ELECTRIC VEHICLE TRAVELLING SALESMAN PROBLEM WITH DRONE
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## ABSTRACT

The idea of deploying electric vehicle and unmanned aerial vehicles, also known as drones, to perform "last-mile" delivery in logistics operations has attracted increasing attention in the past few years. In this paper, an Electric Vehicle Travelling Salesman Problem with Drone (EVTSPD) is formulated as a mixed integer linear program to aid logistic organizations with a new method of delivering parcels which can extend the driving range of both vehicles and decrease the operation cost. An iterative solution heuristic is also developed. Results of numerical experiments show that the heuristic is much more efficient than solving the problem via a standard solver. Incorporating UAVs into EV based routing were found to reduce average delivery times by up to $40 \%$ for the instances tested.

Keywords: Travelling Salesman Problem, Electric Vehicle, Unmanned Aerial Vehicles

## INTRODUCTION

Many government and corporate policies aim to promote transportation modes with lower emissions of pollution and greenhouse gases. Electric vehicles (EVs) are an emerging alternative to internal combustion engines. Besides, unmanned aerial vehicles (UAVs) have also been proposed to assist in delivery of goods.

In the last few years, several companies have started to use EVs in their operations. For example, in 2018 FedEx announced a fleet expansion, adding 1,000 electric delivery vehicles to operate commercial and residential pick-up and delivery services in the United States ${ }^{1}$. Switching to electric fleets not only has long-term effects on mitigating the impact of climate change. There may also be an immediate financial incentive, as fuel cost accounts for $39 \%$ to $60 \%$ of operating costs in the trucking sector (1). Compared to conventional internal combustion engines and petroleum-fuel powered vehicles, EVs are much more energy efficient and require less maintenance, which indicates potential savings to freight and logistics companies. On the other hand, in recent years, UAVs have also been integrated into the operation of e-commerce and on-demand item delivery. The use of UAVs for "last-mile" parcel delivery promises to change the landscape of the logistics industry. Amazon, Google, DHL all announced their project to use UAVs to deliver small packages and has conducted thousands of test flights in Australia. The past few years has witnessed a dramatic increase in UAV applications. According to Teal Group, commercial use of UAVs will grow eightfold over the decade to reach $\$ 7.3$ billion in $2027^{2}$.

However, EVs and UAVs face limitations due to driving range and availability of recharging stations. A commercial UAV has a range of about only 10 miles which indicates a small service area. For the most common EVs used in service operations, the minimum charging time is 0.5 h and the battery capacity is around 22 kWh which indicates a nominal driving range of 142 km , which is approximately one fourth of a petroleum powered vehicle (2). Moreover, the driving range is also affected by road slope, increased speed, loading capacity and the use of peripherals (3). Although this problem could be alleviated in the future by carrying higher-capacity batteries, at present an EV may need to visit charging stations to charge its battery and extend its driving range.

In this paper, we investigate a new problem called the Electric Vehicle Traveling Salesman Problem with Drone (EVTSPD), where an electric truck (or other types of electric vehicle) performs deliveries with an UAV, in an cooperative way. In this problem, the EV and UAV could perform delivery tasks independently, while the EV also serves as a UAVs hub, where it can refresh its battery and load new parcels. Due to driving range limits, EV may need to visit multiple charging stations between customer visits during its daily operation. Note that some charging stations may be visited multiple times, while others may not be visited at all. Another key assumption in this problem - and the primary distinction from recent work on the "flying sidekick traveling salesman problem" - is that the EV and the UAV share their electricity, that is, there is a battery capacity for both EV and UAV and when the UAV is launched from the EV, the remaining electricity of EV also decreases. The main contributions of the paper are:

- The Electric Vehicle Traveling Salesman Problem with Drone (EVTSPD) is introduced and formulated;

[^0]- An efficient heuristic algorithm is proposed to solve EVTSPD;
- The paper demonstrates through computational experiments the improvement of delivery time by utilizing UAV;
- The numerical analysis indicate the proposed heuristic algorithm can obtain good feasible solution in a much shorter time than a commercial solver.
The rest of the paper is organized as follows. First, a literature review of EVRP and UAV is given, focusing on current approaches of using EV and UAV to perform delivery tasks. This is followed by the problem description of EVTSPD and its mixed integer programming (MIP) formulation. Next, an efficient iterative heuristic algorithm is proposed to solve the EVTSPD, follwed by numerical analysis, computational experiments on random instances, and performance comparisons with a commercial solver.


## Literature Review

The vehicle routing problem (VRP) and its special case, travelling salesman problem (TSP) are among the most well-studied optimization problems in operations research. This problem was first proposed by (4). Since then, many variants have been considered, incorporating service time windows, capacities, maximum route lengths, distinguishing pickups and deliveries, fleet inhomogeneities, and so forth. Various exact and heuristic methods have been proposed to solve the problem, e.g. (5) and (6).

As a variant of the classical VRP problem, Green Vehicle Routing Problem (G-VRP) was introduced by (7), in which a battery capacity constraint was added, along with the option of recharging at a station with a constant time. They assumed a full-charge policy and aim to minimize the total travel distance. Since the charging stations are scarce in the network, the vehicle could visit the same station multiple times, modeled through a network transformation. However, this approach also increased the scale of the network and complicates the solution process. They also proposed two heuristics to solve the problem. (8) extended the previous G-VRP models to consider nonlinear charging functions and a hybrid metaheuristic is proposed to solve the problem. (9) formulated the problem of locating charging stations and also designing EV routes as a discrete integer programming optimization problem, based on the classic VRP.

Meanwhile, an increasing number of studies investigate the efficiency of delivery systems that deploy UAVs. (10) introduced the "Flying Sidekick Traveling Salesman Problem" (FSTSP), which assumes that a truck can launch its UAV at the depot or customer node and remains on its own route, while the UAV delivers one small parcel to another customer before meeting again at a rendezvous location (another customer node on the truck's route). (11) presented an iterative algorithm that is based on a decomposition approach to minimize delivery completion time of Traveling Salesman Problem with Drone (TSP-D). (12) provide a randomized variable neighborhood descent heuristic to solve FSTSP, in which the initial solution is created from the optimal TSP solution obtained by the Concorde solver. Next, an implementation of the Randomized Variable Neighborhood Descent (RVND) heuristic is used as a local search to obtain the problem solution. (13) studied combinations of truck and UAV routes between each possible launch and pickup nodes and refer to each combination as an "operation" and propose an operation-based formulation. Local search and dynamic programming are presented as heuristic algorithms. (14) investigated the delivery cost of the TSP-D for the first time. The delivery cost includes transportation cost and waiting cost. Two different heuristics are provided, both of which are inspired from the route firstcluster second heuristic, which is based on local search and greedy randomized adaptive search


FIGURE 1 A simple representation of the EV-UAV coordinated route
procedure (GRASP). TSP with multiple UAVs are also studied. (15) considered a more general case with multi-trucks and multi-UAVs, in which one or more UAVs could travel with every truck. The objective function is to minimize the delivery completion time, that is, the time when the last truck or UAV return to the depot.

## PROBLEM DESCRIPTION AND MATHEMATICAL FORMULATION

The EVTSPD is defined on an undirected, complete graph $G=(V, E)$, with a vertex set $V$ consisting of the customer set $I=\left\{v_{1}, v_{2}, \ldots, v_{c}\right\}$, the depot $v_{0}$, and a set of charging stations $S=$ $\left\{v_{c+1}, v_{c+2}, \ldots, v_{c+s}\right\}$. The vertex set is thus $V=\left\{v_{0}\right\} \cup I \cup F=\left\{v_{0}, v_{1}, \ldots v_{c+s}\right\}$ and $|V|=c+s+1$. It is assumed that all charging stations have unlimited capacities. The edge set $E=\left\{\left(v_{i}, v_{j}\right): v_{i}, v_{j} \in\right.$ $V, i<j\}$ contains the edges connecting vertices of $V$. Each edge ( $v_{i}, v_{j}$ ) is associated with two nonnegative travel time $t_{i j}$ and $t_{i j}^{\prime}$, which corresponds to the travel time needed for the EV and UAV to travel from node $i$ to node $j$, respectively. In addition, no limit is set on the number of stops that can be made for recharging. When recharging is undertaken, it is assumed that the battery is charged to its full capacity (this "full-charge" policy assumption is common in the literature).

The EVTSPD is to find a coordinated tour that starts and ends at the depot, visits a subset of vertices (including charging stations when necessary) such that the total delivery time is minimized. It is assumed that all customers should be served either by the electric vehicle or the UAV. At the start of the tour, all parcels are loaded into the electric vehicle. During the tour, the electric vehicle can launch the UAV at a customer node and retrieve the UAV later at another customer node. The electric vehicle and the UAV works independently after UAV is launched. Note that both the launch node and retrieve node should be in the EV's route. Since it is assumed that there is only one UAV in the EV, so the UAV cannot be relaunched before it is retrieved. As a result, the final feasible solution consists of the EV route and several, nonoverlapping, UAV routes which start and end on the EV route. A simple example is shown in Figure 1, where the EV route is $\{0-1-3-5-6-0\}$ while UAV route is $\{1-2-3,3-4-6\}$.

We assume that the electric vehicle and the UAV share their electricity. There is a battery on the EV which can be used by both the EV and the UAV. If the UAV is launched from the EV at


## FIGURE 2 A simple representation of the electricity assumption

a customer node, the electricity required for the UAV route is deducted from the remaining battery level of the EV. To explain this, denote $b_{i}^{a}$ as the remaining electricity of EV upon arrival of node $i$ and $b_{i}^{d}$ as the remaining electricity of EV upon departure of node $i$. Using the network in Figure 2, assume the electric vehicle launches the UAV at node 1 , travels to node 3 and retrieves the UAV at node 4 while the UAV serves the customer 2. If $b_{1}^{a}=100$, which indicates that EV's remaining battery level upon arrival at node 1 is 100 , then EV's battery level upon departure of node 1 could be calculated as $b_{1}^{d}=100-\tau_{124}^{\prime}=100-20=80$, where $\tau_{124}^{\prime}$ represents the required electricity of the UAV to be launched at node 1 , serves customer 2 and returns to node 4 . The battery level of the other nodes are also shown in Figure 2.

Since the battery level of EV should be non-negative along its route, the EV may need to visit charging stations to charge its battery to full capacity when necessary. It is worth noting that in EVTSPD, the final solution might contain more than one visit to some specific charging station nodes, while some other charging station nodes might not in EV's route and are never visited. To permit multiple (and possibly zero) visits to the charging station nodes, while requiring exactly one visit to the customer nodes, graph $G$ is augmented to create $G_{0}=\left(V_{0}, E_{0}\right)$ with a set of $s^{\prime}$ dummy vertices, $\Phi=\left\{v_{c+s+1}, v_{c+s+2}, \ldots, v_{c+s+s^{\prime}}\right\}$, one for each potential visit to an charging station node. Denote $V^{\prime}$ as the augmented vertices set and $V^{\prime}=V \cup \Phi$. The number of dummy vertices associated with each charging station, $n_{s}$, is set to the number of times the associated $v_{s} \in S$ can be visited. $n_{s}$ should be set as small as possible so as to reduce the network size, but large enough to not restrict multiple beneficial visits.

Additional notation used in formulating the EVTSPD is defined next.

## Sets

$I$ : Set of all customers in the problem, $I=\left\{v_{1}, v_{2}, \ldots, v_{c}\right\}$ and $|I|=c$.
$I^{\prime}$ : Subset of customers that are available to UAV delivery service, $I^{\prime} \subset I$.
$S:$ Set of all charging stations in the original network, $S=\left\{v_{c+1}, v_{c+2}, \ldots, v_{c+s}\right\}$ and $|S|=s$.
$S^{\prime}$ : Augmented set of all charging stations, including the $m$ copies of set $S . S^{\prime}=\left\{v_{c+1}, . ., v_{c+s}, v_{c+s+1}, \ldots, v_{c+m s}\right\}$ and $\left|S^{\prime}\right|=m s$. Note that in the augmented network each node could be visited at most once.
$N$ : Set of all nodes in the augmented network, $N=S^{\prime} \cup C \cup\{0, c+m s+1\}$, where 0 and $c+m s+1$ both represents the depot and $|N|=c+m s+1$.
$N_{0}$ : Set of nodes from which a vehicle may depart in the augmented network. $N_{0}=\left\{v_{0}, v_{1}, \ldots, v_{c}\right\} \cup$
$S$
$N_{+}$: Set of nodes to which a vehicle may visit in the augmented network. $N_{+}=\left\{v_{1}, v_{2}, \ldots v_{c}\right\} \cup$ $S^{\prime} \cup\left\{v_{c+m s+1}\right\}$.
$N^{\prime}$ : Set of all customer nodes and charging station nodes in the augmented network. $N^{\prime}=I \cup S^{\prime}$.
$D$ : Set of tuples of the UAV's feasible route $\langle\mathrm{i}, \mathrm{j}, \mathrm{k}\rangle$, where the UAV is launched from node $i$, travels to node $j$ and returns to node $k . D=\left\{\langle i, j, k\rangle: i \in N_{0}, j \in C^{\prime}, k \in N_{+}, i \neq j, j \neq k, i \neq k, \tau_{i j}^{\prime}+\tau_{j k}^{\prime} \leq\right.$ $\left.Q_{d}\right\}$.

## Parameters

$\tau_{i j}$ : Travel time cost for electric vehicle to travel from node $i$ to node $j$
$\tau_{i j}^{\prime}$ : Travel time cost for UAV to travel from node $i$ to node $j$
$\tau_{i j k}^{\prime}$ : Travel time cost for UAV to launch from node $i$, serves node $j$ and return to node $k$
$Q_{d}$ : Driving time limit of the UAV, which is measured in time unit.
$Q$ : Driving time limit of the electric vehicle, which is measured in time unit.
$M$ : A positive large number which is greater than the upper bound of total travel time

## Decision variables:

$x_{i j} \in\{0,1\}:$ Equals one if the electric vehicle travels from node $i$ to node $j$ and zero otherwise, where $i \neq j$ and $i \in N_{0}, j \in N_{+}$.
$y_{i j k} \in\{0,1\}$ : Equals one if the UAV is launched from node $i$, travels to node $j$ and returns to the EV at node k and zero otherwise.
$p_{i j} \in\{0,1\}$ : Equals one if customer node $i$ is visited before customer $j$ in the EV's path and zero otherwise.
$u_{i}$ : Position of node $i$ in the EV's path.
$b_{i}^{a}$ : Remaining battery charge of EV upon arrival of node $i$ which indicates the remaining maximum driving time of EV.
$b_{i}^{d}$ : Remaining battery charge of EV upon departure of node $i$ which indicates the remaining maximum driving time of UAV.
$t_{j}$ : Time when electric vehicle arrives at node $j$.
$t_{j}^{\prime}$ : Time when UAV arrives at node $j$.

## Mathematical Formulation

Objective :
$\min \quad z=t_{c+m s+1}$
The objective is to minimize the time when both vehicles return to the depot after serving all the customers. There are a large number of constraints in the problem; these are introduced below, interspersed with descriptions.

Routing Constraints:

$$
\begin{equation*}
\sum_{\substack{i \in N_{0} \\ i \neq j}} x_{i j}+\sum_{\substack{i \in N_{0} \\ i \neq j<i, j, k>\in D}} \sum_{\substack{k \in N_{+}\\}} y_{i j k}=1 \quad \forall j \in I \tag{2}
\end{equation*}
$$

$$
\begin{align*}
& \sum_{j \in N_{+}} x_{0 j}=1  \tag{3}\\
& \sum_{i \in N_{0}} x_{i, c+1}=1  \tag{4}\\
& u_{i}-u_{j}+1 \leq(c+m s+2)\left(1-x_{i j}\right) \quad \forall i \in N^{\prime}, j \in N_{+}, j \neq i  \tag{5}\\
& \sum_{\substack{i \in N_{0} \\
i \neq j}} x_{i j}=\sum_{\substack{k \in N_{+} \\
k \neq j}} x_{j k}  \tag{6}\\
& \sum_{j \in C^{\prime}} \sum_{\substack{k \in N_{+} \\
\langle i, j, k>\in D}} y_{i j k} \leq 1  \tag{7}\\
& \sum_{i \in N_{0}} \sum_{j \in C^{\prime}} y_{i j k} \leq 1 \quad \forall k \in N_{+}  \tag{8}\\
& <i, j, k>\in D \\
& \begin{array}{ll}
2 y_{i j k} \leq \sum_{\substack{h \in N_{0} \\
h \neq i}} x_{h i}+\sum_{\substack{l \in N_{0} \\
l \neq k}} x_{l k} & \forall i \in N_{0}, j \in C^{\prime}, k \in N_{+},<i, j, k> \\
y_{0 j k} \leq \sum_{\substack{h \in N_{0} \\
h \neq k}} x_{h k} & \forall j \in C^{\prime}, k \in N_{+},<0, j, k>\in D
\end{array}  \tag{10}\\
& u_{k}-u_{i} \geq 1-(c+m s+2)\left(1-\sum_{\substack{j \in C^{\prime} \\
<i, j, k>\in D}} y_{i j k}\right) \quad \forall i \in N_{0}, k \in N_{+}, k \neq i \tag{11}
\end{align*}
$$

## Battery Constraints:

$b_{j}^{a} \leq b_{i}^{d}-\tau_{i j} x_{i j}+M\left(1-x_{i j}\right)$

$$
\begin{equation*}
\forall i \in N_{0}, j \in N_{+}, i \neq j \tag{12}
\end{equation*}
$$

$$
\begin{equation*}
b_{i}^{d}=Q-\sum_{\substack{j \in C^{\prime} \\ j \neq i}} \sum_{\substack{k \in N_{+}, j, k>\in D}} y_{i j k} * \tau_{i j k}^{\prime} \tag{14}
\end{equation*}
$$

$$
\forall i \in S^{\prime} \cup\{0, c+m s+1\}
$$

$b_{i}^{d}=b_{i}^{a}-\sum_{\substack{j \in C^{\prime} \\ j \neq i}} \sum_{\substack{k \in N_{+} \\<i, j, k>D}} y_{i j k} \tau_{i j k}^{\prime}$

$$
\begin{equation*}
\forall i \in I \tag{15}
\end{equation*}
$$

$b_{i}^{a} \geq 0$

$$
\begin{equation*}
\forall i \in N \tag{16}
\end{equation*}
$$

$b_{i}^{d} \geq 0$

$$
\begin{equation*}
\forall i \in N \tag{17}
\end{equation*}
$$

$$
\begin{equation*}
b_{0}^{a}=Q \tag{13}
\end{equation*}
$$

## Coordination Constraints:

$$
\begin{equation*}
t_{i}^{\prime} \geq t_{i}-M\left(1-\sum_{\substack{j \in C^{\prime} \\ j \neq i}} \sum_{\substack{k \in N_{+} \\ j i, j, k>\in D}} y_{i j k}\right) \quad \forall i \in N_{0} \tag{18}
\end{equation*}
$$

$$
\begin{equation*}
t_{k}^{\prime} \geq t_{j}^{\prime}+\tau_{i j}^{\prime}+S_{R}-M\left(1-\sum_{\substack{i \in N_{0} \\<i, j, k>D}} y_{i j k}\right) \tag{24}
\end{equation*}
$$

$$
\begin{equation*}
t_{i}^{\prime} \leq t_{i}+M\left(1-\sum_{\substack{j \in C^{\prime} \\ j \neq i}} \sum_{\substack{k \in N_{+} \\<i, j, k>\in}} y_{i j k}\right) \tag{19}
\end{equation*}
$$

$$
\begin{equation*}
t_{k}^{\prime} \geq t_{k}+M\left(1-\sum_{\substack{i \in N_{0} \\ i \neq k}} \sum_{\substack{j \in C^{\prime} \\<i, j, k>\in D}} y_{i j k}\right) \quad \forall k \in N_{+} \tag{20}
\end{equation*}
$$

$$
\begin{equation*}
t_{k}^{\prime} \leq t_{k}-M\left(1-\sum_{\substack{i \in N_{0} \\ i \neq k}} \sum_{\substack{j \in C^{\prime} \\<i, j, k>\in D}} y_{i j k}\right) \quad \forall k \in N_{+} \tag{21}
\end{equation*}
$$

$$
t_{k} \geq t_{h}+\tau_{h k}+S_{L} * \sum_{\substack{l \in C^{\prime} \\ l \neq k}} \sum_{\substack{\epsilon \in, l, m>\\+}} y_{k l m}+S_{R} \sum_{\substack{i \in N_{0} \\ i \neq k}} \sum_{\substack{j \in C^{\prime}, j, k>\in D}} y_{i j k}-M\left(1-x_{h k}\right)
$$

$$
\begin{equation*}
t_{j}^{\prime} \geq t_{i}^{\prime}+\tau_{i j}^{\prime}-M\left(1-\sum_{\substack{k \in N_{+} \\<i, j, k>\in D}} y_{i j k}\right) \tag{23}
\end{equation*}
$$

$$
\forall j \in C^{\prime}, k \in N_{+}, k \neq j
$$

Constraints (12)-(17) are associated with the battery electricity level. In particular, constraint (12) states that if electric vehicle travels from node $i$ to node $j$, then the electricity level before arriving node $i$ is less or equal to the electricity level after leaving node $j$, regardless whether node $i, j$ are customer node or charging station. Constraint (13) ensures that when EV departs from the depot it is fully charged. Constraint (14) states that if EV departs from a charging station node $i$ and there is a UAV route that starts at node $i$, then when EV departs from $i$ it is no longer fully charged and the UAV route electricity consumption should be deducted from full-charged battery. Constraint (15) states the same situation as constraint (14) except when node $i$ is a customer. Constraint (16) and (17) ensures that the remaining battery should be non-negative.
$t_{i}^{\prime} \leq t_{i}+M\left(1-\sum_{\substack{j \in C^{\prime} \\ j \neq i}} \sum_{\substack{k \in N_{+} \\<i, j, k>\in D}} y_{i j k}\right) \quad \forall i \in N_{0}$

$$
\begin{equation*}
\forall h \in N_{0}, k \neq h \tag{22}
\end{equation*}
$$

$$
\forall j \in C^{\prime}, i \in N_{0}, i \neq j
$$

Constraints (18)-(24) are associated with travel time of the two vehicles. In particular, constraints (18)-(21) ensure that the travel time and UAV range limit are correctly handled. Constraint (22) indicate that if the electric vehicle travels from $h \in N_{0}$ to $k \in N_{+}$. The electric vehicle's effective arrival time at $k$ must incorporate the electric vehicle's arrival time at $h$, the electric vehicle's travel time from $h$ to $k$, the launch time at node $h$ and the retrieve time at node $k$. This constraint is not binding if the electric vehicle does not travel from $h$ to $k$. Constraint (23) and (24) are associated with the arrival time of UAV. If there is a UAV route of $\langle i, j, k\rangle$, then the arrival time of node $j$ and $k$ should be related to the UAV's travel time between $i$ and $j$ and $j$ and $k$.
Ordering Constraints:
$t_{k}-t_{j}+\tau_{i j} \leq e+M\left(1-y_{i j k}\right)$

$$
\begin{align*}
& \forall k \in N_{+}, j \in C^{\prime}, i \in N_{0},<i, j, k>\in D  \tag{25}\\
& u_{i}-u_{j} \leq-1+(c+m s+2)\left(1-p_{i j}\right)  \tag{26}\\
& p_{i j}+p_{j i}=1 \\
& t_{l}^{\prime} \geq t_{k}^{\prime}-M\left(3-\sum_{\substack{j \in C^{\prime} \\
<i, j, k<\in \in D \\
j \neq l}} y_{i j k}-\sum_{\substack{m \in C^{\prime} \\
m \neq i<l, m, n>\\
m \neq k \\
m \neq i \\
m \neq l \\
n \neq k}} \sum_{\substack{n \in N_{+} \\
m_{l}}} y_{l m n}-p_{i l}\right) \forall i, j \in N^{\prime}, i \neq j  \tag{27}\\
& \forall i, l \in N_{0}, k \in N_{+}, i \neq k \neq l,<i, j, k>\in D,<l, m, n>\in D
\end{align*} \quad \forall i \neq N^{\prime}, i \neq j
$$

## Domain Constraints:

$$
\begin{align*}
t_{0} & =0 & &  \tag{29}\\
p_{0 j} & =1 & & \forall j \in N_{+} \\
x_{i j} & \in\{0,1\} & & \forall i \in N_{0} \\
y_{i j k} & \in\{0,1\} & & \forall i \in N_{0} \\
1 \leq u_{i} & \leq c+m s+2 & & \forall i \in N_{+} \\
t_{i} & \geq 0 & & \forall i \in N \\
t_{i}^{\prime} & \geq 0 & & \forall i \in N \\
p_{i j} & \in\{0,1\} & & \forall i \in N_{0}, j \in N_{+}, j \neq i
\end{align*}
$$

Constraints (29)-(36) specify the domain of all the decision variables.

8 There are several complications in EVTSPL: the vehicle driving range limitations, the existence of a chargings station that can possibly be visited multiple times or not at all, and planning the UAV's route alongside that of the EV, introduce major complications to the problem. In the previous research which did not include electricity constraints, (11) report a solution time of about 3 hours to solve a network containing 10 nodes, using a commercial solver. Thus, heuristics designed for EVTSPD are necessary to solve a problem with practical size. In this section, an iterative three-step decomposition heuristic algorithm is presented to solve the proposed EVTSPD, based on that proposed by (11). The heuristic algorithm decomposes the problem into three subproblems: electric vehicle path construction, UAV node insertion and final solution feasibility check. However, since there are a variety of different combination of electric vehicle node and UAV node, an iterative approach is used to improve the result and record the best-known solution. since it generally has higher travel speed. However, the number of customer nodes that could be served by the UAV is limited. Since it is hard to pre-determine which nodes should be served by

Constraints (25)-(28) are associated with ordering the two vehicles. Constraint (25) ensures that the UAV route should be within the UAV's flight range. Constraint (26) is a sub-tour elimination constraint and constraint (27) ensures the correct ordering of two different nodes. Constraint visited before node $l$ by the EV, then node $l$ must be visited after node $k$.
he decision variables

## SOLUTION METHODS

## The iterative heuristic algorithm

With the objective to minimize delivery time, the UAV should be deployed as much as possible the electric vehicle and which nodes should be served by the UAV, the algorithm partitions $V$ into (28) indicates that if their exists two UAV route deliveries $\langle i, j, k\rangle$ and $<l, m, n>$ and node $i$ is
two subsets: a set of customer nodes that is served by the UAV $N_{U}$ (the UAV nodes), and a set of remaining customer nodes that should be served by EV plus the depot $N_{E}$ (the $E V$ nodes). Thus $N_{U} \cup N_{T}=I \cup\{0\}$. Since there is a finite (albeit exponential) number of such partitions, a subset of them can be explored for route generation. The specific steps of the algorithm are as follows:

- Step 1 For all the customer nodes $i: i \in C$, list all the combinations of the EV nodes and UAV nodes and store the combinations in set $B$. Set the optimal cost to infinity, Cost ${ }^{\text {opt }} \leftarrow$ $\infty$. (The number of combinations grows exponentially with network size; if necessary another heuristic rule can be used to select a subset of all possible combinations).
- Step 2 While set $B$ is nonempty, pick the first combination Comb in set $B$ and identify the EV nodes set $N_{E}$ and UAV nodes set $N_{U}$. Delete Comb from $B$ and set $B \leftarrow B \backslash C o m b$.
- Step 3 For all the nodes in the combined set $N_{E} \cup S$, solve the Electrical Vehicle Travelling Salesman Problem (EVTSP) using the MCWS heuristic proposed in (7) and obtain an feasible EV route Route $_{E V}$ and route cost Cost $_{E V}$. (See below for details.) If no feasible solution exists or $\operatorname{Cost}_{E V}>=\operatorname{Cost}^{\text {opt }}$, return to Step 2.
- Step 4 With set $N_{U}$ and EV's temporary route Route ${ }_{E V}$, solve the UAV inserting problem (see below for details) and obtain the optimal UAV route Route ${ }_{U A V}$ and corresponding waiting time Wait $_{U A V}$. If $\operatorname{Cost}_{E V}+$ Wait $_{U A V}>=$ Cost $^{\text {opt }}$, return to Step 2.
- Step 5 Check the battery feasibility of the final solution. If Route $e_{E V}$ and Route $_{U A V}$ satisfies the battery level constraint, update the optimal cost Cost $^{\text {opt }} \leftarrow \operatorname{Cost}_{E V}+$ Wait $_{U A V}$. Otherwise, return to Step 2.
The algorithm terminates with an empty set $B$. The latest Cost ${ }^{\text {opt }}$ and its corresponding Route $_{E V}$ and Route $_{U A V}$ are returned as the best solution found by the algorithm. The detailed explanation of three key steps are presented below.


## Solve EVTSP

In Step 3 of the algorithm, an EVTSP should be solved with with nodes $\left\{i: i \in N_{T} \cup S\right\}$. Note that $N_{E}$ is a subset of customer set $C$. The purpose of solving EVTSP is to construct a feasible EV route that visits all the customer nodes in set $N_{E}$, satisfies the EV driving range constraint and minimizing the total travel time at the same time. In this paper, a Modified Clarke-Wright Savings algorithm (MCWS) is implemented to solve the problem. MCWS is proposed in (7) and it is a greedy-based maximum saving algorithm. To solve EVTSP a augmented network is constructed, where the set of charging station $S$ should be replicated to ensures that a single charging station could be potentially visited multiple times. For all the generated instances in this paper the charging station set $S$ are replicated twice in the network.

## UAV node insertion

In Step 4 of the algorithm, a subproblem of UAV node insertion is implemented and solved to obtain the optimal insertion type such that every customer node in set $N_{U}$ and the total waiting time of the EV is minimized. The input data of this problem is the feasible EV route obtained in step 3 and all the possible UAV routes along the EV route which satisfied the UAV's flight range constraint. The MILP formulation of this subproblem is proposed in (11) and the reader could refer to it for more information.

Final solution feasibility check
In step 5 of the heuristic algorithm the feasibility check of the solution obtained from previous steps is implemented. Note that although the EV's route and UAV's route both satisfy all the constraints separately, the final solution that incorporates both of them might not be feasible because of the shared electricity assumption. More specifically, the electricity level constraint might be violated when UAV's routes are incorporated into EV's route and the electricity consumption of UAV's route $\langle i, j, k\rangle$ is deducted from the $b_{i}^{d}$. If the final coordinated route still satisfies the electricity constraint, it is then compared to the best-known solution. Otherwise it is discarded and the algorithm moves to step 2 to explore another combination in set $B$.

## NUMERICAL ANALYSIS

In order to validate and evaluate the performance of the proposed heuristic algorithm, numerical analysis is conducted and described in this section. The experimental setting is described in the first subsection, while the second one presents the computational result of the instances.

## Experimental Setting

The purpose of the experiments is to compare the performance of the proposed heuristic algorithm against solving the MILP formulation directly via a commercial solver. However, since both the related problems of EVRP and TSP-D are introduced in recent years, benchmark instances are limited and most of them are not available publicly. Furthermore, according to (11), commercial solvers can only obtain optional solutions for instances containing up to 10 customers in two hours. Because of the complexity of the TSP-D and the extra complexity incurred by adding the driving range limit constraint, the feasible instance that could be solved by a commercial solver is relatively in small scale. So in this paper, we conduct the numerical analysis on randomly generated instances. Most of the experimental settings are adopted from (11). For all the generated instances, the single depot is located at $(0,0)$ and the coordinates of the customer nodes are uniformly distributed between -10 km and 10 km . The EV travels at the speed of $40 \mathrm{~km} / \mathrm{h}$ while the UAV's speed is $56 \mathrm{~km} / \mathrm{h}$. EV has a driving time limit of 4000 seconds while the UAV has a driving time limit of 1200 seconds, which is adopted from (10). The launch/retrieve time and charging time are set to zero in these instances. Distances for the electric vehicle are calculated employing Manhattan metric, while the Euclidean metric is chosen for the UAV, reflecting the greater mobility options available to a drone.

The MILP model is implemented in Pyomo with ILOG's CPLEX Concert Technology solver (version 12.6.3). The proposed heuristic algorithm is coded in Python. All numerical experiments are run on a 2.8 GHz Intel Core i5 quad-core machine with 16 GB RAM.

## Computational Results

The first experimental test aims to evaluate the performance of the proposed heuristic by comparing it to an exact solver. The computational results for ten randomly generated instances are shown in Table 1. For the case name of " 5 C 2 S 2 R 01 ", " 5 C " represents that this instance includes five different customers, " 2 S " represents that this instance contains two different charging stations, " $2 R$ " represents that the augmented network contains two copies of all the charging stations and " 01 " is the index for a specific type of instance. As a result, in the augmented network of case "5C2S2R01" the actual number of nodes is 11 including the depot.

As can be seen from Table 1, for instances containing 5 customers the average computation
time of CPLEX is 2202 seconds while that of the proposed heuristic algorithm is less than 1 second. On average the optimality gap of the heuristic algorithm is 0.162 . However for instances including 10 customers CPLEX fails to find the optimal solution within two hours while the heuristic find a feasible solution with an average of 26.5 seconds. This result shows that the proposed heuristic is capable of obtain a good feasible solution with a much less computational time compared to solve the MILP formulation via a commercial solver. However, since the computational time grows exponentially with the scale of the network, although it can obtain a good feasible result in a relatively short time for small instances, for larger instances the computational time might be prohibitive. In this situation, a heuristic that could pre-decide the number of EV nodes and UAV nodes could be implemented to decrease the number of combinations and computational time.

The second experimental test aims to evaluate the improvement of the final solution with the assistance of UAV delivery. The final solution of EVTSPD is compared with solving the same instance as a electric travelling salesman problem (EVTSP). Two different groups of instances are generated where the instances in the first group have 5 customers and the instances in the second one has 10 customers. The heuristic algorithm for EVTSP is MCWS as proposed in (7). The results are shown in Table 2. As illustrated, the utilization of UAV delivery would greatly decrease the delivery time. On average the final delivery time of EVTSPD is $39.17 \%$ lower than EVTSP solution for 5 -customer instances and $28.55 \%$ lower for 10 -customer instances. This improvement indicates that the logistics company might have a great business benefit by utilizing UAV delivery considering not only the delivery time decrease but also UAV could be operated without a human pilot at a lower operation cost.

## CONCLUSION

In this paper, the EVTSPD is formulated and an efficient iterative heuristic algorithm is proposed. This problem is to find a coordinated EV-UAV route minimizing total travel time, to serve a set of customers while incorporating stops at charging stations in route plans to ensure sufficient charge. The case study on randomly generated instances indicates that the proposed algorithm performs well compared to exact solution methods, with significantly less computational time. We therefore plan to apply this solution method to solve larger problem instances. The ability to formulate the EVTSPD, along with the solution techniques, will aid organizations with EV fleets in overcoming difficulties that exist as a result of limited rechargeing infrastructure. The new delivery concept of using UAV and EV to perform last-mile delivery would result in financial and environmental benefits when considering the reduced operation cost of fueling and switching to UAV which does not require a human pilot. This also allows deliveries companies to understand the potential impact of their decision on daily operations and costs.

Additional topics for future research include developing heuristics with relaxed charging assumptions, allowing partial recharges. The EVTSPD could also be extended to a fleet of electrical vehicles while seeks optimal tours and considering fuel prices and heterogeneous properties.

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## TABLE 1 Computational results for performance evaluation

|  | Computational Time (s) |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Case Name | CPLEX | Heur. Algorithm | Heur. Solution (s) | Opt. Solution (s) | Opt. Gap |
| 5C2S2R01 | 240 | $<1$ | 4950 | 4390 | 0.127 |
| 5C2S2R02 | 486 | $<1$ | 4890 | 4500 | 0.087 |
| 5C2S2R03 | 2103 | $<1$ | 5000 | 4600 | 0.087 |
| 5C2S2R04 | 2329 | $<1$ | 2730 | 2720 | 0.004 |
| 5C2S2R05 | 5912 | $<1$ | 4960 | 4140 | 0.198 |
| 5C2S2R06 | 259 | $<1$ | 6650 | 6460 | 0.029 |
| 5C2S2R07 | 2775 | $<1$ | 3760 | 2930 | 0.2835 |
| 5C2S2R08 | 771 | $<1$ | 6350 | 4780 | 0.328 |
| 5C2S2R09 | 3038 | $<1$ | 4430 | 3970 | 0.116 |
| 5C2S2R10 | 4107 | $<1$ | 4010 | 2930 | 0.369 |
| Average | $\mathbf{2 2 0 2}$ | $<\mathbf{1}$ | $\mathbf{4 7 7 3}$ | $\mathbf{4 1 4 2}$ | 0.162 |
| 10C4S2R01 | $>7200$ | 42 | 4210 | None | None |
| 10C4S2R02 | $>7200$ | 36 | 5670 | None | None |
| 10C4S2R03 | $>7200$ | 17 | 6400 | None | None |
| 10C4S2R04 | $>7200$ | 32 | 6130 | None | None |
| 10C4S2R05 | $>7200$ | 17 | 5630 | None | None |
| 10C4S2R06 | $>7200$ | 19 | 5740 | None | None |
| 10C4S2R07 | $>7200$ | 16 | 6680 | None | None |
| 10C4S2R08 | $>7200$ | 10 | 5160 | None | None |
| 10C4S2R09 | $>7200$ | 52 | 5260 | None | None |
| 10C4S2R10 | $>7200$ | 24 | 6030 | None | None |
| Average | $>7200$ | $\mathbf{2 6 . 5}$ | $\mathbf{5 6 9 1}$ | None | None |

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TABLE 2 Computational results for final delivery time comparison

| Case Name | EVTSPD Solution (s) | MCWS Solution (s) | Difference Gap | \#UAV Routes |
| :---: | :---: | :---: | :---: | :---: |
| 5C4S2R01 | 5320 | 5680 | $6.77 \%$ | 3 |
| 5C4S2R02 | 4510 | 5930 | $31.49 \%$ | 2 |
| 5C4S2R03 | 5000 | 8000 | $60.00 \%$ | 2 |
| 5C4S2R04 | 2030 | 3690 | $81.77 \%$ | 2 |
| 5C4S2R05 | 3560 | None | None | 4 |
| 5C4S2R06 | 4520 | 6010 | $32.96 \%$ | 1 |
| 5C4S2R07 | 3590 | 4790 | $33.43 \%$ | 4 |
| 5C4S2R08 | 4360 | 6900 | $58.26 \%$ | 2 |
| 5C4S2R09 | 4130 | 4800 | $16.22 \%$ | 3 |
| 5C4S2R10 | 3100 | 4080 | $31.61 \%$ | 4 |
| Average | $\mathbf{4 0 1 2}$ | $\mathbf{5 5 4 2}$ | $\mathbf{3 9 . 1 7 \%}$ | $\mathbf{2 . 7}$ |
| 10C5S2R01 | 5320 | 7920 | $48.87 \%$ | 3 |
| 10C5S2R02 | 6400 | 7240 | $13.13 \%$ | 7 |
| 10C5S2R03 | 6490 | 8150 | $25.58 \%$ | 2 |
| 10C5S2R04 | 5730 | 7060 | $23.21 \%$ | 7 |
| 10C5S2R05 | 5690 | 6990 | $22.85 \%$ | 3 |
| 10C5S2R06 | 7250 | 9100 | $25.52 \%$ | 4 |
| 10C5S2R07 | 5270 | 6350 | $20.49 \%$ | 3 |
| 10C5S2R08 | 5440 | 7330 | $34.74 \%$ | 3 |
| 10C5S2R09 | 5410 | 8020 | $48.24 \%$ | 3 |
| 10C5S2R10 | 5860 | 7200 | $22.87 \%$ | 7 |
| Average | $\mathbf{5 8 8 6}$ | $\mathbf{7 5 3 6}$ | $\mathbf{2 8 . 5 5 \%}$ | $\mathbf{7}$ |

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