Optimized UAV Placement for Resilient Crisis Communication and Power Grid Restoration

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***Abstract*—During crises where both communication networks and the electricity grid break down, restoring each individual infrastructure for disaster relief becomes generally infeasible. To tackle this challenge, we propose a disaster management solution using mobile ad-hoc networks (MANETs) formed by unmanned aerial vehicles (UAVs), offering a promising solution for emergency response. Apart from establishing emergency communications for rescue teams, UAV-enabled MANETs can also enable the formation of electrical microgrids based on distributed energy resources (DER) to locally restore the electric power. We determine the optimal locations and the number of UAVs for this purpose, taking the UAVs' needs for repeated recharging into account. The problem is formulated on a discrete grid of potential places as a mixed-integer linear program (MILP) and solved via an accelerated feasibility query algorithm (FQA). The framework is evaluated for a toy-example and a modified version of the IEEE 123 node test feeder. Simulation results show that compared with conventional MILP approaches, the proposed FQA algorithm can significantly lower the computation times, particularly for large scale MANETs.**

***Index Terms*—mobile ad-hoc network, UAV, communication, microgrid, distributed energy source, optimization, MILP, constraint-satisfaction problem**

I. Introduction

In recent years an increasing number of critical infrastructure failures occurred due to external threats (e.g. natural disasters and cyber attacks) [1]. Considering the progressing climate change as well as the ongoing digitization, automation, and interconnection of infrastructural systems, aforementioned threats will have even more severe consequences in the future [2]. Establishing resilient disaster management systems and infrastructure restoration measures is therefore essential. In this paper, we focus on a fast-response measure in form of mobile ad-hoc networks (MANETs) to temporarily restore communication in case of a failure of the ground communication network.

A MANET can be formed dynamically by autonomous mobile nodes that are connected via wireless links. It can operate independently of the regular infrastructure as a highly flexible backup network [3]. There are numerous uses for unmanned aerial vehicle (UAV)-based MANETs in the context of disaster management:

- Re-establishing the communication network: Provides the possibility to inform the citizens about the current situation and to give instructions and/or recommendations [4], [5].
- Restoration of infrastructure and coordination of disaster management: Can be used to built up a communication link for technical staff on site or connect emergency response teams and operations centers [6].
- Observing and monitoring: Search-and-rescue missions can be effectively and quickly executed using UAV [7]. The UAV's autonomous, unmanned character allows them to operate in dangerous or inaccessible areas [8].

Analogously to the use of UAV-based MANETs, the ad-hoc formation of local electrical microgrids in crisis situations shows large potential for local power restoration [9]. Using decentralized energy resources (DER), small independent microgrids can be formed inside a damaged area to rapidly restore the electric energy supply locally, giving a fast response to power outages for both critical and regular customers [10], [11]. DERs can be traditional power plants, renewable energy installations, or non-energy-related facilities that are equipped with emergency power units, such as hospitals. Multiple close microgrids can subsequently be merged into larger microgrids [12] or eventually connected to the main grid [13]. Merging several microgrids results in a more stable grid operation as it increases the available primary and secondary power reserves to deal with imbalances. Grid control can be achieved with central or decentralized consensus-based controllers [14], [15]. However, both microgrid merging and control require communication links to be available between the various microgrid components, especially the grid-forming generators. The UAV-based MANET is well suited for this task, since it can create a flexible communication network that can dynamically adapt to the changing microgrid topology without depending on power-dependent ICT infrastructure. To our knowledge, no application of UAV-based MANET for microgrid communication has been reported in the literature yet.

One central issue for UAV-based MANETs is the UAVs' power supply [16], [17]. Since the UAV's battery capacities are limited, UAVs need to return to the ground and be charged

This work has been funded by the LOEWE initiative (Hesse, Germany) within the emergenCITY center.

978-1-6654-8032-1/22/$31.00 ©2022 IEEE

periodically during their missions. This can severly limit the mission duration, mission range, and performance of the communication equipment onboard the UAVs.

In this work, we aim to find optimal deployment locations for the UAVs to form a MANET that connects all potential users with the smallest number of UAVs in service. We take the UAVs' energy supply requirements into account, by assuming that the UAVs can be supplied with energy at dedicated charging stations that are located in close proximity to DERs that are part of a microgrid.

We formulate a mixed-integer linear program (MILP) for minimizing the number of deployed UAVs as well as their distances to the closest charging station. The use of MILP has been proven suitable for various UAV communication and coverage problems [18] [19]. However, MILP problems are known to be NP-hard, which can result in high computation times for large-scale problems. Therefore, we introduce an alternative optimization approach, referred to as the feasibility query algorithm (FQA). By iteratively checking the feasibility of the program for an increasing number of UAVs, the FQA approach can attain a solution close to the global optimum without running the optimization over the number of UAVs. In highly symmetric problems as considered in this work, the FQA approach can significantly lower computation times.

The remainder of this paper is structured as follows: We present the problem formulation and our modelling decisions in chapter II and describe the MILP optimization model in chapter III. The subsequent chapter IV provides the simulation results for two exemplary setups. Finally, Section V concludes the paper with an outlook of potential future directions.

II. Problem formulation

We consider a geographical area that is discretized into a symmetric 2D-coordinate grid with arbitrary non-dimensional length units. It defines the potential deployment location for a UAV. Furthermore, we consider different relevant points of interests (POIs) located either on the grid nodes or within the border of the grid. POIs can be both network users or DERs. We consider network users as target nodes that must be reached by the MANET, thus be within communication range of at least one UAV. In case of the MANET being the microgrids communication network, grid-forming generators are the users. Additionally, all types of DER in the observed area, e.g. chp power plants or renewable energies are assumed to be charging stations for UAVs. For microgrid communication, we distinguish two types of DERs: Grid-forming generators that require a communication link in order to form and run a microgrid. Non-grid-forming energy sources do not require a MANET coverage and are regarded as charging stations. POI can be located on any coordinate in the observed area, extending the grid node set by its coordinates.

For the communication model we assume that a network user can connect to the MANET only if it is within communication range of at least one UAV. Moreover, information exchange between two UAVs of the MANET is possible only if they are within the communication range of each other. It is possible to communicate via multiple units (multi-hopping) without losses of data. For simplified notation, we assume that all UAVs have the same communication range and all information exchanges can be executed bidirectionally. Thus, each UAV spans a circular coverage area and a connection can be established with all devices inside that area, both user devices and other UAV.

III. Optimization Model

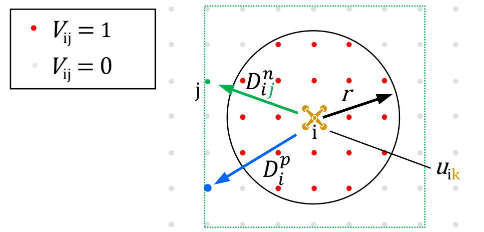

Fig. 1. Graphical representation of D_i^p, D_{ij}^n and V_{ij}.

The model consists of grid nodes $i, j \in \mathcal{N} = \{1, 2, ..., n\}$. $\mathcal{D}$ denotes the available set of UAV d with k being the corresponding index. Furthermore, the decision variable is designated as u, other (binary) variables are denoted by Greek letters. Multi-dimensional parameters are denoted by capital letters, while lower case letters are assigned to scalar parameters. The objective function is given as

$$\min_{\text{s.t. } (2)-(10)} w_d \sum_{i=1}^{n} \sum_{k=1}^{d} u_{ik} + w_s \sum_{k=1}^{d} u_{ik} \cdot D_i^p. \tag{1}$$

In (1), the first term denotes the weigthed minimization of the number of UAVs in service. $u_{ik} = 1$ if UAV k is placed at node i and $u_{ik} = 0$ otherwise. Moreover, the second term of (1) minimizes the (weighted) distance between the UAVs position and the charging stations. Parameter D_i^p is the euclidean distance to the closest charging station from node i (see Fig. 1). Parameters w_s and w_d are weighting factors defined according to the relevance of each term in the objective function.

$$\sum_{i=1}^{n} \sum_{k=1}^{d} u_{ik} \cdot V_{ij} \geq \zeta_i, \forall\, i \in \mathcal{N} \tag{2}$$

Equation (2) defines ζ_i, with $\zeta_i = 1$ if node i is covered by dat least one UAV and zero otherwise. Parameter V_{ij} indicates which nodes j are in communication range of a UAV deployed on node i. $V_{ij} = 1$, if node j is within communication range of a UAV placed on node i. Given a UAV communication range, we check which nodes j are reached by a UAV located at node i and save the values in a binary way (see Fig. 1).

The number of network users reached by the MANET is determined by (3) setting the sum of all users within the coverage area equal to the total number of users.

$$\sum_{i=1}^{n} \zeta_i \cdot M_i = \sum_{i=1}^{n} M_i \tag{3}$$

Here, the binary parameter $M_i = 1$, if a user is located on node i.

Theoretically, there is no upper limit to the number of UAVs forming the network. Anyways, since the number of UAVs is finite and given by set $\mathcal{D}$, an upper boundary is set in

$$\sum_{i=1}^{n}\sum_{k=1}^{d} u_{ik} \leq d. \tag{4}$$

Parameter d, which is also the cardinality of set $\mathcal{D}$, denotes the maximum number of available UAVs and should be set greater than the expected number of necessary UAVs to build the network.

Equation (5) and (6) ensure that exactly one UAV $k \in \mathcal{D}$ can be assigned to one potential placement location.

$$\sum_{i=1}^{n} u_{ik} \leq 1, \forall\ k \in \mathcal{D} \tag{5}$$

$$\sum_{k=1}^{d} u_{ik} \leq 1, \forall\ i \in \mathcal{N} \tag{6}$$

Each UAV may be deployed once and there may be at most one at each node i. We introduce an upper boundary to the charging station distance in (7) that is particularly necessary for the Feasibility-Query-Algorithm described in subsection III A.

$$u_{ik} \cdot D_i^p \leq s, \forall\ i \in \mathcal{N},\ k \in \mathcal{D} \tag{7}$$

So far, the MILP model determines the deployment locations to reach all network users, but does not guarantee an interconnected network in which all UAV in service are able to communicate with each other. Such an interconnection is ensured by

$$\alpha_{ijk} \cdot D_{ij}^n \leq r, \forall\ i, j \in \mathcal{N},\ k \in \mathcal{D} \cap D_{ij}^n \neq 0. \tag{8}$$

We introduce the auxiliary variable α_{ijk} that is equal to 1, if two adjacent UAV are placed on nodes i and j and zero otherwise. Furthermore, the distances between all nodes i and j are defined by parameter D_{ij}^n , while r denotes the UAV communication range. We reduce the calculation time for parameter D_{ij}^n by reducing the set of potentially nodes to reach by a square-shaped area arround i with a side length sligthly larger than r, see Fig. 1. Technically, the auxillary variable α_{ijk} is defined as $u_{ik} \cdot u_{jk+1}$ in order to determine the distance between k and $k+1$. We linearize this logical AND condition as

$$\alpha_{ijk} \leq u_{ik}, \forall\ i, j \in \mathcal{N},\ k \in \mathcal{D} \tag{9a}$$

$$\alpha_{ijk} \leq u_{jk+1}, \forall\ i, j \in \mathcal{N},\ k \in \mathcal{D} \tag{9b}$$

$$\alpha_{ijk} \geq u_{ik} + u_{jk+1} - 1, \forall\ i, j \in \mathcal{N},\ k \in \mathcal{D}. \tag{9c}$$

Since the number of UAVs in service is lower than the total number of available UAVs d, they must be numbered consecutively. Otherwise, some values of k will be skipped during the optimization which results in (8) being ignored and therefore no interconnected network will be established. To address aforementioned problem, we introduce (10) as

$$\sum_{i=1}^{n} u_{ik} \geq \sum_{i=1}^{n} u_{ik+1}, \forall\ k \in \mathcal{D}, \tag{10}$$

ensuring that if UAV $k+1$ should be deployed, then k must have been deployed first.

A. Feasibility query algorithm

The optimization model is conventionally solved using GAMS [20] with CPLEX. However, as the problem is of large combinatorial and potentially ambiguity nature, lots of network users as well as a large numbers of UAVs increase the computation times to unacceptable levels (hours - unsolvable). Therefore, we introduce an alternative approach, we call feasibility query algorithm (FQA), transforming the optimization model into a multi-iterative constraint-satisfaction-problem, see Fig. 2. We incrementally increase the number of UAVs, given by parameter d and the maximum charging station distance s in a nested loop. To set the number of UAVs fix we need to adjust (4) to state $=$ instead of $\leq$. In each iteration, we check whether there exists any feasible solution for an exact value of d and s. If the optimization is feasible, the first solution that is found by the solver will be saved and no further possible solutions will be searched. To decrease the number of iterations we start by iterating the distances s with the largest number of UAVs to find the lower bound for the distance s. If an iteration with less UAVs reaches its first feasible solution with this lower bound of s, no further iteration with more UAVs is necessary. To further decrease the number of iterations we then check for each iteration of d if there exists a solution with the largest s. If this results in infeasibility there exists no solution for this amount of UAV. Here we introduce a flip variable σ_d, set to 0 as long as no solution with the highest s has been found. As soon as the lowest number of UAVs d with a feasible solution is found, σ_d is set to 1 and the lowest possible s for higher values of d will be searched.

This method greatly reduces computation times in large-scale problems and is used in case study 2), while in case study 1) we use the conventional optimization formulation.

IV. Experimental Evaluation

We evaluate our approach with a test case of a point to point connection and one larger example connecting distributed generators in a modified version of the IEEE 123-bus test feeder. All calculations are made on a Laptop equipped with a 2.2 GHz Quad-Core Intel Core i7 processor and 16 GB of RAM.

A. Example 1 - point-to-point connection

We consider a small model with two network users located at the northwest and southeast corners of a 10x10 node grid and use the optimization model to find the optimal placement and amount of UAVs. This resembles a real world situation in which a communication channel between a control

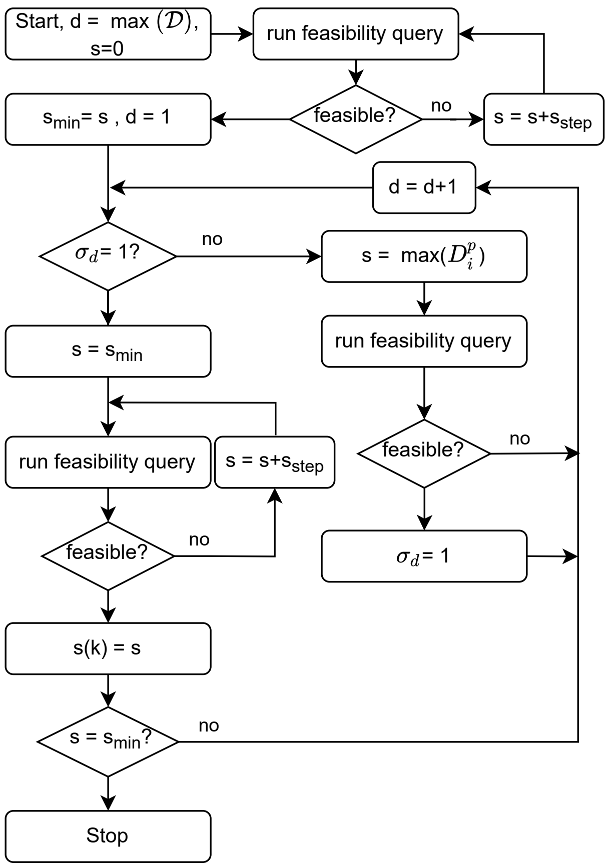

Fig. 2. Feasibility query algorithm.

center and emergency vehicle, or among emergency teams themselves is established. DERs are placed on the coordinate grid, concentrated in the area in the southwest in order to evaluate proximity to the deployment locations. UAV have a communication range of $r = 2.5$ length units. The expected network shape (shifted to the southwest) is thus formed with the UAV placed close to the stations, see Fig. 3.

To build an interconnected network in reasonable distance to the charging stations, five UAV are needed. The solution is found in 31 sec with an 5% optimality gap.

B. Example 2 - IEEE 123-node test feeder

In order to give an extended application of our method and a possible example for a microgrid communication system, we showcase an electric grid based on the IEEE 123-node test feeder. The POIs are grid-forming distributed generators that act both as a charging station locations and a network users (red dots). Also, we add locations that solely serve as charging stations but do not require a connection to the communication network, thus non-grid-forming energy sources like PV plants (blue dots). The communication range is set to $r = 2.5$ length units.

The full optimization with a 10% optimality gap tolerance takes more than an hour to solve. However, making use of the FQA results in four solutions for specific combinations of

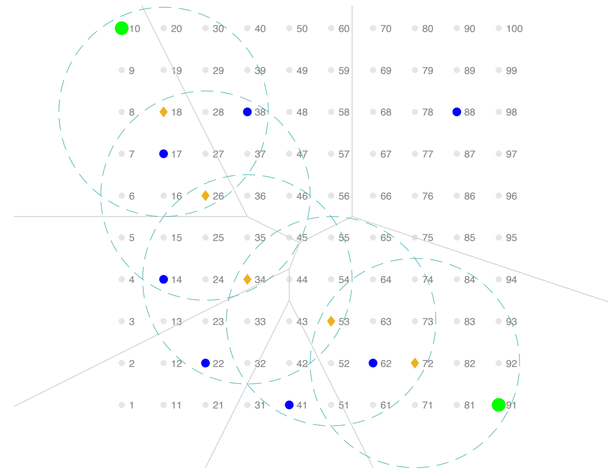

Fig. 3. Point-to-point connection. Green dots resemble network users, e.g. operation center and emergency vehicle. DERs with connected charging stations are displayed by blue dots, a Voronoi tessellation shows the closest charging station from any point in the area. The orange diamonds display the UAV deployment locations, the blue dotted rings show their coverage area. Weighting factors are set to $w_d = 1$ and $w_s = 0.5$

UAV number and charging station distance after 393 seconds, displayed in Fig. 4. We hereby prove the FQA's effectiveness in reducing computation times in large scale problems.

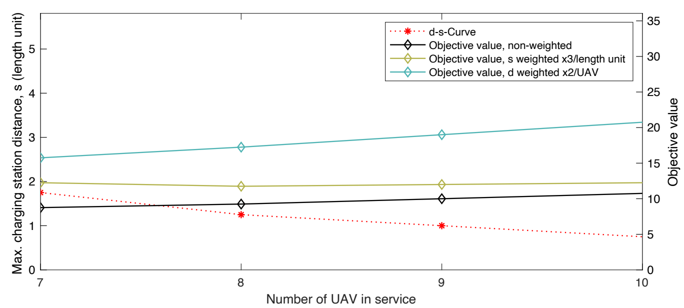

Fig. 4. Objective value and weights of the FQA. The red curve displays the minimum charging station distance that can be achieved by a given number of UAVs in service. The other curves represent the objective value for various weightings. A higher emphasis on the costs per UAV operations ($w_d = 2$) results in the blue curve that has the minimum at 7 UAVs. A higher weight on costs per charging station distance ($w_s = 3$) results in a minimum at 8 UAVs, shown by the golden curve. Setting both coefficients to 1, results in the black curve.

Furthermore, we implemented an objective value curve that can be interpreted as a cost function. The corresponding values of d and s are multiplied by their respective weights w_d and w_s and summed up. The weight coefficients w_s and w_d resemble the cost per UAV in service and cost per length unit, respectively. Adjusting the weights according to individual situations or preferences leads to different objective values as optima. As this can be done in retrospect, no new FQA needs to be performed.

The FQA minimizes the charging station distance individually by defining an upper boundary that cannot be exceeded. Thus, it merely makes sure that the placing takes place within the boundary, while the UAVs are not necessarily placed on

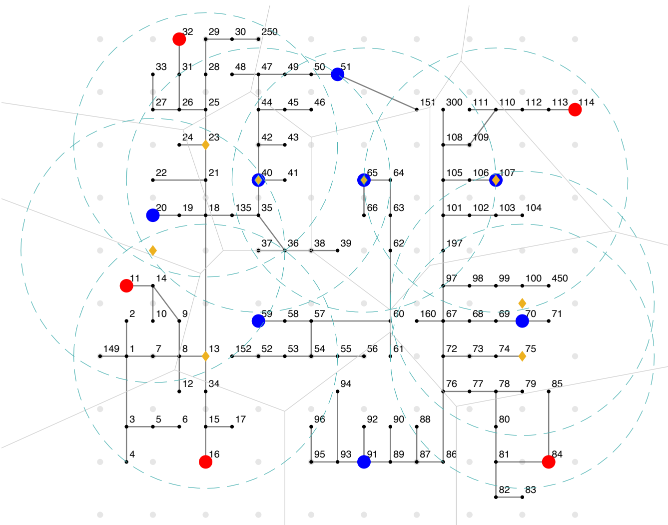

Fig. 5. Microgrid communication system. The setting is a 10x10 node coordinate grid (grey dots) combined with the IEEE 123-node test feeder (black dots and edges). It contains 5 distributed generators (red dots) and 8 non-grid-forming energy sources (blue dots). Possible deployment locations are all nodes of the coordinate grid, as well as the energy sources' coordinates. UAV placement is displayed by orange diamonds and blue rings represent the UAV's communication range.

the very optimum. In contrast, the conventional optimization aims to minimize the distance for every UAV placement to find collective minimum, so the solution might be closer to optimality, given an according optimality gap tolerance. To further increase optimality, the conventional optimization model is executed with values of d and s of the minimum objective value (after an appropriate weighting of the FQA results). The number of UAVs is fixed here, the objective function can therefore be reduced to the right-hand term of (1) and constraint 10 is irrelevant. We perform the optimization with an optimality gap of 10% for $d = 8$, the value that provides the minimum objective value for $w_s = 3$, taking 400 seconds. The results are displayed in Fig. 5.

V. Conclusion

In this paper, we presented a method to establish an emergency network based on the MANET technology. We implemented an energy-optimized method to deal with UAV battery capacities and showed an explicit application in form of a microgrid communication network. By developing and using the FQA method, we showed a significant reduction in computation times compared to the conventional optimization model. However, ways to reduce computation times in the conventional optimization, as well as in certain iterations of the FQA method, are left for further research. Furthermore, a scheduling concept could prove useful for practical applications, adding a time component, time-dependent UAV states and activities to the optimization.

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