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RESEARCH ARTICLE

Single-drone energy efficient coverage path planning with multiple charging stations for surveillance

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ABSTRACT

Drones have started to be used for surveillance within the cities, visually scanning the predefined zones, quickly detecting abnormal states such as fires, accidents, and pollution, or assessing the disaster zones. Coverage Path Planning (CPP) is a problem that aims to determine the most suitable path or motion plan for a vehicle to cover the entire desired area in the task. So, this paper proposes a novel two-dimensional coverage path planning (CPP) mathematical model with the fact that a single drone may need to be recharged within its route based on its energy consumption, and the obstacles must be avoided while constructing the route. Our study aims to create realistic routes for drones by considering multiple charging stations and obstacles for surveillance. We tested the model for a grid example based on the scenarios obtained by changing the layout, the number of obstacles and recharging stations, and area size using the Python Gurobi Optimization library. As a contribution, we analyzed the impact of the number of existing obstacles and recharging stations, the size and layout of the area to be covered on total energy consumption, and the total solution time of CPP in our study for the first time in the literature, through a detailed Scenario Analysis. Results show that the map size and the number of covered cells affect the total energy consumption, but different layouts with shuffled cells are not effective. The area size to be covered affects the total computation time, significantly. As the number of obstacles and recharging stations increases, the computation time decreases up to a certain limit, then stabilizes.

1. Introduction

Technological developments such as unmanned aerial vehicles (UAVs) have significantly affected all industries in recent years. UAVs, which were first used for military purposes [1-2], soon attracted the attention of the private sector and commercial industries. With the new regulations made for air traffic management, drone studies have been channeled and increased accordingly. According to researchers, drones (UAVs) are currently used mostly in outdoor areas [3], and outdoor applications tend to increase in the future.

When UAV technologies are examined under the title of sustainable cities, it aims to be a solution to the problems that come with sustainable cities [4]. It will be possible to use UAVs, which are expected to have an important role in the field of smart and sustainable cities, in city problems such as flood detection, disaster management, traffic management, health needs distribution, and last-mile delivery by connecting to all data links with IoT technology [5]. Otto et al. [6] also emphasized that UAVs may provide cost savings and capabilities for difficult-to-access infrastructure, environmental monitoring, and medical supplies distribution, and help save lives.

In this study, we developed a mathematical model for the two-dimensional Coverage Path Planning Problem, which aims to minimize total energy consumption while considering the drone's recharging and the obstacles to be avoided within the path plan. Our study has the following contributions: Unlike the existing models for other vehicle types, the specialized energy consumption function for the drone has been added to the two-dimensional Coverage Path Planning (CPP) model. Besides, recharging the drones in the predetermined stations is decided in the model to overcome battery drain problems, and the obstacles are avoided during the path planning.

Although the related CPP problem has been examined

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from many perspectives, we analyzed the impact of the number of existing obstacles and recharging stations, the size and layout of the area to be covered on total energy consumption, and the total solution time in our study for the first time in the literature, through a Scenario Analysis. This is a unique aspect of our study. This comprehensive analysis brings useful insights to this field. To the best of our knowledge, none of the past studies included all these aspects in the two-dimensional Coverage Path Planning of drones.

The paper is organized as follows: In the following section, the related works are briefly explained. In Section 3, the CPP problem is introduced. In Section 4, the Proposed Mathematical Model is explained. Then, in Section 5, Scenario Analysis and application results are discussed in detail. Finally, the Conclusion and future work are presented.

2. Literature review

In this section, a brief overview of the civil applications of drones/UAVs will be made. Later, past studies regarding the CPP will be discussed, and the merit of our study in the current literature will be explained. Cai et al. [7] made a survey of advances in UAVs and future application prospects. Drone technologies were studied for different application areas such as logistics [8-9], manufacturing [10], surveillance [11], intralogistics [12-13], disaster management [14], inventory management [15-16], and agriculture [17-18]. Ozkan and Kaya [11] studied UAV path planning for border security and patrolling missions and solved the problem using a Genetic Algorithm-based Matheuristic for different scenarios based on departure basis, daily patrol numbers, and ranges of UAVs.

Besides, Otto et al. [6] performed a comprehensive review study of the optimization approaches for civil applications of drones/UAVs. Coverage path planning for full and partial coverage, as well as, coverage from stationary positions were discussed in detail [6]. Readers may refer to this study for a comprehensive literature review. Glock and Meyer [19] developed a unified view for path planning and vehicle routing studies from many different disciplines that aim at spatial coverage. This study is also an interesting one that discusses the similarities between and the solution methods of these two problem types.

The CPP problem has been studied for not only single-drone but also multiple drones [20]. Avellar et al. found the optimum number of drones required to cover the entire designated area and tried to execute the task with multiple drones in a minimum time [21]. In another study, a suitable covering path was created for the mapping task to determine post-disaster risk with more than one drone [22]. Besides, Wang et al. [23] developed a model that allowed drones to cover the area more than once each time by improving the only one-time coverage constraint. Zhang and Duan [24] added constraints for drones with different starting battery capacities to cover the space. The path routing problem for multiple drones that minimizes total traveling time was studied in an urban setting, considering battery limitations, obstacles, and recharging stations [25]. Although this study is like our work, one minimized total time spent during the route rather than total energy consumption.

In addition to 2-dimensional studies, there are also instances of 3-dimensional (3D) CPP articles [26-27]. Bircher et al. [26] developed the routing optimization model and mostly focused on 3D structure inspections; while Balasubramanian et al. [27] determined the optimum route by considering different 3D static obstacles.

Besides, there are some past studies that focused on energy-efficient CPP which is the main topic of this study. Balasubramanian et al. [27] used the ant colony optimization model to calculate the 3-dimensional energy-efficient route. Vasquez-Gomez et al. [28] developed an efficient route planning algorithm for the coverage of the convex regions of the drones, based on different starting and end points, but the algorithm did not guarantee optimality. Choi et al. [29] developed a column generation algorithm for solving the CPP based on a precise computation of the energy consumption during the missions. Aiello et al. [30] developed an energy-efficient algorithm for route planning of drones, but the authors did not consider the recharging stage within the routes. Modares et al. [31] formulated the energy-efficient CPP for multiple drones and minimized the maximum energy consumption among all of the UAVs paths. Shivgan and Dong [32] modeled the energy-efficient CPP in a similar way to the traveling salesman problem and solved it by means of Genetic and Greedy Algorithms. To sum up, algorithm-based past papers for energy-efficient CPP are more common, but these do not guarantee optimality. Most of them do not consider recharging needs. However, our study considers both recharging states in the route and the time spent during the route including flight time and recharging time.

Bezas et al. [33] studied the CPP for swarms of UAVs and solved the model considering paths of parallel lines and spiral coverage. Vazquez-Carmona et al. [34] developed an efficient algorithm for the CPP, especially for disinfecting the areas, and simulated the routes that they developed. Tevyashov et al.[35] solved the multi-drone CPP of the agricultural fields, by minimizing the maximum time needed to cover assigned areas. The common objectives of the CPP models are maximum area coverage, minimum energy consumption, and minimum time [36]. For a detailed survey of the CPP with drones/UAVs, the readers may refer to [20].

The impact of the number of existing obstacles and recharging stations, the size and layout of the area to be covered on total energy consumption, and the total solution time of the Energy-Efficient CPP were analyzed for the first time in the literature, using a comprehensive Scenario Analysis. This is a unique aspect of our study.

3. Problem definition

Coverage Path Planning (CPP) is a problem that reveals the appropriate motion plan for a vehicle to cover the entire desired area in the task [20]. The mentioned vehicle could be a human, robot, flying vehicle, or any other mechanism which can move and turn. In this study, the area to be covered is thought to be covered with a multi-rotor UAV, commonly known as a drone.

To properly construct the CPP problem, the area to be covered is identified as a certain map and it is assumed that the UAV knows the map beforehand. As also stated in the research, the problem logic is similar to the problem of TSP [32], in that the vehicle has to consecutively visit all of the nodes in the system. A similar type of this method is used in literature by dividing the space into grids for discretizing it, the only difference is that the CPP problem is turned into a VRP problem [37]. In the CPP problem, the map is divided into cells that have an equal area, and the cell is assumed to be covered when the drone is positioned in the center of the cell since the drone has a specific hovering height and the camera can capture an area at a time [31]**.** The area of the cell is proportionate to the camera angle of view and it is assumed to be a square view. UAV hovers at a specific height which makes the map a 2-D space. Because of the fixed hovering height, at all points of the map, the camera sees cells that have the same dimensions.

Different types of UAVs can perform different movement types. To define the problem much more strictly, the type of movement that the UAV can perform has to be decided. In the literature, there are two types of approaches called the Von-Neumann and Moore Neighborhood movements which can be seen in Figure 1 [38]. Since drones can make diagonal moves by changing the power of rotors and it is more realistic, the Moore Neighborhood approach is more suitable for the application.

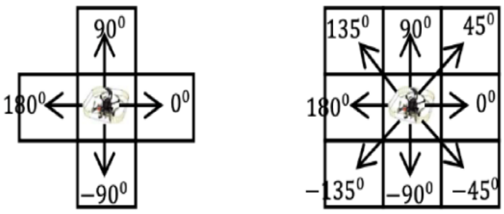

Figure 1. Von-Neumann movements (left) and Moore Neighborhood movements (right).

To make the application more realistic the map includes obstacle cells that UAV has to avoid and does not have to cover. These obstacles can range from no-fly zones to buildings. In the literature, multi-UAV applications [39] and single-UAV applications [40] are available. In this work, a single UAV is chosen. The drones are fit for the use areas. However, the main problem with drones is the low fly durations because of the battery [41]. To solve the problem of battery recharging stations that are spread across the map are added to the problem definition. To calculate the energy consumption a unit energy cost is defined per cell, and this consumption is correlated with the distance traveled. While straight movements cost one unit of energy, diagonal movements cost according to the distance traveled. Recharging stations allow the drone to fully charge its battery when it lands at the cell of the recharging station. Although technology development studies are conducted to achieve better energy management in electric vehicles [42], recharging station cells still must be covered in the path planning.

4. Mathematical model

We proposed a new mathematical model for the single-vehicle (i.e. UAV), energy-efficient two-dimensional CPP, in this study. The model consists of sub-elements such as assumptions, sets, parameters, variables, objective functions, and constraints that are expressed mathematically. Each element has been meticulously developed to validate that the model is sustainable and does not give infeasible solutions, and is explained in detail in the following sections:

Some assumptions have been made to reach feasible results and to increase the computational speed of the model. These assumptions are explained one by one in the following part:

- A drone is deployed from and returned to a predefined point inside the grid, called the base.
- If the area is not convex, it is converted into the convex hull of the area (square or rectangle).
- A drone is equipped with an onboard camera/sensor pointing down and has a square viewing aspect, which equals one-grid size.
- No external forces affecting the drones are considered, such as weather conditions (i.e. wind).
- The number of visiting recharging stations must be equal to 1 for the other cells. Cells that contain recharging stations are also considered to be covered.
- All coverage areas and recharging stations are at the same altitude; therefore, the problem is 2-dimensional.
- At any recharging station, the battery is charged to 100% battery level. In other words, no partial charging is allowed.
- The time spent at the charging stations varies according to the remaining charge of the drone.
- The spent time for landing and take-off movements from the starting and charging points is neglected in the model.
- Drone always moves at a constant speed, disregarding the extra time spent in turns.
- Total energy consumption is related to the distance traveled and unit energy consumption of the vehicle per meter.
- The battery needs to be always higher than a certain percent of its full battery level to provide enough energy to return home base in case of emergencies.

- The battery change times will not be included in the model since this is an energy-consumption-based model.

4.1. Sets

The sets that are used in the model are described below.

k: Step number (k = 0, 1, 2, …, K).

i: The cell that the drone is leaving (i = 1, 2, …, I).

j: The cell that the drone is entering (j = 1, 2, …, I) (i=j=1 represents depot/base).

OC: The set of cells that have an obstacle.

CC: The set of cells that needs to be covered.

SC: The set of cells that have a charging station.

4.2. Parameters

The parameters used in the construction of the model are described below.

p: Initial position of the drone.

d: Energy spent in the movement of one cell.

B: Full battery capacity of the drone.

I: Number of cells to be covered.

s_i: Whether cell i has a charging station or not. (s_i=1 ∀ i ∈ SC, s_i=0 ∀ i ∉ SC)

c_{ij}: Energy consumption between cell i and cell j.

r_{ij}: Time spent between cell i and cell j.

g: Total amount of time to fully charge the drone battery.

4.3. Decision variables

The decision variables that the model decides on are described below.

y_k: The battery of the drone at the end of step k.

h_k: The cumulative sum of energy consumption from step 1 to k.

u_i: Dummy variable for sub-tour constraints.

m_{ij}^k: Dummy multiplication variable.

t: The total time of flight for the drone to cover all cells.

x_{ij}^k={1, if the drone moves from cell i to cell j at step k; 0, otherwise} .

4.4. Mathematical model

The objective function of the model is as given in (1).

$$Minimize\ \sum_{i,j,k} c_{ij} x_{ij}^k \tag{1}$$

Subject to

$$\sum_i x_{ij}^k = \sum_i x_{ji}^{k+1}, \forall j,k,k \neq 0, k \neq K \tag{2}$$

$$\sum_i x_{ip}^K = 1 \tag{3}$$

$$x_{ij}^k = 0,\ \forall i,j,k,\ i = j \tag{4}$$

$$\sum_{i,k} x_{ij}^k \geq 1, \forall j, j \in CC \tag{5}$$

$$u_i - u_j + I \sum_k x_{ij}^k \leq I - 1, \forall i \neq j, i > 1, j > 1 \tag{6}$$

$$c_{ij} x_{ij}^k \leq d\sqrt{2}\ \forall i,j,k \tag{7}$$

$$\sum_k x_{ij}^k \leq 1, \forall i,j,i \neq j, k \neq 0 \tag{8}$$

$$x_{ij}^0 = 0, \forall i,j,i \neq j \tag{9}$$

$$\sum_{i,j} x_{ij}^k = 1, \forall k, k \neq 0 \tag{10}$$

$$h_k = h_{k-1} + \sum_{i,j} x_{ij}^k c_{ij}, \forall k, k \neq 0 \tag{11}$$

$$h_0 = 0 \tag{12}$$

$$h_k \leq h_{k+1}, \forall k, k \neq K \tag{13}$$

$$\sum_j x_{pj}^1 = 1 \tag{14}$$

$$y_0 = B \tag{15}$$

$$m_{ij}^k = s_i x_{ij}^k, \forall i,j,k \tag{16}$$

$$y_k = y_{k-1} - \sum_{i,j} x_{ij}^k c_{ij} + \sum_{i,j} m_{ij}^k (B - y_{k-1})\ \forall k, k \neq 0 \tag{17}$$

$$t = \sum_{i,j,k} x_{ij}^k r_{ij} + \sum_{i,j,k;k\neq 0} g m_{ij}^k (B - y_{k-1})/B \tag{18}$$

$$y_k \geq 0.2B, \forall k \tag{19}$$

$$x_{ij}^k = \{0,1\}, \forall i,j,k \tag{20}$$

$$m_{ij}^k = \{0,1\}, \forall i,j,k \tag{21}$$

$$y_k, h_k, u_i, t \geq 0\ \forall i,k \tag{22}$$

Objective (1) calculates the total energy consumption by the sum product of the given unit consumption cost and the decisions made by the model about the nodes to be visited at each step, considering all the decisions overall steps. Constraint in (2) applies the classical TSP approach by making sure that the number of elements that go into a cell goes out from it at all points. The only modification to the original equation is making sure the equality is according to the steps. With the constraint in (3) the UAV returns to its original position after covering every cell at the last step.

Constraint in (4) is a simple constraint that prohibits the movement from a cell to itself. The Constraint in (5) is the main constraint that ensures every single cell is covered. This is an inequality that is greater than or equal to one, and there can be some circumstances where the UAV has to visit the same cell twice. Here, the set CC does not contain the obstacle cells, which means obstacle cells must be avoided. Constraint in (6) is the sub-tour elimination constraint which is a well-known and standard constraint that prevents the system from going into a sub-tour and; thus, not being able to complete the whole path. Constraint in (7) ensures the drone movement is a type of Moore Neighborhood movement and other types of movements are not allowed. With the Constraint in (8) the same movement cannot be made in different steps. In other words, one movement can be made only in one step. Since the steps are defined starting from 0, the constraint in (9) ensures that there is no movement in step 0. Constraint in (10) ensures that one step includes only one movement. Constraint in (11) calculates the cumulative energy consumption to be used in the other constraints. Constraint in (12) initializes the sum of energy consumption to 0 at step 0. Constraint in (13) is the constraint that provides continuity to the model in terms of the steps. With this constraint, the order of steps is correctly evaluated in the model. Constraint in (14) ensures the UAV starts from the initial point *p* at step 1. Constraint in (15) is the initialization of battery level to B which is the maximum, at step 0. Constraint in (16) is added to the model as an intermediate calculation that calculates the auxiliary multiplication variable of whether the UAV is leaving the charging station or not. The Constraint in (17) is the battery update constraint which ensures the battery is lowered after a movement is made at any step. With the second part of the equation, the battery is fully charged if the UAV is exiting a charging station. The charging is made after the drone is done with its last step to ensure that there is no overplus of energy used when there is none. Constraint in (18) calculates the total flight time of the drone to fully cover all the cells that can be covered as well as the charging times in stations according to the amount of battery charged. Constraint (19) ensures that the battery is always more than 20% of full capacity [43]. Constraints in (20) and (21) are binary constraints for the variables x and m. Constraints in (22) are the nonnegativity constraints for the non-binary decision variables.

5. Experimental design

In this section, scenario analysis is performed to analyze the model under different circumstances. The effects of parameters such as layout, number of obstacles, area size, and number of recharging stations of the model are examined in detail with four different main scenarios.

The grid example shown below in Figure 2 illustrates the grid and cell design used by the model throughout the scenario analysis. While black cells represent barriers, the blue cell represents the recharging stations. Arrows also represent the optimal route that the model finds to cover all cells. As can be seen, the route manages to avoid obstacles while at the same time stopping by the charging station to avoid running out of battery. The battery needs to be always higher than 20% of its full battery level to provide enough energy to return home base in case of emergencies according to DJI which is one of the best drone producers [43].

As mentioned above, the model was examined under four different main scenarios. The changing parameters are as follows:

1. Layout Design
2. The number of Obstacles
3. Area Size
4. The number of Recharging Stations (RS)

There are also the fixed parameters of the model which are not changed across scenarios. The list of parameters and their values are given in Table 1. However, other than these, drone type, processor power, and battery type situations, which may vary in real life, are not considered in our analysis.

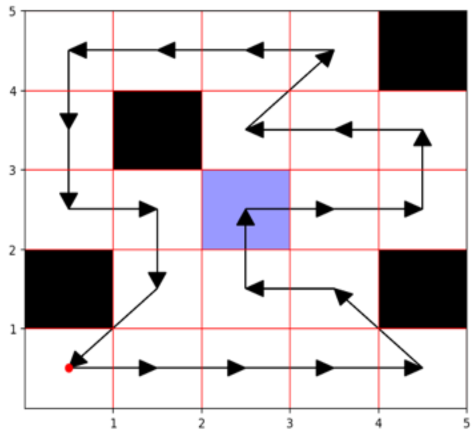

Figure 2. Grid example of the scenario analysis.

Table 1. Fixed-parameter values.

Parameter	Value
Starting Cell	1
Speed (Square/Unit Time)	1
Average Energy Consumption Per Cell	1
Maximum Battery Capacity (Unit Energy)	100

In addition to the fixed parameters above, each scenario has Controlled Parameters (C), Independent (Changing) Parameters (I), and Dependent Parameters (D). The controlled parameters have fixed values through the associated scenario runs. The Independent Parameters are the ones with changing values within different runs of the associated scenario. The dependent parameters are the ones whose values may change according to the change of the Independent Parameters. The matrix of the scenarios and parameters is presented in Table 2. The dependent *variables* to be observed were determined as total energy consumption, average energy consumption, and computation time. In Scenario 1, area size, the number of obstacles, the number of covered cells, and the number of recharging stations were kept constant to observe the impact of the layout change, by shuffling only their places. In Scenario 1, ten different layouts were considered. In scenario 2, only one new obstacle is added each time, keeping the previous obstacle positions constant while increasing the number of obstacles. The layout is not shuffled every time. As the number of obstacles increased from two to eleven at each run, the number of covered cells decreased.

Table 2. Parameters of the scenarios.

	Number of Cells Covered	Layout	Number of obstacles	Area Size	Number of Recharge Stations
S-1	C	I	C	C	C
S-2	D	C	I	C	C
S-3	D	C	C	I	C
S-4	C	C	C	C	I

In scenario 3, only the area size is increased by keeping the numbers and position of all obstacles and recharging stations constant. Accordingly, the number of coverable cells has increased. Six different area sizes changing from 3*3 to 8*8 were considered, at different runs. In scenario 4, the number of obstacles and area size are fixed. One new recharging station is added in each run, keeping the previous recharging stations' positions constant. The number of charging stations was increased from one to six at each iteration. The layout is not shuffled.

6. Scenario results and discussion

After deciding on the scenario setup, inputs, and outputs, the mathematical model was run by changing the parameter values at each scenario, iteratively, through the Gurobi Optimization Library. Recorded outputs were further prepared as bar/combo charts for each scenario. Throughout the analysis, the code for the model was compiled on the Gurobi Optimization Library in Python 3.8. The Gurobi version 9.1.2 was used to run the algorithm. The computer which was used to run the scenarios had a microprocessor of Intel(R) Core (TM) i7-7700HQ, and a total of four physical cores, and eight logical processors were used to run the scenarios with eight threads. We shared the Python codes of the mathematical model in [44].
For the study, the total energy consumption which is the objective of the model is the primary concern in terms of the outputs. As shown in the scenario details, since some of the models included different numbers of cells, the total energy consumption would not provide accurate or meaningful results. Hence, not to lose any type of information and to better interpret the results, the average energy consumption per cell was also logged. Lastly, for any scenario application of the mathematical model, the total computational time was recorded and a chart of the computation time was created.

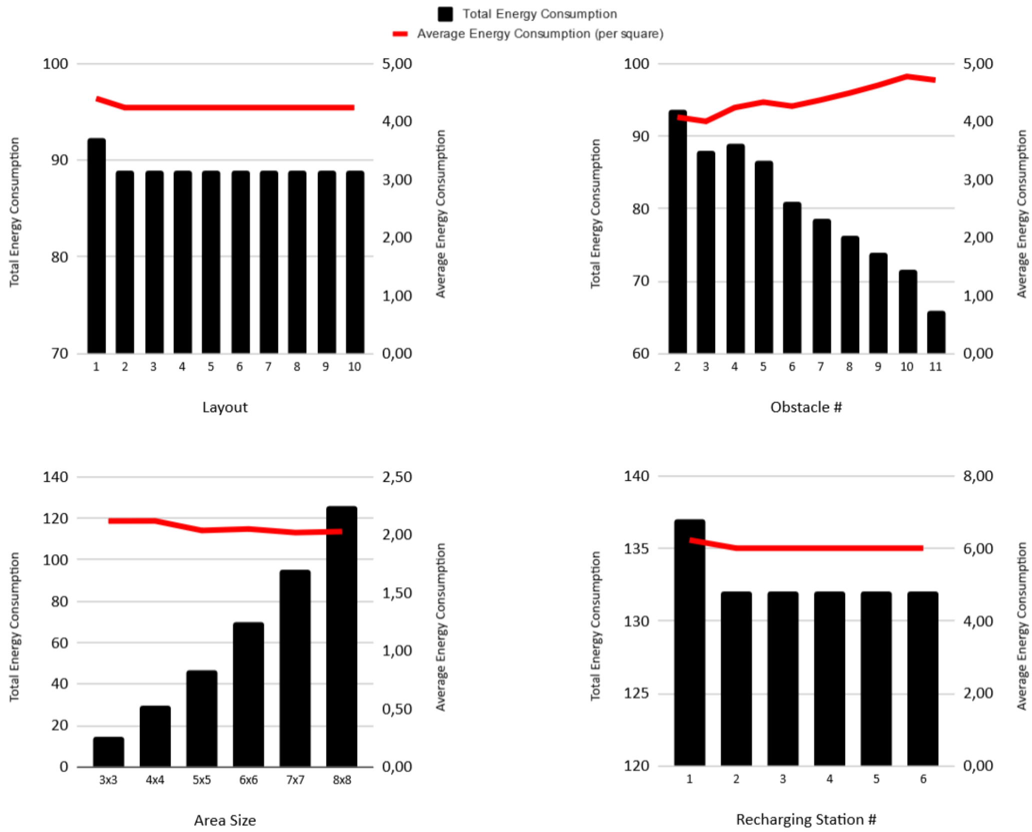

Figure 3. Scenario results for energy consumption.

6.1. Total energy consumption analysis

With the possible applications in mind, the most important performance metric in the covering mission is energy consumption. Drones are inadequate in terms of their battery capacity. Hence, utmost importance is given to the energy consumption. The four different scenarios have resulted as shown in Figure 3. The bars show the total energy consumption, whereas the red lines show the average energy consumption per cell.

The first scenario was constructed to observe if the total energy consumption changes in different layouts. The model was found to be resilient for different types of layouts by having similar results in terms of both total and average energy consumption. This shows that the model accomplishes what it was constructed for. In scenario 2, as the number of obstacles increases, the total energy consumption decreases. However, if average energy consumption per cell is observed (that is plotted in red), it increases as the number of obstacle cells increases. This indicates that the movements of the drone become more inefficient as the area becomes more restricted. In scenario 3, if there are more cells present on the map, the total energy consumption increases since the total area to be covered increases. The average energy consumption decreases slightly when the map size increases, but no significant changes are observed. Scenario 4 depicts the cases where the number of recharging stations increases in the same map setup (layout). The drone behaves differently and changes its path until a certain number of recharging stations. After that, the drone follows the same path since the battery does not become its primary concern. This behavior can be seen in Figure 3. After increasing the number of recharging stations beyond two, the model gives the same result in terms of total energy consumption.

As a result, in different scenarios, the model manages the battery of the drone as efficiently as possible, while covering the whole area. The map size, the number of covered cells, and to a certain extent the number of recharging stations affect the total energy consumption. However, different layouts with shuffled cells do not affect the total energy consumption.

6.2. Computation time analysis

We illustrate the computational times spent in each scenario, in Figure 4. In Scenario 3, the computation time is affected at most, since the number of cells increases exponentially. Scenario 1 has similar computation times through different layouts with some variation. This shows that the model acts efficiently in different layouts. In the second scenario, except for the model that has three obstacles, the computation time decreases. This decrease can be due to the decrease in the total cells that need to be covered. In the fourth scenario, the computation time decreases until the saturation point of the charging stations. After that, the computation time stabilizes. To sum up, the area size to be covered affects the total computation time, significantly. As the number of obstacles and recharging stations increases, the computation time decreases up to a certain limit, then stabilizes. The layout does not much affect the computational time.

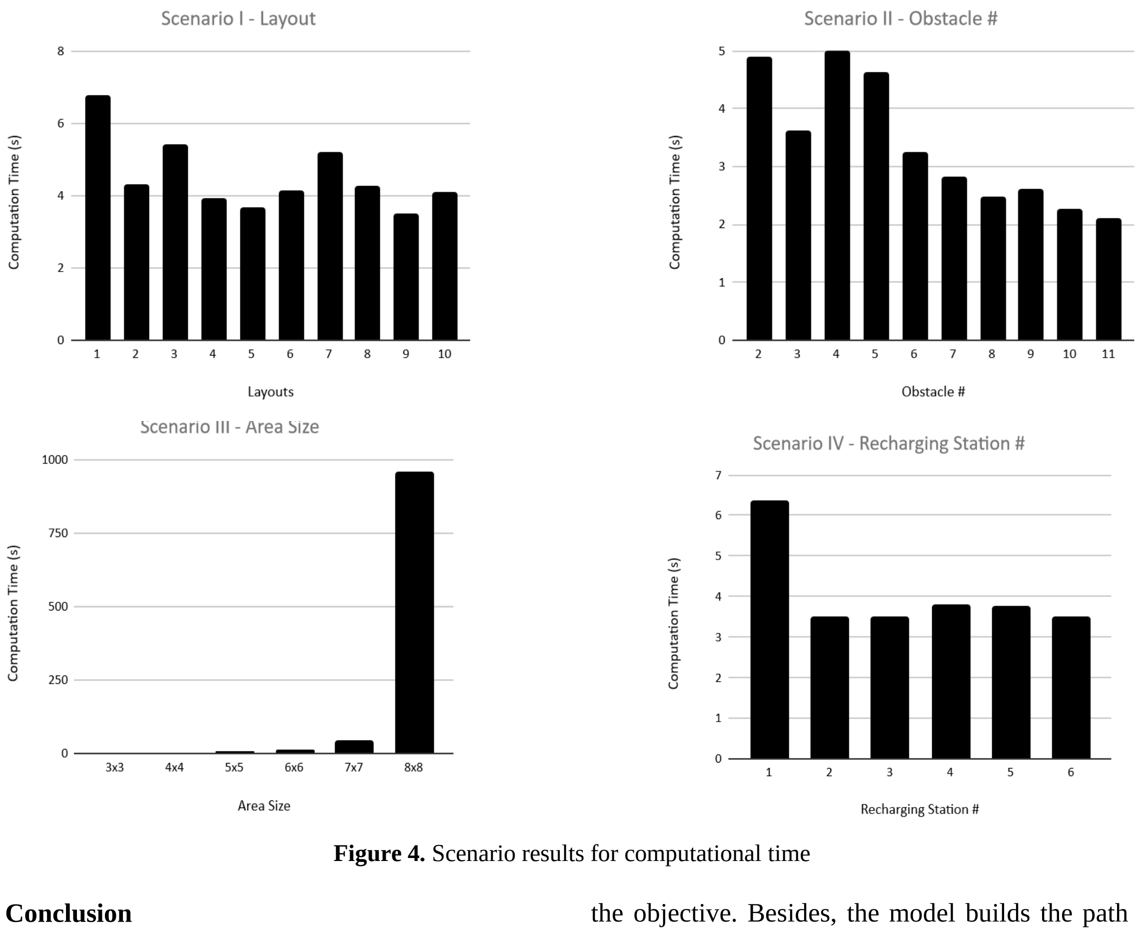

Figure 4. Scenario results for computational time

7. Conclusion

In this study, a novel mathematical model was proposed for the single-drone two-dimensional Coverage Path Planning that minimized the total energy consumption. The specialized energy consumption function for the drone has been defined in the objective. Besides, the model builds the path and decides at which step the battery must be recharged in the predetermined recharging stations while avoiding obstacles during the path planning. In addition, the impacts of the number of existing obstacles and recharging stations, the size and layout of the area to be covered on the total and average energy consumption, and total computational time were examined using a comprehensive Scenario Analysis. We explained our findings and proposed some insights. Some of the practical implications of this study are as follows:

- Disaster commanders and local government officials may employ the proposed model embedded in a software platform to plan the route of the UAVs, in order to assess the impact of the disaster and determine the affected disaster zones.
- For very big-size disasters, the area to be covered may be broken into segments, and the model can be solved, in shorter computational times.
- The availability of charging stations is a significant issue, especially for electric vehicles' adaptation. The total flight time results of our model can be exploited for the new recharging stations' location decisions.

To give perspectives for future studies in this field, more detailed studies can be performed on battery, algorithm, time, camera parameters, and movement. Firstly, the model can be modified to allow partial battery charging. In this way, it will provide more convenient routing for a drone that needs a limited time at the charging station or needs a partial charge to complete the route. Secondly, while dividing the areas where CPP will be applied, the real camera angle can be considered and the grid can be created accordingly. In this way, a more realistic routing matrix will be obtained.

Third, an objective function such as minimum time or latency can be written instead of energy consumption. In this way, the task assigned to the drone can be completed in a certain time instead of with minimum energy. Besides, the existing constraints in the model can be simplified, or some heuristic models can be developed for a faster solution. Because of the current complexity, serious computational power and time are needed. Lastly, the turning, accelerating, or decelerating movement of the drone can be added to make the work more realistic and applicable. For more advanced work, there could be an expansion by transitioning the 2-D space to a 3-D space with different obstacles, which could be buildings of different heights in the smart city application.

Acknowledgments

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