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A Fuzzy Two-Echelon Model to Optimize Energy Consumption in an Urban Logistics Network with Electric Vehicles

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Abstract: With the increase in pollutants, the need to use electric vehicles (EVs) in various urban logistics activities is an increasingly important issue. Currently, there are issues with the efficiency of transport companies in recognizing the effects of uncertain factors in daily logistics operations. Thus, this research proposes a novel fuzzy two-echelon vehicle routing problem involving heterogeneous fleet EVs and internal combustion vehicles (ICVs). The first echelon is recyclable wastes collected from waste pickup points and transported to the primary centers by EVs. The second echelon is transporting recyclable wastes to recycling centers by ICVs. In the proposed models, fuzzy numbers are used to express the rate and energy consumption depending on the amount of load, vehicle speed, and recyclable waste. In addition, a penalty cost of the time windows is considered in both echelons. The models are solved by CPLEX and two meta-heuristic algorithms, gray wolf optimizer (GWO) and tabu search (TS), based on different instance sizes. The results show the efficiency of the proposed algorithms.

Keywords: electric vehicles; heterogeneous fleet; mixed-fleet vehicles; two-echelon logistics network; meta-heuristic algorithm

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Citation: Ghobadi, A.; Fallah, M.; Tavakkoli-Moghaddam, R.; Kazemipoor, H. A Fuzzy Two-Echelon Model to Optimize Energy Consumption in an Urban Logistics Network with Electric Vehicles. *Sustainability* **2022**, *14*, 14075. https://doi.org/10.3390/su142114075

Academic Editors: Soroush Avakh Darestani and Md Yusof Bin Ismail

Received: 9 September 2022
Accepted: 24 October 2022
Published: 28 October 2022

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1. Introduction

The recent COVID-19 pandemic spreading in many countries shows that climatic changes are not limited to industrial countries, and all governments are responsible for reducing their environmental impact. The Paris agreement is limited in its targets, but it represents a moderate achievement of cooperation between all countries against climate change. By considering the Paris climate goals, the transportation sector must immediately address its CO_2 emissions [1].

The impacts of pollution in large cities, in the rich industrial world or across Asia and even in Latin America and Africa, are the most convincing reasons for using EVs in the fight against unhealthy air [2]. Public electric transportation with buses, rail, and taxis has been the norm in many of the world's more populated cities for years. However, transportation with an EV fleet is still limited. Sixteen percent of greenhouse gases (GHGs) worldwide is produced by trucks [3]; therefore, the use of EVs is inevitable. Although generating electricity using renewable resources, the emission of GHGs by these vehicles is nearly zero, which is a sustainable alternative for fossil fuel vehicles [4]. In 2018, CO_2 emission standards were suggested for truck manufacturers by the European Commission for the first time. Considering that trucks producing GHGs are a significant concern in the European Union, the long-term strategy in Europe is to reduce GHG emissions by 80% by 2050 compared with 1990 standards [5].

There is a possibility of plug-in electric vehicles reaching 30% of new sales by 2030, with encouraging policies and an increased share of zero-polluting vehicles in Canada [6]. In Asia, China and India have changed their transportation methods in large cities, focusing

on preventing the worsening climate and its effect on human health [7]. In addition, Turkey optimized its garbage truck fleet to manage environment impacts and ensure sustainable energy in Istanbul [8]. Another example is trucks with electrical batteries—class 8 trucks in the US. Despite increasing costs and emissions relating to electric production, these trucks generally are better than other similar vehicles [9]. In addition, although charging of the electrical trucks on a local network near the charge station is more affected, the yearly consumption increases the electric consumption only by 1 to 3% [10].

The above ideas show the importance of this research addressing different countries' conditions to reduce pollution emissions. In this paper, we use the combination of ICVs and EVs based on prevailing conditions in developing countries. The objective function is to minimize the total cost of each echelon, considering the type of vehicles used. In the first-echelon network, the recyclable wastes of pickup points in the city are collected with a heterogeneous EV fleet. In the second-echelon network, the conventional trucks transfer the recyclable wastes to the recycling centers out of cities. The studies on two-echelon networks for EV routing problems are done in a certain environment. In the real world, uncertain parameters play a prominent role in the efficiency of the network. To deal with uncertainty parameters, researchers often use the accidental optimization method. In this way, describing these parameters as random variables in practical applications is difficult because of inadequate historical data and analysis. Despite this, fuzzy variables can be used to deal with these uncertainty parameters [11].

Proposed models of the problem in this paper are solved for small-sized problems using GAMS software and CPLEX. Then, by considering that the classical VRP is NP-hard [12] and its variant fuzzy two-echelon electric vehicle routing problem with mixed fleet and time window (F2E-EVRP-MF-TW) is undoubtedly an NP-hard problem class as well, two meta-heuristic algorithms, namely GWO and TS, are used to solve the models. Generally, algorithms such as LNS, ALNS, and hybrid genetic with LNS have been used to solve 2E-EVRP models. The reason for using the optimization method of GWO, in addition to not having a specific requirement for the objective function and the exact characteristics of the optimization problem, is that it is easy to implement and has few parameters to adjust [13]. The TS algorithm is a global optimization technique, and search memory is an important component [14]. On the other hand, Glover pointed out the ability of the TS algorithm for network design issues. In addition, the use of the fuzzy approach and meta-heuristic algorithms for complex problems is expanding (e.g., [15,16]). According to the studies done so far, this is the first time that GWO and TS algorithms are used for F2E-EVRP-MF-TW. Meanwhile, the two-echelon network is compared in deterministic and fuzzy forms.

This paper is a valuable supplementary for studying the present EVRP on reverse logistics because it aims to support the use of EFVs in urban logistics operations in particular. The main contributions of this work are as follows:

- To consider recyclable wastes, speed of vehicles, quantity of energy consumption of the vehicle, and energy consumption rate depending on the value load of the vehicle in fuzzy form.
- In the first echelon, the time windows are considered to pick up the recyclable waste from citizens of the city/wastebaskets (waste pickup points).
- In the second echelon, the time windows are considered to deliver the recyclable waste to the central station.
- To solve the models by both the grey wolf optimizer and tabu search algorithms.

The rest of the paper is organized as follows. Section 2 reviews the related studies. Section 3 presents the models and their descriptions. Then, Section 4 suggests the proposed algorithms for solving the presented model. Section 5 illustrates the results. Finally, Section 6 summarizes and concludes the study with further research.

2. Literature Review

The field of literature review related to F2E-EVRP-MF-TW can be seen in Figure 1.

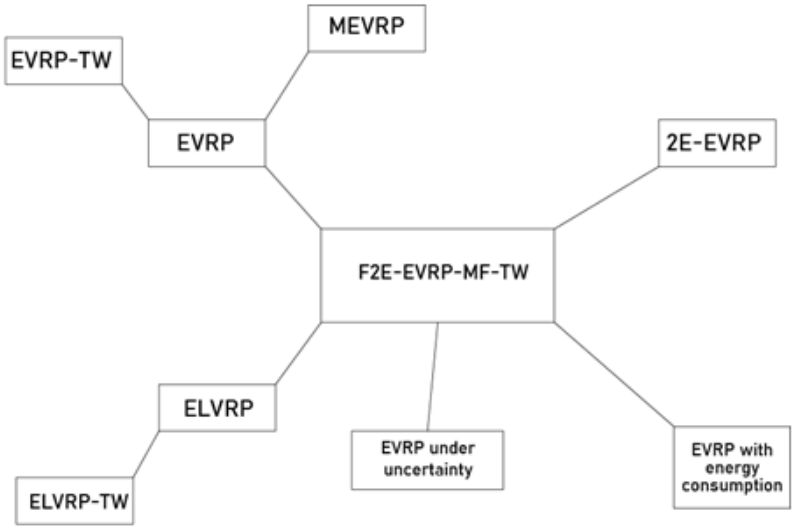


Figure 1. The literature review related to the F2E-EVRP-MF-TW.

The EVRP issues are based on VRP issues, and the salient role of research in this area cannot be overlooked (e.g., [17–26]). Worley et al. [27], in a paper presented to a conference, proposed the integration of charging station location with the routing decision problem (ELRP). Schiffer and Walther [28] addressed the issue of location routing with time windows and partial charging. However, there are fundamental differences between them, including the limited driving range, battery capacity limitation, limited charging, the swapping station number, and gradual technology development in electric flight vehicle (EFV) complexity of EVRP.

2.1. EVRP/ELRP with and without TW

Since the early 21st century, researchers have considered EFV routing problems, which are often used in goods distributing operations. The overall purpose is to deliver goods to customers. However, the popularity of electric vehicles in densely populated cities, such as quietness and non-emission of pollution, led to their use in other municipal services, such as garbage/waste transportation. For papers dealing with EV routing problems, the reader can refer to Shao et al. [29] and Kancharla and Ramadurai [4].

One of the challenges of electric vehicles is the limitation of their range of motion, which requires recharging the battery after a limited distance. Although in urban areas, from the initial movement of vehicles to their return, the need to charge the battery is less; however, charging/swapping battery stations on the route must be considered. Therefore, some studies on the routing issues of electric vehicles consider charging/swapping battery stations (e.g., [30–34]), and some consider routing–locating charging or swapping stations (e.g., [35,36]). The EV location routing problem with time windows was first introduced by Schneider et al. [37] and then by other researchers (e.g., [28]). Keskin and Çatay [38] investigated the EVRPTW proposed by Schneider et al. [37] for a location-routing problem with time windows and partial charges. The use of different types of chargers and battery replacement have also been studied (e.g., [39–42])).

2.2. A Mixed Fleet of ICEVs and EVs

The issue of routing electric vehicles with a mixed fleet, with and without a time window, is another issue that has been addressed by researchers (e.g., [43–48]).

2.3. Related Review on the EVRP with Energy Consumption

The other challenge of EVs is the limited capacity of the battery. Thus, the routing problem needs exact methods for controlling the quantity of energy consumed on the roads. In many studied, the battery is considered to be emptied linearly in terms of distance.

Barth et al. [49] reported on the amount of consumed energy required to move any certain arc based on the characteristic of the vehicle and arc. This model considers speed, acceleration, mass, elevation, frontal area, rolling friction, and air drag in energy consumption. Yi and Bauer [50] demonstrate how environmental factors such as wind speed, climate, road conditions, and temperature can significantly change the attainable limitation of EVs. Xiao et al. [51] proposed EV routing with time windows without considering charge station location. They presented the energy consumption rate based on speed and load along the route under the linear planning model. They made linear the non-linear relation between speed and travel time with internal and external estimation and then solved the model by the exact method for small instances and by the heuristic method for a hundred customers. Some papers have considered EV routing and energy consumption (e.g., [52–55]).

2.4. Related Review on the EVRP under Uncertainty

Most research is conducted in a certain environment; however, involving the uncertain factors of the problem more closely approximates the real environment. Urban and interurban logistics operation planning includes two uncertain factors. The first one is related to the vehicle. The other is related to external factors, such as claimant conditions, traffic, road conditions, charge or swap battery stations, and customer uncertainty demand. The studies mentioned above relate to certain conditions, and there are limited studies regarding uncertain factors. Uncertain factors often influence the results. Therefore, Keskin and Çatay [38] and Nejad et al. [56] suggested considering these uncertain factors in future studies.

Some of the recent EVRP studies are presented in an uncertain condition; however, it is difficult to measure the probability distribution of uncertain factors and approach them in a real operation. Fontana [57] reported on the uncertainty in EV energy consumption. This author modeled the problem with a robust optimization framework. Zhang et al. [58] expressed that the data for the factors (e.g., the instability of human behavior and estimation of probability distribution relating to energy consumption and travel time) are limited and more complex. Thus, in this paper, fuzzy numbers are used in some parameters. This study builds uncertainty proposed by others to establish the proposed model (e.g., [59,60]).

2.5. Related Review on the 2E-EVRP

A multi-echelon network of electric vehicles has been proposed in some articles (e.g., [39,61,62]. Figure 2 depicts an example of a two-echelon distribution network problem for electric vehicles [63].

A limited number of papers were found with a focus on 2E-VRP involving EVs; works on mixed fleets and two echelons under uncertainty are rare.

A summary of the EVRP mixed fleet under uncertainty and involving a two-echelon electric vehicle is given in Table 1. In addition, the literature review is given in detail in Table A1 in Appendix A.

For information on articles related to electric vehicles, see [64,65].

Table 1. Review of studies related to F2E-EVRP-MF-TW and features of these papers.

Reference	Objective Function	Solution Method	Explanation
EVRP-MF (electric and conventional vehicles)			
[48]	Min TOC	LS	Conventional, hybrid, or electric vehicles, E (electric)-urban freight
[47]	Min TOC	CWS + tree branching	
[44]	Min VN, EC, BSSC	ALNS	Multi-objective, TW

Table 1. *Cont.*

Reference	Objective Function	Solution Method	Explanation
[46]	Min TOC, VN	Branch-and-price algorithm and ALNS	
[45]	Min TOC	Metaheuristic consists of a genetic algorithm, LS/LNS	Time windows, conventional, A plug-in hybrid and electric vehicles
EVRP uncertainty			
[57]	UE	LR	Electric car, robust
[60]	Max AI		Robust optimization
[59]	Min TOC	VNS, SA	Multi-depot electric vehicle routing problem with fuzzy time windows, pickup/delivery constraints
2E-EVRP/2S-EVRP			
[61]	Min TOC	LNS	Based on the method in Baldacci et al. [66], BSSs
[39]	Min TOC	BL	Electric buses in public transportation/2sEVRP with topography and speed profile, improve energy consumption Only uses EVs in the second echelon distribution stage
[63]	Min TOC, BSSC	CG + ALNS	EVs in both echelons
[62]	Min TOC	HG + LNS	Heterogeneous fleet
[67]	Min TOC	VNS	TW
This Paper	Min TOC	GWO, TS	Mix fleet, fuzzy numbers are used to express the rate and energy consumption depending on the amount of load, vehicle speed, and recyclable waste

Note: TOC: total cost (vehicle fixed/time/distance/labor/driver wage costs); VN: vehicle number; TW: time window; AI: annual income; UE: uncertainty in EV energy consumption; LR: Lagrange relaxation; LNS: large neighborhood search; ALNS: adaptive large neighborhood search; VNS: variable neighborhood search; SA: simulated annealing; CWS: savings method of Clarke and Wright; BSSs: battery swapping stations; BSSC: battery swapping costs at the battery swapping stations; HG + LNS: hybrid genetic algorithm with LNS algorithm; BL: Bellman-Ford algorithm (linear programming solver); GWO: grey wolf optimizer; TS: tabu search.

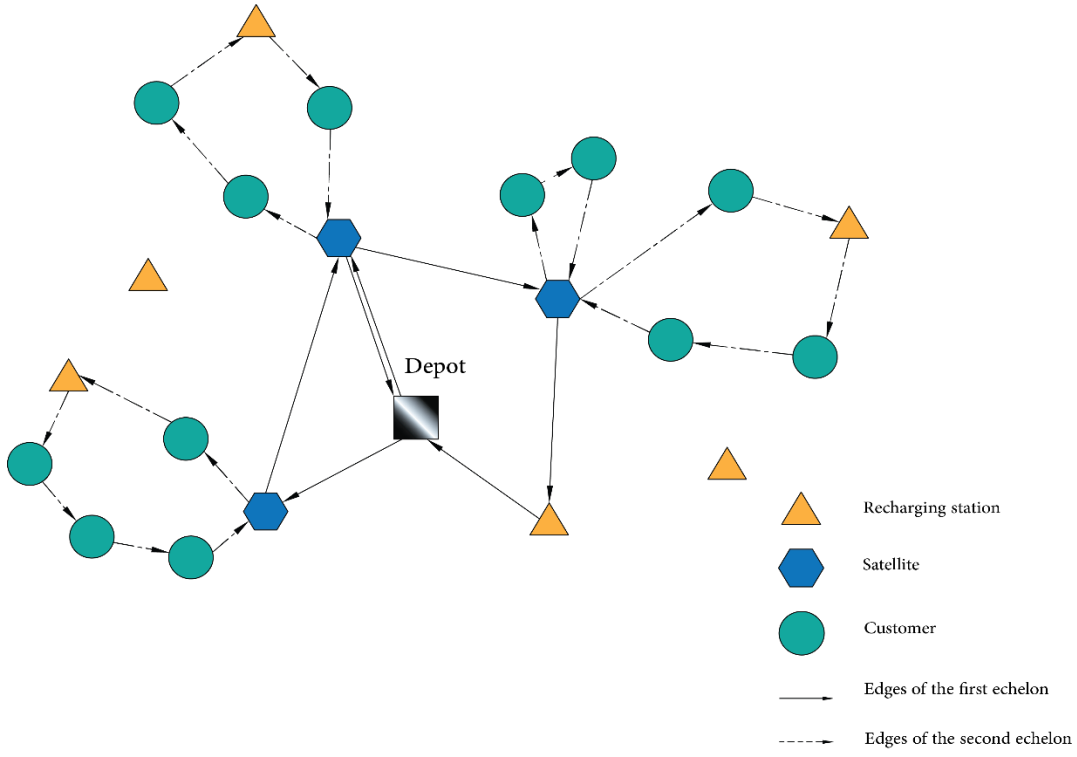


Figure 2. Example of the E2EVRP network.

3. Problem Definition and Mathematical Modeling

In this paper, the mathematical model relating to a two-echelon recyclable waste collection network for the problem of heterogeneous freight electric vehicle routing is considered by considering the time window for pickup waste from city citizens/waste containers to collection centers and then transferring it to the main recycling center with conventional vehicles. Two important and practical issues are presented in this model. The first issue is to consider the time window, in which city citizens/waste containers (waste pickup points) have a defined time limit for the pickup of recyclable waste and can only have waste picked up during those hours. There is a penalty outside this period. Due to the limited driving range of electric vehicles, it is practical to consider this issue. In the second issue, the application of fuzzy numbers in the calculations of energy consumption, vehicle speed, and recyclable waste is very close to real problems. Figure 3 shows an example of the network expressed in this paper.

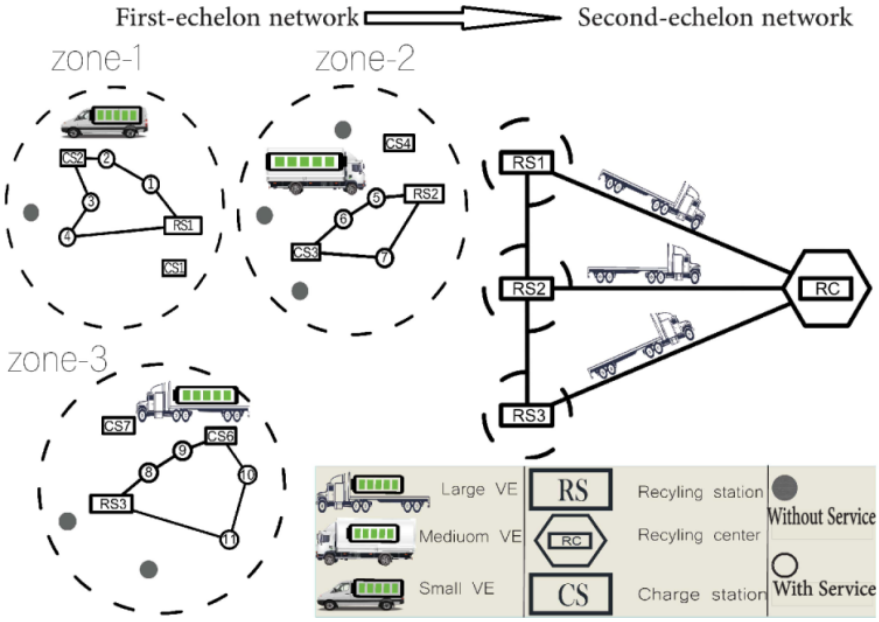


Figure 3. Two-echelon urban logistics network.

In this paper, the mathematical model of a two-echelon recyclable waste collection network for the problem of heterogeneous freight electric vehicle routing is considered by considering the time window for waste pickup from city citizens/garbage containers to collection centers and then transferring it to the main recycling center with traditional vehicles; thus, two models were proposed. Solving methods in the deterministic and fuzzy environments were applied for both models. This paper emphasizes that the factors affecting energy consumption in the real world are uncertain and should be considered in the total cost. Explanations were added to the introduction to clarify the issue.

In Sections 3.1 and 3.2 respectively, the set, parameters, and variables for creating the proposed models of the first and second echelons are presented. Then, in Section 3.3, the changes needed by the models to consider the uncertainty of some parameters are stated.

3.1. First Echelon of Notation and Model

In this section, the signs and abbreviations relating to the model of the first-echelon network are presented. These signs include three groups of sets, parameters, and decision variables. The sets, parameters, and variables are summarized in Table 2.

Table 2. Definitions of sets, parameters, and variables of first-echelon.

Notations	Definition
Sets:	
$I_t = \{0, 1, \ldots, N\}$	Sets of nodes of all waste pickup points in one area and recycling station relating to areas $i, j, p \in I_t$.
$F \subset I_t$	Sets of the nodes of candidates for charge stations.
$F_1 \subset I_t$	Sets of the nodes of candidates for charge station and virtual nodes relating to all of charge stations.
$F_{2f} \subset I_t$	Sets of the nodes of relating to each charge station (including node itself and its related virtual nodes.
$I = \{0, 1, \ldots, n\},\ I \subset I_t$	Set of the nodes of all waste pickup points in one area and recycling station relating to areas $i, j, p \in I$.
$I_1 = \{1, 2, \ldots, n\},\ I_1 \subset I$	Set of the nodes of waste pickup points.
o	Recycling collection station node.
$K = \{1, \ldots, k\}$	Set of fleet vehicle $k \in K$.
$G = \{s, m, l\}$	Heterogeneous fleet electric vehicle $g \in G$.
$K_g \subset K$	Vehicle type g.
$C = \{1, 2, 3\}$	Recyclable wastes class in waste pickup points (the recyclable wastes divided in three groups of 1, 2, and 3) $c \in C$.
Parameters:	
q_{ic}	Amount of recyclable waste of class C in waste pickup point i(kg).
d_{ij}	Distance between nodes of i, j(m).
$c\prime_g$	Unit cost of transportation between two nodes i and j relating to vehicle type g.
c^{fl}	Cost of energy consumption.
c^r	Cost of recharge unit.
v_g	Speed of vehicle type g (m/s)
F_g	Cost of using vehicle type g.
F_s	Cost of constructing each charge station.
Q_g	Loading capacity of each transportation means of vehicle type g (kg).
e_i	Earliest time to arrive to waste pickup point i (lower limit of the acceptable time windows of the node) (s).
l_i	Latest time to arrive to waste pickup point i (upper limit of the expected time windows of the node) (s).
p	Penalty cost relating to time windows being exceeded.
M	A very large number.
η_g	Efficiency rate of a generator of vehicle type g.
ω_g	Weight of vehicle type g (kg).
α_g	Acceleration of vehicle type g (m/s ^{2}).
α_{ijg}	Acceleration of g type of vehicle between nodes i and j (m/s ^{2}).
gr	Gravitational constant (9.81 m/s^2).
θ_{ij}	Average the angle of road between nodes i and j (m/s^2).
A_g	Level in frontal surface area of vehicle type g (kg).
ρ	Air density (kg/m^3).
λ_g	Coefficient relating to rolling resistance of vehicle type g.
μ_g	Coefficient relating to rolling drag of vehicle type g.
Φ_{ijk}	Constant quality of energy consumption of the vehicle k between nodes i and j after simplification of Formula (2) $\Phi_{ijk} = \frac{\alpha_{ijg}\omega_g d_{ij}}{\eta_g} + \frac{0.5\mu_g A_g \rho {v_g}^2 d_{ij}}{\eta_g}$.
Θ_{ijk}	Energy consumption coefficient depends on the weight load of the vehicle k between nodes i and j after simplification of Formula (3) $\Theta_{ijk} = \frac{\alpha_{ijg} d_{ij}}{\eta_g}$.
Γ_g	Battery capacity g type of vehicle.
r_g	Recharge speed of battery in the charge station.
Decision Variables:	
x_{ijk}	1 if vehicle k leaves from node i to node j; 0, otherwise.
y_k	1 if vehicle k is used; 0, otherwise.
s_{ik}	Continuous variable shows at what time recyclable wastes carried in vehicle k arrived in node i.
u_{ik}	Continuous variable is used to eliminate the sub-tour.
z_i^1	1 if waste pickup point i is visited in time interval $[0,\ e_i]$; 0, otherwise.
z_i^2	1 if waste pickup point i is visited in time interval $[e_i,\ l_i]$; 0, otherwise.
z_i^3	1 if waste pickup point i is visited in time interval $[l_i, +\infty]$; 0, otherwise.
sz_i^1	Continuous variable is used to linearize the expression of $z_i^1 \sum_{k=1}^{K} s_{jk}$.
sz_i^3	Continuous variable is used to linearize the expression of $z_i^3 \sum_{k=1}^{K} s_{jk}$.
l_{jk}	Continuous variable shows vehicle k for transporting the recyclable wastes from node i to node j with how much load.
b_{ijk}	Continuous variable shows vehicle k for transporting the recyclable wastes and how much energy consumed while moving from node i to node j.
h_{jk}	Continuous variable shows the total amount of consuming charge by vehicle k in the arrival node.
$h^1{}_{jk}$	Continuous variable is related to the node of the charge station and its virtual node, showing how the quantity of vehicle charge is consumed to the node before the charge station.
lx_{ijk}	Continuous variable is used to linearize the expression of $l_{jk} * x_{ijk}$.

The energy relating to vehicle type g between nodes i and j is calculated as follows [52]:

$$\alpha_{ijg} = \alpha_g + gr(sin\theta_{ij}) + gr\lambda_g(cos\theta_{ij}), \forall g \in G, i \in I, j \in I_t \quad (1)$$

Equation (1) calculates the acceleration of vehicle type g between nodes i and j, which is a function of other parameters.

$$b_{ijk} = \frac{\alpha_{ijg}\left(\omega_g + l_{ijk}\right)d_{ij}}{\eta_g} + \frac{0.5\mu_g A_g \rho {v_g}^2 d_{ij}}{\eta_g}, \forall g \in G, k \in K_g, i \in I, j \in I_t \tag{2}$$

Equation (2) calculates energy consumption relating to vehicle k when moving from node i to node j, which is a function of variable l_{ijk} and related parameters. By simplifying this expression, it yields the following equation:

$$b_{ijk} = \Phi_{ijk} + l_{ijk}\Theta_{ijk}, \forall g \in G, k \in K_g, i \in I, j \in I_t \tag{3}$$

In the following, a mathematical model proposes the vehicle routing of the first-echelon network. The model of the problem is shown in Equations (4)–(40). In this model, small-sized vehicles can load only class 1 of recyclable wastes, medium-sized vehicles can load classes 1 and 2, and large-sized vehicles can load recyclables of all three classes.

$$\begin{aligned} \min \sum_{g\in G}\sum_{k=1}^{K_g} F_g y_k + \sum_{g\in G} c\prime_g \sum_{k=1}^{K_g}\sum_{i=0}^{I_t}\sum_{j=0}^{I_t} d_{ij}x_{ijk} + p\sum_{i=1}^{I_1}\left\{\left(z_i^1 e_i - sz_i^1\right) + \left(sz_i^3 - z_i^3 l_i\right)\right\} \\ + c''\sum_{k=1}^{K}\sum_{i=1}^{I_t}\sum_{j=1}^{I_t}\left\{\Phi_{ijkij}x_{ijk} + \Theta_{ijk}l x_{ijk}\right\} + F_s\sum_{k=1}^{K_g}\sum_{i\in I_t}\sum_{j\in F} x_{ijk} \\ + c^r\sum_{g\in G}\sum_{k=1}^{K_g}\sum_{j\in F}^{F_1}\left\{\frac{h^1{}_{jk} + \sum_{i=1}^{I_t}\left\{\Phi_{ijkij}x_{ijk} + \Theta_{ijk}l x_{ijk}\right\}}{\mathrm{r}_g}\right\} \end{aligned} \tag{4}$$

s.t.

$$\sum_{j=1}^{I_1} x_{0jk} = y_k, \qquad \forall k \in K \tag{5}$$

$$\sum_{k=1}^{K}\sum_{i=0}^{I_t} x_{ipk} - \sum_{k=1}^{K}\sum_{j=0}^{I_t} x_{pjk} = 0, \qquad \forall p \in I_t \tag{6}$$

$$\sum_{i=1}^{I_1}(q_{i1} + q_{i2} + q_{i3})\sum_{\substack{j=1\\ j\neq i}}^{I_t} x_{ijk} \leq Q_g y_k, \qquad \forall g \in G,\ k \in K_g \tag{7}$$

$$\sum_{\substack{i=1\\ j\neq i}}^{I_t} x_{ijk} \leq 0, j \in I_1,\ k \in K_s,\ q_{j2} + q_{j3} > 0 \tag{8}$$

$$\sum_{\substack{i=0\\ j\neq i}}^{I_t} x_{ijk} \leq 0,\ j \in I_1, k \in K_l,\ q_{j3} > 0 \tag{9}$$

$$s_{ik} + \frac{d_{ij}}{v_g} - M\left(1 - x_{ijk}\right) \leq s_{jk}, \qquad \forall g \in G,\ k \in K_g, i \in I_t, j \in I_t,\ j \neq 0 \tag{10}$$

$$s_{ik} + \frac{d_{ij}}{v_g} + M\left(1 - x_{ijk}\right) \geq s_{jk}, \qquad \forall g \in G,\ k \in K_g, i \in I_t, j \in I_t, i \neq 0 \tag{11}$$

$$\sum_{k=1}^{K}\sum_{\substack{j=1\\ j\neq i}}^{I_t} x_{ijk} = 1, \quad \forall i \in I_1 \tag{12}$$

$$\sum_{k=1}^{K}\sum_{\substack{i=1\\ j\neq i}}^{I_t} x_{ijk} = 1, \quad \forall j \in I_1 \tag{13}$$

$$u_{jk} - u_{ik} + |I_t| x_{ijk} \leq |I_t - 1|, \quad \forall i \in I_t,\ j \in I_t,\ k \in K, i \neq j \tag{14}$$

$$z_i^1 + z_i^2 + z_i^3 = 1,\ \forall\, i \in I_1 \tag{15}$$

$$\sum_{k\in K} s_{ik} \leq e_i + M\left(1 - z_i^1\right),\ \forall\, i \in I_1 \tag{16}$$

$$e_i - M\left(1 - z_i^2\right) < \sum_{k\in K} s_{ik} \leq l_i + M\left(1 - z_i^2\right),\ \forall\, i \in I_1 \tag{17}$$

$$l_i - M\left(1 - z_i^3\right) < \sum_{k\in K} s_{ik},\ \forall\, i \in I_1 \tag{18}$$

$$s_{ik} \leq M \sum_{j=1}^{I_t} x_{ijk},\ \forall\, k \in K, i \in I_t \tag{19}$$

$$sz_i^1 \leq M z_i^1,\ \forall\, i \in I_1 \tag{20}$$

$$sz_i^1 \leq \sum_{k\in K} s_{ik},\ \forall\, i \in I_1 \tag{21}$$

$$sz_i^1 \geq \sum_{k\in K} s_{ik} - M\left(1 - z_i^1\right),\ \forall\, i \in I_1 \tag{22}$$

$$sz_i^3 \leq M z_i^3,\ \forall\, i \in I_1 \tag{23}$$

$$sz_i^3 \leq \sum_{k\in K} s_{ik},\ \forall\, i \in I_1 \tag{24}$$

$$sz_i^3 \geq \sum_{k\in K} s_{ik} - M\left(1 - z_i^3\right),\ \forall\, i \in I_1 \tag{25}$$

$$lx_{ijk} \leq M x_{ijk}, \forall k \in K, i \in I_t, j \in I_t \tag{26}$$

$$lx_{ijk} \leq l_{jk},\ \forall k \in K, i \in I_t, j \in I_t \tag{27}$$

$$lx_{ijk} \geq l_{jk} - M\left(1 - x_{ijk}\right),\ \forall k \in K, i \in I_t, j \in I_t \tag{28}$$

$$l_{ik} + \left(q_{j1} + q_{j2} + q_{j3}\right) - M\left(1 - x_{ijk}\right) \leq l_{jk}, \qquad \forall k \in K, i \in I_t, j \in I_t,\ j \neq 0 \tag{29}$$

$$l_{ik} + \left(q_{j1} + q_{j2} + q_{j3}\right) + M\left(1 - x_{ijk}\right) \geq l_{jk}, \qquad \forall\, k \in K, i \in I_t, j \in I_t, i \neq 0 \tag{30}$$

$$h_{ik} + \left(\Phi_{ijkij} x_{ijk} + \Theta_{ijk} l x_{ijk}\right) - M\left(1 - x_{ijk}\right) \leq h_{jk}, \qquad \forall k \in K, i \in I_t, j \in I,\ j \neq 0 \tag{31}$$

$$h_{ik} + \left(\Phi_{ijkij} x_{ijk} + \Theta_{ijk} l x_{ijk}\right) + M\left(1 - x_{ijk}\right) \geq h_{jk}, \quad \forall\, k \in K, i \in I_t, j \in I, i \neq 0 \tag{32}$$

$$h_{ik} + \Phi_{i0kij} x_{i0k} + \Theta_{i0k} l x_{i0k} \leq \Gamma_g, \qquad \forall g \in G\ k \in K_g, i \in I_t \tag{33}$$

$$\sum_{j=1}^{F_1} x_{0jk} = 0, \qquad \forall k \in K \tag{34}$$

$$h_{ik} = 0, \qquad \forall\, k \in K, i \in F_1 \tag{35}$$

$$h^1{}_{jk} \geq h_{ik} - M\left(1 - x_{ijk}\right), \qquad \forall\, k \in K, j \in F_1, i \in I_t, \tag{36}$$

$$\sum_{i=1}^{I_t} x_{ijk} \leq \sum_{i=1}^{I_t} x_{ifk}, \qquad \forall k \in K, f \in F, j \in F_{2f} \tag{37}$$

$$\sum_{k=1}^{K}\sum_{i=1}^{I_t} x_{ijk} \leq 1, \qquad \forall k \in K, j \in F_1 \tag{38}$$

$$x_{ijk}, y_k, z_i^1, z_i^2, z_i^3 \in \{0,1\}, \qquad \forall k \in K, i \in I, j \in I \tag{39}$$

$$s_{ik}, sz_i^1, sz_i^3, l_{ijk}, , lx_{ijk}, h_{ijk}, {h^1}_{jk} \geq 0, \qquad \forall k \in K, i \in I \tag{40}$$

Constraint (4) shows the objective function of the problem is of the minimize type and contains six parts. Parts 1 and 2 respectively represent the fixed cost to use EVs and the cost of transportation between two nodes. The third part of the objective function minimizes the extent of the unsatisfactory citizens of the city/wastebaskets (waste pickup points) of the penalty cost of time windows. The fourth part of the objective function minimizes the cost of energy consumption. The fifth part is the cost of constructing the charge station. Finally, the sixth part is the recharging costs in each charge station.

Constraint (5) shows that if a vehicle leaves the recycling station, it is used. Constraint (6) suggests that each node should be visited exactly once. Constraint (7) ensures that the load of the vehicle is not more than the vehicle's loading capacity. Constraint (8) ensures that if there is a waste pickup point for class 2 or 3 recyclable waste, the waste pickup point cannot be visited by a small vehicle. Constraint (9) ensures that if there is a waste pickup point for class 3 recyclable waste, the waste pickup point node cannot be visited by small and medium-sized vehicles. Constraints (10) and (11) determine the arrival time to enter each node. Constraints (12) and (13) ensure that each node should be visited only once.

Constraint (14) eliminates the sub-tour. Constraint (15) suggests that visiting each node only can be done in one of three possible time intervals ($[0, e_i, e_i, l_i, l_i, +\infty]$). Constraint (16) determines if the waste pickup point is visited before the time windows of the waste pickup point. Constraint (17) determines if the waste pickup point is visited within the time windows of the waste pickup point. Constraint (18) determines if the waste pickup point is visited after the time windows of the waste pickup point. Constraint (19) suggests that the arrival time to a node with a vehicle can be more than zero if the vehicle arrives at the node.

Constraints (20) to (22) linearize the expression of $z_i^1 \sum_{k=1}^{K} s_{jk}$ so that the coefficient of a binary variable is continuous in a variable. Constraints (23) to (25) linearize the term of $z_i^3 \sum_{k=1}^{K} s_{jk}$ so that the coefficient of a binary variable is continuous in a variable. Constraint (26) suggests that the changing amount of arriving time to each node only for the vehicle that visits it is larger than zero. Constraints (27) to (28) linearize the expression of lx_{ijk}. Constraints (29) and (30) show the loading weight of a vehicle k has gone from node i to node j. Constraints (31) and (32) suggest the sum of consumed charges by a vehicle when it enters each node. Constraint (33) suggests that an EV has charged so long it can move. The remaining charges must be a quality that a vehicle can return to the recyclable waste station node. Constraint (34) suggests that after exiting from the recycling station, a vehicle cannot directly go to the charge station and should visit at least one waste pickup point first because it departs from the recycling station with a complete charge. Constraint (35) ensures that a vehicle will be charged completely at a charge station. Thus, the sum of consumed charges of the vehicle will be zero. Constraint (36) addresses the vehicle of variable ${h^1}_{jk}$. Constraint (37) ensures that it can go to a virtual node relating to a charge station while its charge station is constructed.

Constraint (38) means that each node of the charge station or each virtual charge station can be visited once more at maximum. Finally, Constraints (39) and (40) indicate the binary and non-negative auxiliary variables.

3.2. Second-Echelon of Notation and Model

In this section, signs and abbreviations relating to a mathematical model of the second-echelon network are presented. These signs include three groups of sets, parameters, and decision variables. The sets, parameters, and variables are summarized in Table 3.

Table 3. Definitions of sets, parameters, and variables of second-echelon.

Notations	Definition
Sets:	
$I = \{0, 1, \ldots, n,\}$	Sets of nodes of all recycle stations and recycle center station $i, j, p \in I$.
$I_1 = \{1, 2, \ldots, n\}$	Set of recycling stations.
0	Recycle center station node.
$K = \{1, \ldots, k\}$	Set of vehicles conventional fleet $k \in K$.
Parameters:	
q_i	Amount of recyclable waste in recycle center i.
d_{ij}	Distance between nodes i and j.
c	Cost of transportation unit between two nodes i and j.
v	Speed of the vehicles.
F	Cost of using vehicles.
Q	Loading capacity of each vehicle.
e_i	Earliest time to arrive to waste pickup point i (lower limit of acceptable time windows of nodes).
l_i	Latest time to arrive to waste pickup point i (upper limit of expected time windows of the nodes).
p	The penalty cost relating to time windows being exceeded.
M	A very large number.
Decision variables:	
x_{ijk}	1 if vehicle k leaves from node i to j; 0, otherwise.
y_k	1 if vehicle k is used; 0, otherwise.
s_{ik}	Continuous variable shows at what time that recyclable wastes carried by vehicle k arrived in node i.
u_{ik}	Continuous variable is used to eliminate the sub-tour.
z_i^1	1 if waste pickup point i is visited in time interval $[0, \quad e_i]$; 0, otherwise.
z_i^2	1 if waste pickup point i is visited in time interval $[e_i, \ l_i]$; 0, otherwise.
z_i^3	1 if waste pickup point i is visited in time interval $[l_i, +\infty]$; 0, otherwise.
sz_i^1	Continuous variable is used to linearize the expression of $z_i^1 \sum_{k=1}^{K} s_{jk}$
sz_i^3	Continuous variable is used to linearize the expression of $z_i^3 \sum_{k=1}^{K} s_{jk}$

In the following, a mathematical model presents a route to optimize the second-echelon network. The problem model is shown in Constraints (41)–(62).

$$\min \sum_{k=1}^{K} F y_k + c \sum_{k=1}^{K} \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} x_{ijk} + p \sum_{i=1}^{n} \{(z_i^1 e_i - sz_i^1) + (sz_i^3 - z_i^3 l_i)\} \tag{41}$$

s.t.

$$\sum_{j=1}^{n} x_{0jk} = y_k, \qquad \forall k \in K \tag{42}$$

$$\sum_{k=1}^{K} \sum_{i=0}^{n} x_{ipk} - \sum_{k=1}^{K} \sum_{j=0}^{n} x_{pjk} = 0, \qquad \forall p \in \{1, \ldots, n\} \tag{43}$$

$$\sum_{i=1}^{n} q_i \sum_{\substack{j=1 \\ j \neq i}}^{n} x_{ijk} \leq Q y_k, \qquad \forall k \in K \tag{44}$$

$$s_{ik} + d_{ij}/v - M\left(1 - x_{ijk}\right) \leq s_{jk}, \qquad \forall k \in K, i \in I, j \in I, \ j \neq 0 \tag{45}$$

$$s_{ik} + d_{ij}/v + M\left(1 - x_{ijk}\right) \geq s_{jk}, \qquad \forall k \in K, i \in I, j \in I, j \neq 0 \tag{46}$$

$$\sum_{k=1}^{K} \sum_{\substack{j=1 \\ j \neq i}}^{n} x_{ijk} = 1, \quad \forall i \in \{1 \ldots, n\} \tag{47}$$

$$\sum_{k=1}^{K}\sum_{\substack{i=1\\ j\neq i}}^{n} x_{ijk} = 1, \quad \forall j \in \{1\ldots,n\} \tag{48}$$

$$u_{jk} - u_{ik} + |I|x_{ijk} \leq |I-1|, \quad \forall i \in I,\ j \in I,\ k \in K, i \neq j \tag{49}$$

$$z_i^1 + z_i^2 + z_i^3 = 1,\ \forall\, i \in I_1 \tag{50}$$

$$\sum_{k\in K} s_{ik} \leq e_i + M\left(1 - z_i^1\right),\ \forall\, i \in I_1 \tag{51}$$

$$e_i - M\left(1 - z_i^2\right) < \sum_{k\in K} s_{ik} \leq l_i + M\left(1 - z_i^2\right),\ \forall\, i \in I_1 \tag{52}$$

$$l_i - M\left(1 - z_i^3\right) < \sum_{k\in K} s_{ik},\ \forall\, i \in I_1 \tag{53}$$

$$sz_i^1 \leq Mz_i^1,\ \forall\, i \in I_1 \tag{54}$$

$$sz_i^1 \leq \sum_{k\in K} s_{ik},\ \forall\, i \in I_1 \tag{55}$$

$$sz_i^1 \geq \sum_{k\in K} s_{ik} - M\left(1 - z_i^1\right),\ \forall\, i \in I_1 \tag{56}$$

$$sz_i^3 \leq Mz_i^3,\ \forall\, i \in I_1 \tag{57}$$

$$sz_i^3 \leq \sum_{k\in K} s_{ik},\ \forall\, i \in I_1 \tag{58}$$

$$sz_i^3 \geq \sum_{k\in K} s_{ik} - M\left(1 - z_i^3\right),\ \forall\, i \in I_1 \tag{59}$$

$$s_{ik} \leq Mx_{ijk}, \forall k \in K, i \in I, j \in I \tag{60}$$

$$x_{ijk}, y_k, z_i^1, z_i^2, z_i^3 \in \{0,1\}, \qquad \forall k \in K, i \in I, j \in I \tag{61}$$

$$s_{ik}, sz_i^1, sz_i^3 \geq 0, \qquad \forall k \in K, i \in I \tag{62}$$

Constraint (41) shows the objective function of the problem that is the sum of the constant costs of the use of vehicles and costs of visiting the nodes; it should be minimized. The last part of the objective function minimizes the dissatisfaction of the time window penalty cost. Constraint (42) shows that if a vehicle exits from the recyclable center station h, it is used. Constraint (43) suggests each node is opened exactly one time. Constraint (44) ensures that the vehicle capacity is observed. Constraints (45) and (46) determine the arrival time to each node. Constraints (47) and (48) ensure that each node should be visited only once. Constraint (49) is for eliminating the sub-tour. Constraint (50) suggests that visiting each node only can be done in one of three possible time intervals ($[0, e_i, e_i, l_i, l_i, +\infty]$). Constraint (51) determines if visiting a recyclable station occurred before its time window or not. Constraint (52) determines if a recyclable station is visited within its time window. Constraint (53) determines if a recyclable station is visited after its time window. Constraints (54) to (56) linearize the expression of $z_i^1 \sum_{k=1}^{K} s_{jk}$ so that the coefficient of a binary variable is continuous in a variable. Constraints (57) to (59) linearize the expression of $z_i^3 \sum_{k=1}^{K} s_{jk}$ so that the coefficient of a binary variable is continuous in a variable. Constraint (60) suggests that the value of entering the time variable for each node only relates to the vehicle that visited the node. It can be more than zero. Finally, Constraints (61) and (62) indicate the binary and non-negative auxiliary variables.

3.3. Uncertainty in the First-Echelon Model

In this section, considering the use of heterogeneous electric vehicles, the uncertain energy consumption and energy consumption rate depend on the value load of the vehicle, the extent of recyclable waste, and the vehicle's speed in this echelon. In this section, using

the method of Jiménez et al. [68], we develop a fuzzy model to confront the uncertainty in some parameters of the first-echelon network problem. Table 4 shows the parameters under uncertainty.

Table 4. Definitions of parameters of uncertainty.

Notations	Definition
q_{ic}	Amount of recyclable waste class C in waste pickup point i(kg).
v_g	Speed of g type of vehicle (m/s).
Φ_{ijk}	Constant quality of energy consumption of vehicle k between nodes i and j after simplification of Formula (2) $\Phi_{ijk} = \frac{\alpha_{ijg}\omega_g d_{ij}}{\eta_g} + \frac{0.5\mu_g A_g \rho {v_g}^2 d_{ij}}{\eta_g}$.
Θ_{ijk}	Energy consumption coefficient depends on the weight load of vehicle k between nodes i and j after simplification of Formula (3) $\Theta_{ijk} = \frac{\alpha_{ijg} d_{ij}}{\eta_g}$.

With this propose, each parameter is modeled as a triangular fuzzy number. The reason for a triangular fuzzy number is that each parameter has an average value that might be more or less than the real value. The uncertainty in two parameters Φ_{ijk} and Θ_{ijk} can show uncertainty in all the parameters constructing the two parameters (this case can be calculated easily using algebra). In the method Jiménez et al. [68] for each fuzzy number, $\widetilde{a} = [a_1, a_2, a_3]$ is defined as an expected interval that will be a formula for a triangular fuzzy number and an expected value:

$$EL(\widetilde{a}) = [E_1, E_2] = \left[\frac{a_1 + a_2}{2}, \frac{a_2 + a_3}{2}\right] \tag{63}$$

$$EV(\widetilde{a}) = \frac{a_1 + 2a_2 + a_3}{4} \tag{64}$$

where EL is the expected distance and EV is the expected value. By considering the calculations of Jiménez et al. [68] for inequality equations, the determined equation is Equation (65), and the determined equation of object function is Equation (66).

$$\widetilde{a}x \geq \widetilde{B} => [(1-\beta)E_{2a} + (\beta)E_{1a}]x \geq [(\beta)E_{2B} + (1-\beta)E_{1B}] \tag{65}$$

$$\min\widetilde{c}x = \min EV(\widetilde{c}) = \frac{c_1 + 2c_2 + c_3}{4}x \tag{66}$$

where β is the least degree of satisfaction of the constraint, which has uncertainty.

In the first-echelon network model discussed in Section 3.1, the objective function and Constraints (7) to (11) and (29) to (33) have uncertainty. Thus, the objective function and these constrains will be substituted with the following constraints. Then, the fuzzy model is presented according to Constraints (67)– (77), and the rest will be unchanged. Therefore, Constraint (4) (the objective function of the first echelon) is replaced by Equation (67). In addition, Constraints (7) to (11) are replaced by Constraints (68) to (72), and finally, Constraints (73) to (77) are replaced by Constraints (29) to (33).

In addition, the equations for computation formulas are applied in discussing the model fuzzy in Appendix B.

$$\begin{aligned}\min \sum_{g\in G}\sum_{k=1}^{K_g} F_g y_k + \sum_{g\in G} c'_g \sum_{k=1}^{K_g}\sum_{i=1}^{I_t}\sum_{j=0}^{I_t} d_{ij}x_{ijk} + p\sum_{i=1}^{I_1}\left\{\left(z_i^1 e_i - sz_i^1\right) + \left(sz_i^3 - z_i^3 l_i\right)\right\} \\ + c''\sum_{k=1}^{K}\sum_{i=1}^{I_t}\sum_{j=1}^{I_t}\left\{EV\left(\widetilde{\Phi}_{ijk}\right)x_{ijk} + EV\left(\widetilde{\Theta}_{ijk}\right)l x_{ijk}\right\} + F_s\sum_{k=1}^{K_g}\sum_{i\in I_t}\sum_{j\in F} x_{ijk} \\ + c^r\sum_{g\in G}\sum_{k=1}^{K_g}\sum_{j\in F}^{F_1}\left\{\frac{h^1{}_{jk} + \sum_{i=1}^{I_t}\left\{EV\left(\widetilde{\Phi}_{ijk}\right)x_{ijk} + EV\left(\widetilde{\Theta}_{ijk}\right)l x_{ijk}\right\}}{\mathrm{r}_g}\right\}\end{aligned} \tag{67}$$

$$\sum_{i=1}^{I_1} \beta E_2(q_{i1}+q_{i2}+q_{i3}) + (1-\beta)E_1(q_{i1}+q_{i2}+q_{i3}) \sum_{\substack{j=1 \\ j\neq i}}^{I_t} x_{ijk} \leq Q_g y_k, \qquad \forall g \in G,\ k \in K_g \tag{68}$$

$$\sum_{\substack{i=1 \\ j\neq i}}^{I_t} x_{ijk} \leq 0, j \in I_1,\ k \in K_s,\ EV(q_{j2}+q_{j3}) > 0 \tag{69}$$

$$\sum_{\substack{i=0 \\ j\neq i}}^{I_t} x_{ijk} \leq 0,\ j \in I_1, k \in K_l,\ EV(q_{j3}) > 0 \tag{70}$$

$$s_{ik} + \beta E_2\left(\frac{d_{ij}}{v_g}\right) + (1-\beta)E_1\left(\frac{d_{ij}}{v_g}\right) - M\left(1-x_{ijk}\right) \leq s_{jk}, \qquad \forall g \in G,\ k \in K_g, i \in I_t, j \in I_t,\ j \neq 0 \tag{71}$$

$$s_{ik} + \beta E_2\left(\frac{d_{ij}}{v_g}\right) + (1-\beta)E_1\left(\frac{d_{ij}}{v_g}\right) + M\left(1-x_{ijk}\right) \geq s_{jk}, \qquad \forall g \in G,\ k \in K_g, i \in I_t, j \in I_t, i \neq 0 \tag{72}$$

$$l_{ik} + \beta E_2(q_{i1}+q_{i2}+q_{i3}) + (1-\beta)E_1(q_{i1}+q_{i2}+q_{i3}) - M\left(1-x_{ijk}\right) \leq l_{jk}, \qquad \forall k \in K, i \in I_t, j \in I_t,\ j \neq 0 \tag{73}$$

$$l_{ik} + \beta E_2(q_{i1}+q_{i2}+q_{i3}) + (1-\beta)E_1(q_{i1}+q_{i2}+q_{i3}) + M\left(1-x_{ijk}\right) \geq l_{jk}, \qquad \forall\, k \in K, i \in I_t, j \in I_t, i \neq 0 \tag{74}$$

$$h_{ik} + \left(\left(\beta E_2\left(\widetilde{\Phi}_{ijk}\right) + (1-\beta)E_1\left(\widetilde{\Phi}_{ijk}\right)\right)x_{ijk} + \left(\beta E_2\left(\widetilde{\Phi}_{ijk}\right) + (1-\beta)E_1\left(\widetilde{\Theta}_{ijk}\right)\right)lx_{ijk}\right) - M\left(1-x_{ijk}\right) \leq h_{jk}, \quad \forall k \in K, i \in I_t, j \in I,\ j \neq 0 \tag{75}$$

$$h_{ik} + \left(\left(\beta E_2\left(\widetilde{\Phi}_{ijk}\right) + (1-\beta)E_1\left(\widetilde{\Phi}_{ijk}\right)\right)x_{ijk} + \left(\beta E_2\left(\widetilde{\Phi}_{ijk}\right) + (1-\beta)E_1\left(\widetilde{\Theta}_{ijk}\right)\right)lx_{ijk}\right) + M\left(1-x_{ijk}\right) \geq h_{jk}, \quad \forall\, k \in K, i \in I_t, j \in I, i \neq 0 \tag{76}$$

$$h_{ik} + \left(\beta E_2\left(\widetilde{\Phi}_{i0k}\right) + (1-\beta)E_1\left(\widetilde{\Phi}_{i0k}\right)\right)x_{i0k} + \left(\beta E_2\left(\widetilde{\Phi}_{i0k}\right) + (1-\beta)E_1\left(\widetilde{\Theta}_{i0k}\right)\right)lx_{i0k} \leq \Gamma_g, \qquad \forall g \in G\, k \in K_g, i \in I_t \tag{77}$$

4. Solution Methods

In this section, the methods of solving the models are explained in detail.

4.1. Exact Method

The proposed models of this article in small-size are considered by commercially available solvers (such as CPLEX) and GAMS win64 25.1.3 software. The results of solving the models in small size are given in Section 5.1.

4.2. Meta-Heuristic Algorithms

Meta-heuristic algorithms include a set of approximate optimization techniques. These methods suggest "acceptable" solutions in a reasonable time for NP-hard. This paper uses the two meta-heuristics of GWO and TS to solve the two-echelon models. The proposed algorithms are run by software MATLAB (2018b) on a PC with Intel Core i7, CPU 2.30 GHz.

4.2.1. Tabu-Search Algorithm

Tabu search (TS) was first presented in a paper by Glover [69]. Then, in two articles, he introduced the applications of the TS algorithm [70,71]. Hertz and Werra [72] from the Swiss Federal Institute of Technology had an important role in developing this algorithm. Later, the complete book of "Tabu search" was produced by Glover and Laguna [73].

This algorithm takes advantage of methods that use memory to store information during the search. The search method of this algorithm in solving the optimization problems is as follows: the algorithm starts from a point or initial solution and searches the neighborhood around that point. It chooses the best among the neighbors and goes to that point. This search is continued to estimate a stop criterion. The optimize point is reported in the end of the search. As already said, this algorithm uses the short-time memory to

prevent falling in a local optimization. Task of this short-time memory is to keep the latest movements (with the defined limited numbers). These movements are kept in a list (a tabu list). In every movement, if the movement point is in the tabu list, it will be prevented from being transferred, unless there are special conditions for the tabu movement.

The steps of implementing the TS protocol's pseudo-code in this paper are summarized in Algorithm 1.

Algorithm 1: The TS pseudo-code

1. Generating the initial solution X_0, the best solution X*, tabu list T.
2. Generating a set of neighborhood solutions (multiple neighborhoods).
3. Choosing the best neighborhood from the set of neighborhood solutions X′.
4. Is X′ on the tabu list? Yes.
5. Is the aspiration criterion satisfied? Yes, go to 7. No, X′ will be removed from the set of neighborhood solutions. Then go to step 3.
6. Is X′ better than X*? Yes, go to 7. No, go to 8.
7. X′ replaces X*.
8. Then X′ replaces X.
9. Has the stopping criterion been reached? Yes, Go to 10 No Update the tabu list. No, back to step 2.
10. X* is selected.

The neighborhood search method of this algorithm is done as multiple neighborhoods. In each step of the algorithm iteration, if the network determined in the current step is more suitable than the previous network, this network is replaced. In the case that the number of iterations reaches the maximum number of times, the iterations will end at finding a network with a certain size. Then, by increasing the number of routes in the network, the previous steps are iterated until the network reaches the maximum possible number of routes. The best network among all the networks obtained from the previous steps is determined as the solution to the route network design problem.

4.2.2. Grey Wolf Optimizer Algorithm

This algorithm is one of the nature-inspired meta-heuristic algorithms that imitate grey wolf behavior, including their hierarchical leading and method of their hunt. This algorithm was first presented by Mirjalili et al. [74], based on collective hunting. The GWO is inspired by hunting behavior and the leadership hierarchy of grey wolves [75]. These grey wolves are from the Canadian wolf family and are placed at the top of food chains and live collectively in groups of 5–12. The strict governance of these wolfs is that the alpha (α) wolf governs and his commands should be followed by the rest of group. The alpha determines where the group moves and other commands. In grading grey wolves, it is the beta (β) wolves that are subject to the α and assist in decision making and other group activities. The other class is the delta (δ) grey wolf. In addition, there are wolves in the group. These are wolves who play the role of victims of the other members of the group, and they are the last wolves allowed to eat. In this algorithm, wolves (α, β, δ) become the leaders and the other wolves, the omega (ω), follow these three categories.

The application of this algorithm is successful and has very high performance in solving various engineering optimization problems [76]. In addition, this algorithm has few parameters and can be easily implemented. In the research of Gupta et al. [77], its superiority over similar algorithms was proven. For mathematical modeling of wolf social hierarchy, the most appropriate solution is called α wolf. The second and third best solutions are called β and δ wolves, respectively. The remaining solutions use wolves ω. The grey wolf algorithm comprises the following:

- ➢ First, exploring the search space for prey;
- ➢ Encircling the prey;
- ➢ Attacking the prey.

The following equations are proposed to describe the encirclement behavior:

$$X(t+1) = Xp(t) - A \cdot D \tag{78}$$

$$D = |C \cdot Xp(t) - X(t)| \tag{79}$$

$$A = 2a \cdot r1 - a \tag{80}$$

$$C = 2r2 \tag{81}$$

$$a = 2 - 2\frac{t}{MaxIt} \tag{82}$$

In the above equations:

$X(t)$	position vector of the gray wolf
$Xp(t)$	position vectors of prey
D	distance between the wolf and the prey
A, C	coefficient vectors
r1, r2	random vectors in [0, 1]
a	distance control parameter
t	current iteration
MaxIt	maximum iteration

To mathematically simulate the hunting of these wolves, we assume that alpha (the best candidate solution), beta, and delta are sufficiently aware of the potential hunting situation. We save these three so far and force other searches (omega wolves) to update their position [76]. The pseudo-code of the grey wolf algorithm is given below (Algorithm 2).

Algorithm 2: GWO pseudo-code.

```
Initialize the grey wolf population Greywolves_num_i (I = 1, 2, . . . , n)
Initialize the parameters
Assessment the fitness function of search agents[each wolf)
// The exploring for the prey
// Encircling the prey(start)
Select the best wolf
Select the second-best wolf
Select the third-best wolf
// Encircling the prey(end)
While (It_GWO < Maxit)
    For each wolf 1 in Greywolves_num do
        Update the position of current search
        // Attacking the prey
    End
    Update the parameters
     Assessment the fitness all wolves
    Update the best, second-best-third-best wolf
     It_GWO = It_GWO + 1
  End while
Return the best wolf
```

The alpha, beta, delta, and omega gray wolves mainly search for prey. They search for prey separately, but they attack prey together. In a discrete search space, there is no idea about the optimal location (prey). To mathematically simulate the gray wolf's hunting behavior, it is assumed that in terms of alpha priority (the best solution among the current solutions), it has better information about the hunting place than beta and delta. Therefore, three solutions are saved. Other search agents (including ω) are forced to update their

position according to the position of the best search agent. The following mathematical equations describe these situations:

$$\vec{D\alpha} = |\mathrm{C1}.\, \mathrm{X}\alpha(\mathrm{t}) - X(\mathrm{t})| \tag{83}$$

$$\vec{D\beta} = |\mathrm{C2}.\, \mathrm{X}\beta(\mathrm{t}) - X(\mathrm{t})| \tag{84}$$

$$\vec{D\delta} = |\mathrm{C3}.\, \mathrm{X}\delta(\mathrm{t}) - X(\mathrm{t})| \tag{85}$$

In the above equation, $\vec{D\alpha}$, $\vec{D\beta}$, and $\vec{D\delta}$ represents the distance between the current candidate wolves and the best three wolves.

During the exploration of prey, wolves move away from each other to explore different points of the solution space. For mathematical modeling of this process, A is used with a value greater than 1 to -1. In addition, to model the attack on the prey, the value of A is reduced. The following equations are proposed to describe attacking the prey:

$$\mathrm{X1} = \mathrm{X}\alpha(\mathrm{t}) - A.\vec{D\alpha} \tag{86}$$

$$\mathrm{X2} = \mathrm{X}\beta(\mathrm{t}) - A.\vec{D\beta} \tag{87}$$

$$\mathrm{X3} = \mathrm{X}\delta(\mathrm{t}) - A.\vec{D\delta} \tag{88}$$

$$\mathrm{X}(\mathrm{t}+1) = \frac{\mathrm{X1} + \mathrm{X2} + \mathrm{X3}}{3} \tag{89}$$

where X1, X2, and X3 are the position vectors of the wolves.

4.2.3. Approach of Algorithms

To solve the model in the first echelon, the program is executed considering the number of zones and the heterogeneous nature of eclectic vehicles. For example, for six zones, the program should be run 6 times to route from the waste pickup point to the primary recycling waste collection station in that zone. Each zone has a different waste pickup point and electric vehicles. Uncertainty also applies to some parameters this echelon. In the second echelon, six collection zones are indexed, where a type of vehicle takes the waste to the main recycling center, and routing is done in the second echelon. In addition, uncertainty is not considered at this echelon.

Solution Methods (Decoding and Encoding of Problems)

To maximum optimization of the meta-heuristic algorithm, the answer of each problem should be represented in a way that is understandable for the algorithm. In addition, the display of the solution to the problem should be in a way that covers the maximum number of constraints.

Solution Representation Method with TS Algorithm for the First-Echelon Network

This problem is for each zone in clouding k electric vehicles, which collect recyclable waste from n waste pickup points in the zone. If there is m nodes relating to charge stations, for each zone (that is a separate problem), one array in a length of $n + m + k - 1$ is regarded. This array shows the visiting arrangement of vehicles of waste pickup points. Figure 4 shows small problems for a zone with five waste pickup points, five nodes relating to battery charge stations, and three electric vehicles.

3	**5**	**8**	**10**	**11**	**1**	**2**	**9**	**12**	**4**	**6**	**7**

Figure 4. Example of a solution representation for tabu search.

In this way of representing the problem solution, the number is bigger than the number of the last waste pickup point (e.g., 10) and is operated as a separate construction. Thus, nodes o (e.g., 3, 5, 8, and 10) are visited by the first vehicle, nodes (e.g., 1, 2, and 9) by the second vehicle and nodes (e.g., 4, 6, and 7) by the last vehicle. By this way of representing the problem solution, the hard constraints of problems relating to correct routing construction are estimated. In this way, the route relating to each vehicle is constructed.

A node relating to collecting the recyclable waste is placed at the beginning and end of the route of each vehicle, to complete the route of each vehicle. Then, having the route, each vehicle can calculate the arrival time to each node and the weight load moved by the truck from each node to the next node and the consumption energy of reaching each node and the object function. Thus, the calculated constraints of the problem (constraints in order to calculate one variable like arrival time to a node) also can be calculated by this way of representing the problem solution.

In this problem, there are three constraints that cannot be applied with this way of displaying the solutions. These constraints are the loading capacity of vehicles, constraints relating to the maximum vehicle energy, and constraints relating to the capacity of vehicles based on the type of recyclable wastes. In order to apply these three constraints, an improved approach is used.

At the time of a vehicle arriving to a node, each of these three constraints is checked. In the event that the constraint of maximum capacity of vehicle is not satisfied or the type of the recyclable wastes in the node cannot be carried with the vehicle, the waste pickup point by the next vehicle in the array relating to the way of representing the problem solution is allocated. If the constraint relating to the battery charge of the vehicle is not satisfied, the waste pickup point will be transmitted to the next charge station in the arrays relating to the way of representing the problem solutions. It must be noted that if in the path relating to the last vehicle in the array relating to the way of representing the problem solutions these constraints are not placed, the waste pickup point is not omitted from the vehicle route, and some penalty cost will be added to object function.

Solution Representation Method with GWO for First-Echelon Network

This algorithm is continuous; thus it must represent the problem solutions, which are continuous. Thus, we will have the same array as the previous section (e.g., Section 4.2), where instead of integer values, we use values between zero and one. Then, in each execution of an object function, we firstly arrange the array from small to large. Figure 5 shows an example.

0.48	**0.51**	**0.15**	**0.28**	**0.63**	**0.86**	**0.71**	**0.1**	**0.94**	**0.03**	**0.41**	**0.54**

Figure 5. Example of a solution representation for the GWO algorithm.

Arranging this solution, we reach the solution in Figure 6.

10	**8**	**3**	**4**	**11**	**1**	**2**	**12**	**5**	**7**	**6**	**9**

Figure 6. Problem solution after arranging.

Solution Representation Method for the Second-Echelon Network

Representing the second-echelon network solution problem is similar to the first echelon. The difference is that the second echelon has no charge station nodes. Therefore, it is not required to calculate battery charge. Only the arrival time to nodes and the amount of load transported by vehicles are calculated. It also needs to assess the constraint capacity of the vehicle, and if it is not assessed, the problem solution, as mentioned, should be improved.

4.2.4. Parameter Tuning

The purpose of parameter tuning is to choose the best quantity or state for each meta-heuristic algorithm to ensure the algorithm's performance is at an optimization level. Parameter tuning impacts the effectiveness of the algorithm significantly [78]. One of the parameter tunings is the design of experiments (DOE). This technique can determine the optimal level of effective parameters by considering the mutual effect. One of the most common statistical methods for setting parameters is the Taguchi analysis. Using the Taguchi method [79] reduces the number of experiments without affecting the validity of the final results. Each influencing parameter in algorithms is considered in four levels. The main ones are the GWO's parameters (i.e., population size (Greywolves_num), number of iterations (MaxIt)) and TS's parameters (i.e., tabu list (Tabu_lengh), number of iterations (MaxIt_Ts)). Then, with the help of data analysis software (Minitab 18), the number of selected factors and levels for analysis were selected based on the orthogonal standard table. The results of best values of these parameters are illustrated in Table 5. Additionally, Figures 7 and 8 show the values of GWO and TS parameters. The best parameters values of the meta-heuristic algorithms used in this paper are shown in Table 6.

Table 5. Factor levels in the proposed algorithms.

Level	The Algorithm GWO		The Algorithm TS	
	Greywolves_Num	**MaxIt**	**MaxIt_Ts**	**Tabu_Length**
1	10	15	10	0.25
2	30	35	25	0.4
3	50	55	40	0.55
4	70	75	65	0.75
Values selected	70	75	10	0.75

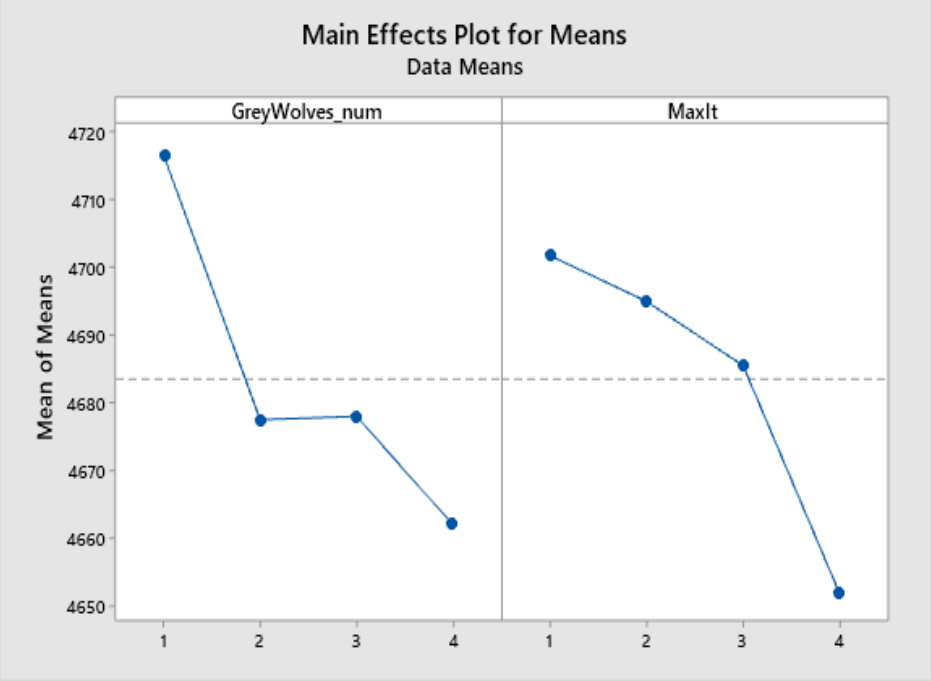


Figure 7. Analysis diagrams of the GWO parameter tuning.

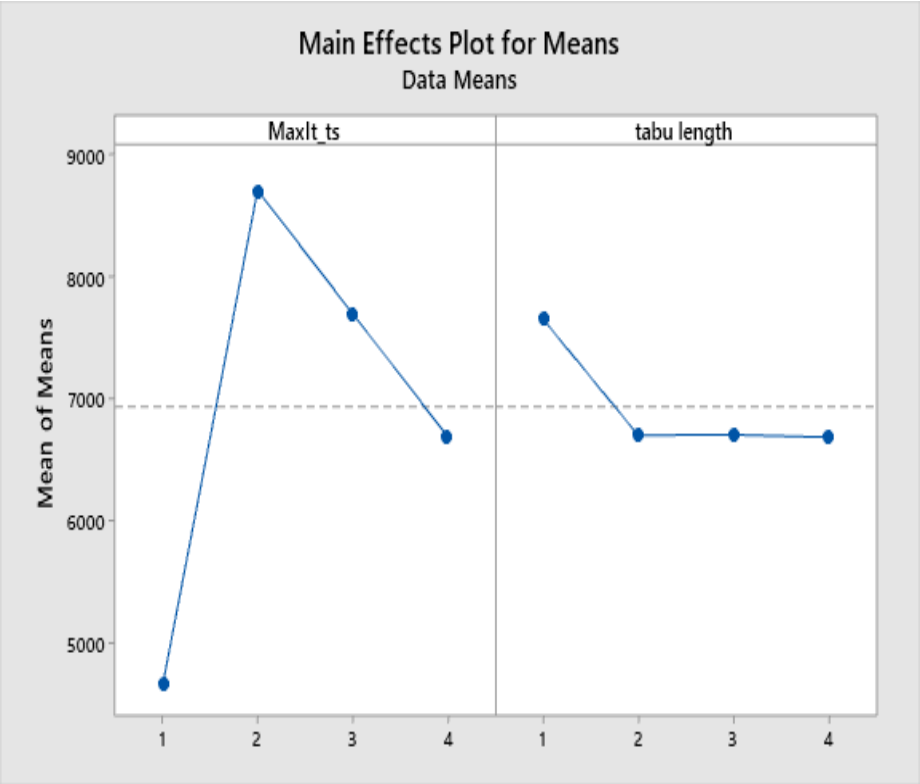


Figure 8. Analysis diagrams of the TS parameter tuning.

Table 6. Parameter setting of the proposed algorithms.

GWO		TS	
Parameter	Value	Parameter	Value
Greywolves_num	70	Tabu_lengh	0.75
MaxIt	75	MaxIt_Ts	10

5. Numerical Results

In this section, the results of different aspects as well as the sensitivity analysis are presented. One of the commonly used benchmarks in VRP problems is the Solomon benchmark. To produce required instances for solving the models of this paper in different sizes in addition to the Solomon benchmark, we used the proposed instances in the literature, with a slight change. Five zones with different waste pickup points in the first echelon is considered to illustrate better proposed methods. Each zone has a collecting station and several battery charging stations. The second echelon uses the previous five zones to transmit recyclable waste from homogeneous conventional vehicles to the main recycling center.

The problem's nodes include waste pickup points, charging stations, and ending and primary recyclable waste-collecting centers. The Solomon benchmark is used for the Euclidean distance between these nodes. The number of charging stations is expressed as an interval ([2 + 0.05C,3 + 0.1C]), and the quantity of recyclable waste for each waste pickup point is randomly generated. The amount of recyclable waste of each class, time windows, and other parameters are shown in Tables 7–10. In Table 11, parameters relating to EVs used in the first echelon are shown. The parameters relating to the second echelon are shown in Table 12.

Table 7. The first-echelon primary data for different instances.

Number of Waste Pickup Points	Number of Small Vehicles	Number of Medium Vehicles	Number of Large Vehicles
5	0	1	1
5	1	1	1
10	1	2	1
10	1	1	2
15	2	1	1
15	2	2	1
25	1	1	1
25	1	1	1
50	1	1	1
50	1	1	1
75	2	2	2
75	2	2	2
100	2	1	1
100	1	2	1

Table 8. Parameters related to the calculation of energy consumption of electric vehicles.

Air Density (kg/m^3)	Gravitational Constant (m/s^2)	Unit Cost of Energy Consumption ($)
1.2041	9.81	4

Table 9. Parameters related to time window and charging.

The Cost of Constructing Each Charging Station (1000$)	Recharge Unit Cost ($)	The Penalty Cost for Violation of the Time Window ($)
25	0.12	20

Table 10. Recyclable waste domain.

Recyclable Waste Amount of Class 1	Recyclable Waste Amount of Class 2	Recyclable Waste Amount of Class 3
[0, 20]	[20, 40]	[40, 70]

Table 11. Parameters relating to EVs used in the first echelon.

Parameter Description	Small Vehicle	Medium Vehicle	Large Vehicle
Cost of the transport unit between the two nodes	0.5	1	1.5
Vehicle speed	1	1	2
Cost of using a vehicle	20	30	50
Load capacity	100	300	500
Vehicle engine efficiency rate	0.7	0.75	0.79
Vehicle curb weight (tons)	3.322	3.629	3.855
Acceleration (m/s^2)	0.011	0.013	0.015
Front surface of vehicles (m^2)	5	8	10
Coefficient of rolling resistance (unitless)	0.01	0.015	0.018
Coefficient of rolling drag (unitless)	0.6	0.7	0.8
Battery capacity (kwh)	20	25	30
Battery recharge rate at the charging station	210	225	250

Table 12. Required parameters of the second-echelon network.

Recyclable Waste Amount	Penalty Cost for Violation of the Time Windows ($)	Load Capacity	Cost of Using a Vehicle	Vehicle Speed	Unit Cost of Energy Consumption	Latest Time to Arrive the Node	Earliest Time to Arrive at the Node	Distance between the Nodes
[0, 70]	20	300	80	30	2.5	[85, 179]	[12, 96]	[0, 20]

5.1. Different Size Instances

The models in each echelon for small instances with 5, 10, and 15 waste pickup points are solved in a deterministic and fuzzy environment by commercial software GAMS (version 25.1.3.) and CPLEX solver. Tables 13 and 14 and Figure 9 show the comparison values.

Table 13. Results in small sizes to solve the model in a deterministic environment.

	Vehicle Used			
Problem	**Large Vehicle**	**Medium Vehicle**	**Small Vehicle**	**Deterministic**
1	1	1	0	4159.65
2	1	1	1	4365.75
3	1	2	1	5122.33
4	2	1	1	5195.15
5	1	1	2	5495.22
6	1	2	2	5845.15

Table 14. Results in small sizes to solve the model in a fuzzy environment.

	Vehicle Used			
Problem	**Large Vehicle**	**Medium Vehicle**	**Small Vehicle**	**Fuzzy**
1	1	1	0	5012.66
2	1	1	1	5294.58
3	1	2	1	6102.47
4	2	1	1	6325.42
5	1	1	2	7215.68
6	1	2	2	8307.18

In Table 13, in problems 4 and 5, the number of large and small vehicles is the same, but the total cost in the deterministic and fuzzy environment is less for problem 4. So, for small-size problems, the use of large vehicles is economical. In addition, from the comparison of Tables 13 and 14, it can be seen that the cost increase in the fuzzy environment is closer to the cost in the real world.

The value of total cost relating to the capacity of vehicles in the deterministic and fuzzy environment is shown in Tables 15 and 16, respectively. Meanwhile, Figure 10 shows this comparison schematically.

Meta-heuristic methods with the proposed algorithms of gray wolf and tabu-search with the help of MATLAB (2018b) software are used to solve the models in both echelons in medium and large sizes. Different samples combining 25, 50, 75, and 100 customers and waste pickup points in five zones with the number of electric and conventional vehicles on two echelons were designed as candidates. Then, the objective function values were calculated with the help of the proposed algorithms. Table 17 presents instances of the number of vehicles used in each zone.

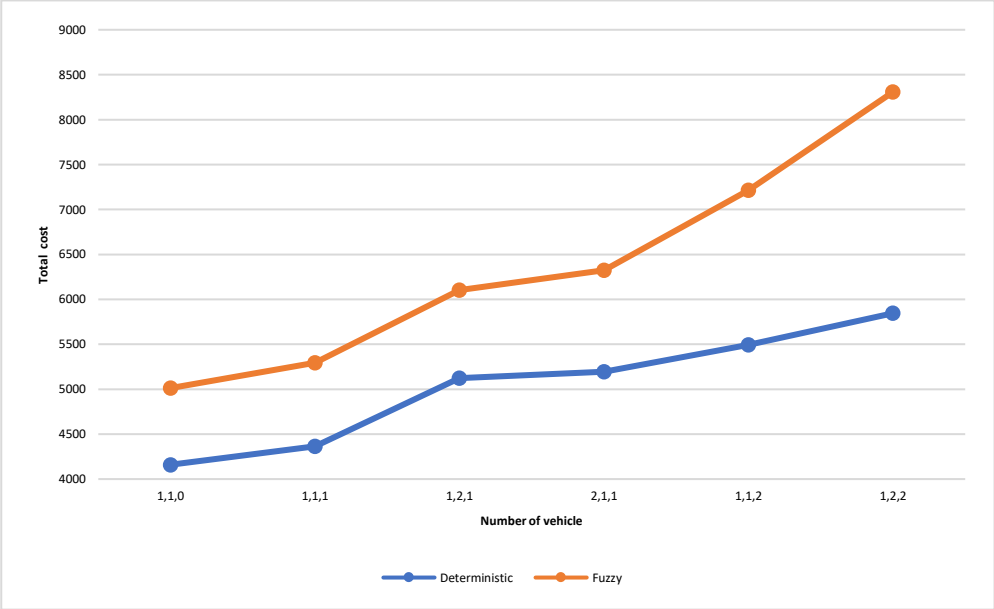


Figure 9. Comparison of results in deterministic and fuzzy environments in small sizes.

Table 15. Total cost values related to the vehicle capacity in the deterministic environment.

Problem	Capacity of Vehicles	Deterministic
1	50	3456.00
2	60	4851.00
3	80	5264.00
4	85	5451.00
5	95	5621.95
6	115	6514.54
7	130	7458.26

Table 16. Total cost values related to the vehicle capacity in the fuzzy environment.

Problem	Capacity of Vehicles	Fuzzy
1	50	4100.56
2	60	5151.25
3	80	5364.45
4	85	6582.39
5	95	6825.13
6	115	7915.41
7	130	8416.44

Table 17. Example of number of vehicles used in each zone.

Zone	Small Vehicle	Medium Vehicle	Large Vehicle
1	0	0	1
2	1	0	1
3	0	1	1
4	1	0	1
5	1	2	1

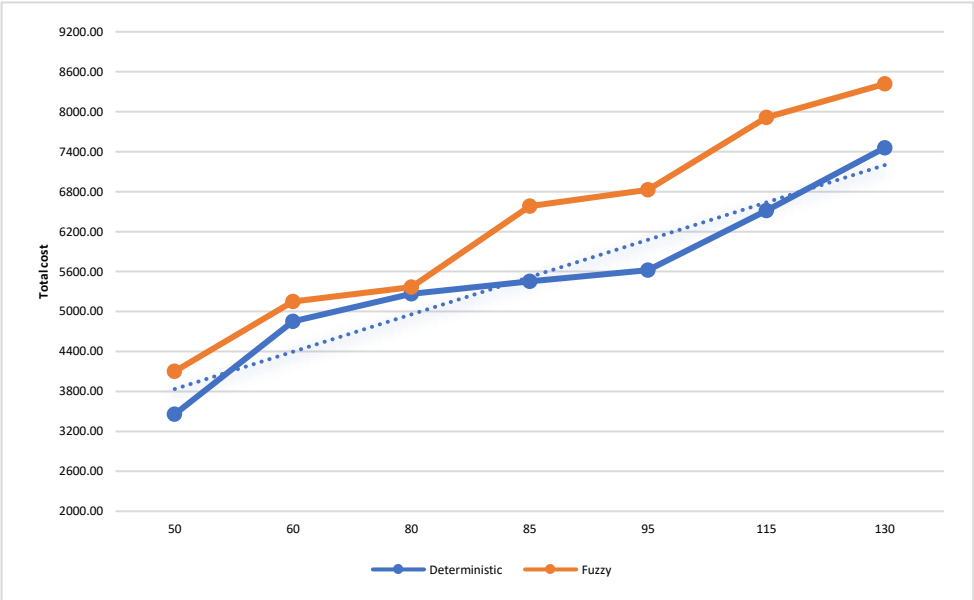


Figure 10. Comparison of the total cost associated with vehicle capacity in a deterministic and fuzzy environment.

In Table 18, the operation of the proposed GWO and TS algorithms shows that the minimum cost related to GWO is obtained in all five zones.

Table 18. Example of total cost calculated with the proposed algorithms in five zones.

Zone	Total Cost (GWO)	Total Cost (TS)
1	448,000	469,855
2	219,727	249,658
3	1,571,059	1,653,230
4	2,306,301	2,631,415
5	1,757,962	1,846,522

5.2. Sensitivity Analysis

In this section, to make more use of managers' decisions from the issues raised, we will discuss the effect of important parameters on the value of the objective function. First, we deal with the relationship between the type of electric vehicle used in different zones of the first echelon and the value of the objective function. Table 19 presents the objective function values in each of the five zones. Figure 11 shows that using one type of vehicle at the first echelon increases the total cost of the network.

Table 19. Objective function values of the types of vehicles in the first-echelon's five zones.

Zone	One Type of Vehicles	Three Types of Vehicles
1	651,911.68	451,599.56
2	558,941.40	193,391.26
3	2,018,662.50	1,580,968.86
4	2,842,020.49	2,309,129.95
5	2,187,199.97	1,740,298.76

We then deal with the relationship between the number of small vehicles and the amount of the objective function. Table 20 and Figure 12 show how much the use of small vehicles is effective in reducing costs.

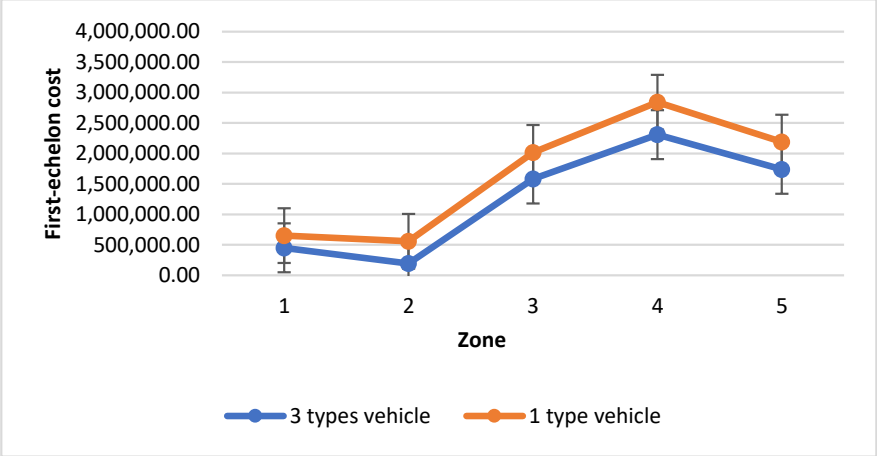


Figure 11. Relationship between one type of vehicle/three types of vehicles and the cost of the first echelon.

Table 20. Relationship between the number of small vehicles and the cost.

Number of Small Vehicles	Vehicle Used			First-Echelon Cost
	Large Vehicle	Medium Vehicle	Small Vehicle	
0	2	1	0	85,317
1	1	1	0	94,250
2	1	1	0	79,558
3	1	1	0	95,992
4	2	0	1	82,408
5	1	1	1	12,739

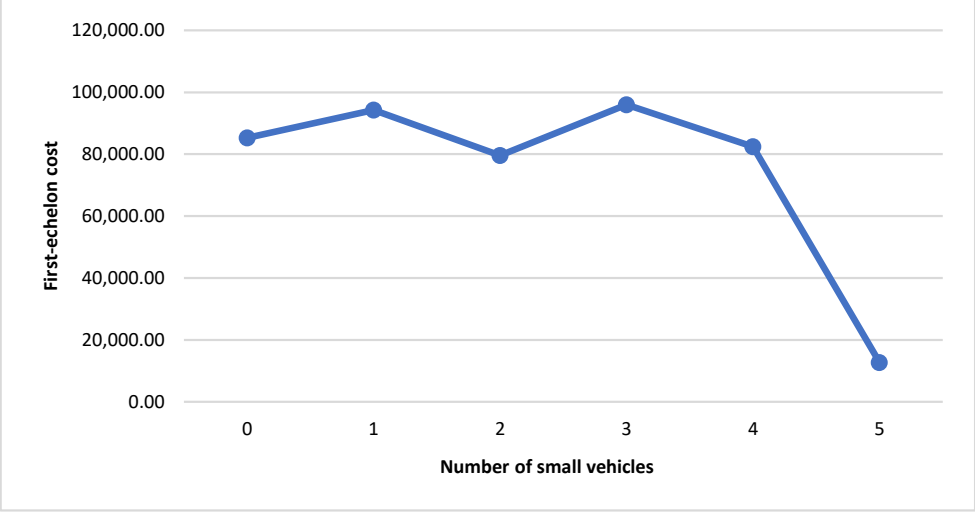


Figure 12. Relationship between the number of small vehicles and the cost of the first echelon.

5.3. Performance of Algorithms

To measure the efficiency of algorithms, we first calculate the value of the objective function of the two echelons with the proposed algorithms (Alg_{Gow}, Alg_{Ts}). The best value obtained from the instance problems ($Best_{sol}$) is then determined. Finally, Equations (90) and (91) are used to compare the performance of algorithms.

$$RPI_{Gow} = \frac{Alg_{Gow} - Best_{sol}}{Best_{sol}} * 100 \quad (90)$$

$$RPI_{Ts} = \frac{Alg_{Ts} - Best_{sol}}{Best_{sol}} * 100 \quad (91)$$

Table 21 shows the performance measurement of the algorithms. Examination of the results shows the superiority of the GWO algorithm.

Table 21. Results in a two-echelon network.

Problem	Alg_{Ts}	Alg_{Gow}	$Best_{sol}$	RPI_{Gow}%	RPI_{Ts}%
1	8144.68	4236.65	4236.65	0.00	92.24
2	4165.41	4987.95	4165.41	19.75	0.00
3	4468.56	8265.85	4468.56	84.98	0.00
4	8154.22	4896.74	4896.74	0.00	66.52
5	4565.74	7236.14	4565.74	58.49	0.00
6	4562.17	5167.52	4562.17	13.27	0.00
7	7268.46	4898.66	4898.66	0.00	48.38
8	7636.54	7821.84	7636.54	2.43	0.00
9	8234.19	4986.15	4986.15	0.00	65.14
10	4985.33	5236.14	4985.33	5.03	0.00

6. Conclusions and Further Research

This paper presents the two-echelon logistics network, including electric vehicles. This paper aims to provide an efficient and environmentally friendly system for collecting recyclable waste. For the method to be more exploitable in developing countries, in the first echelon of this network, recyclable wastes are received from waste pickup points with heterogeneous electric vehicles and taken to stations in different zones. Then, in the second echelon, the waste is transported out of town by conventional vehicles to the recyclable center station. In this paper, the parameters of recyclable waste rate, vehicle speed, vehicle energy consumption, and energy consumption coefficient depending on the vehicle load are considered as a triangular fuzzy number. The models were solved for small size with the exact method. Then, due to the NP-hard nature of the model, it was solved with the help of two proposed meta-heuristic algorithms, GWO and TS. The GWO showed better results. In addition, although the fuzzy results show higher values, they do not bring the problem closer to the real world. This article also emphasizes the economics of using electric vehicles in large cities.

Implementing the second echelon with heterogeneous electric vehicles suggests the creation of a similar network for repair goods and model solutions with other meta-heuristic algorithms for future research.

Author Contributions: Writing—original draft, A.G.; writing—review and editing, M.F., R.T.-M., H.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on reasonable request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Overview of the EVRPs in This Paper

Table A1. Overview of the EVRP variants and features in this paper.

Reference	Objective	Solution Method	Explanation
EVRP			
[29]	Total costs: travel, charging, penalty, and fixed vehicle costs	Hybrid genetic algorithm	Fixed charging time
[4]	Minimize the total time (travel times + charging times)	ALNS	EVRP with non-linear charging and load-dependent discharging
EVRP-TW			
[37]	Minimizes the total distance traveled	VNS/TS	Homogenous EV fleet
[40]	Vehicle number and total routing costs	Branch-price and-cut GENCOL + CPLEX	Four E-VRPTW variants recharge battery
[38]	Minimizes total distance traveled	ALNS	Time windows and partial recharging policy
[42]	Minimizes energy cost + vehicle acquisition cost + driver wage		
ELRP/ELRP-TW			
[36]	Total routing and construction costs	Combines tabu search algorithm and modified Clarke–Wright saving algorithm and SIGALNS	Locations of battery-swapping stations and EVRP
[35]	Total routing and construction costs	AVNS + LS	BSS-EV-LRP
[33]	Total travel and recharging time	ILS (VND) + heuristic concentration	EVRP with a non-linear recharging
[28]	Total distance, number of vehicles, and charge stations used	ALNS/LS	ELRP with time windows and partial recharging
[34]	Minimum cost number and location of battery-swapping stations (BSSs)	Hybrid heuristic composed of a binary PSO algorithm and VNS heuristic	Locations of BSSs, EVRP, and stochastic demands
[30]	Total travel, service, charging and waiting time	Heuristic for FRVCP	EVRP-NL
[31]	Minimize the sum of the fixed opening cost of charge stations and the driver cost	Multi-start ALNS heuristic	Locations of BSS, EVRP, multiple depots, and investment in charging stations
[32]	Minimize a cost function (energy cost, drivers' wages, fixed cost)	VNS	Time-dependent electric vehicle routing, routing electric vehicles to serve a set of customers, and determining the speed
[43]	Minimizes BBS variable cost and shipping cost	Branch-and-price algorithm with an adaptive selection	ELRP, BSS LRP for mix fleet electric vehicles

Note: Reference: referenced paper; TW: time windows; AI: annual income; LNS: large neighborhood search; ALNS: adaptive large neighborhood search; VNS: variable neighborhood search; SA: simulated annealing; CWS: savings method of Clarke and Wright; BSSs: battery swapping stations; BSSC: battery swapping costs at the battery swapping stations; HG+LNS: hybrid genetic algorithm with LNS algorithm; BL: Bellman–Ford algorithm (linear programming solver); TS: tabu search.

Appendix B. Other Equations for Fuzzy Model Calculation Formulas

$$EV\left(\widetilde{\Phi}_{ijk}\right) = \frac{\Phi_{1i0k} + 2\Phi_{2i0k} + \Phi_{3i0k}}{4} \tag{A1}$$

$$EV\left(\widetilde{\Theta}_{ijk}\right) = \frac{\Theta_{1i0k} + 2\Theta_{2i0k} + \Theta_{3i0k}}{4} \tag{A2}$$

$$E_1\left(\widetilde{\Phi}_{ijk}\right) = \frac{\Phi_{1i0k} + \Phi_{2i0k}}{2} \tag{A3}$$

$$E_1\left(\widetilde{\Theta}_{ijk}\right) = \frac{\Theta_{1i0k} + \Theta_{2i0k}}{2} \tag{A4}$$

$$E_2\left(\widetilde{\Phi}_{ijk}\right) = \frac{\Phi_{2i0k} + \Phi_{3i0k}}{2} \tag{A5}$$

$$E_2\left(\widetilde{\Theta}_{ijk}\right) = \frac{\Theta_{2i0k} + \Theta_{3i0k}}{2} \tag{A6}$$

$$E_1(q_{i1} + q_{i2} + q_{i3}) = \frac{q_{1i1} + q_{2i1}}{2} + \frac{q_{1i2} + q_{2i2}}{2} + \frac{q_{1i3} + q_{2i3}}{2} \tag{A7}$$

$$E_2(q_{i1} + q_{i2} + q_{i3}) = \frac{q_{2i1} + q_{3i1}}{2} + \frac{q_{2i2} + q_{3i2}}{2} + \frac{q_{2i3} + q_{3i3}}{2} \tag{A8}$$

$$EV(q_{j2} + q_{j3}) = \frac{1}{2}\left[\frac{q_{1i2} + q_{2i2}}{2} + \frac{q_{1i3} + q_{2i3}}{2} + \frac{q_{2i2} + q_{3i2}}{2} + \frac{q_{2i3} + q_{3i3}}{2}\right] \tag{A9}$$

$$EV(q_{j3}) = \frac{q_{1i3} + q_{2i3}}{2} + \frac{q_{2i3} + q_{3i3}}{2} \tag{A10}$$

$$E_1\left(\frac{d_{ij}}{v_g}\right) = \frac{d_{ij}}{2(v_{2g} + v_{3g})} \tag{A11}$$

$$E_2\left(\frac{d_{ij}}{v_g}\right) = \frac{d_{ij}}{2(v_{1g} + v_{2g})} \tag{A12}$$

$$EV\left(\frac{d_{ij}}{v_g}\right) = \frac{1}{2}\left[\frac{d_{ij}}{2(v_{2g} + v_{3g})} + \frac{d_{ij}}{2(v_{1g} + v_{2g})}\right] \tag{A13}$$

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