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Mesh Routers Placement in Wireless Mesh Networks:

Clients coverage and Network connectivity

Une thèse Présentée par

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I would like to dedicate this thesis to my loving parents, my wife and my children…

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Abstract

Wireless mesh networks (WMNs), in the form of WiFi (802.11x) or WiMax (802.16x), or their integrations, have been proposed as an effective communication alternative for ubiquitous last mile wireless broadband access. They can be viewed as a hybrid between traditional cellular, point-to-point wireless systems, and ad-hoc networks. They offer more flexibility, mobility, coverage, and expandability compared to their traditional counterparts at the expense of complex architecture and deployment structure. Though WMNs hold great promise in abetting network ubiquity, there still remain several challenges in the design and development of WMNs to support diverse services with different quality of service (QoS) requirements and large-scale deployment. The focus of this thesis is to address some of the core issues that directly affect the mesh client's coverage, mesh routers connectivity and guarantee some QoS level.

In this thesis, we investigate the placement problem of the wireless mesh routers. The deployment issue of WMNs has a significant impact on the network's throughput and performance, cost, and capacity to satisfy the quality of service requirements. In the context of mesh router placement, the QoS is influenced by the location of mesh routers, the number of mesh clients served by each mesh router, and the load on each wireless router.

While finding an optimal solution to simultaneously satisfy all the above constraints is known to be an NP-hard problem, near-optimal solutions can be found within the feasibility region in polynomial time using various meta-heuristic methods. In the initial part of this thesis, we first present a near-optimal meta-heuristics algorithm called Accelerated PSO for mesh routers placement that facilitates QoS provisioning in WMNs. We then propose a new objective function to achieve optimal client coverage as well as to fine-tune the network connectivity for optimum performance with no need for knowledge of an aggregation coefficient.

ملخص

تم اقتراح الشبكات العروية اللاسلكية (WMN's)، ممثلة في (802.11x) WiFi أو WiMax (802.16x) كبديل اتصال فعال للوصول إلى النطاق اللاسلكي العريض في كل مكان. حيث يمكن اعتبارها هجينة بين الأنظمة اللاسلكية الخلوية التقليدية من نقطة إلى نقطة والشبكات اللاسلكية المخصصة. أنها توفر المزيد من المرونة والتنقل والتغطية والتوسع مقارنة بنظيراتها التقليدية ذات الهيكل المعقد وبنية النشر الصعبة. على الرغم من أن شبكات WMN تساعد بشكل كبير في انتشار التغطية في كل مكان، إلا أنه لا تزال هناك العديد من التحديات في تصميمها وتطويرها لدعم الخدمات المتنوعة بمتطلبات جودة الخدمة (QoS) المختلفة والنشر على نطاق واسع. ينصب تركيز هذه الأطروحة على معالجة بعض المشكلات الأساسية التي تؤثر بشكل مباشر على تغطية عملاء الشبكة وتوصيل أجهزة توجيه الشبكة وتضمن بعض مستوى جودة الخدمة.

في هذه الأطروحة، نقوم بدراسة مشكلة وضع الموجهات الشبكية اللاسلكية. حيث لنشر وتثبيت شبكات WMN تأثير كبير على إنتاجية الشبكة وأدائها، والتكلفة والقدرة على تلبية متطلبات جودة الخدمة. تتأثر جودة الخدمة بموقع الموجهات المعشقة وعدد عملاء الشبكة التي تخدمها اجهزة توجيه الشبكة وكذلك العبء على اجهزة توجيه اللاسلكية.

من المعروف أن إيجاد حل مثالي لتلبية جميع القيود المذكورة أعلاه في وقت واحد هو مشكلة NP-hard ،بالرغم من ذلك يمكن العثور على الحلول المثلى تقريبًا داخل منطقة الجدوى في وقت متعدد الحدود باستخدام طرق meta-heuristic المختلفة. في الجزء الأول من هذه الأطروحة، نقدم أولاً خوارزمية تسمى Accelerated PSO لوضع أجهزة التوجيه المعشقة التي تسهل توفير جودة الخدمة في الشبكات العروية اللاسلكية (WMN) ثم نقترح دالة جديدة لتحقيق تغطية العميل المثلى بالإضافة إلى ضبط اتصال الشبكة للحصول على الأداء الأمثل دون الحاجة إلى معرفة معامل التجميع.

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Acronyms

Acronyms / Abbreviations

ACO Ant Colony Optimizer

AOF Aggregate Objective Function

AP Access Point

APSO Accelerated Particle Swarm Optimizer

BAC Building Automation and Control Networks

GA Genetic Algorithm

GWO Grey Wolf Optimizer

IGW Internet GateWay

IoT Internet of Things

ISP Internet Service Provider

LDWPSO Linearly Decreasing Weight Particle Swarm Optimizer

LOS Line of Sight

MAC Medium Access Control

MC Mesh Client

MR Mesh Router

MRP Mesh Router Placement

NFL No Free Lunch

NIC Network Interface Card

NLOS Non-Line of Sight

OFDM Orthogonal Frequency Multiple Access

PSO Particle Swarm Optimizer

RCP Rate Control Protocol

RFID Radio-Frequency Identification

RTT Round-Trip Time

SA Simulated Annealing

TCP Transmission Control Protocol

UDP User Datagram Protocol

UWB UltraWideBand

WiFi Wireless-Fidelity

WiMAX Worldwide Interoperability for Microwave Access

WISP Wireless Internet Service Provider

WLAN Wireless Local Area Network

WMAN Wireless Metropolitan Area Network

WMN Wireless Mesh Network

Chapter 1

Introduction

1.1 Background

Over the last two decades, the proliferation and the usage of WiFi devices have been explored, and the penetration rates of this emerged technology are massive in many deployment areas, thanks to the decreasing wireless device costs. In this context, the Wireless Internet Service Provider (WISP) expects to cover a large outdoor area and provide internet connectivity to a large geographically dispersed user base. Regardless of the scale of the system being deployed, some separate parameters have relations with each other. For example, selecting locations for installing the Mesh Routers (MRs) will be influenced by coverage and connectivity needs by the system. Moreover outdoor WMNs deployments attempt to cover a larger area than indoor wireless networks while dealing with the issues of less control over interference sources. However, in the real world, finding an optimal deployment for the mesh network devices is vital because outdoor installation may suffer from a lower user density than indoor deployments in some regions [7, 59], and it can be deployed in a far less regulated system than inside a building. Accordingly, we have plenty of deployment possibilities as user coverage and connectivity needs, for example, in critical situations such as natural disasters, oil rigs, mines, battlefield surveillance, in public transport or mobile video gaming, etc. Additionally, by appropriate tuning of quality of service parameters, the WMNs may become a good alternative to support local telephone calls from one edge to another by the mesh [7, 57].

In order to deploy WMNs, we need a good understanding of the relationship between network topology, the density of wireless nodes, and transmission power, among other factors because network deployment is a crucial mission that influences the network life cycle and the deployment of wireless mesh routers without taking into consideration the technical limitations of the underlying topology and the real deployment area would lead to low client coverage and poor network connectivity [59]. Although WMNs have become more and more mature. Planning mobile networks involve multiple challenges due to the high complexity of the network to be managed. Typically, every parameter that exists in the network may undergo optimization. But the situation might be more complicated, where an optimization process attained some performance improvements locally, while globally led to worsening in the network performance.

During the planning phase of WMN, routers placement is estimated to ensure that the client coverage and network connectivity requirements are met, and initial optimization must be performed to achieve acceptable QoS constraints. Therefore, mesh routers placement optimization is essential in WMNs planning and design, especially at the earlier stages of network design, which usually based on topology considerations to minimize overheads of using sophisticated protocols that will be used in the future to overcome the problem of MRs placement in high levels of network planning and configuration. Therefore, the network performance depends largely on the optimal placement of MRs.

The efficient deployment of WMNs problem can be described as a facility location problem [45, 9, 92]. This problem has been studied in the literature for a long time where it has been proved to be an NP-hard problem. No Free Lunch (NFL) theorem states that it is impossible to have a single meta-heuristic that can deal with all kinds of problems of optimization [87]. Therefore, many works using different meta-heuristics algorithms have been proposed to find the desired network characteristics in a reasonable time and thereby assist the network engineer during the planning process.

Evaluating what we want to accomplish is often challenging, even that we continue to work hard for optimum performance. In reality, decision-makers must evaluate the objectives several times, regardless of what they are. Most of the time, the evaluation of the objective functions requires a lot of time and effort, which is expensive in terms of design time and money. Any effective algorithm that reduces the number of objective function evaluations will save time and keeps costs down. Thus, in order to solve the mesh routers placement problem, several works have been proposed [90, 92, 88, 91, 89] using different meta-heuristics where they have considered two metrics: client coverage and network connectivity.

Recently, nature-inspired algorithms such as Swarm Particles Optimization algorithms (PSO) were widely used to solve optimization problems. In this context, PSOs algorithms recently have proved their usefulness and efficiency to solve optimization problems, especially the combinatorial optimization problems in a reasonable time [60].

1.2 Research hypothesizes / philosophy

The Mesh Routers Placement (MPR) in WMN is considered to be an NP-Hard problem, and it can be modeled as a combinatorial optimization problem. Hence, it is difficult to find the optimal solution, or it is unlikely to be solvable in a reasonable amount of time [92, 46]. Therefore, methods to find the near-optimal solution are needed in this situation, and the meta-heuristic methods are widely used as resolution methods. There are many (Meta) heuristics methods such as Genetic Algorithm (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Simulated Annealing (SA). PSOs have shown their usefulness in the resolution of many computational and combinatorial optimization problems [100]. In addition, to enhance the performance of the WMN, more focus should be given to the network topology rather than only focusing on routing optimization techniques, which is not sufficient to achieve a good performance and also to avoid the overhead generated by the routing protocol themselves as much as possible.

1.3 Problem statement and research objectives

The performance of WMNs mainly depends on the geographical placement of mesh routers and mesh clients. The placement of mesh routers plays a crucial role as it determines the connectivity and coverage of the whole network. In a real deployment of WMN, the automatic or purely random mesh router placements produce a poor performance since the resulting placement could be far from optimal, which causes many problems such as packet loss and delay. If the mesh routers were placed without taking into account specific restrictions of the real geographic area and the topology underlying WMNs, it would lead to poor networking performance. Therefore, if the MRs are placed in unsuitable positions, then the MCs that are far away from their MRs will be uncovered or use low bit rate due to auto rate algorithms [33]. In practice, it would be impossible to find an optimal placement of mesh nodes since the distribution of real mesh clients cannot be predicted. Owing to the generally complex nature of problems associated with each layer of WMNs, most studies have focused on the simplified problems after some degree of abstraction and assumptions. To fulfill more practical requirements.

An efficient meta-heuristic algorithm for mesh router placement in topology planning stages is required to alleviate the effects of the above issues. In this thesis, in light of the issues raised, the following research questions will be addressed:

- What are the most effective meta-heuristic strategies for providing the optimal mesh routers placement to the formulated questions?

- How will the suggested objective function be assessed?

The contribution of this thesis is two-fold: Firstly, we investigate the problem of optimal placement of wireless mesh routers in a wireless mesh network with some QoS constraints. We formulate a multi-objective aggregate function to maximize mesh client coverage and mesh routers connectivity simultaneously, and we evaluate two meta-heuristic algorithms: Accelerated PSO (APSO), Linearly Decreasing Weight PSO (LDWPSO) for wireless mesh network that incorporates QoS constraints. We further compare their convergence, computational complexity, and implementation details. This result has been published in [55].

Secondly, prior approaches to solve MRP-WMN have used a hierarchical approach or aggregate objective function (AOF) for solving bi-objective client coverage and network connectivity optimization problems [92, 89, 48, 12, 69]. The concern here is assigning weights to coefficients of each objective. The coefficients do not necessarily correspond directly to the relative importance of the objectives or allow trade-offs between the objectives to be expressed. In order to avoid this limitation, we proposed a new objective function to achieve optimal client coverage as well as to fine-tune the network connectivity for optimum performance without the need for knowledge of an aggregation coefficient. These results have been under major revision in journal of "Concurrency and Computation: Practice and Experience".

1.4 Thesis organization

In chapter 2, we discuss wireless mesh networks, and we examine what differentiates them in detail. In addition, we present some of the open research issues in WMNs, and we take a glance at some of their applications.

In chapter 3, we present the problem statement of mesh routers placement issue in WMN deployment and review the most relevant related studies to our work.

In chapter 4, we present multi-objective optimization, and we discuss the Pareto optimality concept; finally, we present the swam optimization algorithms used during this thesis.

In chapter 5, we present and evaluate LDWPSO and APSO algorithms for the problem of optimal mesh router node placement in WMNs. We consider aggregated bi-objective function to maximize the network connectivity of the WMN measured by the number of connected mesh routers to maximize the number of covered mesh clients.

In chapter 6, to maximize the client's coverage in WMNs by optimizing the mesh router's locations to avoid fragmented network topology obtained by previous solutions, we consider a novel single objective function, and we evaluate three algorithms: LDWPSO, GWO, and APSO algorithm performance.

Finally, we summarize our findings and discuss ideas on how to extend this research.

Chapter 2

Overview of wireless mesh network

2.1 Introduction

The traditional network is formed by several intermediate wired nodes and hotspots to offer internet connection to final users. Whereas in WMNs, the network is formed with the help of several wireless nodes to communicate with each other. Typically, WMN consists of two types of nodes: Mesh Routers (MRs) and Mesh Clients (MCs) that form a multi-hop wireless mesh network to access the internet through Internet GateWay (IGW). WMN may contain either mobile or static nodes. Intermediate nodes between the clients and internet gateway operate as a cooperative forwarding node in making route prediction decisions based on network topology [7, 8].

Figure 2.1 illustrates a generic wireless mesh network consists of MRs and MCs. In this architecture, mesh routers are static nodes, forming the wireless backbone, and mesh clients are mobile users who can access the network through these routers.

This chapter highlights wireless mesh networks, their characteristics and discusses the applications of this technology as well as its importance. In addition, the architecture of wireless mesh networks is explored, Additionally, the emerging problems related to them.

2.2 Wireless mesh network

A wireless mesh network is a particular form of a wireless network. It provides a promising solution to issues that frequently encounter in cellular and WLAN networks. The main problem with cellular and WLAN is that their scope of connectivity is limited. These systems are quite costly, and their transmission data rate is poor. On the contrary, wireless mesh networks are less expensive and provide faster data transfer rates.

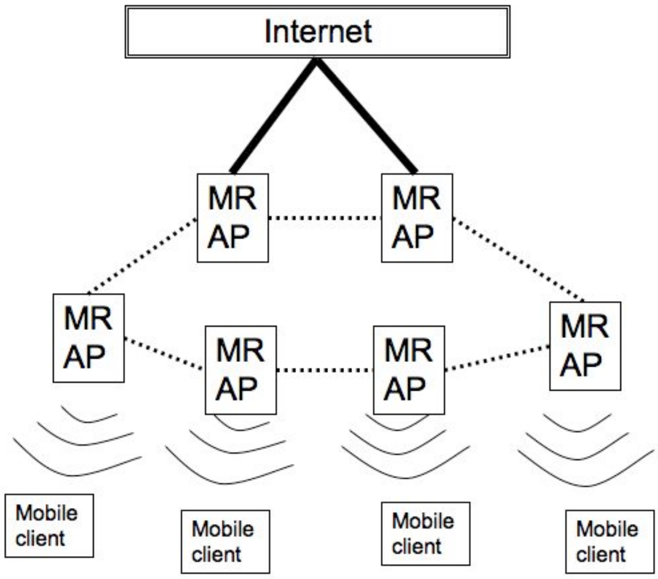


Fig. 2.1 Generic wireless mesh network

Typically, wireless mesh networks are composed of two types of nodes.

- Wireless mesh routers.
- Wireless mesh clients.

Mesh routers operate as the infrastructure's backbone of the mesh network. The main role of the WMN's core nodes is to forward data to and from clients, establishing mobile ad-hoc networks (MANET) [5]. This feature allows the network to provide a better quality of services, ensure self-organization, self-configuration, and the ability to self-healing. For example, if one of the nodes fails, a new path is chosen automatically to preserve connectivity. Hence, these features increase the network performance and maintain the network connectivity where all nodes became connected.

WMNs are easy to deploy, easy to maintain, flexible, scalable, reliable, and essentially cost-effective. The users in WMNs only connect to mesh routers via their integrated Network Interface Card (NIC), and the communication between devices in WMNs is Non-Line of Sight (NLOS). Due to gateway/bridge WMNs capabilities, WMN can operate in conjunction with existing networks such as cellular networks, wireless sensors, wireless-fidelity (WiFi), worldwide interoperability for microwave access (WiMAX), and WiMedia networks.

WMNs are highly flexible, enabling manufacturers to enter the mesh networking market with a wide variety of products and applications.

Most internet service providers (ISPs) look for a low-cost, scalable, and reliable technology such as WMN can offer. The mesh nodes in WMN can be added as needed, where an additional node can improve network reliability, performance and enhance backup by increasing the number of cooperating nodes. Figure 2.2 shows the basic architecture of WMNs.

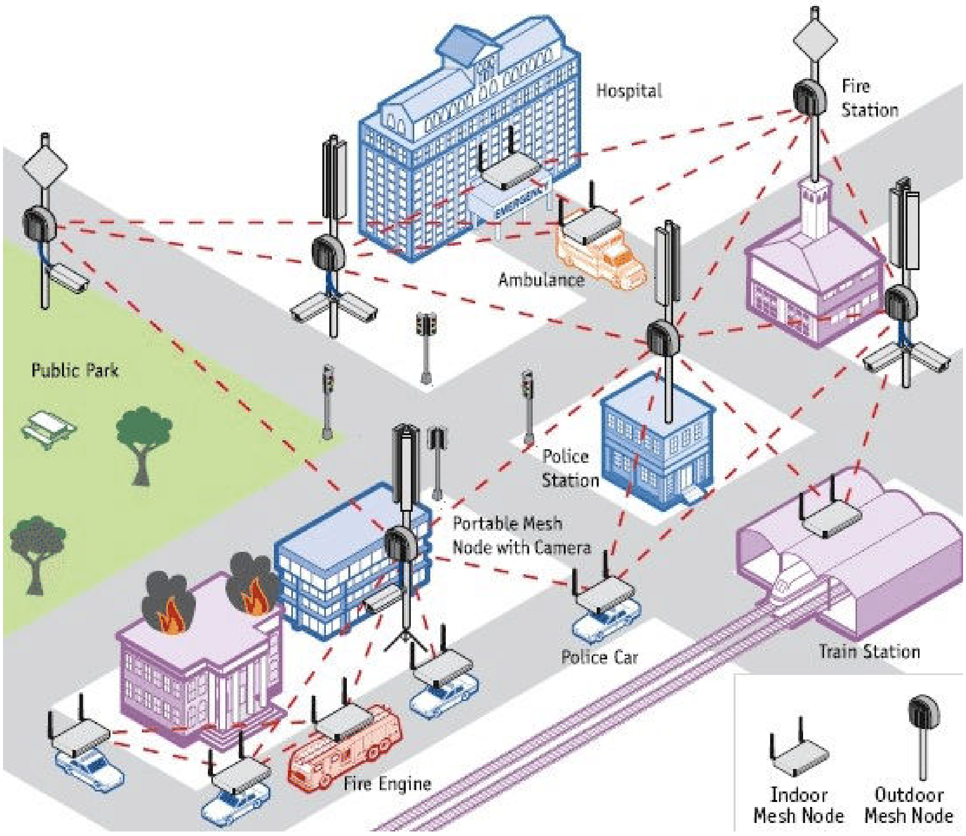


Fig. 2.2 Wireless mesh network [80]

2.3 Components of WMNs

2.3.1 Mesh Routers

Along with the capabilities provided by conventional routers, a wireless mesh router has additional routing capabilities that enable mesh networking. In order to improve the network's performance, a mesh router is typically equipped with several wireless interfaces installed on either the same or separate wireless technologies [64].

- In contrast to a traditional wireless router, a wireless mesh router can provide the same coverage with more transmission capacity through multi-hop communications [82].
- The medium access control (MAC) protocol in a mesh router is improved with better scalability in a multi-hop mesh environment [82].

Note that mesh and traditional wireless routers are typically built over the same network applications. Mesh routers can be installed on dedicated computer systems, such as embedded systems, or they can be adjusted and used on general-purpose computer systems like laptops and desktop PCs [31].

2.3.2 Mesh clients

Mesh clients do not have any gateway/bridge features. However, with some adjustments, they can act as routers thanks to their networking functions.

Mesh client and mesh routers can share similar software and hardware function. Typically, mesh clients have a single wireless adapter. In addition to mesh routers, mesh clients consist of a broader family of equipment. They can be laptop/desktop PCs, pocket PCs, PDAs, IP phones, RFID readers, BAC network (Building Automation and Control Networks), controllers, and many other devices [3].

2.4 WMN architecture

Wireless mesh networks are classified into three main categories:

- Infrastructural backbone.
- Client WMNs.
- Hybrid WMNs.

2.4.1 Infrastructural backbone

Figure 2.3 depicts the architecture of WMN, where dashed lines representing wireless connections and solid lines represent wired links. This type of network provides connectivity for a client using mesh routers.

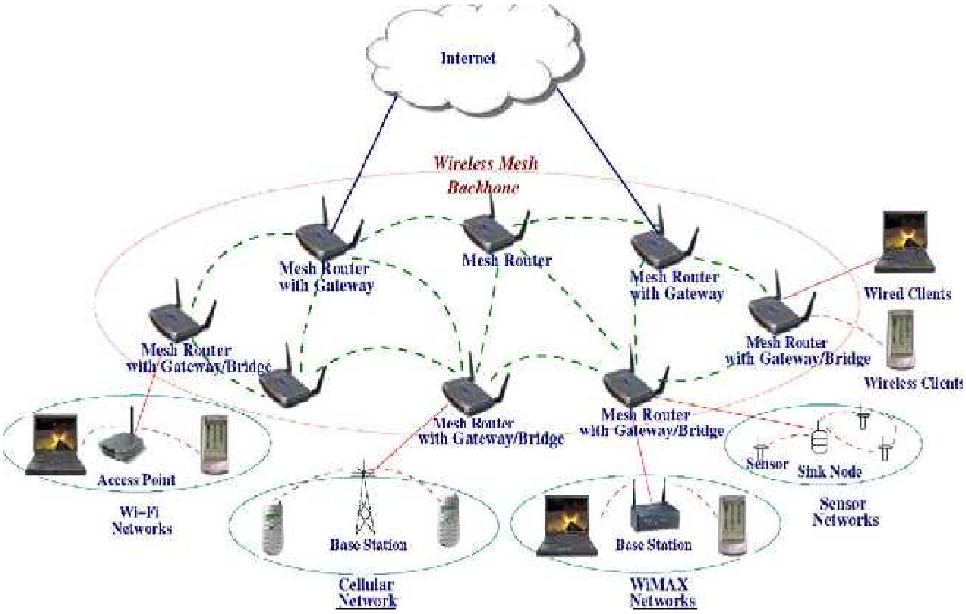


Fig. 2.3 Infrastructure/Backbone WMNs [6]

A variety of radio technologies, such as IEEE 802.11 technology, can be used to build the infrastructure backbone of a wireless network. Mesh routers can form self-configuring, self-healing individual groups. Additionally, they can be connected to the internet via internet gateway [37].

This topology is known as *mesh infrastructure* because it is split up the network into individual groups. It provides backbone connectivity for traditional clients and allows WMNs to be integrated with existing wireless networks through gateway/bridge thanks to mesh routers features.

Clients without wireless network interfaces connect to the mesh routers through Ethernet links [32]. Clients with similar radio technologies can communicate, but if different radio technologies are used, the communication will be assured via a base station connected to mesh routers via Ethernet connections.

WMNs flexibility can bring many advantages to the IoT networks providing a solid infrastructure backbone to the network. Mesh routers can work as access points for users in dense areas such as homes, shopping malls, or open areas along the roads. When using the WMN topology, adding a new router only requires a new device to be placed directly into the existing network. The network's capacity and range are extended without additional cables and links. In this situation, two types of radio transmissions are used, one to communicate with backbones and the other to intercommunicate with users. The communication in the mesh backbone can be done using long-range communication techniques such as directional antennas [17].

2.4.2 Client WMNs

Client meshing enables peer-to-peer networks between client devices, resulting in an extensive ad-hoc network. In this type of architecture, client nodes form part of the existing network enabling routing and configuration functions and providing applications to end-users. Hence, mesh routers are not needed for this type of network as they can work individually within the group. This type of network is usually can not access the Internet.

Figure 2.4 depicts the architecture of client WMNs. It describes how packets travel through nodes using multi-hops to reach their destination. Mesh clients can access the network through mesh routers as well as directly connect to other mesh clients. However, these client WMNs are built up with one type of radio technology to communicate directly. In the end, the requirements of client devices are more compared to standard infrastructure meshing routers, as they perform additional functions such as routing and self-configuring [35].

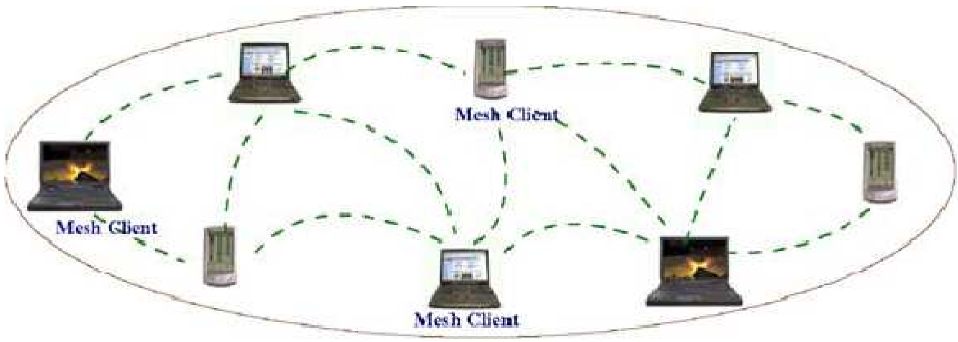


Fig. 2.4 Client WMNs [4]

2.4.3 Hybrid WMNs

Figure 2.5 depicts the architecture of hybrid WMNs. This architecture consists primarily of infrastructure and mesh clients. It has more capabilities compared to infrastructure and clients separately [4]. Unlike mesh clients, infrastructure allows interconnecting other network technologies such as Wi-Fi, Wi-MAX, wireless, and sensor networks. In contrast, the routing functionality for clients improves connectivity and coverage within the WMN [31].

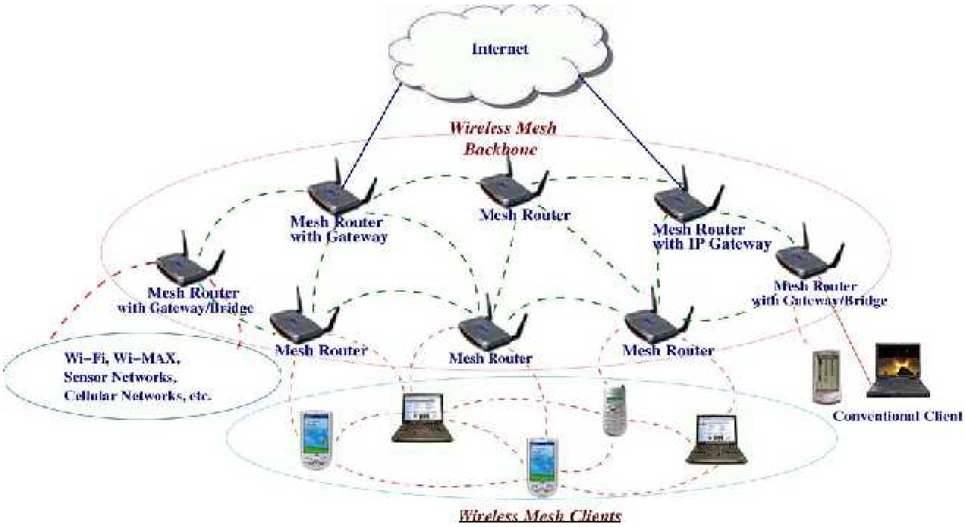


Fig. 2.5 Hybrid WMNs [4]

2.5 Open research problems in WMNs

2.5.1 Physical layer

In wireless mesh networks, various advanced physical layer techniques have been developed and used. For example, *multiple transmission rates* can be offered by combining various modulation and coding techniques. In addition *link adjustment* makes possible to provide error correction and prevention due to unstable radio transmission conditions. Also, new *multiplexing schemes* such as Orthogonal Frequency Multiple Access (OFDM) and the Ultra-WideBand (UWB) can achieve high transmission speeds. Moreover, using *antenna diversity* and *smart antenna* improves the physical layer's capacity and decreases the impairment of fading. *Frequency agile* or *intelligent radios* can be used to make effective use of the underutilized spectrum and *directional antenna*s can help to reduce transmission power by reducing interference between different transmissions [35].

2.5.2 Medium access layer

MAC protocols for WMNs vary from their traditional counterparts for wireless networks in different ways. For example, classical wireless MAC is limited to one-hop communication, where the routing protocol takes care of multi-hop communication. On the contrary, a wireless mesh network is characterized by multiple hops. In this paradigm of networking, communication needs more than one hop. Therefore the MAC layer needs to support multiple hops nature to enable communication. This presumption simplifies protocol architecture since MAC and routing are open to each other. However, in WMNs, this approach fails because data transmission and reception at a node are affected not only by nodes within one hop but also by nodes, two or more hops apart. Furthermore, the WMNs do not have a centralized controller; instead, the MAC functions are distributed. The MAC protocol ensures that all nodes in a transmission network are collaborating with each other [34, 51].

A WMN network node can also connect with all nearby nodes in the mesh network. This function allows nodes to communicate with one another in a multi-point-to-multi-point fashion. Mesh network topology promotes greater node coordination, and MAC protocols are more familiar with these topologies. Hence, this will improve the *efficiency* of the MAC in a multi-hop environment [76].

MAC protocol should be aware of network topology to facilitate better communication between adjacent nodes and nodes separated by several hops. In a multi-hop environment, this can significantly boost MAC performance. In addition, when self-organized networks control the *power (transmission range)*, the network topology will be optimized, and interference between neighboring nodes is reduced, resulting in improved network capacity.

When a user is moving, the performance of MAC is affected. Mobility changes the network configuration on the fly, which can significantly impact MAC protocol performance. Thus, the network nodes must share network topology information in order to be tolerant to mobility or even to support mobility properly [76].

Also, scalability of WMNs at the MAC layer is accomplished in two ways: to maximize end-to-end throughput in a single channel network, existing protocols can be enhanced, or a new protocol can be proposed. For example, it can be accomplished by resizing the size of the *contention window*, which would increase throughput in one-hop communications. Along with this, cross-layer architecture with advanced physical layer techniques also tends to increase performance [33, 75]. The other option is to allow transmission on multiple channels in each node by setting a *multi-channel single transceiver* MAC, using a *multi-channel multi-transceiver* MAC, and a multi-radio MAC.

2.5.3 Network layer

Developing routing protocols for wireless mesh networks is a challenging task. It must address many performance metrics such as minimum hop count and preventing disruption of services based on robustness concepts. In addition, it must make mesh infrastructure routing processes as efficiently as possible and increasing its scalability to install or maintain paths. For this reason, many routing protocols are proposed to have low overhead and need complete information to cover as many nodes as possible. In case of a broken connection or other problem, the reconfiguration protocol should be enabled. This will keep the WMN network reliable. Additionally, if a single route is congested, routing should also be performed in such a manner that data packets should be sent from a alternative route [3].

2.5.4 Transport layer

The primary role of the transport layer is to transfer data from one location to another. However, existing wireless mesh network architectures lack a standard transport protocol and use traditional ad hoc network transport protocols. The TCP protocol is inefficient when the packet loss ratio is high. As a result, if we use standard TCP on a wireless network, nodes will experience more losses, congestion packet losses, unexplained connection breakdown, asymmetric network, and wide RTT variations. Therefore, the challenging task of implementing a transport protocol that provides efficient data transport based on current TCP variants is indispensable [27]. In addition, UDP is a promising alternative solution and a safer one [29]. It can be used with Real-Time Protocol (RTP) to support real-time applications; aside from that, it is essential to keep an eye on network congestion. The session control can be performed by the Rate Control Protocol (RCP), which manages the number of packets sent over a particular path [74].

2.5.5 Application layer

WMNs enable easy, fast, and cost-effective installation of Internet access services. Information can be processed typically in wireless mesh networks. However, they also have the advantage of allowing information exchange through many wireless networks, thanks to mesh routers with multiple access points since information flows through a wide range of networks before reaching the end application. Due to the characteristics of wireless mesh networks, new application possibilities have emerged. Many factors distinguish these applications from one another, such as low-cost, simple setup, faster capacity, internet access, and so forth. Accordingly, the application layer protocol should manage network heterogeneity, and it is essential to understand the network's application infrastructure. Therefore, innovative methods in the application layer must be coded to implement all of these applications [17].

2.6 Characteristics of WMNs

WMNs have the following main characteristics:

Multi-hop wireless network The primary goal of deploying WMNs is to enlarge the coverage range of traditional wireless networks without sacrificing channel capacity.

Another purpose is to obtain NLOS access to users who do not have direct LOS to the network [82]. A multi-hops mesh scheme is required to meet these requirements by reduce node interference, increase frequency re-use, and provide higher throughput without sacrificing efficient radio range by reducing communication distances [74].

Support for ad-hoc networking and capability of self forming, self healing and self organization Due to the robust architecture, WMNs can support ad hoc networking, self-formation, self-healing, self-organization capabilities, fast deployment, set-up, fault tolerance, and mesh connectivity. They can optimize network performance. Due to all these features, the network can be gradually expanded as needed with little investment [10].

Mobility depends on the type of mesh nodes Mesh routers are generally static or with limited mobility, while mesh clients may be either mobile or stationary [7].

Multiple types of network access There are several forms of network access. WMNs guarantee both backhaul Internet access and peer-to-peer (P2P) communications. Furthermore, WMNs can cooperate and provide services to end-users of these networks.

Dependence on power-consumption constraints on the type of mesh nodes The impact of power consumption constraints is regarded as a vital feature of mesh clients. Unlike mesh routers, mesh clients require power-efficient protocols. For instance, wireless sensor networks' primary concern is power efficiency [30]. Therefore, the mesh clients need a power-efficient communication protocol since MAC/routing protocols designed for mesh routers may not suit clients such as sensors.

Capability and inter-operability with existing wireless networks Since WMNs are based on IEEE 802.11 technology, they must be compatible with IEEE 802.11 specifications. In addition to that, WMNs must be compatible with other wireless networks, such as Wi-MAX and cellular networks [102].

2.7 Comparison between WMN and ad-hoc networks

WMNs are regarded as an *ad hoc network* because they lack the infrastructure that exists in cellular or standard Wi-Fi networks through the placement of base stations or access points. The networking technologies used by WMNs must provide more advanced algorithms and architecture concepts to be compatible with the new constraints of communication. To demonstrate this point, let us compare wireless mesh networks and ad-hoc networks.

2.7.1 Wireless infrastructure/backbone

WMNs consist of a wireless mesh routers backbone, providing broader coverage, connectivity, and stability. On the contrary, connectivity in ad hoc networks often relies on the individual effort of end-users [7].

2.7.2 Integration

WMNs use the same radio technologies used with mesh routers to support conventional clients. WMNs integrate numerous existing networks such as Wi-Fi, cellular, and sensor networks via gateway or bridge functionality in mesh routers to enable users from one network to connect to users using wireless infrastructure across other networks. Since a network node's physical location became less significant than capacity and network topology, the embedded wireless network becomes similar to an internet backbone [4].

2.7.3 Dedicated routing and configuration

In ad hoc networks, end-user devices handle routing and configuration functions. In contrast, in WMNs, mesh routers perform these functions for other nodes [4]. As a result, the workload on end-user devices is considerably reduced, which enables high-end application capabilities and lowers energy usage. Furthermore, end-user resource requirements are minimal, which leads to reducing the cost of devices that can be used in WMNs.

2.7.4 Multiple radio frequency

Routing and medium access capabilities of mesh routers can be configured with different radio frequencies. Routing and deployment are done between mesh routers, and a different radio frequency can assure network connectivity, which dramatically increases the network's capacity. When it relates to ad-hoc networks, these functionalities are carried out on the same channel, resulting in lower overall performance [4].

2.7.5 Mobility

End-user devices in ad-hoc networks provide routing capabilities. The topology and connectivity of the network depend on user mobility, routing protocols. While the deployment problems are challenging in WMNs [93, 76].

2.8 Application scenarios

2.8.1 Broadband home networking

Nowadays, IEEE 802.11 WLANs are widely used for home broadband networking. However, since we work with domestic places, choosing the access points and their positioning is the hardest task. Moreover, it is very costly and not feasible to use multiple access points because it needs Ethernet wires from the access points to backhaul network access. As a result, mesh networking is a better way to solve this issue [32]. Figure 2.6 depicts the concept.

Standard access points must be replaced with wireless mesh routers for mesh networking at homes—this will versatile and secure communication between nodes against network loss and connection degradation. As a result, old drawbacks can be mitigated by clever mesh networking between homes, which, in turn, helps store distributed files, distribute links to files, and stream content.

Fig. 2.6 WMNs for broadband home networking [4]

2.8.2 Enterprise networking

Enterprise networking is essentially regarded as commercial networking because it is primarily used in offices, between offices, and across multiple buildings. The network can be a small intra-office network, a medium network that connects all of the offices in the building, or an extensive network that connects multiple buildings. Earlier, such a network was built using IEEE 802.11 standards and Ethernet connections, which made enterprise networks very expensive [17]. Although increasing the number of backhaul access points and modems does not improve the enterprise network's resilience to link failures, network configuration, and other similar issues, it can only improve local capacity. Figure 2.7 shows how a mesh network can be used to solve the problem described above.

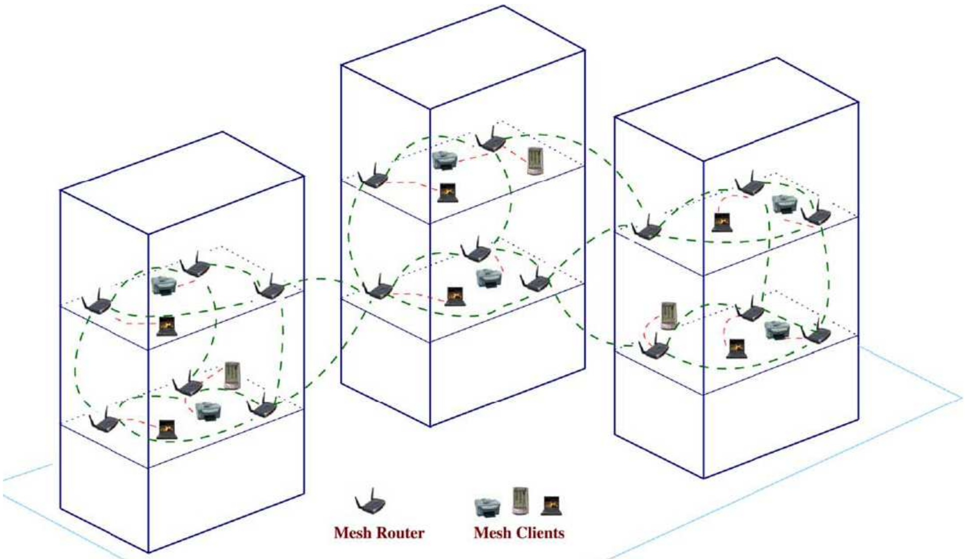


Fig. 2.7 WMNs for enterprise networking [16]

By using WMNs, we are reducing or eliminating Ethernet connections. Network nodes can be used for multiple access modems, improving the robustness and resource efficiency of the whole network. Thus, WMNs can be beneficial and allow easy growth as the size of the organization expands. Since enterprise networks are required for relatively large organizations, mesh networks can support more complex topologies as more nodes and networks are added. Corporation networks can be beneficial for self-service in airports, malls, hotels, and sports centers.

2.8.3 Metropolitan area networking

WMNs bring many advantages compared to other networks, including a much faster transmission rate than in any cellular network. In addition, in WMNs, communication between nodes is not dependent on a wired infrastructure.

WMAN is a cost-effective alternative to wired or cable broadband networks. Figure 2.8 shows that the WMAN network covers a wider area than the home enterprise, building, or community networks. Therefore, the main advantage of WMAN is a *scalable* alternative [3, 63, 76].

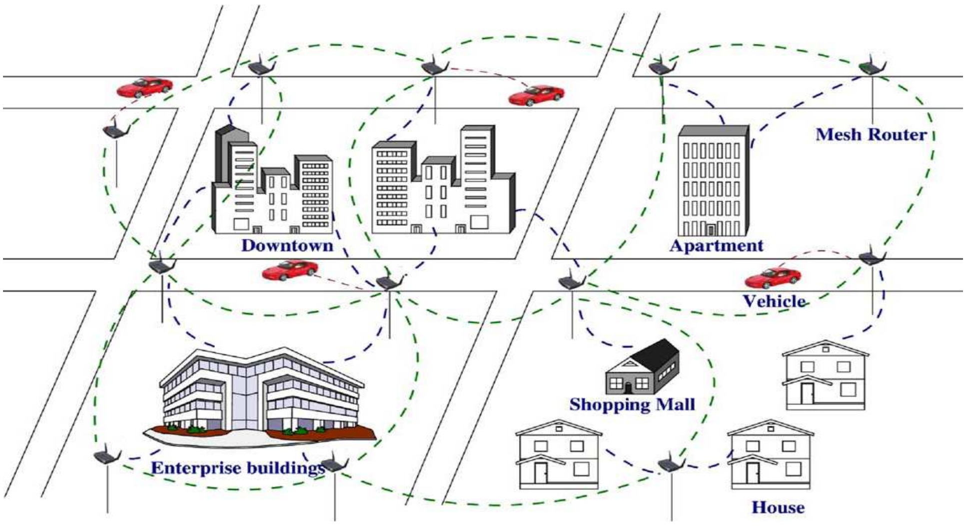


Fig. 2.8 WMNs for metropolitan area network [4]

2.8.4 Transportation systems

Although IEEE 802.11 and 802.16 are built on Ethernet links, their use has been restricted to stations and waiting bus stops. WMNs can prove to be a far preferable alternative. In addition, WMNs can help with passenger information systems, remote control, and in-vehicle security connectivity. As seen in figure 2.9, the fundamental concept behind these systems is high-speed mobile backhaul from a vehicle to the internet and mobile mesh networks within the vehicle [3, 51].

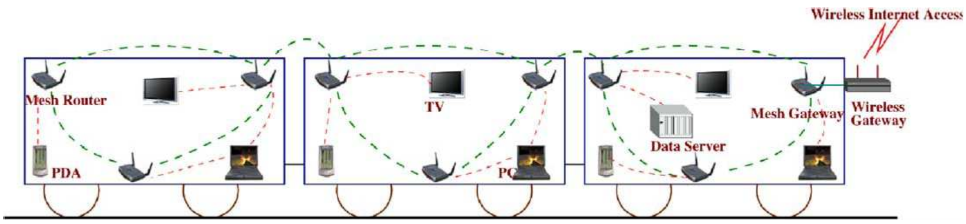


Fig. 2.9 WMNs for Transportation systems [4]

2.8.5 Building automation

When we consider an apartment or a company building, we observe various electrical equipment types as seen in figure 2.10. Therefore, this latter equipment must be constantly supervised and monitored. The old system for monitoring these devices is by wired networks. However, this method is costly due to the difficulty and heavy maintenance cost of the wired network. Wi-Fi-based networks have been introduced to overcome this problem. However, since they include wired distribution systems, they are often still expensive and have not achieved satisfactory results. To alleviate these issues, we should replace BAC access points with network routers [4], which would significantly reduce the final cost. Because the network routers are wirelessly connected, and the deployment process is often much easier [75].

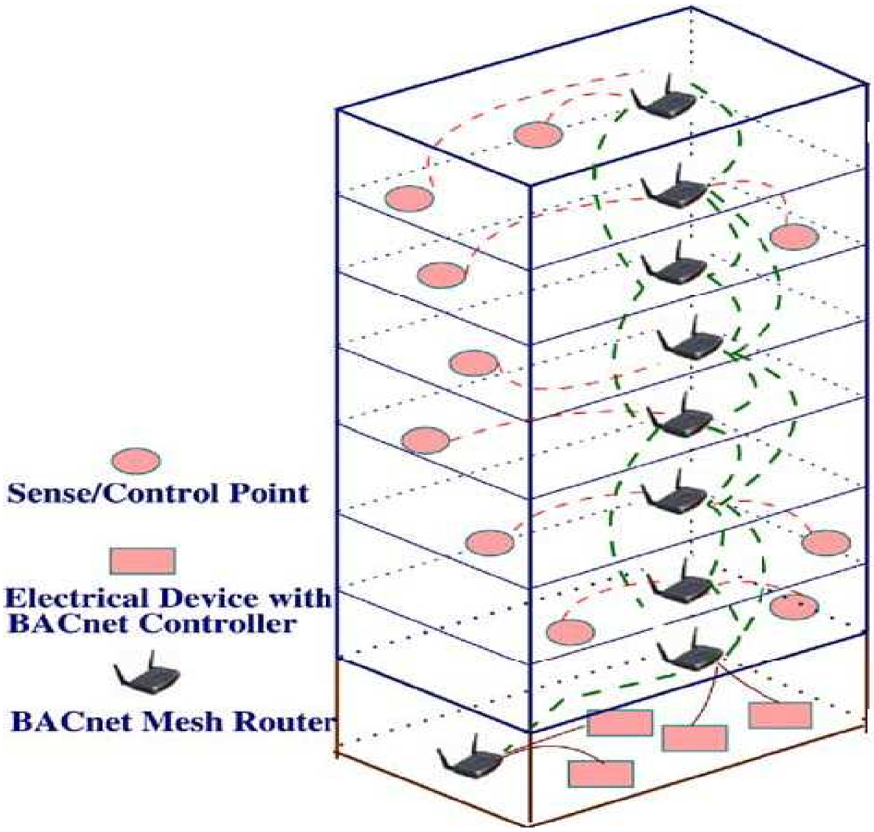


Fig. 2.10 WMNs for building automation [4]

2.8.6 Health and medical sciences

Today, the traditional wired network technology is used for frequent data monitoring and diagnostic in a medical center, which is useless because periodic monitoring produces a large amount of data and the continuous device location changes. Hence wired networks cannot used to a satisfactory level [58]. If we consider Wi-Fi networks, they are based on Ethernet connections which may cause high system cost and complexity. WMNs can overcome all of the above issues [38, 101].

2.8.7 Safety and surveillance systems

Nowadays, in the commercial world, safety and surveillance play a significant role in the enterprise, shopping malls, stores, etc. When it comes to improving the security of these systems, WMNs outperform wired networks. However, insecurity surveillance systems, images, and video streaming are still the primary solutions, so it requires the capacity and freedom that WMN provides [4, 64].

WMNs are used in the case of disaster systems and peer-to-peer communication and . For example, in the case of emergency networks, firefighters dealing with fire often lack access to the necessary details. If WMNs are accessible at the desired location in such scenarios, identifying the places that need attention becomes obvious. Likewise, devices with wireless networking, such as laptops and PDAs establish an effective solution for information sharing through peer-to-peer communication [35]. Again, WMNs are designed to make these possible [75].

WMN networks in safety and monitoring systems show how WMNs can perform all of the functions offered by ad hoc networks [38].

2.9 Conclusion

This chapter summarizes the essential characteristics and details provided by WMNs. Also, it discusses the fundamental functions of WMN, system architectures, the MAC layer, and some other essential WMN levels. Furthermore, it discusses WMN application situations. Also, a comparison between a WMN and ad hoc networks is presented.

Chapter 3

Mesh routers placement problem

3.1 Introduction

Over the past two decades, the deployment of WMNs has been accelerated in both developing and developed countries. Where WMNs are becoming a vital solution to offer access to the internet. This emerging networking paradigm extends coverage to difficult areas and creates a self-healing topology that is resilient to wired network failures [7, 8].

Regardless of that WMNs have several advantages, specific issues must be addressed to enhance global network performance, including connectivity, coverage, security, compatibility, etc [59].

Outdoor WMNs deployments attempt to cover a larger area than indoor wireless networks while dealing with less control over interference sources. However, in the real world, finding an optimal deployment for the mesh network devices is vital because outdoor installation may suffer from a lower user density than indoor deployments in some regions [7, 59], and it can be deployed in a far less regulated system than inside a building. Accordingly, we have plenty of deployment possibilities as user coverage and connectivity needs, for example, in critical situations such as natural disasters, oil rigs, mines, battlefield surveillance, in public transport or mobile video gaming, etc. Additionally, by appropriate tuning of QoS parameters, the WMNs may become an excellent alternative to support local telephone calls from one edge to another by the mesh [7, 57].

In order to deploy WMNs, we need a good understanding of the relationship between network topology, the density of wireless nodes, and transmission power, among other factors. The deployment of wireless mesh routers without taking into consideration the technical limitations of the underlying topology and the actual deployment area would lead to a low client coverage and poor network connectivity [59].

The efficient deployment of the WMNs can be described as a facility location problem [45, 9, 92]. This problem has been studied in the literature for a long time where it has been proved to be an NP-hard problem [92]. However, as the No Free Lunch (NFL) theorem states that it is impossible to have a single meta-heuristic that can deal with all kinds of optimization problems [87]. Therefore, many works using different meta-heuristics algorithms have been proposed to find the desired network characteristics in a reasonable time and thereby assist the network engineer during the planning process.

In this chapter, we present the problem of the optimal placement of wireless mesh routers in a wireless mesh network with some QoS constraints. Then, we present the system assumptions, and we formulate multi-objective problem variables to maximize mesh client coverage and mesh routers connectivity simultaneously.

3.2 Related work

In order to solve the router nodes placement problem, different methods have been proposed. The authors of [13] addressed the multi-radio multi-channel WMNs placement problem where they proposed a multi-objective approach for nodes placement problem. In this work, they considered minimizing placement cost while maximizing total client coverage and load balancing. Also, the authors of [9] expressed the planning model of WMNs as an Integer Linear Problem (ILP) based on mesh client coverage constraints. The model is solved using a greedy heuristic. In [18] authors proposed an evolutionary algorithm to construct network topology by maximizing the mesh client coverage proportion and minimizing the node degree while allowing cycles in the graphs. The authors of [14] tried to optimize the placement of mesh routers by maximizing the client's coverage and reducing deployment cost while mitigating the interference and ensuring decent performances. The work of [15] proposed a Multi-Objective Particle Swarm Optimization (MOPSO) to deploy internet gateways while taking into account QoS constraints and end-to-end delay.

In [54], a relays placement algorithm that affords network connectivity has been proposed. Similarly, the authors of [52] adopted MOPSO algorithm. In addition, they proposed a multi-objective model to optimize simultaneously cost, coverage, links congestion, and gateways congestion minimization with a set of constraints, namely interference, robustness, and load balancing. While the same authors in [53] alongside minimizing cost and maximizing total client's coverage, they devised two new models to balance links and gateways. Other authors [79, 103] have presented diverse approaches to convert a minimum number of mesh routers to internet gateways while satisfying QoS requirements. The authors in [43] addressed a placement problem in 3-D space. They presented a 3D coverage location model of Wi-Fi access points (APs) in an indoor environment. [25] considered establishing cost-optimized multi-hop paths between clients by setting up infrastructure routers at suitable locations. A new multi-objective model for node placement problem was presented by [2] that optimizes four objectives simultaneously: maximizing users coverage, maximizing the total capacity bandwidth, minimizing the costs of the active structures, and minimizing the network noise level. They have implemented a multi-objective variable-length genetic algorithm (VLGA) that concurrently tries to find the positions, optimal number and communication devices, and nature of heterogeneous nodes.

In addition, to solve the same problem in next-generation networks (NGN), the work in [1] established a local search approach. Mainly, by adequately placing new nodes, a multi-objective variable-length Pareto local search algorithm has been used to improve the current coverage of networks.

Regardless that meta-heuristic methods find only locally optimal solutions. It is still widely gained success and development among other methods in solving the mesh routers placement problems because they suffice to find the best and most robust network topology for most practical situations.

Earlier works [9, 90] considered mesh routers deployment in a discrete grid area where this hypothesis restricts the distribution of mesh routers. In contrast, other works consider continuous deployment areas, which allow more freedom in the distribution of mesh routers to ensure better network planning. Additionally, they considered a hierarchical optimization approach for network connectivity and client coverage which is not suitable for non-convex objective functions [48, 12, 68].

In the literature, several works have been used different meta-heuristics to optimize client coverage and network connectivity, where they have considered two parameters [90, 92, 88, 91, 89]. In [90], authors proposed a genetic algorithm for router node placement; then in [11], they studied the effect of the mutation in GAs. Additionally, in [88, 66], a simulated annealing algorithm has been implemented hierarchically in two stages to find the locations of mesh routers. Also, in [91], they have proposed a hill-climbing approach to optimize hierarchically the same parameters. In addition, in [89], the same authors solved the same problem by using a Tabu Search (TS) algorithm. The obtained results showed that the TS algorithm had presented better performances than Simulated Annealing (SA). The authors of [56] compared genetic algorithm, tabu search, hill-climbing, and simulated annealing by applying the Friedman test.

A PSO meta-heuristic has been used to maximize the network connectivity, mobile client coverage [46, 49]. The performance of the PSO algorithm has been discussed by evaluating the effects of different parameters on the network design. Same authors, in their work [46] have assumed a scenario with service priority constraint, such that each mesh client is provided with a value representing its service priority. Additionally, in [47] a Bat-inspired algorithm has been used where authors introduced an additional variant that takes into account client mobility with service priority constraints. Similarly, in [49], they proposed a PSO approach with social awareness in dynamic WMNs. Then, they adopted an aggregated objective function of WMN-RNP in a dynamic environment. The work in [48] proposed an approach of a simulated annealing algorithm with momentum terms. It has been used for the problem with service priority in WMNs. In [69], an electromagnetism-like mechanism algorithm has been used to optimize client coverage and network connectivity.

Similar works on wireless sensor node placement have been proposed. [84, 85] have proposed an improved grey wolf optimizer (IGWO) algorithm to improve the slow convergence, low search precision, and the quick stagnation into local optimum. The same authors in [83] have proposed a Virtual Force-Levy-embedded Grey Wolf Optimization (VFLGWO) algorithm for the same problem.

The work in [73] has addressed relay nodes placement in Fiber-Wireless networks where they have investigated Whale Optimization Algorithm (WOA) for optimal placement of multiple ONUs based on a different distribution of wireless routers and ONUs. The results have been compared to existing algorithms: Greedy and Moth Flame Optimization (MFO) algorithms.

3.3 System assumptions and problem model formulation

In this section, we describe the supposed model for the WMN-RNP based on the notation specified in table 3.1.

Firstly, we present the general assumptions of the model. Next, some key aspects are discussed: the number of deployed connected mesh routers in the network, and the number of covered mesh clients.

3.3.1 System model

In this work, we consider the common assumptions and models used in the previously presented works; therefore, we assume that the mesh client locations are uniformly or normally distributed and static within the deployment area. Note, even with this strong assumption, and the RNP problem stays computationally hard to achieve the optimality [9, 45].

In addition, we consider the following assumptions:

Table 3.1 List of variables used in model formulation

Symbol	Meaning
n	Number of mesh routers
m	Number of mesh clients
P	Placement vector of mesh routers
$P(x_i, y_i)$	Node location
W	Deployment area width
H	Deployment area height
R	Mesh routers set
C	Mesh clients set
c_i	The i-th mesh client
E	Set of links between mesh routers
G	The network topology graph
G^*	The greatest sub-graph of connected mesh routers
G_i	i-th subgraph component
$\|G_i\|$	Size of the i-th subgraph component
h	Number of subgraph components
$\phi(G)$	Network connectivity
$\psi_1(G)$	Client coverage
$\psi_2(G)$	Our new definition of client coverage
ρ_i	Transmission range of mesh router i
δ_i	Boolean determines if client i is covered
X_i	The i-th particle
$gBest$	The Global best solution
$pBest_i$	The i-th personal best solution
Max_{Itr}	Maximum step movement

- In order to respond to the heterogeneity of WMNs in practice, each mesh r_i router is assumed to have a different transmission range ρ_i.
- Only, a limited number of mesh clients can associate to a mesh route.

Free space propagation model is generally considered for this issue [92, 89, 12, 46, 48]. Therefore, we have:

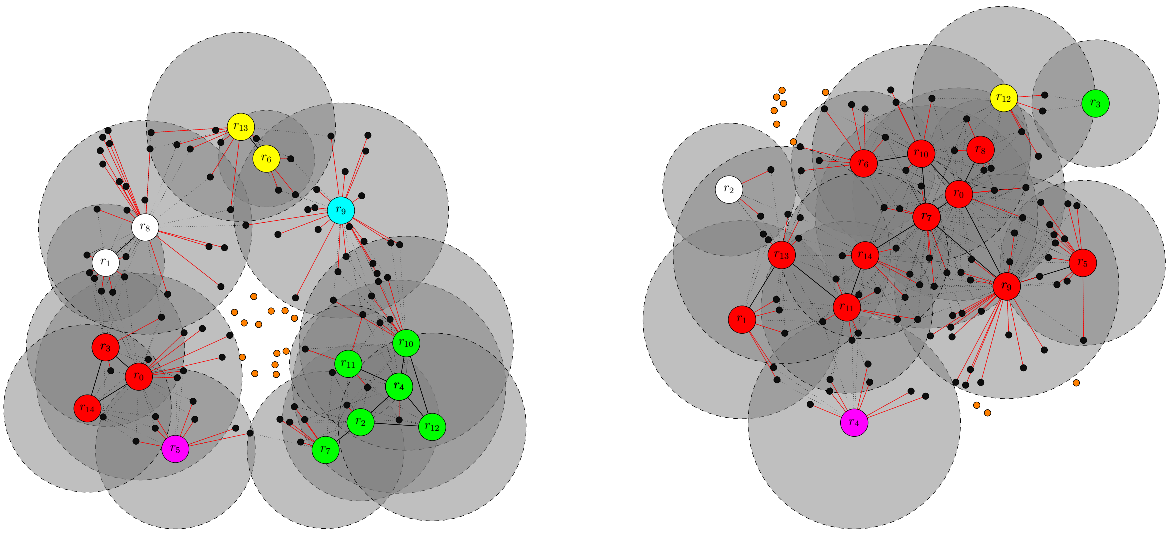
- Router r_i covers client c_j if and only if $\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \leq \rho_i$.

- Two mesh routers r_i and r_j can communicate if and only if $\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \leq min(\rho_i, \rho_j)$.

3.3.2 Problem formulation

This work considers a WMN scenario in which both mesh routers and mesh clients are static. The locations of mesh clients need to be known because the locations of mesh routers are calculated based on the distribution of mesh clients in the deployment area.

Figure 3.1a illustrates an example of a network with fifteen mesh routers $n = 15$ and 100 mesh clients $m = 100$, each mesh router has a different transmission range. If two mesh routers are in the transmission range of each other, they will be connected by a dark link (e.g., see the dark link between r_1 and r_8). If a mesh client is located within the transmission range of a mesh router, it will be connected by a red link to the nearest router and by black dashed links to other mesh routers because it is within the transmission ranges of these routers too. Furthermore, the topology graph has six sub-graph components where the size of the greatest component is 6 (i.e., $\phi(G) = 6$), and 87 mesh clients are covered (i.e., $\psi_1(G) = 87$). If we move some mesh routers toward the most crowded area of mesh clients as shown in figure 3.1b then nearly all the sub-graphs will be merged into a single large sub-graph with size 11 (i.e., $\phi(G) = 11$), and 90 mesh clients will be covered (i.e., $\psi_1(G) = 90$). Therefore, both metrics: client coverage and network connectivity, will be improved by changing the location of some mesh routers.



(a) Fragmented network topology

(b) Near-optimal network topology

Fig. 3.1 Network connectivity and clients coverage

Our goal is to find a near-optimal placement $P = \{P(x_1, y_1), P(x_2, y_2), \ldots, P(x_n, y_n)\}$ of the n mesh routers so that the mesh *clients coverage* is maximized while maintaining full network connectivity.

Consider a WMN with n mesh routers and m mesh clients deployed in a two-dimensional $W \times H$ area. Let R denotes the mesh routers set in the network, and C represents mesh clients. Each mesh client $c_i \in C$ is located at $P(x_i, y_i) \in \mathbb{R}^2$ in the deployment area.

Depending on the mesh client's locations, we calculate the placements of mesh routers.

For a given mesh routers placement, we have an undirected topology graph $G = (R, E)$, where:

- There is a link between two mesh routers if and only if they are within the transmission range of each other.
- A mesh client is covered by a mesh router if and only if it is located within the transmission range ρ of this router.

It should be noted that graph G may be fragmented, i.e., G may consist of several sub-graph components. Therefore, to increase the mesh client coverage, we must select the size of the greatest sub-graph component.

Assume that there are h sub-graph components $G_1, \ldots, G_h$ in G, i.e., $G = G_1 \bigcup G_2 \bigcup\ G_h$, and $G_i \cap G_j = \emptyset$; for $i, j \in 1, \ldots, h$.

In this work, *Network connectivity* is measured by the size of the greatest sub-graph of connected mesh routers G^* in G, which can be expressed as follows:

$$\phi(G) = \max_{i \in \{1, \ldots, h\}} |G_i| \tag{3.1}$$

To find the network's greatest sub-graph components, we need to do Breadth-First Search (BFS) start from every unvisited mesh router. We can obtain a fully connected topology graph, which means that all n mesh routers will be connected. Therefore, the worst-case time complexity will $\binom{n}{2} = O(n^2)$.

To the best of our knowledge, previous works defined the *clients coverage* as follows:

$$\psi_1(G) = \sum_{i=0}^{m} \delta_1^i \tag{3.2}$$

where

$$\delta_1^i = \begin{cases} 1 & \text{if the client } i \text{ is covered by at least one mesh router in } G \text{ (i.e. whole network graph) .} \\ 0 & \text{Otherwise} \end{cases}$$

where client coverage and network connectivity are two conflicting objectives.

However, to maintain the network connectivity in our new formulation, we consider only mesh clients covered by the greatest connected sub-graph therefore the client coverage can be expressed as follows:

$$\psi_2(G^*) = \sum_{i=0}^{m} \delta_2^i \tag{3.3}$$

where

$$\delta_2^i = \begin{cases} 1 & \text{if the client } i \text{ is covered by at least one mesh router in } G^* \text{ (i.e. only greatest sub-graph component).} \\ 0 & \text{Otherwise} \end{cases}$$

We can check that the worst-case time complexity computation of clients coverage is $O(n \times m)$.

In addition, during our experiments to find the placement of the router nodes, we observed that the obtained topologies by the different algorithms suffer from router overlap issues, where some mesh routers are very close cover nearly the same mesh clients. We suggest the following constraints to reduce this issue:

1. The distance between every two routers r_i and r_j must always greater than provided threshold $Thres$.

2. The interference ratio of the network is determined by its density. Our network is an undirected graph; therefore, the graph density is the ratio of the number of edges with respect to the maximum possible edges [40].

$$D = \frac{|E|}{\binom{|V|}{2}} = \frac{2|E|}{|V|(|V|-1)}$$

3.4 Conclusion

In this chapter, meh routers placement in wireless mesh networks is formally introduced. The used assumptions for the problem are stated while discussing the network connectivity and client coverage concepts. We have also shown that accurate definition for client coverage remains a problem in previous formulations.

Chapter 4

Multi-objective optimization and swarm intelligence algorithms

4.1 Introduction

In real life, we often have to optimize multiple objectives simultaneously. In our case, we want to improve the client coverage of a network while trying to maximizing the mesh routers' connectivity at the same time. In this case, we are dealing with multi-objective optimization problems. Furthermore, these multi-objectives can be conflicting, and thus some trade-offs are needed. As a result, a set of Pareto-optimal solutions must be found rather than a single solution. This often requires multiple runs of solution algorithms. In contrast with exact algorithms whose worst-case complexity is known, meta-heuristics do not provide that kind of bound. They can be very effective on a given instance of a problem and, at the same time, show long-running times on another without finding a satisfactory solution. For complex problems of an increasing size, such guarantees are useless in practice since the problems become intractable. This was precisely why we looked at meta-heuristics as a generally efficient way of tackling challenging problems.

In this chapter, A multi-objective optimization overview is outlined, followed by a discussion of swarm intelligence. A particular focus is devoted to three algorithms LDWPSO, GWO, and APSO. We discuss their inspiration, their modeling, and their parameters.

4.2 Multi-objective optimization

Since the optimization problem generally reaches a single global optimal value or a scalar, an optimization problem with a single objective can be classified as a *scalar optimization* problem. Multi-objective optimization, on the other hand, is known as *vector optimization* since the different objectives construct a vector [21, 24, 20].

In general, every multi-objective optimization problem can be described as

$$\underset{x \in \mathscr{R}^n}{\text{minimize}}\, f(x) = [f_1(x), f_2(x), ..., f_M(x)],$$

$$subject\ to\ g_j(x) < 0,\ j = 1, 2, \ldots, J, \tag{4.1}$$

$$h_k(x) = 0,\ k = 1, 2, \ldots, K, \tag{4.2}$$

where, the decision variables are represented by the vector $x = (x_1, x_2, .., x_d)^T$. Though an equality $\phi(x) = 0$ can be transformed into two inequalities $\phi(x) \leq 0$ and $\phi(x) \geq 0$ under certain formulations used in the optimization literature, inequalities $g_j (j = 1, \ldots, J)$ can also involve any equalities. However, for clarity's sake, we have separated the equalities and inequalities.

The *search space* is defined as the area $\mathscr{F} = \mathscr{R}^d$ covered by the vectors of decision variables x. The *solution space*, also known as *objective space*, is the space $\mathscr{S} = \mathscr{R}^M$ defined by all possible values of objective functions. The solution space for multi-objective optimization is significantly greater than that of a single objective function, which has a solution space of (at most) $\mathscr{R}$. Furthermore, since we know we are working with $f(x) = [f_i]$ multi-objectives, we can write f_i as $f(x)$ without creating any ambiguity.

In contrast to single-objective optimization problems, multi-objective optimization problems do not always have an optimal solution that minimizes all multi-objective functions simultaneously. Different objectives frequently conflict with one another, and the optimal solution of one objective sometimes contributes to the optimality (sometimes makes them worse). For example, we want better wireless user coverage and support while using the smallest number of mesh routers to keep costs down. The high user coverage (one objective) would ultimately cost much more, directly opposing the other objective (to minimize cost).

As a result, we must choose a tradeoff or a certain equilibrium of priorities among these often conflicting objectives. If neither of those strategies is feasible, we must make a list of preferences to determine which goals should be given priority. More fundamentally, we must weigh the pros and cons of various objectives and agree. This typically requires developing a new analysis modeling problem. Among the most common approaches is finding a scalar-valued function representing a weighted combination or preference order of all objectives. The *preference function* or *utility function* is the term referring to such a scalar function.

The weighted sum is a simple and effective way to define this scalar function.

$$\Phi(f_1(x),\ldots,f_M(x)) = \sum_{i=1}^{M} w_i f_i(x) \tag{4.3}$$

where w_i are represent the weighting coefficients.

Some of us can optimistically ask what happens if we try to optimize each objective separately to ensure the best possible outcome (the minimum for a minimization problem). In this scenario, we have

$$F^* = (f_1^*, f_2^*, \ldots, f_M^*), \tag{4.4}$$

which is *ideal objective* vector. However, no solution exists that matches this ideal objective vector. To put it another way, it is a solution that does not exist. The exception is when all of the objectives converge to the same solution. In this circumstance, the multi-objective are not in conflict, resulting in the Pareto front folding into a single point [19].

We must introduce some new concepts related to Pareto optimality in order to perform multi-objective optimization.

4.2.1 Pareto Optimality

A vector $u = (u_1,\ldots u_d)^T \in \mathscr{F}$, is said to dominate another vector $v = (v_1,\ldots,v_d)^T$ if and only if $u_i \leq v_i$ for $\forall i \in \{1,\ldots,d\}$ and $\exists i \in \{1,\ldots,n\} : u_i < v_i$. This "partial less" or component-wise relationship is denoted by

$$u \prec v, \tag{4.5}$$

which is equivalent to

$$\forall i \in 1,\ldots,d : u_i \leq v_i \wedge \exists i \in 1,\ldots,d : u_i < \ v_i \tag{4.6}$$

That is to say, no component of u is greater than the equivalent component of v, as well as the fact that at least one component is smaller.

Similarly, another dominance relationship $\preceq$ can be described as follows:

$$u \preceq v \Longleftrightarrow u \prec v \vee u = v \tag{4.7}$$

It is important to keep in mind that dominance can be characterized for maximization problems by substituting $\prec$ with$\succ$.

A point or a solution $x_* \in \mathscr{R}^d$ is called a *Pareto optimal solution* or non-inferior solution to the optimization problem if there is no $x \in \mathscr{R}^d$ satisfying $f_i(x) \leq f_i(x_*), (i = 1,2,\ldots,M)$. That is to say, If there is no feasible vector (of decision variables in the search space) that would decrease some objectives while simultaneously increasing at least one other objective, then $x*$ is Pareto optimal. In other words, optimal solutions are those that are not dominated by other solutions. They reflect various trade-offs between multiple objectives when mapped to objective vectors.

In addition, if no solution can be found that dominates a point $x_* \in \mathscr{F}$, it is called a *non-dominated* solution. A vector is called ideal if it contains the decision variables that correspond to the optima of objectives when each objective is considered separately.

Unlike single-objective optimization, which usually yields a single optimal solution, multi-objective optimization yields a set of solutions, called the Pareto optimal set $\mathscr{P}^*$, and the decision vectors x_* for this solution set are thus called non-dominated. To put it another way, the Pareto (optimal) set is formed by the set of optimal solutions in the decision space. The *Pareto front* is the image of this Pareto set in objective or response space. The set x_* in the decision space that corresponds to the Pareto optimal solutions is often referred to as an efficient set in literature. The $\mathscr{P}$ or *Pareto front* is the set (or plot) of the objective functions of these non-dominated decision vectors in the Pareto optimal set.

Briefly, $u \preceq v$ means that u dominates v; that is, u is nondominated by v, or v is dominated by u. This definition may be a little too abstract. To put it another way,, u is noninferior to v (i.e., u is better or no worse than v). Intuitively, when u dominates v, we can loosely say that u is better than v. The dominance concept is a useful tool for comparing multi-objective optimization solutions, and the goal of multi-objective optimization is to identify such nondominated solutions. For any two solution vectors x_1 and x_2, there are only three possibilities: x_1 dominates x_2, or x_2 dominates x_1, or x_1 and x_2 do not dominate each other. Transitivity remains one of the many intriguing properties of dominance. That is, if x_1 dominates x_2, and x_2 dominates x_3, then x_1 dominates x_3.

Using the above notation, the Pareto front $\mathscr{P}$ can be defined as the set of non-dominated solutions so that

$$\mathscr{P} = \{s \in \mathscr{S} \mid \nexists s' \in \mathscr{S} : s' \prec s,\} \tag{4.8}$$

or in term of the Pareto optimal set in the search space

$$\mathscr{P}^* = \{x \in \mathscr{F} \mid \nexists x' \in \mathscr{F} : f(x') \prec f(x)\} \tag{4.9}$$

The so-called globally Pareto-optimal set, also known as the Pareto front, is composed of all nondominated solutions in the overall feasible search space.

The determination of the Pareto front is a difficult task that often necessitates a parametric analysis, say, by focusing on all but one objective, say, f_i, in a p-objective optimization problem so that f_i is a function of $f_1, \ldots, f_{i-1}, f_{i+1}, \ldots$ and f_p. By maximizing the f_i when varying the values of the other $p-1$ objectives so that the solutions will trace out the Pareto front.

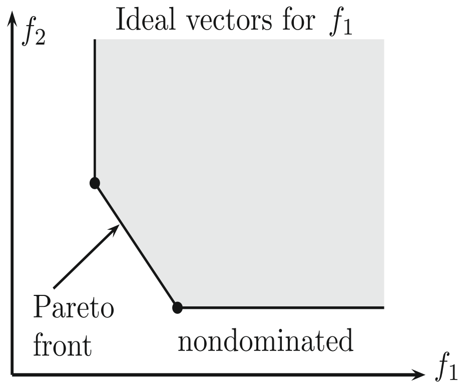


Fig. 4.1 Non-dominated set, Pareto front and ideal vectors in a minimization problem with two objectives f_1 and f_2.

4.2.2 Example

For example, we have four Internet service providers A, B, C and D.

We have two objectives to choose their service 1) as cheap as possible, and 2) higher bandwidth. Their details are listed below [95]:

IP provider	Cost (£/month)	Bandwidth (Mb)
A	20	12
B	25	16
C	30	8
D	40	16

From the table, we know that option C is dominated by A and B because both objectives are improved (low cost and faster). Option D is dominated by B. Thus, solution C is an inferior solution, and so is D. Both solutions A and B are non-inferior solutions or non-dominated solutions. However, which solution (A or B) to choose is not easy, as provider A outperforms B on the first objective (cheaper) while B outperforms A on another objective (faster). In this case, we say these two solutions are *incomparable*. The set of the non-dominated solutions A and B forms the Pareto front which is a mutually incomparable set.

For a minimization problem with two objectives, the basic concepts of nondominated set, Pareto front, and ideal vectors are shown in figure 4.1. Obviously, if we combine these two into a single composite objective, we can compare, for example, the cost per unit Mb. In this case, we essentially reformulate the problem as a scalar optimization problem. For choice A, each Mb costs £1.67, while it costs about £1.56 for choice B. So we should choose B.

However, in reality, we usually have many incomparable solutions, and it is often impossible to comprise in some way. In addition, the real choice depends on our preference and emphasis on objectives.

Multi-objective optimization is usually difficult to solve. Loosely speaking, there are three ways to deal with multi-objective problems: direct approach, aggregation or transformation, and Pareto set approximation. However, the current trends tend to be evolutionary approaches to approximating Pareto fronts [19, 36].

Direct approach is difficult, especially in the case when multiple objectives seem conflicting. Therefore, we often use aggregation or transformation by combining multiple objectives into a single composite objective so that the standard methods for optimization discussed in this thesis can be used. We will focus on this approach in the rest of the chapter. However, with this approach, the solutions typically depend on the way how we combine the objectives. A third way is to try to approximate the Pareto set so as to obtain a set of mutually non-dominated solutions.

To transform a multi-objective optimization problem into a single objective, we can often use the method of weighted sum, and utility method. We can also choose the most important objective of our interest as the only objective, while rewriting other objectives as constraints with imposed limits.

4.2.3 Weighted sum method

The weighted sum approach uses the scalar, linear objective function to aggregate all multi-objective functions into one scalar, aggregated objective function:

$$F(x) = w_1 f_1(x) + w_2 f_2(x) + \cdots + w_M f_M(x) \tag{4.10}$$

The assignment of the weighting coefficients $(w_1, w_2, \ldots, w_M)$ presents a problem since the solution is highly dependent on the weighting coefficients chosen. Clearly, these weights have be positive, satisfying:

$$\sum_{i=1}^{M} w_i = 1, w_i \in (0, 1) \tag{4.11}$$

Consider the following example.

4.2.4 Example

The classical three-objective functions are commonly used for testing multi-objective optimization algorithms [95]. These functions are

$$f_1(x,y) = x^2 + (y-1)^2, \tag{4.12}$$

$$f_2(x,y) = (x-1)^2 + y^2 + 2, \tag{4.13}$$

$$f_3(x,y) = x^2 + (y+1)^2 + 1, \tag{4.14}$$

where $(x,y) \in [-2,2] \times [-2,2]$.

If we combine all the three functions into a single function $f(x,y)$ using the weighted sum, we have

$$f(x,y) = \alpha f_1 + \beta f_2 + \gamma f_3, \alpha + \beta + \gamma = 1.$$

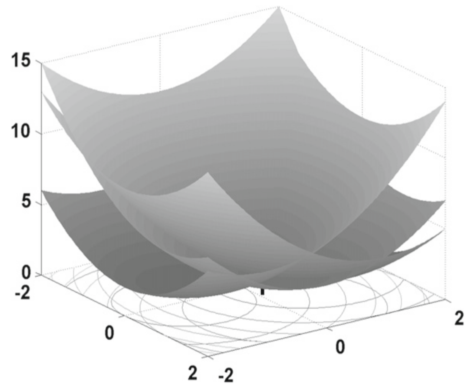


Fig. 4.2 Three functions reach the global minimum at $x_* = \beta$, $y_* = \alpha - \gamma$.

The stationary point is determined by

$$\frac{\partial f}{\partial x} = 0, \frac{\partial f}{\partial y} = 0, \tag{4.15}$$

which lead to

$$2\alpha + 2\beta(x-1) + 2\gamma = 0, \tag{4.16}$$

and

$$2\alpha(y-1) + 2\beta y + 2\gamma(y+1) = 0. \tag{4.17}$$

The solutions are

$$x_* = \beta, y_* = \alpha - \gamma \tag{4.18}$$

This implies that $x_* \in [0,1]$ and $y_* \in [-1,\ 1]$. Consequently, $f_1 \in [0,5]$, $f_2 \in [2,4]$ and$f_3 \in [1,6]$. In addition, the solution or the optimal location varies with the weighting coefficients α,β and γ. In the simplest case$\alpha = \beta = \gamma = 1/3$, we have

$$x_* = \frac{1}{3}, y_* = 0. \tag{4.19}$$

This location is marked with a short thick line in figure 4.2.

The initial multi-objective optimization problem has now been reduced to a single-objective problem. As a result, all solution methods for single-objective problems are legitimate. For example, we can use the particle swarm algorithm to find the best solution for a set of parameters α, β and γ. Figure 4.3 shows the final locations of 40 particles at $t = 5$ iterations. The particles converge towards the true optimal location, indicated by the letter o. Clearly, If we keep iterating, the accuracy will increase.

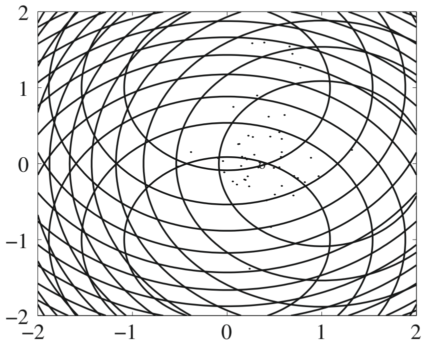


Fig. 4.3 Final locations of 40 particles after 5 iterations. The optimal point is at (1/3, 0) marked with o

Regrettably, there is a crucial point to consider. The aggregate weighted sum simplifies the optimization problem by reducing it to a single objective. However, since the added weighting coefficients could be random, this is not necessarily analogous to the original multi-objective problem, while, these coefficients continue to affect the final solutions. In addition, there are several different ways to construct the weighted sum function, and there is no simple way to know which one is better for a particular problem. Where there are no rules to obey, the linear form is clearly the most straightforward choice. On the other hand, the weighted sum does not have to be linear. Indeed, We may also use other variations, such as the quadratic weighted sum shown below.

$$\Pi(x) = \sum_{i=1}^{M} w_i f_i^2(x) = w_1 f_1^2(x) + \cdots + w_M f_M^2(x), \tag{4.20}$$

Another critical issue is how to choose the weighting coefficients, as the solutions are dependent on them. The decision maker assigns a preference order to the multi-objectives by choosing weighting coefficients. As a result, a more general definition of utility function (or preference function) emerges, which represents the decision maker's preferences.

A different weight vector could, in theory, result in a different Pareto trade-off point; however, this is rarely the case in practice. Different weight coefficient combinations may result in the same or very similar points, and as a result, the points on the Pareto front are not distributed uniformly. Moreover, on the Pareto front, a single trade-off solution represents only one sampling point. and there is no way to guarantee uniform sampling in the front. Many of these issues are still being researched.

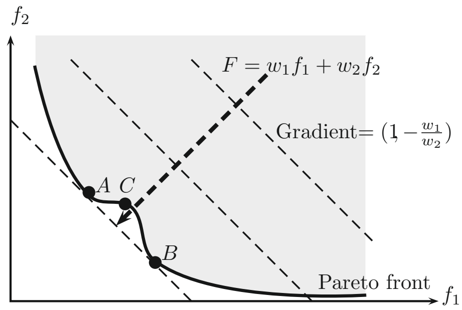


Fig. 4.4 Weighted sum method for two objectives f_1 and f_2 and $w_1 + w_2 = 1$.

It is important to note that the linear weighted sum approach is only applicable to convex Pareto front problems.

$$\Pi(x) = \sum_{i=1}^{M} w_i f_i(x), \sum_{i=1}^{M} w_i = 1, w_i > 0, \tag{4.21}$$

Figure 4.4, where two objectives are combined into one for a given set of $w_1 + w_2 = 1$, the composite function F is minimized. For any given set (w_1, w_2), a (dashed) line has a gradient $(1, -w_1/w_2)$ that will become tangent to the Pareto front when moving downward to the left, and that touching point is the minimum of F. However, at the nonconvex segment, if the aim is point C, the weighted sum method will usually lead to either point A or point B, depending on the values of w1 (since $w_2 = 1 - w_1$).

Because of its simplicity, the weighted sum strategy is one of the most commonly used. However, It is usually difficult to come up with a decent set of uniformly distributed points on the Pareto front. In addition, proper scaling or normalization of the objectives is often needed in order for the ranges/values of each target to be comparable; otherwise, the weight coefficients are not evenly distributed, leading to biased Pareto sampling.

4.2.5 Utility method

The weighted sum method is deterministic because we consider weighted linear coefficients as aggregation coefficients. This implies that the outcome of each aggregation coefficients can be accurately predicted. This method can be used to investigate the consequences of different value judgments. Because there is always some level of uncertainty about the outcome of a particular solution, *utility method*, on the other hand considers uncertainty in the evaluation parameters for each alternative, which is a more realistic method.

The utility (or preference) function is linked to risk attitudes and preferences. For example, if you are offered a choice between a guaranteed £500 and a 50/50 chance of zero and £1000. How much are you willing to pay to take the gamble? The expected payoff of each choice is £500 and thus it is fair to pay 0.5 x 1000 + (1 - 0.5) x 0 = £500 for such a gamble. A risk seeking decision maker would risk a lower payoff in order to have a chance to win a higher prize, while a risk-averse decision maker would be happy with the safe choice of £500.

For a risk-neutral decision maker, the choice is indifferent between a guaranteed £500 and the 50/50 gamble since both choices have the same expected value of £500. In reality, the risk preference can vary from person to person and may depend on the type of problem. The utility function can have many forms, and one of the simplest is the exponential utility (of representing preference)

$$u(x) = \frac{1 - e^{-(x - x_a)/\rho}}{1 - e^{-(x_b - x_a)/\rho'}} \tag{4.22}$$

where x_a and x_b, are the lowest and highest level of x, and ρ is called the *risk tolerance* of the decision maker.

The utility function defines combinations of objective values $f_1, \ldots, f_M$ which a decision maker finds equally acceptable or indifference. So the contours of the constant utility are referred to as the *indifference curves*. The optimization now becomes the maximization of the utility. For a maximization problem with two objectives f_1 and f_2 the idea of the utility contours (indifference curves), Pareto front and the Pareto solution with maximum utility (point A) are shown in figure 4.5. When the utility function touches the Pareto front in the feasible region, it then provides a maximum utility Pareto solution (marked with A).

For two objectives f_1 and f_2, the utility function can be constructed in different ways. For example, the combined product takes the following form [95]:

$$U(f_1, f_2) = k f_1^{\alpha} f_2^{\beta}, \tag{4.23}$$

where α and β are non-negative exponents and A; a scaling factor. The aggregated utility function is given by

$$U(f_1, f_2) = \alpha f_1 + \beta f_2 + [1 - (\alpha + \beta)] f_1 f_2. \quad (4.24)$$

There are many other forms. The aim of utility function constructed by the decision maker is to form a mapping $U : \mathscr{R}^p \mapsto \mathscr{R}$ so that the total utility function has a monotonic and/or convexity properties for easy analysis.

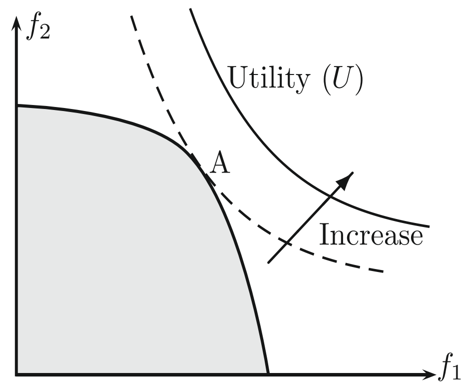


Fig. 4.5 Finding the Pareto solution with maximum utility in a maximization problem with two objectives

It will also improve the quality of the Pareto solution(s) with maximum utility.

Let us look at a simple example.

4.2.6 Example

We now try to solve the simple two-objective optimization problem:

$$\underset{(x,y)\in\mathscr{R}^2}{\text{maximize}}\, f_1(x,y) = x + y, f_2(x,y) = x,$$

subject to

$$x + \alpha y \leq 5, x \geq 0, y \geq 0,$$

where $0 < \alpha < 1$. Let us use the simple utility function

$$U = f_1 f_2$$

which combines the two objectives. The line connecting the two corner points $(5,0)$ and $(0,5/\alpha)$ forms the Pareto front (see figure 4.6). It is easy to check that the Pareto solution with maximum utility is $U_* = 25$ at $A(5,0)$ when the utility contours touch the Pareto front with the maximum possible utility.

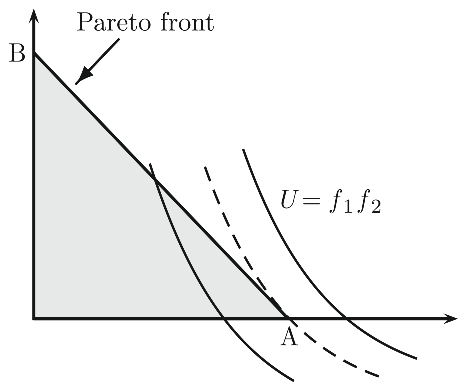


Fig. 4.6 The Pareto front is the line connecting A(5, 0) and B(0, $5/\alpha$). The Pareto solution with maximum utility is $U_* = 25$ at point A.

The complexity of multi-objective optimization makes the construction of the utility function a difficult task as it can be constructed in many ways.

Another commonly used and more robust method for more complex multi-objective optimization problems is the ε-constraint method.

4.2.7 The ε-Constraint Method

An interesting way of dealing with multi-objective optimization is to write objectives except one as constraints. Let us try to rewrite the following unconstrained optimization as a single-objective constrained optimization problem:

$$\text{Minimize}\, f_1(x), f_2(x), \ldots, f_M(x).$$

To achieve this goal, we often choose the most important objective of our preference, say, $f_q(x)$, as the main objective, while imposing limits on the other objectives. That is,

$$\text{Minimize}\, f_q(x)$$

subject to

$$f_i \le \varepsilon_i, (i = 1, 2, q-1, q+1, \ldots, M),$$

where the limits ε_i are given. In the simplest case, we can choose $q = 1$. Haimes et al. were probably the first to suggest this reformation method [44].

In principle, the problem can be solved using the standard optimization algorithms for single-objective optimization. In essence, this is a slicing method that splits the objective domain into different subdomains. For example, in the case of a bi-objective problem, as shown in figure 4.7, we take f_2 as the constraint. This problem becomes

$$\text{Minimize}\, f_1(x) \tag{4.25}$$

subject to

$$f_2(x) \le \varepsilon_2, \tag{4.26}$$

where ε_2 is a number, not necessarily small. For any given value of ε_2, the objective domain is split into two subdomains: $f_2 \le \varepsilon_2 = \delta_1$ (feasible) and $f2 > \varepsilon_2 = \delta_1$ (infeasible). The minimization of f1 in the feasible domain leads to the globally optimal point A. Similarly, for a different value of $\varepsilon_2 = \delta_2$, the minimum of f_1 gives point B.

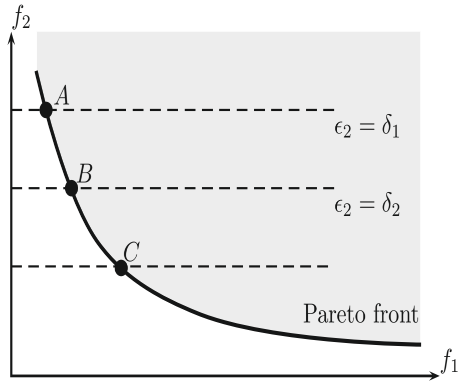


Fig. 4.7 Slicing the objective domain in the ε-constraint method.

Let us look at a bi-objective optimization example, called *Schaffer's min-min function* [70]:

$$\text{Minimize}\, f_1(x) = x^2, f_2(x) = (x-2)^2, x \in [-103, 103]. \tag{4.27}$$

If we use f_1 as the objective and $f_2 \le \varepsilon_2$ as the constraint, we can set $\varepsilon_2 \in [0,4]$ with 20 different values. Then we can solve it using a single-objective optimization technique. The 20 points of approximated Pareto-optimal solutions and the true Pareto front are shown in figure 4.8. However, if we use f_2 as the objective and f_1 as the constraint, we follow exactly the same procedure, with the results shown in figure 4.9. As we can see from both figures, the distributions of the approximate Pareto points are different, though they look similar.

As this example has demonstrated, the distributions of the sampling points on the Pareto front may depend on the actual formulation and the order of choosing the main objective.

The advantage of this method is that it works well for complex problems with nonconvex Pareto fronts. However, it does have some disadvantages. There could be many different formulations for choosing the main objectives and the rest of objectives as constraints.

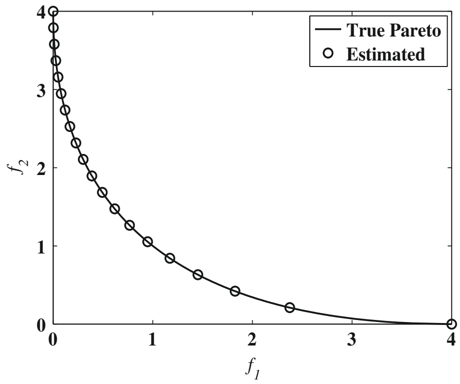


Fig. 4.8 A true Pareto front and the estimated front when setting f_1 as the objective and f_2 as the constraint.

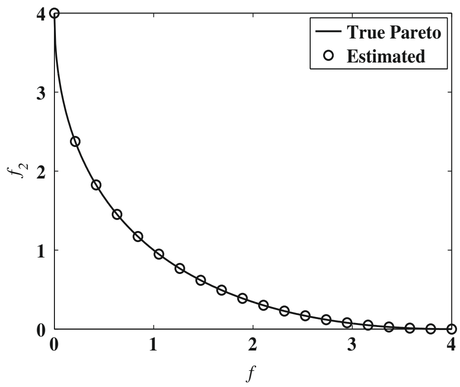


Fig. 4.9 The true Pareto front and the estimated front when setting f_2 as the objective and f_1 as the constraint.

Different formulations may lead to different computational efforts. In addition, there is no guarantee that the points generated on the Pareto front are uniformly distributed, as we saw in the previous example.

Furthermore, it is difficult to impose the right range of ε_i. In the previous example, if we set ε_2 too small, say, $\varepsilon_2 \longrightarrow 0$, there may not be a feasible solution. On the other hand, if we set too high, it will be difficult to find the minimum of f_1 even if it exists, because the number of evaluations for this single-objective optimization problem may increase. In practice, some prior knowledge is required to impose the correct limits. Otherwise, the solutions obtained may not be the solution to the original problem.

The good news is that recent trends tend to use evolutionary approaches such as genetic algorithms. We briefly introduce some of these meta-heuristic methods in the rest of this chapter.

4.3 Meta-heuristic search

Multi-objective optimization solutions are typically difficult to find, even using the simple weighted sum method or utility function. Nonetheless, there are a number of other successful multi-objective optimization methods that can be used, particularly the meta-heuristic methods. such as tabu search and genetic algorithms, particle swarm optimization, etc. [78, 94, 28, 86, 22].

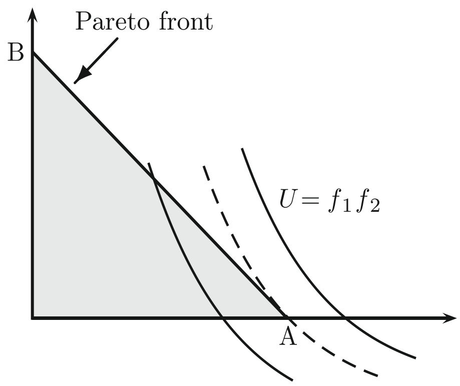


Fig. 4.10 Finding the Pareto solution with maximum utility in a maximization problem with two objectives

What algorithm to use for a specific problem is an important question? This is a challenging question. It is dependent on a number of factors, including the type of problem, the required solution quality, computing resource, time frame (time before which a problem must be solved), balance of each algorithm's benefits and drawbacks, to a large extent determine the type of problem they can solve and their potential applications. and finally, the expertise of the decision-makers.

4.3.1 Swarm intelligence algorithms

Over billions of years, nature has evolved to find nearly perfect solutions to almost every problem she has encountered. Where, most of the bad population members have been eliminated by natural selection. The optimal members appear at the evolutionary stable equilibrium. Accordingly, when we confronted with new difficult challenges and we do not have workable method, a question arises "why not try to be inspired by the nature". For this reason, in the last two decades, Swarm Intelligence (SI) has gained considerable attention and various algorithms have been proposed such as Particle Swarm Optimizer (PSO) [22, 71, 72, 23].

PSO family algorithm is inspired by studies of fish, bird, and bees swarming. It evolves populations or swarms of individuals called *particles* where these particles work under social behavior in *swarms*. This algorithm's family has become one of the most widely used algorithms due to their fast convergence to a near-optimal acceptable solution and because unlike other SI-based population algorithms, it needs low computational processing power, less memory resources and usually and their simple implementation.

In this subsection, the investigated optimization algorithms we selected for our concerned problem are primarily for problems with clear and specific objective functions. We summarize them, as well as, we present a comparison of their computational complexity and implementation.

Linearly Decreasing Weight Particle Swarm Optimizer (LDWPSO)

The particle swarm optimizer (PSO) is introduced by Kennedy and Eberhart in 1995 and has become one of the most widely used SI-based algorithms [22].

For an optimization problem of k objectives, a swarm of p particles is specified, where in the k-dimensional search space each particle represents a *candidate solution*. Every single particle has its different personal trajectory. Let x_i and v_i be the position vector and velocity for particle i, respectively.

The algorithm initializes a set of particles with random positions and then explorers the search space by updating consecutive generations to find global best optimum. At every iteration, each swarming particle moves toward the position of the current global best *gBest* solution which is the best obtained so far by the entire swarm and its own best personal $pBest_i, i = 1, \dots, p$ found so far by adjusting the trajectory vector of each particle in the direction of its *personal best (cognition aspect)* and the *global best (social aspect)* positions of the entire swarm at each iteration. The movement of particles is schematically represented in figure 4.11.

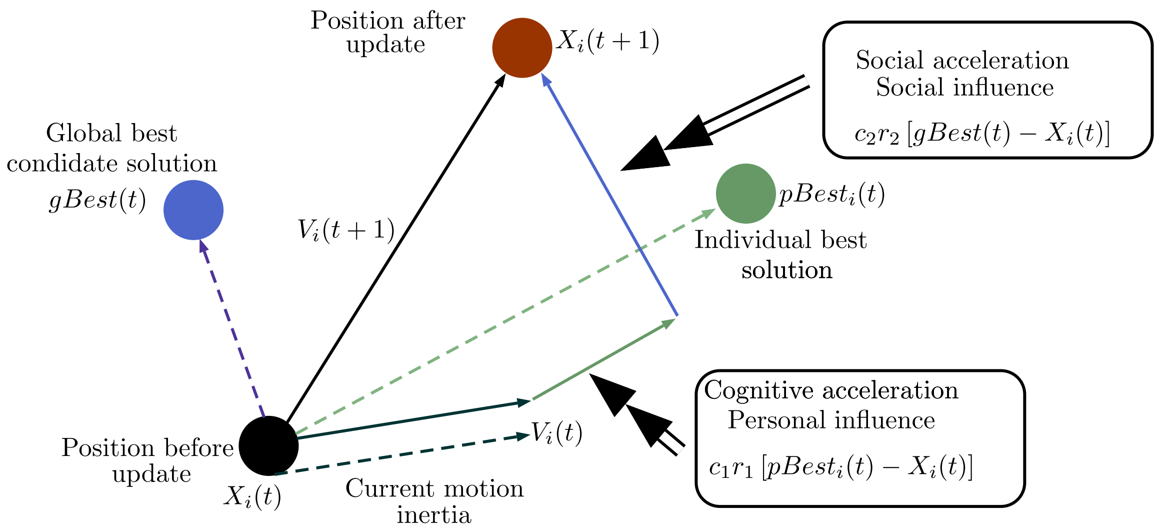


Fig. 4.11 Illustration of velocity and position updates in LDWPSO algorithm.

At iteration $t+1$, the new velocity and position vectors can be updated by the following formulas:

$$\begin{aligned} v_i(t+1) = v_i(t) + cr_1(gBest - x_i(t)) + \\ cr_2(pBest_i - x_i(t)) \end{aligned} \tag{4.28}$$

$$x_i(t+1) = x_i(t) + v_i(t+1), i = 1, \ldots, p \tag{4.29}$$

where the acceleration constant $c > 0$, r_1 and r_2 are uniform random numbers within $[0,1]$. Additionally, initial v_i values can be chosen randomly, it is usually bounded in some range $[0, v_{max}]$. However, the velocities cannot be too high.

Basic PSO can converge to the region of an optimum faster than evolutionary algorithms (EAs). Despite that, as soon it moves to this region it increases slowly because of the fixed velocity *stepsize*. Therefore, Linearly Decreasing Weight PSO (LDWPSO) [71, 72, 23] is proposed to efficiently balances the global and local search capabilities of the swarm by introducing a linearly decreasing *inertia weight* on the previous velocity of the particle into equation 4.28:

$$\begin{aligned} v_i(t+1) = \omega(t)v_i(t) + c_1r_1(gBest - x_i(t)) + \\ c_2r_2(pBest_i - x_i(t)) \end{aligned} \tag{4.30}$$

where ω is called the *inertia weight*, and the positive constants c_1 and c_2 are, respectively, *cognitive* and *social* parameters. Typically, $c_1 = 2.0$, $c_2 = 2.0$, and ω gradually decreases from $\omega_{max}$to ω_{min}:

$$\omega(t) = \omega_{max} - (\omega_{max} - \omega_{min})\frac{t}{Max_{Itr}} \tag{4.31}$$

Max_{Itr} being the maximum number of iterations. One can select $\omega_{max} = 1$ and $\omega_{min} = 0.1$.

The essential steps of the LDWPSO can be shown in algorithm 1.

Algorithm 1: Pseudo code of Linearly Decreasing Weight Particle Swarm Optimization algorithm

```
Input: LDWPSOparams(c1, c2, ω_max, ω_min, v_max), Swarm size and MCs locations
Output: The global best MRs placement gBest
foreach MR_i in the swarm do
    x_i ← Generate random position of MR_i
    pBest_i ← x_i                               ▷ set the initial local best of MR_i
    if f(pBest_i) > f(gBest) then
        gBest ← pBest_i
    end
    v_i ← initialize the velocity of MR_i
end
while t < Max_Itr do
    t = t + 1
    foreach MR_i in the swarm do
        v_i ← Update the velocity of MR_i using equation 4.30
        x_i ← Update the position of MR_i using equation 4.29
        if f(x_i) > f(pBest_i) then
            pBest_i ← x_i
            if f(pBest_i) > f(gBest) then
                gBest ← pBest_i
            end
        end
    end
end
```

Grey Wolf Optimizer algorithm

The Grey Wolf Optimizer (GWO) algorithm is introduced by Mirjalili et al [50]. It is a recent nature inspired population meta-heuristic algorithm based on the social behavior of grey wolves. The algorithm mimics the leadership hierarchy and hunting mechanism of wolf flock. This algorithm considers four types of wolves: *alpha, beta, delta, and omega* based on their leadership hierarchy. Moreover, three main steps of hunting, searching for prey, encircling prey, and attacking prey.

To summarize, the search process starts with creating a random population of grey wolves (candidate solutions). Over the course of iterations, alpha, beta, and delta wolves estimate the probable position of the prey. Each candidate solution updates its distance from the prey. The subsequent equations are given to model this *encircling* logic.

$$\vec{D} = \vec{C} \times \vec{X}_p(t) - \vec{X}(t) \tag{4.32}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \times \vec{D} \tag{4.33}$$

And the *hunting* process is modeled by following equation:

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{4.34}$$

where t denotes the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}_p$ represents the position vector of the prey, and $\vec{X}$ indicates the position vector of a current wolf. The vectors $\vec{A}$ and $\vec{C}$ are given by:

$$\vec{A} = 2 \times \vec{a} \times \vec{r}_1 - \vec{a} \tag{4.35}$$

$$\vec{C} = 2 \times \vec{r}_2 \tag{4.36}$$

where components of $\vec{a}$ is a temporal parameter and it is decreased linearly from 2 to 0 during the search process by

$$a = 2 - t \times \frac{2}{Max_{Itr}} \tag{4.37}$$

and r_1, r_2 are vectors uniform randomly chosen between 0 and 1.

The pseudo code of the GWO algorithm is presented in algorithm 2.

Accelerated Particle Swarm Optimizer

The Accelerated Particle Swarm Optimizer (APSO) algorithm is introduced by Xin-She Yang et al [96]. Recently, more attention has been drawn to this algorithm due to its rapid convergence and low computational complexity. The results show that APSO algorithm is able to provide very promising results compared to LDWPSO [96]. For example, authors in [61] effectively used APSO to minimize the volume of straight bevel gears. In [96], APSO and a nonlinear support vector machine were introduced to solve business optimization problem. Initially, it was applied to production optimization, and then for income prediction

Algorithm 2: Pseudo-code of Grey Wolf Optimizer algorithm

Input: GWOparams(), Swarm size and MCs locations

Output: The global best MRs placement $X_{\alpha}^{fitness}$

foreach MR_i *in the swarm* **do**
  $x_i \leftarrow$ Generate random position of MR_i
  if $f(x_i) > X_{\alpha}^{fitness}$ **then**
    $X_{\alpha} \leftarrow x_i$
  end
  if $f(x_i) > X_{\beta}^{fitness}$ **and** $f(x_i) < X_{\alpha}^{fitness}$ **then**
    $X_{\beta} \leftarrow x_i$
  end
  if $f(x_i) > X_{\gamma}^{fitness}$ **and** $f(x_i) < X_{\beta}^{fitness}$ **then**
    $X_{\gamma} \leftarrow x_i$
  end
end
while $t < Max_{Itr}$ **do**
  foreach MR_i *in the swarm* **do**
    Update a, A and C by equations 4.35, 4.36 and 4.37
    Update the position of each MR_i by equations 4.32 to 4.34
  end
  foreach MR_i *in the swarm* **do**
    if $f(x_i) > X_{\alpha}^{fitness}$ **then**
      $X_{\alpha} \leftarrow x_i$
    end
    if $f(x_i) > X_{\beta}^{fitness}$ **and** $f(x_i) < X_{\alpha}^{fitness}$ **then**
      $X_{\beta} \leftarrow x_i$
    end
    if $f(x_i) > X_{\gamma}^{fitness}$ **and** $f(x_i) < X_{\beta}^{fitness}$ **then**
      $X_{\gamma} \leftarrow x_i$
    end
  end
  $t \leftarrow t+1$
end

and project scheduling. The work in [77], reported that the performance of APSO used for image enhancement is superior to LDWPSO. In addition, APSO algorithm was proposed for an effective design of DFCWs signal used in MIMO radar [65]. In [62], APSO is used for an efficient maximum power point tracking in partially shaded photovoltaic systems. Also, the authors of [26] combined APSO and differential evolution (DE) mutation operator algorithm to solve numerical optimization problem. Similarly, APSO is used effectively to solve large-scale network plan optimization of resource-leveling with a fixed duration [99]. [39] adapted APSO to speech enhancement and in [81] for antenna array design problems.

Standard PSO variants use both the current global best *gBest* and the personal best $pBest_i$. Increasing the diversity of solutions quality is possibly one of the reasons why the personal best is used. However, using some randomness, this variety can be simulated. Subsequently, unless the optimization problem of interest is strongly nonlinear and multimodal, there is no valid justification for using the personal best. The use of only the global best is a simplified version that could accelerate the algorithm convergence. The APSO algorithm has been developed further in recent years [96].

In APSO, a simpler formula defines the velocity vector:

$$v_i(t+1) = v_i(t) + c_2 \times (\omega - \frac{1}{2}) + c_1 \times (gBest - x_i(t)) \tag{4.38}$$

Where ω is a random variable between 0 to 1. Here, the 1/2 shift is purely for convenience. A standard normal distribution $c_2 \times \omega(t)$ can also be used where $\omega(t)$ is obtained from $N(0,1)$ to replace the second term. The velocity vector becomes:

$$v_i(t+1) = v_i(t) + c_1 \times (gBest - x_i(t)) + c_2 \times \omega(t) \tag{4.39}$$

where $\omega(t)$ can be obtained from a normal distribution or other relevant distributions. Here, c_2 is a scaling factor that governs the move size or randomness intensity, while c_1 is a parameter that guides particles' movement.

The new particle position update is simply as follows:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{4.40}$$

In order to further simplify the formulation, additionally, the position update could be written in one single step:

$$x_i(t+1) = (1 - c_1) \times x_i(t) + c_1 \times gBest + c_2 \times \omega(t) \tag{4.41}$$

For the APSO algorithm, the typical values are $c_2 \approx 0.1-0.4$ and $c_1 \approx 0.1-0.7$, however, for most unimodal objective functions, $c_2 \approx 0.2$ and $c_1 \approx 0.5$ can be specified as the initial values. It should be mentioned that, in general, the parameters c_1 and c_2 should be related to the scales of the independent x_i variables and the domain of search. Remarkably, under suitable conditions, this simplified APSO can have global convergence.

A further enhancement to the APSO algorithm is the reduction of randomness over the course of iterations. This means, a function that is monotonically decreasing could be used as:

$$c_2 = c_2^* \times e^{-\gamma t} \tag{4.42}$$

or

$$c_2 = c_2^* \times \gamma^t (0 < \gamma < 1) \tag{4.43}$$

where $c_2^* \approx 0.5-1$ is the initial value of the randomness parameter. $0 < \gamma < 1$ is a control parameter. For example, in most implementations, we can use $\gamma = 0.9-0.99$. Clearly, other non-increasing function forms $c_2(t)$ can also be used. Moreover, these parameters should be fine-tuned to fit our optimization problems.

The pseudo code of the APSO algorithm is presented in algorithm 3.

Algorithm 3: Pseudo code of Accelerated Particle Swarm Optimization algorithm

Input: APSOparams(c_1, c_2^*, γ), Swarm size and MCs locations
Output: The global best MRs placement *gBest*

foreach MR_i *in the swarm* **do**
    $x_i \leftarrow$ Generate random position of MR_i
    if $f(x_i) > f(gBest)$ **then**
        $gBest \leftarrow x_i$
    end
end
while $t < Max_{Itr}$ **do**
    $t = t + 1$
    foreach MR_i *in the swarm* **do**
        $x_i \leftarrow$ Update the position of MR_i using equation 4.41
        if $f(x_i) > f(gBest)$ **then**
            $gBest \leftarrow x_i$
        end
    end
end

4.3.2 Other algorithms

Other powerful algorithms exist, some of which are well-known. such as the tabu search and genetic algorithms, and others are highly specific and growing in popularity. such as photosynthetic algorithm, enzyme algorithm, cuckoo search, bat algorithm, bacteria foraging algorithm, and immune-system based algorithms.

Tabu search, for instance, was developed by Fred Glover in the 1970s and it is one of the most effective optimization algorithms. Basically, to keep track of the search moves, it uses memory or search history in the form of tabu lists, with the goal of avoiding a recently visited region or neighborhood and promote a more efficient search for optimal solutions. In reality, more and more meta-heuristic algorithms using history and selection are becoming more popular and powerful in a wide range of applications.

Additionally, in 1985, Schaffer was probably the first to use vector evaluated genetic algorithms (VEGA) to solve multi-objective optimization, without using any composite aggregation, by combining all objectives into a single objective [70]. Since then, many meta-heuristic algorithms such as PSO, SA, and GWO have been extended to solve multi-objective optimization problems successfully.

4.3.3 Mesh routers placement representation using LDWPSO, GWO and APSO

Note that, at each iteration, the solution to our problem is the placement of n mesh routers in two-dimensional $W \times H$ area.

Where the algorithms particle updating process is controlled by:

- LDWPSO by $gBest$ vector and by $pBest_k$, $Velocity_k$ and P_k vectors where $gBest$ stores the position of the global best solution found so far by entire population and $pBest_k$, $Velocity_k$ and P_k store the personal best, velocity and placement of the particle k respectively.
- GWO by X_{alpha}, X_{beta}, X_{gamma} vectors and by P_k vector where X_{alpha}, X_{beta}, X_{gamma} stores the position of the three global best solution found so far and P_k stores the placement of the particle k
- APSO by $gBest$ vector and by P_k vector where $gBest$ stores the position of the global best solution found so far by entire population and P_k stores the placement of the particle k.

Given that all mesh routers are deployed inside a $W \times H$ area, we have the constraints: $\forall i \in 1, \ldots, n$,

$$0 \leq x \leq W;$$

$$0 \leq y \leq H;$$

Space/Time complexity of analysis of the investigated algorithms

This subsection presents space/time complexity of LDWPSO, GWO and APSO based on the pseudo-codes illustrated in algorithm 1, 2 and 3 respectively.

At each iteration, the solution to our problem is a placement of n mesh routers in two-dimensional $W \times H$ area. Given that n mesh routers are deployed within a $W \times H$ area, we have the constraints: $\forall MR_i \in 1, \ldots, n$, $0 \leq x \leq W$, $0 \leq y \leq H$

LDWPSO particle updating process is controlled by variables:

1. P_i vector stores the current mesh routers placement of particle i.
2. $gBest$ vector stores the global best mesh routers placement found so far.
3. $pBest_i$ vector stores the personal best mesh routers placement found so far by particle i.
4. v_i vector stores the updated velocity of mesh routers found so far by particle i.

GWO particle updating process is controlled by variables:

1. P_i vector stores the current mesh routers placement of particle i.
2. X_α vector stores the global best mesh routers placement found so far.
3. X_β and X_γ vectors store respectively the second and third global best mesh routers placement found so far.

APSO particle updating process is controlled only by:

1. P_i vector stores the current mesh routers placement of particle i.
2. $gBest$ vector stores the global best mesh routers placement found so far.

According to LWDPSO pseudo-code the subsequent steps are performed:

- Initialization:

1. Initialization of p particles $\rightarrow 2 \times n \times p$
2. Initialization of p velocities $\rightarrow 2 \times n \times p$
3. p evaluations of the objective function $\rightarrow p$

- Main search loop (repeat main loop Max_{Itr} times):

1. updates of p velocities $\rightarrow 2 \times n \times p$
2. updates of p particles $\rightarrow 2 \times n \times p$
3. p evaluations of the objective function $\rightarrow p$

According to GWO pseudo-code the subsequent steps are performed:

- Initialization:

1. Initialization of p particles $\rightarrow 2 \times n \times p$
2. p evaluations of the objective function $\rightarrow p$

- Main search loop (repeat main loop Max_{Itr} times):

1. updates of p particles $\rightarrow 2 \times n \times p$
2. p evaluations of the objective function $\rightarrow p$
3. finding new X_α, X_β and X_γ particles

According to APSO pseudo-code the subsequent steps are performed:

- Initialization:

1. Initialization of p particles $\rightarrow 2 \times n \times p$
2. p evaluations of the objective function $\rightarrow p$

- Main search loop (repeat main loop Max_{Itr} times):

1. updates p velocities $\rightarrow 2 \times n \times p$
2. p evaluations of the objective function $\rightarrow p$

Finally, both algorithms compute the same objective function 5.1 or 6.2 as follows:

- Firstly, we need to find the network greatest sub-graph components. Therefore, we need to do Breadth First Search (BFS) starting from every unvisited mesh router, and we will find the greatest strongly connected component. Time complexity of this solution is $O(R+E)$ as it does simple BFS for the given network. However, we can get a fully connected network, as a result, $|R| = n$ (i.e. all mesh routers are connected) and the edges number will $|E| = C_2^n = (n \times (n-1))/2$. Therefore, worse-case time-complexity will $O(R+E) = O(n + C_2^n) \approx O(n^2)$
- We can simply compute clients coverage by $O(n \times m)$.

Table 4.1 provides a summary of the main components of the three algorithms.

Table 4.1 Main components of the three applied algorithms

	APSO	LDWPSO	GWO
Population	n	n	n
Global Best Solution	✓	✓	X_α, X_β and X_γ
Personal Best Solution	✗	✓	✗
Velocity	✗	✓	✗
Control parameters	c_1, c_2	c_1, c_2, v_{max}, v_{min},ω_{max},ω_{min}	✗
Main steps	Position Update equ. 4.41	Velocity update equ. 4.30	Searching prey
		Position Update equ. 4.29	Encircling prey equ. 4.32 and 4.33
			Attacking prey equ. 4.34

4.4 Conclusion

In this chapter, an overview of multi objective optimization and Pareto optimality have been presented and the most known techniques for multi-objective optimization were discussed including the weighted sum method, the utility method and the ε-constraint methods. In addition, swarm intelligence algorithms used in our work were presented where the time complexity and the space of each algorithm were stated.

Chapter 5

Accelerated PSO algorithm applied to clients coverage and routers connectivity in wireless mesh networks

5.1 Introduction

The deployment of wireless mesh routers is a crucial task for improving network performance. Therefore, it should be taken seriously to ensure network accessibility in terms of coverage and connectivity. This placement problem of mesh routers in wireless mesh networks represents multi-objective optimization problems with a considerable searching space to explore. Various optimization algorithms have been applied in the literature to find a trade-off between client coverage and network connectivity. In this chapter, we consider APSO to find an optimal mesh router placement due to its rapid convergence and low computational complexity compared to other population-based algorithms. We have experimentally evaluated it using different generated benchmarks of multiple configurations. The experimental results show that the APSO algorithm provides promising results compared to LDWPSO.

5.2 The objective function

We consider maximizing two objectives: network connectivity $\phi(G)$ and client coverage $\psi_1(G)$, which are defined by equation 3.1 and equation 3.2, respectively. Therefore, we use the weighted sum method that transforms the multi-objective problem into a scalar problem by summing each objective pre-multiplied by a user-provided weight.

Our aggregated fitness function $f(X)$ is defined as follows:

$$f(X) = \lambda.\frac{\phi(G)}{n} + (1-\lambda).\frac{\psi_1(G)}{m} \tag{5.1}$$

Where $0 < \lambda < 1$ is a weighting coefficient that characterizes each objective's relative rank. For normalization, the denominator should be used for each term of the equation.

5.3 Results and discussion

In order to confirm the performance of the APSO algorithm, many experiments were performed and compared to the LDWPSO algorithm results obtained in the literature [97, 12, 46, 41, 67, 98, 42]. The experiments were carried out in Intel core i7-4710HQ (8 CPUs), clocked at 2.5 GHz, memory 16GB, Windows 10 environment. We have implemented an experimental software to compare LDWPSO and APSO performance using C programming language for speed and Matlab 2017Ra based on the pseudo-code presented in algorithm 1 and algorithm 3. The simulation parameters settings of both algorithms are given in table 5.1.

Table 5.1 LDWPSO/APSO parameters setting

Parameter	Value
Population number	30
λ	0.5
LDWPSO	
c_1	2
c_2	2
v_{max}	6
ω_{max}	0.9
ω_{min}	0.2
APSO	
c_1	0.2
c_2^*	0.9
γ	1

5.3.1 Experimental setup

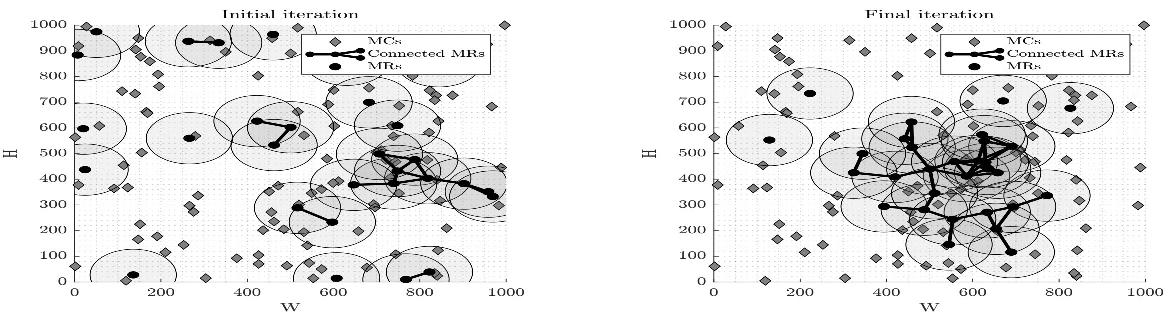
The experiments were conducted in a rectangular area of $1000m \times 1000m$, and the mesh clients were distributed in the deployment area based on a normal/uniform distribution density. The network parameters were set according to table 5.2.

Table 5.2 Network Parameters

Parameter	Value	Initial value
Mesh routers number	[10, 100]	30
Mesh clients number	[50, 275]	100
Transmission range	[60, 240]	100m
Area width	1000m	1000m
Area height	1000m	1000m

5.3.2 Results

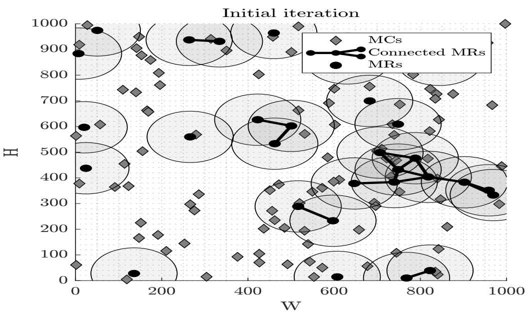
An example of the obtained topologies of LDWPSO and APSO algorithms are shown in figures 5.1a, 5.2a, 5.3a and 5.4a for different network parameters. The low coverage of the mesh clients is significant. In addition, the network suffers from poor connectivity. After several iterations of LDWPSO/APSO, figures 5.1b, 5.2b, 5.3b and 5.4b show that the client coverage rate is greatly improved, and mesh router positions are well-chosen to ensure the optimum network connectivity. However, LDWPSO algorithms lead to several mesh routers overlapping, resulting in more interference, while the network topology obtained by the APSO algorithm is more spread out to cover more clients.



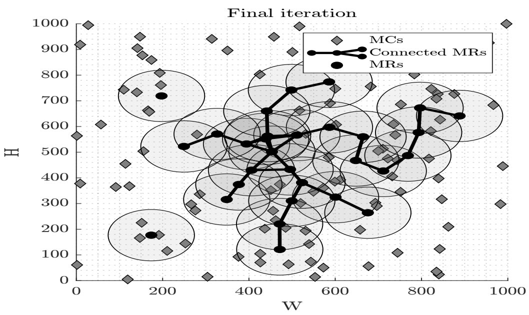
(a) Intial iteration

(b) Final iteration

Fig. 5.1 Topology found by LDWPSO algorithm (MRs=30, MCs=100 and Trans. Range=100)($\phi = 26, \psi_1 = 55$)

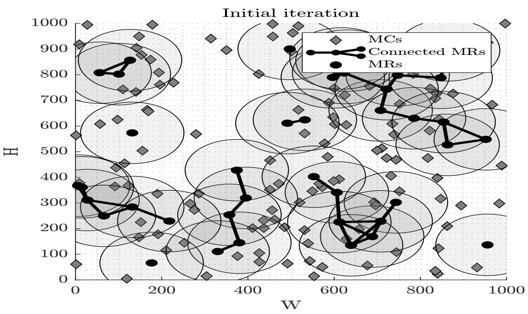


(a) Intial iteration

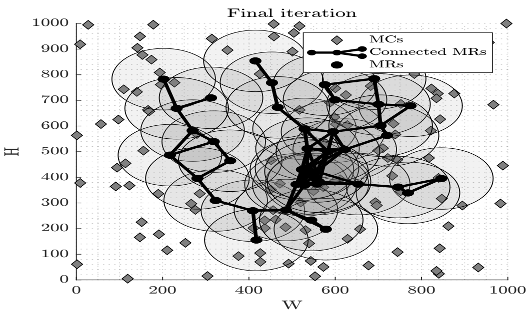


(b) Final iteration

Fig. 5.2 Topology found by APSO algorithm (MRs=30, MCs=100 and Trans. Range=100)($\phi = 28, \psi_1 = 62$)

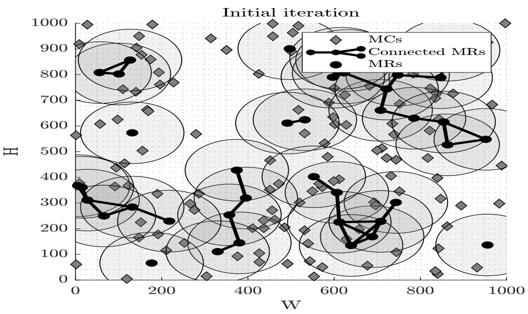


(a) Intial iteration

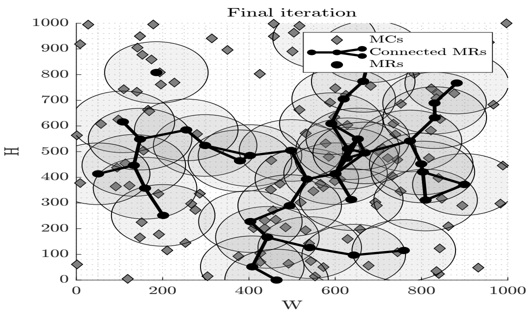


(b) Final iteration

Fig. 5.3 Topology found by LDWPSO algorithm (MRs=40, MCs=120 and Trans. Range=120)($\phi = 40, \psi_1 = 77$)



(a) Intial iteration



(b) Final iteration

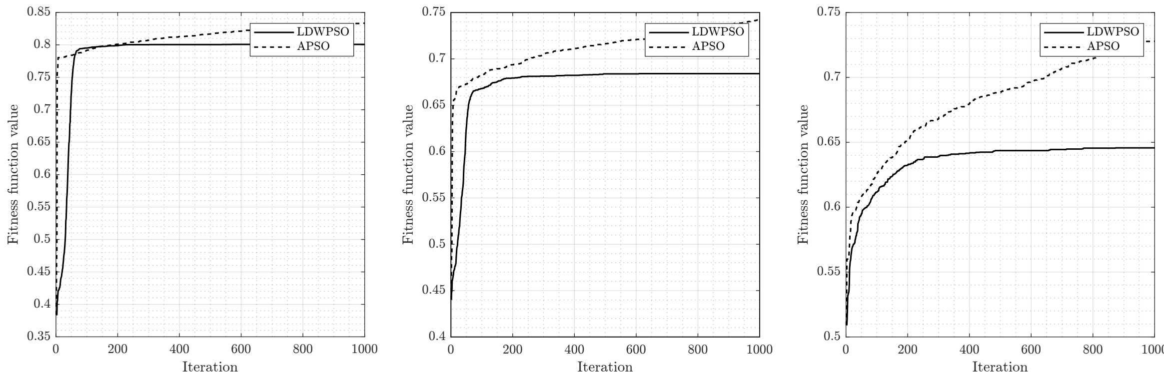
Fig. 5.4 Topology found by APSO algorithm (MRs=40, MCs=120 and Trans. Range=120)($\phi = 39, \psi_1 = 104$)

5.3.3 Convergence study

This subsection presents a comparison of the convergence speed of the APSO and LDWPSO algorithms using the fitness function defined in equation 5.1. In order to prove the convergence of the APSO algorithm, nine experiments are conducted. Nine convergence curves with respect to different values of λ against the average fitness value of ten independent runs have been plotted in figures 5.5, 5.6 and 5.7 respectively. The obtained results were performed with respect to different network configuration values.

For both algorithms, it can be seen that in the early phase of iterations, there are rapid changes that are reduced significantly throughout iterations. However, the LDWPSO algorithm suffers from premature convergence, that it is likely to get stuck into a local optimum instead of a global optimum.

An important factor that influences the performance of an algorithm is its evolution speed. As shown in figures 5.5, 5.6 and 5.7, APSO performs well after a number of iterations and converges faster than LDWPSO and finds better value for the fitness function. To conclude, the results confirm the performance of the APSO algorithm in solving mesh routers placement problem compared to LDWPSO for different aggregation values of λ.



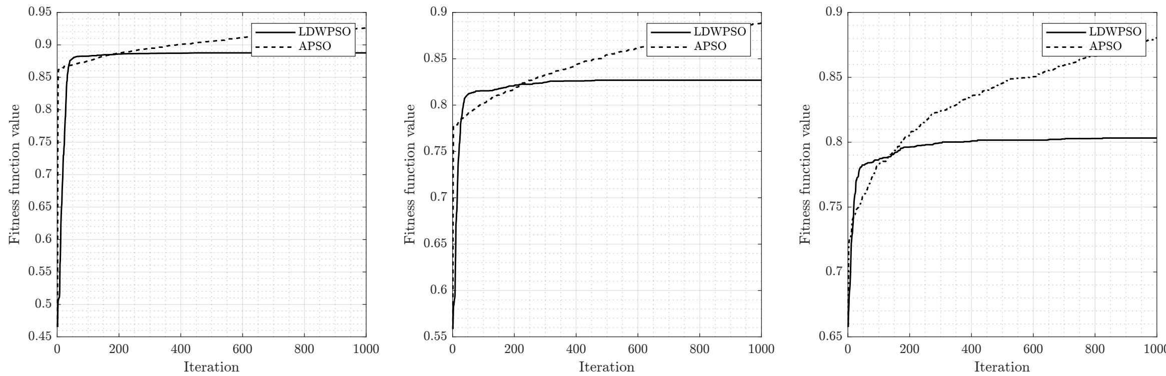
(a) $\lambda = 0.3$ (b) $\lambda = 0.5$ (c) $\lambda = 0.7$

Fig. 5.5 Convergence curve of LDWPSO vs APSO (MRs=30, MCs=100, Trans.Range=100)

5.3.4 Effect of MRs, MCs number and transmission range on coverage and connectivity

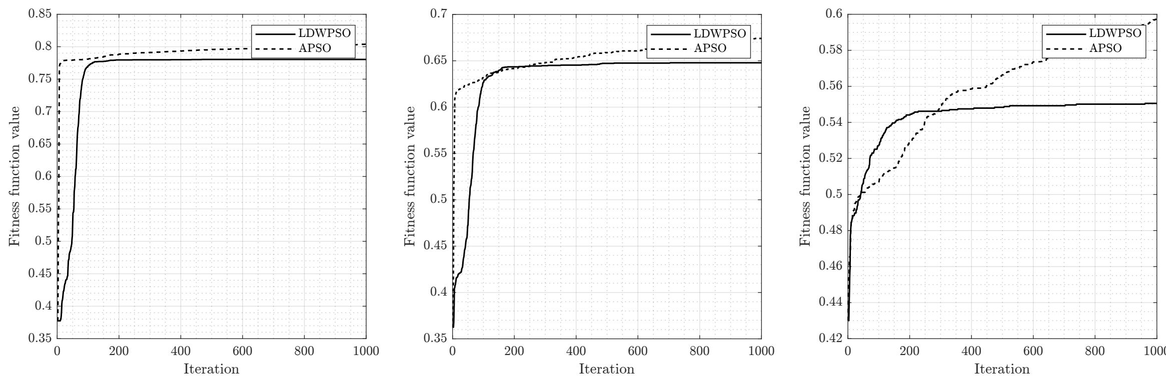
In next subsections, to compare both algorithms, three performance indicators are used: Network connectivity (ϕ), Client coverage (ψ_1) and Objective function value f. We have computed client coverage and network connectivity by varying:

- Number of mesh clients.



(a) $\lambda = 0.3$ (b) $\lambda = 0.5$ (c) $\lambda = 0.7$

Fig. 5.6 Convergence curve of LDWPSO vs APSO (MRs=40, MCs=120, Trans.Range=120)



(a) $\lambda = 0.3$ (b) $\lambda = 0.5$ (c) $\lambda = 0.7$

Fig. 5.7 Convergence curve of LDWPSO vs APSO (MRs=20, MCs=100, Trans.Range=80)

- Number of mesh routers.
- Transmission range of mesh routers.

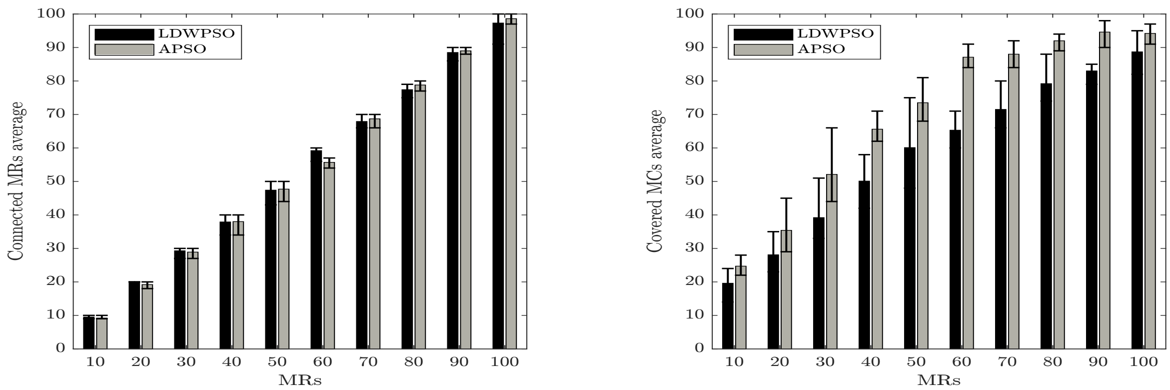
We have examined the APSO algorithm by comparing its performance with the LDWPSO algorithm. The obtained results have been calculated by averaging over ten runs with different seeds. 95% confidence intervals are shown by the error bars in figures 5.8, 5.9 and 5.10.

Effect of mesh routers number

In figure 5.8, the total number of mesh routers was varied between 10-100.

Figure 5.8a shows that the number of the connected mesh routers, which represents network connectivity, increases when adding more mesh routers. Indeed, add more mesh routers to the network leads to more network connectivity as expected because adding more mesh routers to isolated networks will connect them. As a result, a more extensive network will be established. Also, both algorithms show similar results.

Similarly, figure 5.8b shows the effect of the mesh routers number on the total number of covered mesh clients. The results prove that the two algorithms find optimal coverage where the number of covered clients increases as expected. However, APSO surpasses the LDWPSO approaches for all deployment scenarios.



(a) Network connectivity

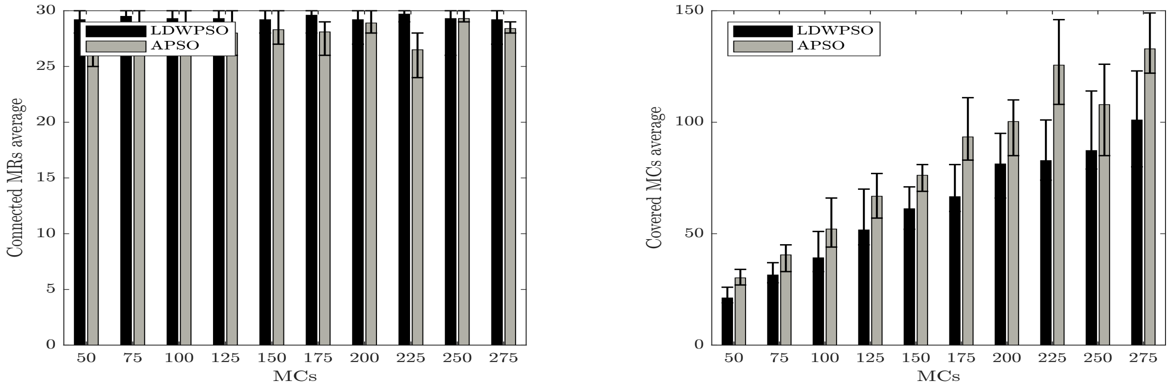
(b) Client coverage

Fig. 5.8 Effect of mesh routers number on coverage and connectivity

Effect of mesh clients number

In figure 5.9, the total number of mesh clients was varied between 50-275.

Figure 5.9a shows that the connected mesh routers number is always between 28-30 because both algorithms try to connect all available routers to cover more clients. Also, APSO presents approximately equivalent network connectivity to LDWPSO. Additionally, figure 5.9b, shows that the network coverage increases due to the new mesh client's adhesion to the network. However, the APSO algorithm consistently outperforms LDWPSO and covers more mesh clients. For example, when the number of mesh clients is 175, the APSO algorithm covers 32.9 clients more than LDWPSO, representing more than 18.8% of the total number of clients in the network.



(a) Network connectivity

(b) Client coverage

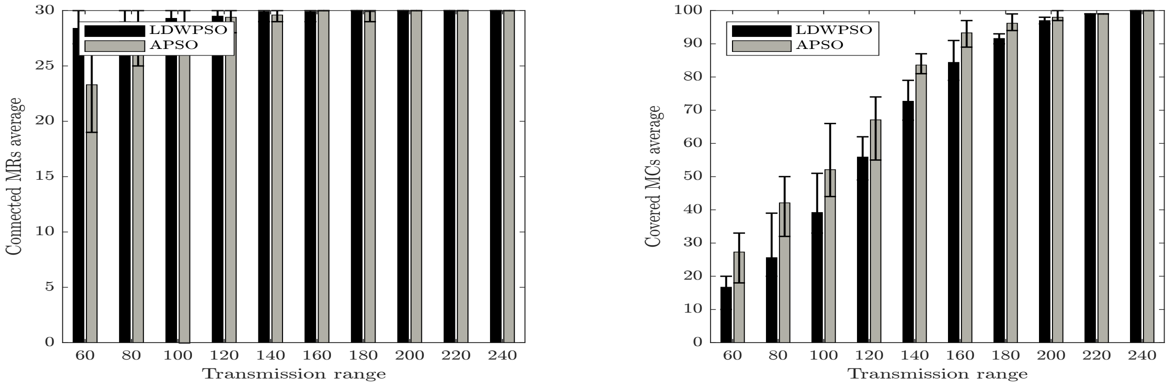
Fig. 5.9 Effect of mesh clients number on coverage and connectivity

Effect of transmission range

In figure 5.10a, we have examined the effect of increasing the transmission range from 60m to 240m on the network connectivity. When increasing the transmission range, MRs attempt to connect. Due to this, when the transmission range exceeds 120m nearly all the sub-graph components are merged into a single large giant component. Moreover, our proposed APSO algorithm presents equivalent results compared to the LDWPSO algorithm when the transmission range is greater than 80m. Figure 5.10b shows that when increasing the transmission range, the number of covered clients increases correspondingly. According to figure 5.10b, 180m is the critical transmission range that results in full network coverage.

5.3.5 Analyzing the objective function evolution

In this subsection, the best-obtained value (Q4 or 100th percentile) of the fitness function f defined in equation 5.1 was considered. In addition, the same parameters were used as the previous experiments to analyze client coverage and network connectivity for APSO versus LDWPSO approach.



(a) Network connectivity (b) Client coverage

Fig. 5.10 Effect of the transmission range on coverage and connectivity

As shown in table 5.3, when we increase number of mesh routers from 10 to 100, the covered MCs percentage and value of f increases correspondingly for both algorithms. In addition, nearly all the time, we obtained a connected network topology. However, our APSO approach provides better client coverage and value of fitness function f when adding new MRs to the network.

In table 5.4, the number of MCs is increased from 50 to 275. The results show that even though the number of MCs is increased, the value of f and the percentage of client coverage and network connectivity remains roughly constant. This observation is justified by the use of a uniform distribution for MCs locations. As we have total network connectivity, even if we add more MCs to the network, every mesh router will cover the same percentage of MCs. Again, the studied APSO algorithm outperforms LDWPSO and finds better client coverage.

Finally, table 5.5 shows the effect of mesh routers transmission range on client coverage and network connectivity. Straightforwardly, client coverage and fitness value increase similarly to transmission range. In addition, our proposed APSO approach obtains a better fitness value than the LDWPSO approach.

Table 5.3 Coverage, connectivity and fitness value vs MRs number

	LDWPSO			APSO		
MRs	Covered MCs(%)	Connected MRs(%)	Fitness	Covered MCs(%)	Connected MRs(%)	Fitness
10	22.0000	100.0000	0.6100	23.0000	100.0000	0.6150
20	35.0000	100.0000	0.6750	45.0000	95.0000	0.7000
30	51.0000	93.3333	0.7217	66.0000	90.0000	0.7800
40	53.0000	95.0000	0.7400	64.0000	100.0000	0.8200
50	75.0000	86.0000	0.8050	74.0000	100.0000	0.8700
60	71.0000	96.6667	0.8383	88.0000	93.3333	0.9067
70	80.0000	94.2857	0.8714	92.0000	97.1429	0.9457
80	88.0000	95.0000	0.9150	94.0000	98.7500	0.9638
90	85.0000	100.0000	0.9250	98.0000	97.7778	0.9789
100	94.0000	99.0000	0.9650	97.0000	98.0000	0.9750

Table 5.4 Coverage, connectivity and fitness value vs MCs number

	LDWPSO			APSO		
MCs	Covered MCs(%)	Connected MRs(%)	Fitness	Covered MCs(%)	Connected MRs(%)	Fitness
50	52.0000	93.3333	0.7267	64.0000	93.3333	0.7867
75	44.0000	100.0000	0.7200	57.3333	96.6667	0.7700
100	51.0000	93.3333	0.7217	66.0000	90.0000	0.7800
125	56.0000	90.0000	0.7300	50.4000	100.0000	0.7520
150	47.3333	96.6667	0.7200	51.3333	100.0000	0.7567
175	45.1429	96.6667	0.7090	63.4286	86.6667	0.7505
200	45.0000	96.6667	0.7083	54.0000	96.6667	0.7533
225	42.6667	100.0000	0.7133	59.1111	93.3333	0.7622
250	38.4000	96.6667	0.6753	50.4000	96.6667	0.7353
275	40.3636	96.6667	0.6852	54.1818	93.3333	0.7376

Table 5.5 Coverage, connectivity and fitness vs Transmission range.

	LDWPSO			APSO		
Transmission range	Covered MCs(%)	Connected MRs(%)	Fitness	Covered MCs(%)	Connected MRs(%)	Fitness
60	17.0000	96.6667	0.5683	21.0000	90.0000	0.5550
80	39.0000	86.6667	0.6283	49.0000	90.0000	0.6950
100	51.0000	93.3333	0.7217	66.0000	90.0000	0.7800
120	59.0000	100.0000	0.7950	70.0000	100.0000	0.8500
140	79.0000	100.0000	0.8950	87.0000	100.0000	0.9350
160	91.0000	100.0000	0.9550	97.0000	100.0000	0.9850
180	93.0000	100.0000	0.9650	99.0000	100.0000	0.9950
200	98.0000	100.0000	0.9900	100.0000	100.0000	1.0000
220	99.0000	100.0000	0.9950	99.0000	100.0000	0.9950
240	100.0000	100.0000	1.0000	100.0000	100.0000	1.0000

5.4 Conclusion

In this chapter, we have presented and evaluated the APSO algorithm for optimal mesh router node placement in WMNs. We have considered aggregated bi-objective function to maximize the network connectivity of the WMN measured by the number of connected mesh routers and to maximize the number of covered mesh clients. The results showed that the APSO algorithm affords promising results compared to the LDWPSO with rapid convergence and low computational complexity. Additionally, experimental results demonstrated the efficiency of APSO at finding network connectivity. It almost always finds total network connectivity. However, client coverage is strongly affected by the number and distribution of mesh clients in the deployment area.

Chapter 6

Performance comparison of LDWPSO, GWO and Accelerated PSO algorithms for client's coverage problem in WMNs using novel objective function

6.1 Introduction

In wireless mesh networks, to solve network connectivity and client coverage, former approaches have used a hierarchical approach or aggregate objective function (AOF) for solving bi-objective client coverage and network connectivity optimization problems [92, 89, 48, 12, 69]. The concern here is assigning weights to coefficients of each objective. The coefficients do not necessarily correspond directly to the relative importance of the objectives or allow trade-offs between the objectives to be expressed.

For example, as illustrated in figure 6.1, if the aggregation coefficient is less than 0.3, which favors clients coverage over network connectivity, we obtain fragmented mesh network topology, which is a useless network. If the aggregation coefficient is great than 0.7, which favors network connectivity over clients coverage, we obtain many overlapped mesh routers.

In this chapter, we propose a new objective function to achieve optimal client coverage. We fine-tune the network connectivity for optimum performance without the need for knowledge of an aggregation coefficient. In addition, we select three meta-heuristics algorithms: APSO, LDWPSO, and GWO, and we compare their convergence, computational complexity. Finally, we have experimentally evaluated the proposed function by using a different benchmark. The results show that the APSO algorithm can provide very competitive

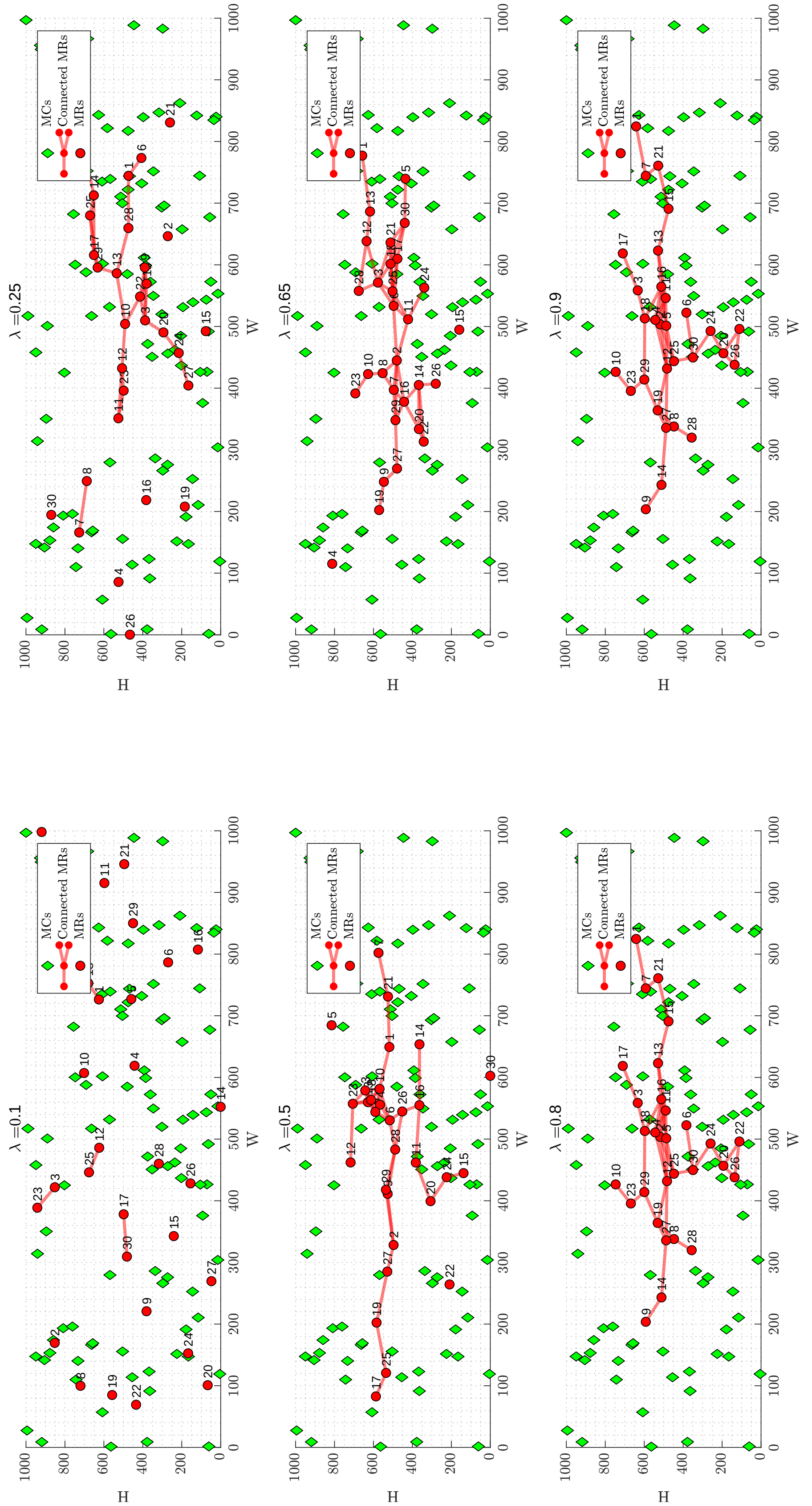


Fig. 6.1 Network topologies for different aggregation coefficient values

results than LDWPSO and GWO algorithms and our proposed function provides higher client coverage with less computation power.

6.2 The proposed objective functions

6.2.1 Standard aggregate objective function (AOF)

In previous works [46, 48, 12, 69], authors considered two objectives: maximizing the size of the greatest subgraph component $\phi(G)$ and the client coverage $\psi_1(G)$, which are defined by equation 3.1 and equation 3.2, respectively. Therefore, they used the weighted sum method that transforms the multi-objective problem into a scalar problem by summing each objective pre-multiplied by a user-provided weight.

$$f_1(X) = \lambda . \frac{\phi(G)}{n} + (1-\lambda) . \frac{\psi_1(G)}{m} \tag{6.1}$$

Where $0 < \lambda < 1$ is a weighting coefficient that characterizes the relative rank of each objective. Note that the denominator of each term of the equation is used for normalization.

6.2.2 Our proposed objective function

In our approach, only we maximize the client coverage of the greatest sub-graph component of the network to avoid isolated, fragmented networks. Therefore, the following objective function f_2 is defined as:

$$f_2(X) = \frac{\psi_2(G^*)}{m} \tag{6.2}$$

where G^* is the greatest sub-graph component of the network.

6.3 Results and discussion

In order to confirm the performance of the proposed objective function f_2 for solving the MRP-WMP issue, many experiments were performed and compared to the aggregated objective function f_1 results obtained in the literature [97, 12, 46, 98]. The experiment is carried out in Intel core i7-4710HQ (8 CPUs), clocked at 2.5 GHz, memory 16GB, Windows 10 environment. In addition, we have implemented experimental software using C programming language for speed and Matlab 2017Ra based on the pseudo-code presented in algorithms 1, 2 and 3.

6.3.1 Experimental setup

To evaluate the performance of the aggregated objective function f_1 and our proposed objective function f_2 for different problem instances. Several experiments were carried out in a rectangular area of $1000m \times 1000m$, and the mesh clients were distributed in the deployment area based on a normal/uniform distribution density. The network parameters and parameters settings of the three algorithms were set according to table 6.1 and table 6.2. The obtained results were calculated by averaging over ten runs with different seeds.

Table 6.1 Network Parameters

Parameter	Value	Initial value
Mesh routers number	[10, 100]	30
Mesh clients number	[50, 275]	100
Transmission range	[60, 240]	100m
Area width	1000m	1000m
Area height	1000m	1000m

6.3.2 Comparison of algorithms convergence

We have examined the APSO algorithm approach by comparing its convergence with the existent LDWPSO, and GWO algorithms described in [71, 72, 23].

Three experiments were carried out to verify the convergence of the three algorithms for the aggregated objective function f_1 defined in equation 6.1.

The convergence curves concerning different values of λ have been plotted in figure 6.2. Furthermore, figure 6.3 shows the convergence of our proposed function defined in equation 6.2.

For both objective functions in figure 6.2 and 6.3, it can be seen that there are abrupt changes in the initial steps of iterations which are decreased gradually over the course of iterations. An important factor that influences the performance of an algorithm is its evolution speed. As shown in both figures, the APSO algorithm performed well after a number of iterations. However, in figure 6.2, lower λ values gave superior fitness value because clients number consistently higher than mesh routers which lead to client's coverage objective dominance. Note that our function solves this shortcoming. To conclude, the results confirm the convergence of the APSO algorithm in solving the mesh routers placement problem for the two functions.

Table 6.2 APSO, LDWPSO and GWO parameters setting

Parameter	Value
Population number	30
λ	0.5
APSO	
c_1	0.2
c_2^*	0.9
γ	1
LDWPSO	
c_1	2
c_2	2
v_{max}	6
ω_{max}	0.9
ω_{min}	0.2
GWO	
has no control params	

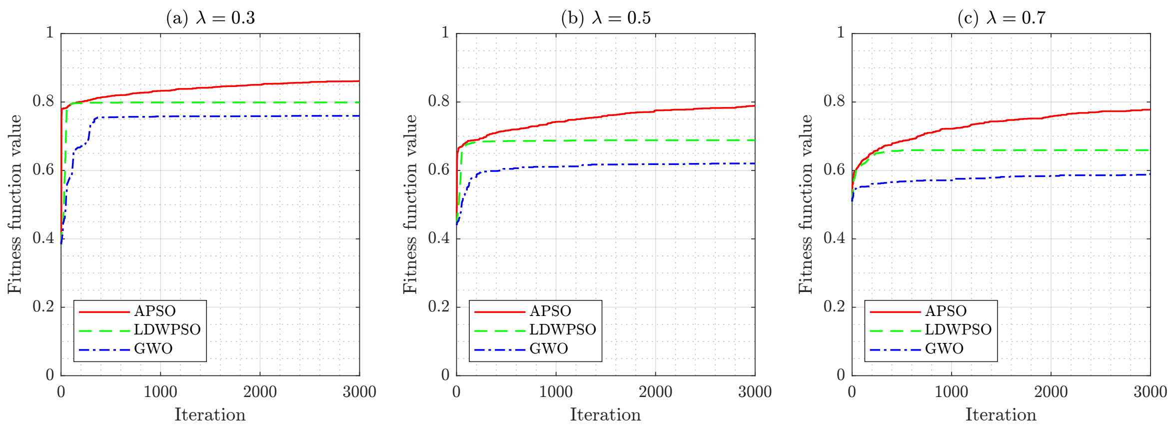


Fig. 6.2 Convergence curve of AOF for different algorithms

6.3.3 Comparison of the aggregated objective function vs our proposed function

Two experiments with 80m and 120m transmission ranges respectively have been performed to determine the optimal λ value for client coverage and network connectivity and to check

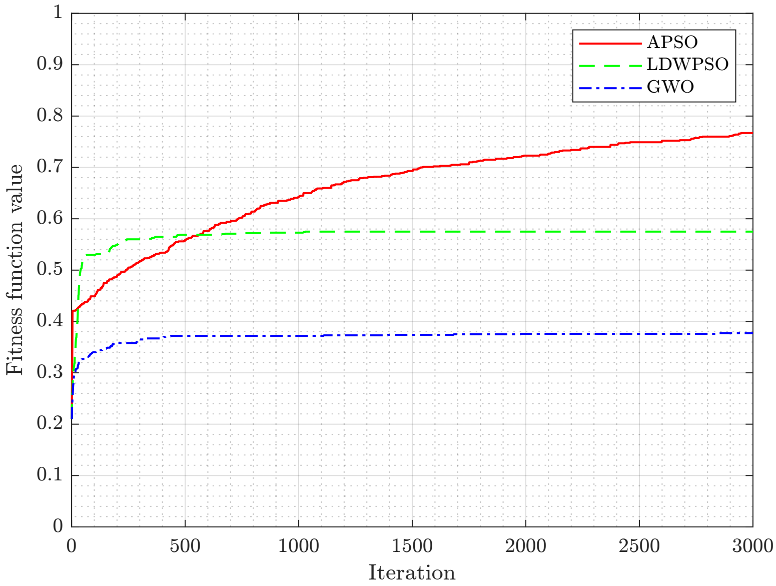


Fig. 6.3 Convergence curve of our function for different algorithms

the effectiveness of our proposed objective function f_2 defined in equation 6.2 vs. the aggregated objective function (AOF) f_1 defined in equation 6.1.

In figures 6.4, AOF f_1 for λ values below 0.4 result in full network connectivity (30 MRs), but we only obtained about 40 percent of client coverage. In addition, as the λ value starts to increase above 0.4, the number of connected mesh routers begins to decline, which means that the network is starting to break. The routers move away from each other to cover more clients because "AOF covered 1" ψ_1 considers all fragmented sub-graphs. In practice, such a topology is useless since clients cannot communicate with each other. However, if we choose only the largest connected sub-graph to measure client coverage, we can see that "AOF covered 2" ψ_2 decreases as the number of connected mesh routers decreases.

In addition, in figure 6.5, the best λ value is around 0.6. Therefore, each network setting has its best λ value to ensure better client coverage and network connectivity.

In figure 6.4 and 6.5, we can see that our proposed function, which does not depend on λ value, gave the same results for network connectivity and always get the best clients coverage "AOF covered 2" ψ_2

In figure 6.4 and 6.5, our proposed function f_2, that does not depend on λ, provides identical network connectivity to the aggregated objective function (AOF) f_1 and always achieves the best possible client coverage (see. "AOF covered 2" ψ_2).

To summarize, the results confirm the effectiveness of our proposed objective function f_2 to solve the mesh routers placement problem where a single execution of our function leads to a significant gain in computing resources and frees us from analyzing the λ value.

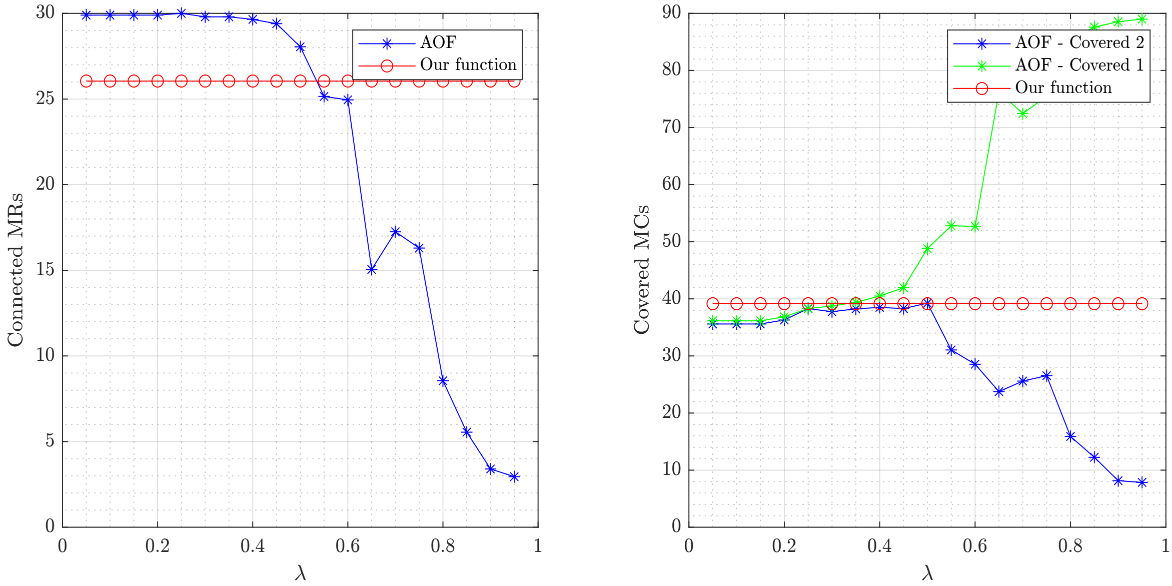


Fig. 6.4 Connected MRs/Covered MCs number vs aggregation coefficient λ(transmission range = 80m)

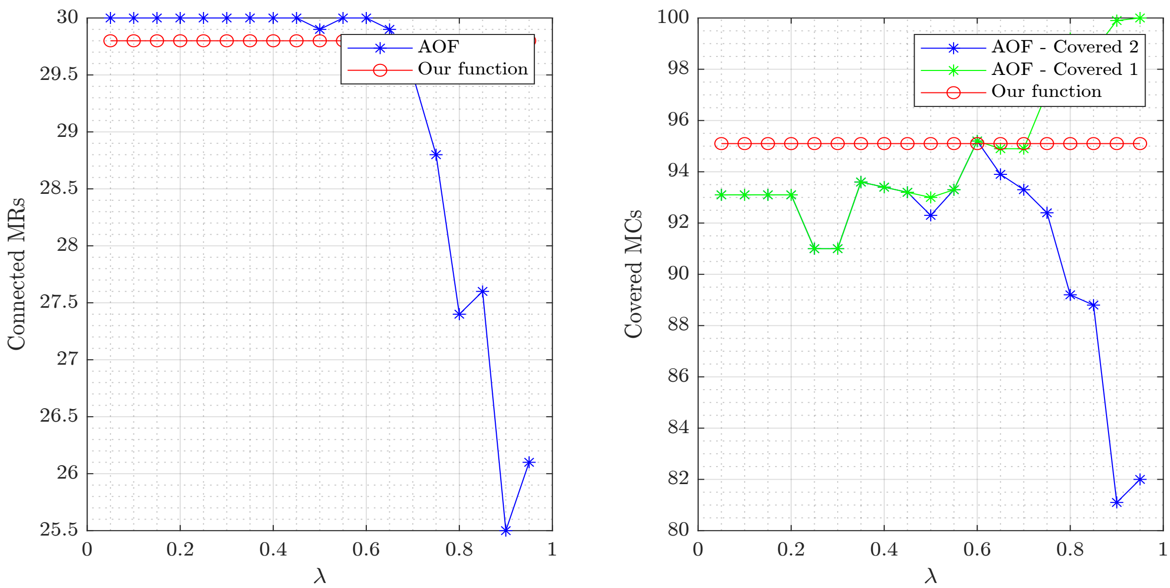


Fig. 6.5 Connected MRs/Covered MCs number vs aggregation coefficient λ(transmission range = 120m)

6.3.4 Example of obtained network topologies

Figures 6.6 and 6.7 show the obtained topologies by APSO algorithm for the aggregated objective function f_1 and our objective functions f_2. In figures 6.6(a) and 6.6(b), It can be seen the low coverage of the mesh clients. As shown in figures 6.7(a) and 6.7(b). After increasing the transmission range and applying the APSO algorithm to find near-optimal mesh routers location, the coverage rate is greatly improved, and mesh routers locations are well chosen to guarantee the best network connectivity. However, the network topology obtained by our function is more spread out to cover more clients.

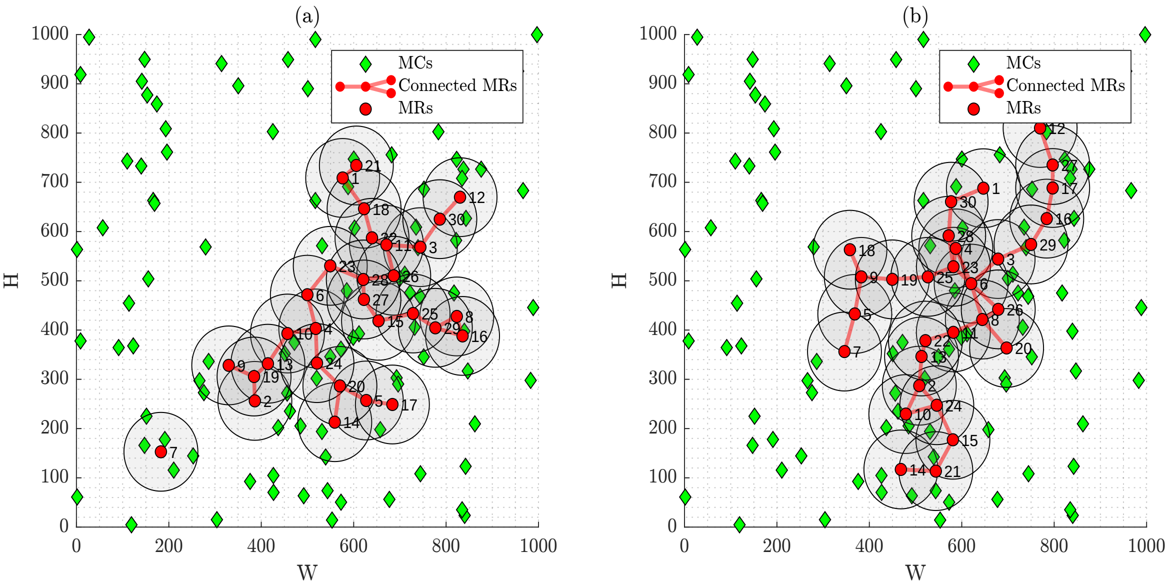


Fig. 6.6 Obtained topologies for transmission range 80m

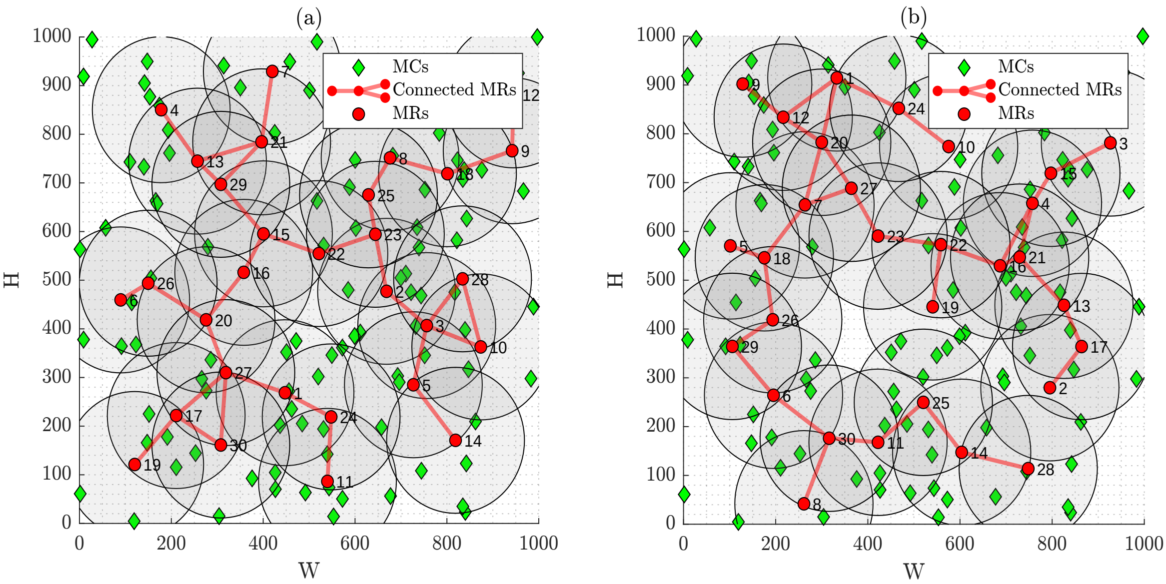


Fig. 6.7 Obtained topologies for transmission range 120m

6.3.5 Effect of MRs, MCs number and transmission range on coverage and connectivity

The next subsections discuss the performance of the APSO algorithm and the results obtained by varying the number of mesh routers, the number of mesh clients, and the transmission range of mesh routers. Independently, we show their effect on clients' coverage (ψ_2) and network connectivity (ϕ).

Effect of mesh routers number

In figure 6.8, the total number of mesh routers varies from 10 to 100. Figure 6.8(b) shows the effect of the mesh router number on the overall number of covered mesh clients. The results demonstrate that optimal topologies are found by the APSO algorithm where the number of covered clients increases as anticipated. Additionally, Figure 6.8(a) demonstrates that the number of connected mesh routers representing network connectivity increases by installing additional mesh routers.

In practice, adding more mesh routers to the network leads, as planned, to more network connectivity since adding more mesh routers to isolated networks will connect them, and a larger network will be formed as a result.

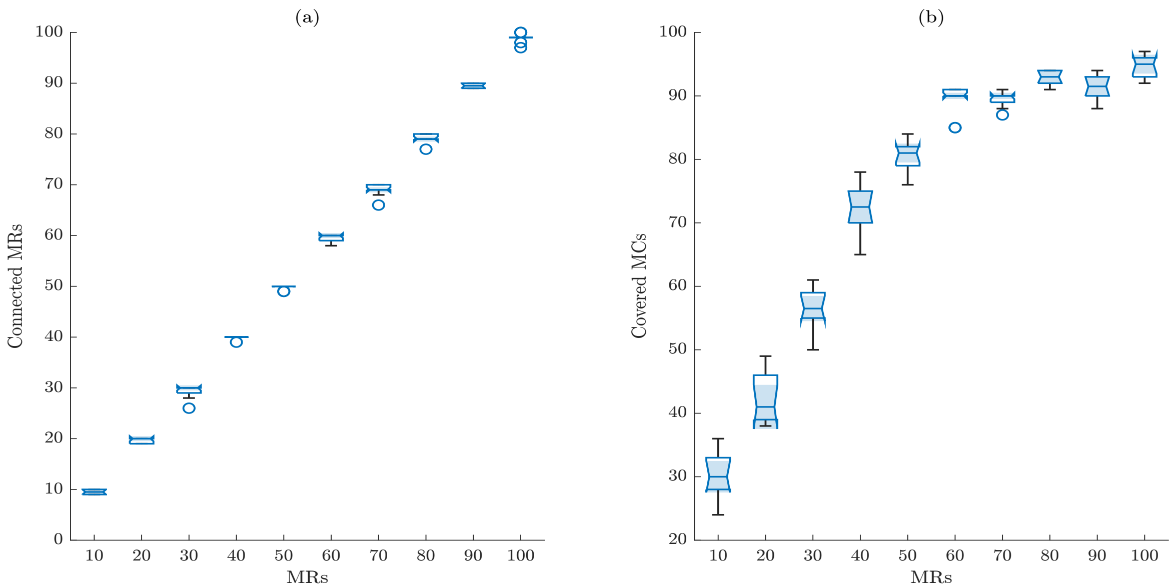


Fig. 6.8 Effect of the number of mesh routers on coverage and connectivity

Effect of mesh clients number

In figure 6.9, the total number of mesh clients varied from 50 to 275. Figure 6.9(b) illustrates that network coverage increases as a consequence of the introduction of new mesh clients to the network. In addition, Figure 6.9(a) shows that the number of connected mesh routers is always between 28-30 when adding new mesh clients, since the APSO algorithm attempts to connect all available routers.

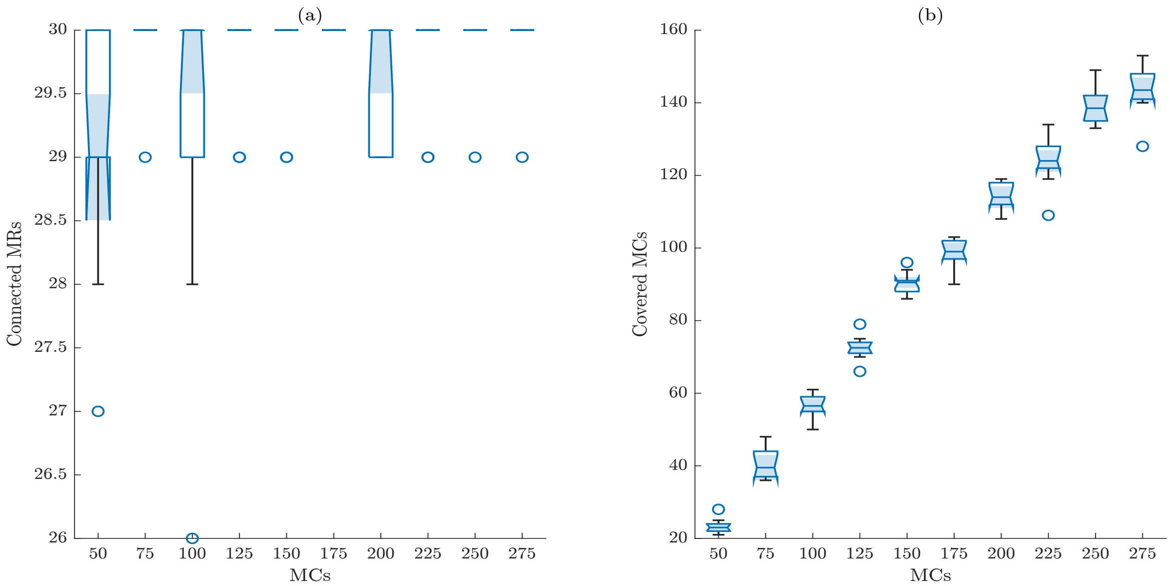


Fig. 6.9 Effect of the number of mesh clients on coverage and connectivity

Effect of transmission range

In figure 6.10(a), we examined the effect of increasing the transmission range of mesh routers on network connectivity, from 60m to 240m. Mesh routers tend to connect while increasing the transmission range. Additionally, almost all the sub-graph components are merged into a single large giant component when the transmission range reaches 100m. Figure 6.10(b) indicates that the number of covered clients increases proportionately as the transmission range of mesh routers increases. According to figure 6.10(a), the crucial transmission range that results in maximum coverage of the network is 180m.

6.3.6 Analyzing our objective function evolution

In this subsection, the best value of the fitness function f_2 defined in equation 6.2 was taken into consideration. Moreover, the same parameters were used to measure the client's

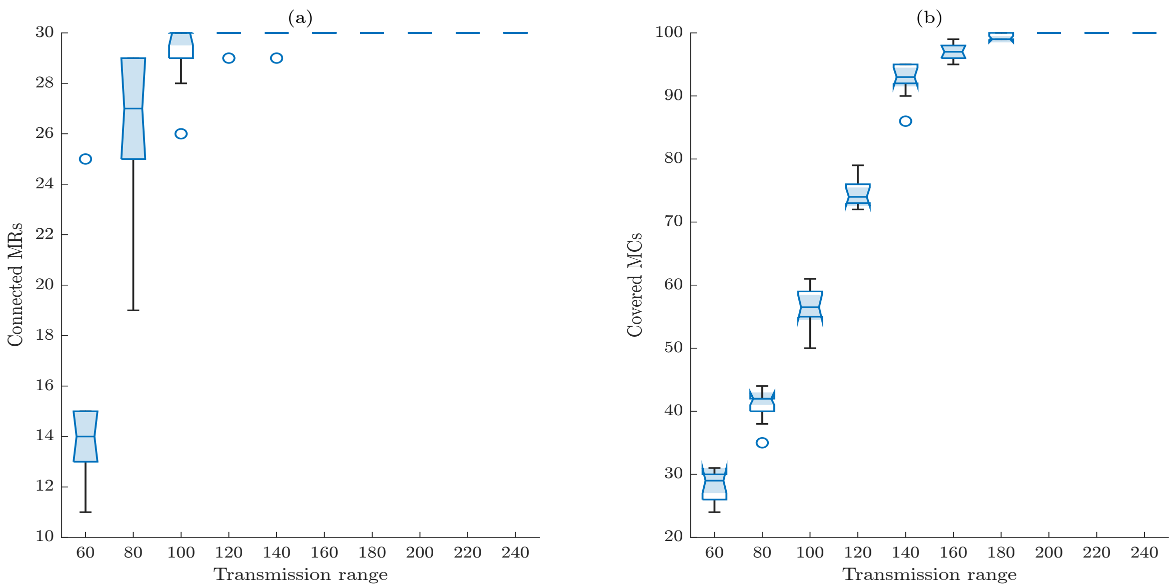


Fig. 6.10 Effect of the transmission range on coverage and connectivity

coverage and network connectivity against the value of f_2 for our examined APSO algorithm as in previous experiments.

As shown in table 6.3, for APSO algorithms, the covered mesh client's percentage and the value of f_2 increase correspondingly when the number of mesh routers is increased from 10 to 100. Furthermore, we have obtained a connected network topology almost all the time.

Table 6.3 Coverage, connectivity and fitness value vs MRs number

MRs	*Max* Connected MRs	*Max* Covered MCs	$Avg(\phi)$ Connected MRs(%)	$Avg(\psi_2)$ Covered MCs(%)
10	10	36	95.00	30.10
20	19	49	98.00	42.30
30	30	61	97.33	56.50
40	39-40	78	99.75	72.30
50	50	84	99.60	80.40
60	59-60	91	99.00	89.30
70	69	91	98.43	89.50
80	79-80	94	99.00	92.70
90	90	94	99.44	91.20
100	98	97	98.90	94.70

In table 6.4, the number of mesh clients has increased from 50 to 275. The results show that even though the number of mesh clients is increased, the value of f_2 remains relatively steady and the percentage of client coverage and network connectivity. The use of a uniform distribution for the locations of mesh clients justifies this finding. As we have complete network connectivity, every mesh router would cover the same percentage of mesh clients, even if we add more mesh clients. Once more, improved client coverage is found in the suggested APSO algorithm.

Table 6.4 Coverage, connectivity and fitness value vs MCs number

MCs	*Max* Connected MRs	*Max* Covered MCs	$Avg(\phi)$ Connected MRs(%)	$Avg(\psi_2)$ Covered MCs(%)
50	29	28	97.00	46.80
75	29-30	48	99.67	53.87
100	30	61	97.33	56.50
125	30	79	99.33	58.00
150	30	96	99.33	60.27
175	30	103	100.00	56.11
200	29	119	98.67	56.95
225	30	134	99.33	55.20
250	30	149	99.67	55.64
275	30	153	99.67	52.11

Finally, table 6.5 shows the effect of mesh routers' transmission range on client's coverage and network connectivity. Noted, the coverage of the clients and the fitness value increase accordingly to the transmission range.

Table 6.5 Coverage, connectivity and fitness vs Transmission range.

Transmission range	Max Connected MRs	Max Covered MCs	$Avg(\phi)$ Connected MRs(%)	$Avg(\psi_2)$ Covered MCs(%)
60	14	31	48.67	28.10
80	24	44	87.33	41.00
100	30	61	97.33	56.50
120	30	79	99.67	74.40
140	30	95	99.67	92.50
160	30	99	100.00	97.10
180	30	100	100.00	99.30
200	30	100	100.00	100.00
220	30	100	100.00	100.00
240	30	100	100.00	100.00

6.4 Conclusion

To maximize the client's coverage in WMNs by optimizing mesh routers' locations, we have considered a novel single objective function. We have applied and evaluated three algorithms: LDWPSO, GWO, and APSO algorithm. The results demonstrated the efficiency of our proposed function at finding optimum client coverage and almost always attain connectivity of all mesh routers with fewer computation resources. The results showed that APSO offers promising results.

Chapter 7

Conclusion and future recommendations

7.1 Conclusion

In this thesis, the MRP issue in WMN has been studied and addressed where a novel meta-heuristic has been proposed to solve this problem. Three algorithms have been developed based on LDWPSO, GWO, and APSO algorithms to find the near-optimal solution for the MRP. The proposed approach aimed to maximize the client coverage and the network connectivity to ensure that each MRs were placed in a near-optimal position to ensure the MRs were distributed among the MCs. The problem has been formulated as a mathematical model, and the network was represented as an undirected graph of one-unit weights. The Breadth-first search (BFS) algorithm has been used to calculate the giant component of the network graph among the MRs for network connectivity.

In our first work, the APSO and the LDWPSO have been used to find the near-optimal solution based on the aggregated objective functions in the mathematical model. The two algorithms have been evaluated based on generating instances to show the convergence rate, the scalability, and the robustness of the algorithms. The experimental results have shown promising results for both algorithms. Further optimization has been done for both algorithms using different parameters that formed, the processes of these algorithms, and the size of the networks to test the algorithms in high and low-intensity situations. Also, a comparison between APSO and LDWPSO has been made. The results have shown that the APSO achieved better than LDWPSO in the all-generated networks, and it has better opportunities for further optimization through many generations. Nevertheless, the APSO can achieve better performance quickly, and it is better than LDWPSO when the time is an important issue.

In our second work, a new objective has been formulated to solve the fragmented network topology obtained by the bi-objectives aggregated function formulated earlier. We propose a new objective function to achieve optimal client coverage and fine-tune the network connectivity for optimum performance without the need for knowledge of an aggregation coefficient. In addition, we select three meta-heuristics algorithms: APSO, LDWPSO, and GWO, and compare their convergence, computational complexity. Finally, we have experimentally evaluated the proposed function by using a different benchmark. The results show that the APSO algorithm can provide very competitive results than standard PSO and GWO algorithms and our proposed function provides higher client coverage with less computation power.

7.2 Future Works

In our future work, we would like to consider other objectives as internet gateway deployment, channel assignment, and k-vertex connectivity to enhance network reliability and consider more quality of services constraints by adopting a penalty approach to resolve the problem through a general Pareto-like approach.

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