Designing a Network of Battery Swap Stations for Supporting UAVs in Long-range Delivery Operations

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***Abstract*—Recently, the use of Unmanned Aerial Vehicle (UAV) for delivery services has become a topic of interest and research for large commercial service providers such as Google and Amazon. The delivery speed of UAVs provides such companies with a significant advantage in their market. Although utilizing the UAVs in product delivery has received tremendous excitement, several issues need to be resolved prior to real-world implementation. The first issue with using UAVs as a transportation mode is their limited flying range. Small UAVs are not able to fly long distances due to their limited battery life. Flight range can be improved by using battery swapping stations in the planning horizon. UAVs can replace their depleted batteries at these stations and continue their fights. In our research, we attempt to develop a model to construct a network of such stations in order to enable the UAVs to fly long distances for making deliveries to far-reaching demand points. In addition, we develop a Tabu-Search heuristic to solve several instances of the proposed problem.**

***Keywords*—Last mile delivery, Network design, Unmanned Aerial Vehicle (UAV), Facility location, Optimization, Transportation.**

I. Introduction

The application of Unmanned Aerial Vehicles (UAVs) for last mile delivery has gained much attention as it has taken serious legal steps toward becoming a viable alternative. Two well-known companies, Google and Amazon, are exploring this type of delivery mechanism as a part of their newest technology innovation strategy (Google X [1] Amazon Prime Air [2]). Other applications of UAVs include disaster relief, border security, and agriculture. UAVs are most effective in developing countries with road deficiencies as well as in developed countries with congestion problems. In disaster relief missions, when roads become unpassable, UAVs can become very effective in delivering medicine and first aid packages.

Small UAVs can fly at low altitudes and avoid obstacles; however, due to their battery capacity, they have limited payload size and travel distance. For example, Micro UAVs can fly for only one hour and carrying a maximum load of 5 kilograms [3]. Operations with intensive time and distance requirements would need a system of UAVs along with a set of automated service stations to enable battery swapping. Such stations currently exist and they operate automatically without the need for labor [4].

II. Problem Definition

The problem that is considered in this paper is constructing a network of battery swap stations (BSS) to support UAV delivery routes. In order to enhance the flying range of the UAVs, a set of BSS should be located in the planning area such that a UAV can use them in order to satisfy the demand at the delivery points. The planning area is the geographical area that covers the demand points that should be visited by UAVs. There are two cost components associated with establishing a BSS: 1) construction cost and 2) operational cost. Construction cost is the cost of building the BSS and is a one-time cost. Operational cost is the cost of maintaining the BSS, which includes the energy cost of recharging the batteries once they become depleted. Alternatively, operational costs can account for a ground crew that regularly visits the stations and replaces the depleted batteries with charged ones. Once a station runs out of batteries, it becomes not functional. The mathematical model, presented in section 5, allows for considering different types of BSS; because in practice, BSS are not necessarily identical and can have different battery capacities. A Tabu search (TS) is proposed as the methodology in section 6. The operators of the TS are developed based on performance measures that

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focus on demand potential, network enhancement, and cost-benefit ratio of the location candidates. In section 6, an initialization procedure for finding a feasible solution is developed based on dynamic programming. The effectiveness of dynamic programming on both solution quality and running time is studied and discussed in section 7, computational study. The computational study is performed to provide useful insights on the use of the model and the solution methodology. The results are based on 300 instances that differ in the area of coverage, number of demand locations, and demand magnitudes. The results show that as the complexity of the instances grows, the developed TS outperforms CPLEX both in solution quality and running time. The computational study considers four types of BSS with different costs and battery capacities.

It is worth noting that the difference between classic problems in the literature and the proposed research problem are in two areas. The first area of difference is within the facility location problem (FLP). Our research problem is partly a facility location problem for a network of BSS. The classical FLP assumes independence among facility locations, meaning that there is no relationship between them. However, the nature of our problem requires consideration of relationships between locations because each UAV depends on several BSS in order to access the demand points. In other words, a single BSS cannot support the UAV trip independently. The closest class of FLP to our problem, that is studied in the literature is FLP problems with a backup facility for each customer [5] but still does not consider the relationship between two facilities. The second area of difference is within the location routing problem (LRP). Our research problem is partly a location routing problem (LRP). In this class of research, the main focus of the literature is to locate the facilities such that the cost of routing between customers is minimized [6], [7]. Similar to FLP, this category of problems does not study the routing between depots. It focuses on the vehicles that start their trips from a depot and deliver products to customers on the route before going back to the depot. In our research problem, in order to deliver a product to a customer, UAVs rely on a network of BSS which are essentially depots, not customers. As a result, unlike LRP, that studies the location of one depot, our research problem requires determining the locations of multiple depots (battery swap stations). The only known locations in the problem are the demand points. The same difference exists with our problem and the coverage problem (CP). CP does not study the relationship between facilities nor the routing between them. The only impact of two facilities on each other is whether their covered areas overlap or not. In figure 1, the difference between FLP, CP and the proposed problem in this paper is illustrated. Let $C1$, $C2$, and $C3$ be considered as potential locations, in addition, let S and D be the supplier and a customer (demand point) respectively. The arcs around $C1$ and $C3$ represent the coverage radius. A facility location formulation would locate $C3$ in order to cover the customer and a coverage formulation would locate $C1$ and $C3$ to cover the maximum area. However, for the proposed problem in the present paper, all three locations should be properly located in order to route a UAV from the supplier to the customer.

The remainder of this paper is structured as follows: Section 3 reviews the existing literature. Section 4 describes the assumptions considered as well as the notations used. Section 5 presents the mathematical model and is followed by a detailed discussion on the solution methodology in section 6. A computational study is discussed in section 7 to illustrate the model and the performance of the developed solution methodology. We conclude by summarizing the paper and presenting future work in the last section.

III. Literature Review

Due to the increasing popularity of both UAVs and Electric Vehicles (EV) among the public and businesses, there has been increased attention toward designing and expanding their support systems. EVs have gained a significant market share in the automobile market due to its economical and environmental incentives. Similarly, the use of UAVs in the last mile delivery has become a more realistic alternative since it has taken serious legal steps toward becoming a mode of delivery. Several research studies have begun to explore the design of service stations for both. Such service stations are generally to provide energy support for the vehicles' operations. Although this paper is focused on designing a network for commercial UAVs, EVs have a similar logistics system that involves charging stations. Therefore, in addition to UAV papers, EV papers are reviewed in this section. The focus is on reviewing a portion of literature that is closely related to the present topic, designing a network of BSS to support delivery operations. The existing literature has investigated the problem from three different perspectives of 1) locating, 2) routing and 3) scheduling/planning (Figure 2). Figure 2 classifies the literature and positions published articles in their corresponding areas. We believe the present paper is best positioned in the crossover of locating and routing where the simultaneous decision making of both locating the stations and routing the vehicles is studied.

Locating: The first group of research articles is concerned with locating the service stations; therefore

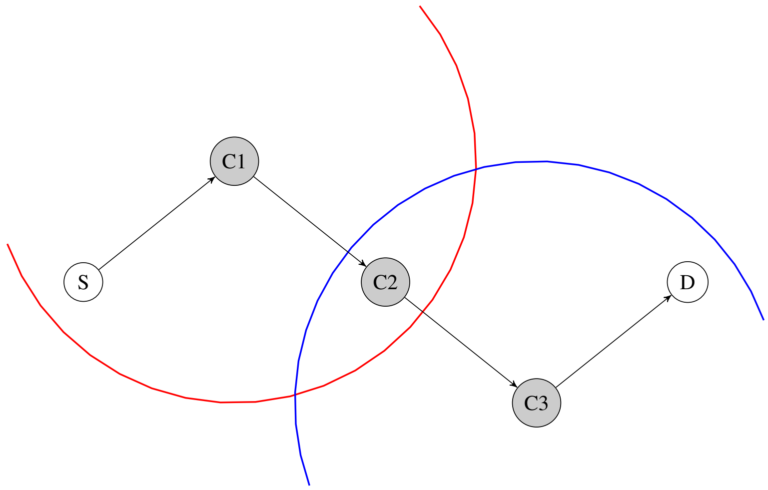


Figure 1: Small sample to show the difference of facility location and coverage problem with proposed problem.

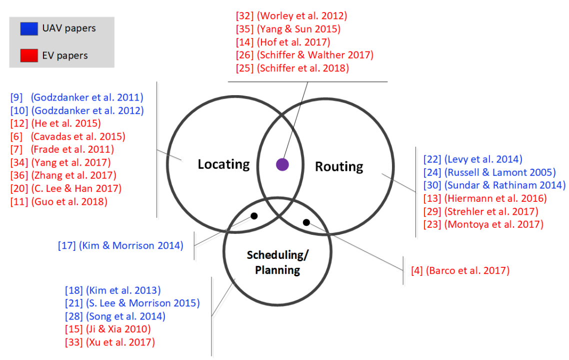


Figure 2: Classification of literature based on the modeling approach and application area

the approach taken is typically modeling the problem as a Facility Location Problem (FLP) or Flow-Refueling Location Model (FRLM). A range of different constraints is considered in the literature to customize the problem for different purposes. Godzdanker et al. [8] proposes a p-median problem to locate a fixed number of stations. They extended their work in [9] by studying the station location problem while considering the UAV flight path. He et al. [10] optimizes the location of public charging stations for electric vehicles on a network of roads with the assumption of determining tour paths and recharging plans simultaneously by drivers. They formulated the problem as a bi-level mathematical program to minimize the travel and recharging time and solved it using a genetic algorithm. Cavadas et al. [11] proposes a mixed integer programming model to locate the EV slow-charging stations. In this problem, drivers can stop at various locations but they can only charge the EV at one of the charging stations. The travelers parking locations and their daily activities are considered in this model. Frade et al.[12] studies the location of EV charging stations in Lisbon, Portugal by developing a maximal covering model. They determine the number and capacity of the stations to be installed. Yang et al. [13] develops a linear integer model to maximize the profit by determining the location of BSS. The model contains constraints to guarantee a customer satisfaction level. Customer satisfaction, which is modeled as a function of ”range anxiety” and ”loss anxiety”, is represented in both deterministic and fuzzy scenarios. A Tabu search combined with a greedy randomized adaptive search is developed to efficiently solve the problem. In a similar work, Guo et al. [14] examines the battery charging station location problem, considering users range anxiety and distance deviations, the two major barriers to the mass adoption of electric vehicles. Zhang et al. [15] studies the capacitated FRLM for EVs with consideration of multiple time periods and different demand dynamics over time. The model determines the location of charging stations as well as the number of charging modules at each station. Lee and Han [16] develops a mixed integer nonlinear model to formulate an extended version of FRLM problem to account for probabilistic travel range. This is due to factors such as road conditions. They propose a solution methodology that combines Benders decomposition and column generation.

Routing: Another group of articles focuses on routing the EVs and UAVs (Figure 2). They generally use variations of the Vehicle Routing Problem (VRP) and consider relevant constraints to model a specific application area [17]. Russell and Lamont [18] studies Genetic Vehicle Representation (GVR), an approach to solving instances of VRP with a genetic algorithm. They argue the effectiveness of the method for UAV routing. Levy et al. [19] considers the routing of unmanned vehicles (UV) with fuel constraints for multiple target locations while multiple fuel stations (or depots) exist. They minimize the total travel cost of vehicles, while each target is visited at least once by a vehicle and the fuel constraint is satisfied. Two heuristic methods of variable neighborhood decent (VND) and variable neighborhood search (VNS) are developed to find reasonable solutions for large instances. Sunder et al. [20] considers a single UAV routing problem with fuel constraints and multiple depots when the UAV is allowed to refuel at any depot. The objective is to minimize the total fuel required while each target is visited once. They propose a mixed-integer linear programming (MILP) model to find optimal solutions. Hiermann et al. [21] introduces a new approach by combining two problems, Fleet Size Mix Vehicle Routing Problem with Time Windows (FSMFTW), and Electric Vehicle Routing Problem with Time Windows and Recharging Stations (EVRPTW). They propose a mixed integer programming (MIP) model for the problem and solve smaller instances using a branch-and-price method. To solve real size problems, they develop a meta-heuristic approach based on an Adaptive Large Neighborhood Search. Strehler et al. [22] develops a general model for routing of electric and hybrid vehicles with intermediate stops at charging stations. It shows that recharging both in nodes and on edges adds combinatorial variety to the classic constrained shortest path problem, which may lead the energy efficient routes to contain cycles. Montoya et al. [23] investigates the impact of the non-linear nature of battery charging time on the routing of electric vehicles. They also propose a hybrid meta-heuristic as a solution methodology. The results suggest that neglecting the non-linearity in charging time may lead to infeasible or expensive solutions.

Scheduling/Planning: This area of research is mainly concerned with the deployment of UAVs and EVs for various missions. Kim et al. [24] develops a MILP model to schedule the movements of a system of UAVs with multiple shared bases in disparate geographic locations to complete a mission. They provide a genetic algorithm to solve problem instances. Song et al. [25] extends the work in [24] by allowing for arbitrary UAV initial locations and fuel levels over a finite horizon. They improve the heuristic method described in [26] and propose a new algorithm to allow for arbitrary fuel levels and UAV locations. Lee and Morrison [27] develops a MILP to efficiently use a system of UAVs for maritime search and rescue operations when accidents occur. They do not determine optimal UAV motion paths but address the task allocation to complete search and rescue missions. They consider limited UAV fuel capacity and changing the priority of the search task over time. Ji and Xia [28] proposes an approximate analytical method to minimize the number of identical automated guided vehicles (AGVs) in order to guarantee the ”stability” of the corresponding transportation system. Stability is defined as maintaining a stable level of waiting orders over time. A numerical example based on simulation is provided to illustrate the analytical method. There is a rise of predictive analytics in this research space; for example, Xu et al. [29] proposes a predictive mixed logit model that reveals the behavioral preferences of EV users in Japan toward charging mode selection (normal or fast) and charging location selection (home/company or public station). This study shows that battery capacity, midnight indicator, initial state of charge and number of past fast charging events are the main predictors. In a different study [30] distribution of similar products to cities within the same region where each supplier has an extensive distribution network is investigated. They developed solution procedures that guide the problem-solving process and quickly lead to a good routing solution.

Routing & Scheduling/Planning: One of the relevant papers in the crossover of routing and scheduling/planning areas is written by Barco et al. [31]. They present a differential evolution algorithm for solving an electric vehicle routing problem. The problem is formulated in order to coordinate routing and recharge scheduling with the objective of minimizing operational and battery degradation costs. The effect of scheduling and route assignment on battery life and degradation is investigated.

Locating & Scheduling/Planning: Kim and Morrison in [26] focuses on the joint determination of 1) the number and locations of UAV service stations and 2) their schedules to provide service to customers. They propose a MILP model to optimally locate service stations and schedule a fleet of capacitated UAVs. The authors assume returning flights and deterministic demand. They also develop a branch and bound algorithm as the solution methodology.

Locating & Routing: This research area is focused on the simultaneous optimization of location and routing decisions. It contains papers that mostly use the Location Routing Problem (LRP) as their modeling framework. They study the problem for EVs with the objective of locating the charging stations as well as routing the vehicles. Worely et al.[32] formulates the problem of locating charging stations as well as designing routes using discrete integer programming. Vehicles originate from a single depot and must satisfy the entire demand at demand locations. The setting of the problem is identical to the traditional assumptions of the VRP. One of the prominent studies in this research space is performed by Yang and Sun [33] who models BSS location routing problem for EVs as an integer program and develops two heuristic solution methodologies to solve the problem. One of the methodologies uses Tabu search and the Clarke Wright algorithm while the other is a four-stage method composed of sweep algorithm, adaptive large neighborhood search, an iterative greedy, and a split procedure. The problem assumes a single depot and determines the location of BSSs, allocate customers to EVs, allocate EVs to BSSs, and designs the tours to serve customers. They introduce two versions of the problem, basic and extended. In the basic version, the maximum number of visits to each BSS is restricted to one visit per vehicle, while the extended version allows multiple visits per vehicle. Hof et al. in [34] extends the work presented by Yang and Sun [33] by introducing a new solution methodology, Adaptive Variable Neighborhood Search (AVNS), and providing new best solutions. Another variant of LRP for EVs is introduced by Schiffer and Walther [35] where time widows and partial recharging are allowed. They also examine additional objective functions besides minimizing the total travel distance. In a recent study, Schiffer et al. [36] introduces a location routing problem (LRP) with intra-route facilities and multiple resources (LRPIF-MR) which allows for intra-route facilities of three types: recharging energy, replenishing freight, and combined facilities. The numerical study shows that adding both pure replenishment and combined facilities would lower vehicle costs and routing costs in electrical commercial vehicle logistics networks.

To the best of our knowledge, the paper by Yang and Sun in [33] which addresses a simultaneous routing and locating decision for EVs with swappable batteries is the closest research in the literature to our paper. However, their model considers uncapacitated BSS which can be a valid assumption for electric vehicles system but certainly not a realistic assumption for UAV battery swap stations. Capacitated BSS does not allow one to form a queue of vehicles at each station which is a reasonable assumption for UAVs that are in the flying mode and are running out of battery. Another main area of difference is in the routing modeling approach. In this paper, we route the UAVs with the objective of minimizing the lost sales, while Yang and Sun in [33] takes a more conventional approach by minimizing the routing cost. Depending on the application area and the business model, any of these two approaches can be utilized to serve the customers.

IV. Assumptions

This section explains the fundamental assumptions that are considered for developing the mathematical model.

- All UAVs are considered identical and have a limited flying range which is assumed to be constant.
- A UAV can only carry one unit of product during a trip from a supplier to a customer.
- The returning flight from a customer back to the supplier is through the same route as the delivery trip. This implies that the same number of battery will be needed for the returning flight.
- The supplier point in the network (i.e., depot node) is where UAVs initiate their trips.
- The depot node does not have any restriction concerning the number of UAVs it can serve.
- Customer points in the network (i.e., demand points) are the destinations.
- Battery Swap Stations (BSS) are the transient nodes in the network to support the battery need of UAVs along their trips to the demand points.
- The serving capacity of a BSS is one UAV at a time.
- Any point inside the planning area can be a positional location candidate for a BSS due to the small size of this device. A BSS can be placed on the top of a building or in a vacant field.
- There can be different types of BSS with the main difference being the number of batteries that they can hold (i.e., referred to as K in notations).
- The number of batteries to hold directly impacts the construction and operational cost of a BSS.
- Since each station gradually depletes as it serves the UAVs, a pre-determined schedule is considered to replenish the BSS with full batteries. This can be achieved in two ways, by a ground crew that delivers batteries to the stations or allocating the time needed for recharging the used batteries inside the BSS.
- Each customer location has a stochastic demand with a known probability function prior to the planning.
- A lost sale with a large penalty cost is permitted.
- Time is treated via discrete time slots (i.e. referred to as T in notations).

A. Notations

This section lists the notations used in the paper and their associated definitions.

- Sets
  - S: Set of all suppliers
  - D: Set of all demand points
  - B: Set of all candidate locations for battery swap stations

- A: Set of all arcs between locations
- T: Set of all time slots. At the end of each time slot, all the batteries are assumed to be available, charging or ground crew replenishing.
- K: Set of all types of battery swap stations
- Ω: Set of all scenarios
- $FS(i)$: Set of all node j that arc $i-j$ exist in the network
- $RS(i)$: Set of all node j that arc $j-i$ exist in the network

- Parameters
  - d_i^{ω}: Demand size of demand point i in scenario ω
  - b_k: Number of batteries available at battery swap stations type k
  - c_l: Penalty cost for each lost sale
  - c_s^k: Cost of constructing a battery swap station type k
  - c_o^k: Operational cost of a battery swap station in one period type k
  - p^{ω}: The probability of each scenario ω

- Decision Variables
  - $X_{ij}^{\omega t}$ Number of travels between locations i and j at time t in scenario ω
  - $V_i^{\omega t}$ the total amount of satisfied demand for location i in period t in scenario ω (unrestricted in sign)
  - L_i^{ω} Lost sale for demand point i in period t in scenario ω
  - Z_i^k 1 if we construct batteries swap station i. 0 Otherwise
  - O_i^{kt} 1 if battery swap station type k is functional in period t. 0 otherwise.

V. Mathematical Model

The mathematical model of the problem using the defined notations is presented below:

$$Min \quad \sum_{i\in B,k\in K} c_s^k * Z_i^k + \sum_{i\in B,k\in K,t\in T} c_o^k * O_i^{kt} + \sum_{i\in d,\omega\in\Omega} p^{\omega} * c_l * L_i^{\omega} \tag{1}$$

Subject to

$$\sum_{j\in FS(i)} X_{ij}^{\omega t} - \sum_{j\in RS(i)} X_{ji}^{\omega t} + V_i^{\omega t} = 0, \quad \forall i\in(S\cup D\cup B), \forall t\in T, \forall\omega\in\Omega \tag{2}$$

$$\sum_{i\in D} V_i^{\omega t} + \sum_{i\in S} V_i^{\omega t} = 0, \quad \forall t\in T, \forall\omega\in\Omega \tag{3}$$

$$L_i^{\omega} + \sum_{t\in T} V_i^{\omega t} = d_i^{\omega}, \quad \forall i\in D, \forall\omega\in\Omega \tag{4}$$

$$\sum_{j\in FS(i)} 2 * X_{ij}^{\omega t} \le \sum_{k\in K} b_k * O_i^{kt}, \quad \forall i\in B, \forall t\in T, \forall\omega\in\Omega \tag{5}$$

$$\sum_{k\in k} Z_i^k \le 1, \quad \forall i\in B \tag{6}$$

$$\sum_{t\in T} O_i^{kt} \le |T| * Z_i^k, \quad \forall i\in B, \forall k\in K \tag{7}$$

$$V_i^{\omega t} = 0, \quad \forall i\in B, \forall t\in T, \forall\omega\in\Omega \tag{8}$$

$$X_{ij}^{\omega t} \ge 0,\ O_i^{kt}, Z_i^k \in \{0,1\} \quad \forall i\in S, t\in T, k\in K, \forall\omega\in\Omega \tag{9}$$

The objective function (2) includes three parts; First is the construction cost function associated with the selected locations. The second term represents the operational cost of the network, and the latter part is the penalty cost for the lost sales. Constraint set (3) is the flow balance constraint for suppliers, customers, and BSS. Constraint set (4) assures that the amount of supplied product is equal to the demanded product at each time slot and scenario. $V_i^{\omega t}$ is positive when $i\in D$ and is negative when $i\in S$. Constraint set (5) calculates the amount of lost sales over all time slots. Constraint set (6) assures that a UAV can only use an operational BSS which has sufficient number of batteries to support a round trip; therefore the multiplier 2 assures the batteries are available for both originating and returning trips. Constraint set (7) allows the problem only to construct one type of station at each location. Constraint set (8) assures that stations can only be operational if we construct them and finally constraint set (**??**) does not allow the BSS to become a demand point or the supplier.

Lastly, constraint set (9) enforces non-negativity on the decision variables.

A. Valid inequality

In this section, we introduce a valid inequality in order to tighten the feasible region of the problem. This inequality is estimated to reduce the time needed to reach optimality by 35%. In order to develop this inequality, the following proposition is defined:

Proposition 1 *Each selected BSS candidate in the optimal solution is adjacent to at least one other selected BSS candidate or a supplier.*

Proposition Assume the selected BSS candidate in the optimal solution is not adjacent to any other selected BSS candidate or a supplier. Thus, the UAV can access it only from demand locations. Since loaded UAVs will not be able to use the selected BSS candidate on their delivery route, we can remove this BSS candidate from the solution and obtain a better objective function value which is a contradiction to our assumption. By using this proposition, we can introduce a new valid inequality to the problem in order to tighten the feasible region.

$$\sum_{k\in K} Z_i^k \leq \sum_{j\in RS(i),k\in K} Z_j^k \quad \{i\in B|(i,s)\notin A, s\in S\} \tag{10}$$

This constraint set is defined on the BSS candidates that are not adjacent to any supplier. In order to evaluate the impact of the valid inequality, 10 random instances are generated and solved optimally. Table I shows the number of processed nodes when CPLEX solves the instances with the valid inequality as well as without it. Based on the random sample, the valid inequality reduces the number of nodes processed by on average 11%.

VI. Solution methodology

In this section, the details of the developed Tabu search for the proposed model is discussed. Tabu search was first introduced by Fred W. Glover [37] as a meta-heuristic search method to find a potential solution to an optimization problem and explore its neighbors in order to find an improved solution. This approach uses a memory construct to enhance the quality of the neighborhood search. In TS, a list is utilized to escape local optima and make the neighborhood search more efficient. At each iteration, a set of neighbors for the current solution is generated and the best neighbor, in terms of objective function, will be selected. If the selected neighbor does not violate the Tabu list moves, it will be used in the next iteration as the current solution. The Tabu list consists of all moves that we cannot make at each iteration. These moves are determined based on previous iterations. The Tabu list facilitates the process of escaping the local optima. Note that in the selection process of TS, the best neighbor among the generated neighbors will be selected, which means it is possible to move to an inferior solution compared to the current solution. For our problem, the Tabu list structure is straightforward; however, tuning the Tabu tenure and aspiration criterion is essential to improve the results. Since, the element of our Tabu list is BSS, an acceptable ratio between the number of BSS and Tabu tenure has to be determined. If the length of Tabu tenure is too long, it will prevent good candidates from entering as new solutions. On the other hand, if it is too short, the Tabu list will not be effective in finding new areas that contain desirable solutions.

A. Solution Structure

The structure of the solution for the proposed algorithm consists of three components. First, which BSS candidates are selected to be constructed. Second, which types of BSS are to be constructed at the selected location, and the last one is at which time slost the stations are functioning. In order to incorporate all three components in the solution, the following structure is developed. Each solution consists of three arrays. The size of the first array is equal to the number of candidates (n), the size of the second one is equal to the number of different types of stations multiplied by the number of candidates ($k*n$). The last array is the number of time slots multiplied by the number of candidates ($t*n$). To further clarify, assume we have two candidates, two types of BSS, and three time slots. The following is an example of a solution:

In this solution, the first row shows which candidate is

<table>
<tr><td colspan="6">1</td><td colspan="6">0</td></tr>
<tr><td colspan="3">1</td><td colspan="3">0</td><td colspan="3">0</td><td colspan="3">0</td></tr>
<tr><td>1</td><td>1</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td></tr>
</table>

Figure 3: Structure of each solution in TS approach

selected. Second row indicates which types of stations are selected to be constructed and finally the last row shows in which time slots the stations are functioning.

B. Operators

In this section, we introduce the operators that are used in the TS algorithm. In order to find an immediate neighbor for a solution, two solution components can be altered. First is the type of BSS and second is either adding or removing a BSS based on some performance measures.

Table I: Results of 10 Instances run with and without the valid inequality

	# of Nodes Processed		
	With Valid Inequality	Without Valid Inequality	Difference
1	37	37	0%
2	91	91	0%
3	457	573	20%
4	721	722	0%
5	120	120	0%
6	4366	5245	17%
7	16461	28032	41%
8	6017	6871	12%
9	14439	16902	15%
10	147167	148891	1%

In the following section, the operators used in the TS are introduced. We first define the performance measures for adding operators.

1) Performance Measures

Different performance measures can be considered in placing a station. First is the distance from demand locations. A populated area with multiple demand points, supplier locations, and other charging stations is an excellent choice since they are in close proximity. The new station can be used for delivering goods to the demand points located in its coverage area, or to other parts of the network, or even to improve the coverage area of other charging stations. To this end, the following performance measure, namely *Performance Measure Station*, is defined:

$$PM_i^S = \frac{\sum_{j \in FS(i)} \sum_{\omega \in \Omega} d_j^{\omega}}{|\Omega|} \tag{11}$$

Equation 11 is the average accessible demand from station i across all the scenarios. It essentially measures the demand potential of a location candidate for a BSS. The other impact of adding a new station is on improving the coverage of the entire network. The selection process favors the stations that make the entire network more connected. For example, if selecting station i connects two unconnected clusters of the network, it is preferable than selecting a station that solely covers some demand points and is disconnected from other parts of the network. This performance measure seeks to incentivize the creation of a coherent and well-connected network. Let set N_s the largest connected component of a network before adding station i and N_s' be the largest connected component of the network after adding station i. Hence, we can define this performance measure, namely Network Performance Measure. as follows:

$$PM_i^N = |N_s'| - |N_s| \tag{12}$$

Equation 12 calculates the number of new stations that become connected to the network ($|N_s|$ is the cardinality of set N_s).

So far, we have discussed the positive impacts of adding a new station to the network. The other aspect is the cost of adding a new station. To this end, we introduce the Total Performance Measure of station i as follows:

$$PM_i^T = \frac{PM_i^N * PM_i^S}{\max_{k \in K} c_s^k} \tag{13}$$

Equation 13 is an indicator of the benefit-cost ratio (BCR) for station i. The numerator is the potential benefits of adding station i (Connectivity and Coverage). Since PM_i^N does not increase with a rapid slope, it is more representative of the impact when it is multiplied by PM_i^S. The denominator is the maximum cost of constructing the station.

Given the performance measures above, we can define the following insertion operators:

- Performance Measure Insertion (PM Insertion):
  This operator constructs the BSS candidate that has the highest value of PM^S. If the BSS is already constructed, the next station with the highest PM^S will be selected.
- Network Performance Insertion (PN Insertion):
  The station with the highest value of PM^N is selected to be constructed.
- Total Performance Insertion (TP Insertion):
  The station with the highest PM^T value will be inserted into the solution.
- Random Insertion:
  A random station will be selected to be inserted into the solution.

Another type of operator used in the TS is removal operators. These operators help to refine the solution and reduce the cost by removing undesirable stations. More specifically, they evaluate stations to see if the savings on the construction cost is greater than the lost sales they might cause. Removal operators include:

- Smart Removal:
  A utilization value is calculated for each constructed station. The utilization value is equal to the number of used batteries divided by the total number of batteries at that station. In other words, utilization of a station shows what percentage of the available resources within the station is utilized over time. Smart removal strategy eliminates the station with the least utilization value.
- Random Removal:
  A random station will be removed from the solution.

Hybrid operators, that combine both the insertion and removal strategies, are developed as well. The first operator is the *Swap Operator*. The swap operator randomly selects a station (C_1) to be removed from the solution. Then, among all stations that are reachable by the removed station C_1, one is randomly selected to be inserted to the solution. Similarly and for improving the coverage area of the network, a *Broading Operator* is developed to choose two stations to be inserted instead of one station.

So far, all the introduced operators are meant to change the selection of stations. There are two other operators that can change the type of the selected stations: *Upgrade* and *Downgrade*. These operators change the type of station to include more batteries (Upgrade) or less batteries (downgrade). Finally, it is worth noting that a station is only operational when a UAV passes through; otherwise, the station will not be functioning.

C. Objective Function Evaluation

The objective function of the problem consists of three terms. The first and second terms are associated with the construction and operating costs. Since the unit cost parameters are deterministic, they can be calculated based on the solution. On the other hand, the third term, which is associated with the lost sales, cannot be calculated directly. The problem that arises is that we need to calculate the maximum flow possible between all suppliers and demand points via the constructed network. The solution of the maximum flow problem will determine the demand magnitude that the network is capable of satisfying. Therefore, lost sales can be calculated by deducting the solution of the maximum flow problem from the total demand.

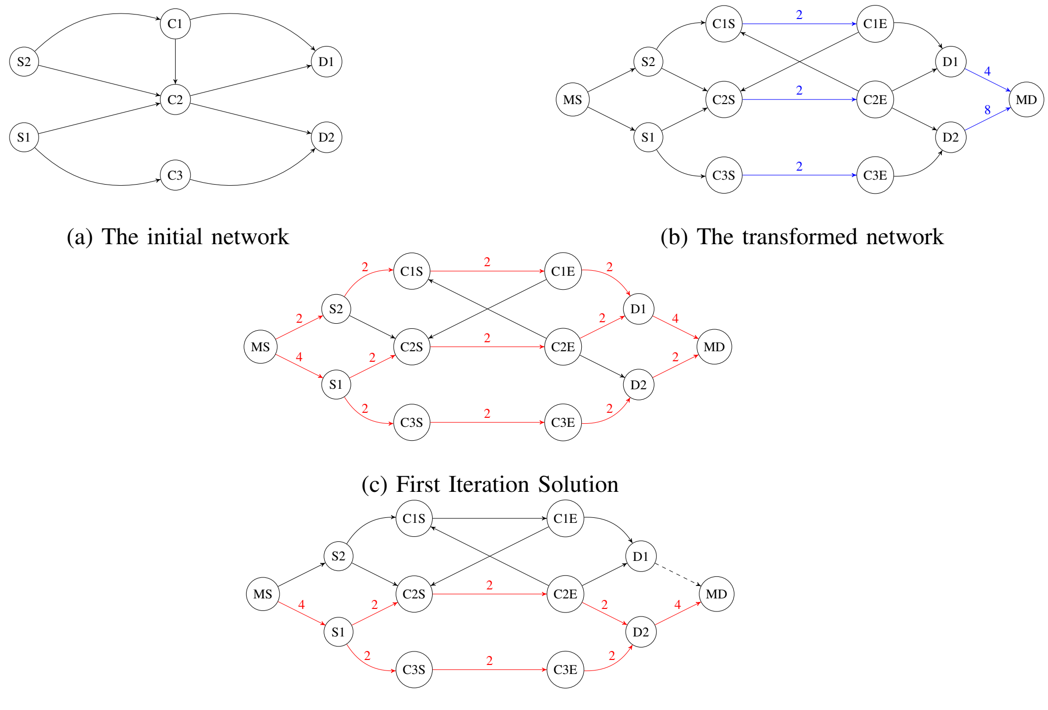
In order to develop a network, the two key components, nodes and arcs, should be defined. All the locations including demand locations, suppliers and selected BSS are considered as nodes. In order to calculate the maximum flow of the constructed network, We have to add a *MainSupplier (MS)* node as well as *MainDemand (MD)* node. MS is connected to all of the suppliers, while all the demand locations are connected to MD. With respect to the arcs, we define set A as the set of all the arcs. The arcs have no capacity except for those that are connecting the demand locations to MD. The capacity of those arcs are equal to the demand of the corresponding demand locations.

Using the described network, we need to solve a maximum flow problem via CPLEX repeatedly. At each iteration, the maximum flow problem is solved and given the obtained solution; we can determine the satisfied demand points. Then, we update the demand status, which means the amount of satisfied demand reduces the capacity of those arcs that connect the demand locations to MD. This procedure repeats for the next time slot. The procedure is explained in more detail for the following network:

The network as shown in Figure 4a consists of two suppliers ($S1$, $S2$), three BSS ($C1$, $C2$, and $C3$) and two customers ($D1$, $D2$). We are planning for two time slots and each BSS has two batteries in each time slot. $D1$ and $D2$ demands are equal to 4 and 8 respectively. The current structure of the network does not allow us to solve the maximum flow problem. First, there is a capacity on the nodes, and second, we do not have source-sink nodes. As a result, we need to transform the network to the network in Figure 4b. There are three steps for the transformation. First, adding the nodes mentioned above, *MD* and *MS*. Then, we break each BSS node into two nodes (*Start*, *End*), connected with an arc, in order to eliminate the capacities on the node. The arc between the two nodes has a capacity equal to the number of batteries at the BSS. Finally, we need to limit the capacity of arcs going into *MD* from each demand point. This ensures not delivering more than what is required to each demand point. Blue arcs in figure 4b are the capacitated arcs. Now, we solve the maximum flow problem for the first time slot. Figure 4c illustrates the flow on the transformed network. In this solution, 4 and 2 units of demand at $D1$ and $D2$ are satisfied. Therefore, we change the capacity of ($D1$-MD) arc to zero and ($D2$ - MD) arc to 6. In the second iteration, 4 units delivered to $D2$, 6 in total. So there is 2 unit of lost sale associated with $D2$. Note that the capacity of ($D1$-MD) is zero in the second iteration since we satisfied all the demands in the previous iteration.

By executing this procedure in all the time slots, not only the exact value of lost sales is obtained, but also the stations that are operating within each time slot are identified. Hence the exact value of the objective function can be calculated.

We discuss the NP-hardness of the problem in the following. The capacitated fixed charge network design



(a) The initial network

(b) The transformed network

(c) First Iteration Solution

(d) Second Iteration Solution

Figure 4: An example of different steps of calculating the lost sale for a network.

problem (CFCNDP) is a well known NP-hard problem [38]. Here is the definition for a general CFCNDP problem. A given network consists of (N,A). Each arc $(a_{ij} \in A)$ has a fixed charge (f_{ij}), a variable charge (c_{ij}) and a capacity (u_{ij}). The problem is to minimize the cost of flow in the network to satisfy the demand. The formulation of the CFCNDP problem is:

$$Z = min \sum_{(i,j)\in A} c_{ij}x_{ij} + \sum_{(i,j)\in A} f_{ij}y_{ij} \tag{14}$$

Subject To:

$$\sum_{(i,j)\in A} x_{ij} - \sum_{(j,i)\in A} x_{ji} = \begin{cases} d & \text{if } i = O(k), \\ -d & \text{if } i = D(k), \\ 0 & \text{Otherwise} \end{cases} \tag{15}$$

$$0 \leq x_{ij} \leq u_{ij}y_{ij}, \qquad \forall (i,j) \in A \tag{16}$$

$$y_{ij} \in \{0,1\}, \qquad \forall (i,j) \in A \tag{17}$$

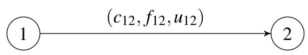
$O(K)$ represents the set of depots and $D(K)$ represents the set of demand locations. This problem can be reduced to our problem with the following transformation steps:

- Each arc transforms to a BSS station (ij) with a construction cost of f_{ij}, operational cost of c_{ij} and battery capacity of u_{ij}.
- BSS station (ij) is reachable from all adjacent nodes of node i and node j.
- All nodes with a negative demand act as demand node and the ones with positive demand as supplier.
- The cost of lost sales is equal to zero.

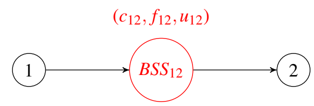
In figure 5, it is shown how to reduces CFCNDP problem into a BSS in our research problem. Each new arc in figure 5b has unlimited capacity and zero cost associated with it. This transformation can happen in an $O(|A|)$ which is polynomial. Now that we have illustrated how a general form of CFCNDP can be reduced to our research problem, it can be said that if there is an algorithm that solves our problem to optimality, it would also solve the CFCNDP to optimality by using the reverse of the transformation (i.e. Each constructed BSS in the solution is equivalent to use of the corresponding arc in CFCNDP). This proves that our problem is NP-Hard.

D. Initialization

In this step, a feasible solution is identified for the problem. Although we can start with no selected station, this is not a valid initialization state because, given the defined operators, the algorithm is not capable of adding multiple numbers of stations in one iteration. Therefore, no product can be delivered to the demand locations, which in turn increases the objective function value. As a result, the algorithm will find the initial solution (i.e., no stations) more attractive than adding a station to the solution. Therefore it is necessary for an initial solution



(a) General Arc of CFCNDP



(b) Transformed Arc

Figure 5: Transformation of each arc in the fixed charge network design problem to our research problem.

to contain a network of BSS to cover all the demand locations. In order to obtain such a network, first, the farthest demand location to the depot is selected. Then, using a dynamic programming approach, a chain of connected BSS is constructed to which the farthest demand location is connected. In the next step, the next farthest unconnected demand location to the network is selected. This process will continue until we obtain a connected network that covers all the demand locations. In the following, we explain the dynamic programming procedure to find a connected route between two nodes. In order to find a route between two nodes (S, M), start from one node (S) and using equations 18 and 19 find the route with the highest value. R_S is all the demand locations that are reachable from node S. R is the set of all demand locations covered by a node on the route. N_S is the set of all nodes adjacent to Node S. v_i is the demand value of demand location i and d_{iS} is the distance between i and S.

$$V_M(S,R) = \begin{cases} D, & \text{if } S = M \\ F_S(R_S,R) & \\ +Max_{S' \in N_S} V_M(S', R \cup R_S), & \text{O.W} \end{cases} \tag{18}$$

where:

$$F_S(R_S,R) = \sum_{i \in R_S/R} v_i + \sum_{i \in R_S \cap R} 0.5 * v_i + \sum_{i \in R'_S/R} v_i/d_{iS} \tag{19}$$

Equation 18 is the recursive function to find the best-connected chain of stations from node S to node M. Equation 19 is the value function. This function consists of three terms. The first term (i.e., covering demand term) is equal to the summation of all the demand nodes that are not covered by the route yet. This term ensures that among the adjacent stations to S, one becomes selected that is able to cover the demand nodes that are not already covered by the network. In other words, a route that covers most of the demand nodes will be created. The second term (i.e., back up station term) is a partial value for the covered demand. It favors a station that is closest to a covered demand area. Although other stations already cover these demand nodes, the second term ensures that when the magnitude of demands is significant, the obtained network has several stations covering the area. The last term (i.e., direction term) gives a higher score to the stations that are closer to the uncovered demand. As the distance of station S from demand node i becomes smaller, the term v_i/d_{iS} becomes larger.

In Figure 6, the route is at node (M) (green node) and now it should select among S_1 (red node) and S_2 (blue node). The dashed circles show the coverage of each node. Orange rectangles are demand points in the network. The demand node with a value of 2 is already covered by the network. Now we compare S_1 and S_2 in terms of the value function. The covering demand term for S_2 is higher than S_1 as it covers a demand point with the magnitude of 6. On the other hand, the backup station term for S_2 is equal to zero while S_1 covers the demand that is already covered by M. Finally, comparing S_1 and S_2, S_1 is closer to the demand node with the value of 11. Therefore, the value function returns S_1 as the selected station for the next step. Another obstacle of using dynamic programming for finding an initial solution is the curse of dimensionality. It means when the two nodes, that are considered for finding a route between them, are distant from each other, the computational time of calculating the best route grows exponentially. In order to overcome this issue, we break down the routes that are longer than ten times of the UAV flying range. Figure 7 represents an initial solution example for the TS using dynamic programming. The grid is the planning area and each intersection represents a candidate location for a BSS. Red circles on the left represent the location of the demand points while the number inside them indicate the magnitude of demand. The black circles on the right are the output of dynamic programming. Each circle shows the location of BSS on the grid. The first digit inside the circle is the ID of the BSS while the second digit indicates the type of BSS.

E. Tabu Search steps

A brief description of the developed Tabu search is as follows:

- **Step 1. Initialization**
  This steps obtains the initial solution of the Tabu search using the dynamic programming discussed above.

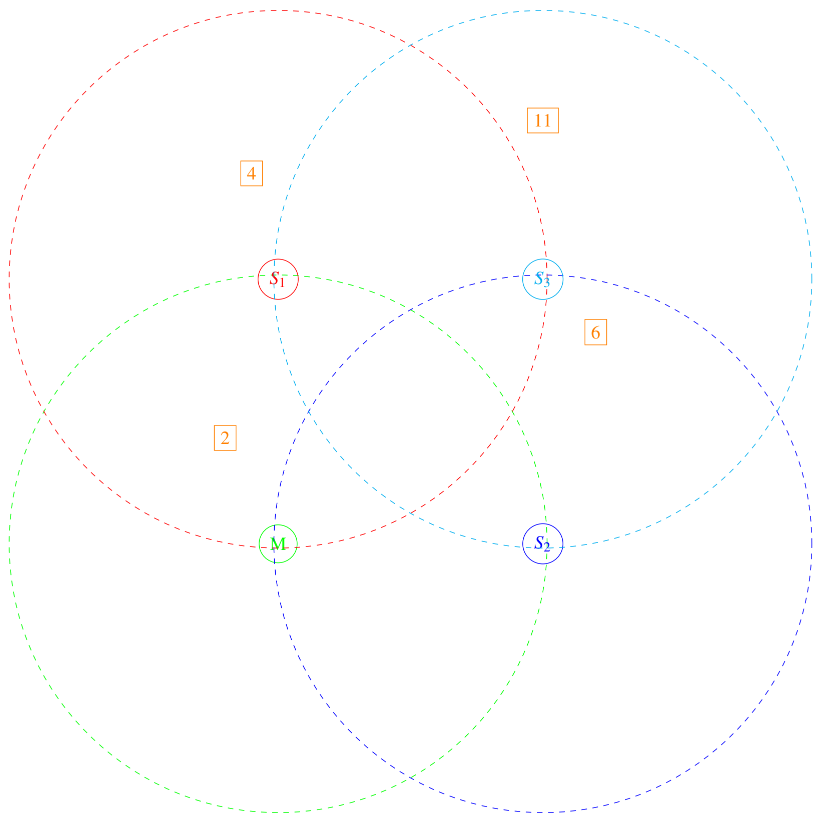


Figure 6: Illustration of the value function of dynamic programming

- **Step 2. Creating Neighborhood Solutions**
  Using the defined operators, we generate a list of solutions that are immediate neighbors of the current solution. In order to calculate the objective function value for each solution, we have to solve the maximum flow problem in each time slot. This would determine the demand magnitude that can be satisfied during each time slot.
- **Step 3. Finding the Best Neighbors**
  A solution with the minimum objective function value, which is not forbidden by the Tabu list, is chosen to be the next solution. There are two types of Tabu lists. The first one avoids adding a recently removed station and the second one does not allow to remove a recently added station. Note that if any of the solutions are better than what the TS has identified so far, the algorithm will pick up the solution regardless of the Tabu lists.
- **Step 4. Update the tabu lists and Termination**
  The Tabu lists are updated accordingly. If the algorithm reaches a predetermined number of iterations, the process terminates and the best solution will be reported. Otherwise, we repeat steps 2 and 3.

VII. Computational Study

In this section, numerical tests are conducted for the proposed model. We present the characteristics of instances followed by a discussion on the computational results.

A. *Characteristics of Instances*

There are four different parameters for each instance: area of coverage, number of demand locations, magnitude of demand at each location, and number of available time slots. The instances are categorized into three different groups based on the number of demand points and BSS locations. Size of the region has a direct impact on the number of BSS candidates, while the number of demand locations impacts the complexity of the BSS network. The following table shows how the instances are categorized.

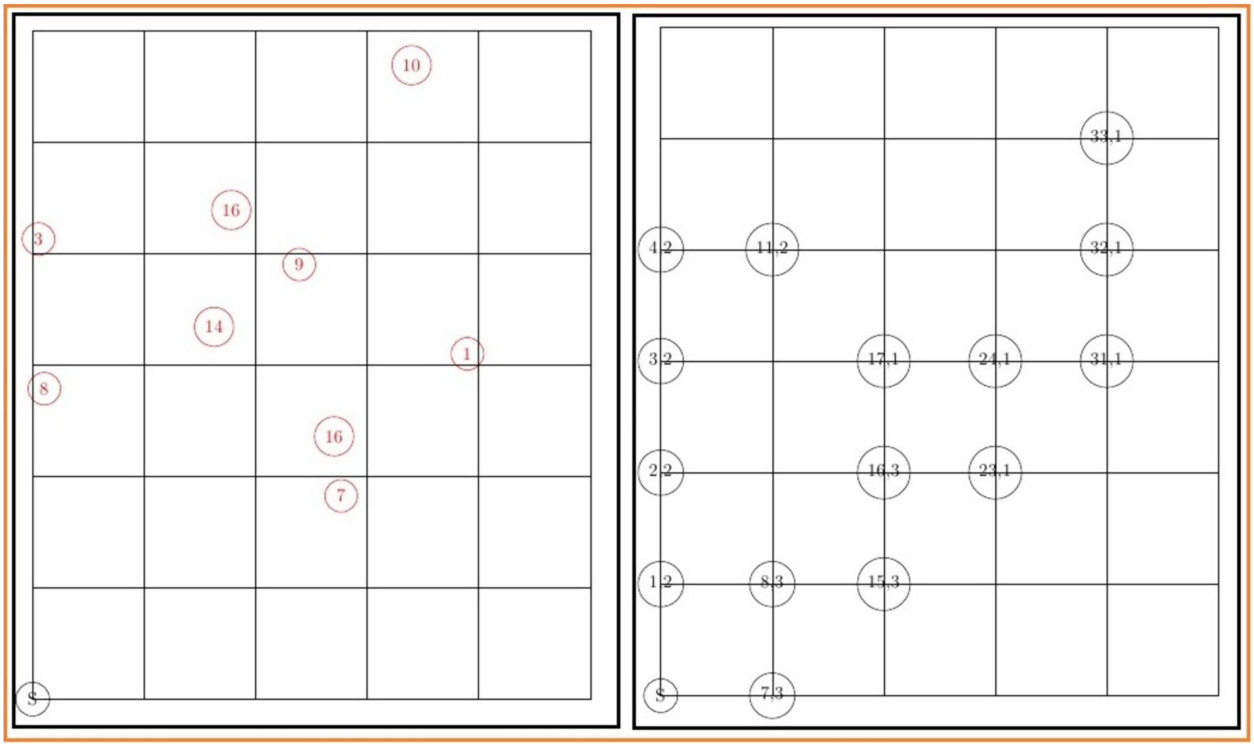


Figure 7: Example of an initial solution for Tabu Search

Table II: Characteristics of instances

Scenario	Distribution
Number of low demand nodes (L)	*Uniform*(5, 15)
Number of high demand nodes (H)	*Uniform*(15,20)
Small region side length (S)	*Uniform*(20,30)
Medium region side length (M)	*Uniform*(50,60)
Large region side length (LA)	*Uniform*(80,90)
Demand size at each node	*Uniform*(1, 15)

For each category, the number of demand locations is generated based on a *Uniform* distribution function. Each location is randomly placed throughout the region. Also, BSS candidates are generated using a grid created in the region. Each square inside the grid has a side length equal to the UAV flying distance. Each BSS Candidate is located at the intersection of the grid. These instances contain four types of BSS with different attributes (Table III). Only one depot is considered and the penalty cost associated with the lost sales is $50,000$. The reason for using a sizeable lost sale value is to justify the high cost of constructing a path from a depot to a customer.

In addition to the parameters mentioned above, we utilize the cost figures presented in table III. There is limited information available about the cost of constructing a new BSS; however, based on our research, the smallest stations cost at least $20,000$ dollars. We estimate the cost figures for type B through D based on the assumption that number of batteries is the cost driver with economy of scale for larger stations. The same rule applies to the operational cost because as stations become larger it is more costly to recharge its batteries.

In total, 300 instances are generated and solved using the developed TS and CPLEX. There is a 60-minute time limit for the CPLEX algorithm. This time limit allows us only to solve 46% of the instances optimally, which is sufficient to evaluate the performance of the TS. We run the TS for the following number of iterations: 100, 200, 500 and 1000. An ANOVA test at 5% significance level shows that there is a significant difference between the results of different iterations. The Tukey HSD test confirms that the results of 1000 iterations out-perform others.

The solution methodologies discussed here are coded in JAVA and executed on Intel Core-i7 3.6 Mhz, 16 GB RAM under Windows operating system.

B. Results

The results are represented in Table IV. The first column indicates the category of instances based on their characteristics. For example LS_1 is a low demand scenario in a small region with one time slot. Thirty categories of instances, with 10 instances in each category, adds up to 300 instances.

It is apparent that by growing the complexity of the instances, the performance of TS with regards to the

Table III: BSS attributes

BSS Type	BSS Attributes			
	Construction Cost	Operational Cost	Number of Batteries	UAV Usage
A	\$20000	\$10	10	5
B	\$30000	\$20	20	10
C	\$35000	\$40	30	15
D	\$40000	\$80	50	25

Table IV: Tabu search results for 300 instances

	CPLEX			Tabu Search		
	Time (s)	# Optimal	Gap	Time (s)	CPLEX Solution Gap	Out Perform CPLEX
LS_1	1.35	10	0%	0.11	6%	0
LS_2	18.03	10	0%	3.03	2%	0
LS_3	1093.72	7	2%	217.70	10%	0
LS_4	798.72	8	0%	31.49	10%	0
LS_5	2973.77	2	36%	182.34	10%	0
LM_1	388.52	9	0%	29.64	18%	0
LM_2	2966.88	2	5%	555.50	10%	2
LM_3	3600.12	0	39%	622.01	16%	1
LM_4	3600.31	0	67%	28.52	8%	1
LM_5	3600.17	0	87%	602.92	9%	0
LLA_1	3140.88	1	4%	35.14	11%	2
LLA_2	3600.35	0	32%	224.52	10%	1
LLA_3	3600.27	0	62%	90.66	9%	4
LLA_4	3600.29	0	78%	451.99	12%	0
LLA_5	3600.29	0	92%	86.40	10%	2
HS_1	0.02	10	0%	0.00	10%	0
HS_2	0.06	10	0%	0.01	1%	0
HS_3	13.80	10	0%	2.42	9%	0
HS_4	464.89	10	0%	73.49	10%	0
HS_5	547.87	8	0%	83.62	3%	0
HM_1	0.33	10	0%	0.06	8%	0
HM_2	160.39	9	0%	131.20	10%	0
HM_3	864.13	8	0%	97.39	22%	0
HM_4	2731.11	2	1%	268.51	8%	1
HM_5	3150.97	1	4%	622.98	8%	3
HLA_1	221.31	9	0%	179.10	10%	0
HLA_2	2650.51	3	2%	411.67	6%	0
HLA_3	3346.79	0	6%	326.74	11%	2
HLA_4	3600.32	0	19%	387.56	11%	1
HLA_5	3600.27	0	22%	397.76	9%	4

objective function value improves. In the small region instances, TS cannot outperform the CPLEX because it is trivial for CPLEX find the optimal network. However, as the region size increases to medium and large, TS outperforms the CPLEX more frequently. The reason is that, while CPLEX struggles to find an initial solution, TS is able to construct a base network using the dynamic programming initialization, regardless of the size of the region. Among the other benefits of using TS is the consistency with the running time. The average running time for TS is about three minutes, while CPLEX uses 32 minutes on average. Table V summarizes the result of the 300 instances based on the region size.

Figure 8 is an example of the final solution of TS for 4 time slots. Figure 7 shows the initial solution of this instance. Each black arc in Figure 8 indicates the flow between two BSS, while red arcs indicate the delivery to customers. The number on each arc is the total number of UAV trips. In each period, the depot will serve the nearest customer until one of the BSS runs out of battery, in which case it waits until the next period for making new deliveries.

In this part, we provide a detailed analysis on the impact of dynamic programming as the method of generating initial solutions for the Tabu search. Fifteen instances are created based on LS_1, LM_1, and LLA_1.

Table **??** shows that dynamic programming on average accounts for 9% of the TS running time. Also, TS on average improves the result of dynamic programming initial solution by 29%. Still, TS solutions are on average 8% worse than CPLEX solutions but 69% faster.

Lastly, we select five instances where the best solutions are obtained by CPLEX (*C_Instances*) and 5 instances where CPLEX is out-performed by TS ($TS\_Instances$) (Instances selected among 300 instances presented in table IV). These ten instances are solved by CPLEX twice. In the first round, the initial solution that is provided to CPLEX is the final solution obtained from TS. *C_Instances* solutions did not show any improvement and in one case leads to a worse solution. Regarding the $TS\_Instances$, 3 out of 5 instances are improved in comparison to the current best solution. The reduction in the optimality gap is on average 3.18%. The second time, CPLEX solves the instances where the initial solutions are obtained from dynamic programming. In those cases, no impact on the CPLEX solution is observed.

VIII. Conclusion and Future Work

In this paper, we focus on locating battery swap stations for UAVs that transport commodities from suppliers to customers. The problem is designing a network of battery swap stations with a limited number of batteries in order to enhance the flying range of UAVs. The customer demands are assumed to be uncertain while a penalty cost is considered for lost sales. We developed a scenario-based stochastic programming model to satisfy the customer demand across the planning area. The proposed model allows constructing different types of BSS with different costs and battery capacities. To address the computational complexity of this problem, a Tabu search heuristic is developed as the solution methodology. The initial solution is generated using dynamic programming. Numerous numerical tests are conducted to illustrate the model and discuss the solution methodology. The results show that, compared with CPLEX, TS generates significant improvements in the running time and quality of solutions, especially for large problems.

As a future work, other solution approaches can be explored to solve the stochastic programming model with a larger number of scenarios. Adding the time dimension to the problem is also a significant extension that would allow constructing battery swap stations over time.

Table V: Summary of results of 300 instances based on the region size.

	Small	Medium	Large
CPLEX Gap (%)	4%	20%	32%
TS and CPLEX Gap (%)	7%	12%	10%
# of Instances TS out performs CPLEX	0	8	16
# of Optimal solutions by CPLEX	85	41	13
Average CPLEX running time (s)	591.22	2106.29	3096.13
Average TS running time (s)	59.42	283.36	259.15

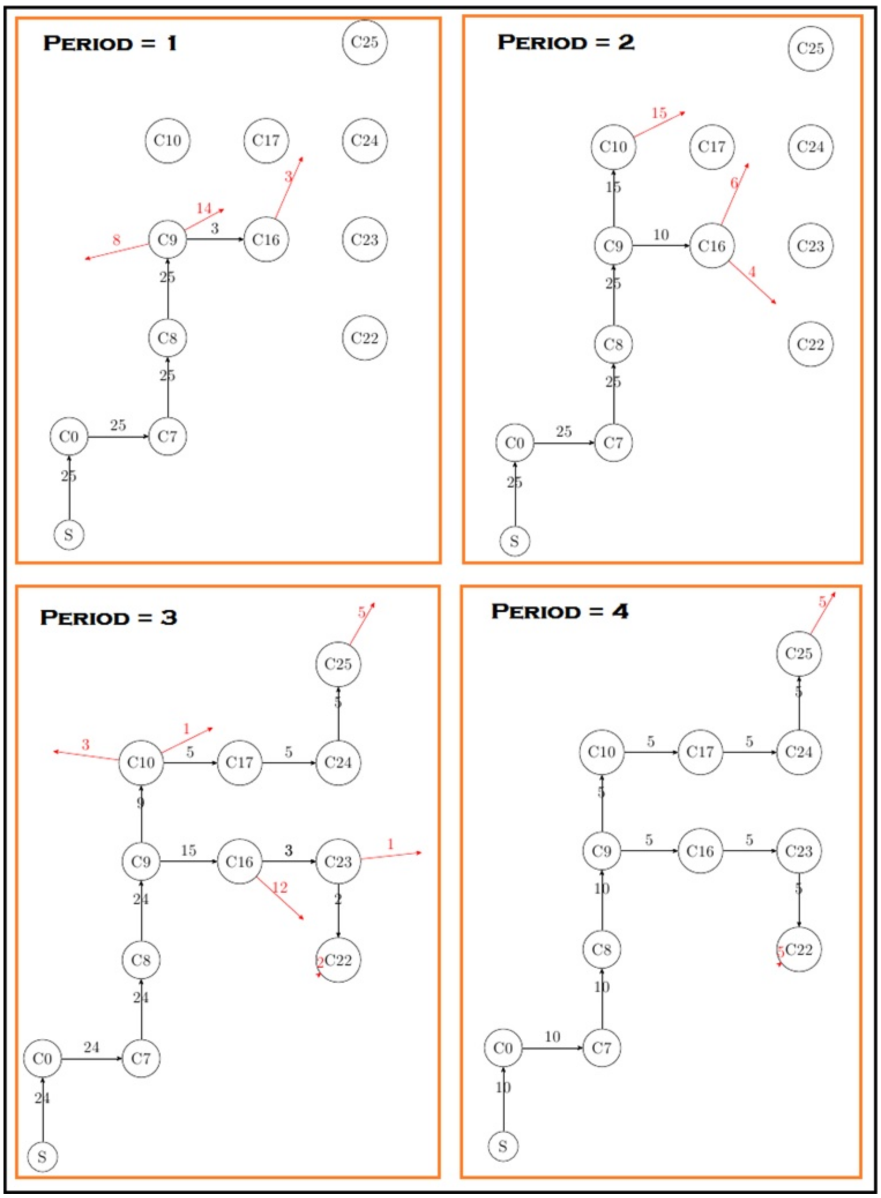


Figure 8: Final Solution from Tabu Search for an instance

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