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“Opportunistic wireless networks based on mobile access points”

“Ευκαιριακά ασύρματα δίκτυα βασισμένα σε κινητά σημεία πρόσβασης”

A M.Sc. Thesis Presented

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Περίληψη

Βασικός στόχος της παρούσας διπλωματικής είναι να σχεδιάσει, να αναπτύξει και να επικυρώσει τους μηχανισμούς για τη λήψη αποφάσεων σχετικά με τη δημιουργία των ευκαιριακών δικτύων που βασίζονται σε κινούμενα σημεία πρόσβασης (moving access points - MAPs). Τα κινούμενα σημεία πρόσβασης μπορεί να είναι έξυπνα / συνδεδεμένα αυτοκίνητα σε περιπτώσεις μη στρατιωτικής χρήσης, ή οποιοδήποτε είδος των επιχειρησιακών οχημάτων και / ή drones σε στρατιωτικές υποθέσεις.

Τα ευκαιριακά δίκτυα θα διαμορφώνονται με έναν ad hoc τρόπο και δυναμικά μέσω του κατάλληλου μηχανισμού αυτο-οργάνωσης και καθορισμού της θέσης, ώστε να παρέχουν το κατάλληλο Quality of Service (QoS). Οι εφαρμογές αυτές μπορούν να αξιοποιηθούν σε ένα εμπορικό ή στρατιωτικό πλαίσιο, προκειμένου να αποκαταστήσουν την επικοινωνία σε απομακρυσμένες περιοχές και πεδία μάχης όπου η σταθερή υποδομή επικοινωνίας δεν είναι διαθέσιμη ή έχει καταστραφεί. Επιπροσθέτως, οι προτεινόμενες λύσεις οδηγούν σε βελτίωση της αποδοτικότητας επιτυγχάνοντας: (i) καλύτερη χρήση των διαθέσιμων πόρων, (ii) ενεργειακή αποδοτικότητα, (iii) μείωση των λειτουργικών και κεφαλαιουχικών δαπανών.

Τα ευκαιριακά δίκτυα δημιουργούνται δυναμικά και προσωρινά αποτελώντας επεκτάσεις των βασικών υποδομών των δικτύων. Τα ευκαιριακά δίκτυα και τα κινούμενα σημεία πρόσβασης (MAPs) αποτελούν εναλλακτικές λύσεις για επικοινωνία χωρίς την απαραίτητη χρήση σταθερής υποδομής. Επίσης είναι ικανά να κινούνται αυτόνομα και να δημιουργούν δίκτυο επικοινωνίας με περιορισμένη κεντροποιημένη διαχείριση.

Η μελέτη δομείται ως εξής: περιγραφή της υπάρχουσας κατάστασης, περιγραφή προτεινόμενων σεναρίων και λύσεων. Τέλος, παρουσιάζονται αποτελέσματα με χρήση προσομοιώσεων.

Abstract

The concept of this study is to design, develop and validate mechanisms for deciding on the creation and set-up of opportunistic networks based on moving access points (MAPs) for mobile client nodes. Mobile client nodes can be smart/connected cars in civilian use cases, or any kind of operational vehicles and/or robots/drones in military cases. Opportunistic networks will be formed in an ad hoc manner and will be dynamically reconfigured through the suitable self-organization and adjustment of the position and coordination of MAPs so as to provide appropriate Quality of Service (QoS) levels towards mobile client nodes.

In general wireless and wired infrastructure is expensive to build and maintain. In addition, mobile communication networks (either in a commercial or in a military context) are faced with challenging situations such as moving hotspots, areas with difficult morphology where it is difficult to set up infrastructure or areas where infrastructure has become unavailable due to natural disasters or hostile actions. These continuously increasing requirements and challenges motivate the quest for further efficiency in resource provisioning. Efficiency can be coupled with targets like: (i) the higher utilization of resources; (ii) the reduction of transmission powers and energy consumption; (iii) the reduction of operational expenditures (OPEX) and capital expenditures (CAPEX).

Opportunistic networks (ONs) are temporary, coordinated extensions of the infrastructure. They are dynamically created, in places and at the time they are needed and can comprise network elements of the infrastructure, Moving Access Points (MAPs) and mobile client nodes/devices potentially organized in an infrastructure-less manner. Opportunistic Networks and MAPs represent efficient means for offering communication services with reduced CAPEX, due to the absence of permanent infrastructure, and increased resource utilization. MAPs are capable of autonomously moving and establishing an opportunistic radio network in short time, with limited centralized management.

The rest of this study is structured as follows: description of related work, description of the proposed scenarios and of course providing information on proposed solutions. Finally evaluation through multiple simulations is provided.

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Contents

1. Introduction	5
1.1. Motivation	5
1.2. Overall concept	5
2. Related work.....	6
3. Problem statement.....	8
4. Scenarios.....	10
5. Management intelligence and validation platform architecture	12
6. Mathematical formulation	14
7. Solution algorithms	17
7.1. Simulated Annealing algorithm.....	17
7.2. Maximum flow algorithm	18
8. Development.....	21
8.1. Simulated Environment.....	21
8.2. Simulated Annealing (SA) Algorithm Simulation settings.....	24
8.3. Maximum Flow (MF) Algorithm Simulation settings	25
9. Evaluation	28
9.1. Evaluation Methodology of SA Algorithm	28
9.1.1. First Scenario	28
9.1.2. Second Scenario	30
9.1.3. Third Scenario	32
9.2. Result Overview.....	33
9.3. Evaluation Methodology of MF Algorithm	36
9.3.1. First Scenario	37
9.3.2. Second Scenario	39
9.3.3. Third Scenario	41
9.4. Result Overview.....	42
10. Final Evaluation.....	46
10.1. Results.....	46
11. Conclusions.....	51
12. References.....	53

Chapter 1

1. Introduction

In the world of wireless networks, devices and services, the expectations of users are shifting towards greater, constantly available connectivity. Mobile-connected devices are expected to exceed ten billion within the next 4 years, including diverse devices ranging from smartphones to connected vehicles [1]. In this context, significant increases in network capacity are required. However, infrastructure is expensive to build and maintain. In addition, mobile communication networks (either in a commercial or in a military context) are faced with challenging situations such as moving hotspots, areas with difficult morphology where it is difficult to set up infrastructure or areas where infrastructure has become unavailable due to natural disasters or hostile actions. These continuously increasing requirements and challenges motivate the quest for further efficiency in resource provisioning. Efficiency can be coupled with targets like: (i) the higher utilization of resources; (ii) the reduction of transmission powers and energy consumption; (iii) the reduction of operational expenditures (OPEX) and capital expenditures (CAPEX).

1.1. Motivation

The **motivation** for this thesis is to address these challenges with the use of Opportunistic Networks of Moving Access Points. Opportunistic networks are temporary, coordinated extensions of the infrastructure. They are dynamically created, in places and at the time they are needed and can comprise network elements of the infrastructure, Moving Access Points (MAPs) and mobile client nodes/devices potentially organized in an infrastructure-less manner. Opportunistic Networks and MAPs represent efficient means for offering communication services with reduced CAPEX, due to the absence of permanent infrastructure, and increased resource utilization. MAPs are capable of autonomously moving and establishing an opportunistic radio network in short time, with limited centralized management [2][3].

1.2. Overall concept

The **concept** of this thesis is to design, develop and validate **mechanisms for deciding on the creation and set-up of opportunistic networks of MAP entities for mobile client nodes.**

Mobile client nodes can be smart/connected cars in civilian use cases, or any kind of operational vehicles and/or robots/drones in military cases. Opportunistic networks will be formed in an ad hoc manner and will be dynamically reconfigured through the suitable self-organisation and adjustment of the position and coordination of MAPs so as to provide appropriate Quality of Service (QoS) levels towards mobile client nodes.

Chapter 2

2. Related work

This section provides an overview of state-of-the-art work related to MAPs and opportunistic networks. For cellular network systems positioning of APs/ base stations is always a challenging problem and has been extensively studied in the past [6],[7],[8]. It has already been demonstrated that identification of optimum APs locations is an NP-hard problem [9] and analytical solutions are too difficult to drive. First studies on the topic of autonomous functionalities in a wireless network, using robots, were targeted to the provision of adaptive sensor functionality in a dynamic environment. In [10], to guarantee communication for a mobile robot involved into a dynamic coverage problem, a static network of markers is autonomously dispersed by the robot during its motion. The authors in [11] presented a distributed model for cooperative multiple mobile robot systems in which each mobile robot has sensing, computation and communication capabilities. The mobile robots spread out across certain area and share sensory information through an ad hoc wireless network. A fault tolerant algorithm for autonomous deployment of the mobile robots was also discussed that maximizes the coverage area of the network.

The authors in [12] proposed sub-optimal distributed algorithms to optimize routes in a wireless network, maintained by a set of mobile robots acting as communication relays. Further extension of this work was presented in [13] using a new algorithm to a wireless network optimization problem, in which robots act as access points with the objective of maximizing signal strength in the network by changing their positions.

The concept of moving base stations has been used, primarily in military, and also in civilian communications [14],[15]. However, the mixing of this concept with self-organizing networks is relatively new. The concept of self-deploying and moving wireless AP was used in [16]. Performance gains were quantified for self-deploying networks in a highly dynamic environment (airport) and it has been shown that by using self-deployment and optimization algorithms significant reduction in number of base stations can be possible with improved network performance. In addition, the concept of robotic base stations was outlined in [17], and the need for such type of base stations was highlighted.

The topic of wireless sensor networks deployment, redeployment and post-deployment network maintenance based on mobile robotic nodes in order to achieve optimal connectivity and minimum energy consumption is addressed as well [18]. The research is based on the CORE-TX platform, which provides the necessary hardware and software modules used for evaluation and testing of the solutions discussed. The quality of the communication link has an important role in energy saving due to packet loss ratio and the required power level of the transceiver. The authors proposed and discussed an automated approach to network deployment and network maintenance based on local connectivity evaluation.

The availability of infrastructure in wireless networks is often limited. Such networks become dependent on wireless ad-hoc networking, where nodes communicate and form paths of communication themselves. Wireless ad-hoc networks present novel challenges in contrast to fixed infrastructure networks. The unpredictability of node movement and route availability become issues of significant importance where reliability is desired. To improve reliability in wireless ad-hoc networks, predicting future connectivity between mobile devices has been proposed. Predicting connectivity can be employed in a variety of routing protocols to improve route stability and reduce unexpected drop-offs of communication [19].

Operator governed opportunistic networks were addressed in [20]. These are temporary/local extensions of the infrastructure, created at places and for the time they are needed for resolving cases of no (or poor) coverage or of low capacity. The proposed work is a complementary contribution bringing cost-efficient solutions to difficult and unpredictable situations like moving hotspots, areas with no infrastructure or hard morphology (e.g., construction/manufacturing sites), etc. Such environments are especially relevant to a naval context. Such cases are especially important also in a wider emerging military context as is the one described in [21].

The MAPs concept is related to the field of robotics, optimization and automatic control. However, the MAPs project enhances the classical approach by integrating modern wireless communication and networking principles and achievements. Most of the state-of-the-art (networked robotics) envisages robots as moving wireless network nodes. The MAPs solutions optimize robots movement, in order to offer adequate QoS to users, while maintaining inter-robot communication links. In addition, the problem of finding the optimum routing path in such a network will be elaborated. Many application areas will benefit from the MAPs approach. It should be stressed that the ultimate MAPs system objective is to offer the most satisfactory QoS to the users who are using the MAPs opportunistic radio network. In this direction, it is envisaged (as one of the likely solutions) that MAP entities will be dynamically moving near the area where the users are concentrated. Such an approach is rarely encountered in the state-of-the-art research reports.

It should be noted that a similar problem, i.e. the position optimization of Moving Access Points (MAPs), was studied in [4][5]. A hybrid algorithm was developed, namely the Pheromone-based Simulated Annealing (PSA) which enriched the Simulated Annealing Algorithm with the pheromone feature of the Ant Colony Optimization (ACO). In order to improve even more the quality of the solution a bio-inspired approach was also followed, i.e. the Artificial Bee Colony Optimization. This thesis aims to extend previous work by considering more, diverse types of MAPs, taking into account various specifications in the deployment of MAPs and addressing mobility aspects of client nodes to a greater extent.

Chapter 3

3. Problem statement

This section provides a description on the MAPs problem that is considered in this document. Specifically, a remote area where deployed, wireless infrastructure is not widely available will be considered. The area shall comprise network entities, i.e., the moving access points (MAPs) and the APs that offer access to remote users. In addition, it will be assumed that users require services at specific QoS levels (e.g., in terms of bitrate, latency, etc.), while a capacity (e.g. in terms of bitrate, number of users that can be served) and a transmission range based on standardized propagation models will be assigned to the MAPs and the fixed access points.

The thesis will be focused on the solution of a complex optimization problem that can be generally expressed as follows:

“Given information and knowledge on:

- The context that has to be handled, in terms of (i) a set of mobile clients that need coverage, (ii) mobility and traffic profiles of the client nodes, (iii) radio quality, (iv) options for connecting to wide area networks, (v) the locations of docking/charging stations for drone MAPs, (vi) the current locations of the MAP elements, a (potentially large) set of candidate final positions to which the MAP entities can move. MAPs can assume position characterized by latitude, longitude and altitude, i.e. of the form(x, y, z);
- The capabilities of the mobile client nodes and the MAP entities in terms of (i) communication networking (e.g., RATs and spectrum that can be operated, capacity and coverage that can be provided etc.), (ii) physical movement, (e.g., possible speed of the element, path-types and obstacles that it can overcome, etc.); (iii) the type of the MAP (e.g. drone/flying MAP);
- Potential policies that need to be followed by the mobile client nodes, the MAP entities and their network;

Find the optimal:

- Positions to which each MAP entity should move;
- Configuration of the radio network of the MAP entities;
- Allocation of nodes to MAPs
- Selection of nearby docking/charging stations for drone MAPs

So as to ensure connectivity of the appropriate QoS to mobile nodes.”

MAPs can be considered as RAT-agnostic, since the proposed solution is not bound to a specific RAT e.g., 3GPP-based or WiFi-based etc. That means that the concept will work with any RAT, within the limitations of the particular technology. Solutions will be validated based on applications in a wide set of very indicative test cases and through simulation.

In order to achieve the main objective, we will conduct work for addressing the following technical challenges:

- Acquisition and exchange of contextual information (e.g., of (i) a set of mobile clients that need coverage, (ii) mobility and traffic profiles of the client nodes, (iii) radio quality, (iv) options for connecting to wide area networks, (v) the locations of docking/charging stations for drone MAPs, (vi) the current locations of the MAP elements, a (potentially large) set of candidate final positions to which the MAP entities can move).

- Development and evaluation mainly through simulations of optimization strategies on the joint radio network optimization and position selection, for enabling the creation of opportunistic networks of moving access points in a highly dynamic environment.

Furthermore, ways of solving the problem in a distributed way, or by assigning one node to solve it (centralized way) will be investigated.

Chapter 4

4. Scenarios

When we face unfortunate situations such as earthquake, hurricane and other disasters or even at battlefields, wireless networks can prove to be very useful in search-and-rescue or other tactical operations. In general these situations leave large areas without power and communication capabilities for they destroy the infrastructures. Moving access points can communicate with each other using wireless networks and coordinate their activities in a specified region. Also, based on the size of the area affected an appropriate number of these moving access points need to be deployed by using for example learning/predictive algorithms. Various algorithms could be introduced into the computational model in order to create for example a distributed system of access points that can be self-organized for expanding communication capabilities in the area that military/navy units operate. These access points can be deployed in the area not only providing communication but also for example gathering and analyzing information so that appropriate relief or help can be readily directed where needed.

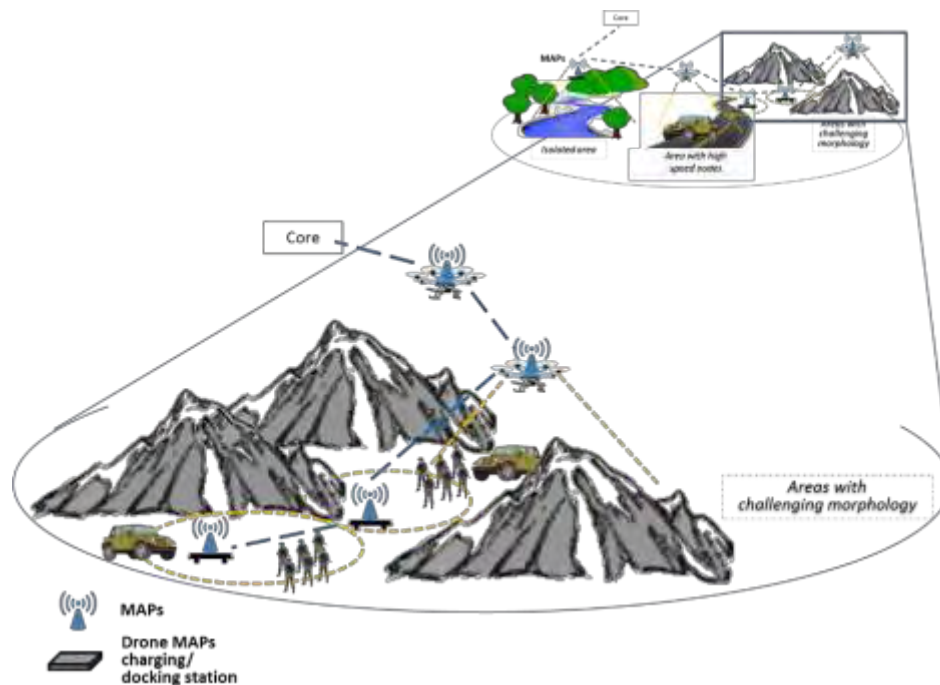


Figure 1: Indicative scenario illustration

Robust communication capabilities is one of the key aspects of any successful operation. Also many (e.g. defense) operations, take place in locations where communication infrastructure is not available. Use of moving wireless networks in such situations becomes very

useful and expedient. Different units involved in operations also need to maintain communication with each other. A nice feature of such a communication environment is that the network moves with you as individuals move in order to provide continuous connection between units. In general machine-to-machine communications can be very promising and feasible on tactical and operational architecture.

Chapter 5

5. Management intelligence and validation platform architecture

This section discusses on the management intelligence and validation platform architecture that will be used for the development and validation of the concepts and algorithms of the thesis.

Management intelligence is essential in order to be able to exploit contextual information from the environment in order to make optimized decisions for the creation and usage of ONs. Moreover, management intelligence can lead to the creation of knowledge with respect to decisions e.g., decisions that led to good network performance in the past, can be re-enforced to the network if similar context is encountered. Also, apart from the management intelligence, the validation platform will comprise software modules that will be used to simulate the operations of the examined network entities. Each module includes specific functionalities that are described below.

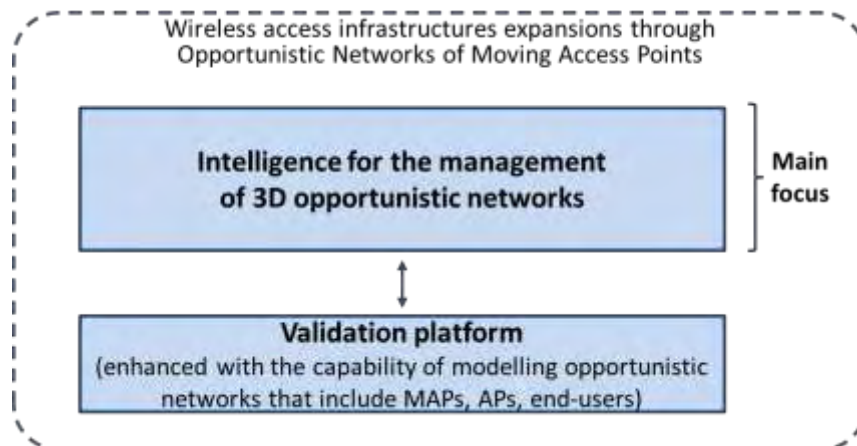


Figure 2: Management intelligence and validation platform

Four main software modules will be implemented in the validation platform:

- **User Equipment (UE)** that will correspond to the main UE operations. It comprises 3 functionalities, i.e. *context generation*, *profiles* and *policy acquisition*. The context generation functionality is responsible for the context of each UE in terms of traffic demand, mobility level and location, radio conditions, etc. Furthermore, the profiles functionality provides details on communication and service capabilities, e.g. supported RATs, transmission power, services, etc. In addition, the policy acquisition functionality is responsible for acquiring necessary policies and constraints.
- **Static Access Points (APs)** that will correspond to the main infrastructure element operations. It comprises 3 functionalities, i.e. *context acquisition*, *profiles* and *policy derivation*. The context acquisition functionality is responsible for acquiring the context of the AP's serving

UEs. Also, the profiles functionality provides information about the AP capabilities, e.g. supported RATs, transmission power, location, etc. In addition, the policy derivation functionality designates high level rules that should be followed in context handling.

- **Moving Access Points (MAPs)** that will correspond to the main operations of MAPs. It comprises 5 functionalities, i.e. *context acquisition*, *profiles*, *policy derivation*, *decision making* and *solution enforcement*. The context acquisition functionality is responsible for acquiring contextual information from the MAPs and the UEs context. Furthermore, the profiles functionality provides information about the MAP capabilities, e.g. supported RATs, maximum speed, potential obstacles, etc. The policy derivation functionality designates the policies and constraints that need to be followed by the MAPs and their network. The aforementioned functionalities provide the main input for the decision making functionality which will execute the algorithm that will compute the solution of the MAPs problem. The resulting solution will be forwarded to the solution enforcement functionality in order to be executed or transmitted to other network entities.

- **Management entity** which includes the network management functions which are needed for collecting measurements in order to ensure that the desired performance is guaranteed. If network performance is inadequate or an AP failure occurs, it notifies the MAP entities to solve the situation.

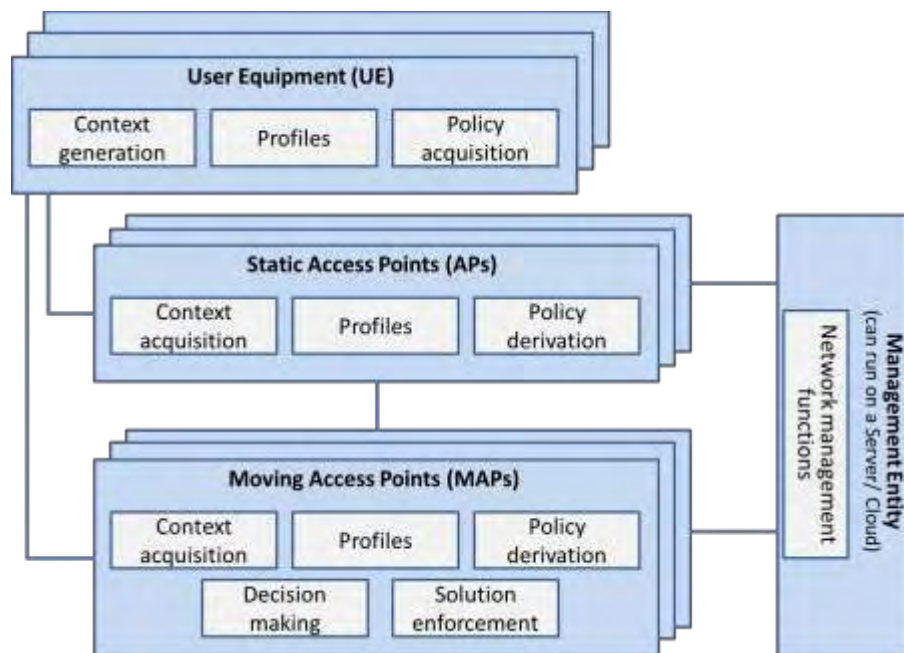


Figure 3: Envisaged validation platform

Figure 3 describes the aforementioned architecture. The entities can communicate in order to exchange information, e.g. profile, context and decision information as it was described above. The communication mechanisms depend on the validation platform that is utilized (for instance, Java-based simulators can exploit TCP/UDP sockets).

Chapter 6

6. Mathematical formulation

In this section the main problem is mathematically formulated. Specifically, let M be the set of the MAP entities, A will be the set of the APs, while U will denote the set of users (with mobile clients) and D will be the set of docking stations e.g., for charging drones. In addition, L will denote the set of the locations at which the network elements (MAPs, APs) can be placed, while $e(i)$ will depict the element that is located at $i \in L$. Also, each MAP $m \in M$ has a capacity cap_m . Capacity can reflect for instance the number of users that are served by a specific MAP. In order to avoid congestion issues (e.g., a lot of users are served at the same time by one only MAP), we can set low values of capacity to MAPs.



Figure 4: Identified mathematical sets

Moreover, the following decision variables are considered:

$$X_{mi} = \begin{cases} 1, & \text{if MAP } m \in M \text{ is located in } i \in L \\ 0, & \text{otherwise} \end{cases} \quad (0)$$

$$Y_{mn} = \begin{cases} 1, & \text{if MAP } m \in M \text{ is connected with MAP } n \in M \\ 0, & \text{otherwise} \end{cases} \quad (0)$$

$$Z_{um} = \begin{cases} 1, & \text{if user } u \in U \text{ is connected with MAP } m \in M \\ 0, & \text{otherwise} \end{cases} \quad (0)$$

$$Q_{ma} = \begin{cases} 1, & \text{if MAP } m \in M \text{ is connected with AP } a \in A \\ 0, & \text{otherwise} \end{cases} \quad (0)$$

$$D_{md} = \begin{cases} 1, & \text{if MAP/dronem} \in M \text{ is not connected with docking station } d \in D \\ 0, & \text{otherwise} \end{cases} \quad (0)$$

Furthermore, the connection of two entities (e.g. when two MAPs are connected, when a MAP is connected to an AP, or when a MAP serves a user) results in a communication cost ct . In general, this cost depends on the frequency used for the communication and the distance of the entities. As a result ct values can be high for entities that are far away between each other, in order to let the algorithm determine closer entities (if available). Also, the movement of drone/MAP to a docking station for charging results in a moving cost mc . In general, this cost depends on the distance of the drone/MAP from the current position to the docking station.

Accordingly, the overall optimization problem can be formulated as follows:

Minimize

$$OF = \sum_{m \in M} \sum_{i \in L} (X_{mi} \cdot ct(m,i)) + \sum_{m \in M} \sum_{\substack{n \in M \\ m \neq n}} (Y_{mn} \cdot ct(m,n)) + \sum_{m \in M} \sum_{u \in U} (Z_{um} \cdot ct(m,u)) + \sum_{m \in M} \sum_{a \in A} (Q_{ma} \cdot ct(m,a)) + \sum_{m \in M} \sum_{d \in D} (D_{md} \cdot mc(m,d)) \quad (0)$$

Constraints:

$$\sum_{i \in L} X_{mi} = 1, \forall m \in M$$

$$\sum_{m \in M} X_{mi} \leq 1, \forall i \in L$$

$$\sum_{n \in M} Y_{mn} \geq 1, \forall m \in M$$

$$\sum_{m \in M} Q_{ma} \geq 1, \forall a \in A$$

$$\sum_{m \in M} Z_{um} = 1, \forall u \in U$$

$$\sum_{m \in M} D_{md} = 1, \forall d \in D$$

$$\phi_m \leq cap_m, \forall m \in M$$

Where

$$\phi_m = \sum_{u \in U} Z_{um} + \sum_{n \in M} (Y_{mn} \cdot \phi_n), \forall m \in M$$

The objective function OF in (0) monitors the location of all MAPs and calculates the total communication costs that are related from these locations, as well as the finding of the nearest docking station for charging (of drone MAPs). The first term of the function illustrates the communication cost related to the MAPs location. The second term depicts the communication cost due to the connections among MAPs. The third term denotes the communication cost because of the connections among users and MAPs. The fourth term depicts the communication cost of the connections of the MAPs with the APs. The fifth term depicts the cost related to the docking station where the drones should go for charging.

Regarding the constraints, the first constraint denotes that every MAP can be placed at one only location. The second constraint denotes that at each location one MAP at most can be placed. The third constraint depicts that every MAP should be connected with at least another MAP (in order to realize the opportunistic network). The fourth constraint denotes that all APs should be connected with at least one MAP and the fifth constraint denotes the fact that each user can be served by one only MAP at a time. The sixth constraint denotes that each docking station can serve one drone/MAP at a time. Also, φ_m represents the MAP's load which cannot exceed its capacity cap_m .

Chapter 7

7. Solution algorithms

Finding an optimal solution for certain optimisation problems can be an incredibly difficult task, often practically impossible. This is because when a problem gets sufficiently large we need to search through an enormous number of possible solutions to find the optimal one. Even with modern computing power there are still often too many possible solutions to consider. In this case because we can't realistically expect to find the optimal one within a sensible length of time, we have to settle for something that's close enough.

7.1. Simulated Annealing algorithm

Simulated annealing (SA) is a probabilistic technique for approximating the global optimum of a given function. Specifically, it is a metaheuristic to approximate global optimization in a large search space.

SA mimics the annealing process to solve an optimization problem. It uses a temperature parameter that controls the search. The temperature parameter typically starts off high and is slowly "cooled" or lowered in every iteration. At each iteration a new point is generated and its distance from the current point is proportional to the temperature. If the new point has a better function value it replaces the current point and iteration counter is incremented. It is possible to accept and move forward with a worse point. The probability of doing so is directly dependent on the temperature. This unintuitive step sometime helps identify a new search region in hope of finding a better minimum.

This algorithm is a well-known way to reach to an optimal solution (e.g., with respect to the MAPs positions as this study suggests). The SA algorithm takes into account simulation steps and in its step it replaces the current solution by a random neighbouring solution $s_i \in S$, chosen with a probability that depends on the difference between the corresponding *OF* values and on a global parameter temperature T which is gradually decreasing during the process (cooling) with a cooling rate c . In this manner, the algorithm searches the solution space in a random way and at the same time it avoids becoming stuck at local minima [24]. The input of the algorithm can include the following aspects:

Input:

- Sets of MAPs and their positions with respect to users, other MAPs, final APs and docking stations (if drone MAPs are considered)
- An initial solution $s_0 \in S$
- The initial temperature T_0
- The temperature's cooling rate c
- The maximum number of iterations i_{max}

The process of the algorithm is described in *Figure 5*. It starts by getting the input and initialization of the solutions and the temperature. SA starts with a relatively high value of temperature T . The algorithm proceeds by attempting a certain number of neighboring moves at each temperature, while the temperature parameter is gradually dropped. When the lower allowed temperature is reached the algorithm ends. The output of the algorithm will lead to a sub-optimal solution $s_{final} \in S$. Apart from the SA algorithm (which has been widely studied e.g., in [25] [26] [27]), it can be mentioned that suitable distributed heuristic (e.g., bio-inspired solutions) can follow as well.

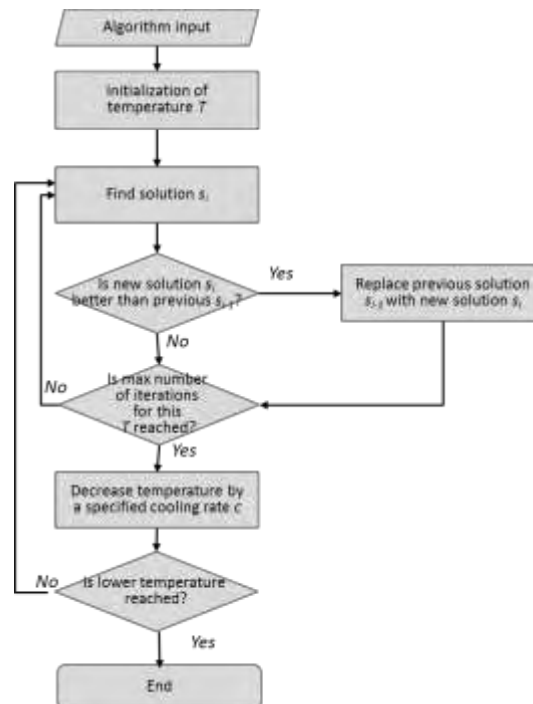


Figure 5: Flowchart of simulated annealing

7.2. Maximum flow algorithm

The Ford–Fulkerson algorithm is a greedy algorithm that computes the Maximum Flow (MA) in a flow network. It is called a "method" instead of an "algorithm" as the approach to finding augmenting paths in a residual graph is not fully specified or it is specified in several implementations with different running times.

The Ford-Fulkerson algorithm is an algorithm that tackles the max-flow min-cut problem. That is, given a network with vertices and edges between those vertices that have certain weights, how much "flow" can the network process at a time. Flow can mean anything, but typically it means data through a computer network.

The idea behind the algorithm is as follows: as long as there is a path from the source (start node) to the sink (end node), with available capacity on all edges in the path, we send flow along one of the paths. Then we find another path, and so on. A path with available capacity is called an augmenting path. As soon as the positions of MAPs known, then the flow of traffic

between MAPs can be optimized (in order to resolve any potential congestion issues e.g., when many users are trying to connect to only one specific MAP). An algorithm based on the Ford-Fulkerson maximum flow algorithm [28] [29] [30] can be used. The main notion of the algorithm is that each user $u \in U$ tries to connect to an access point $a \in A$, by making use of MAPs $m \in M$. Each user should find a set of paths to some of the indicated APs in order to gain access to a network. Each path has a set of MAPs/nodes, the capacity of these MAPs cap_m , and the communication cost ct of the links. As mentioned in Section 3, capacity can reflect for instance the number of users that are served by a specific MAP. In order to avoid congestion issues (e.g., a lot of users are served at the same time by one only MAP), we can set low values of capacity to MAPs. Also the communication cost depends on the frequency used for the communication and the distance of the entities. As a result ct values can be high for entities that are far away between each other, in order to let the algorithm determine closer entities (if available).

Input:

The input of the algorithm consists of the following:

- Sets of MAPs and APs that are considered in the solution;
- Set of users that want to connect to MAPs and APs;
- Paths from sources (users) to destinations (APs) through MAPs. Each path can originate from a ‘virtual’ source where all users are connected and ends to a ‘virtual’ destination where all APs are connected;
- Capacity of each MAP and AP (in order to know how many users can be supported).

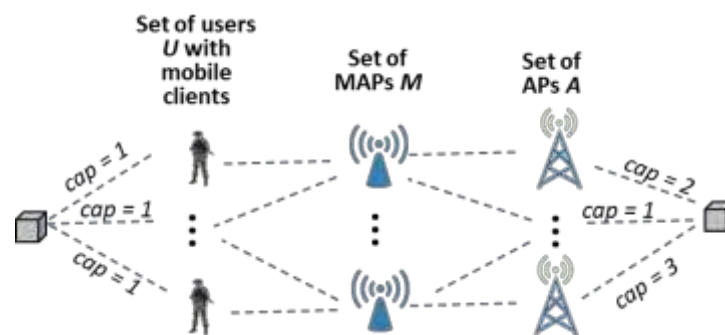


Figure 6: Main sets taken into account by the algorithm

The process of the algorithm is described in Figure 7. It starts by getting the input and assuming that a path consists of many links which are distinguished by starting, ending points and capacity (which can be associated also to the available radio access technology-RAT). For instance, 3G links for sure would have lower capacity value compared to 4G etc. Once, the input is retrieved, the algorithm picks one of the discovered paths according to the breadth-first search method which yields the shortest path. From the selected path, it finds the link with the smallest capacity. Then, it sets the flow of the path equal to the smallest link capacity and updates the residual capacities of the rest of the links. The algorithm continues until there is no unchecked path from source to destination. Once all paths are checked, a set of MAPs from

source to destination is created. As a result, the problem of achieving wireless access infrastructures expansions through opportunistic networks of MAPs is solved.

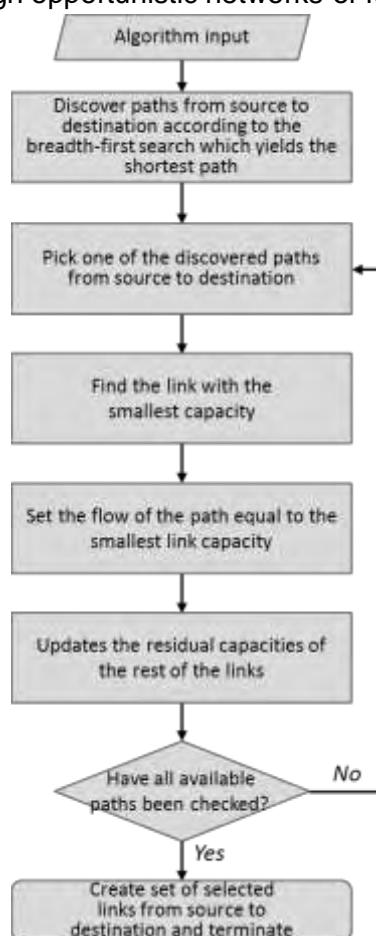


Figure 7: Flowchart of the algorithm

In order to evaluate the performance of the proposed algorithm, several simulations will be performed. In the following chapter, the solutions specification and development will be elaborated and some initial results could be provided in order to initially check the performance of such solution. Detailed evaluation and results will also follow.

Also, the simulation environment that will be used will be described in detail in order to show the potentials of the tool and the solution for the realization of networks consisting of MAPs. Different aspects of MAPs will be taken into account in order to run various scenarios with different parameters and check their respective performance.

Chapter 8

8. Development

8.1. Simulated Environment

For the evaluation of our model, we use one of the broadly used simulation tools in academy which is a very powerful open source network simulator OMNeT++ [32].

In order to allow the most accurate modeling of MAPs (Rovers and Drones) and UEs movements a hybrid simulation framework is required which is composed of the network simulator OMNeT++, a road traffic simulator SUMO [33] which is well-established in the domain of traffic engineering and the appropriate framework that combines those two simulators, called VEINS [31].

SUMO (Simulation of Urban Mobility) is an open source microscopic traffic simulator licensed under General Public License (GNU) and developed by Institute of Transportation Systems at the German Aerospace Center using C++ standard. It allows users to create a road network of their preferences containing buildings and streets or to import a road network from different format and convert it into a SUMO network. Also each vehicle can be modeled explicitly, in order to move individually through the network and has their own route updating the position of each vehicle every time step, which gives SUMO the feature of time-discrete vehicle movement. This traffic simulator also provides an OpenGL graphical user interface. Traffic simulation in SUMO can be conducted in two ways as described below and the overview of the simulation process is given in Figure 8.

Traffic simulations facilitate the evaluation of infrastructure changes as well as policy changes before implementing them on the road. For example, the effectiveness of environmental zones or traffic light control algorithms can be tested and optimized in a simulation before being deployed in the real world.

SUMO is a free and open traffic simulation suite which is available since 2001. SUMO allows modelling of intermodal traffic systems including road vehicles, public transport and pedestrians. Included with SUMO is a wealth of supporting tools which handle tasks such as route finding, visualization, network import and emission calculation. SUMO can be enhanced with custom models and provides various APIs to remotely control the simulation.

The simulation platform SUMO offers many features:

- Microscopic simulation - vehicles, pedestrians and public transport are modeled explicitly
- Online interaction – control the simulation with TraCI
- Simulation of multimodal traffic, e.g., vehicles, public transport and pedestrians

- Time schedules of traffic lights can be imported or generated automatically by SUMO
- No artificial limitations in network size and number of simulated vehicles
- Supported import formats: OpenStreetMap, VISUM, VISSIM, NavTeq
- SUMO is implemented in C++ and uses only portable libraries

SUMO has been used within several projects for answering a large variety of research questions:

- Evaluate the performance of traffic lights, including the evaluation of modern algorithms up to the evaluation of weekly timing plans.
- Vehicle route choice has been investigated, including the development of new methods, the evaluation of eco-aware routing based on pollutant emission, and investigations on network-wide influences of autonomous route choice.
- SUMO was used to provide traffic forecasts for authorities of the City of Cologne during the Pope's visit in 2005 and during the Soccer World Cup 2006.
- SUMO was used to support simulated in-vehicle telephony behavior for evaluating the performance of GSM-based traffic surveillance.
- SUMO is widely used by the V2X community for both, providing realistic vehicle traces, and for evaluating applications in an on-line loop with a network simulator.

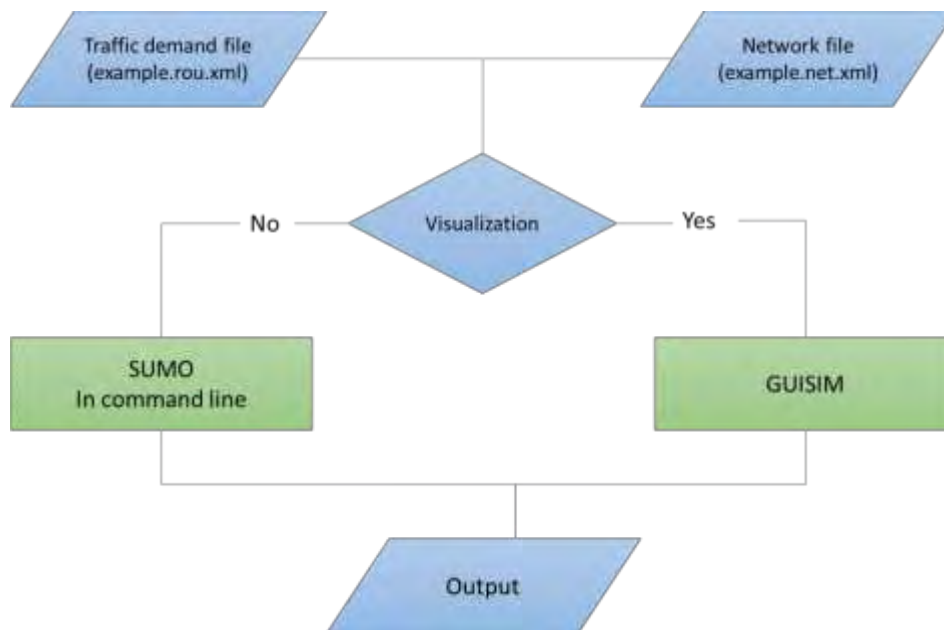


Figure 8: Flowchart of traffic simulation process of SUMO.

OMNeT++ is an extensible, modular, component-based C++ simulation library and framework, primarily for building network simulators. "Network" is meant in a broader sense that includes wired and wireless communication networks, on-chip networks, queuing networks, and so on. Domain-specific functionality such as support for sensor networks, wireless ad-hoc networks, Internet protocols, performance modeling, photonic networks, etc., is provided by model frameworks, developed as independent projects. OMNeT++ offers an Eclipse-based IDE, a graphical runtime environment, and a host of other tools. There are extensions for real-time

simulation, network emulation, database integration, System C integration, and several other functions.

OMNeT++ provides a component architecture for models. Components (modules) are programmed in C++, then assembled into larger components and models using a high-level language (NED). Reusability of models comes for free. OMNeT++ has extensive GUI support, and due to its modular architecture, the simulation kernel (and models) can be embedded easily into your applications.

Components

- simulation kernel library
- NED topology description language
- OMNeT++ IDE based on the Eclipse platform
- GUI for simulation execution, links into simulation executable (Tkenv)
- command-line user interface for simulation execution (Cmdenv)
- Utilities (makefile creation tool, etc.)
- Documentation, sample simulations, etc.

Platforms

- OMNeT++ runs on Windows, Linux, Mac OS X, and other Unix-like systems.
- The OMNeT++ IDE requires Windows, Linux, or Mac OS X.

Veins, the Open Source vehicular network simulation framework, ships as a suite of simulation models for vehicular networking. These models are executed by an event-based network simulator (OMNeT++) while interacting with a road traffic simulator (SUMO). Other components of Veins take care of setting up, running, and monitoring the simulation.

This constitutes a simulation framework. What this means is that Veins is meant to serve as the basis for writing application-specific simulation code. While it can be used unmodified, with only a few parameters tweaked for a specific use case, it is designed to serve as an execution environment for user written code. Typically, this user written code will be an application that is to be evaluated by means of a simulation. The framework takes care of the rest: modeling lower protocol layers and node mobility, taking care of setting up the simulation, ensuring its proper execution, and collecting results during and after the simulation.

Veins contains a large number of simulation models that are applicable to vehicular network simulation in general. Not all of them are needed for every simulation -- and, in fact, for some of them it only makes sense to instantiate at most one in any given simulation. The simulation models of Veins serve as a toolbox: much of what is needed to build a comprehensive, highly detailed simulation of a vehicular network is already there. Still, a researcher assembling a simulation is expected to know which of the available models to use for which job. To give a trivial example, one would not want to use a path loss model designed for cities to simulate a freeway scenario.

Veins is an Open Source vehicular network simulation framework. What this means is that it (and all of its simulation models) are freely available for download, for study, and for use. Nothing about its operation is (or needs to be) kept secret. Any simulation performed with Veins can be shared with interested colleagues -- not just the results, but the complete tool chain

required for an interested colleague to reproduce the same results, to verify how they were derived, and to build upon the research performed.

As discussed before, with Veins each simulation is performed by executing two simulators in parallel: OMNeT++ (for network simulation) and SUMO (for road traffic simulation). Both simulators are connected via a TCP socket. The protocol for this communication has been standardized as the Traffic Control Interface (TraCI). This allows directionally-coupled simulation of road traffic and network traffic. Movement of vehicles in the road traffic simulator SUMO is reflected as movement of nodes in an OMNeT++ simulation. Nodes can then interact with the running road traffic simulation, e.g., to simulate the influence of IVC on road traffic.

The simulation models of Veins constitute the current state of the art in vehicular network simulation research. Aside from numerous publications that base their conclusions wholly or in part on simulations conducted with Veins, many proposed new and improved simulation models or techniques, implemented for the first time in Veins.

The bidirectional communication between OMNeT++ network simulator and SUMO road network simulation is shown in Figure 9.

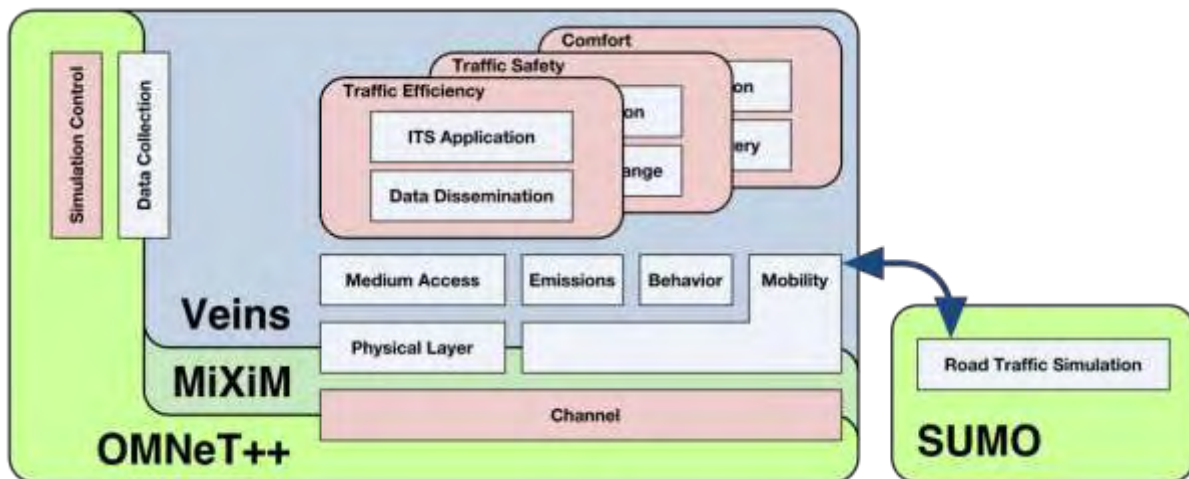


Figure 9: Flowchart of communications between SUMO-VEINS-OMNeT++.

8.2. Simulated Annealing (SA) Algorithm Simulation settings

- The simulation will start the computations of the Simulated Annealing (SA) algorithm when the roads are fully populated and run for s seconds.
 - Beacon intervals are set to 1 sec, for example 5 messages will be transmitted and received in about 5 seconds.
 - The SA algorithm will run every 5 seconds and run for 200 iterations, i.e. 1000 seconds in simulation time.
 - Virtual Source and Sink are used in order to better simulate our algorithm. Thus virtual Source is linked with the UEs and virtual Sink is linked with APs respectively.

- The map (Figure 10), has been created from scratch, in sumo simulator a 7 by 7 grid with two lanes in every direction. Two diagonal Aerial “roads” (illustrated with red color) used by Drones in order to provide better coverage in situations that rovers cannot.
- One junction from another is 100 meters apart, giving a total of 490000 square meter area.
- UEs, MAPs and Aps have a starting wireless transmission coverage range of about 150, 200 and 250 meters respectively (mentioned as 1st case) and then this range expands.
- All the entities in our simulation can exchange information regarding their ids, speed, position and direction of movement and even their battery life. Hence every node have the knowledge of the surrounding area and can create a list of its one hop neighbors.
 - From the exchange messages an adjacency matrix of all the network is created.
 - We compute the distance between every two entities that are used for the Objective Function (OF) computation. The objective function has been elaborated and presented in detail in the second deliverable (D2) of this study.
 - For the UEs and MAPs (except Drones) a maximum speed of 5m/s has been set, i.e. about 18Km/h.
 - Drones which fly above ground have speeds at about 36Km/h (10m/s), but they lower their speed when near APs or UEs giving them more connection time with those entities and move with their higher speeds during the middle sections of their aerial lanes (Figure 10).

8.3. Maximum Flow (MF) Algorithm Simulation settings

In the same way as SA, the simulation setting for the MF algorithm are provided below.

- The simulation will start the computations of the Maximum Flow (MF) algorithm when the roads are fully populated and run for s seconds.
 - Beacon intervals are set to 1 sec, for example 5 messages will be transmitted and received in about 5 seconds.
 - The MF algorithm will run every 5 seconds and run for 200 iterations, i.e. 1000 seconds in simulation time.
 - Virtual Source and Sink are used in order to better simulate our algorithm. Thus virtual Source is linked with the UEs and virtual Sink is linked with APs respectively.
 - For the map (Figure 3), has been created from scratch, in sumo simulator a 7 by 7 grid with two lanes in every direction. Two diagonal Aerial “roads” (illustrated with red color) used by Drones in order to provide better coverage in situations that rovers cannot.
 - One junction from another is 100 meters apart, giving a total of 490000 square meter area.
 - UEs, MAPs and Aps have a starting wireless transmission coverage range of about 150, 200 and 250 meters respectively (mentioned as 1st case) and then this range expands.
 - All the entities in our simulation can exchange information regarding their ids, speed, position and direction of movement and even their battery life. Hence every node have the knowledge of the surrounding area and can create a list of its one hop neighbors.

- From the exchange messages an adjacency matrix of all the network is created.
- We compute the distance between every two entities that are used for the Objective Function (OF) computation. The objective function has been elaborated and presented in detail in the second deliverable (D2) of this study.
 - The computation of capacity of a link (cap) and the communication cost (ct) is done based on the distance of one entity to another, proportionally to their transmission areas, their speed and positions.
 - Cap values are given to each link from 0 to 10, with 0 meaning that informations cannot be send and 10 is the best connection between two entities.
 - For the UEs and MAPs (except Drones) a maximum speed of 5m/s has been set, i.e. about 18Km/h.
 - Drones which fly above ground have speeds at about 36Km/h (10m/s), but they lower their speed when near APs or UEs giving them more connection time with those entities and move with their higher speeds during the middle sections of their aerial lanes (*Figure 10*).

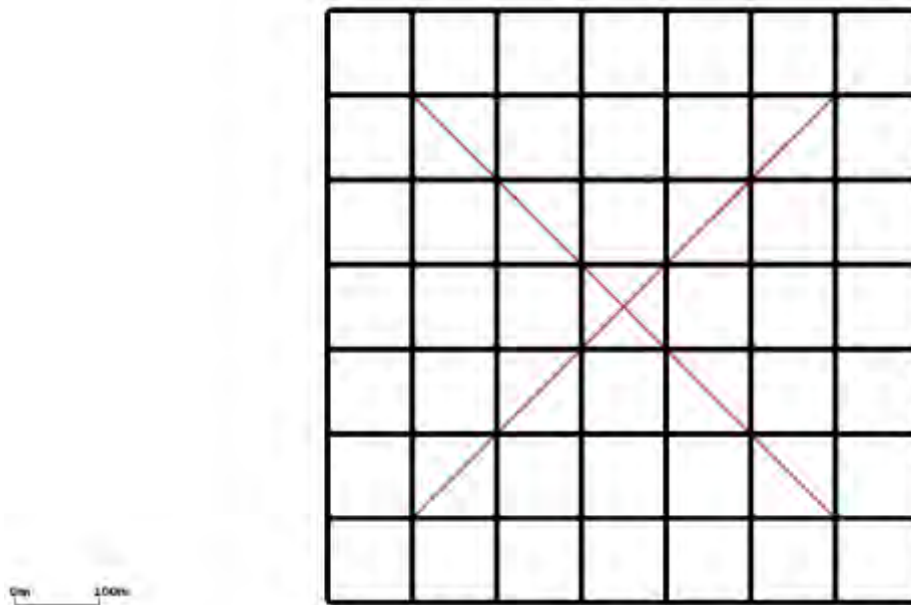


Figure 10: Grid created in SUMO for the simulation.

Figure 11 illustrates the defined topology with all the entities and their instantaneous positions. In our experimentation topology participate two groups of UEs, two groups of MAPs; the Rovers presented as MAP_CAR in this screenshot of the SUMO simulator and the Drones as MAP_DRONES and also two stationary APs at the positions 1 and 2 in our grid. The UEs can move inside the light blue area and the MAPs only at the yellow area while the MAP Drones can fly anywhere in the red X road providing better coverage inside our map.

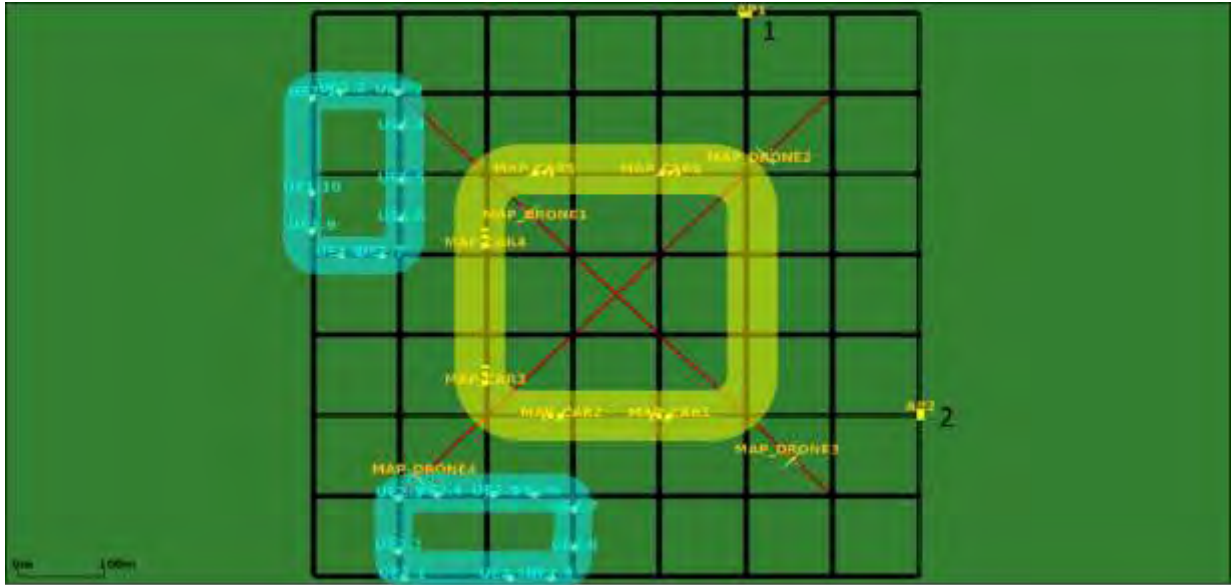


Figure 11: Screenshot from SUMO with the simulation topology with the different entities.

Figure 12 illustrates a screenshot from the OMNet++ simulator. Specifically, the blue arrows correspond to an indicative paths of the beacons that are sent from one node (MAP) to its vicinity, demonstrating the coverage area of MAPs in our simulation.

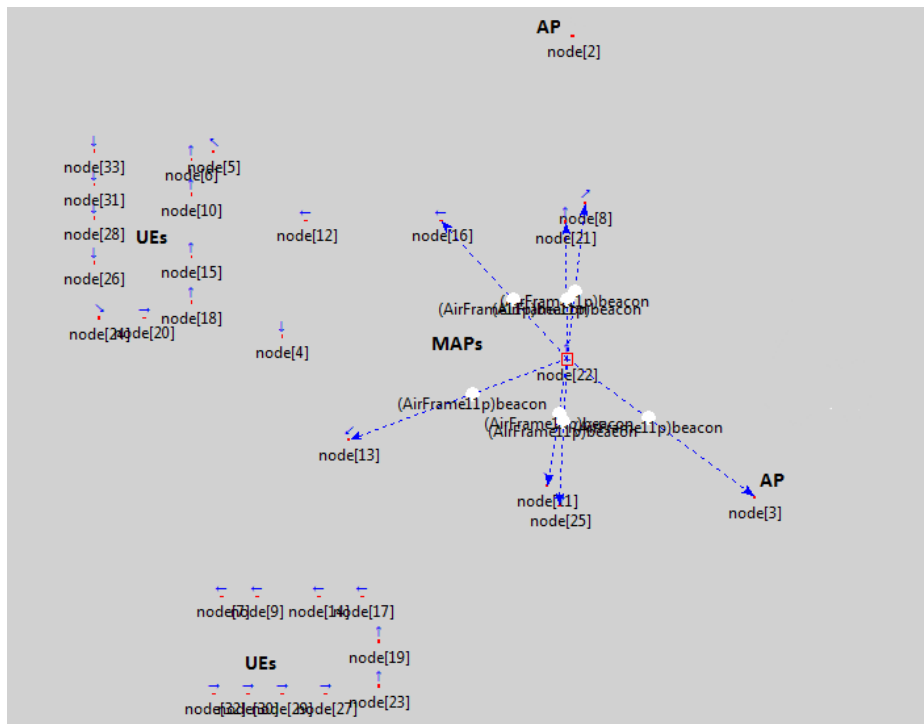


Figure 12: Screenshot from the OMNet++ simulator illustrating communication with beacons.

Chapter 9

9. Evaluation

9.1. Evaluation Methodology of SA Algorithm

In order to evaluate the SA algorithm, some Scenarios have been created in our simulation with the general values of the parameters illustrated at Table 1.

Table 1: Simulation parameters

Parameter	Value
Terrain size	700m x 700m
Grid size	7 x 7
Number of APs	2
Number of UEs	20

First set of results

As mentioned above our network is considered that comprises two APs and two sets of UEs with 10 users each giving a total of 20 users and a number of MAPs that will change in every scenario.

Explanation of all the Figures presented in this chapter will be provided as an overview at the end of this section.

9.1.1. First Scenario

For our first scenario we have used 10 MAPs and specifically 6 Rovers and 4 Drones with the range of coverage as referred to in Table 2.

Table 2: Simulation parameters for the first scenario

Parameter	Value
Number of MAPs total	10
Drones	4
Rovers	6
1 st test case: UEs, MAPs, APs range of coverage	150-200-250m
2 nd test case: UEs, MAPs, APs range of coverage	170-220-270m

3 rd test case: UEs, MAPs, APs range of coverage	200-250-300m
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Figure 13 illustrates the progress of the OF during the iterations of the SA algorithm. It can be seen that the line is not continuous, this phenomenon is due to the small number of the entities participating in our simulation and also that for the first case test the ranges are not big enough to compensate for the low number of MAPs.

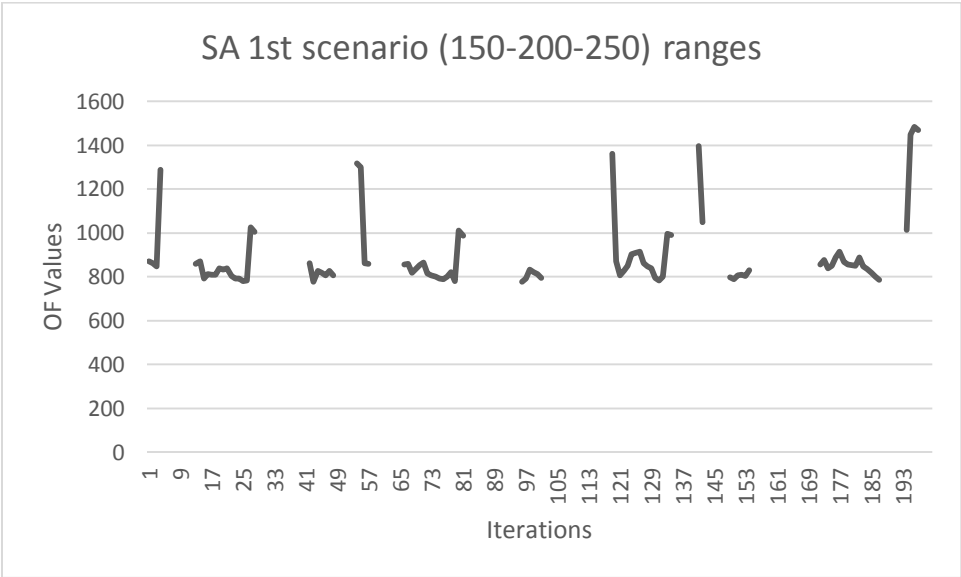


Figure 13: OF values for each iteration of the SA algorithm 1st scenario – 1st case.

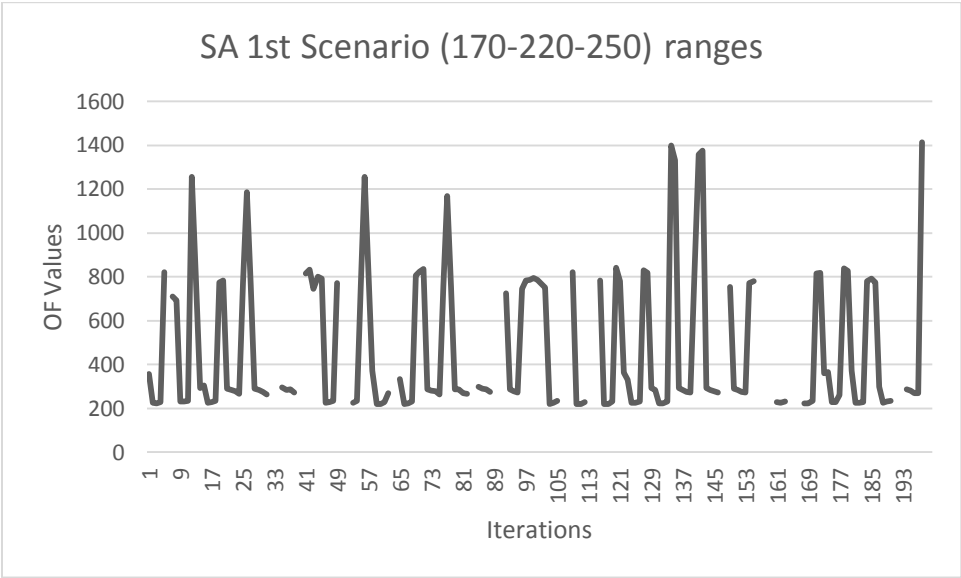


Figure 14: OF values for each iteration of the SA algorithm 1st scenario - 2nd case.

Having the same number of entities but with larger coverage areas, Figure 14 illustrate that the line has only some pieces missing and for Figure 15 the line is smoother without any values missing.

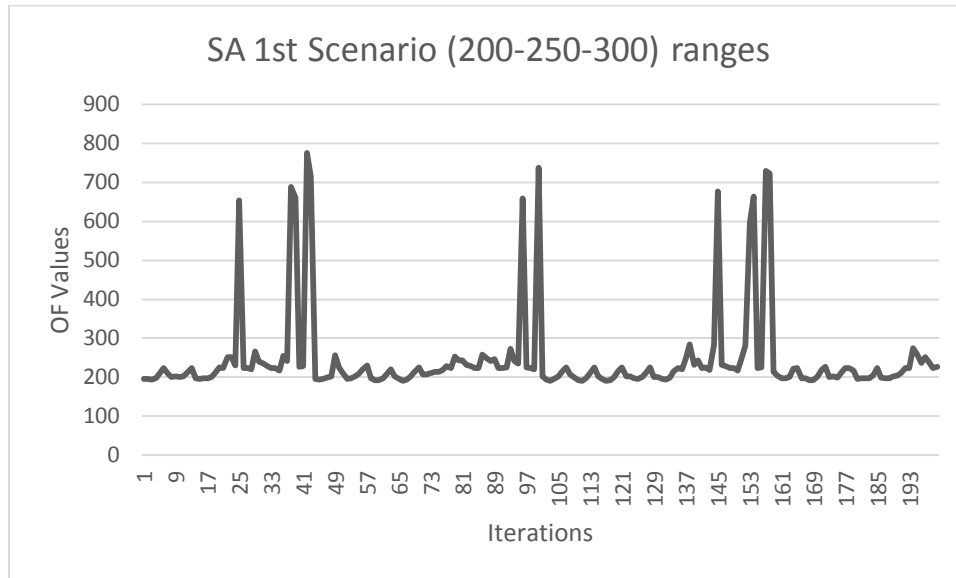


Figure 15: OF values for each iteration of the SA algorithm 1st scenario – 3rd case.

9.1.2. Second Scenario

For the second scenario the same number of UEs and APs have been kept and have been also added two Drones that give us a total number of 12 MAPs. Three different cases of transmission areas will be also tested.

Table 3: Simulation parameters for the second scenario

Case	Position
Number of MAPs total	12
Drones	6
Rovers	6
1 st test case: UEs, MAPs, APs range of coverage	150-200-250m
2 nd test case: UEs, MAPs, APs range of coverage	170-220-270m
3 rd test case: UEs, MAPs, APs range of coverage	200-250-300m

As previously mentioned, Figure 16 illustrates some void spaces but with lower frequency than before (Figure 13). Figure 17 and Figure 18 show that there was a connected network for longer periods of time or for the entire simulation.

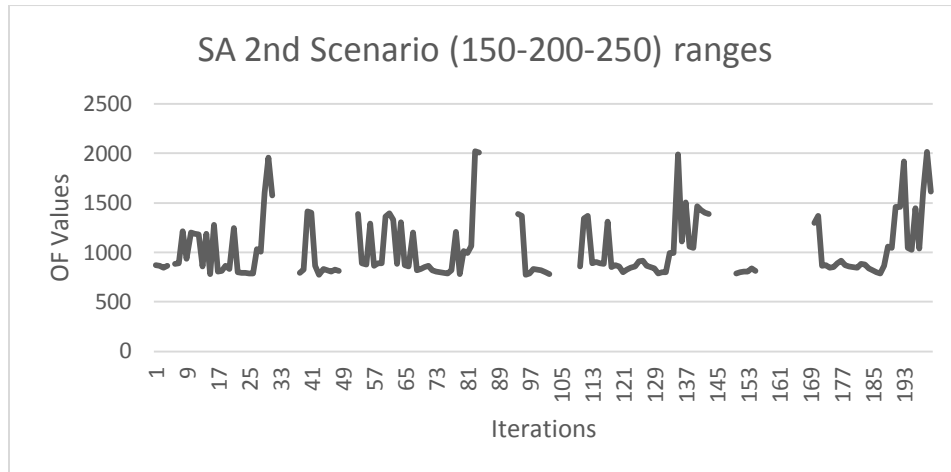


Figure 16: OF values for each iteration of the SA algorithm 2nd scenario – 1st case.

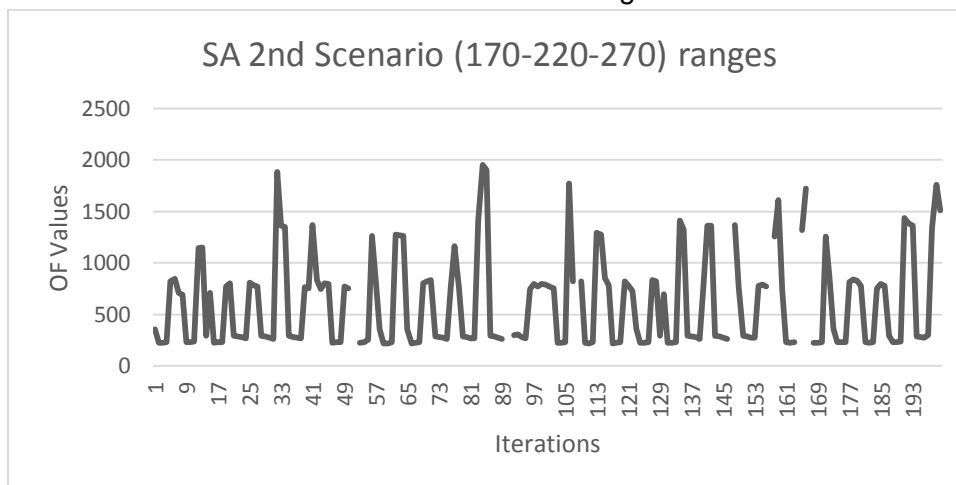


Figure 17: OF values for each iteration of the SA algorithm 2nd scenario - 2nd case.

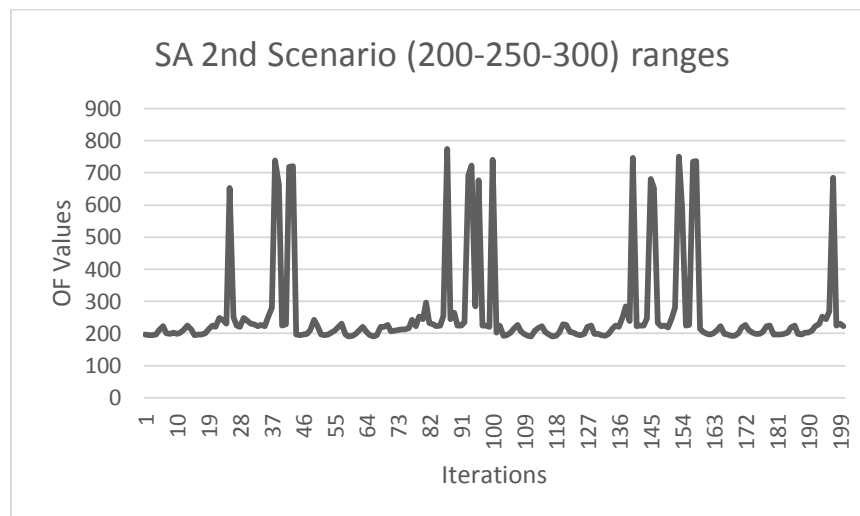


Figure 18: OF values for each iteration of the SA algorithm 2nd scenario – 3rd case.

9.1.3. Third Scenario

At the third and last scenario we have once again add 2 more entities (this time Rovers) with 14 MAPs in total as *Table 4* shows.

Table 4: Simulation parameters for the third scenario

Parameter	Value
Number of MAPs total	14
Drones	6
Rovers	8
1 st test case: UEs, MAPs, APs range of coverage	150-200-250m
2 nd test case: UEs, MAPs, APs range of coverage	170-220-270m
3 rd test case: UEs, MAPs, APs range of coverage	200-250-300m

In this case the number of the MAPs that are present and moving around our simulation area are enough in order to fully resolve any communication request even if the ranges are small. This result is shown clearly in Figure 19.

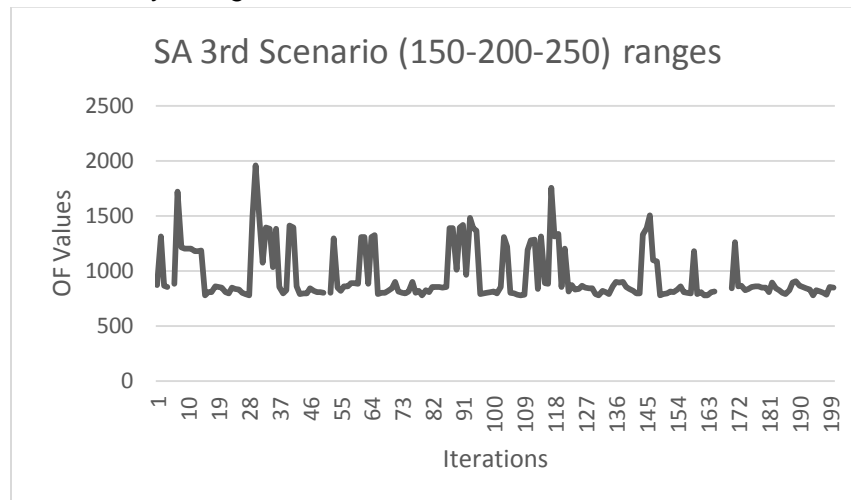


Figure 19: OF values for each iteration of the SA algorithm 3rd scenario - 1st case.

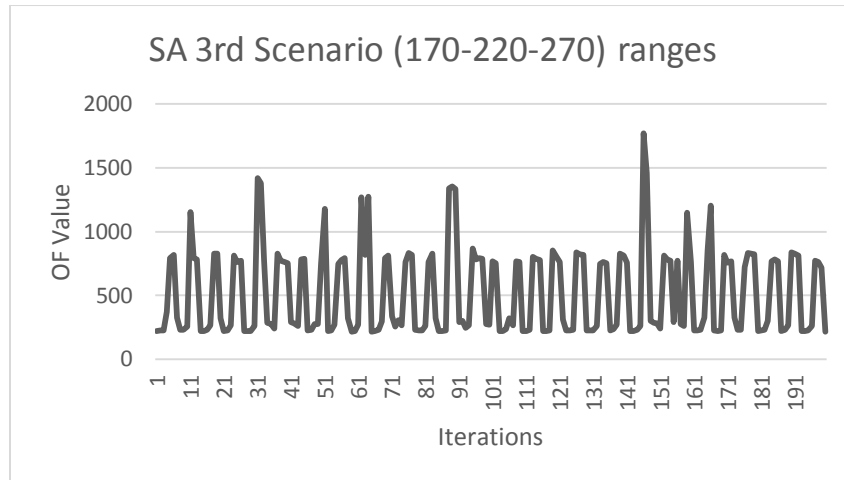


Figure 20: OF values for each iteration of the SA algorithm 3rd scenario - 2nd case.

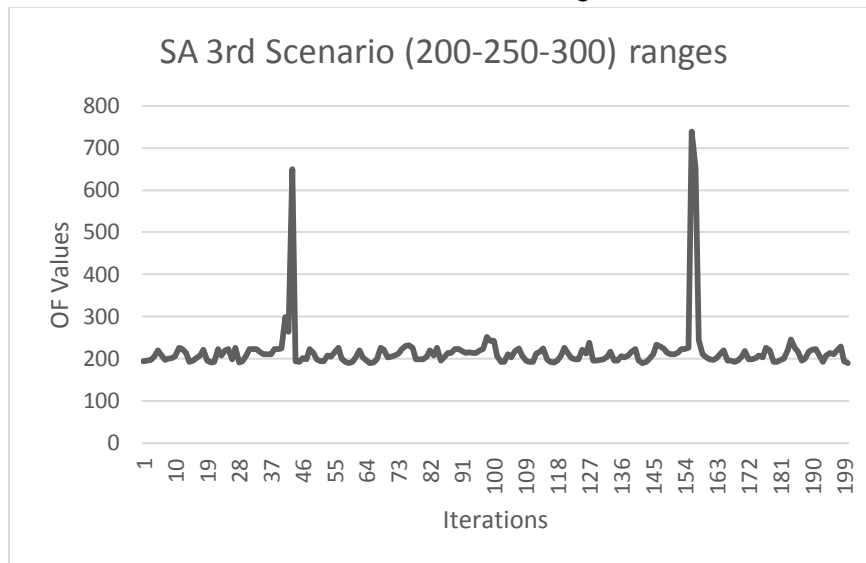


Figure 21: OF values for each iteration of the SA algorithm 3rd scenario – 3rd case.

9.2. Result Overview

Final we present the results from our tests for every scenario and case, providing the best solution SA algorithm had generated and the number of iteration that happened.

Table 5: Simulation results

CASE	Best SA Solution
1 st Scenario, 1 st test case	OF Value: 776, Iteration: 96
1 st Scenario, 2 nd test case	OF Value: 219, Iteration: 59
1 st Scenario, 3 rd test case	OF Value: 191, Iteration: 66
2 nd Scenario, 1 st test case	OF Value: 776, Iteration: 43

2 nd Scenario, 2 nd test case	OF Value: 218, Iteration: 117
2 nd Scenario, 3 rd test case	OF Value: 191, Iteration: 59
3 rd Scenario, 1 st test case	OF Value: 778, Iteration: 163
3 rd Scenario, 2 nd test case	OF Value: 217, Iteration: 187
3 rd Scenario, 3 rd test case	OF Value: 190, Iteration: 59

All these test case scenarios has given us important information through the graphs (Figure 13 to Figure 21) already presented considering the topology and the settings used. The scattering that the first test case of each scenario graphs (Figure 13, Figure 16, Figure 19) illustrate a problem that might present in a situation that a small group of MAPs try to cover a large area, with many users that want to connect with them and send/receive data to an AP at a remote location. In those situations the MAPs need to move from one place to another in order to realize these communications with all the users in the area (UEs).

With that in mind we can analyze these results and understand how the SA algorithm may solve the problem of a continuously changing topology.

The second test case of every scenario corresponding to Figure 14, Figure 17 and Figure 20, show that the multiple service the MAPs need to provide can be solved via a higher density of MAPs or with the use of higher transmission ranges for the entities. This time the graphs lines are more contiguous than before, which means that the network is connected at almost all the time.

At last, the highest transmission ranges that we have used in our simulation have given us the graphs for 3rd test case of each scenario (Figure 15, Figure 18 and Figure 21). From the experiments conducted, we realize that even if we have 10 or 14 MAPs the outcome is quite the same. The network is connected at almost all times and the algorithm generate paths with the lowest OF values as shown in Table 5 and the iterations kept without changes at under 60. Small ranges create a multi-hop network environment resulting in higher computation time and greater OF values as opposed to bigger transmission areas that cover larger areas and create a denser network.

Also Figure 14, Figure 17 and Figure 20 show that these simulated environments are not too stable. These graphs illustrate the OF Values that the algorithm compute have a range from 200 up to a higher value of about 800 without considering some spikes (which could be due to the great mobility and alternation of the network topology). From these figures we conclude that these transmission ranges proportional to the environment and with not any connection to the density of the network (10 to 14 MAPs) do not give us a good result even if the best OF value is fairly low.

Finally Table 12 present the average values of the objective function of the maximum flow algorithm execution for every test case in our experimentation. The 3rd test of every scenario gave us the lowest values of the OF, meaning that in those cases the network had better signal quality than all the other tests.

Table 6: Average OF values for every test case.

CASE	Average OF Value
1 st Scenario, 1 st test case	889
1 st Scenario, 2 nd test case	470

1 st Scenario, 3 rd test case	245
2 nd Scenario, 1 st test case	1042
2 nd Scenario, 2 nd test case	610
2 nd Scenario, 3 rd test case	260
3 rd Scenario, 1 st test case	955
3 rd Scenario, 2 nd test case	518
3 rd Scenario, 3 rd test case	216

Figure 22 and Figure 24 illustrate the outcome of the simulation using the SA algorithms as already explained. In Figure 24 the transmission ranges are a little bigger, giving the opportunity of connection between nodes at higher distances. Thus the algorithm gives a solution with less hops i.e., has chosen only two of the available MAPs as opposed to 4 MAPs in Figure 22, in order to create the path from the UE to the AP.

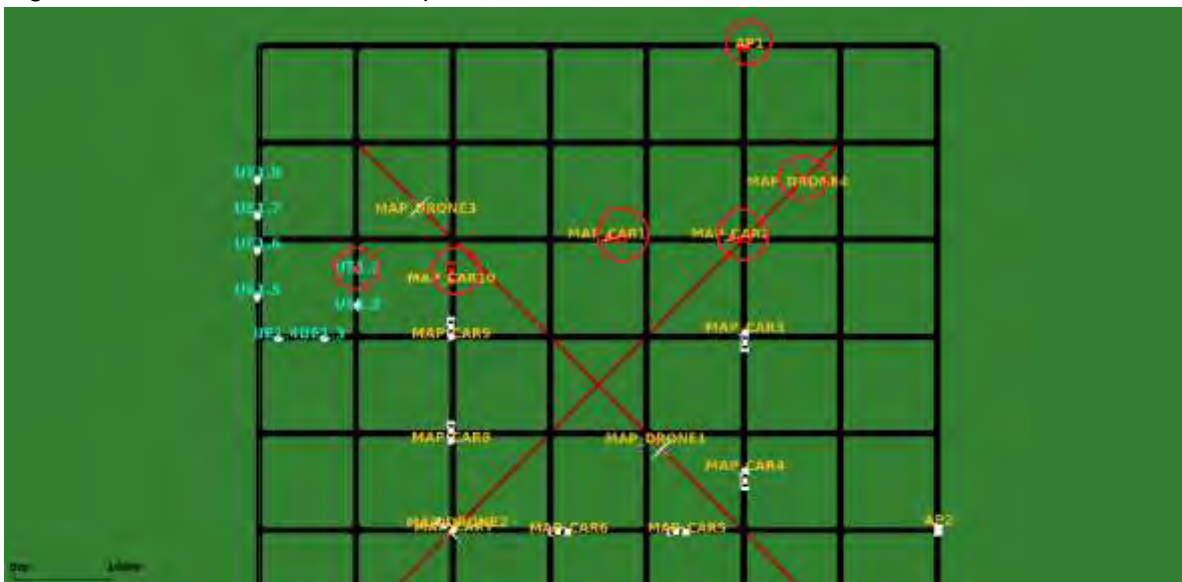


Figure 22: Screenshot from the output path of Simulated annealing (SA) algorithm.

Figure 23 illustrate an approximation of the environment that Drones and Rover will work together in order to resolve any communication problems that demanding environments could present.

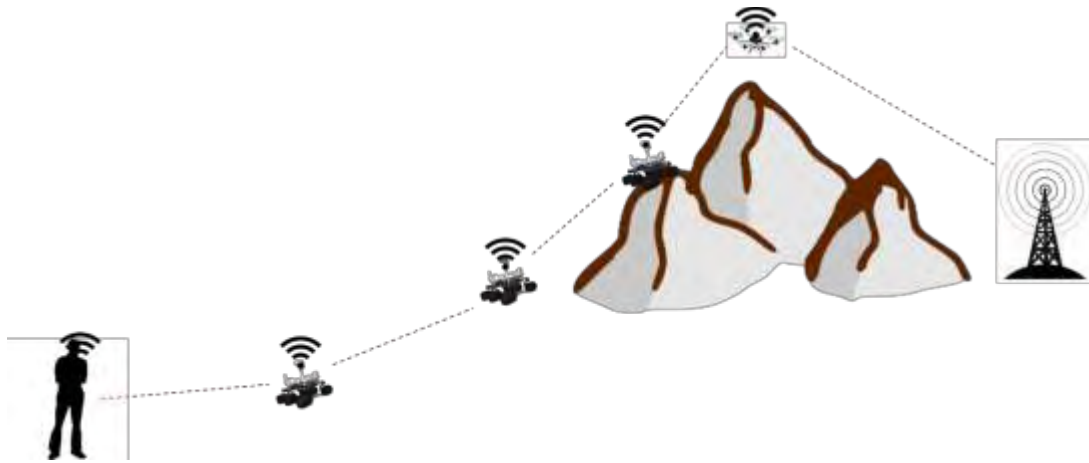


Figure 23: Schematic approximation of the SA output.

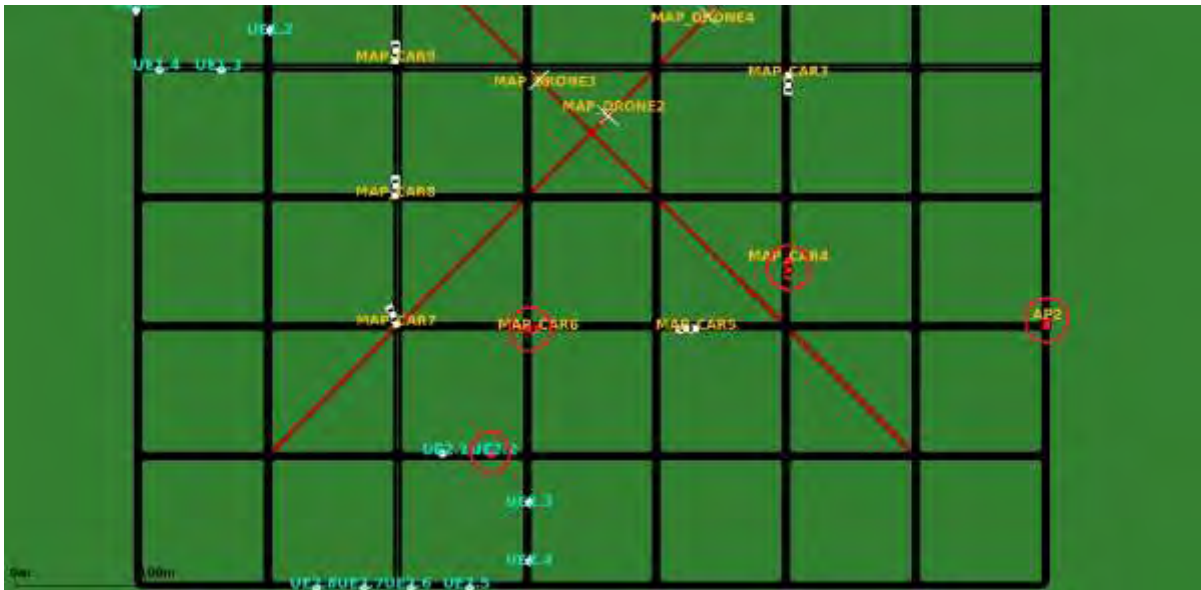


Figure 24: Screenshot from the output path of Simulated annealing (SA) algorithm.

9.3. Evaluation Methodology of MF Algorithm

In this section, indicative results for the evaluation of the solution will be provided. Methodology

In order to evaluate the MF algorithm, we have created some Scenarios in our simulation with the general values of the parameters illustrated in *Table 7*.

Table 7: Simulation parameters

Parameter	Value
Terrain size	700m x 700m
Grid size	7 x 7

Number of APs	2
Number of UEs	20

As mentioned above our network is considered that comprises two APs and two sets of UEs with 10 users each giving a total of 20 users and a number of MAPs that will change in every scenario.

The Maximum Flow algorithm always compute the max flow from every network. As shown in *Figure 6* the flow of every path has to be 0 or 1, so in our simulation the MF algorithm is creating multiple paths (of Flow=1) in order to create the maximum flow output that we need. For example one computation of the MF algorithm can produce a Max Flow output of 4, meaning that there are 4 paths from 4 different users at this distinct time. In this chapter will be provided only the best output of the MF algorithm, i.e. the best path based on the OF value of every path.

Explanation of all the Figures presented in this chapter will be provided an overview at the end of this section.

9.3.1. First Scenario

For our first scenario we will run the simulation with 10 MAPs and specifically 6 Rovers and 4 Drones with the range of coverage as referred to in *Table 8*.

Table 8: Simulation parameters for the first scenario

Parameter	Value
Number of MAPs total	10
Drones	4
Rovers	6
1 st test case: UEs, MAPs, APs range of coverage	150-200-250m
2 nd test case: UEs, MAPs, APs range of coverage	170-220-270m
3 rd test case: UEs, MAPs, APs range of coverage	200-250-300m

Figure 25 illustrates the progress of the OF during the iterations of the MF algorithm. As we can see the line is not continuous, this phenomenon is due to the small number of the entities participating in our simulation and also that for the first case test the ranges are not large enough to compensate for the low number of MAPs. Also the cap and ct values used in MF algorithm can create this phenomenon as well. For example if the distance between two entities are at the end of their transmission ranges and the link is not configured for more than one flow, then maybe the computed result is zero (cap=0) and the link does not exist.

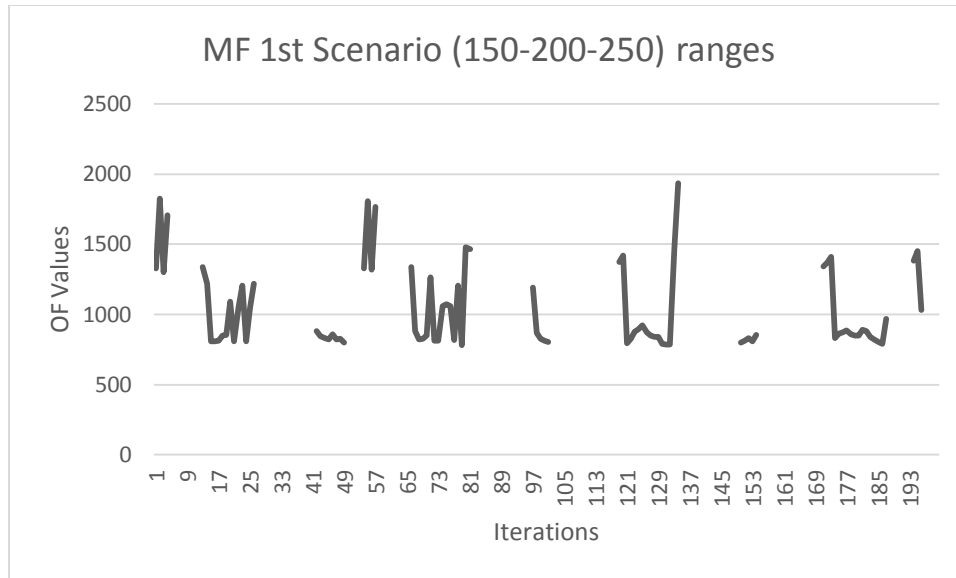


Figure 25: OF values for each iteration of the MF algorithm 1st scenario – 1st case.

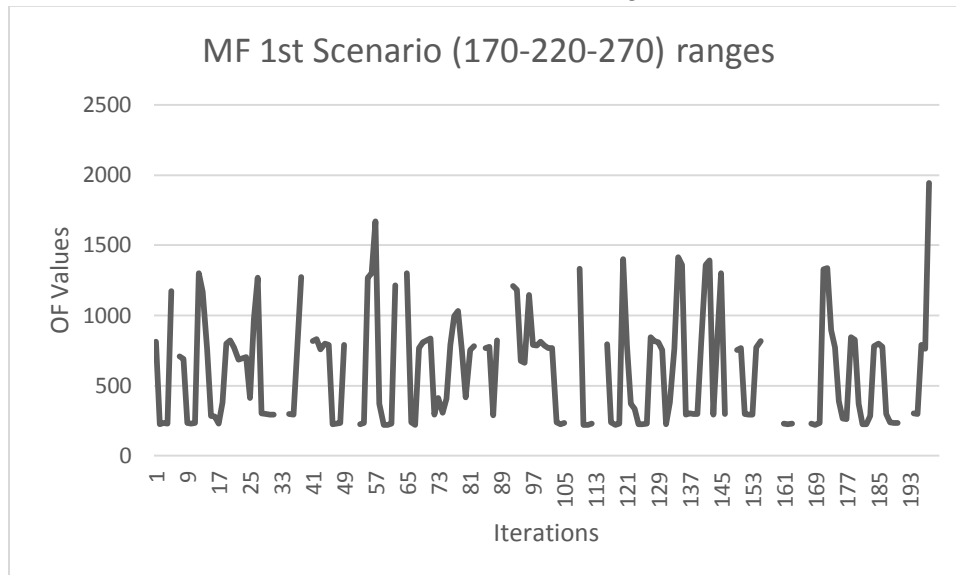


Figure 26: OF values for each iteration of the MF algorithm 1st scenario – 2nd case.

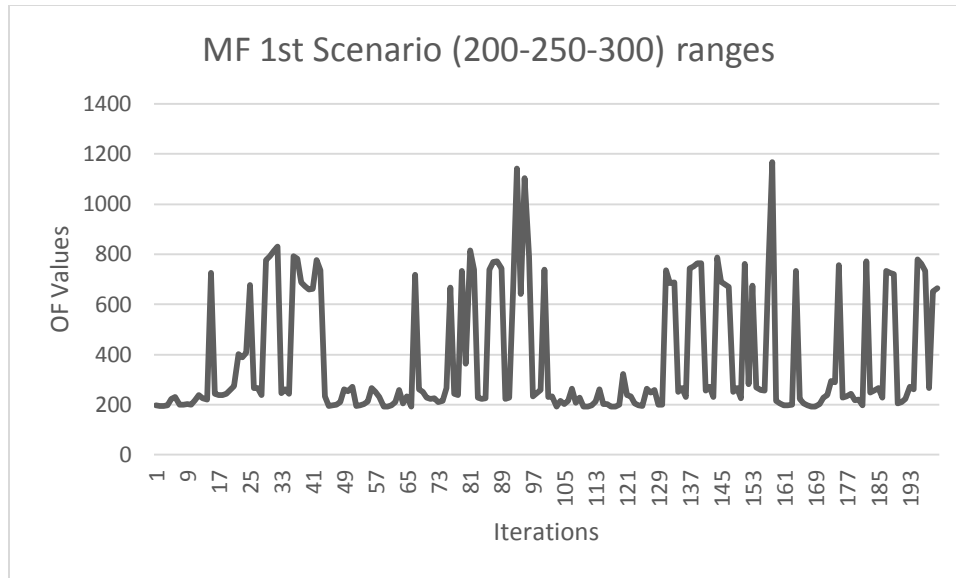


Figure 27: OF values for each iteration of the MF algorithm 1st scenario – 3rd case.

Having the same number of entities but with larger coverage areas we can see from the Figure 26 that the line has only some pieces missing and for the Figure 27 the line is perfect without any values missing.

9.3.2. Second Scenario

For the second scenario we keep the same number of UEs and APs and we add +2 Drones that give us a total number of 12 MAPs. We will also test three different cases of transmission areas.

Table 9: Simulation parameters for the second scenario

Case	Position
Number of MAPs total	12
Drones	6
Rovers	6
1 st test case: UEs, MAPs, APs range of coverage	150-200-250m
2 nd test case: UEs, MAPs, APs range of coverage	170-220-270m
3 rd test case: UEs, MAPs, APs range of coverage	200-250-300m

As previously Figure 28 illustrates some void spaces but with lower frequency than before (Figure 25). Figure 29 and Figure 30 show that we had a connected network for longer periods of time or for the entire simulation.

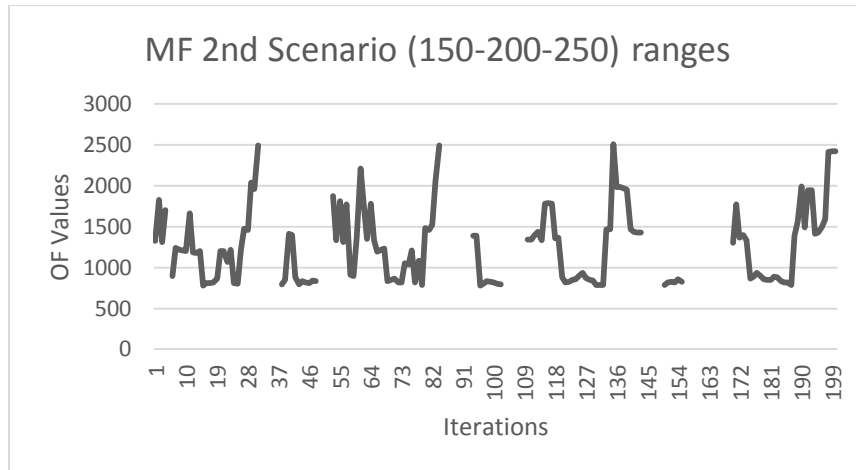


Figure 28: OF values for each iteration of the MF algorithm 2nd scenario – 1st case.

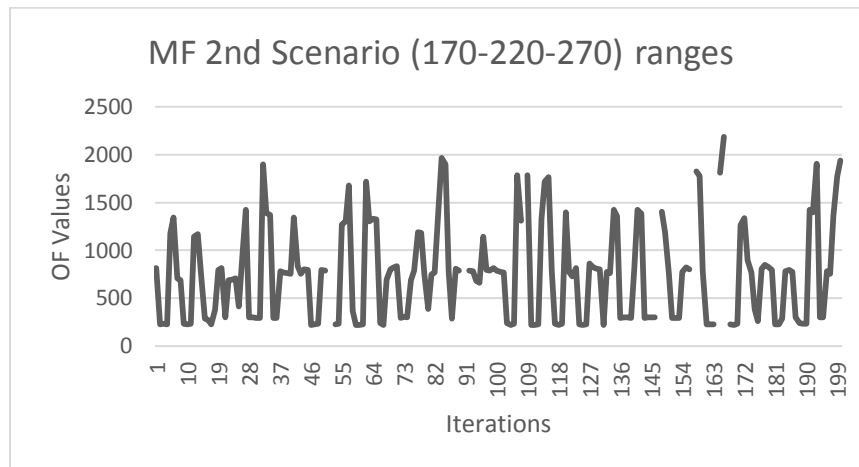


Figure 29: OF values for each iteration of the MF algorithm 2nd scenario – 2nd case.

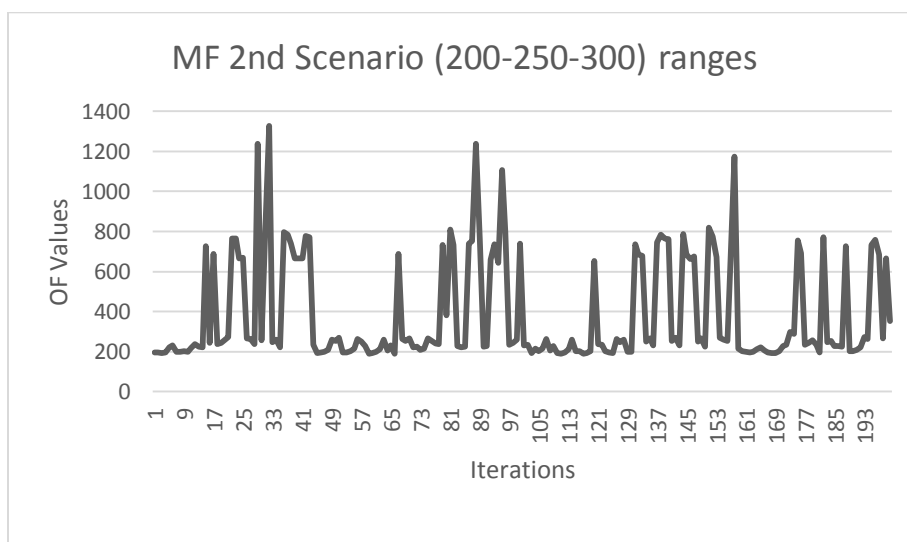


Figure 30: OF values for each iteration of the MF algorithm 2nd scenario – 3rd case.

9.3.3. Third Scenario

At the third and last scenario we have once again add 2 more entities (this time Rovers) with 14 MAPs in total as *Table 10* shows.

Table 10: Simulation parameters for the third scenario

Parameter	Value
Number of MAPs total	14
Drones	6
Rovers	8
1 st test case: UEs, MAPs, APs range of coverage	150-200-250m
2 nd test case: UEs, MAPs, APs range of coverage	170-220-270m
3 rd test case: UEs, MAPs, APs range of coverage	200-250-300m

In this case the number of the MAPs that are present and moving around our simulation area are enough in order to fully resolve any communication request even if the ranges are small.

This result is shown clearly in Figure 31.

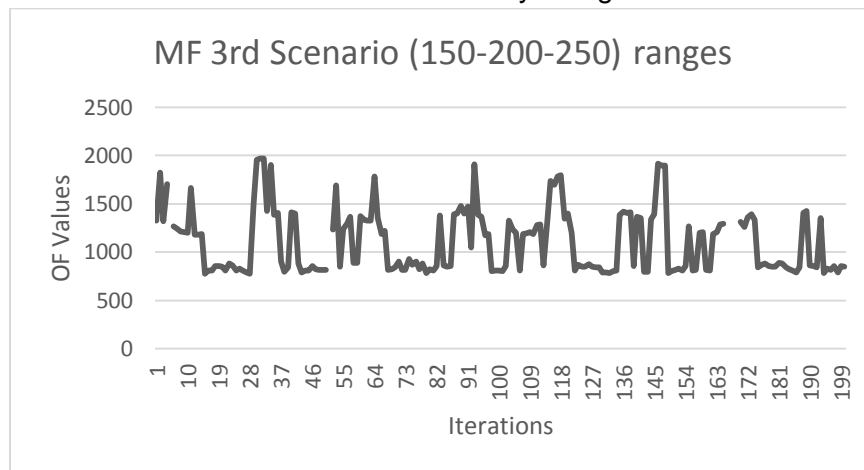


Figure 31: OF values for each iteration of the MF algorithm 3rd scenario – 1st case.

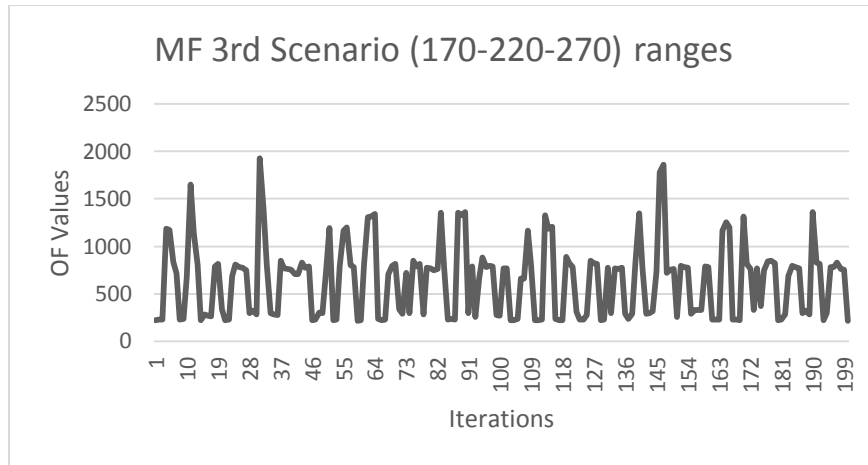


Figure 32: OF values for each iteration of the MF algorithm 3rd scenario – 2nd case.

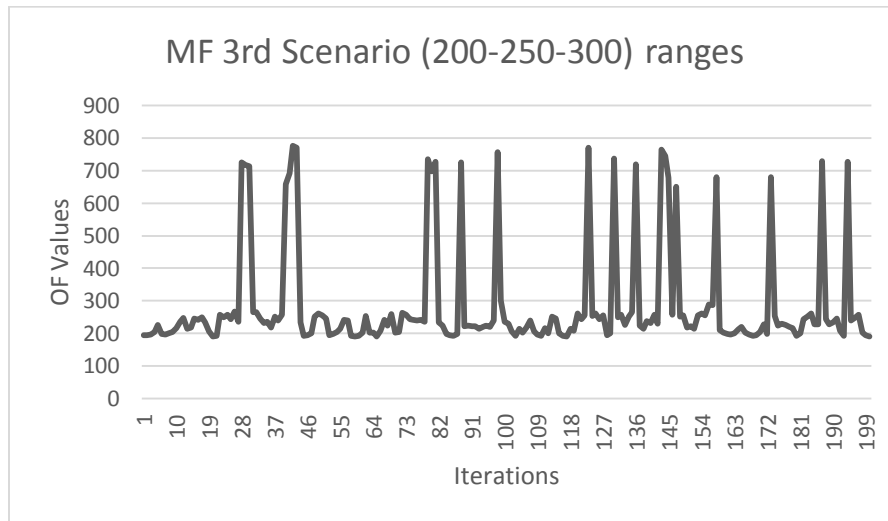


Figure 33: OF values for each iteration of the MF algorithm 3rd scenario – 3rd case.

9.4. Result Overview

Final we present the results from our tests for every scenario and case, providing the best solution MF algorithm had generated and the number of iteration that happened.

Table 11: Simulation results

CASE	Best MF Solution
1 st Scenario, 1 st test case	OF Value: 783, Iteration: 79
1 st Scenario, 2 nd test case	OF Value: 219, Iteration: 59
1 st Scenario, 3 rd test case	OF Value: 191, Iteration: 66
2 nd Scenario, 1 st test case	OF Value: 779, Iteration: 15
2 nd Scenario, 2 nd test case	OF Value: 219, Iteration: 59
2 nd Scenario, 3 rd test case	OF Value: 191, Iteration: 59

3 rd Scenario, 1 st test case	OF Value: 779, Iteration: 15
3 rd Scenario, 2 nd test case	OF Value: 217, Iteration: 169
3 rd Scenario, 3 rd test case	OF Value: 190, Iteration: 59

As mentioned previously, the graphs Figure 25 to Figure 33 illustrate how the various scenarios and test cases that have been used in our simulation have provide us with a realization of the computation of the algorithm.

Maximum Flow algorithm can compute the best OF value fastest at the scenarios in which the density of the network is equal or over 12 MAPs and the transmission ranges are the smallest of all our experiments presented in *Table 11* (1st test case of 2nd and 3rd Scenario) Just like SA algorithm the MF is computing better OF values (better signal quality) in the 3rd test case of every scenario (Figure 27, Figure 30 and Figure 33) with around 61 iterations on average.

From the figures presented in this chapter for the MF algorithm, we can deduce that the algorithm does not compute quite continuously the same results for every iteration in all the graphs presented here. This realization is making it a little difficult to conclude to the best case scenario for the utilization of the algorithm. For this reason we have include *Table 12* which illustrates the average values of the Objective Function for each test case. This table can help us understand the differences between the 2nd and 3rd test case of every scenario we have been experimenting. The apparently same results that *Table 11* illustrate are actually different by a factor of two, meaning that for the MF algorithm gives good OF values at those cases.

Table 12: Average OF values for every test case.

CASE	Average OF Value
1 st Scenario, 1 st test case	1034
1 st Scenario, 2 nd test case	618
1 st Scenario, 3 rd test case	376
2 nd Scenario, 1 st test case	1261
2 nd Scenario, 2 nd test case	754
2 nd Scenario, 3 rd test case	381
3 rd Scenario, 1 st test case	1101
3 rd Scenario, 2 nd test case	639
3 rd Scenario, 3 rd test case	282

Figure 34, Figure 35, Figure 36 illustrate three outcomes of the simulation using the MF algorithm as already explained. The nodes that are colored green are the entities participating in the lowest OF value of all the paths the MF is creating.



Figure 34: Screenshot from the output path of Maximum Flow (MF) algorithm.

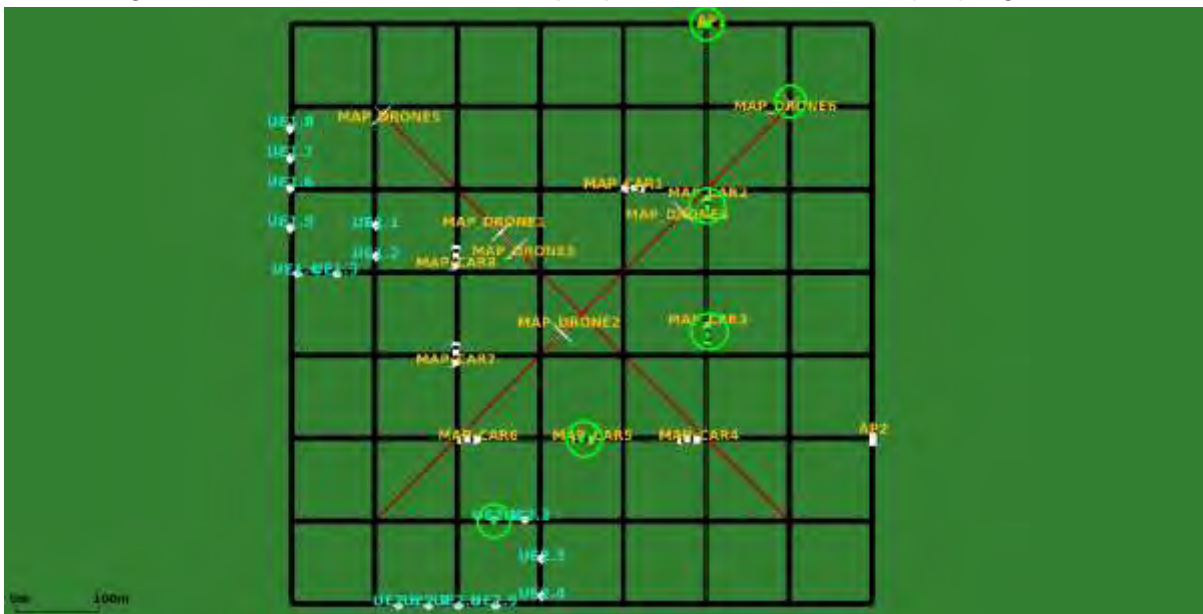


Figure 35: Screenshot from the output path of Maximum Flow (MF) algorithm.

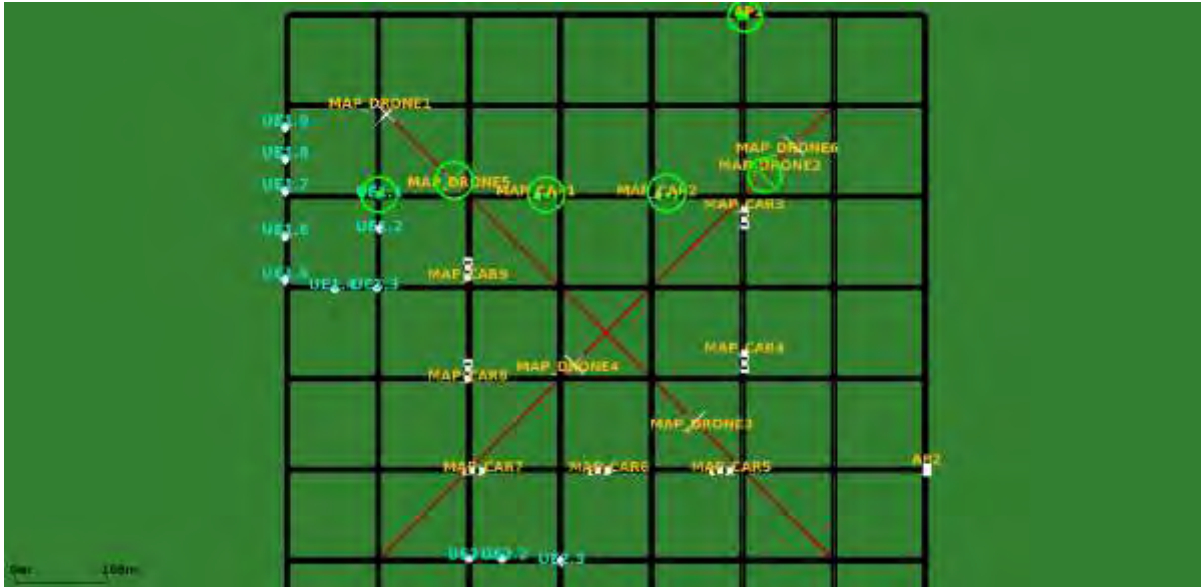


Figure 36: Screenshot from the output path of Maximum Flow (MF) algorithm.

Figure 37 shows the output of the MF algorithm for two paths in order to create the maximum flow of the network the current time. Every path has a flow of 1, so the total value is 2. The one path is coloured with the colour red and the second path is green. The blue node is a mutual node for these two paths and that why is painted with a different colour. Every time an entity is a part of two or more different paths is indicated with the colour blue.



Figure 37: Screenshot from the output path of Maximum Flow (MF) algorithm indicating two paths.

Chapter 10

10. Final Evaluation

In this section, comparative results for the evaluation of the solution will be provided.

10.1. Results

Table 13 presents all the test cases we have used in our simulation already presented previously, but also have been included 3 more experimentation cases (10,11 and 12).

Our simulation now has a density that ranges from 10 to 16 MAPs with 32 up to 38 nodes in total participating.

Table 13: Simulation parameters

Test Case	Drone Number	Car Number	UE Range (m)	MAP Range (m)	AP Range (m)
1	4	6	150	200	250
2	4	6	170	220	270
3	4	6	200	250	300
4	6	6	150	200	250
5	6	6	170	220	270
6	6	6	200	250	300
7	6	8	150	200	250
8	6	8	170	220	270
9	6	8	200	250	300
10	6	10	150	200	250
11	6	10	170	220	270
12	6	10	200	250	300

Figure 38 illustrates the best OF values solutions for the SA and MF algorithm with respect to the number of iterations past until these values where found. **On average, MF is faster compared to SA by around 32%.**

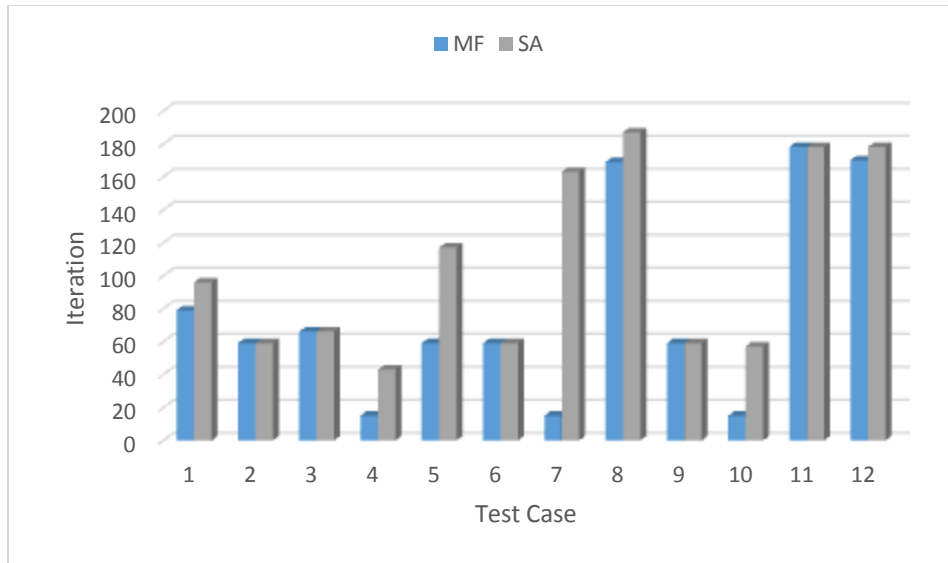


Figure 38: MF and SA for Best Objective Function value (average results)

Figure 39 presents the best OF values for every test case. As we can see these two algorithms are computing almost the same results for these various cases. Cases number 1, 4, 7 and 10 have the highest best values but all the others values are quite at the same level. We can understand that for transmission areas that range from 170 to 200 meters for the UEs and from 200 to 250 meters for the MAPs (via Table 13) the signal quality between these entities is at its best.

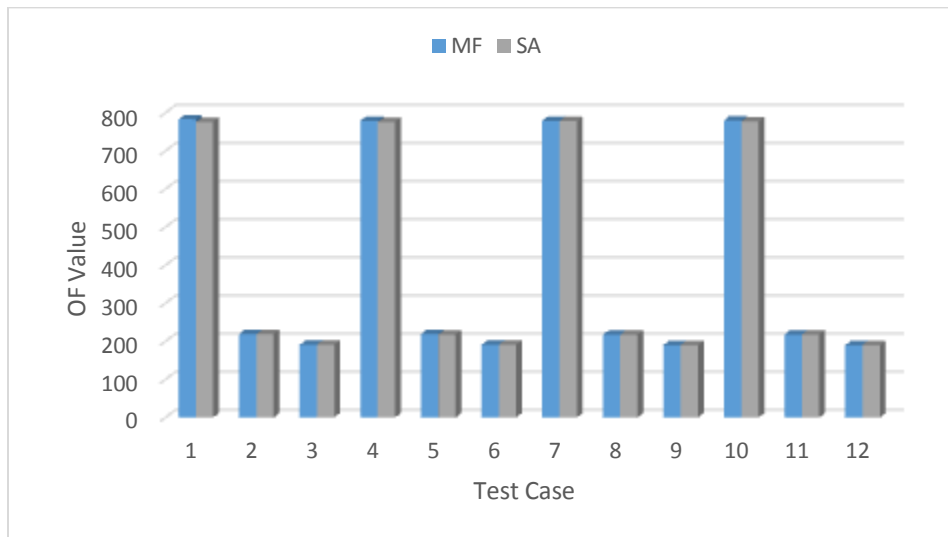


Figure 39: MF and SA Best values for Objective Function for all test cases (average results)

The bar chart from Figure 40 also provides us with some insights of the computation of the MF and SA algorithms. The SA algorithm produces only one path with each execution and tries to optimize the network connection (better signal quality) by choosing the best nodes as already explained previously. On the other hand, the MF algorithm computes the maximum value of paths based on the cap values (and for this reason it can produce up to 3 paths in average for some

test cases. Thus MF algorithm can provide a more distributed result in order to solve the problem via dividing the communication from one UE to one or more APs through multiple paths created by various MAPs nodes. Also by increasing the transmission area of the entities for only 20 meters can result to a higher number of paths computed from the MF algorithm. For example test case 7 is about 1.7 paths (average number) and the next case is at almost 2.25 paths and goes to a little lower than 3 at test case 9.

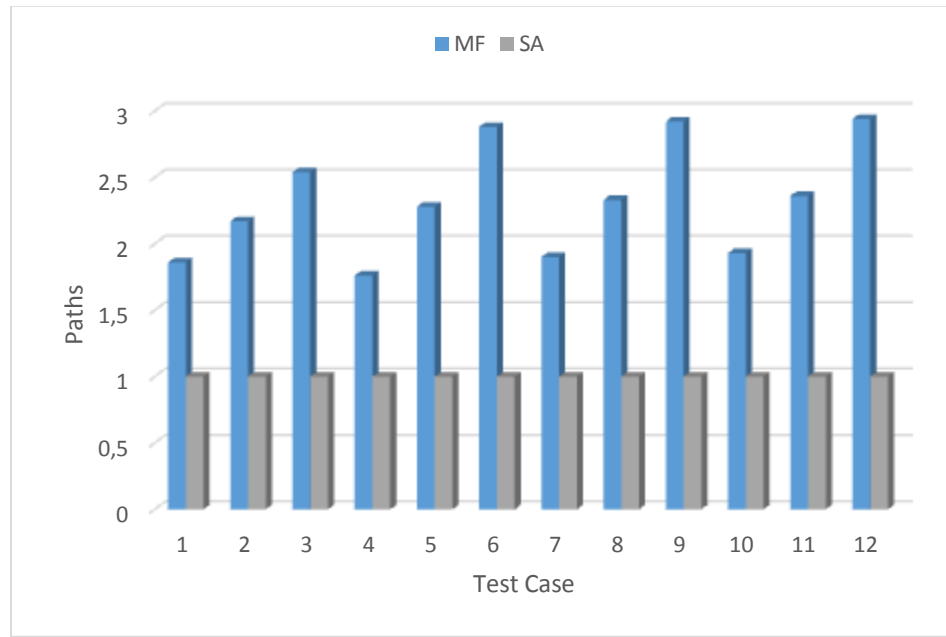


Figure 40: Number of Paths/Flows for MF and SA computations

Figure 41 clearly shows that the SA algorithms is better that MF algorithms when it comes to overall objective function values even if Figure 39 illustrate the same results for the best OF values of these two algorithms. Also the chart compares the OF values for the different changes of the transmission ranges, e.g. the case 5th is only the half value of the 4th case and again the 6th case is almost the half from the 4th case. Overall it highlights that there is no significant change in the average OF value even if the density of the network increase every 3 test cases.

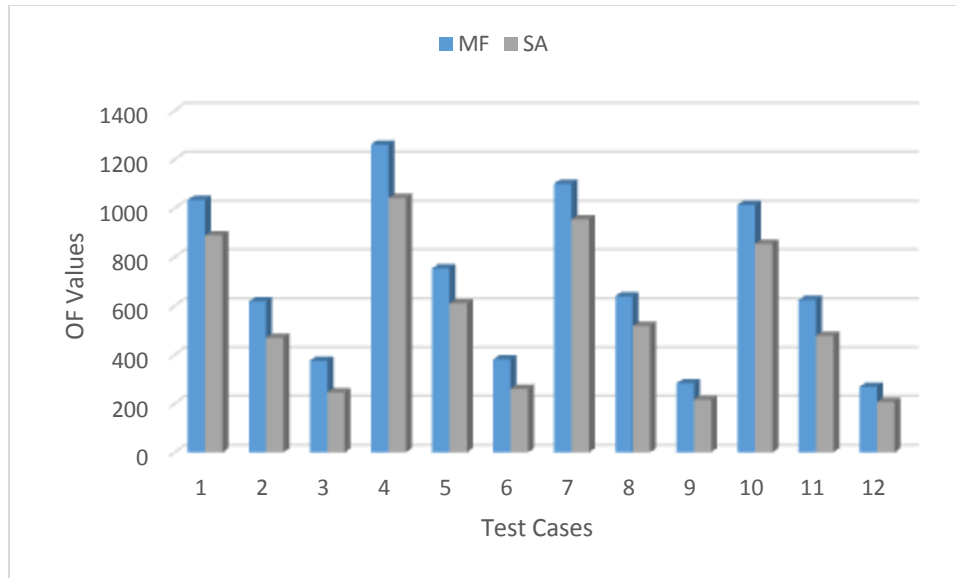


Figure 41: Average OF Values for MF and SA computations on each test case.

Figure 42, Figure 43 and Figure 44 are screenshots from the SUMO simulator that show the results from the MF and SA algorithms. The green color indicate the path created from the SA algorithm, red for the MF algorithm and with blue are the nodes that participate to both the paths produced from the algorithms. These different paths/topologies created by MF and SA generate the differences that we see in all the previous figures.

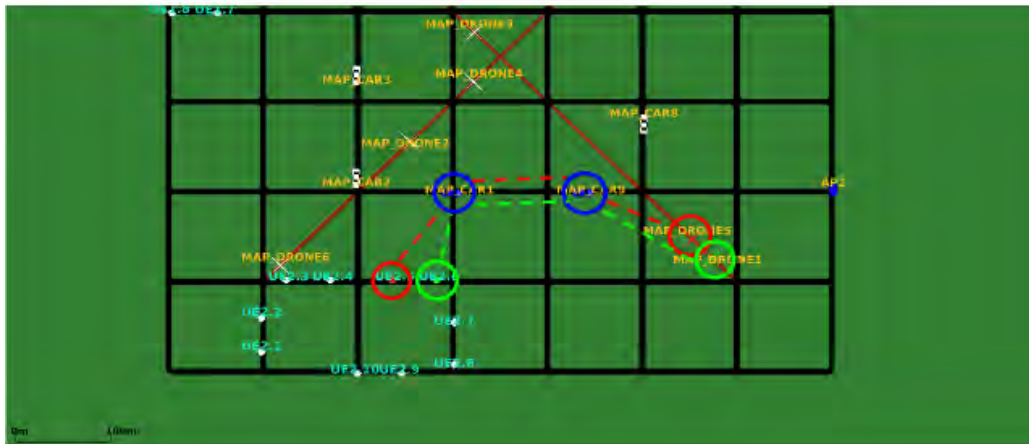


Figure 42: Screenshot of SUMO simulator for MF & SA algorithms

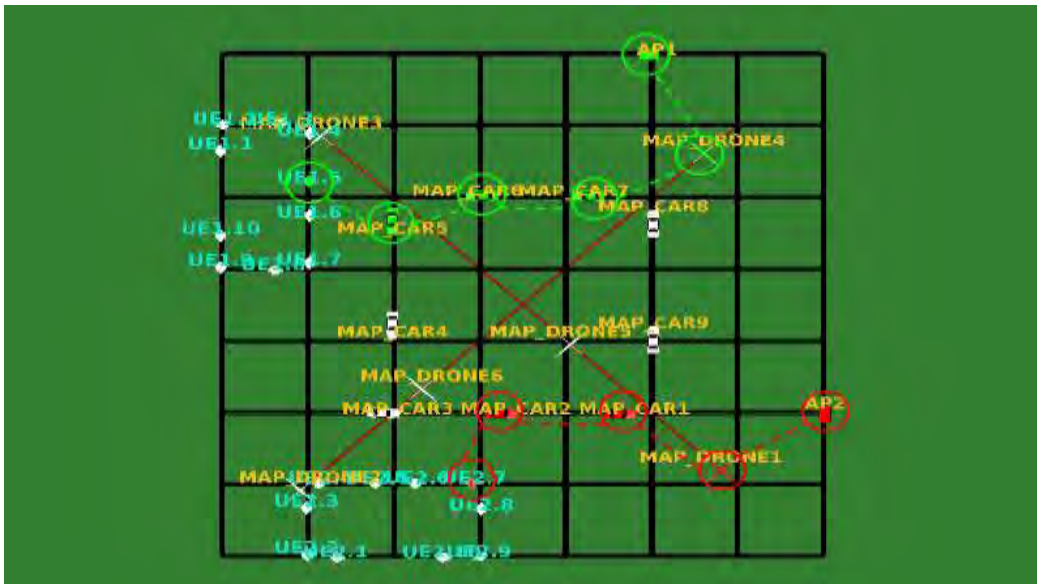


Figure 43: Screenshot of SUMO simulator for MF & SA algorithms

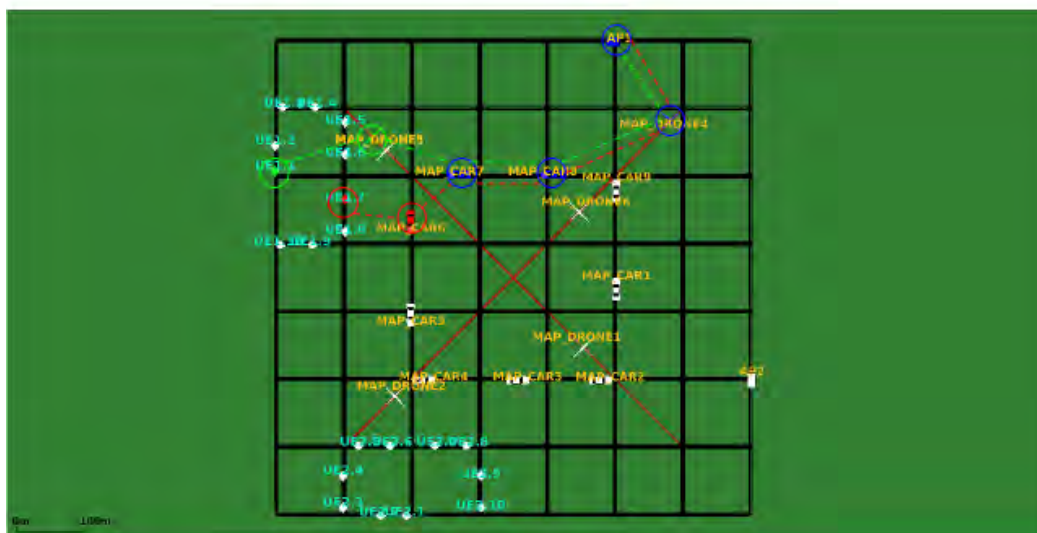


Figure 44: Screenshot of SUMO simulator for MF & SA algorithms

Chapter 11

11. Conclusions

This thesis has considered radio access points which are capable of moving and establishing a radio network connection with other entities (MAPs, APs, and UEs) for efficiently serving users in contexts under stringent conditions. Specifically, the complex problem of finding the best candidates from the MAPs in the vicinity based on their position has been solved by calculating the movement and communication costs, in order to provide connectivity to users in areas that have no infrastructure. The complex optimization problem was mathematically formulated and solved through two algorithms. The Simulated Annealing meta-heuristic and the Maximum Flow Algorithm. Results from testing the algorithms into different cases with different transmission areas and MAP densities showcased that the solutions provided by the Maximum Flow algorithm were around 32% better (in terms of finding the best Objective Function Value faster) than the Simulated Annealing algorithm. Also the MF algorithm produce more than one paths in average while SA only one at the time.

For future work the study will:

- Introduce machine leaning techniques Figure 45.
- Utilize more realistic environments Figure 46.
- Use more real-life scenarios in which usually are in need for applications like this study.

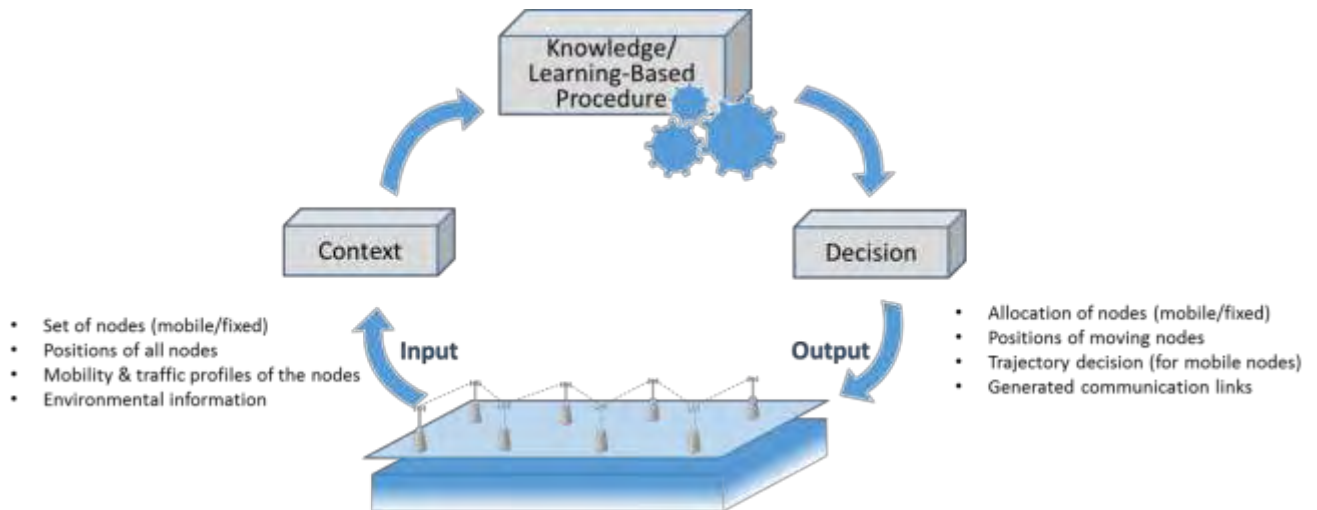


Figure 45: Machine learning procedure



Figure 46: Screenshot of SUMO simulator of realistic map (Athens, Greece)

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