IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 15 February 2024, accepted 17 April 2024, date of publication 29 April 2024, date of current version 14 May 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3394907

RESEARCH ARTICLE

Energy-Efficient Placement of Virtual Network Functions in a Wireless Mesh Network

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The research project VirtO4WMN providing the basis for this publication is partially funded by the Federal Ministry of Education and Research (BMBF) of the Federal Republic of Germany under grant number 13FH018IX6.

ABSTRACT In the context of service provisioning, the integration of Network Functions Virtualization (NFV) enhances the flexibility, scalability, and programmability of telecommunication networks. However, this integration introduces challenges, particularly in optimizing the placement of Virtualized Network Functions (VNFs) within the NFV Infrastructure (NFVI). Existing studies have predominantly focused on well-connected, mains-powered ecosystems like datacentres and cloud networks. In contrast, the aim of this paper is to identify a solution that distributes and deploys a Wireless Mesh Network (WMN) as the backbone for a disaster management communication and service infrastructure. Given the mobility of mesh routers in such scenarios, these devices are often battery-powered. Consequently, the placement of VNFs directly impacts the energy consumption in the network and, subsequently, its lifetime. The proposed solution for the energy-efficient placement of VNF is formulated as a multi-objective optimization problem. This context introduces different approaches and proposes a heuristic algorithm to optimize the placement of VNFs. The evaluation results indicate that the proposed algorithm outperforms prior alternatives in various scenarios. Notably, it surpasses established methods like the Nondominated Sorting Genetic Algorithm II (NSGA-II), commonly used to solve similar problems. This research signifies a significant advancement in addressing the specific challenges associated with NFV integration in wireless mesh networks, particularly in disaster management contexts.

INDEX TERMS Energy efficiency, disaster network, network function virtualization, wireless mesh network.

I. INTRODUCTION

Network Function Virtualization (NFV) strives to enhance flexibility, scalability, and programmability in telecommunication [1]. This framework advocates the separation of network functions into software components within virtual machines or containers, detached from the underlying hardware components (servers with computing power, memories, and switches) [1]. While promising, this paradigm shift introduces challenges, particularly regarding the optimal placement of Virtual Network Functions (VNFs) on the Network Functions Virtualization Infrastructure (NFVI). The placement of a VNF directly impacts the power consumption of the host server (processing component) and indirectly influences the power consumption of the switches involved in packet transport to and from its current location (forwarding components). Consequently, strategically allocating VNFs is crucial for optimizing the energy efficiency of the communication network, as emphasized in previous studies [2], [3], [4], [5], [6], [7]. Notably, no prior research has addressed this challenge in the context of a Wireless Mesh Network (WMN), specifically considering survivability and lifespan [8]. A WMN, characterized by decentralization and wireless communication among devices (wireless routers) through point-to-point links or multiple hops, is particularly suited for disaster communication due to its self-organizing, self-configuring, and self-healing properties [9], [10]. This study builds upon prior research on energy

The associate editor coordinating the review of this manuscript and approving it for publication was Mohammad S. Khan.

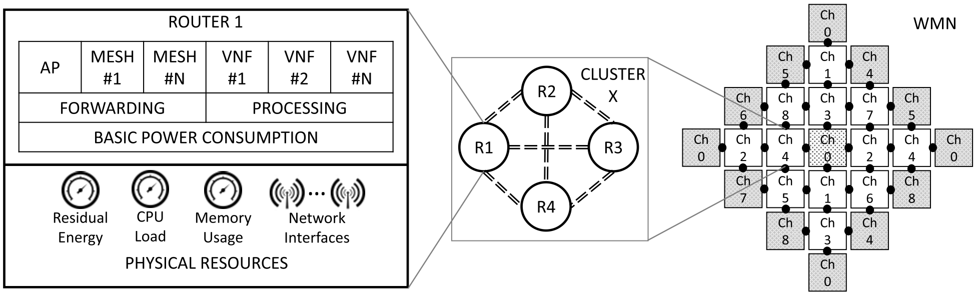


FIGURE 1. NFV optimised WMN architecture.

optimized VNF placement, with a distinct focus on WMN for disaster management, where computational and power resources are inherently limited. The infrastructure characteristics introduce a second objective for optimization alongside minimizing energy consumption, specifically maximizing the network lifetime. In a Wireless Mesh Network (WMN), the network lifetime refers to the duration until a mesh router fails due to energy depletion, an event critical to avoid during disasters as it results in reduced network coverage. Balancing energy consumption and network lifetime is exemplified in a scenario where a user's queries are efficiently handled by placing the Virtual Network Function (VNF) at the network edge, minimizing energy consumption related to packet forwarding. However, if the router has insufficient residual energy, deploying the VNF on another mesh router becomes more efficient to prevent failure.

The paper is structured as follows: Section II introduces the network architecture, outlines requirements for energy efficient VNF placement in the WMN, and analyzes previous works. Section III implements the mathematical formulation of the energy-efficient allocation problem for VNFs in mesh networks. Given the NP-Hard nature of the problem, Section IV proposes various algorithms for its solution. Section V presents simulations evaluating the proposed algorithms, comparing network lifetime increase, tested VNF allocations, and their ability to handle WMN constraints, such as medium sharing and throughput in multi-hop WLAN. Finally, Section VI concludes the paper, summarizing achievements and suggesting potential avenues for future research.

II. USE CASE AND RELATED WORKS

In a disaster scenario, the deployment of a Wireless Mesh Network (WMN) typically involves distributing numerous mesh routers across the affected area, as illustrated in Figure 1 [9], [10], [11], [12]. These routers, often battery-operated due to damage or limited availability of the power supply network, serve as access points for connecting end-user equipment, such as smartphones or laptops, to the network. Communication between WMN routers occurs through multiple radio interfaces, operating on different channels to prevent interference and ensure high throughput for network users [13], [14]. Clusters are formed by routers operating on the same radio channel and within transmitting or receiving range of each other [14]. As depicted in Figure 1, the example WMN comprises 25 clusters configured to run on 9 non-overlapping channels, preventing interference. This scalable network can be expanded by adding new routers as needed. Emergency workers establish and configure the network, intending it to operate throughout the entire rescue operation or until the conventional communication network is restored, serving three critical tasks. The first task involves supporting rescue operations by facilitating communication between rescuers and different leaders in the field's chain of command. The second task is to establish a backbone connecting various user groups participating in the rescue operation, including organizations (e.g., civil protection, police, and Red Cross), individuals in distress (e.g., injured people), and other affected individuals. The third task is to establish connections with external networks, such as mobile or satellite networks, providing an Internet uplink.

In an earlier study [11], we proposed leveraging Network Functions Virtualisation (NFV) to deliver essential services in disaster scenarios. Given the traffic aggregation and network structure, the placement of a Virtual Network Function (VNF) directly impacts the power consumption of the hosting node (mesh router) and indirectly influences nodes involved in packet forwarding to and from its current location. This presents novel opportunities for optimizing energy consumption. For instance, VNF migration to routers with high residual energy can extend the network's lifespan. Real-time migration of network services to follow the movement of helper teams as they progress in their work and move to the next location is another strategy, reducing energy consumption in the forwarding process. This study aims to optimize VNF placement in a WMN infrastructure by using the network lifespan as main optimization criterion.

Previous research in this domain, exemplified by [2], [3], [4], [5], [6], and [7], address the problem of energy-efficient placement of VNFs in telecommunication networks by modelling the network to be optimized including a subset of specific processes and relationships, such as energy consumption, hardware resource constraints, or communication patterns of the enduser terminals. The success of the proposed models can be evaluated against the requirements of a typical WMN for disaster. These requirements can be classified into three main categories.

Service-specific requirements are defined by two characteristics of the requests: their distributed nature and their dynamic nature. In a disaster network, enduser nodes are spread throughout the network and service requests, such as requests sent to a webserver, are sent from different locations, through different nodes, and taking different routes in the network. In contrast, in a data center scenario, all the service requests have the same ingress/egress port and the same communication path through the network infrastructure. This requirement has not been taken into account in any of the previous work. An exception is the work in [4], where the model considers that a VNF can be in charge of handling more than one request. However, this fact is not considered when it comes to finding the optimal location for this VNF within the network, as only the traffic is forwarded to it and no further instance is created if the network capacity allows it. The dynamic nature of the requests relates to the movement of enduser nodes. Due to the mobility of the helpers, progress in the rescue operation, and other users, the number of service requests sent from a specific access point changes over time. This model requirement is fulfilled in [2] and [6], with both studies modelling the network as a dynamic system where the traffic that must be handled by each VNF changes over time and the optimization must be performed repeatedly.

The infrastructure-specific requirements take into account the characteristics and limitations of the hardware ecosystem. In the case of WMN, nodes invariably have limited computing resources and VNFs will have to be run on these nodes. Although the resources (CPU and memory) on a mesh router are much more limited than on a datacentre server, there is no difference in modelling. All the models studied take into account that these resources are limited when choosing the optimal location for the VNFs.

One aspect not considered in models that replicate a wired infrastructure is the dynamic nature of the network. Due to nodes joining and leaving the network, the infrastructure in a disaster scenario is subject to changes. This requirement is included in the model introduced by [2] as the work deals with the energy-efficient placement of VNFs in a mobile environment which includes mobile devices, but the solution presented by the study only partially addreses the impact of network changes.

The biggest challenge faced by WMNs is the limited power, as typical routers in disaster scenarios are battery-powered. As a result, optimization should not be limited to the energy consumption but should also consider and model the total lifetime of the network. Given the constraint, a preferred solution may be one whereby the overall power consumption is higher than a theoretical minimum, but allows the network to run for longer, as VNFs are transferred between the nodes to balance transport and functionality while avoiding blackouts. This requirement is partially addressed in [2], but the model is limited to detecting the battery level and migrating the VNFs when the device they are running on has too little residual energy, rather than ensure survivability.

Finally, the third class of characteristics are wireless-specific and focus on the media and traffic. The link quality in WMN has no fixed capacity. The speed at which data can be transferred over a link depends on the number of stations using the same channel and if they have data to send [15]. The same, link quality (and therefore the link capacity) in WMN is subject to different changes over time (e.g., environmental changes or interferences). Summarizing the two sources of uncertainty, the speed at which data can be transferred over a link depends on the number of stations using the same channel, the amount of data that they are sending, and the characteristics of the medium that connects the communicating nodes. This combination of requirements has not been modelled in previous work.

TABLE 1. Evaluation of previous works with the focus on the energy efficient placement of VNFS.

Model requirements	Prior studies					
	[2]	*[3]*	*[4]*	*[5]*	*[6]*	*[7]*
Distributed service requests	-	-	o	-	-	-
Dynamic service requests	+	-	-	-	+	-
Limited computing resources	+	+	+	+	+	+
Dynamic network infrastructure	+	-	-	-	-	-
Battery-powered	o	-	-	-	-	-
Shared com. medium	-	-	-	-	-	-
Change in the link quality	-	-	-	-	-	-

(+) fulfilled, (o) partially fulfilled and (-) no fulfilled

Table 1 outlines how the prior studies addressed the WMN disaster model requirements. It shows that none of the prior research can be directly applied to the current use case, as they do not encompass all the aspects highlighted in this section. In the scope of this study, we leverage these earlier works as a baseline and construct a more comprehensive model that accounts for all identified requirements and constraints, enabling a more precise optimization process. Notably, we tackle the challenge of limited energy supply by introducing a second optimization objective—maximizing the network's lifetime. In the context of wireless networks, we account for interferences arising when devices operate on the same channel within each other's interference range. Furthermore, recognizing the dynamic nature of the network, we incorporate a dynamic model into our considerations. This forces a new optimization after a period Δt during which the system is considered constant.

III. WMN MODEL

Section II defined the requirements for a WMN disaster network model and, highlighted the limitations of the optimization formulation in prior studies. As mentioned, the

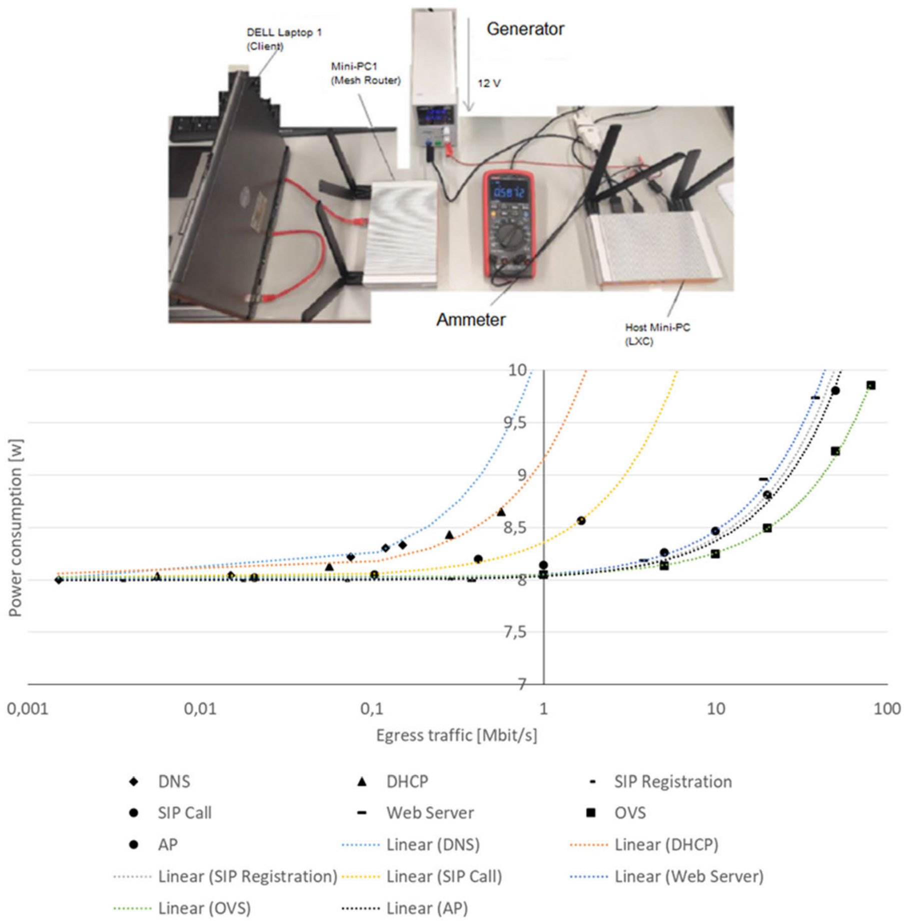


FIGURE 2. **A measurement of the power consumption for different VNFs depending on the egress traffic.**

unique characteristics of WMNs, limited power, wireless communication medium sharing, high dynamics, and distribution of service requests, have not been taken into account by the previous work. We aim to improve the mathematical model by focusing on the energy consumption of a mesh router.

The authors in [5] and [6] deal with the energy-efficient placement of VNFs in datacentres by employing a linear model. There, the energy consumption of a server depends linearly on the current CPU load and a constant base energy consumption. The CPU load in turn depends on the VNFs currently running on the server and the traffic they have to handle. For the energy consumption due to the forwarding of the data packets, a switch is assumed in [7] whose energy consumption depends on the number of active ports. In addition, there is a constant base energy consumption when the switch is on. In [3] the authors instead assume that the energy consumption due to forwarding increases linearly with the traffic.

While the assumptions made for datacentre scenarios are likely to be correct, prior studies did not investigate whether this server model is also applicable to small devices such as mesh routers. It is worth noting that a mesh router combines both server (hosting of VNFs) and forwarding (access point and routing) functionalities. Given the significant differences between the two types of devices, we performed a series of experiments to derive an empirical energy consumption model for the following VNFs: access point (AP), openvswitch (OVS), DHCP, DNS, web and call server. The experimental testbed is outlined in Figure 2. The setup consisted of a mini-PC configured as a mesh router, an ammeter for measuring the current and a constant voltage generator that generates a constant voltage of 12V. The Mini-PC is equipped with an Intel Pentium N4200 processor, 8 GB RAM, two Compex 2×2 MIMO 2.4/5 GHz (WLE600VX) WLAN modules, running Ubuntu Server 18.04.

This infrastructure was used to run three rounds of experiments. The aim of the experiments was to fully describe the energy usage of a WMN node while undertaking various tasks, from idle to full loading. This would produce a more accurate and realistic model in comparison with the linear-additive approach from earlier studies.

The first round of measurements observed the baseline the power consumption of the mesh router, while the machine is in idle mode. This power consumption is the minimum power consumption of a router and corresponds to the energy required to keep the router in ON state. In this series of measurements, the current was repeatedly measured for 12min after the start-up process was completed. The resulting average was 7.3W.

The second series of measurements measured the power consumption for forwarding functions, which required the AP and routing functionality. The WLAN interfaces increased power consumption from 7.3 to 7.5W for one interface and to 7.7W with both interfaces switched on; this increase was independent of the configuration of the WLAN interface as a mesh or access point. A follow-up round of measurements observed the power consumption as a function of the data rate of the trafic forwarded by AP or by the OVS router. The measurement was performed over a period of 2 minutes and for traffic rates of 1, 5, 10, 20, 50 and 80 Mbit/s and the results are displayed in Figure 2. The measured power consumption shows a linear increase with the data rate for both OVS and AP functions. The coefficient of increase is 0.023W/Mb and 0.034W/Mb for OVS and AP respectively. The energy consumption per Mb/s is higher for the AP because it has to switch between transmit and receive mode. This is not the case with the OVS when two interfaces are used and the data is only transmitted in one direction like in the tested scenario.

The final round of experiments measured the impact of processing of incoming service requests on the overall power consumption, with a focus on four typical VNFs: DNS, DHCP, web, and call server. These VNFs were provided within Linux containers (LXC). For each VNF, the power consumption was measured depending on the number of requests to be processed. For the call server, a distinction was made between registration and session setup. The size of the accessed web page on the web server was 20Mbit. In this test, it was not possible to measure the power consumption of the VNFs independently of a forwarding function. For example, the AP which was necessary to access the VNF hosted on the mesh router. Because the highest power consumption is caused by sending and not by receiving data packets, Figure 2 shows the measured power consumption depending on the egress traffic in Mbit/s. The data traffic that is generated in response to a request (egress traffic) was determined with the help of the analysis tool wireshark. Each VNF had to handle 1, 10, 50, 80 and 100 requests/s. Generally, it can be observed that the power consumption increases linearly with the data traffic for each examined VNF. Furthermore, as expected, this increase is higher than with the AP because it could only be measured in combination with the AP. The smallest increase (0.041Ws/Mbit) was measured for user registration and the highest increase (2.320Ws/Mbit) for DNS.

The results of these measurements show that the energy saving potential resulting from adequate positioning of VNFs in WMN is particularly large. As an example, a mesh router consumes about 20% more energy when hosting a web server that has to process 1.6 requests/s (20Mb/request). This underpins the importance of this work. Moreover, these results allow us to make the following assumptions for the rest of the paper: the power consumption of a mesh router v at a specific time t, can be defined as follows: $P_v = P_{basic}(v) + P_{forwarding}(v) + P_{processing}(v)$. The basic power consumption $P_{basic}(v)$ has a constant value. $P_{forwarding}(v)$ and $P_{processing}(v)$ are linear functions from the current traffic that they process.

In this work, the WMN infrastructure is represented by a graph G, where the set of nodes (mesh routers) is annotated by $V(G)$ and the connections between them by $E(G)$, respectively. $E(G)$ represents the set of clusters $C(G)$. For a specific time slot Δt in which the state of the network can be considered constant (no changes in the network infrastructure and the behavior of the users), the energy efficiency can be reached through the minimisation of the total power consumption

$$min\,(Energy\ consumption) = min(\sum_{v \in V(G)} P_v \times \Delta t) \quad (1)$$

The second goal of the optimisation is to maximise the lifetime of the network. This can be reached through the minimisation of the residual energy variance by battery-powered nodes.

$$min\,(variance) = min(\sum_{v \in V(G)} (\bar{R} - R_v)^2) \quad (2)$$

$\bar{R}$ is the expected average residual energy at the end of the upcoming time interval Δt and R_v is the expected residual energy of router v. Both values depend on the chosen allocation for VNFs. Since $\sum_{v \in V(G)} P_{basic}(v) = const$ and $\sum_{v \in V(G)} P_{processing}(v) = const$, minimising the power consumption in equation (1) means minimising the power consumption caused by forwarding packets in the network $\sum_{v \in V(G)} P_{forwarding}(v)$. In a network where all requests come from an single AP, the optimal location is the access router. Since this router is used more often, it loses power quickly and fails sooner. This situation can be avoided by the second objective in equation (2). To achieve a possible equal distribution of the residual energy, the VNF is placed on another router even if the total energy consumption increases.

Besides these two objectives, the following constraints can be defined:

$$\sum_{j \in V(VNF)} \delta_v^j c(j) \leq c_{v,max} \quad (3)$$

$$m_C = sum\ diag(A_C.T_C) \leq 1 \quad (4)$$

$$\sum_{v \in V(G)} \delta_v^j = 1 \quad (5)$$

Equation (3) shows that the maximum capacity $c_{v,max}$ of the physical resources (CPU, memory) on a router must not be exceeded. $c(j)$ represents the physical resources required by the VNF j and δ_v^j is a binary number that is equal to 1 when the j is running on the router v and 0 otherwise. Equation (4) shows that the wireless medium usage m_C in a cluster C must not be overloaded. Here A_C is the inverse of the adjacency matrix where each column represents for a node the quality

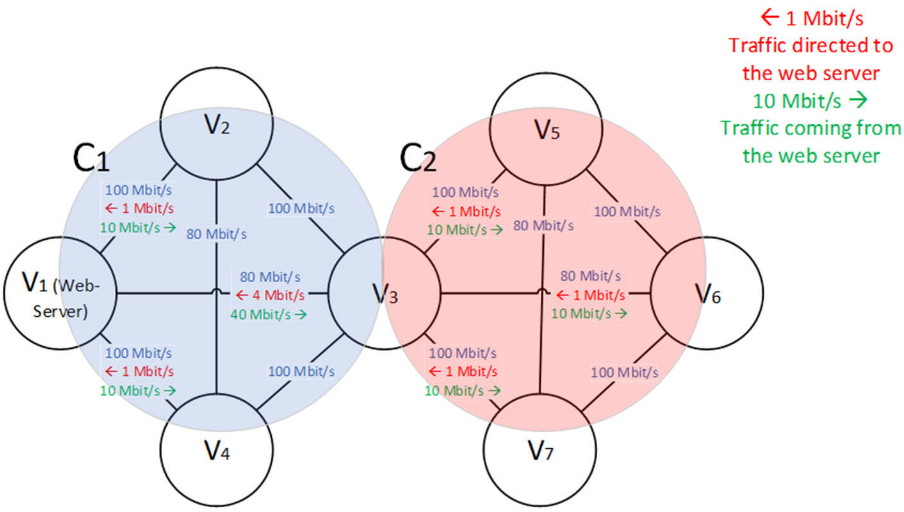


FIGURE 3. Example: Calculation of medium usage in a WMN with two clusters.

of connection with others cluster member in Mbit/s and is equal to 0 for node itself. T_C is the transmission matrix of the cluster. Each column in T_C represents for a node the traffic sends to other cluster members and is equal to zero for the node itself. Equation (5) shows that each VNF can only have one location in the network.

Figure 3 shows an example of a WMN consisting of seven routers $V(\mathrm{G}) = \{V1, V2, V3, V4, V5, V6, V7\}$ and two clusters $C(G) = \{C1, C2\}$. Packets can be transmitted between the routers with a maximum data rate of 80Mbit/s or 100Mbit/s depending on their distance. Assume that each router provides an access point function through which the end devices can connect. Assume that these end devices generate data traffic of 1 Mbit/s in the direction of a web server located on router V1. In response to these requests, the web server generates data traffic of 10 Mbit/s in the direction of the routers. This data traffic is forwarded via the shortest path in the network (see Figure 3). The medium usage of cluster $C1$ or cluster $C2$ can be calculated as follows:

$$m_{C1} = sum\ diag\left(\left(\begin{pmatrix} 0 & \frac{1}{100} & \frac{1}{80} & \frac{1}{100} \\ \frac{1}{100} & 0 & \frac{1}{100} & \frac{1}{80} \\ \frac{1}{80} & \frac{1}{100} & 0 & \frac{1}{100} \\ \frac{1}{100} & \frac{1}{80} & \frac{1}{100} & 0 \end{pmatrix} \cdot \begin{pmatrix} 0 & 1 & 4 & 1 \\ 10 & 0 & 0 & 0 \\ 40 & 0 & 0 & 0 \\ 10 & 0 & 0 & 0 \end{pmatrix}\right)\right)$$
$$= 0,77$$

$$m_{C2} = sum\ diag\left(\left(\begin{pmatrix} 0 & \frac{1}{100} & \frac{1}{80} & \frac{1}{100} \\ \frac{1}{100} & 0 & \frac{1}{100} & \frac{1}{80} \\ \frac{1}{80} & \frac{1}{100} & 0 & \frac{1}{100} \\ \frac{1}{100} & \frac{1}{80} & \frac{1}{100} & 0 \end{pmatrix} \cdot \begin{pmatrix} 0 & 1 & 1 & 1 \\ 10 & 0 & 0 & 0 \\ 10 & 0 & 0 & 0 \\ 10 & 0 & 0 & 0 \end{pmatrix}\right)\right)$$
$$= 0,3575$$

IV. VNF PLACEMENT ALGORITHMS

This section proposes four algorithms to address the placement of VNFs in WMN based on the mathematical formulation of the optimization problem in section III.

A. ENUMERATION (BF)

Similar to a brute force search, all potential network configurations are sampled. For each network configuration, the objective functions (1) and (2) must be calculated and the satisfaction of the constraints in equations (3) to (5) must be checked. Since this is a multi-objective optimisation problem, the algorithm will return the set of network configurations that best optimise the trade-off between the problem objectives, called the Pareto front. These are all feasible configurations where a reduction in energy consumption can only be achieved by a worse distribution of the residual energy. The main disadvantage of this method is the high number of possible network configurations. This number increases exponentially with the number of VNFs s^n, because for each chosen location for a VNF, all possible positions for the other VNFs have to be checked depending on each other. As an example, in a network consisting of 100 routers, and where 8 VNFs have to be placed, there are 100^8 possible configurations. The enumeration method is therefore not possible for large networks with a high number of VNFs. This algorithm will be referred to as ''Brute Force (BF)'' in the rest of the paper.

B. RANDOM MIGRATION (RM)

The random migration of VNFs in the network is a procedure that, in many aspects, can be seen as the opposite of an exact procedure such as enumeration. While all possible network configurations are tested in the enumeration procedure, in random migration, the next location of each VNF is determined at random. The advantages of such a placement algorithm become more apparent with the example of a webserver that has to be placed in a WMN and has to handle equally distributed requests from the entire network. Due to the random migration of the webserver, the energy consumption due to the processing of the requests is evenly distributed across the network. Similarly, the energy consumption due to the forwarding of traffic is also distributed evenly across the network. As a result, in this scenario, the expected gain from the costly optimisation using the enumeration method is similar to the gain from the random migration of the webserver. This method is easily applicable in large networks with a high number of VNFs because it does not require any calculation. Although the expected gain of the random migration in the previously described scenario is supposed to be similar to the gain by an elaborate optimisation using the enumeration method, the outcome is no longer trivial in case of unequal distributions of requests, time-dependent distribution of requests (e.g., due to the movement of helpers), or unequal distribution of residual energy. Furthermore, random migration does not check the fulfillment of constraints such as the available resources on hosting mesh routers.

C. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM (MOEA)

Multi-objective evolutionary algorithms (MOEAs) offer a compromise between the accurate enumeration method and the "possibly" inaccurate random migration of VNFs. The set of solutions that offer the best trade-off between the problem objectives are called *Pareto optimal,* and form the *Pareto front*. MOEAs are inspired by processes in natural evolution and rely on the principles of natural selection to evolve a population of candidate solutions that the Pareto front. A widely used MOEA is the so-called Nondominated Sorting Genetic Algorithm II (NSGA-II) [16]. To apply the NSGA-II, the population size and the number of generations must be specified. The working principle of the NSGA-II algorithm can be explained most simply with an example.

Suppose a webserver needs to be placed in a WMN that consists of 100 routers and NSGA-II is used with a population size of 10 and a number of generations of 5 (see Figure 4a). For the first generation, 10 out of 100 possible network configurations are chosen at random. From these initial solutions, a child population is created by applying crossover and mutation operations to the so-called parent solutions to generate child solutions. These child solutions are evaluated under the problem objectives, and the parent and child populations are combined to perform *elitist* selection – wherein the best solutions from either the parent and child populations are retained. Selection in NSGA-II is based on two mechanisms. First, *non-dominated sorting* is used to identify a partial ordering of solutions that are used as a basis for retaining the fittest solutions according to the objectives Figure 4b illustrates non-dominated ranks, with the rank 1 solutions being the most preferred (assuming, without loss of generality, that both objectives are to be minimised), followed by the rank 2 solutions, and finally the rank 4 ones. Any ties are broken using the *crowding* distance operator, which prefers solutions that have a greater distance to their nearest neighbours to preserve solution diversity. A major advantage of NSGA-II is that the number of network configurations tested can be freely chosen by specifying the population size and the number of generations. The result of optimising the problem with NSGA-II is a set of solutions that approximate the Pareto front, from which a decision maker must identify the final operating solution.

D. PROPOSED HEURISTIC (OBF)

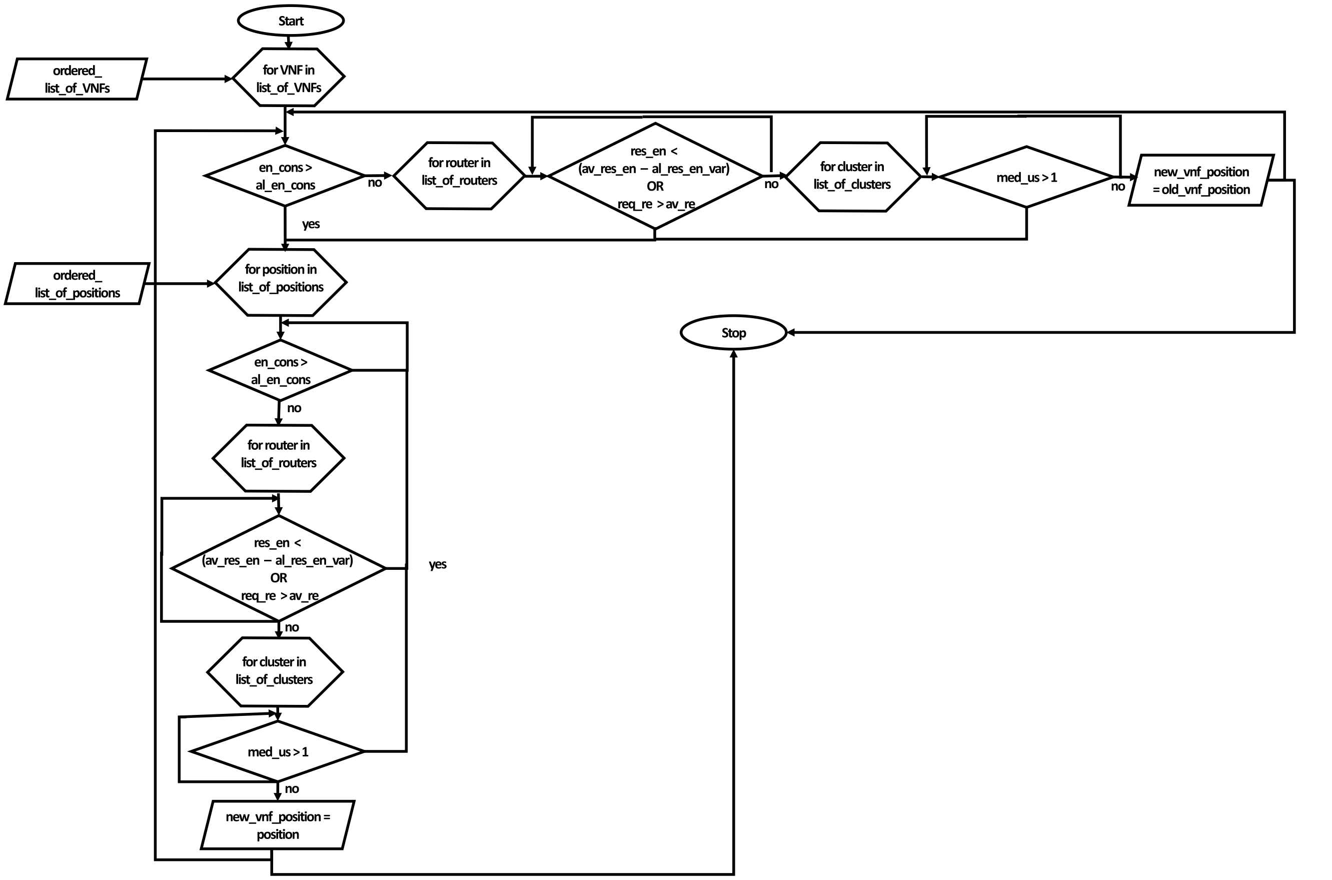
Besides metaheuristic algorithms such as NSGA-II, which can be applied to solve a whole class of problems, heuristic algorithms are developed to solve a specific problem. The last algorithm (OBF) presented in this paper belongs to this group. It was specifically designed to solve the problem of energy-efficient placement of VNFs in WMN. In order to find a suitable network configuration with little effort (few numbers of tested configurations), the optimisation problem in section III is modified as follows:

Step 1: The objective functions in equations (1) and (2) are converted into constraints. The first objective of the optimisation is to minimise the energy consumption in equation (1). Since this is a linear equation, it is equivalent to minimising the energy consumption when placing the individual VNFs. Instead of minimising this energy consumption, allowable energy consumption is now defined for each VNF. This means that the minimisation of energy consumption over the entire network is now ensured by not exceeding the allowed energy consumption when placing the individual VNFs. The allowed energy consumption during the placement of a VNF is variable and depends on three main parameters. Among them is the number of requests it has to handle. The higher the number of requests, the higher the energy consumption for processing them. The second parameter is the type of VNF. The energy consumption of a webserver is different from that of a DHCP server. The third parameter that plays a role is the topology of the network (size and connectivity). The larger and more poorly connected a network, the more likely a packet will have to be forwarded before reaching the destination router. In this paper, the permissible energy consumption for a VNF j is defined as follows.

$$E_{allowed} = \left(\sum_i \alpha_j \times E_i + \sum_i \alpha_{AP} \times E_i + \sum_i (I_i + E_i) \times L \times \alpha_{for} \right) \times \Delta t \qquad (6)$$

Here, I_i respectively E_i is the ingress respectively egress data traffic to the VNF j with the mesh router i as access respectively output router. $\sum_i \alpha_j \times E_i$ is the linear factor describing the power consumption of the VNF j as a function of the egress traffic according to the measurements in section III. The value of α_j depends on the VNF type (e.g. $\alpha_j = 0.0462$ Ws/Mbit for a webserver). $\sum_i \alpha_{AP} \times E_i$ is the linear factor describing the power consumption due to the required access point functionalities at egress routers (e.g. $\alpha_{AP} = 0.034$ Ws/Mbit). Both factors are independent of the network topology. L denotes the average path length (number of hops) in the network. α_{for} is the energy consumption incurred by a router due to forwarding (e.g. $\alpha_{OVS} = 0.023$

Algorithm 1 Proposed Heuristic



Ws/Mbit). Equation (6) allows to define a range around the optimal solution in which the energy consumption is acceptable. For example, assume a webserver needs to be placed in a WMN where all requests come from a single access point. The optimal solution would be to allocate the webserver on the router where the traffic is generated. The acceptable range for the webserver consists of all routers whose distance to this router is less than the average path length in the network. All other positions in the network belong to the existing solutions, which leads to too high energy consumption.

The second objective of the optimisation is to maximise the lifetime of the network. As introduced in section III, this can be achieved by minimising the variance of the residual energies (see equation (2)). This objective function is now to be replaced by a limitation. For this purpose, a tolerable deviation from the average residual energy is defined. That means, during the optimisation, it is avoided that the residual energy of a router falls below a defined percentage of the average residual energy. This ensures in an indirect way that the variance of the residual energies remains low.

Step 2: The locations for the VNFs and, consequently, the tested network configurations are selected randomly. The probability P_i of a mesh router i being selected as a location for a VNF depends on the following parameters:

- Traffic to the VNF and traffic from neighboring routers to the VNF (in the current implementation, both data traffic are weighted with 50 %). Routers with high data traffic or routers whose neighbors have high data traffic are preferred.
- The residual energy on the router. Routers with high residual energy are preferred. By choosing them more frequently as a location for the VNFs, their power consumption increases. As a result, their residual energy decreases, and so does the variance (see equation (2)).
- The congestion of the clusters over which the router communicates.

$$P_i = \left(1 + \frac{\frac{1}{2}\left(I_i + E_i\right) + \frac{1}{2} \times \frac{1}{m}\sum_{j=1}^{m}\left(I_j + E_j\right)}{I + E}\right) \times \left(\frac{R_i}{R}\right) \times \left(\frac{1 - C1_i}{C}\right)\left(\frac{1 - C2_i}{C}\right) \tag{7}$$

The probability of a router being chosen as a host for a VNF is therefore defined by the following equation (7). Where C is the average cluster usage, $C1_i$ respectively $C2_i$ is the medium usage of the cluster, which is reachable via interface 1 respectively 2, and I respectively E is the average ingress respectively egress traffic to the VNF.

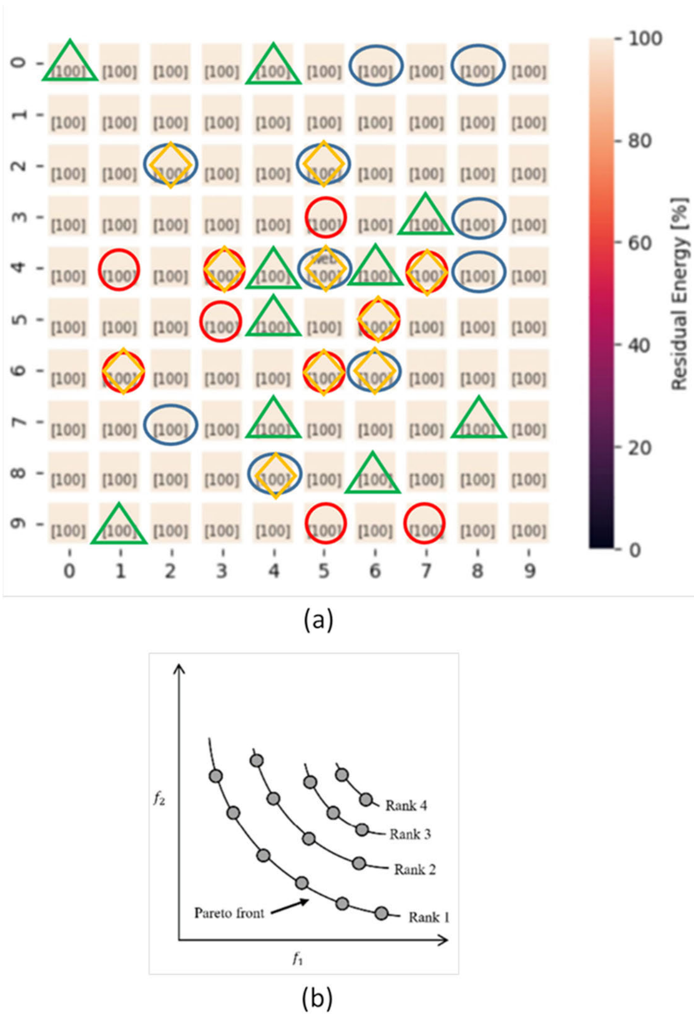


FIGURE 4. **Illustration of the function of the NSGA-II algorithm (a) First (blue), second (red) and third (green) –generation and parents of the third generation (yellow); (b) First, second, third and fourth Pareto front [18].**

The optimisation is terminated when a solution is found that satisfies all the restrictions in step 1 and the constraints (3) to (5) in section III.

Algorithm 1 shows the flow chart of the proposed heuristic algorithm. The VNFs are placed in the network independently of each other. They are first sorted according to their prioritisations (ordered_list_of_VNFs). An example of prioritisation could be the expected amount of data processed by each VNF (VNFs with high traffic are placed first in the network). Another possibility would be to prioritise the VNFs according to the organisations or user groups to which they belong (services for helpers are placed first and those for affected people last). As a third possibility, a combination of both would also be considered. This combination was used for the simulations in section V.

For each VNF in the sorted list of VNFs, it is first checked whether the current location of the VNF can continue to be used. This is the case if the expected energy consumption at the current location (en_cons) is below the allowed value (al_en_cons), the residual energy at no router falls below the allowed variance of the average residual energy due to the newly placed VNF (av_res_en), the current router has enough physical resources available such as CPU or memory and the expected medium usage (med_us) is not overloaded at any cluster. If one of these conditions is not fulfilled (i.e., the previous position can no longer be used), or if it is a new service, the second step is to search for another location for the VNF. For this, the next possible position for the VNF is chosen randomly. The probability of each router being chosen is calculated using equation (7). The draw is repeated until a location is found where all conditions are fulfilled or until all locations in the network are tested.

An important advantage of this algorithm is that the location of each VNF is tested for a maximum of the number s of routers that build the WMN. This results in a maximum number $n \times s$ of tested network configurations. Another advantage

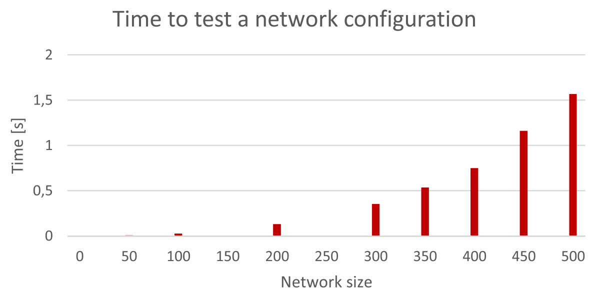


FIGURE 5. Time to test a network configuration.

is that the optimisation can be stopped without all VNFs being placed. This is for example advantageous when the network is working at its limit. Only as many services are made available as the network allows. VNFs with a low priority are not placed in WMN if the resources are not sufficient. The third advantage is that VNFs with a high priority are placed in the network in order of priority and do not have to wait until the end of the optimisation. In the further course of the work, this algorithm will be referred to as ''Optimised Brute Force (OBF)''.

V. EVALUATION

This section evaluates the algorithms for energy-efficient placement of VNFs in WMN, as presented in section IV, by using a number of simulated scenarios. The simulation of the energy consumption of a router is based on laboratory measurements in section III. The implementation of the MOEA50 and MOEA100 solutions uses the NSGA-II algorithm from the Platypus framework. For MOEA50 and MOEA100, the population size and the number of generations are chosen so that the number of network configurations tested equals $\frac{n \times s}{2}$ and $n \times s$, respectively.

A. MAXIMUM NUMBER OF VNFS

The first simulation series is used to determine the maximum number of VNFs that can be placed in a WMN depending on the network size; in terms of performance, the critical parameter is the time required by the algorithm to provide a placing solution for a given network configuration. This time depends not only on the network size but also on the current location of the VNF and the number of routers that are currently acting as entry or exit points for data traffic with the VNF.

Figure 5 shows the measured placement time as a function of network size for a single VNF. The assumption for the simulation is that each router serves as an entry or exit point for the data traffic. The values shown are the average of the measurements from all possible locations for the VNF.

The measured times provide a direct indication of the delay incurred when determining the optimal network configuration, calculated by multiplying the measured time for testing a single configuration by the number of tested configurations. As an example, in a WMN with 100 routers and 8 VNFs, enumeration would require testing a total of 100^8 configuration, while MOEA100 would only require 8×100 tests. Based on the preliminary measurements, a WMN configuration with 100 routers takes 0.0267s on average on a laptop without graphics card optimisation. This results in an expected computation time of 2.67×10^{14}s (approx. 8.4 million years) for the enumeration method and, respectively 21.36s when using the MOEA100 algorithm.

Figure 6 presents the expected computing time depending on the number of VNFs for different network sizes (50, 100, 200, and 400 routers). In order to balance the responsiveness of the network when changes occur with its stability, a theoretical threshold of 10min was set as a maximum duration for the calculation. The two images indicate that the exponential increase in the degree of difficulty (number of network configurations to be tested) lead to problems when using the enumeration method (BF) even in small networks.

The linear increase in the degree of difficulty of MOEA50, MOEA100, and the proposed heuristic algorithm (OBF) allows these algorithms to be used in large networks (e.g., in a network with 100 respectively 200 routers, the optimal network configuration for the placement of more than 100 VNFs, respectively 23 VNFs can be determined with MOEA100 or with the heuristic algorithm). However, even these algorithms are of limited use in networks with more than 200 routers due to scalability reasons.

After confirming the time efficiency of the proposed alternatives, in comparison with the enumeration method, the next step is to determine the quality of the identified network configurations. The evaluation was performed on a simulated WMN consisting of 100 routers, each equipped with two physicals mesh interfaces to communicate with the neighboring routers. The maximum transmission rate between neighboring routers in a row or column was set to 100Mbit/s and 80Mbit/s along a diagonal.

B. INFLUENCE OF THE DATE TRAFFIC

In order to investigate the relationship between data traffic and the performance of the algorithms for the energy-efficient placement of VNF, a set of time-based simulations investigated the optimal position for a webserver and its impact on the network lifetime.

The webserver has a set workload of 3000 requests, uniformly distributed over the entire network and over a time interval of 10 minutes. The following size of the requested page was simulated: 1, 7, and 20Mbit. This leads to a average data traffic of 5, 35, and 100Mbit/s with the webserver depending on the size of the requested webpage. Figure 7 shows the results of the simulation with regards to the network lifetime gain and the number of tested configurations. Firstly, as shown in Figure 7a, it is apparent that the gain in network lifetime through optimisation depends strongly on the web page's size and thus on the traffic. For a 1Mbit request, the average gain is less than 2.2%; this gain increases up to 42.2% for a 20Mbit request. Secondly, as illustrated in Figure 7b, the results are comparable across the four

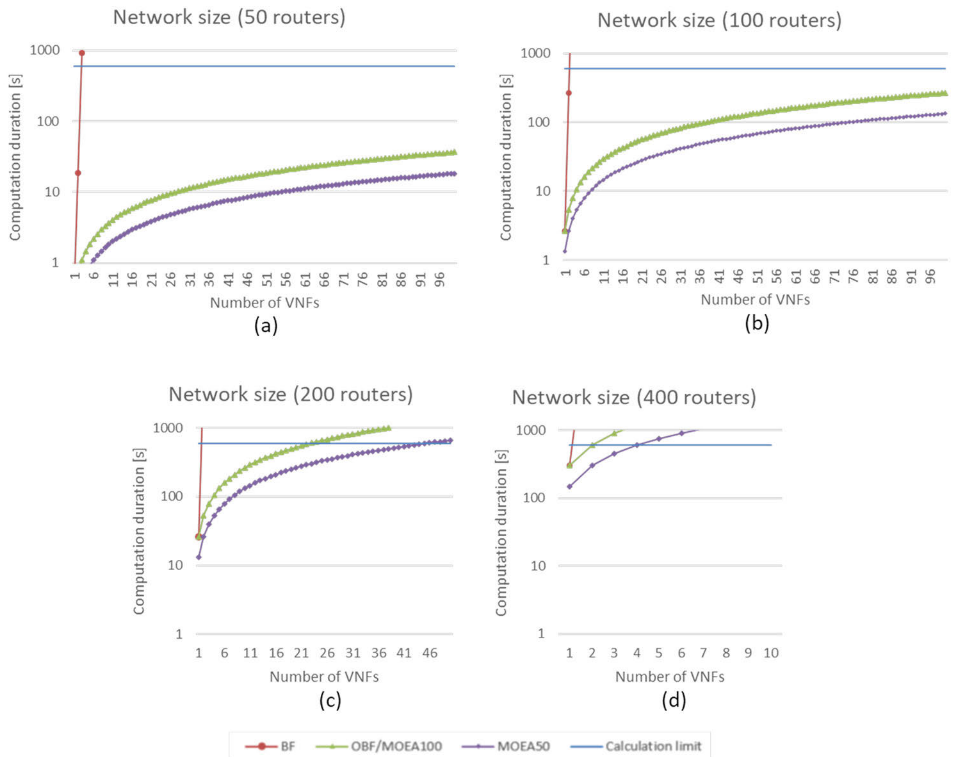


FIGURE 6. Influence of the number of VNFs on the estimated computer duration for network size.

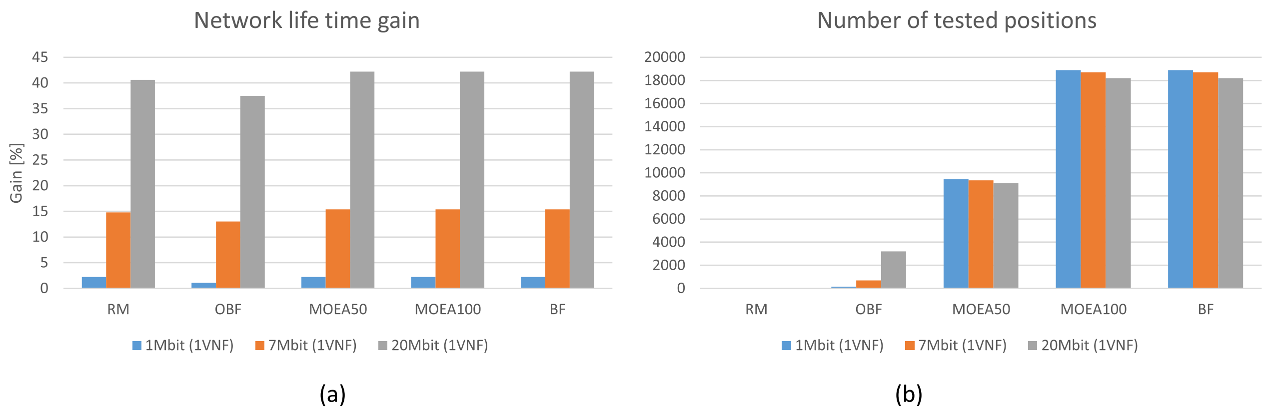


FIGURE 7. Influence of the data traffic on the performance of the proposed algorithms.

algorithms with regards to lifetime gain, but the computational effort varies significantly, as reflected by the number of tested configurations. It can be observed that the number of tested configurations is the same for enumeration and MOEA100. This is because the scenario includes a single VNF to be placed in the network and, for each interval, both algorithms will test 100 configurations, independently of the traffic with the webserver. The slight decrease in the number of tested configurations with the increase in traffic, seen in Figure 7b, is due to the decrease in network lifetime with the increase in traffic, as more energy is used for data forwarding. Comparatively, MOEA50 tests 50 positions per time interval, therefore the cumulative number of tested configurations is half of the number in MOEA100 and the enumeration method (BF). It is also observed that the actual required number of tested configurations in the proposed heuristic solution (OBF) is significantly lower than the other three alternatives. As the traffic increases, the energy consumption increases, which in turns requires the algorithm to run more often in order to determine the optimal position. The random method was included in the set as an extreme case, as it does not require any network configuration testing. The results

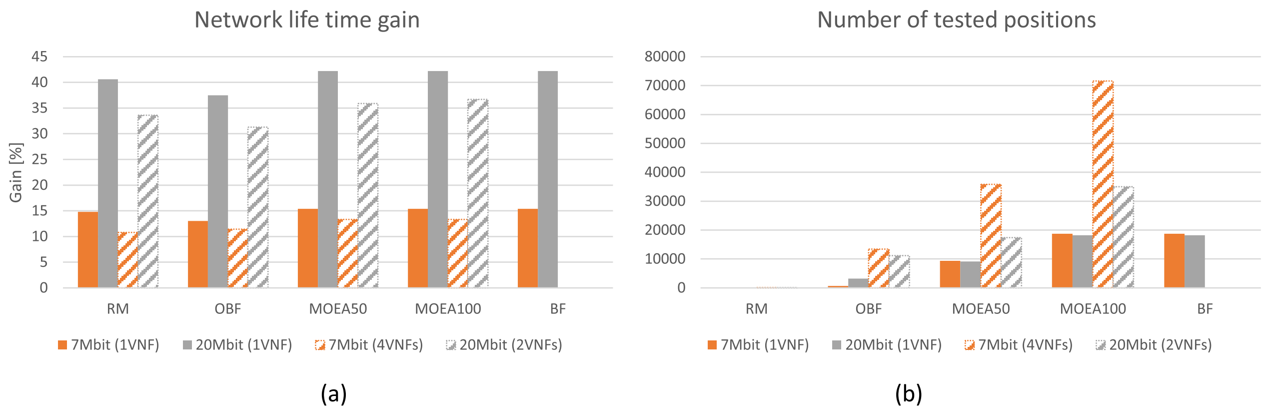


FIGURE 8. Influence of the number of VNFs on the performance of the proposed algorithms.

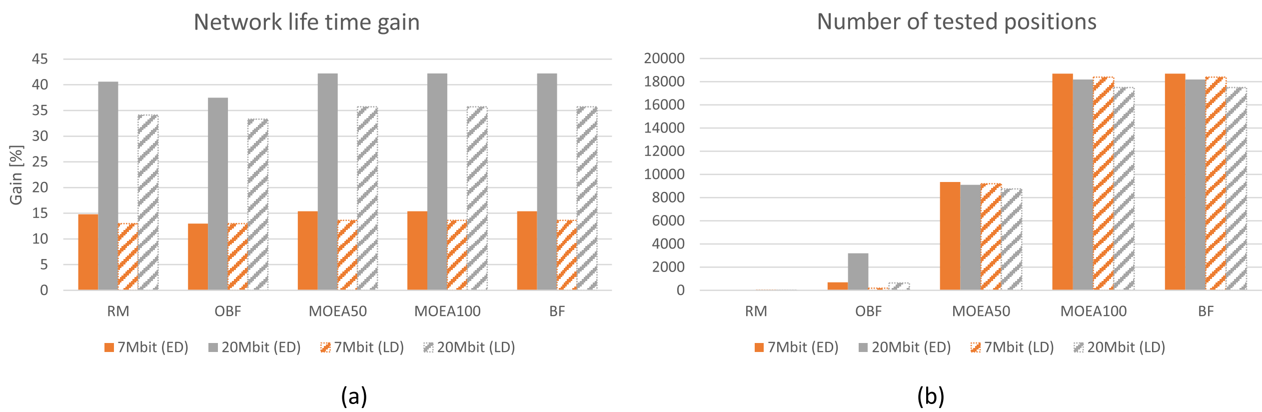


FIGURE 9. Influence of the distribution of requests on the performance of the proposed algorithms – Single VNF.

indicated that the probability of selecting an unfavorable location during migration increases with the data traffic. In the case of 20Mbit requests, the random allocation led to the medium usage being overloaded in 12% of the time.

C. INFLUENCE OF THE NUMBER OF VNFS

A separate set of simulations aimed to determine the relationship between the number of VNFs placed and the performance of the algorithms. This set of simulations consisted of two placement scenarios, one with 2 VNFs and one with 4 VNFs. For consistency with the previous set of experiments, including a single VNF, the simulation assumes the same scenario: the simulated VNFs are webservers, and each webserver has to process 3,000 requests of either 7Mbit or 20MBit within 10 minutes, equally distributed over the entire network. Figure 8a shows the gain in network lifetime compared to service provision without migration of the VNFs. In the simulation of the standard case (without migration), the VNFs to be placed are distributed over the network as optimally as possible. From the graph in Figure 8a, it can be seen that the gain from migrating the VNFs decreases with the number of VNFs when the VNFs are optimally distributed across the network. This result can be explained by the better distribution of energy consumption across the network compared to the case with a single VNF. It can also be noted that the optimisation gain remains relatively high (about 13% when the size of the accessed web page is 7Mbit, respectively 36% when the size of the accessed web page is 20Mbit). Finally, it can be observed from the same graph that the lifetime gain is similar across the analysed algorithms. In Figure 8b, as expected, the number of tested network configurations increases linearly with the number of VNFs when MOEA50 or MOEA100 are applied. For example, the cumulative number of tested configurations increases by 192% respectively by 383% when the number of VNFs increases from 1 to 2 and respectively to 4. The measured increase in the number of tested configurations is less than 200% and 400% because it is a cumulative value. The total lifetime of the network becomes shorter with additional VNFs because more energy is consumed. For the proposed heuristic solution, the number of tested network configurations also

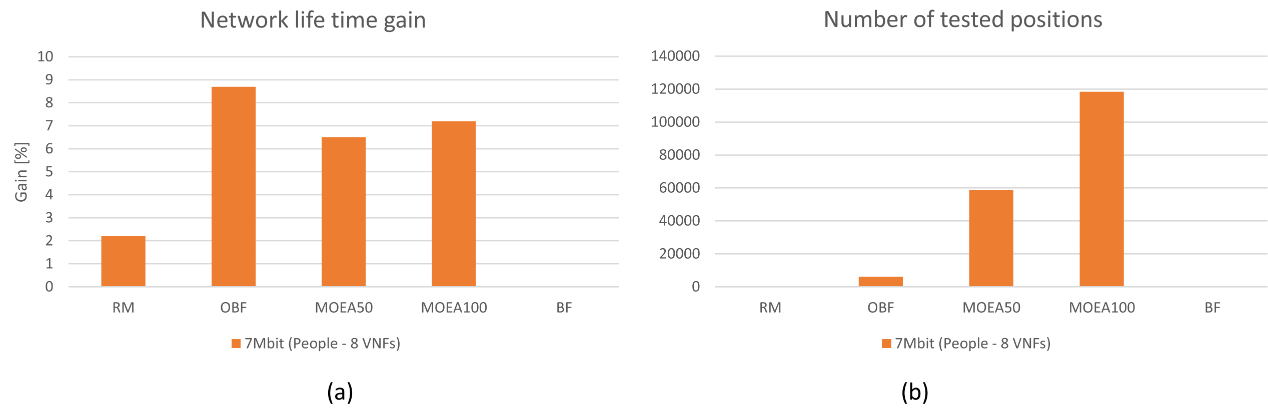


FIGURE 10. Influence of the distribution of requests on the performance of the proposed algorithms – Multiple VNFs.

increases with the number of VNFs, but this number remains far below the maximum theoretical value of 35,000 respectively 71,600 tested in MOEA100. For the random migration, the probability of an invalid network configuration increases with the number of VNFs. For example, approximately 49% of all configurations result in medium congestion in a WMN with two webservers and a web page size of 20Mbit. In a WMN with a single VNF, this number is around 12%.

D. INFLUENCE OF THE DISTRIBUTION OF REQUESTS: SINGLE VNF

Until now, the simulations have assumed that the requests to the VNF are uniformly distributed across the entire network. In practice, in the event of a disaster, population is not uniformly dispersed and the level of impact on across a large area is also variable. The variations of these two factors should also lead to differences in the distribution of requests for a specific VNF. In this test series, the aim is to investigate how the uneven distribution of requests affects the performance of the algorithms. For this purpose, it is assumed that the 3,000 requests that have to be processed by the webserver in 10 minutes are distributed over five areas as follows (see Figure 11):

- City centre (8 routers): 1,200 requests;
- High-rise housing estate (1 router): 300 requests;
- Helper center (2 routers): 300 requests;
- Hospital (1 router): 100 requests;
- Railway station (1 router): 100 requests.

The remaining requests are equally distributed over the rest of the area.

The simulation is performed for a 7Mbit and a 20Mbit big website. Figure 9a shows the relative gain in lifetime compared to the service provision without optimisation. In general, the gain with optimisation in a WMN with unequally distributed requests is smaller than with equally distributed requests. This is due to the fact that the location of the webserver was optimally selected close to both the city center and the high-rise housing estate during the simulation. These two above areas generate, as per our scenario, 1,500 requests. Because of its location, less energy is consumed in the forwarding of packets. Figure 9b shows the cumulative number of tested network configurations. For MOEA50 and MOEA100, this number is independent of the distribution of the requests. The visible difference in the graph can be explained by the difference in the lifetime of the network. A network with unequally distributed requests lives for a shorter time because there is a non-optimisable energy consumption on the routers with more traffic due to the access point functionality. The number of tested network configurations becomes smaller in a WMN with unequally distributed requests when the proposed heuristic algorithm is used. This is because this algorithm uses the traffic as a parameter for selecting the location for the VNF. Finally, the probability of an invalid configuration with random migration increases from 12% to 17%.

E. INFLUENCE OF THE DISTRIBUTION OF REQUESTS: MULTIPLE VNF

The previous subsection investigated the influence of an unequal distribution of requests on the performance of the algorithms for energy-efficient placement of VNFs in WMN. This involved finding the optimal location for a webserver that handles requests from the entire network. In some cases, the number of requests for a particular service may be so high that a single VNF cannot handle them. This may be the case, for example, if there is no router with insufficient computational resources to host the VNF. In this case, additional VNFs are created, and the traffic is distributed between them. For example, if the webserver in the previous scenario must process 30,000 requests in 10 minutes instead of 3,000, this will create an average traffic of 350Mbit/s with the webserver when the requested page size is 7Mbit. Given the network transmission speed is 100Mbit/s in a cluster, this service cannot be provided by a single VNF. A possible solution to this problem would be to provide the service through 8 VNFs, each responsible for one area of the network as follows:

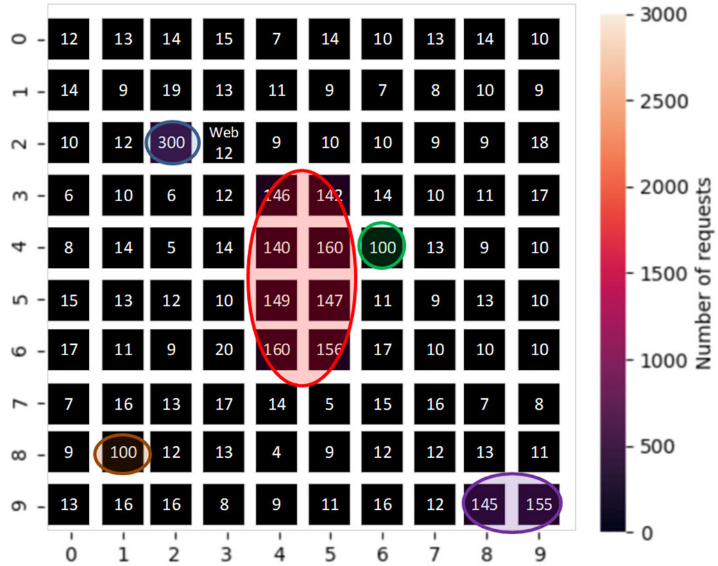


FIGURE 11. Helper distribution – Single VNF: City center (red), High-rise housing estate (blue), Helper center (purple), Hospital (brown), Railway station (green), and Rest of the city.

- City centre (8 routers): 12,000 requests → 2 webservers for the northern and southern part;
- High-rise housing estate (1 router): 3000 requests → 1 webserver;
- Helper centre (2 routers): 3000 requests → 1 webserver;
- Hospital (1 router): 1000 requests → 1 webserver;
- Railway station (1 router): 1000 requests → 1 webserver.
- On the remaining area, 10,000 requests are generated in 10min, processed by two further webservers. One webserver is responsible for the eastern part of the network and one for the western part.

Figure 10a shows the gain in network lifetime compared to the simulation without optimising the VNF locations. The locations of the VNFs were chosen as optimally as possible in the simulation without VNF migration to maximise the network lifetime. This means that they were placed as close as possible to the areas they are responsible for. Figure 10a shows that a gain of about 9% could be achieved when using the proposed heuristic algorithm, despite this optimal positioning. This gain is smaller for the MOEA solution but increases with the number of network configurations tested, from 6.5% for MOEA50 to 7.2% for MOEA100. The worst result is achieved with the random migration of VNFs, where the gain is only 2.2%. When randomly migrating VNFs in a network with unequally distributed requests, the energy consumption due to traffic forwarding increases if the VNFs are not placed near the locations with the most traffic.

As expected, random migration also leads to a very high number (approximately 96%) of invalid network configurations, because they have clusters where the expected medium utilisation is higher than the capacity. For MOEA, the probability of having an invalid configuration at the end of the optimisation decreases with the number of configurations tested, dropping from 30.6% for MOEA50 to 19.6% for MOEA100. In this scenario, the heuristic algorithm alone provided valid network configurations at the end of each optimisation. Moreover, the graph in Figure 10b shows that the real number of tested configurations for the proposed heuristic solution (OBF) is about 5.2% from the theoretical maximum value tested for MOEA100.

VI. CONCLUSION

The aim of this paper is to provide an energy-efficient solution for the placement of VNFs in a WMN. The focus is on a widespread use case of the WMN, namely as a backbone network for disaster communication. Section II defined the requirements for the model, which allowed a systematic performance comparison with previous research in other communication networks. From this comparison, it became apparent that earlier formulations of the optimisation problem cannot be applied to the specific scenario of a disaster WMN, due to the unique properties such as the battery supply of the hardware, shared wireless communication medium, high WMN dynamics, and the distribution of service requests. All these properties represent requirements for the model and have not been considered or had limited priority in previous works. Section III proposed a model by formulating the optimisation problem mathematically. The WMN was defined as a graph consisting of several subgraphs, referred to as clusters. This allowed defining the two objective functions and the associated constraints for the optimisation. The formulated problem is a multi-objective optimisation problem. The first objective of the optimisation is to minimise the energy consumption in the network. This problem was formulated as an Integer Linear Programming (ILP) problem with the objective of finding the location of all VNFs (set all $\delta_v^j \in \{0, 1\}$) such that the objective function in equation (1) has the minimum value and the constraints in equations (3) to (5) are satisfied. As an ILP, this problem is NP-hard as shown by the authors in [17]. The second objective of the optimisation is to maximise the lifetime of the network. This optimisation problem has been defined as Nonlinear Programming (NLP). The objective of the optimisation is to find the location of all VNFs (set all $\delta_v^j \in \{0, 1\}$)) so that the objective function in equation (2) has the minimum value and the constraints in equations (3) to (5) are satisfied. Section IV proposed four algorithms to solve the optimisation problem, using the enumeration method, random migration of the VNFs after each time interval, a multi-objective genetic algorithm (NSGA II) applied in the literature to solve similar problems, and a heuristic algorithm developed specifically for this problem. As a multi-objective optimisation problem, no optimal solution exists for the defined energy-efficient placement of VNFs in WMN. Even if the network allows the use of the enumeration method (small network with a small number of VNFs), the optimisation often provides a list of network configurations where a reduction in energy consumption can only be achieved by a worse distribution of the residual energy. In this case, the network configuration that has the most equal distribution of residual energy while consuming as little energy as possible is chosen (precedence to network lifetime - second objective function). In random migration, no optimal solution is sought. In NSGA II, the network configuration is chosen that gives the best result in terms of residual energy distribution after a defined number of tested network configurations. In the proposed heuristic procedure, without knowing the (theoretical) optimal solution, an attempt is made to guess a solution (using an Oracle). If this solution is considered close enough to the optimal solution, it is chosen as the network configuration. The performance and complexity of these four algorithms was investigated in section V. Beyond lifetime evaluation, the influence of other factors was also observed, including the number of VNFs, the distribution of traffic, and the distribution of service requests. While the results of the simulations for the enumeration method and the random migration of the VNFs provided relatively low benefits, the proposed heuristic algorithm performed significantly better than the MOEA algorithm for the same number of tested network configurations. This result can be explained as follows: If it is assumed that $f_1(\vec{x})$ is the first objective function that gives the total energy consumption depending on the current location of the VNFs $\vec{x}$ and $f_2(\vec{x})$ is the second objective function that gives the variance of the residual energy depending on the current location of the VNFs $\vec{x}$ in the network, the proposed heuristic solution can be considered as a mathematical function ($\vec{x} \rightarrow f_1, f_2$) which tries to select the VNFs positions $\vec{x}$(e.g., based on the traffic or based on the residual energy) so that the resulting energy consumption f_1 and the resulting variance of the residual energy f_2 are above the allowed values. While the MOEA algorithm can be considered as a mathematical function ($f_1, f_2 \rightarrow \vec{x}$) which based on the evaluation of the objectives functions f_1 and f_2, optimises the best possible placement for the VNFs $\vec{x}$. The problem is that parameters such as the residual energy of each router, the data traffic with the VNF, or the current load of the clusters are not considered. This complicates the process of finding a suitable network configuration.

The work presented in this paper has two limitations. First, the comparison of algorithms for the energy-efficient placement of VNFs in WMN was tested based on self-defined scenarios. A better comparison would be possible with data from previous disaster events. Unfortunately, this data could not be found to the desired extent. Second, the monitoring of resources and its influence on energy consumption was only indirectly considered in the model because its contribution to the total energy consumption was assessed as negligible. These two limitations will be addressed in future work.

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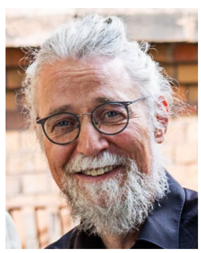

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