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Traveling salesman problem with drone and bicycle: multimodal last-mile e-mobility

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Abstract

Recently, the multimodal last-mile e-mobility concept has been at the center of attention for cleaner, greener, and more accessible urban deliveries. As part of sustainable transportation systems, multimodal e-mobility is proper for a variety of logistics operations as well as medical applications. This work tries to address a novel application of multimodal e-mobility through introducing and modeling the *traveling salesman problem with drone and bicycle* (TSP-D-B). Therefore, a novel mixed integer linear programming model is developed to formulate the problem wherein the total traveling time is minimized. As part of the last-mile delivery, a fleet of three vehicles including a truck, a drone, and a bicycle is taken into account to serve the customers in a single visit. The truck is considered as the main vehicle, while the drone and bicycle can be preferred in case of emergencies such as traffic or route failures. In order to assess the complexity, validity and applicability of the offered model, a dataset including 64 different benchmarks is generated, and according to the findings, the model is able to efficiently solve the benchmarks for up to 50 customers in 685 s maximum. A comparison is also made between TSP-D-B, the classic version of the TSP and the TSP-D, which reveals that TSP-D-B provides appropriate service time savings in all benchmarks. Finally, another comparative analysis is made using several instances adapted from the literature. It is revealed that TSP-D-B leads to significant time savings in most instances.

Keywords: traveling salesman problem with drone and bicycle; multimodal e-mobility; last-mile delivery; bike delivery

1. Introduction

Logistics industry encourages trade activities between different parties by transporting, stockpiling, and delivering goods through business-to-business, business-to-consumer, or consumer-to-consumer supply chain networks (Arumugam et al., 2019). Logistics firms are providing cargo

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transportation services by land, air, and sea while accommodating dynamic economic patterns and digitalization (Zhou et al., 2023). The logistics industry, which is a fundamental component of international trade, had an estimated worth of 8.4 trillion euros in 2021. This figure is expected to rise and surpass 13.7 billion euros by 2027 (Placek, 2023). As a special case of logistics phenomena, city logistics enable the movement of goods from commercial entities to urban areas with the negative consequences of complex city life, traffic density, and air/noise pollution problems (Russo and Comi, 2020). This also refers to urban logistics covering the flow and mobility of people, goods, and vehicles in cities (Lagorio et al., 2016). Moreover, smart city logistics require smart governance, smart economy, smart stakeholders, and smart environment in the urban area (Xenou et al., 2022). Hence, smart delivery has a significant role in city logistics by analyzing the routes and paths with data-driven algorithms (Nalepa, 2020).

Within the scope of city logistics, last-mile delivery refers to a concluding step of the delivery journey, when the package is transferred from a transportation hub to the ultimate destination, which is commonly a personal residence or retail store (Vakulenko et al., 2019). Furthermore, multimodal delivery stands for the shipping activity including more than one mode of transport (Perboli et al., 2018), and therefore multimodal delivery is a must-have for last-mile delivery since there are many challenges like traffic congestion, environmental and noise pollution, high distribution costs that can be overcome by including multimodal options like trains, cars, trucks, drones, bikes, walking, and so forth (Kou et al., 2022). It is even the case for pandemics as a back-up transport system where drones play critical a role (Zhao et al., 2022). E-mobility stands for the use of electric vehicles like e-cars, e-motorbikes, e-scooters, or e-buses, as well as drones, bikes/bicycles/pedelecs for transportation (Arora and Gargava, 2023), and it is a well-known alternative for the multimodal models for e-mobility scenarios (Ferrara et al., 2019a). Besides, e-mobility supports "zero emission" targets as an excellent sustainable mobility option (Cartenì et al., 2020). Therefore, e-mobility is remarkable in last-mile delivery to overcome augmented transport demand due to deliveries and returns with a sustainability perspective (Ehrler et al., 2021).

In order to entail the last-mile delivery, multimodal e-mobility literature is reviewed that involves employee competence configuration in supply chains by mathematical programming (Wikarek et al., 2022), shared-mobility services planning by mixed integer linear programming (MILP) (Enzi et al., 2017), vehicle routing by integer programming (Bessler and Grønbæk, 2012), energy management of e-mobility by simulation (Ferrara et al., 2019b), individuals' travel mode choice behavior by hierarchical clustering (Zhao et al., 2020) and by machine learning (Ferrara et al., 2019a), digitalization and servitization concepts to form the e-mobility (Goehlich et al., 2020), and building feasible scenarios by urban space morphology assessment (Scorza and Fortunato, 2021). As it is clear from the literature review, the number of multimodal e-mobility research is limited, and the majority of these articles adopt mathematical programming techniques with a few applications. Particularly, integer programming is the most preferred one. Therefore, the motivation behind this study grounds on this valuable background knowledge. Moreover, in multimodal e-mobility literature, the traveling salesman problem (TSP) is an essential tool to discover the shortest path that passes through every point in a set exactly one time (Kruskal, 1956) that could be implemented in multimodal e-mobility problems. While there is no article on TSP and e-mobility currently in the literature, there are studies applying TSP in multimodal urban freight transportation (Gladchenko et al., 2019), multimodal transit network design (Huang et al., 2018), multimodal freight locomotive scheduling and routing (Tong et al., 2016), and load-planning for multimodal logistics (Keskin et al., 2014).

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Hence, this is obvious that there is a research gap in multimodal e-mobility based on the *TSP with drone and bicycle* (TSP-D-B). Besides, the industry presents significant applications adopting multimodal e-mobility applications in last-mile delivery (Archetti et al., 2022). For example, "Renault Trucks" has proposed a multimodal delivery vehicle to solve last-mile delivery problems in order to combine three types of electric transportation in one vehicle: an e-Van (truck), an e-Cargo Bike, and a parcel-carrying Drone (RHCV, 2023). There is an innovative vehicle structure (i) delivering large parcels by truck, (ii) by cargo bike in case of increased traffic congestion, and (iii) by drones in case of urgent deliveries that are difficult to reach by road (Randall, 2022).

The purpose of this research is to appraise the concept of multimodal last-mile e-mobility based on TSP-D-B. Then, the problem is formulated and treated with the help of operations research (OR) analytics.

This was accomplished with the following goals in mind:

- To examine multimodal e-mobility as one of the recent developments of urban logistics, which help reduce congestion and improve air quality;
- to extend the previously developed models for the TSP and TSP-D in order to address the main requirements of TSP-D-B;
- to find and evaluate the possible advantages of TSP-D-B over TSP-D and TSP.

Thus, the main contributions of our work are as follows:

I. Evaluating and introducing the application of the multi-model last-mile e-mobility with the help of OR tools;
II. developing a novel MILP model to formulate the TSP-D-B;
III. assessing the complexity of the problem in terms of the number of variables and constraints;
IV. testing the efficiency of the developed model using 64 different benchmarks which are created for the first time;
V. Comparing the performance of the TSP-D-B against TSP-D and TSP in terms of the objective function and central processing unit (CPU) time;
VI. conducting a sensitivity analysis of the speed/traffic-related coefficients to find out the impact of each vehicle.

The remaining sections of the article are structured as follows. Section 2 reviews the literature in detail to address the gap in the field of study. Section 3 states the problem, whereas Section 4 describes the mathematical problem. Section 5 covers the model implementation to test the applicability and validity of the developed model, and finally, Sections 6 and 7 include the discussion and concluding remarks, respectively.

2. Survey on the literature

TSP is known as a mathematical problem that requires discovering the shortest path that passes through every point in a set exactly one time (Kruskal, 1956). It has many applications integrated with the solution approaches such as integer programming (Miller et al., 1960; Carr et al., 2023), branch-and-cut algorithm (Fischetti et al., 1997; Vercesi et al., 2023), dynamic programming

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(Bellman, 1962; Lera-Romero et al., 2022), ant colony algorithm (Dorigo and Gambardella, 1997; Li et al., 2023), particle swarm algorithm (Wang et al., 2003; Akhand et al., 2023), genetic algorithm (Larrañaga et al., 1999; Mondal and Srivastava, 2023), cuckoo search algorithm (Ouaarab et al., 2014; Wang et al., 2021), discrete bat algorithm (Osaba et al., 2016; Saji and Barkatou, 2021), simulated annealing (Lyu et al., 2022; Zhou et al., 2022), tabu search (Osaba et al., 2021), simulation (Černý, 1985), machine learning (Mele et al., 2021), and reinforcement learning (Gao et al., 2023).

TSP is implemented widely in the field of drone-assisted delivery (Murray and Chu, 2015; Agatz et al., 2018; Ha et al., 2018), autonomous aerial vehicles (Greblicki and Walczyński, 2016), order-picking (Ratliff and Rosenthal, 1983), scheduling (Tang et al., 2000), channel allocation (Bhar et al., 2019), fleet routing (Shojaeefard et al., 2022), path planning (Reda et al., 2022), task analysis (Furchi et al., 2022), urban logistics/last-mile delivery (Yu et al., 2021), city logistics (Maggioni et al., 2014), prize collecting (Pantuza and de Souza, 2022), harvesting robot (Plebe and Anile, 2002), smart agriculture (Dolias et al., 2022), and waste collection (Roy et al., 2022).

Unmanned/uncrewed aerial vehicles (UAVs) appeared in the literature for TSP in 2004 as a target visitation problem with the formulation and solution procedure (Grundel and Jeffcoat, 2004) and in 2005 as a UAV mission planning tool (Tan et al., 2005) and as a routing system (Kinney et al., 2005). As of 2012, a significant increasing trend has been observed in the number of publications in the field of "unmanned aerial vehicles/drones/flying sidekicks" concepts of TSP. According to our survey, China, the United States, Turkey, South Korea, Italy, and Germany are the countries of residence for the majority of authors publishing on this topic. Besides, while 48% of the publications are articles, 46% of them are conference papers, and the remaining part includes conference reviews (4%), book chapters (1%), and reviews (1%). In addition, these documents can be categorized by subject areas as engineering (32%), computer science (30%), mathematics (13%), decision science (6%), social sciences (4%), and so forth according to the Scopus database search on 4 April 2023.

TSP with drone/UAV/flying sidekick articles refer to the "TSP-D" abbreviation that covers the concepts of drone delivery, last-mile delivery, parcel deliveries, trajectory planning, task assignment, and route/path planning in the literature (de Freitas and Penna, 2020). The methodologies applied in TSP-D are generally integer programming, dynamic programming, combinatorial optimization, and meta-heuristics (e.g., ant colony optimization, genetic algorithm, and simulated annealing). Moreover, some studies such as Dell'Amico et al. (2022) tried to enhance the formulation of TSP-D in order to improve the previous results.

Table 1 summarizes the relevant studies conducted on TSP with drones/UAVs.

Accordingly, the articles addressing the truck–drone application appear in the literature by 2015 in drone-assisted parcel delivery (Murray and Chu, 2015) and package delivery planning (Mathew et al., 2015). Moreover, truck-and-drone keywords have been widely used in the literature with the TSP-T&D initials covering drone stations and parcel locations in synchronization. Here, heuristics and integer programming are the widely adopted techniques in parcel delivery, logistics, last-mile delivery, and city logistics (Ferrandez et al., 2016; Marinelli et al., 2018).

However, in addition to this background knowledge, "bike" OR "bicycle" delivery applications of TSP-D are just mentioned in Choi and Schonfeld's (2022) review as an alternative supportive delivery mode.

Hence, there is an obvious research gap in the literature covering the TSP-D with bicycles/bikes (TSP-D-B). All in all, the main novelty of this work ground on examining the multimodal e-mobility as a recent urban logistics development that contributes to congestion reduction and air

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Table 1
Comparison of the most relevant studies of traveling salesman problem (TSP) with drone/unmanned/uncrewed aerial vehicle (UAV) in terms of models and solution methods

Reference	Problem	Feature(s)	Model	Objective(s)	Solution method(s)
Grundel and Jeffcoat (2004)	TSP	Single drone, target visitation problem, linear ordering	Linear programming (LP)	Maximizing a multiple objective function that considers both the total distance traveled and the order in which targets are visited	Heuristic algorithm
Rathinam et al. (2007)	TSP	Multiple drones, resource allocation	Mixed-integer linear programming (MILP)	Minimizing the sum of the distances traveled by all vehicles	Resource allocation algorithm
Shetty et al. (2008)	TSP	Multiple drones, fleet routing	MILP	Maximizing the total weighted service to the targets from the UAV fleet	Tabu search algorithm
Vis and Roodbergen (2009)	TSP	Single drone, directed rural postman	-	Determining the shortest route	Dynamic programming
Oberlin et al. (2010)	TSP	Multiple drones, multiple depots, multiple UAV routing	ILP	Minimizing the distance traveled for a UAV between any two targets	Lin–Kernighan–Helsgaun heuristic algorithm
Cons et al. (2014)	TSP	Single drone, task and motion planning	Non-linear programming (NLP)	Minimizing the total traveling cost based on the shortest flyable path	Learning algorithms, Monte Carlo simulation
Ferrandez et al. (2016)	TSP with drone (TSP-D)	Multiple drones, truck-drone delivery network	-	Minimizing overall delivery time and energy for a truck-drone network	K-means and genetic algorithm
Babel (2017)	TSP	Single drone, aerial surveillance, route planning	MILP	Finding a minimum-length tour avoiding obstacles	Heuristic algorithms
Marinelli et al. (2018)	TSP-D	Single drone, truck-drone parcel delivery	Mixed-integer programming (MIP)	Minimizing the total cost of the tour	Routing algorithms
Poikonen and Golden (2020)	TSP-D	Multiple drones, multi-visit truck-drone routing	MILP	Minimizing the total route completion time	Heuristic algorithms

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Table 1
(Continued)

Reference	Problem	Feature(s)	Model	Objective(s)	Solution method(s)
Hoppmann-Baum et al. (2022)	TSP	Multiple drones, UAV routing	MIP	Minimizing the total number of cycles	Most-critical-vertex-based heuristic
Boccia et al. (2023)	TSP-D	Single truck, single drone, launch service time, recovery service time, drone endurance	MILP	Minimizing the makespan of the delivery process	Branch and cut algorithm using CPLEX
Montemanni and Dell'Amico (2023)	TSP-D	Multiple drones, single truck, parallel drone scheduling	MILP	Minimizing the makespan of the delivery process	Constraint programming, CP-SAT solver
This work	TSP with drone and bicycle (TSP-D-B)	Single truck, single drone, single, bicycle, parallel drone scheduling, bicycle application	MILP	Minimizing the total traveling time required to serve all the customers	CPLEX solver

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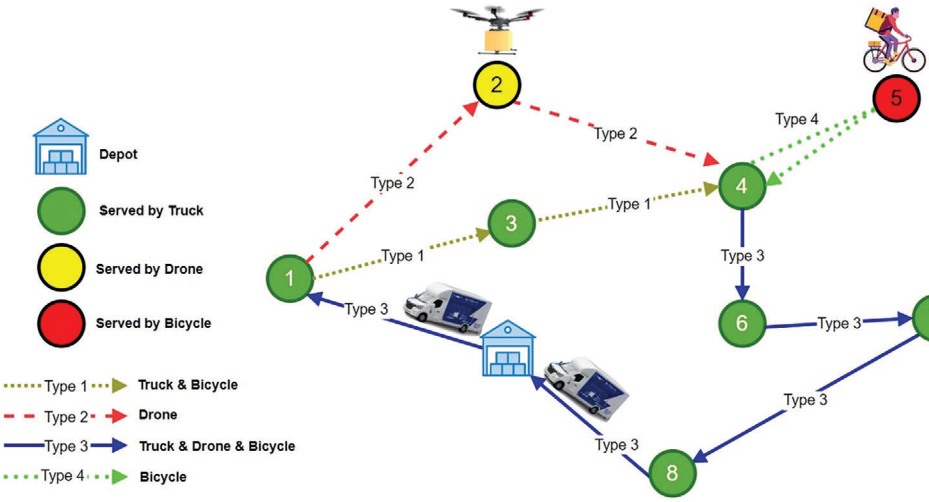

Fig. 1. Schematic view of the proposed traveling salesman problem with drone and bicycle (TSP-D-B).

quality improvement, expanding the previously established models for TSP-D such that they meet the primary requirements of TSP-D-B, determining and assessing the potential benefits of TSP-D-B over TSP-D and TSP.

3. Problem statement

As discussed earlier, multimodal e-mobility is one of the most efficient workarounds in order to deal with last-mile delivery problems. Accordingly, this study introduces and formulates TSP-D-B as one of the most recent extensions of classic TSP. Consider a graph network notated by $G = (V,\ A)$ wherein V and A represent the sets of nodes and arcs. To proceed with specific requirements of the proposed TSP-D-B, $P = \{1, 2, \ldots, p\}$ is defined as the set of customers. Moreover, $P_1 \subseteq P$ and $P_2 \subseteq P$ as the sets of nodes that can be served by drone and bicycle, respectively. Here, $V = \{0, 1, 2, \ldots, p+1\}$, $V_0 = \{0, 1, 2, \ldots, p\}$, and $V_1 = \{1, 2, \ldots, p+1\}$, respectively, stand for the sets of all nodes, the nodes that the truck may depart, and the nodes that the truck may visit in which 0 represents the depot (beginning point) and $p+1$ displays the dummy depot (end point). Since the drone is not forced to return to its beginning node, a set of possible triples $\langle i, j, k\rangle \in D$ is defined wherein i, j, k are the indices showing the network nodes. There are also 1 driver and 1 cyclist in the truck.

To better represent the network, Fig. 1 provides a schematic view of the problem.

In Fig. 1, there are eight customers to be served wherein six customers are served by the truck and the remaining two are served by the drone and bicycle. There are four types of possible delivery shown by different colors. Delivery can be made by (i) truck and drone and bicycle, (ii) truck and bicycle, (iii) drone, and (iv) bicycle. There is no possible delivery by truck and drone without the bicycle since the bicycle must be ridden by the cyclist after parking the truck.

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It is noteworthy to say that some practical constraints are ignored since the main motivation of this study is to introduce a new variant of classic TSP and TSP-D. Moreover, the objective function is to minimize the total traveling time to serve all the customers as a classic and applicable indicator to represent any possible savings made by TSP, TSP-D, and TSP-D-B. Of course, these constraints and other objective functions are the main directions for future studies.

4. Mathematical model

The adopted methodology is to develop an MILP model to formulate the suggested TSP-D-B. Therefore, the problem is studied and modeled according to the following assumptions:

- There is a single depot (node 0) in the network from where the truck starts its trip;
- a dummy depot (node $p + 1$) is considered in the network to facilitate the formulation of the problem;
- a fleet of vehicles is taken into account, which includes one truck, one drone, and one bicycle;
- customers can be served by different vehicles. However, they must be visited once by one of the vehicles;
- it is assumed that the drone will remain in continuous flight for the entire flight time as it takes off from the vehicle and returns to the vehicle. Therefore, if the drone arrives before the truck, it cannot land to conserve battery power (Murray and Chu, 2015);
- the node where the truck and the drone meet must be a node served by the truck. The drone and truck cannot meet at an intermediate location nor can the truck revisit any node to meet the drone (Murray and Chu, 2015);
- drone and bicycle are just able to visit one customer;
- no vehicle can revisit any customer;
- drone can start and end its trip at any possible node to visit an eligible customer;
- the truck can visit another customer when the drone is launched to visit a customer (parallel service), but they will finally meet each other at any possible nodes when the drone finishes its trip;
- there are no simultaneous visits for the truck and bicycle. The cyclist rides the bicycle to visit a customer, and this requires the driver to park the truck first at any possible nodes and then wait until the cyclist returns to that node after serving the customer;
- the drone flies to the meeting point after delivering to the customer. If the truck arrives at the meeting point early, it lands directly on the vehicle and prepares for the next deliveries. If the drone arrives early, it lands at the meeting point and waits for the truck to arrive. It is assumed that there is a suitable place for the drone to land at the meeting point;
- all nodes can be served by truck and are defined as set P. Nodes that can receive service by drone are defined as subset $P_1 \subseteq P$ and nodes that can receive service by truck are defined as subset $P_2 \subseteq P$. The restrictions to receive service by different vehicles are in line with their operational limitations.

Now, the notations of the suggested model are described below:
Indices and sets

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i, j, k, s, t	Indices of nodes,
$P = \{1, 2, \ldots, p\}$	Set of customers,
$P_1 \subseteq P$	Subset of customers that can be served by the drone ($\lvert P_1 \rvert = p_1$),
$P_2 \subseteq P$	Subset of customers that can be served by the bicycle ($\lvert P_2 \rvert = p_2$),
D	Set of possible triples for the drone where $< i, j, k > \in D$, and $i \neq j \neq k$,
$D_1 \subseteq D$	Subset of possible triples for the drone wherein the starting depot is the launching point ($< 0, j, k > \in D_1$ and $j \neq k$),
$V = \{0, 1, 2, \ldots, p+1\}$	Set of all nodes in the network,
$V_0 = \{0, 1, 2, \ldots, p\}$	Set of nodes that the truck may depart,
$V_1 = \{1, 2, \ldots, p+1\}$	Set of nodes that the truck may visit.

Parameters

τ_{ij}	Traveling time to move from node $i \in V_0$ to node $j \in V_1$ by the truck,
$\tau^{/}_{ij}$	Traveling time to move from node $i \in V_0$ to node $j \in P$ by the drone,
$\tau^{//}_{ij}$	Traveling time to move from node $i \in V_0$ to node $j \in P$ by the bicycle,

Decision variables

$$x_{ij} = \begin{cases} 1, & \text{ifthetruckmovesfromnode} i \in V_0 \text{ tonode} j \in V_1, \\ 0, & \text{otherwise}, \end{cases}$$

$$y_{ijk} = \begin{cases} 1, & \text{ifthedroneislaunchedfromnode} i \in V_0 \text{ tonode} j \in P \text{ toserve customer } j, \\ & \text{andthenreturnstothetruckatnode } k \in V_1 \text{ where } <i, j, k> \in D, \\ 0, & \text{otherwise}, \end{cases}$$

$$z_{ij} = \begin{cases} 1, & \text{ifthebicyclemovesfromnode} i \in V_0 \text{ tonode} j \in P \text{ toservecustomer} j, \\ & \text{and then returns tothetruckagainatnode} i \in V_0. \\ 0, & \text{otherwise}, \end{cases}$$

Auxiliary variables

u_i	An auxiliary integer variable used to eliminate sub-tours for the truck (number of customers visited before reaching node $i \in P$),
q_{ij}	An auxiliary binary variable to guarantee that consecutive drone sorties are in compliance with the customers' sequence visited by the truck ($i \in V_0$ and $j \in P$).

Mathematical model

$$\text{minimize } T = \sum_{i \in V} \sum_{\substack{j \in V \\ (i \neq j)}} \tau_{ij} x_{ij} + \sum_{i \in V} \sum_{j \in V_1} \sum_{\substack{k \in V \\ (<i,j,k> \in D)}} (\tau^{/}_{ij} + \tau^{/}_{jk}) y_{ijk} + \sum_{i \in V} \sum_{\substack{j \in V \\ (i \neq j)}} \tau^{//}_{ij} z_{ij} \tag{1}$$

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subject to

$$\sum_{\substack{i\in V_0\\(i\neq j)}} x_{ij}+\sum_{i\in V_0}\sum_{\substack{k\in V_1\\(<i,j,k>\in D)}} y_{ijk}+\sum_{\substack{i\in V_0\\(i\neq j;\, j\in P_2)}} z_{ij}=1 \quad \forall j\in P, \tag{2}$$

$$\sum_{j\in V_1} x_{0j}=1, \tag{3}$$

$$\sum_{i\in V_0} x_{i,p+1}=1, \tag{4}$$

$$\sum_{\substack{i\in V_0\\(i\neq j)}} x_{ij}=\sum_{\substack{k\in V_1\\(j\neq k)}} x_{jk} \quad \forall j\in P, \tag{5}$$

$$u_i-u_j+1\le (p+2)(1-x_{ij}) \quad \forall i\in P,\, j\in V_1;\, i\neq j, \tag{6}$$

$$\sum_{\substack{j\in P_1\\ i\neq j}}\sum_{\substack{k\in V_1\\(<i,j,k>\in D)}} y_{ijk}\le 1 \quad \forall i\in V_0, \tag{7}$$

$$\sum_{\substack{i\in V_0\\ i\neq k}}\sum_{\substack{j\in P_1\\(<i,j,k>\in D)}} y_{ijk}\le 1 \quad \forall k\in V_1, \tag{8}$$

$$\sum_{<i,j,k>\in D} y_{ijk}\le 1, \tag{9}$$

$$\sum_{i\in V_0}\sum_{\substack{j\in P_2\\(i\neq j)}} z_{ij}\le 1\,, \tag{10}$$

$$z_{ij}=z_{ji} \quad \forall i\in V_0,\, j\in P_2;\, i\neq j, \tag{11}$$

$$z_{ij}\le \sum_{\substack{s\in V_0\\(s\neq i)}} x_{si}, \quad \forall i\in P,\, j\in P_2,\, i\neq j, \tag{12}$$

$$2y_{ijk}\le \sum_{\substack{s\in V_0\\(s\neq i)}} x_{si}+\sum_{\substack{t\in P\\(t\neq k)}} x_{tk} \quad \forall i\in P,\, j\in P_1,\, k\in V_1;\, <i,j,k>\in D, \tag{13}$$

$$y_{0jk}\le \sum_{\substack{s\in V_0\\(s\neq 0)}} x_{sk} \quad \forall j\in P_1,\, k\in V_1;\, <0,j,k>\in D_1, \tag{14}$$

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$$u_k - u_i \geq 1 - (p+2)(1 - \sum_{\substack{j \in P_1 \\ (<i,j,k> \in D)}} y_{ijk}) \quad \forall i \in P, k \in V_1; i \neq k, \tag{15}$$

$$q_{ij} + q_{ji} = 1 \quad \forall i, j \in P; i \neq j, \tag{16}$$

$$q_{0j} = 1 \quad \forall j \in P, \tag{17}$$

$$u_i - u_j \geq 1 - (p+2) q_{ij} \quad \forall i, j \in P; i \neq j, \tag{18}$$

$$u_i - u_j \leq -1 - (p+2)(1 - q_{ij}) \quad \forall i, j \in P; i \neq j, \tag{19}$$

$$1 \leq u_i \leq p+2 \quad \forall i \in V_1, \tag{20}$$

$$x_{ij}, z_{ij} \in \{0, 1\} \quad \forall i \in V_0, j \in V_1; i \neq j, \tag{21}$$

$$y_{ijk} \in \{0, 1\} \quad \forall < i, j, k > \in D, \tag{22}$$

$$u_i \in \mathbf{Z}^+ \quad \forall i \in V_1, \tag{23}$$

$$q_{ij} \in \{0, 1\} \quad \forall i \in V_0, j \in P; i \neq j. \tag{24}$$

Here, the first objective function given by Equation (1) represents the total traveling time to be minimized. It includes three different terms associated with the truck, drone, and bicycle. Constraint (2) ensures that each customer must be served by one of the vehicles (i.e., truck, drone, or bicycle). Constraints (3) and (4) guarantee that the truck starts its trip from the depot and ends at the depot (a dummy node representing the ending depot), respectively. Constraint (5) shows the flow balance such that if the truck visits node j, it must also depart from this node. Constraint (6) eliminates any sub-tours of the truck. Constraint (7) expresses that the drone may be launched at most once from any node (including the depot). Likewise, Constraint (8) represents that the drone returns to the truck at most once at any node (including the customers and ending depot). Constraint (9) guarantees that the drone is just employed once within the constructed tour. Constraint (10) guarantees that the cyclist can ride the bicycle at most once from any node to visit a given customer. Since it must at most serve one customer, it is clear that it will return to the starting node; that is why there is no complementary constraint for the bicycle return. Based on Constraint (11), the bicycle must return to the truck after visiting a customer. According to Constraint (12), if the bicycle starts from node i to visit node j, then the truck must be parked at node i. Based on Constraint (13), if the drone is launched from node i and returns to the truck at node k, then the truck should be assigned to both nodes i and k. Moreover, Constraint (14) guarantees that if the drone is launched from the starting depot and returns to node k, then the truck should be assigned to node k. Likewise, Constraint (15) ensures that if the drone is launched from node (customer) i and returns to node k, then the truck should visit node i before node k. Constraints (16–19) set the auxiliary variable q_{ijk}. As was discussed, u_i and q_{ij}, respectively, stand for the number and sequence of nodes visited only by the truck, where their values are inconsequential for any nodes i and j that are served only by the drone. Finally, Constraints (20)–(24) display the domain of the variables.

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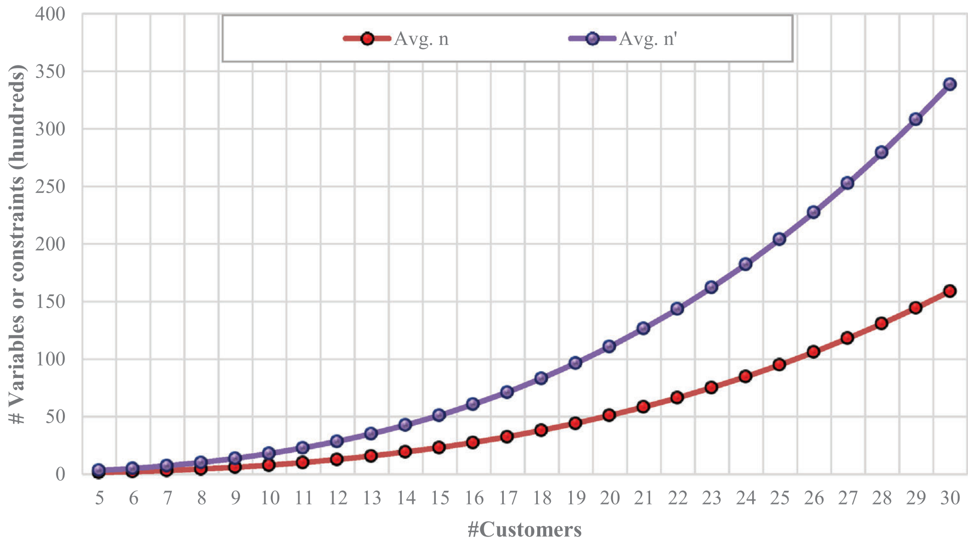

Fig. 2. Complexity of the proposed model.

4.1. Model complexity

The complexity of the proposed model is assessed in terms of the number of variables (n) and constraints (n'). Accordingly, n and n' are equal to $\{|V_0||V_1| + |D| + p|V_0| + p + p|V_0|\}$ and $\left\{\begin{array}{c} p+1+1+p+(p|V_1|-\min(p,|V_1|))+|V_0|+|V_1|+|D|+|D_1| \\ +(p|V_1|-\min(p,|V_1|))+(p(p_2)-\min(p,p_2))+(p^2-\min(p,p))+p \\ +(p^2-\min(p,p))+(p^2-\min(p,p))+|V_1|+(|V_0|(p_2)-\min(|V_0|,p_2)) \\ +1+|V_0||V_1|+|D|+(p|V_0|-\min(p,|V_0|)) \end{array}\right\}$, respectively. Then, we simply have $\{|V_0||V_1| + 2p|V_0| + p + |D|\}$ and $\left\{\begin{array}{c} 3(p^2-p)+(p(p_2)-p_2) \\ +2(p|V_1|-p)+(p|V_0|-p) \\ +(p_2|V_0|-p_2)+|V_0||V_1|+|V_0| \\ +2|V_1|+3p+2|D|+|D_1|+3 \end{array}\right\}$ as the number of variables and constraints, respectively. Since $|V| = p+2$, $|V_0|$and $|V_1| = p+1$, it is also possible to further simplify the number of variables and constraints, where we have $n = (p+1)^2 + 2p(p+1) + p + |D|$ and $n' = 3(p^2 - \text{p}) + 2(p(p_2) - p_2) + 3(p(p+1) - p) + (p+1)^2 + 5p + 2|D| + |D_1| + 5 = 7p^2 + 7p + 1 + 2p_2(p-1) + 2|D| + |D_1| + 5$.

To visualize how complexity grows by raising the scale of the problem based on the number of customers in the network (i.e., p), p changes from 5 to 30, and n and n' are calculated. Since p_2, $|D|$ and $|D_1|$ are customized in each problem instance, minimum and maximum numbers of constraints and variables (lower bound and upper bound) are taken into account to evaluate the complexity. Consequently, $0 \leq p_2 \leq p$, $0 \leq |D| \leq (1 \times p \times p) + (p \times (p-1) \times (p-1))$ (the starting point can be the depot or a customer node), or $0 \leq |D| \leq (p^3 - p^2 + p)$ and $0 \leq |D_1| \leq 1 \times p \times p = p^2$. Finally, the average number of variables and constraints is depicted in Fig. 2. As is obvious, the complexity of the model increases exponentially where considering 30 customers results in 15,916 and 33,907 variables and constraints (on average), respectively, that demonstrates the problem is non-

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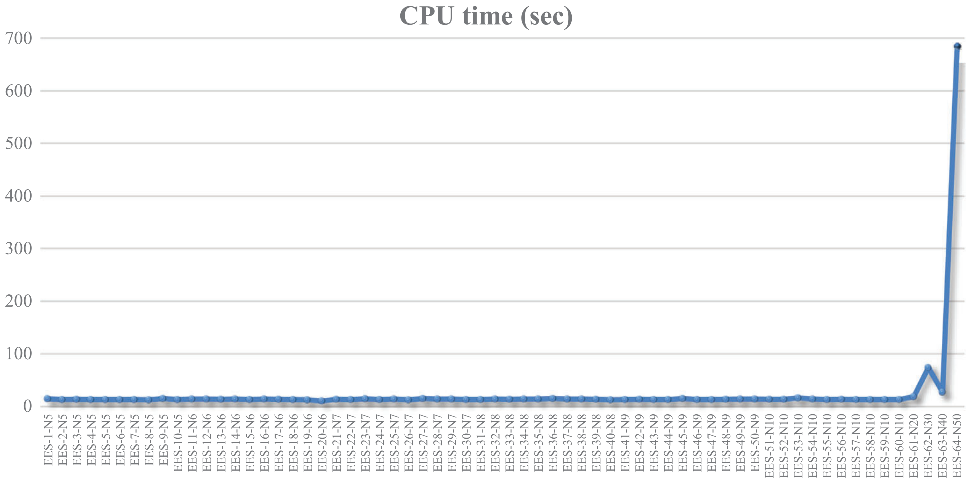

Fig. 3. CPU times comparison.

deterministic polynomial-time hard (NP-hard), which has been previously certified by researchers (cf. Section 2). Moreover, comparing n with n' reveals that the number of constraints is nearly 2.1 times larger than the number of variables. On the other hand, the maximum number of constraints exceeds 1 million for a problem instance with 80 customers. For more details, please see Appendix A.

5. Model implementation

In this section, the applicability and validity of the suggested model are tested on 60 different problem instances. We consider 5–10 customers in benchmarks N5–N10. There are also 10 problem instances in each benchmark with different information about sets and distance matrices. These instances are run on a laptop with Intel Core i7-4720HQ CPU @ 2.60GHz, 12.0 GB RAM, and 64-bit Operating System.

In general, the drone is faster than the truck (Bouman et al., 2018). The speed of the drone is taken to be twice times the speed of the truck in the TSP-D instances treated by Bouman et al. (2018). Considering that the delivery weight affects the drone more than the bicycle, therefore, we assume that the drone is faster than the truck but slower than the bicycle. The benchmarks are built with respect to speed/traffic-related coefficients for the truck, drone, and bicycle, which include $\alpha = 1$, $\beta = 2$, and $\gamma = 2.5$, respectively. The drone and bicycle are assumed to provide faster service than the truck (base vehicle). In other words, they can be caught in less traffic than the truck. With the help of the "distance matrix," the "traveling time matrix" for each vehicle is then built. For further information, please see the Data Availability section. The obtained results are displayed in Table 2. Moreover, Fig. 3 compares the CPU times over different benchmarks.

As can be observed from Table 2, the preference is just to use the drone in some benchmarks. However, both drone and bicycle are used to serve the customers in most problem instances, which highlights the significant role of the bicycle along with the drone in the last-mile delivery.

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Table 2
Computational results

#Benchmark	#Instance	Objective function	CPU time (seconds)	Avg. objective function	Avg. CPU time (seconds)	Drone	Bicycle
N5	EES-1-N5	268.561	14.577	209.8653	13.3828	√	
	EES-2-N5	189.787	13.217			√	√
	EES-3-N5	194.952	13.363			√	√
	EES-4-N5	202.830	12.960			√	√
	EES-5-N5	222.501	13.010			√	√
	EES-6-N5	219.232	12.855			√	√
	EES-7-N5	204.905	12.967			√	
	EES-8-N5	181.102	12.648			√	√
	EES-9-N5	237.837	14.975			√	√
	EES-10-N5	176.946	13.256			√	√
N6	EES-11-N6	160.681	14.074	189.1641	13.2598	√	√
	EES-12-N6	168.054	13.881			√	√
	EES-13-N6	188.091	13.809			√	
	EES-14-N6	223.266	13.903			√	√
	EES-15-N6	216.582	13.214			√	√
	EES-16-N6	179.446	13.954			√	
	EES-17-N6	197.750	13.655			√	
	EES-18-N6	137.313	13.005			√	
	EES-19-N6	192.441	12.676			√	√
	EES-20-N6	228.017	10.427			√	√
N7	EES-21-N7	197.425	13.487	217.0451	13.706	√	√
	EES-22-N7	208.159	12.955			√	
	EES-23-N7	264.288	14.449			√	√
	EES-24-N7	245.995	13.089			√	√
	EES-25-N7	237.603	13.972			√	√
	EES-26-N7	176.640	12.736			√	
	EES-27-N7	197.168	15.222			√	√
	EES-28-N7	251.056	13.891			√	√
	EES-29-N7	209.241	14.082			√	√
	EES-30-N7	182.876	13.177			√	√
N8	EES-31-N8	255.865	12.906	239.4026	13.7911	√	√
	EES-32-N8	192.177	13.895			√	√
	EES-33-N8	270.739	13.383			√	√
	EES-34-N8	238.914	13.851			√	
	EES-35-N8	228.197	14.057			√	√
	EES-36-N8	203.878	15.021			√	√
	EES-37-N8	235.179	14.152			√	√
	EES-38-N8	264.053	14.147			√	√
	EES-39-N8	254.619	13.829			√	
	EES-40-N8	250.405	12.670			√	√
N9	EES-41-N9	244.611	13.065	240.6228	13.625	√	√
	EES-42-N9	251.943	13.538			√	√
	EES-43-N9	302.753	12.833			√	√
	EES-44-N9	246.850	13.209			√	√

Continued

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Table 2
(Continued)

#Benchmark	#Instance	Objective function	CPU time (seconds)	Avg. objective function	Avg. CPU time (seconds)	Drone	Bicycle
	EES-45-N9	232.589	15.028			√	√
	EES-46-N9	221.048	13.067			√	√
	EES-47-N9	230.064	13.304			√	
	EES-48-N9	247.284	13.824			√	√
	EES-49-N9	169.555	14.143			√	√
	EES-50-N9	259.531	14.239			√	√
N10	EES-51-N10	262.336	13.403	264.7204	13.6632	√	√
	EES-52-N10	274.656	13.438			√	
	EES-53-N10	278.567	16.263			√	
	EES-54-N10	249.069	14.228			√	√
	EES-55-N10	255.640	13.049			√	√
	EES-56-N10	323.155	13.490			√	√
	EES-57-N10	223.049	13.085			√	√
	EES-58-N10	245.674	13.283			√	√
	EES-59-N10	295.133	13.230			√	√
	EES-60-N10	239.925	13.163			√	√
N20	EES-61-N20	363.350	18.670	-	-	√	√
N30	EES-62-N30	450.618	73.948	-	-	√	√
N40	EES-63-N40	454.106	26.843	-	-	√	√
N50	EES-64-N50	529.113	684.933	-	-	√	√

According to the results obtained, it is clear that our suggested model is able to efficiently find the optimal solutions for up to 50 customers. There is a spike in the CPU time when the number of customers becomes 50 such that it touches 685 seconds for the benchmark with 69,026 variables and 143,956 constraints on average. This confirms the problem complexity and inefficiency of the exact solution methods/solvers to find the optimal solutions in large scales.

5.1. *TSP-D-B against TSP-D and TSP*

In this sub-section, the aim is to examine the differences between TSP-D-B, TSP-D, and TSP considering one of the instances in each benchmark. TSP-D and TSP models are given in Appendices B and C, respectively. The obtained comparative results are outlined in Table 3 and illustrated in Figs. 4 and 5.

As can be seen from Table 3 and Figs. 4 and 5, TSP-D-B leads to valuable savings in all the benchmarks owing to the possible application of bicycle and drone. In all benchmarks, TSP-D-B performs better than TSP-D and TSP in terms of the objective function value. However, the CPU times reported by TSP-D-B are larger than TSP and TSP-D as expected, where the most significant difference is observed for the last benchmark including 50 customers (approximately 28.281 times larger than TSP). The CPU times are almost the same in TSP-D-B and TSP-D. However, there are small differences in the other benchmarks between these three problems, which can be neglected practically.

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Table 3
TSP-D-B against TSP-D and TSP

	Objective function			CPU time (seconds)		
#Instance	TSP-D-B	TSP-D	TSP	TSP-D-B	TSP-D	TSP
EES-10-N5	176.946	190.051	200.459	13.256	12.996	12.535
EES-20-N6	228.017	240.426	285.976	10.427	13.301	12.650
EES-30-N7	182.876	197.783	218.703	13.177	13.102	12.591
EES-40-N8	250.405	274.177	293.382	12.670	13.141	12.495
EES-50-N9	259.531	280.400	303.314	14.239	13.451	13.036
EES-60-N10	239.925	246.125	256.428	13.163	13.139	12.662
EES-61-N20	363.350	370.535	381.674	18.670	15.098	13.631
EES-62-N30	450.618	452.370	470.255	73.948	43.066	17.290
EES-63-N40	454.106	465.609	497.708	26.843	19.518	13.721
EES-64-N50	529.113	529.113	547.650	684.933	164.429	24.219

Fig. 4. TSP-D-B against TSP-D and TSP: objective functions comparison.

5.2. Sensitivity analysis of speed/traffic-related coefficients

We assumed that two factors of speed and traffic affect the application of the truck, drone, and bicycle (1, 2, 2.5). Here, the aim is to analyze the impacts of any out-of-control fluctuations of the speed/traffic-related coefficients on the problem. To do so, several combinations are taken into account to set these coefficients. EES-62-N30 is considered as an example to conduct the analysis where Table 4 and Fig. 6 represent the obtained results.

Different behaviors of the objective function and CPU time can be observed against various combinations of the speed/traffic-related coefficients where the minimum objective function is obtained for $(\alpha, \beta, \gamma) = (1, 2, 3)$, which demonstrates the remarkable impact of bicycle to make time

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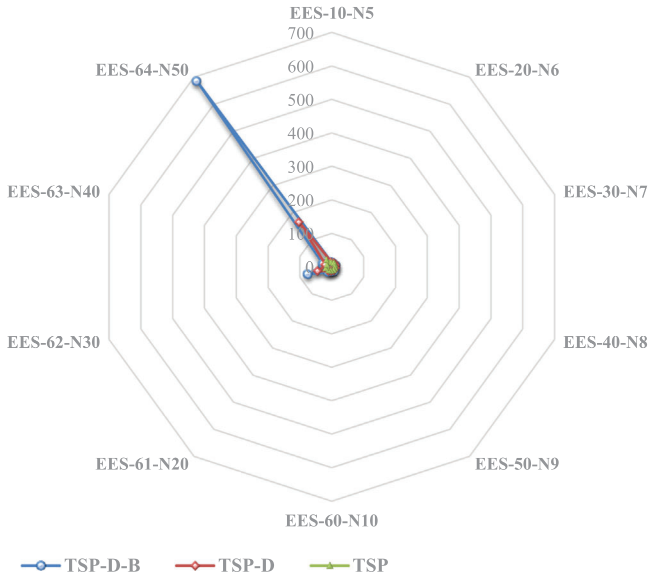

Fig. 5. TSP-D-B against TSP-D and TSP: CPU times comparison.

Table 4
Sensitivity analysis of the speed/traffic-related coefficients

	(α, β, γ)				
Variable	(1, 1.5, 2)	(1, 2, 2)	(1, 2, 2.5)	(1, 2.5, 2)	(1, 2, 3)
Objective function	452.370	452.370	450.618	452.370	448.244
CPU time (seconds)	56.794	86.232	73.948	165.882	82.420
Drone application	√	√	√	√	√
Bicycle application			√		√

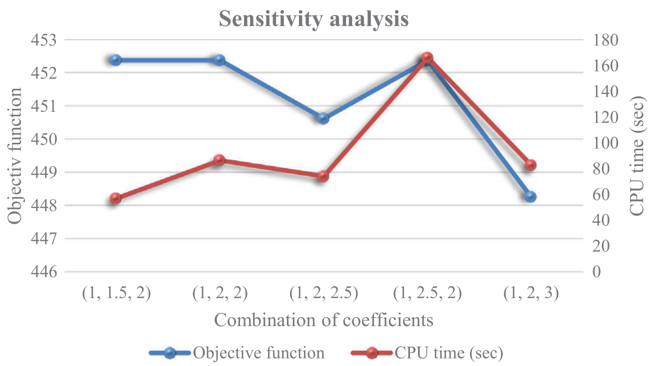

Fig. 6. Behavior of the objective function and CPU time against different combinations of the speed/traffic-related coefficients.

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Table 5
Numerical results of the modified instances adapted from Bouman et al. (2018)

#Instance	No. of customers	Objective function		CPU time (seconds)	
		TSP-D-B	TSP-D	TSP-D-B	TSP-D
Singlecenter-1-N5	4	192.167	213.311	7.491	6.570
Singlecenter-11-N6	5	129.537	130.996	8.067	9.220
Singlecenter-21-N7	6	236.426	257.819	10.127	11.207
Singlecenter-31-N8	7	205.299	205.299	8.857	8.903
Singlecenter-41-N9	8	150.637	171.359	8.454	10.075
Singlecenter-41-N10	9	303.466	303.466	11.273	8.262

savings. The second minimum objective function is attained for $(\alpha, \beta, \gamma) = (1, 2, 2.5)$ in which the bicycle is used as well. There are also some differences between the CPU times reported for these combinations where the minimum value is found for $(\alpha, \beta, \gamma) = (1, 2, 3)$.

5.3. *Model implementation with the literature instances*

In order to further analyze the model validity, several TSP-D instances are adapted from Bouman et al. (2018) and modified according to our model specifications. The obtained results are given in Table 5. Accordingly, TSP-D-B and TSP-D instances are compared in terms of objective function and CPU time. Similar to the comparison made in Section 5.1, TSP-D-B leads to significant savings in most instances. The suggested model is able to treat the instances efficiently where there are just slight differences between the CPU times of TSP-D-B and TSP-D.

6. Discussion

As observed in the model implementation section, the result of our proposed model can find the optimal solutions for up to 50 customers efficiently. In most of the problem instances, both the drone and bicycle are used to serve the customers. The maximum CPU time is approximately 685 seconds, which is expected since EES-64-N50 includes 69,026 variables and 143,956 constraints on average. Moreover, TSP-D-B provides a remarkable saving in all the benchmarks owing to the possible application of bicycle and drone. In some of the benchmarks, TSP-D-B and TSP-D result in equal outputs owing to employing no bicycle there. However, the CPU times required for tackling the benchmarks of TSP-D-B are larger than TSP and TSP-D as expected, where the most significant difference is obtained for the last benchmark including 50 customers. The CPU times are almost the same in TSP-D-B and TSP-D except for the last benchmark. Nevertheless, there are minor differences in the other benchmarks between these three problems, which can be neglected practically. Finally, the sensitivity analysis of the speed/traffic-related coefficients reveals the notable impact of the bicycle on time savings, where the concurrent application of drone and bicycle yields lower objective function values.

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The discussed articles in the existing literature have no bicycle in the application, and there is a limited implementation of parallel drone scheduling. A practitioner can utilize this study's suggested model to schedule its resources for a multimodal delivery by acknowledging that the optimal solutions for up to 50 customers give efficient solutions. In order to compare the TSP-D-B and TSP-D, the CPU times are almost the same, and a practitioner can infer that including a bicycle has no burden for the computational results in small and medium scales. In practice, there are small differences in the other benchmarks between TSP-D-B, TSP-D, and TSP (except for the large scales counted from 50 customers).

As a theoretical contribution, by including the bicycle to a conventional TSP-D problem with a single drone, single truck, and single bicycle, the literature is enriched with the possible applications for the last-mile delivery industry. Theoretical comparisons with the existing mathematical models are presented in detail to demonstrate the compatibility and applicability of the suggested model.

7. Conclusion and outlook

The main aim of this study was to address the concept of multimodal last-mile e-mobility based on a novel OR problem, that is, *TSP-D-B*. Then, the problem was formulated and tackled with the help of CPLEX solver in GAMS as a well-known optimization software, which provides reliable solvers for linear and non-linear models (Amjadian and Gharaei, 2022; Taleizadeh et al., 2023; Tirkolaee et al., 2023). The following goals were also considered while treating the problem: (1) to investigate multimodal e-mobility as a recent urban logistics development that contributes to congestion reduction and air quality improvement, (2) to expand the previously established models for TSP-D such that they meet the primary requirements of TSP-D-B, and (3) to determine and assess the potential benefits of TSP-D-B over TSP-D and TSP. The findings of model implication highlighted that TSP-D-B brings valuable savings in all the benchmarks owing to the possible application of bicycle and drone, which can encourage decision- and policy-makers to consider the application of such a problem and vehicles equipped with drones and bicycles.

To bring the current study to an end and with respect to the main limitation of the study, the following recommendations are given for future research:

I. Taking into account multiple drones and bicycles to enhance the applicability of the model;
II. incorporating real-life constraints such as time windows, fuel consumption, drone energy consumption and charging, flying range of the drone, and riding distance of the bicycle;
III. studying other objective functions at the same time; for example, service cost minimization and environmental impact minimization;
IV. employing heuristic solution methods, such as the Lagrangian relaxation algorithm, to solve the problem in larger sizes more efficiently.

All in all, we not only provided a novel research direction with the help of technology but also tried to introduce and formulate one of the most recent applications of e-mobility to facilitate transportation services, especially for the last-mile delivery.

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Acknowledgments

N/A

Data availability statement

Data and benchmarks can be found at https://github.com/erfanmtl/TSP-D-B-instances/blob/main/TSP-D-B%20instances.rar

References

Agatz, N., Bouman, P., Schmidt, M., 2018. Optimization approaches for the traveling salesman problem with drone. *Transportation Science* 52, 4, 965–981. (accessed 3 October 2022)

Akhand, M.A.H., Rahman, M.M., Siddique, N., 2023. Advances on particle swarm optimization in solving discrete optimization problems. *Studies in Computational Intelligence* 1054, 59–88.

Amjadian, A., Gharaei, A., 2022. An integrated reliable five-level closed-loop supply chain with multi-stage products under quality control and green policies: generalised outer approximation with exact penalty. *International Journal of Systems Science: Operations & Logistics* 9, 3, 429–449.

Archetti, C., Peirano, L., Speranza, M.G., 2022. Optimization in multimodal freight transportation problems: a survey. *European Journal of Operational Research* 299, 1, 1–20.

Arora, S., Gargava, P., 2023. E-mobility: hindrances and motivators for policies implementation in India. *Case Studies on Transport Policy* 11, 100955.

Arumugam, U., Karthick, A.V., Ganesan, S., 2019. Challenges and opportunities in logistics at domestic and international—an overview. *International Journal of Scientific and Technology Research* 8, 11, 3462–3466.

Babel, L., 2017. Curvature-constrained traveling salesman tours for aerial surveillance in scenarios with obstacles. *European Journal of Operational Research* 262, 1, 335–346.

Bellman, R., 1962. Dynamic programming treatment of the travelling salesman problem. *Journal of the ACM (JACM)* 9, 1, 61–63.

Bessler, S., Grønbæk, J., 2012. Routing EV users towards an optimal charging plan. *World Electric Vehicle Journal* 5, 3, 688–695.

Bhar, C., Agrell, E., Keykhosravi, K., Karlsson, M., Andrekson, P.A., 2019. Channel allocation in elastic optical networks using traveling salesman problem algorithms. *Journal of Optical Communications and Networking* 11, 10, C58–C66.

Boccia, M., Mancuso, A., Masone, A., Sterle, C., 2023. A new MILP formulation for the flying sidekick traveling salesman problem. *Networks* 82, 3, 254–276.

Bouman, P., Agatz, N., Schmidt, M., 2018. Instances for the TSP with drone (and some solutions). Available at https://doi.org/10.5281/zenodo.1204676.

Carr, R., Ravi, R., Simonetti, N., 2023. A new integer programming formulation of the graphical traveling salesman problem. *Mathematical Programming* 197, 2, 877–902.

Cartenì, A., Henke, I., Molitierno, C., Di Francesco, L., 2020. Strong sustainability in public transport policies: an e-mobility bus fleet application in Sorrento peninsula (Italy). *Sustainability* 12, 17, 7033.

Černý, V., 1985. Thermodynamical approach to the traveling salesman problem: an efficient simulation algorithm. *Journal of Optimization Theory and Applications* 45, 1, 41–51.

Choi, Y., Schonfeld, P.M., 2022. Review of length approximations for tours with few stops. *Transportation Research Record* 2676, 3, 201–213.

Cons, M.S., Shima, T., Domshlak, C., 2014. Integrating task and motion planning for unmanned aerial vehicles. *Unmanned Systems* 2, 1, 19–38.

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de Freitas, J.C., Penna, P.H.V., 2020. A variable neighborhood search for flying sidekick traveling salesman problem. *International Transactions in Operational Research* 27, 1, 267–290.

Dell'Amico, M., Montemanni, R., Novellani, S., 2022. Exact models for the flying sidekick traveling salesman problem. *International Transactions in Operational Research* 29, 3, 1360–1393.

Dolias, G., Benos, L., Bochtis, D., 2022. On the routing of unmanned aerial vehicles (UAVs) in precision farming sampling missions. *Springer Optimization and Its Applications* 184, 95–124.

Dorigo, M., Gambardella, L.M., 1997. Ant colony system: a cooperative learning approach to the traveling salesman problem. *IEEE Transactions on Evolutionary Computation* 1, 1, 53–66.

Ehrler, V.C., Schöder, D., Seidel, S., 2021. Challenges and perspectives for the use of electric vehicles for last mile logistics of grocery e-commerce—findings from case studies in Germany. *Research in Transportation Economics* 87, 100757.

Enzi, M., Biesinger, B., Knopp, S., Parragh, S.N., Prandtstetter, M., 2017. Planning shared corporate mobility services. *Transportation Research Procedia* 27, 270–277.

Ferrandez, S.M., Harbison, T., Weber, T., Sturges, R., Rich, R., 2016. Optimization of a truck-drone in tandem delivery network using k-means and genetic algorithm. *Journal of Industrial Engineering and Management* 9, 2, 374–388.

Ferrara, M., Liberto, C., Nigro, M., Trojani, M., Valenti, G., 2019. Multimodal choice model for e-mobility scenarios. *Transportation Research Procedia* 37, 409–416.

Ferrara, M., Monechi, B., Valenti, G., Liberto, C., Nigro, M., Biazzo, I., 2019. A simulation tool for energy management of e-mobility in urban areas. MT-ITS 2019—6th International Conference on Models and Technologies for Intelligent Transportation Systems, June 5–7, Kraków, Poland.

Fischetti, M., González, J.J.S., Toth, P., 1997. A branch-and-cut algorithm for the symmetric generalized traveling salesman problem. *Operations Research* 45, 3, 378–394.

Furchi, A., Lippi, M., Carpio, R.F., Gasparri, A., 2022. Route optimization in precision agriculture settings: a multi-steiner TSP formulation. *IEEE Transactions on Automation Science and Engineering* 20, 4, 2551–2568.

Gao, H., Zhou, X., Xu, X., Lan, Y., Xiao, Y., 2023. AMARL: an attention-based multiagent reinforcement learning approach to the min-max multiple traveling salesmen problem. *IEEE Transactions on Neural Networks and Learning Systems*. https://doi.org/10.1109/TNNLS.2023.3236629

Gladchenko, E.A., Saprykin, O.N., Tikhonov, A.N., 2019. Optimization of urban freight transportation based on evolutionary modelling. V International Conference on "Information Technology and Nanotechnology" (ITNT-2019), May 21–24, Samara, Russia, pp. 95–103.

Goehlich, V., Fournier, G., Richter, A., 2020. What can we learn from digitalisation and servitisation to shape a new mobility paradigm? *International Journal of Business and Globalisation* 24, 3, 296–306.

Greblicki, J., Walczyński, M., 2016. Determination of the optimal routes for autonomous unmanned aerial vehicle under varying wind with using of the traveling salesman problem algorithm. In Saeed, K., Homenda, W. (eds) *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 9842 LNCS*, Springer, Cham, pp. 334–341.

Grundel, D.A., Jeffcoat, D.E., 2004. Formulation and solution of the target visitation problem. AIAA 1st Intelligent Systems Technical Conference, September 20–22, Chicago, IL, pp. 1–6.

Ha, Q.M., Deville, Y., Pham, Q.D., Hà, M.H., 2018. On the min-cost Traveling Salesman Problem with Drone. *Transportation Research Part C: Emerging Technologies* 86 597–621.

Hoppmann-Baum, K., Burdakov, O., Mexi, G., Casselgren, C.J., Koch, T., 2022. Length-constrained cycle partition with an application to UAV routing*. *Optimization Methods and Software* 37, 6, 2080–2116.

Huang, D., Liu, Z., Fu, X., Blythe, P.T., 2018. Multimodal transit network design in a hub-and-spoke network framework. *Transportmetrica A: Transport Science* 14, 8, 706–735.

Keskin, B.B., Çapar, I., Sox, C.R., Freeman, N.K., 2014. An integrated load-planning algorithm for outbound logistics at Webb Wheel. *Interfaces* 44, 5, 480–497.

Kinney, G.W., jr., Hill, R.R., Moore, J.T., 2005. Devising a quick-running heuristic for an unmanned aerial vehicle (UAV) routing system. *Journal of the Operational Research Society* 56, 7, 776–786.

Kou, X., Zhang, Y., Long, D., Liu, X., Qie, L., 2022. An Investigation of multimodal transport for last mile delivery in rural areas. *Sustainability* 14, 3, 1291.

Kruskal, J.B., jr. 1956. On the shortest spanning subtree of a graph and the traveling salesman problem. *Proceedings of the American Mathematical Society* 7, 1, 48–50.

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Lagorio, A., Pinto, R., Golini, R., 2016. Research in urban logistics: a systematic literature review. *International Journal of Physical Distribution & Logistics Management* 46, 10, 908–931.

Larrañaga, P., Kuijpers, C.M.H., Murga, R.H., Inza, I., Dizdarevic, S., 1999. Genetic algorithms for the travelling salesman problem: a review of representations and operators. *Artificial Intelligence Review* 13, 2, 129–170.

Lera-Romero, G., Miranda Bront, J.J., Soulignac, F.J., 2022. Dynamic programming for the time-dependent traveling salesman problem with time windows. *INFORMS Journal on Computing* 34, 6, 3292–3308.

Li, H., You, X., Liu, S., 2023. Multi-ant colony optimization algorithm based on finite history archiving and boxed pigs game. *Applied Soft Computing* 138, 110193.

Lyu, Z., Pons, D., Chen, J., Zhang, Y., 2022. Developing a stochastic two-tier architecture for modelling last-mile delivery and implementing in discrete-event simulation. *Systems* 10, 6, 214.

Maggioni, F., Perboli, G., Tadei, R., 2014. The multi-path traveling salesman problem with stochastic travel costs: building realistic instances for city logistics applications. *Transportation Research Procedia* 3, 528–536.

Marinelli, M., Caggiani, L., Ottomanelli, M., Dell'Orco, M., 2018. En route truck-drone parcel delivery for optimal vehicle routing strategies. *IET Intelligent Transport Systems* 12, 4, 253–261.

Mathew, N., Smith, S.L., Waslander, S.L., 2015. Planning paths for package delivery in heterogeneous multirobot teams. *IEEE Transactions on Automation Science and Engineering* 12, 4, 1298–1308.

Mele, U.J., Gambardella, L.M., Montemanni, R., 2021. A new constructive heuristic driven by machine learning for the traveling salesman problem. *Algorithms* 14, 9, 267.

Miller, C.E., Zemlin, R.A., Tucker, A.W., 1960. Integer programming formulation of traveling salesman problems. *Journal of the ACM (JACM)* 7, 4, 326–329.

Mondal, M., Srivastava, D., 2023. A Genetic algorithm-based approach to solve a new time-limited travelling salesman problem. *International Journal of Distributed Systems and Technologies* 14, 2, 1–14.

Montemanni, R., Dell'Amico, M., 2023. Solving the parallel drone scheduling traveling salesman problem via constraint programming. *Algorithms* 16, 1, 40.

Murray, C.C., Chu, A.G., 2015. The flying sidekick traveling salesman problem: optimization of drone-assisted parcel delivery. *Transportation Research Part C: Emerging Technologies* 54, 86–109.

Nalepa, J., 2020. Chapter 7—where machine learning meets smart delivery systems. In J. Nalepa (ed.), *Smart Delivery Systems*. Elsevier, Amsterdam, The Netherlands, pp. 203–226.

Oberlin, P., Rathinam, S., Darbha, S., 2010. Today's traveling salesman problem: heterogeneous, multiple depot, multiple UAV routing problem. *IEEE Robotics and Automation Magazine* 17, 4, 70–77.

Osaba, E., Villar-Rodriguez, E., Oregi, I., Moreno-Fernandez-de-Leceta, A., 2021. Hybrid quantum computing—tabu search algorithm for partitioning problems: preliminary study on the traveling salesman problem. 2021 IEEE Congress on Evolutionary Computation (CEC), June 28–July 1, Kraków, Poland, pp. 351–358.

Osaba, E., Yang, X.-S., Diaz, F., Lopez-Garcia, P., Carballedo, R., 2016. An improved discrete bat algorithm for symmetric and asymmetric Traveling Salesman Problems. *Engineering Applications of Artificial Intelligence* 48, 59–71.

Ouaarab, A., Ahiod, B., Yang, X.-S., 2014. Discrete cuckoo search algorithm for the travelling salesman problem. *Neural Computing and Applications* 24, 7-8, 1659–1669.

Pantuza, G., jr., de Souza, M.C., 2022. Formulations and a Lagrangian relaxation approach for the prize collecting traveling salesman problem. *International Transactions in Operational Research* 29, 2, 729–759.

Perboli, G., Rosano, M., Saint-Guillain, M., Rizzo, P., 2018. Simulation–optimisation framework for City Logistics: an application on multimodal last-mile delivery. *IET Intelligent Transport Systems* 12, 4, 262–269.

Placek, M., 2023. Logistics industry worldwide (p. Statista). Available at https://www.statista.com/topics/5691/logistics-industry-worldwide/ (accessed 15 February 2023).

Plebe, A., Anile, A.M., 2002. A neural-network-based approach to the double traveling salesman problem. *Neural Computation* 14, 2, 437–471.

Poikonen, S., Golden, B., 2020. Multi-visit drone routing problem. *Computers and Operations Research* 113, 104802.

Randall, C., 2022. *R*enault Trucks presents multimodal e-mobility concept—Electrive.com. Available at https://www.electrive.com/2022/05/18/renault-trucks-presents-multimodal-e-mobility-concept/ (accessed 15 February 2023).

Rathinam, S., Sengupta, R., Darbha, S., 2007. A resource allocation algorithm for multivehicle systems with nonholonomic constraints. *IEEE Transactions on Automation Science and Engineering* 4, 1, 98–104.

Ratliff, H.D., Rosenthal, A.S., 1983. Order-picking in a rectangular warehouse: a solvable case of the traveling salesman problem. *Operations Research* 31, 3, 507–521.

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Reda, M., Onsy, A., Elhosseini, M.A., Haikal, A.Y., Badawy, M., 2022. A discrete variant of cuckoo search algorithm to solve the Travelling Salesman Problem and path planning for autonomous trolley inside warehouse. *Knowledge-Based Systems* 252, 109290.

RHCV., 2023. Industry first for last mile deliveries: introducing the new Renault Trucks E-Tech Master OptiModale. Available at https://www.rhcv.co.uk/news/industry-first-for-last-mile-deliveries-introducing-the-new-renault-trucks-e-tech-master-optimodale/(accessed on 15 February 2023).

Roy, A., Manna, A., Kim, J., Moon, I., 2022. IoT-based smart bin allocation and vehicle routing in solid waste management: a case study in South Korea. *Computers and Industrial Engineering* 171, 108457.

Russo, F., Comi, A., 2020. Investigating the effects of city logistics measures on the economy of the city. *Sustainability* 12, 4, 1439.

Saji, Y., Barkatou, M., 2021. A discrete bat algorithm based on Lévy flights for Euclidean traveling salesman problem. *Expert Systems with Applications* 172, 114639.

Scorza, F., Fortunato, G., 2021. Cyclable cities: building feasible scenario through urban space morphology assessment. *Journal of Urban Planning and Development* 147, 4.

Shetty, V.K., Sudit, M., Nagi, R., 2008. Priority-based assignment and routing of a fleet of unmanned combat aerial vehicles. *Computers and Operations Research* 35, 6, 1813–1828.

Shojaeefard, M.H., Mollajafari, M., Reza Mousavitabar, S.H., Khordehbinan, M.W., Hosseinalibeiki, H., 2022. A TSP-based nested clustering approach to solve multi-depot heterogeneous fleet routing problem. *Revista Internacional de Metodos Numericos Para Calculo y Diseno En Ingenieria* 38, 1, 7.

Taleizadeh, A.A., Amjadian, A., Hashemi-Petroodi, S.E., Moon, I., 2023. Supply chain coordination based on mean-variance risk optimisation: pricing, warranty, and full-refund decisions. *International Journal of Systems Science: Operations & Logistics* 10, 1, 2249808.

Tan, H., Li, Y.-F., Wang, J.-Y., He, Y.-Z., Shen, C.-L., 2005. AC-PSO algorithm for UAV mission planning. *Transactions of Nanjing University of Aeronautics and Astronautics* 22, 3, 264–270.

Tang, L., Liu, J., Rong, A., Yang, Z., 2000. A multiple traveling salesman problem model for hot rolling scheduling in Shanghai Baoshan Iron & Steel Complex. *European Journal of Operational Research* 124, 2, 267–282.

Tirkolaee, E.B., Goli, A., Mardani, A., 2023. A novel two-echelon hierarchical location-allocation-routing optimization for green energy-efficient logistics systems. *Annals of Operations Research* 324, 1, 795–823.

Tong, S., Chen, S., Zhao, Y., Long, X., Bai, Y., 2016. Improving the operational reliability of scheduling and routing for multi-type freight locomotives. *CICTP 2016*, June 6–9, Shanghai, China, pp. 998–1006.

Vakulenko, Y., Shams, P., Hellström, D., Hjort, K., 2019. Service innovation in e-commerce last mile delivery: mapping the e-customer journey. *Journal of Business Research* 101, 461–468.

Vercesi, E., Gualandi, S., Mastrolilli, M., Gambardella, L.M., 2023. On the generation of metric TSP instances with a large integrality gap by branch-and-cut. *Mathematical Programming Computation* 15, 2, 389–416.

Vis, I.F.A., Roodbergen, K.J., 2009. Scheduling of container storage and retrieval. *Operations Research* 57, 2, 456–467.

Wang, A., Guo, L., Chen, Y., Wang, J., Liu, L., Song, Y., 2021. An improved cuckoo search algorithm with stud crossover for Chinese TSP problem. *International Journal of Cognitive Informatics and Natural Intelligence* 15, 4, 1–26.

Wang, K.-P., Huang, L., Zhou, C.-G., Pang, W., 2003. Particle swarm optimization for traveling salesman problem. Proceedings of the 2003 International Conference on Machine Learning and Cybernetics (IEEE Cat. No.03EX693), November 5, Xi'an, China, pp. 1583–1585.

Wikarek, J., Sitek, P., Szwarc, E., 2022. Model of employee competence configuration in SCM. *Lecture Notes in Networks and Systems* 332, 19–30.

Xenou, E., Madas, M., Ayfandopoulou, G., 2022. Developing a smart city logistics assessment framework (SCLAF): a conceptual tool for identifying the level of smartness of a city logistics system. *Sustainability* 14, 10, 6039.

Yu, Y., Lian, F., Yang, Z., 2021. Pricing of parcel locker service in urban logistics by a TSP model of last-mile delivery. *Transport Policy* 114, 206–214.

Zhao, L., Bi, X., Dong, Z., Xiao, N., Zhao, A., 2022. Robust traveling salesman problem with drone: balancing risk and makespan in contactless delivery. *International Transactions in Operational Research* 31, 1, 167–191.

Zhao, P., Bucher, D., Martin, H., Raubal, M., 2020. A clustering-based framework for understanding individuals' travel mode choice behavior. In Kyriakidis, P., Hadjimitsis, D., Skarlatos, D., Mansourian, A. (eds) *Lecture Notes in Geoinformation and Cartography*. Springer, Cham, pp. 77–94.

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Zhou, H., Wang, Q., Wang, L., Zhao, X., Feng, G., 2023. Digitalization and third-party logistics performance: exploring the roles of customer collaboration and government support. *International Journal of Physical Distribution & Logistics Management* 53, 4, 467–488.

Zhou, Y., Xu, W., Fu, Z.-H., Zhou, M., 2022. Multi-neighborhood simulated annealing-based iterated local search for colored traveling salesman problems. *IEEE Transactions on Intelligent Transportation Systems* 23, 9, 16072–16082.

Appendix A

Model complexity of TSP-D-B

Here, Table A1 and Fig. A1 provide more details about the complexity of the problem. Accordingly, we consider up to 80 customers to analyze the minimum and maximum numbers of variables and constraints.

Table A1
Details on the model complexity

p	min $\lvert D\rvert$	max $\lvert D\rvert$	min $\lvert D_1\rvert$	max $\lvert D_1\rvert$	min p_2	max p_2	min n	max n	min n'	max n'	Avg. n	Avg. n'
5	0	105	0	25	0	5	101	206	201	476	153.5	338.5
6	0	186	0	36	0	6	139	325	282	750	232	516
7	0	301	0	49	0	7	183	484	377	1112	333.5	744.5
8	0	456	0	64	0	8	233	689	486	1574	461	1030
9	0	657	0	81	0	9	289	946	609	2148	617.5	1378.5
10	0	910	0	100	0	10	351	1261	746	2846	806	1796
11	0	1221	0	121	0	11	419	1640	897	3680	1029.5	2288.5
12	0	1596	0	144	0	12	493	2089	1062	4662	1291	2862
13	0	2041	0	169	0	13	573	2614	1241	5804	1593.5	3522.5
14	0	2562	0	196	0	14	659	3221	1434	7118	1940	4276
15	0	3165	0	225	0	15	751	3916	1641	8616	2333.5	5128.5
16	0	3856	0	256	0	16	849	4705	1862	10,310	2777	6086
17	0	4641	0	289	0	17	953	5594	2097	12,212	3273.5	7154.5
18	0	5526	0	324	0	18	1063	6589	2346	14,334	3826	8340
19	0	6517	0	361	0	19	1179	7696	2609	16,688	4437.5	9648.5
20	0	7620	0	400	0	20	1301	8921	2886	19,286	5111	11,086
21	0	8841	0	441	0	21	1429	10,270	3177	22,140	5849.5	12,658.5
22	0	10,186	0	484	0	22	1563	11,749	3482	25,262	6656	14372
23	0	11,661	0	529	0	23	1703	13,364	3801	28,664	7533.5	16,232.5
24	0	13,272	0	576	0	24	1849	15,121	4134	32,358	8485	18,246
25	0	15,025	0	625	0	25	2001	17,026	4481	36,356	9513.5	20,418.5
26	0	16,926	0	676	0	26	2159	19,085	4842	40,670	10,622	22,756
27	0	18,981	0	729	0	27	2323	21,304	5217	45,312	11,813.5	25,264.5
28	0	21,196	0	784	0	28	2493	23,689	5606	50,294	13,091	27,950
29	0	23,577	0	841	0	29	2669	26,246	6009	55,628	14,457.5	30,818.5

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Table A1
(Continued)

p	min $\lvert D\rvert$	max $\lvert D\rvert$	min $\lvert D_1\rvert$	max $\lvert D_1\rvert$	min p_2	max p_2	min n	max n	min n'	max n'	Avg. n	Avg. n'
30	**0**	**26,130**	**0**	**900**	**0**	**30**	**2851**	**28,981**	**6426**	**61,326**	**15,916**	**33,876**
35	0	41,685	0	1225	0	35	3851	45,536	8721	95,696	24,693.5	52,208.5
40	0	62,440	0	1600	0	40	5001	67,441	11,366	140,966	36,221	76,166
45	0	89,145	0	2025	0	45	6301	95,446	14,361	198,636	50,873.5	106,498.5
50	0	122,550	0	2500	0	50	7751	130,301	17,706	270,206	69,026	143,956
55	0	163,405	0	3025	0	55	9351	172,756	21,401	357,176	91,053.5	189,288.5
60	0	212,460	0	3600	0	60	11,101	223,561	25,446	461,046	117,331	243,246
65	0	270,465	0	4225	0	65	13,001	283,466	29,841	583,316	148,233.5	306,578.5
70	0	338,170	0	4900	0	70	15,051	353,221	34,586	725,486	184,136	380,036
75	0	416,325	0	5625	0	75	17,251	433,576	39,681	889,056	225,413.5	464,368.5
80	0	505,680	0	6400	0	80	19,601	525,281	45,126	1,075,526	272,441	560,326

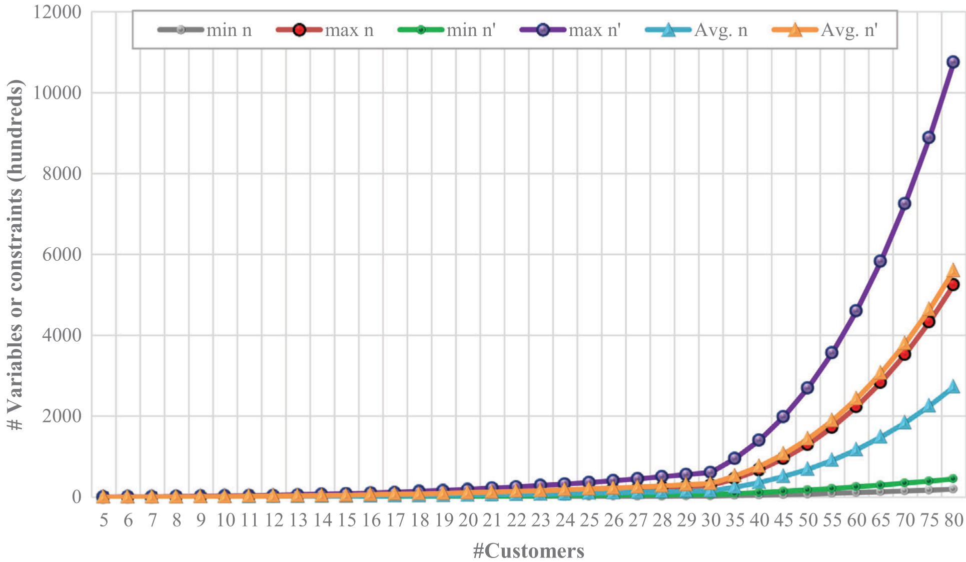

Fig. A1. Complexity of the proposed model for 5–80 customers.

TSP-D model

TSP-D model is attained through excluding the bicycle and its corresponding expressions from the TSP-D-B model as follows:

$$\text{minimize } T = \sum_{i\in V}\sum_{\substack{j\in V\\(i\neq j)}} \tau_{ij}x_{ij} + \sum_{i\in V}\sum_{j\in V_1}\sum_{\substack{k\in V\\(<i,j,k>\in D)}} (\tau^{/}_{ij} + \tau^{/}_{jk})y_{ijk} \tag{B1}$$

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subject to

$$\sum_{\substack{i\in V_0\\(i\neq j)}} x_{ij}+\sum_{i\in V_0}\sum_{\substack{k\in V_1\\(<i,j,k>\in D)}} y_{ijk}=1 \quad \forall j\in P, \tag{B2}$$

$$\sum_{j\in V_1} x_{0j}=1, \tag{B3}$$

$$\sum_{i\in V_0} x_{i,p+1}=1, \tag{B4}$$

$$\sum_{\substack{i\in V_0\\(i\neq j)}} x_{ij}=\sum_{\substack{k\in V_1\\(j\neq k)}} x_{jk} \quad \forall j\in P, \tag{B5}$$

$$u_i-u_j+1\leq (p+2)(1-x_{ij}) \quad \forall i\in P, j\in V_1; i\neq j, \tag{B6}$$

$$\sum_{\substack{j\in P_1\\i\neq j}}\sum_{\substack{k\in V_1\\(<i,j,k>\in D)}} y_{ijk}\leq 1 \quad \forall i\in V_0, \tag{B7}$$

$$\sum_{\substack{i\in V_0\\i\neq k}}\sum_{\substack{j\in P_1\\(<i,j,k>\in D)}} y_{ijk}\leq 1 \quad \forall k\in V_1, \tag{B8}$$

$$2y_{ijk}\leq \sum_{\substack{s\in V_0\\(s\neq i)}} x_{si}+\sum_{\substack{t\in P\\(t\neq k)}} x_{tk} \quad \forall i\in P, j\in P_1, k\in V_1; <i,j,k>\in D, \tag{B9}$$

$$y_{0jk}\leq \sum_{\substack{s\in V_0\\(s\neq 0)}} x_{sk} \quad \forall j\in P_1, k\in V_1; <0,j,k>\in D_1, \tag{B10}$$

$$u_k-u_i\geq 1-(p+2)(1-\sum_{\substack{j\in P_1\\(<i,j,k>\in D)}} y_{ijk}) \quad \forall i\in P, k\in V_1; i\neq k, \tag{B11}$$

$$q_{ij}+q_{ji}=1 \quad \forall i,j\in P; i\neq j, \tag{B12}$$

$$q_{0j}=1 \quad \forall j\in P, \tag{B13}$$

$$u_i-u_j\geq 1-(p+2)q_{ij} \quad \forall i,j\in P; i\neq j, \tag{B14}$$

$$u_i-u_j\leq -1-(p+2)(1-q_{ij}) \quad \forall i,j\in P; i\neq j, \tag{B15}$$

$$1\leq u_i\leq p+2 \quad \forall i\in V_1, \tag{B16}$$

$$x_{ij}\in\{0,1\} \quad \forall i\in V_0, j\in V_1; i\neq j, \tag{B17}$$

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$$y_{ijk} \in \{0, 1\} \quad \forall < i, j, k > \in D, \tag{B18}$$

$$u_i \in \mathbf{Z}^+ \quad \forall i \in V_1, \tag{B19}$$

$$q_{ij} \in \{0, 1\} \quad \forall i \in V_0, j \in P; i \neq j. \tag{B20}$$

TSP model

TSP model is attained by excluding the bicycle and drone and their corresponding expressions from the TSP-D-B model as follows:

$$\text{minimize } T = \sum_{i \in V} \sum_{\substack{j \in V \\ (i \neq j)}} \tau_{ij} x_{ij} \tag{C1}$$

subject to

$$\sum_{\substack{i \in V_0 \\ (i \neq j)}} x_{ij} = 1 \quad \forall j \in P, \tag{C2}$$

$$\sum_{j \in V_1} x_{0j} = 1, \tag{C3}$$

$$\sum_{i \in V_0} x_{i,p+1} = 1, \tag{C4}$$

$$\sum_{\substack{i \in V_0 \\ (i \neq j)}} x_{ij} = \sum_{\substack{k \in V_1 \\ (j \neq k)}} x_{jk} \quad \forall j \in P, \tag{C5}$$

$$u_i - u_j + 1 \leq (p + 2)(1 - x_{ij}) \quad \forall i \in P, j \in V_1; i \neq j, \tag{C6}$$

$$x_{ij} \in \{0, 1\} \quad \forall i \in V_0, j \in V_1; i \neq j, \tag{C7}$$

$$u_i \in \mathbf{Z}^+ \quad \forall i \in V_1. \tag{C8}$$

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