conference on Electronic Technology, Communication and Information, ICETCI 2023*, [e-journal] pp.682–687. https://doi.org/10.1109/ICETCI57876.2023.10176594.

Abdalla, A.S., Behfarnia, A. and Marojevic, V., 2022. *Aerial Base Station Positioning and Power Control for Securing Communications: A Deep Q-Network Approach*. In: IEEE (Institute of Electrical and Electronics Engineers), 2022 IEEE Wireless Communications and Networking Conference (WCNC). Austin, TX, USA, 10-13 April 2022. New York: IEEE.

Viet, P.Q. and Romero, D., 2022. Aerial Base Station Placement: A tutorial introduction. *IEEE Communications Magazine*, [e-journal] 60(5), pp.44–49. http://dx.doi.org/10.1109/mcom.001.2100861.

Informs, n.d. *Metaheuristics in Optimisation: Algorithmic Perspective*. [online] Available at: <https://www.informs.org/Publications/OR-MS-Tomorrow/Metaheuristics-in-Optimisation-Algorithmic-Perspective> [Accessed 2 September 2023].

Mirjalili, S., Mirjalili, S.M. and Lewis, A., 2014. Grey Wolf Optimiser. *Advances in Engineering Software*, [e-journal] 69, pp.46–61. https://dx.doi.org/10.1016/j.advengsoft.2013.12.007.

Qawqzeh, Y., Alharbi, M. T., Jaradat, A. and Sattar, K. N. A., 2021. A review of swarm intelligence algorithms deployment for scheduling and optimization in cloud computing environments. *PeerJ Computer Science*, [e-journal] 7(6). https://dx.doi.org/10.7717/peerj-cs.696.

Jiang, S., Lee, Y.L., Tham, M.L., Qin, D., Chang, Y.C., Sim, A.G.H., 2023. Proportionally fair load balancing with statistical quality of service provisioning for aerial base stations. *ETRI Journal*, [e-journal] 45(5), pp.887-898. http://dx.doi.org/ 10.4218/etrij.2023-0035.

Long, Y. and Cen, N., 2022. *Sum-Rate Optimisation for Visible-Light-Band UAV Networks Based on Particle Swarm Optimisation*. In: IEEE (Institute of Electrical and Electronics Engineers), 2022 IEEE 19th Annual Consumer Communications and Networking Conference (CCNC). Las Vegas, NV, USA, 8-11 January 2022. New York: IEEE.

Zhang, W. and Zhang, W., 2022. An Efficient UAV Localization Technique Based on Particle Swarm Optimisation. *IEEE Transactions on Vehicular Technology*, 71(9), pp.9544–9557. https://doi.org/10.1109/TVT.2022.3178228.

Nadimi-Shahraki, M.H., Zamani, H., Asghari Varzaneh, Z. and Mirjalili, S., 2023. A Systematic Review of the Whale Optimisation Algorithm: Theoretical Foundation, Improvements, and Hybridizations. *Archives of Computational Methods in Engineering*, [e-journal] 30(7), pp.4113-4159. https://doi.org/10.1007/s11831-023-09928-7.

Liu, K., Xv, C., Huang, D. and Ye, X., 2021. *UAV Path Planning based on Improved Whale optimisation Algorithm*. In: IEEE (Institute of Electrical and Electronics Engineers), 2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE). Guangzhou, China, 15-17 January 2021. New York: IEEE.

Yuan, Z., Li, J., Yang, H. and Zhang, B., 2021. *A Hybrid Whale Optimisation and Particle Swarm Optimisation Algorithm*. In: IEEE (Institute of Electrical and Electronics Engineers), 2021 IEEE International Conference on Progress in Informatics and Computing (PIC). Shanghai, China, 17-19 December 2021. New York: IEEE.

Jin, F., Zhang, R., and Hanzo, L., 2015. Resource Allocation Under Delay-Guarantee Constraints for Heterogeneous Visible-Light and RF Femtocell. *IEEE Transactions on Wireless Communications*, [e-journal] 14(2), pp.1020-1034. http://dx.doi.org/ 10.1109/TWC.2014.2363451.

Niu, H., Zhao, X. and Li, J., 2021. 3D Location and Resource Allocation Optimization for UAV-Enabled Emergency Networks Under Statistical QoS Constraint. *IEEE Access*, [e-journal] 9, pp.41566-41576. http://dx.doi.org/ 10.1109/ACCESS.2021.3065055.

Lim, Y. K., Jiang, S., Khor, K. C., Lee, Y. L. and Ke, F., 2023. *Fairness-Aware Unmanned Aerial Vehicle-Mounted Base Station Placement with Quality of Service Provisioning*. In: IEEE (Institute of Electrical and Electronics Engineers), International Conference on Computer, Control, Informatics and its Applications (IC3INA). Bandung, Indonesia, 04-05 October 2023. New York: IEEE.