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Electric Vehicle Routing Problem with Battery Swapping Stations in a Multi-Echelon Distribution Network

Ergül KISA TOĞRUL[1]

Abstract

Increasing environmental considerations force the logistics sector to develop more environmentally friendly approaches. Thus, the concept of "green logistics" is becoming more crucial. The use of electric vehicles, which become prominent with their low energy consumption, less cost and environmentally friendly features, is a part of green logistics. Moreover, taking into consideration of multi-echelon distribution networks can also be effective in reducing the negative outcomes of urban logistics. In this context, the Two-Echelon Electric Vehicle Routing Problem with Battery Swapping Station (2E-E-VRP-BSS) is considered in this study. A Mixed Integer Programming (MIP) model is presented for the problem in which the total cost consisting of fixed cost, transportation cost, battery swapping cost and handling cost is minimized. To test the validity of the model, three different data sets, each of different sizes, simulating a realistic distribution network were created. In addition, sensitivity analyses were carried out in order to examine the impact of changes in customer demand and battery capacities of electric vehicles on optimal solutions. The analyses indicate the applicability of the model. The findings suggest that fluctuations in customer demand directly impact the total cost, with higher demand leading to increased costs and lower demand resulting in cost reductions compared to the base case scenario. Furthermore, there is a negative correlation between the battery capacity of electric vehicles and the total cost, meaning that as battery capacity increases, the overall cost tends to decrease.

Keywords: Green Logistics, Sustainability, Multi-Echelon Distribution Network, Electric Vehicles, Two-Echelon Electric Vehicle Routing Problem.

1. R.A., Hitit University, ergultogrul@hitit.edu.tr, https://orcid.org/0000-0002-7755-5173

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1. INTRODUCTION

Global warming, air pollution, traffic accidents, noise, and other factors worldwide are causing environmental and social concerns. To address these issues and meet the demand for energy sources, there is a necessity to develop sustainable solutions in the transportation sector. Sustainable transportation requires the development of environmentally friendly, economical, and socially compatible systems. In this context, the concept of "Green Logistics" has been introduced with the aim of increasing the transportation sustainability by taking into account social and environmental concerns. Using electric vehicles instead of fossil fuel-based vehicles constitutes a considerable area of these green logistics efforts (Jie et al., 2019).

Electric vehicles, which stand out as an environmentally friendly option, have found their place not only in individual preferences but also in the transportation sector, with many logistics companies starting to use electric vehicles in their operations (Pelletier et al., 2016; Qin et al., 2021). The environmental advantages of electric vehicles, such as zero greenhouse gas emissions, reduced noise, and increased energy efficiency, might contribute logistics companies obtain a green image and even qualify for subsidies for environmental protection (Wang & Zhou, 2021). While past charging technologies for electric vehicles required several hours for a full charge, advancements in fast charging or battery swapping stations now enable energy replenishment within a very short time (Breunig et al., 2019). All processes related to replacing an almost exhausted battery with a fully charged battery can take under 10 minutes, which can be faster than charging the battery (Kim, 2011, as cited in Jie et al., 2019). Compared to charging stations, battery swapping stations can provide a faster solution by significantly reducing waiting times for charging, allowing vehicles to travel longer distances more efficiently and enabling more flexible route planning. In some cases, the battery swapping option can be more cost-effective than investing in charging infrastructure. It is particularly beneficial in rural areas where power grids and charging stations are insufficient, ensuring uninterrupted vehicle operations. Moreover, charging multiple electric vehicles simultaneously can place considerable strain on the energy grid. Battery swapping helps alleviate this issue by allowing depleted batteries to be recharged during off-peak hours, thereby reducing grid stress. Integrating battery swapping stations into routing problems is crucial for ensuring continuous and faster operations, lowering costs, improving customer satisfaction and significant competitive advantage. Therefore, this approach is an important and promising solution for logistics companies that have or aim to acquire electric vehicles in their fleets (Li, 2014).

One of the solutions developed to reduce/eliminate the social and environmental negative impacts of urban logistics is the use of two-echelon (multi-echelon) distribution networks. In such distribution systems, instead of delivering products directly from warehouses to customers, products are first delivered to satellites located outside the city center (the first echelon), and then from the satellites to customers (the second echelon). While large trucks are used in the first echelon of distribution, relatively more environmentally friendly and smaller vehicles are preferred in the second echelon. This prevents the entry of large trucks into city centers and aims to solve some of the problems created by urban logistics, such as noise, traffic congestion, and environmental pollution (Li et al., 2018; Zhou et al., 2018). The Two-Echelon Vehicle Routing Problem (2E-VRP) is a type of problem aimed at determining vehicle routes that minimize objective functions such as total time, total distance, total fuel consumption, etc., for delivering products to customers in two-echelon distribution networks.

2E-VRP, compared to the Vehicle Routing Problem (VRP) referring to single-echelon distribution networks, is a more recent and therefore less researched area. The problem, when electric vehicles are utilised instead of fossil fuel-based vehicles in one or both echelons of distribution, is referred to as Two-Echelon Electric Vehicle Routing Problem (2E-E-VRP). Due to the limited driving range of electric vehicles depending on the capacities of their batteries, they need to be charged on the road or have their batteries replaced. This may require planned visits to charging stations or battery swapping stations, making the problem more challenging (Breunig et al., 2019; Goli et al., 2022; Wu & Zhang, 2023).

Studies focusing on VRPs have generally centered around traditional vehicles, with only a limited number of studies aiming to investigate routing problems for electric vehicles. Therefore, routing electric vehicles still require more attention and research (Agardi et al., 2019). Furthermore, although the number of studies on 2E-VRP is increasing, only a small part of them consider electric vehicles. In this context, this study was conducted with the motivation to address the challenges brought about by using of electric vehicles in routing problems and to contribute to the gap in the relevant literature. In the problem referred to as 2E-E-VRP-BSS, traditional vehicles are used in the first echelon, whereas electric vehicles with relatively lower load-carrying capacity and limited driving range are used in the second echelon. Thus, the distribution network includes a central warehouse, satellites, customers, and battery swapping stations. The objective of the problem is to set optimal routes for primary and secondary echelon vehicles to minimize the total cost, which consists of fixed costs of vehicles, transportation costs, battery swapping costs for electric vehicles, and handling costs at satellites. Sensitivity analyses were conducted in the research to examine the effects of changes in customer demand levels and battery capacities of electric vehicles on optimal solutions.

The contributions of this study are threefold: (1) We propose a 2E-E-VRP-BSS model that integrates battery swapping stations into a two-echelon logistics system, a relatively underexplored area in the literature. (2) We conduct extensive sensitivity analyses to assess the impact of key parameters such as customer demand fluctuations and battery capacity variations on cost efficiency. (3) We validate the model with realistic datasets and provide practical insights for logistics operators on optimal vehicle routing and BSS placement. By addressing these aspects, the study offers a structured framework for improving the efficiency of green logistics operations.

The study consists of six sections. The second section gives information about relevant studies from the literature. The problem definition and mathematical model are presented in the third section. The details of the application are conveyed in the fourth section titled "Application Design". Findings from the study are mentioned in the fifth section, and conclusions are given in the final section.

2. LITERATURE

Vehicle routing optimization is a heavily researched field that has been the subject of many studies in various sectors such as manufacturing and transportation (Agardi et al., 2019). Over time, various authors have studied new variants of the basic capacitated VRP by making changes to some of its assumptions. These variants include the multi-depot VRP, heterogeneous VRP, VRP with time-windows, periodic VRP, electric VRP (E-VRP), and 2E-VRP.

This study involves the intersection of two fundamental areas of VRPs – namely, 2E-VRP and E-VRP. In this context, particular emphasis will be placed on studies focusing on 2E-E-VRP.

2E-VRP studies, which represent a specialized form of multi-echelon distribution networks where products flow from a central warehouse to satellites and then to customers instead of directly from the central depot to customers, are increasingly gaining attention. 2E-VRP is a problem type addressed to solve some of the problems created by urban logistics, such as noise, traffic congestion, and environmental pollution. Distribution is carried out using large vehicles in the first echelon, while relatively smaller/environmentally friendly vehicles are used in the second echelon (Cuda et al., 2015; Soysal et al., 2015).

Two-echelon distribution networks, resulting from the interaction between the two tiers of the logistics network, involve more complex planning models and require coordination and synchronization of vehicle fleets and operations compared to single-echelon networks (Crainic & Sgalambro, 2014). Various exact solution methods and/or heuristic/metaheuristic algorithms have been presented for solving the 2E-VRP. From exact solution methods, one can observe studies utilizing dynamic programming (Baldacci et al., 2013; Wang et al., 2020), branch and cut algorithm (Jepsen et al., 2013; Perboli et al., 2009; Perboli et al., 2018; Wei et al., 2020), branch and price algorithm (Santos et al., 2013), logical constraint programming (Sitek & Wikarek, 2014), and various mathematical models (Babaee Tirkolaee et al., 2019; Babagolzadeh et al., 2019; Soysal et al., 2015). On the other hand, because of the NP-hardness of the problem (Belgin et al., 2018; Soysal et al., 2015; Wang et al., 2017), there are studies focusing on providing solutions through heuristic and/or metaheuristic algorithms such as fast clustering heuristic (Crainic et al., 2012), multi-start heuristic (Crainic et al., 2011), adaptive large neighborhood search heuristic (Grangier et al., 2016; Hemmelmayr et al., 2012; Zhou et al., 2024), island-based memetic algorithm (Bevilaqua et al., 2019), ant colony optimization algorithm (Meihua et al., 2011), and others. Cuda et al. (2015) and Sluijk et al. (2023) have conducted detailed examinations on 2E-VRP in their studies.

With increasing environmental awareness, there has been a shift towards using vehicles that operate with alternative fuels such as natural gas and biodiesel, which cause relatively lower greenhouse gas emissions in comparison of traditional fossil fuel-consuming vehicles. Additionally, the use of electric vehicles has become more widespread since the mid-2000s. As electric vehicles gradually integrate into distribution activities, E-VRP has emerged (Koç & Özceylan, 2018). The literature on E-VRP has been extensively examined by Pelletier et al. (2016), Erdelic and Caric (2019), Kucukoğlu et al. (2021), and Qin et al. (2021).

While there are numerous studies on the VRP and its versions in the literature, research specifically focusing on the 2E-E-VRP is quite limited. Agardi et al. (2019) analyzed the 2E-E-VRP in a distribution network comprising a central depot, satellites, customers, and charging stations for electric vehicles. They employed constructive and improvement heuristics to generate solutions, considering electric vehicles only in the second echelon. Breunig et al. (2019) proposed both exact mathematical programming and metaheuristic algorithms based on large neighborhood search to minimize the total cost. They conducted tests with various types of instances to analyze the performance of the recommended algorithms and concluded that the approach was beneficial. Jie et al. (2019) addressed electric vehicles with battery driving ranges, battery swapping costs, power consumption rates and varying load capacities. The authors recommended a hybrid algorithm incorporating an integer programming model and column generation with adaptive large neighborhood search in their study. Additionally, sensitivity analysis was conducted to investigate the interaction between battery driving range and vehicle emissions. Another study conducted by Wang et al. (2019) involved the delivery of products to customers using electric vehicles in a two-echelon distribution network. Considering time windows, the study aimed to minimize total costs encompassing transportation, handling, battery swapping, fixed, and penalty costs. Numerical experiments were conducted with randomly generated 14 instances to assess the effectiveness of the developed mixed integer linear programming (MILP) model. Li et al. (2020) focused on satellites located on streets in a two-echelon urban logistics system. They employed time windows and satellite transfer constraints to regulate interaction between the two echelons. Additionally, an economic analysis was performed on the difference between diesel and electric vehicles. In the study by Wang and Zhou (2021), the time-windows and battery replacement station-based 2E-E-VRP problem was addressed. Conventional vehicles were used in the first echelon of the distribution network, while electric vehicles were employed in the second echelon. They proposed a MILP model to minimize the total cost comprised of transportation costs for both echelon, fixed costs, handling costs at satellites, and battery swapping costs for electric vehicles. Additionally, they developed a metaheuristic procedure based upon the large neighborhood search algorithm to generate solutions for large instances. In another study by Akbay et al. (2022), focusing on a two-echelon distribution network where electric vehicles were used in the second echelon and considering time windows for customer deliveries, a MILP model was introduced to solve the problem. They proposed a constructive heuristic algorithm based on the Clarke and Wright savings algorithm for solution generation. In the study by Goli et al. (2022), they developed the MILP model and improved moth-flame optimization algorithm for solving the problem where electric vehicles were routed in both echelons. They found that the algorithm had an approximate error of about 1.2% for small and medium-sized problems. Sensitivity analyses were made to observe the impact of changes in demand and time window parameters. In the study by Wu and Zhang (2023), where conventional vehicles were routed in the first-tier and electric vehicles in the second-tier, a column-generation algorithm was presented for solving the problem. The effectiveness of the algorithm was demonstrated using small and medium-sized examples. The study investigated the effect of the density of charging stations, battery capacity, and fixed costs of electric vehicles on the optimal solution. An overview on 2E-E-VRP is provided in Table 1, summarizing the type of problem addressed, solution method, objective function, and assumptions included in the studies.

Table 1. Studies on 2E-E-VRP

Author(s)	Acronym of Problem Studied	Acronym of Solution Method	Objective Function (Minimization)	Assumption Numbers
Agardi et al. (2019)	2E-VRP-RS	NNA, AIA HCA, GA	Route length	3, 4, 6
Breunig et al. (2019)	E-2E-VRP	MPA LNS	Total cost (fixed and travel costs)	3, 4, 6, 7, 8
Jie et al. (2019)	2E-CEVRP-BSS	IP, CGA ALNSA	Total cost (travel, handling and battery swapping costs)	2, 3, 5, 6, 7, 9
Wang et al. (2019)	2E-EVRP-TW-BSS	MILP	Total cost (travel, handling, battery swapping, fixed and penalty costs)	1, 3, 5, 6, 7
Li et al. (2020)	2E-CLS-OS	MILP VNSA SA	Total time (running times of vehicles and waiting times at customers) Total fuel consumption	1, 3, 6
Wang and Zhou (2021)	2E-EVRP-TW-BSS	MIP VNSA	Total cost (travel, fixed, handling and battery swapping costs)	1, 3, 5, 6, 7
Akbay et al. (2022)	2E-EVRP-TW	MILP, SA VNSA	Total distance	1, 3, 4, 6, 7
Goli et al. (2022)	E-2E-VRP	MILP IMFOA	Total cost (travel, handling and battery swapping costs)	1, 2, 3, 4, 6, 7
Wu and Zhang (2023)	E-2E-VRP	BPA, CGA LA	Total cost (fixed and travel costs)	3, 4, 6, 8
This study	2E-E-VRP-BSS	MIP	Total cost (fixed, travel, handling and battery swapping cost)	3, 5, 6, 7

***2E-VRP-RS:** Two-Echelon Vehicle Routing Problem with Recharge Stations, **E-2E-VRP:** Electric Two-Echelon Vehicle Routing Problem, **2E-CEVRP-BSS:** Two-Echelon Capacitated Electric Vehicle Routing Problem with Battery Swapping Stations, **2E-EVRP-TW-BSS:** Two-Echelon Electric Vehicle Routing Problem with Time Windows and Battery Swapping Stations**, 2E-CLS-OS:** Two-Echelon City Logistics System with On-Street Satellites, **2E-EVRP-TW:** Two-Echelon Electric Vehicle Routing Problem with Time-Windows, **NNA:** The Nearest Neighbor Algorithm, **AIA:** Arbitrary Insertion Algorithm, **HCA:** Hill Climbing Algorithm, **GA:** Genetic Algorithm, **MPA:** Mathematical Programming Algorithm, **LNS:** Large Neighborhood Search, **IP:** Integer Programming, **CGA:** Column Generation Algorithm, **ALNSA:** Adaptive Large Neighborhood Search Algorithm, **MILP:** Mixed Integer Linear Programming, **VNSA:** Variable Neighborhood Search Algorithm, **SA:** Savings Algorithm, **MIP:** Mixed Integer Programming, **IMFOA:** Improved Moth-Flame Optimization Algorithm, **BPA:** Branch-and-Price Algorithm, **LA:** Labeling Algorithm, **1:** Time windows are present, **2:** Electric vehicles are used in the first echelon, **3:** Electric vehicles are used in the second echelon, **4:** Electric vehicles are charged, **5:** Batteries of electric vehicles are swapped, **6:** Electric vehicles have limited driving range, **7:** Charging or battery swapping facilities are available at depots and/or satellites, **8:** Sequential visits to charging stations are prevented, **9:** Primary and secondary echelon vehicles can use the same stations.

As mentioned before, the number of studies on 2E-E-VRP is quite limited. When Table 1 is examined, it is seen that the studies generally adopt heuristic or metaheuristic solution approaches. It is observed that almost all of the studies that address the exact solution method use the mixed integer linear programming model. Various objective functions are taken into account in the studies, but they generally focus on total cost minimization. These studies were built upon various assumptions, including the presence of time windows, the driving range limitations of electric vehicles, and the necessity for charging or battery replacement at specific intervals to ensure operational feasibility. Some studies assume that electric vehicles are used exclusively in the second echelon, while others consider their use in both echelons. Additionally, while some studies focus on charging electric vehicles, others incorporate battery swapping as an energy replenishment method. Despite the growing interest in electric vehicle routing problems in two-echelon distribution network, only three studies have incorporated the battery replacement approach. This indicates a significant research gap that requires further exploration to fully understand the implications of battery swapping on cost efficiency, route optimization and overall logistics performance. From this point of view, in addition to proposing a methodological framework, this research was undertaken to focus on a deeper understanding of the challenges associated with integrating the battery swapping approach of electric vehicles into multi-echelon logistics networks. By exploring how key factors such as customer demand fluctuations and battery capacity variations influence routing decisions and cost structures, we offer a more comprehensive perspective on the efficiency drivers in electric vehicle-based distribution networks. Moreover, this study bridges the gap between theory and practice by validating the model with realistic datasets in Turkey, ensuring that the findings reflect real-world operational conditions. Through this in-depth analysis, we not only highlight the critical constraints and trade-offs in electric vehicle routing but also provide valuable insights for optimizing sustainable logistics strategies.

3. 2E-E-VRP-BSS DEFINITION AND MODEL FORMULATION

The problem definition and MIP model for 2E-E-VRP-BSS are presented in this section of the study.

3.1. Problem Definition

In the problem considered in the study, product deliveries are made from a central depot to a set of customers through a certain number of satellites. In the distribution network consisting of two echelons, in the first echelon, deliveries are made from the central depot to the satellites; in the other echelon, deliveries are made from the satellites to the customers. While travels between satellites are allowed in the first echelon, they are prevented in the second echelon. In the problem given on a complete network G (V,A), there is one central depot ($V_0 = 0$), a certain number of satellites ($V_U=\{1,2,\ldots,u\}$), customers ($V_M=\{1,2,\ldots,m\}$) and battery swapping stations ($V_B=\{1,2,\ldots,b\}$). A_1 and A_2 respectively denote the sets of arcs for the first and second echelons ($A_1=\{(i, j) \mid i, j \in V_0 \cup V_U , i \neq$

j}, A_2={(i, j) | i, j ϵ V_U U V_M U V_B , i ≠ j} \ A_2' , A_2' = {(i, j) | i, j ϵ V_U} U {(i, j) | i, j ϵ V_B}). In the first echelon of distribution, conventional vehicles start their route from the depot, visit one or more satellites, and then return back to the depot. In the second echelon, electric vehicle travelling starts from a satellite, may stop at a battery swapping station if necessary, visit one or more customers, and then return back to the same satellite. In the first echelon of distribution, multiple vehicles can visit a single satellite, but a vehicle cannot visit the same satellite more than once. In the second echelon, each customer is prevented from being visited by multiple vehicles. K^1={1,2,…,k^1} and K^2={1,2,…,k^2} define the sets, E^1 and E^2 denote the capacities, while f^1 and f^2 represent the fixed costs of first and second echelon vehicles, respectively. Satellite capacities are expressed by the number of vehicles that can be directed from there, and k_u^2 symbolizes the maximum number of second echelon vehicles that can be used at each satellite. Handling costs arise from unloading products from first echelon vehicles at the satellites and loading them onto second echelon vehicles. In this context, h_u represents the unit handling cost at satellite u. The customer demand quantities, denoted by t_i, are deterministic and known in advance.

$d_{i\,j}$ represents the distance between nodes i and j. $c_{i\,j}^1$ and $c_{i\,j}^2$ are the travel costs for primary and second echelon vehicles, respectively. r^2 denotes the charge consumption rate of the electric vehicle in the second echelon. It is assumed that travel costs and charge consumption rate are linear functions of distance (α, β, θ >0, $c_{i\,j}^1$=α.$d_{i\,j}$ (i, j) ϵ A_1, $c_{i\,j}^2$=β.$d_{i\,j}$ (i, j) ϵ A_2, $r_{i\,j}^2$=θ.$d_{i\,j}$ (i, j) ϵ A_2). s^2 represents the battery swapping cost for the electric vehicles, while W^2denotes the battery capacity.

It is assumed that the electric vehicles' battery is fully charged whenever they visit any satellite or battery swapping station. Sequential visits to battery swapping stations are prohibited. Each satellite and battery swapping station in the distribution network do not have to be utilized.

To assist the reader, all the notations used in the problem are demonstrated in Table 2. The distribution network example of 2E-E-VRP-BSS is illustrated in Figure 1.

Figure 1 represents the central depot as a square, satellites as hexagons, customers as circles, and battery swapping stations as triangles. Additionally, the numbers on the arcs indicate the distance between two nodes, while the numbers on the vehicle indicate the driving range (battery capacity) when departing from the respective node. In the first echelon, load distribution is carried out from the central depot to the satellites. In the second echelon, distribution is directed from the satellites to the customers for delivery. During the second echelon of distribution, the vehicle serving customers 6, 7, and 8 departs from the satellite with a fully charged battery (driving range = 65,000 m). The vehicle first delivers products to customer 6. Upon departing from this customer, the battery capacity is reduced to 45,000 m (65,000 - 20,000, θ=1). Since the battery would not be sufficient, the vehicle visits customer 7 and then stops at a battery swapping station, where a battery replacement is performed. After leaving the station with a fully charged battery, the vehicle continues its route, delivers products to customer 8, and then returns to the satellite point where it started, completing its route.

Figure 1. An Example of 2E-E-VRP-BSS Distribution Network

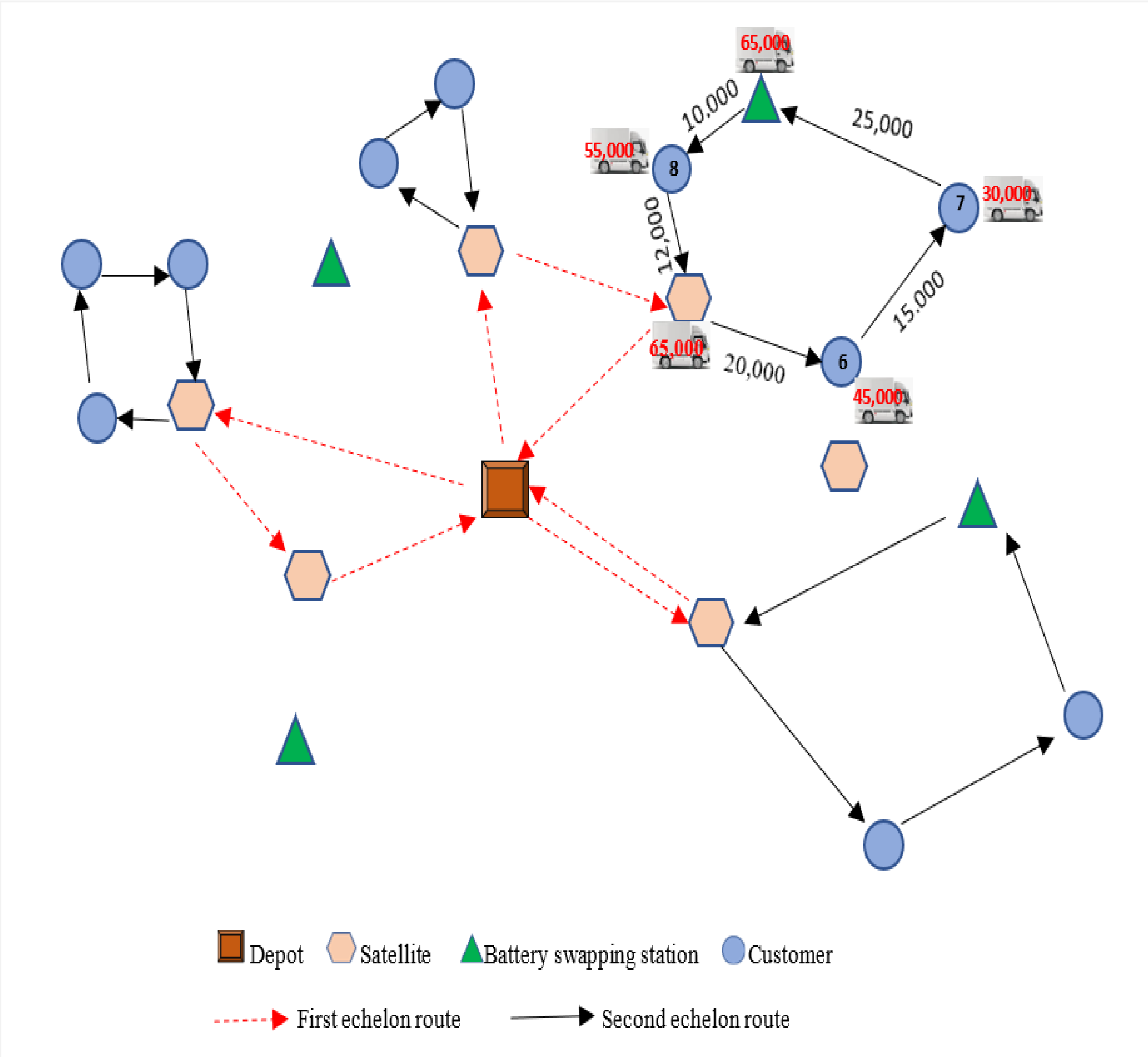


Table 2. Sets, Parameters and Decision Variables in the 2E-E-VRP-BSS Model

Group	Symbol	Definition
Sets	V_0	Depot, $V_0=\{0\}$
	V_U	Sets of satellites, $V_U=\{1,2,\ldots,u\}$
	V_M	Sets of customers, $V_M=\{1,2,\ldots,m\}$
	V_B	Sets of battery swapping stations, $V_B=\{1,2,\ldots,b\}$
	V_1	$V_0 \cup V_U$
	V_2	$V_U \cup V_B \cup V_M$
	A_1	Sets of the first echelon arcs, $A_1=\{(i,j) \mid i,j \in V_0 \cup V_U, i \neq j\}$
	A_2	Sets of the second echelon arcs, $A_2=\{(i,j) \mid i,j \in V_U \cup V_M \cup V_B, i \neq j\} \setminus A_2'$, $A_2' = \{(i,j) \mid i,j \in V_U\} \cup \{(i,j) \mid i,j \in V_B\}$
	K^1	Sets of the first echelon vehicles, $K^1=\{1,2,\ldots,k^1\}$
	K^2	Sets of the second echelon vehicles, $K^2=\{1,2,\ldots,k^2\}$

(Table 2 cont.)

Group	Symbol	Definition
Parameters	k^1	Number of first echelon vehicles
	k^2	Number of second echelon vehicles
	k^2_u	Maximum number of second echelon vehicles that can be routed at the satellite u, $u \in V_U$
	h_u	Unit handling cost at satellite u, $u \in V_U$
	E^1	Vehicle capacity of first echelon vehicles
	E^2	Vehicle capacity of second echelon vehicles
	f^1	Fixed cost of first echelon vehicles
	f^2	Fixed cost of second echelon vehicles
	t_i	Demand of customer i, $i \in V_M$
	c^1_{ij}	Transportation cost of first echelon vehicle travels on arc (i, j), $(i, j) \in A_1$
	c^2_{ij}	Transportation cost of second echelon vehicle travels on arc (i, j), $(i, j) \in A_2$
	d_{ij}	Distance of arc (i, j)
	r^2_{ij}	Charge consumption rate of electric vehicles on arc (i, j)
	s^2	Battery swapping cost of electric vehicles
	W^2	Battery capacity of electric vehicles
Decision Variables	x_{ijk}	Binary decision variable that takes a value of 1 if vehicle k travels from i to j, and 0 otherwise, $(i, j) \in A_1, k \in K^1$
	v_{uk}	Amount of cargo transported to satellite u by vehicle k, $u \in V_U, k \in K^1$
	z^1_{ijk}	The load on vehicle k when departing from node i, $(i, j) \in A_1, k \in K^1$
	y_{ijuk}	Binary decision variable that takes a value of 1 if vehicle k dispatched from satellite u travels from node i to j, and 0 otherwise, $(i, j) \in A_2, u \in V_U, k \in K^2$
	q_u	The total demand transported from satellite u, $u \in V_U$
	z^2_{ijuk}	The load on vehicle k when departing from node i directed from satellite u, $(i, j) \in A_2, u \in V_U, k \in K^2$
	p^{2+}_{iuk}	The residual battery power when the vehicle k directed from satellite u arrives at node i in the second echelon
	p^{2-}_{iuk}	The residual battery power when the vehicle k directed from satellite u departs from node i in the second echelon

3.2. Mathematical Model

The 2E-E-VRP-BSS model inspired by the studies of Jepsen et al. (2013), Jie et al. (2019), and Wang et al. (2019) is presented below.

$$\text{Min} \sum_{k \in K^1} \sum_{(i,j) \in A_1} c^1_{ij} x_{ijk} + \sum_{k \in K^2} \sum_{u \in V_U} \sum_{(i,j) \in A_2} c^2_{ij} y_{ijuk} + \sum_{k \in K^1} \sum_{j \in V_U} f^1 x_{0jk} + \sum_{k \in K^2} \sum_{u \in V_U} \sum_{(u,j) \in A_2} f^2 y_{ujuk} + \sum_{k \in K^2} \sum_{u \in V_U} \sum_{i \in V_B} \sum_{j \in V_u \cup V_M} s^2 y_{ijuk} + \sum_{u \in V_U} h_u q_u \qquad (1)$$

subject to

$$\sum_{(i,j) \in A_1} x_{ijk} = \sum_{(i,j) \in A_1} x_{jik} \qquad \forall\, i \in V_1,\ k \in K^1 \qquad (2)$$

$$\sum_{(i,j) \in A_1} x_{ijk} \leq 1 \qquad \forall\, j \in V_0 \cup V_U,\ k \in K^1 \qquad (3)$$

$$v_{ik} = \sum_{(i,j)\in A_1} z^1_{jik} - \sum_{(i,j)\in A_1} z^1_{ijk} \qquad \forall\, i \in V_U,\, k\in K^1 \qquad (4)$$

$$z^1_{ijk} \le E^1 x_{ijk} \qquad \forall\, (i,j)\in A_1,\, k\in K^1 \qquad (5)$$

$$\sum_{(i,j)\in A_1} z^1_{ijk} \le 0 \qquad \forall\, j\in V_0,\, k\in K^1 \qquad (6)$$

$$\sum_{k\in K^1} v_{ik} = q_i \qquad \forall\, i\in V_U \qquad (7)$$

$$\sum_{k\in K^2}\sum_{u\in V_U}\sum_{(i,j)\in A_2} y_{ijuk} = 1 \qquad \forall\, j\in V_M \qquad (8)$$

$$\sum_{(i,j)\in A_2} y_{ijuk} = \sum_{(i,j)\in A_2} y_{jiuk} \qquad \forall\, i\in V_2,\, u\in V_U,\, k\in K^2 \qquad (9)$$

$$\sum_{u\in V_U}\sum_{(u,j)\in A_2} y_{ujuk} \le 1 \qquad \forall\, k\in K^2 \qquad (10)$$

$$\sum_{\bar{u}\in V_U\setminus\{u\}}\left(\sum_{(u,j)\in A_2} y_{uj\bar{u}k} + \sum_{(i,u)\in A_2} y_{iu\bar{u}k}\right) = 0 \qquad \forall\, u\in V_U,\, k\in K^2 \qquad (11)$$

$$\sum_{k\in K^2}\sum_{(u,j)\in A_2} y_{ujuk} \le k^2_u \qquad \forall\, u\in V_U \qquad (12)$$

$$\sum_{k\in K^2}\sum_{u\in V_U}\sum_{(u,j)\in A_2} y_{ujuk} \le k^2 \qquad (13)$$

$$\sum_{k\in K^2}\sum_{u\in V_U}\sum_{(i,j)\in A_2} z^2_{ijuk} = \sum_{k\in K^2}\sum_{u\in V_U}\sum_{(i,j)\in A_2} z^2_{jiuk} - t_i \qquad \forall\, i\in V_M \qquad (14)$$

$$\sum_{(i,j)\in A_2} z^2_{ijuk} = \sum_{(i,j)\in A_2} z^2_{jiuk} \qquad \forall\, i\in V_B,\, u\in V_U,\, k\in K^2 \qquad (15)$$

$$z^2_{ijuk} \le E^2 y_{ijuk} \qquad \forall\, (i,j)\in A_2,\, u\in V_U,\, k\in K^2 \qquad (16)$$

$$q_u = \sum_{k\in K^2}\sum_{(u,j)\in A_2} z^2_{ujuk} \qquad \forall\, u\in V_U \qquad (17)$$

$$\sum_{u\in V_U} q_u = \sum_{i\in V_M} t_i \qquad (18)$$

$$p^{2-}_{iuk} = W^2 \qquad \forall\, i\in V_U \cup V_B,\, u\in V_U,\, k\in K^2 \qquad (19)$$

$$p^{2-}_{iuk} = p^{2+}_{iuk} \qquad \forall\, i\in V_M,\, u\in V_U,\, k\in K^2 \qquad (20)$$

$p^{2+}_{juk} \le p^{2-}_{iuk} - r^{2}_{ij}\, y_{ijuk} + W^{2}\ (1- y_{ijuk})$ $\quad \forall\ (i, j) \in A_2, u \in V_U, k\epsilon K^2$ (21)

$p^{2+}_{juk} \ge p^{2-}_{iuk} - r^{2}_{ij}\, y_{ijuk} - W^{2}\ (1- y_{ijuk})$ $\quad \forall\ (i, j) \in A_2, u \in V_U, k\epsilon K^2$ (22)

$x_{ijk} \in \{0,1\}$ $\quad \forall\ (i, j) \in A_1, k\epsilon K^1$ (23)

$y_{ijuk} \in \{0,1\}$ $\quad \forall\ (i, j) \in A_2, u \in V_U, k\epsilon K^2$ (24)

$v_{uk} \ge 0$ $\quad \forall\ u \in V_U, k\epsilon K^1$ (25)

$q_u \ge 0$ $\quad \forall\ u \in V_U$ (26)

$z^{1}_{ijk} \ge 0$ $\quad \forall\ (i, j) \in A_1, k\epsilon K^1$ (27)

$z^{2}_{ijuk} \ge 0$ $\quad \forall\ (i, j) \in A_2, u \in V_U, k\epsilon K^2$ (28)

$p^{2+}_{iuk} \ge 0$ $\quad \forall\ i \in V_U U\ V_M U\ V_B, u \in V_U, k\epsilon K^2$ (29)

$p^{2-}_{iuk} \ge 0$ $\quad \forall\ i \in V_U U\ V_M U\ V_B, u \in V_U, k\epsilon K^2$ (30)

The objective function, denoted by (1), minimizes the total cost, comprising of first and second-echelon transportation costs, fixed costs of first and second-echelon vehicles, battery swapping costs for second echelon vehicles, and handling costs at satellites. Constraints (2) -(6) concern the first echelon. Constraints (7) relate to the synchronization of the first and second echelons. Constraints (8) -(22) pertain to the second echelon. Additionally, constraints (19) -(22) regulate the battery powers of second echelon electric vehicles. Constraints related to defining decision variables are provided in (23) -(30). Constraints (2) regulate flow conservation for vehicles. Constraints (3) indicate that each first echelon vehicle can visit depots and satellites at most once. The load flow of each vehicle at satellites is regulated through constraints (4). Constraints (5) guarantee that capacity of vehicles are not exceeded. Constraints (6) mandate that each vehicle must distribute all its load upon returning to the depot. Constraints (7) balance the flow of goods in satellites by equalizing the amount of goods coming from the first echelon and distributed to the second echelon. Each customer is ensured to be visited exactly once through constraints (8). Constraints (9) ensure flow conservation for second echelon vehicles. The constraints (10) allow second echelon vehicles to go out for distribution at most once. Constraints (11) prevent vehicles in the second echelon from traveling from satellite to satellite. The number of satellites and vehicles available in the second echelon is regulated by constraints (12) -(13). Constraints (14) -(15) guarantee flow conservation at customers and battery swapping stations. Second echelon vehicle capacities are controlled through constraints (16). Constraints (17) -(18) regulate the quantity of products sent from satellites. Constraints (19) ensure that the battery of a second echelon vehicle is fully charged when it leaves a satellite or a battery swapping station. Constraints (20) ensure that the battery power remains the same for each second echelon electric vehicle when visiting a customer. Constraints (21) -(22) control the battery powers of electric vehicles traveling from node i to node j. These constraints guarantee that electric vehicles have enough battery power to travel remaining customers and return back to the satellite.

4. APPLICATION DESIGN

Applications using real/realistic data can contribute to the generalization of results by reflecting practical difficulties beyond theoretical models. More concrete and applicable strategies can be created. Studies with real/realistic data are important to test the validity of theoretical findings in practice. Therefore, the datasets used in this research were designed to simulate realistic multi-echelon distribution networks with electric vehicles and battery swapping stations to ensure the generalizability of the findings and test the accuracy of the model. For this purpose, three different datasets, each representing the real distribution network of a health and personal care products company operating in Türkiye with varying sizes, have been considered. This diversity allows for analyzing the model's performance under various operational conditions, including different numbers of customers, satellites and battery swapping stations.

In the first dataset, there is 1 depot, 2 satellites, 2 battery swapping stations, and 5 customers. The second dataset consists of 1 depot, 3 satellites, 3 battery swapping stations, and 8 customers. Finally, the third dataset includes 1 depot, 4 satellites, 4 battery swapping stations, and 11 customers. The number of batteries swapping stations has been determined based on the recommendation in the literature, which suggests that the number of batteries swapping stations should be 1/5 of the total number of nodes in the distribution network (Schneider et al., 2014). The locations of nodes (depot, satellites, battery swapping stations, and customers) have been determined using the central depot of the company, along with intermediate depots and store locations in three metropolitan cities, as reference points. These locations have been randomly marked on a map to ensure distributed representation. Distances between nodes have been obtained from Google Maps, ensuring geographical accuracy.

The numbers of primary and second echelon vehicles are, respectively, 2 and 4 for dataset 1, 3 and 6 for dataset 2, and 4 and 8 for dataset 3. The maximum number of second echelon vehicles that can be used at satellites is the same for each dataset. Traditional vehicles are utilized in the first echelon of distribution, while in the second echelon, relatively smaller and thus environmentally friendly electric vehicles with lower carrying capacities are used. The data on vehicle capacities and purchase prices (fixed costs) were sourced from sahibinden.com, an online marketplace in Türkiye, ensuring that the values reflect real-world market conditions (Sahibinden, n.d.). The capacity of the first echelon vehicle is 3,500 kg for all datasets, while the capacity of the second echelon vehicle is 1,700 kg. The fixed costs of the first and second echelon vehicles are 3,400,000 TL and 2,100,000 TL, respectively, for all datasets.

Since obtaining precise real-world data for certain parameters is challenging, some values were selected randomly, while others were derived from relevant literature. Customer demands have been randomly generated to not exceed vehicle capacities, within the range of (0, 1700]. Customer demand quantities for each dataset are presented in Table 3 below. The handling cost per unit at all satellites is 5 TL. To the best of our knowledge, there are no battery swapping stations in Türkiye. Therefore, the battery swapping cost was chosen randomly. The battery swapping cost for electric vehicles is 1,000 TL. The battery capacities of electric vehicles have been considered to be 1.3 times the maximum second echelon distance in the distribution network (Jie et al., 2019; Schneider et al., 2014). For all datasets, α, β, and θ values are taken as 1 (Jie et al., 2019).

Table 3. Customer Demand Quantities (kg)

Data Set	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	Total
1	800	600	300	1,000	1,300	-	-	-	-	-	-	4,000
2	1,200	300	1,000	500	300	900	500	400	-	-	-	5,100
3	500	700	200	300	1,000	350	250	400	900	100	150	4,850

* **M:** Customer

5. RESULTS OF ANALYSIS

The optimal results of three different-sized samples, whose details were shared in the previous section, are presented in this section. These analyses are referred to as "base case analysis" throughout the rest of the study. In addition to the base case analysis, sensitivity analyses were conducted to examine whether changes in customer demand quantities and battery capacities of electric vehicles affect the optimal results, and to what extent and in which direction. The relevant results are discussed in subsections 5.2 and 5.3.

The solutions were obtained using SolverStudio (SolverStudio, n.d.) and Gurobi 11.0.0 (Gurobi, n.d.) programs on a computer equipped with an Intel(R) i7 processor running at 2.4 GHz and 6 GB of memory.

5.1. Base Case Analysis

Optimal results for all datasets were obtained within reasonable timeframes. Table 4 presents these optimal results, showing vehicle routes, product transportation amounts, and battery power levels at different nodes.

Upon examining Table 4, it can be observed that in the optimal solutions of dataset 1, all vehicles in the first echelon and three out of four vehicles in the second echelon are utilized for distribution. Both satellites in the distribution network are utilized. More goods are delivered to satellite point 2 in the first echelon compared to the other satellite point, and more vehicles serve from this satellite point in the second echelon. Since the battery capacities of the vehicles are sufficient, all customer demands have been met without the need to visit any battery swapping stations. The total cost, consisting of transportation costs, fixed costs of vehicles, battery swapping costs for electric vehicles, and handling costs of products at satellites, is found to be 14,943,300 TL.

Table 4. Base Case Optimum Results

Data Set	Total Cost (TL)	Vehicle No	Optimal Route	Amount of Product Transported in Arcs (kg)	Battery Power of Vehicles at Nodes (m)
1	14,943,300	K1	D-U1-D	1,400-0	-
		K2	D-U2-D	2,600-0	-
		E1	U1-M1-M2-U1	1,400-600-0	37,180-32,480-21,280-4,180
		E2	U2-M4-U2	1,000-0	37,180-27,780-18,680
		E4	U2-M5-M3-U2	1,600-300-0	37,180-22,680-15,280-2.380
2	14,788,300	K2	D-U2-D	3,400-0	-
		K3	D-U1-D	1,700-0	-
		E2	U2-M6-M5-M7-U2	1,700-800-500-0	53,430-46,530-39,430-29,730-22,930
		E4	U2-M3-M2-B3-M8-U2	1,700-700-400-400-0	53,430-38,530-27,730-53,430-44,630-31,730
		E6	U1-M4-M1-U1	1,700-1,200-0	53,430-37,030-30,730-19,230
3	13,428,950	K2	D-U3-D	1,700-0	-
		K3	D-U2-D	3,150-0	-
		E1	U2-M8-M5-M4-U2	1,700-1,300-300-0	93,990-77,090-70,690-57,690-53,490
		E2	U3-M1-M2-M7-M10-M11-U3	1,700-1,200-500-250-150-0	93,990-84,090-59,690-36,290-26,390-21,490-12,790
		E8	U2-M9-M6-M3-U2	1,450-550-200-0	93,990-83,890-81,790-65,490-59,590

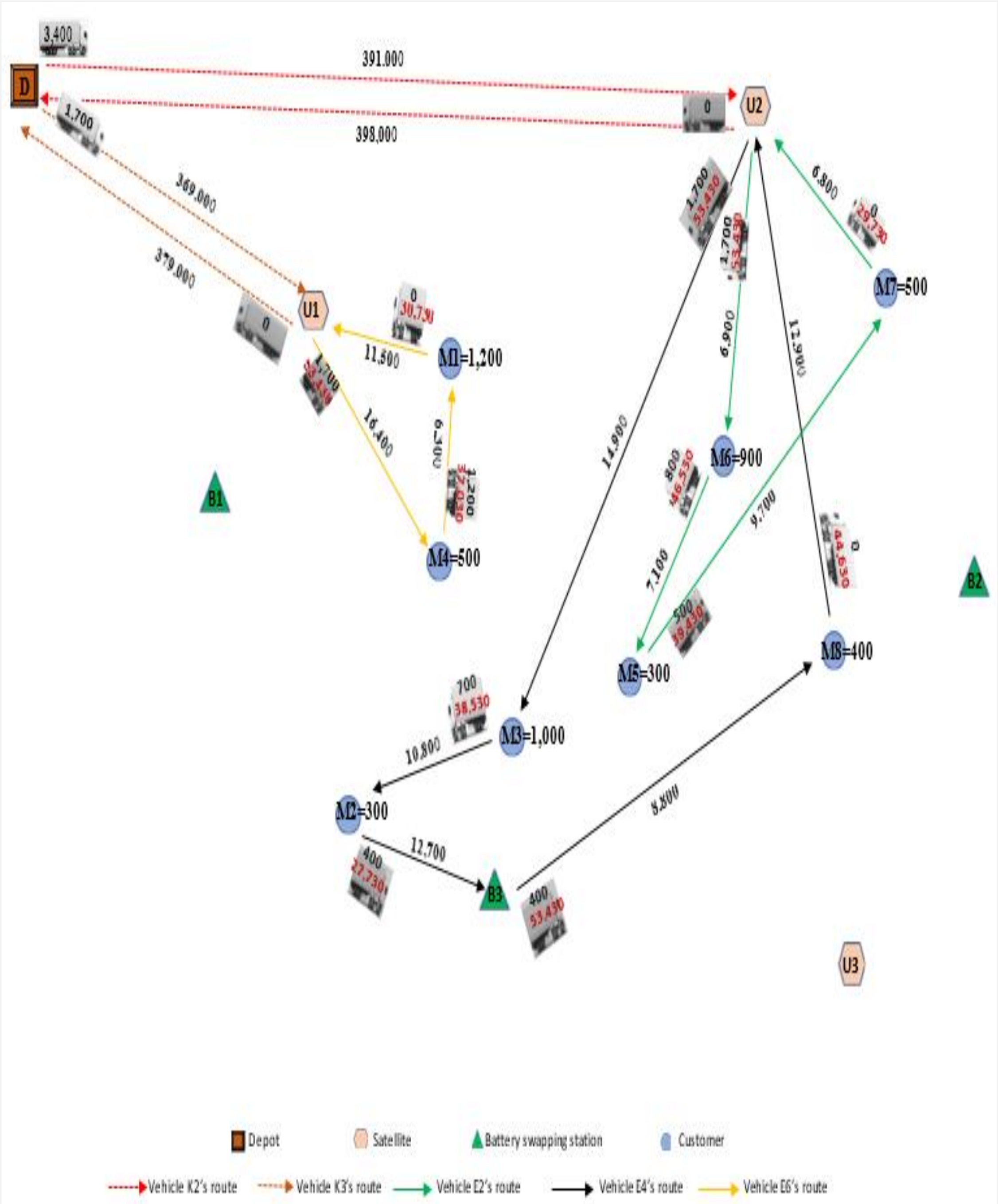
* **K:** First-echelon vehicle, **E:** Second-echelon vehicle, **D:** Depot, **U:** Satellite, **B:** Battery swapping station, **M:** Customer

In the optimal results for dataset 2, it is observed that 2 out of 3 first echelon vehicles and 3 out of 6 second echelon vehicles are deployed for distribution. Satellite 3 in the distribution network is not utilized. In other words, no goods have been transported to this point in the first echelon, and therefore, there is no flow of goods from here to the second echelon. In the second echelon, it is observed that 2 out of 3 vehicles originate from satellite 2. All second echelon vehicles start their routes fully loaded. After servicing customer 2, second echelon vehicle 4 visits battery swapping station 3 due to insufficient battery capacity, replenishes its battery to full capacity (53,430 m), and continues its route. The optimal total cost is 14,788,300 TL.

The optimal results for dataset 3 show that 2 first echelon vehicles and 3 second echelon vehicles are utilized, resulting in an optimal total cost of 13,428,950 TL. Out of the 4 satellite points in the distribution network, only two (U2 and U3) are utilized. More goods are delivered to satellite point 2, and consequently, more vehicles serve from there. Similar to the results of dataset 1, the vehicles complete their routes without the need to visit any battery swapping stations.

In order for the reader to interpret the results more easily, the optimal routes of vehicles for dataset 2 are shown in Figure 2 as an example. In the Figure, the black numbers on the vehicles represent the amount of load in the vehicle and the red numbers represent the battery capacity, in other words, the driving range, when leaving the relevant node. The numbers on the blue circles representing customer locations show the customer demand amounts. The numbers on the arcs indicate the distance between two nodes.

Figure 2. Representation of Optimal Routes for Data Set 2



5.2. Effect of Change in Demand Quantities

The variation of parameters within the VRP can significantly impact the optimal solutions. Among these parameters, customer demand plays a crucial role in shaping distribution costs. An increase in demand leads to a higher load per vehicle, potentially exceeding the existing fleet capacity and necessitating the deployment of additional vehicles. Furthermore, as vehicles operate under heavier loads, fuel consumption rises, which may be particularly critical for electric vehicles, as it accelerates battery depletion, requiring more frequent stops for recharging or battery replacement. Consequently, an increase in demand not only escalates fixed costs but also raises fuel, driver, handling and maintenance costs, among others. In extreme cases, it may even render certain solutions infeasible. Conversely, a decrease in demand can have the opposite effect, leading to improved cost efficiency and greater feasibility in routing solutions. In this context, sensitivity analyses have been conducted for each dataset to examine the effect of changes in demand on the total cost. Sensitivity analyses were performed by varying the demand quantity for all customers within the range of -20% to +20%. The determination of this range was based on the research of Goli et al. (2022). Moreover, if the demand quantity increase for Dataset 1 exceeds 30.77%, it will result in insufficient vehicle capacity and lead to an infeasible solution. Detailed results for the optimal solutions are provided in Tables A1, A2, and A3 for datasets 1 to 3, respectively, in the appendix. The change in total cost due to demand variation is summarized in Figure 3.

Figure 3. Change in Total Cost Depending on Demand

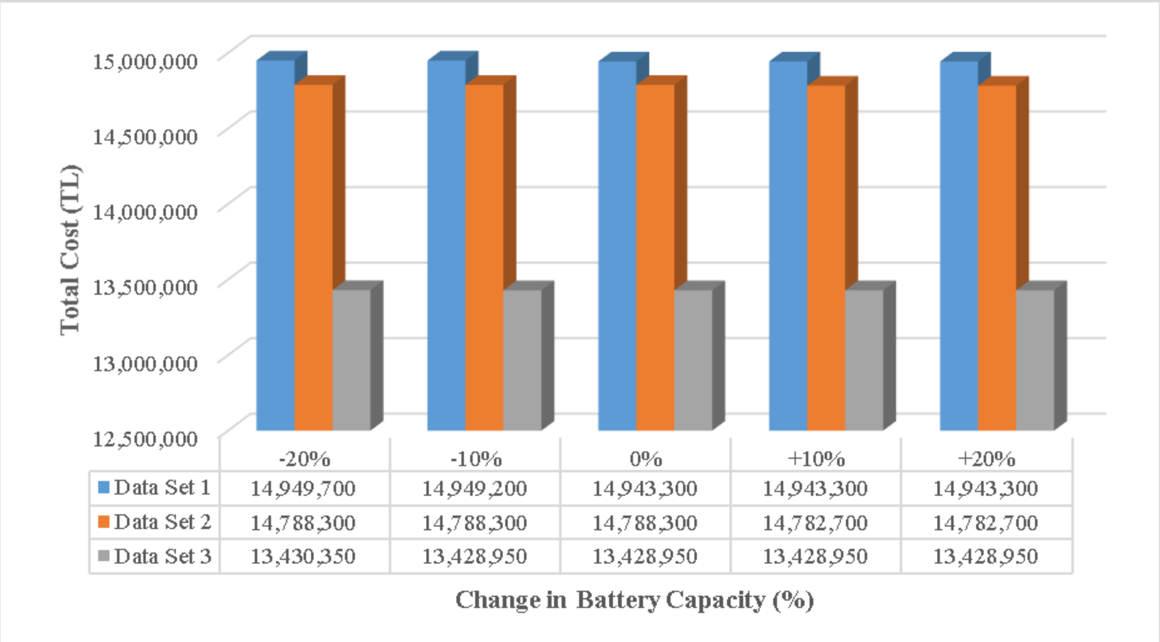
According to the results, as expected, it is observed that an increase/decrease in demand quantity causes to a corresponding increase/decrease in total cost compared to the base case for all datasets. The most significant change in the objective function value is caused by a 20% decrease in demand for dataset 1, while for datasets 2 and 3, it is caused by a 20% increase in demand. In this context, it can be said that dataset 1 is more sensitive to negative changes in demand, while datasets 2 and 3 are more sensitive to positive changes in demand.

In cases where demand changes are highly sensitive, both the number of vehicles used and the vehicle routes have changed. Except for a 10% increase in demand for datasets 2 and 3, other percentage changes in demand have resulted in minor changes in the objective function values without causing any changes in the number of vehicles or routes.

5.3. Effect of Change in Battery Capacities

Changes in the battery capacities (driving ranges) of electric vehicles can affect vehicle routes and thus the objective function value. A higher battery capacity enables vehicles to travel longer distances, thereby reducing the frequency of energy replenishment. In regions with limited charging infrastructure, high-capacity batteries offer a significant advantage by mitigating the challenges associated with insufficient charging or swapping stations. Moreover, a reduced need for charging can enhance operational efficiency by minimizing delays caused by energy replenishment times. Given these factors, an increase in battery capacity can contribute to both cost reduction and improvements in overall operational efficiency. On the other hand, as the battery capacities of vehicles decrease, they will need to visit charging stations or battery swapping stations more frequently. Consequently, vehicles will be able to make fewer customer visits on their routes, more frequent energy replenishment, longer travel distances, experience more time loss and more costly operations. In this context, sensitivity analysis was conducted by varying the battery capacities of second echelon electric vehicles within the range of -20% to +20% for all datasets to analyze the impact of changes in battery capacities on the total cost. In choosing this range, the knowledge that decreases in battery capacity exceeding 30% compared to the base case in all data sets will lead to infeasible results was utilized. Detailed optimal results are provided in Tables A4 to A6 for datasets 1 to 3, respectively, in the appendix. The change in total cost due to battery capacity variation is summarized in Figure 4.

Figure 4. Total Cost Change Depending on Battery Capacity



Upon examining the relevant tables and figure, in dataset 1, increases in battery capacities have not changed the total cost. However, decreases in battery capacities have led to an increase in the total cost, creating a reverse situation. Although the decreases in battery capacities have not changed the number of vehicles used, changes in routes are observed. Additionally, while there was no need to visit any battery swapping stations in the base case, a 20% decrease in capacity necessitated a visit to the station. In dataset 2, unlike dataset 1, an increase in battery capacities has resulted in a decrease in the total cost, while decreases in battery capacities have not changed the total cost. In the base case, an electric vehicle visits the battery swapping station, but with an increase in capacity, it completes its route without the need to visit the station. In dataset 3, a change in the total cost occurred only with a 20% decrease in battery capacity. Here, with the decrease in capacity, the vehicle had to visit the battery swapping station, leading to an increase in the total cost. It can be said that there is an inverse relationship between the battery capacity of electric vehicles and the total cost.

In conclusion, the sensitivity analysis indicates that customer demand levels and the battery capacities of electric vehicles may significantly impact both fixed and variable costs. These parameters may influence critical factors such as the number of vehicles required, vehicle routes, energy consumption, and energy replenishment frequency, all of which can directly or indirectly affect overall costs. Analyzing the sensitivity of total costs to customer demand and battery capacity enables logistics companies to improve operational efficiency, reduce expenses, and establish a more sustainable distribution network. By leveraging these insights, companies can implement dynamic route optimization, ensuring that delivery schedules and fleet deployment adapt to fluctuations in demand. Additionally, flexible fleet management allows for optimal utilization of available vehicles, preventing underutilization during low-demand periods and avoiding capacity shortages during peak times. Furthermore, strategic investment decisions regarding battery capacity and charging infrastructure can be optimized, ensuring cost-effective and energy-efficient operations. Ultimately, integrating sensitivity analysis into decision-making processes helps logistics companies maintain resilience, minimize financial risks, and improve overall service quality in an increasingly competitive and environmentally conscious market.

6. CONCLUSION

Sustainability-focused VRPs aim to optimize transportation operations to minimize their environmental and social impacts. Towards these objectives, studies in the literature consider fuel consumption and/or carbon emissions, use environmentally friendly vehicles such as electric vehicles instead of traditional vehicles, or consider multi-echelon distribution networks. As far as is known, there are limited studies focusing on optimizing the routes of electric vehicles in two-echelon distribution network. To contribute to this gap in the literature, the 2E-E-VRP-BSS was addressed in this study. In the study, which considers the battery capacities of electric vehicles with limited driving range, a MIP model was proposed to minimize the total cost. To test the accuracy of the model, three different datasets were created, each representing a realistic distribution network of different sizes. Additionally, sensitivity analyses were conducted to examine whether customer demands and the battery capacities of electric vehicles affect the optimal solutions, and if so, in what direction. Sensitivity analyses were performed by varying customer demands and electric vehicle battery capacities within the range of -20% to +20% for all datasets. The results indicate that increases/decreases in customer demand lead to corresponding increases/decreases in the total cost in comparison with the base case scenario. Furthermore, there is an inverse relationship between the battery capacity of electric vehicles and the total cost.

From a managerial perspective, this research can contribute to companies in managing their vehicle fleets, increasing operational efficiency, improving service quality, reducing costs and establishing a more sustainable distribution network.

The limitations of this study are that the findings are valid within the framework of the assumptions used in the modeling and the data sets in the application. Although the application was made on real data as much as possible, precise data could not be used for some parameters and some were derived hypothetically. Since the method adopted in the study was MIP, the application was made on small/medium-sized samples and the findings were obtained.

In the future, researchers in this field may consider incorporating customer service times, battery replacement times, and station capacities into their studies. Researchers may propose heuristic/metaheuristic methods to generate solutions for large-scale problems. Different sensitivity analyses can be performed to analyze the impact of various factors such as the number and location of battery swapping stations.

Ethics Committee approval was not required for this study.

The author declares that the study was conducted in accordance with research and publication ethics.

The author confirms that no part of the study was generated, either wholly or in part, using Artificial Intelligence (AI) tools.

The author declares that there are no financial conflicts of interest involving any institution, organization, or individual associated with this article.

The author affirms that the entire research process was performed by the sole declared author of the study.

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APPENDIX

Table A1. Optimum Solution Results According to The Change in Demand for Data Set 1

Change in Demand	Total Cost (TL)	Vehicle No	Optimal Route	Amount of Product Transported in Arcs (kg)	Battery Power of Vehicles at Nodes (m)	Change (%)
-20%	8,576,700	K2	D-U1-D	3,200-0	-	-42.605
		E2	U1-M2-B1-M5-U1	1,520-1,040-1,040-0	37,180-21,980-37,180-25,580-280	
		E4	U1-M3-M4-B1-M1-U1	1,680-1,440-640-640-0	37,180-21,280-14,380-37,180-28,080-22,780	
-10%	14,941,300	K1	D-U2-D	2,340-0	-	-0.013
		K2	D-U1-D	1,260-0	-	
		E1	U2-M4-U2	900-0	37,180-27,780-18,680	
		E2	U2-M5-M3-U2	1,440-270-0	37,180-22,680-15,280-2,380	
		E4	U1-M1-M2-U1	1,260-540-0	37,180-32,480-21,280-4,180	
+10%	14,951,200	K1	D-U1-D	1,540-0	-	0.052
		K2	D-U2-D	2,860-0	-	
		E2	U1-M1-M2-U1	1,540-660-0	37,180-32,480-21,280-4,180	
		E3	U2-M4-M3-U2	1,430-330-0	37,180-27,780-20,380-7,480	
		E4	U2-M5-U2	1,430-0	37,180-22,680-7,680	
+20%	14,953,200	K1	D-U1-D	1,680-0	-	0.066
		K2	D-U2-D	3,120-0	-	
		E1	U2-M5-U2	1,560-0	37,180-22,680-7,680	
		E2	U1-M1-M2-U1	1,680-720-0	37,180-32,480-21,280-4,180	
		E3	U2-M4-M3-U2	1,560-360-0	37,180-27,780-20,380-7,480	

*Change (%) represents the percentage change in total cost compared to the base case.

Table A2. Optimum Solution Results According to The Change in Demand for Data Set 2

Change in Demand	Total Cost (TL)	Vehicle No	Optimal Route	Amount of Product Transported in Arcs (kg)	Battery Power of Vehicles at Nodes (m)	Change (%)
-20%	14,763,800	K1	D-U2-D	2,480-0	-	-0.165
		K2	D-U1-D	1,600-0	-	
		E1	U1-M1-M4-M2-U1	1,600-640-240-0	53,430-41,630-33,930-22,730,4,830	
		E3	U2-M7-M6-U2	1,120-720-0	53,430-45,930-39,730-33,130	
		E4	U2-M3-M5-M8-U2	1,360-560-320-0	58,430-38,530-33,830-28,830-15,930	
-10%	14,771,450	K1	D-U2-D	3,240-0	-	-0.113
		K3	D-U1-D	1,350-0	-	
		E1	U2-M6-M8-M7-U2	1,620-810-450-0	53,430-46,530-37,430-28,030-21,230	
		E2	U2-M5-M3-M4-U2	1,620-1,350-450-0	53,430-40,230-35,730-27,830-13,830	

		E4	U1-M2-M1-U1	1,350-1,080-0	53,430-35,430-25,230-13,730	
+10%	16,899,550	K1	D-U1-D	3,300-0	-	14.276
		K3	D-U2-D	2,310-0	-	
		E1	U2-M5-M8-M7-U2	1,320-990-550-0	53,430-40,230-35,230-25,830-19,030	
		E2	U2-M6-U2	990-0	53,430-46,530-39,930	
		E3	U1-M3-M4-U1	1,650-550-0	53,430-30,330-22,430-6,530	
		E4	U1-M2-M1-U1	1,650-1,320-0	53,430-35,430-25,230-13,730	
+20%	16,905,200	K1	D-U1-D	3,000-0	-	14.314
		K2	D-U2-D	3,120-0	-	
		E1	U2-M7-M6-U2	1,680-1,080-0	53,430-45,930-39,730-33,130	
		E3	U1-M3-M2-U1	1,560-360-0	53,430-30,330-19,530-1,630	
		E4	U2-M4-M5-M8-U2	1,440-840-480-0	53,430-39,730-29,130-24,130-11,230	
		E5	U1-M1-U1	1,440-0	53,430-41,630-30,130	

Table A3. Optimum Solution Results According to The Change in Demand for Data Set 3

Change in Demand	Total Cost (TL)	Vehicle No	Optimal Route	Amount of Product Transported in Arcs (kg)	Battery Power of Vehicles at Nodes (m)	Change (%)
-20%	13,421,200	K1	D-U3-D	1,160-0	-	-0.057
		K3	D-U2-D	2,720-0	-	
		E2	U2-M7-M8-M5-M4-U2	1,560-1,360-1,040-240-0	93,990-80,290-75,990-69,590-56,590-52,390	
		E7	U2-M9-M6-M3-U2	1,160-440-160-0	93,990-83,890-81,790-65,490-59,590	
		E8	U3-M1-M2-M10-M11-U3	1,160-760-200-120-0	93,990-84,090-59,690-30,390-25,490-16,790	
-10%	13,425,425	K1	D-U2-D	3,060-0	-	-0.026
		K3	D-U3-D	1,305-0	-	
		E2	U3-M1-M2-M10-M11-U3	1,305-855-225-135-0	93,990-84,090-59,690-30,390-25,490-16,790	
		E5	U2-M5-M8-M7-U2	1,485-585-225-0	93,990-78,290-71,490-67,190-52,490	
		E8	U2-M9-M6-M4-M3-U2	1,575-765-450-180-0	93,990-83,890-81,790-69,190-63,590-57,690	
+10%	15,554,475	K2	D-U3-D	3,135-0	-	15.827
		K4	D-U2-D	2,200-0	-	
		E3	U3-M1-M2-M11-U3	1,485-935-165-0	93,990-84,090-59,690-27,590-18,890	
		E4	U3-M8-M5-M10-U3	1,650-1,210-110-0	93,990-71,990-65,590-51,490-38,690	
		E5	U2-M9-M6-M7-U2	1,650-660-275-0	93,990-83,890-81,790-73,690-58,990	
		E8	U2-M4-M3-U2	550-220-0	93,990-91,690-86,090-80,190	
+20%	15,573,800	K2	D-U3-D	2,760-0	-	15.971
		K3	D-U2-D	3,060-0	-	
		E1	U2-M9-M6-U2	1,500-420-0	93,990-83,890-81,790-66,490	
		E2	U3-M1-M2-M3-U3	1,680-1,080-240-0	93,990-84,090-59,690-45,190-6,990	
		E3	U3-M7-M8-M10-M11-U3	1,080-780-300-180-0	93,990-73,590-69,290-58,890-53,990-45,290	
		E5	U2-M5-M4-U2	1,560-360-0	93,990-78,290-65,290-61,090	

Table A4. Optimum Solution Results According to The Change in Battery Capacities for Data Set 1

Change in Battery Capacity	Total Cost (TL)	Vehicle No	Optimal Route	Amount of Product Transported in Arcs (kg)	Battery Power of Vehicles at Nodes (m)	Change (%)
-20%	14,949,700	K1	D-U2-D	2,300-0	-	0.042
		K2	D-U1-D	1,700-0	-	
		E1	U2-M4-U2	1,000-0	29,744-20,344-11,244	
		E2	U2-M5-U2	1,300-0	29,744-15,244-244	
		E4	U1-M2-B1-M3-M1-U1	1,700-1,100-1,100-800-0	29,744-14,544-29,744-24,744-10,844-5,544	
-10%	14,949,200	K1	D-U1-D	1,400-0	-	0.039
		K2	D-U2-D	2,600-0	-	
		E1	U2-M4-M3-U2	1,300-300-0	33,462-24,062-16,662-3,762	
		E2	U1-M1-M2-U1	1,400-600-0	33,462-28,762-17,562-462	
		E4	U2-M5-U2	1,300-0	33,462-18,962-3,962	

+10%	14,943,300	K1	D-U2-D	2,600-0	-	0
		K2	D-U1-D	1,400-0	-	
		E2	U1-M1-M2-U1	1,400-600-0	40,898-36,198-24,998-7,898	
		E3	U2-M5-M3-U2	1,600-300-0	40,898-26,398-18,998-6,098	
		E4	U2-M4-U2	1,000-0	40,898-31,498-22,398	
+20%	14,943,300	K1	D-U2-D	2,600-0	-	0
		K2	D-U1-D	1,400-0	-	
		E2	U1-M1-M2-U1	1,400-600-0	44,616-39,916-28,716-11,616	
		E3	U2-M5-M3-U2	1,600-300-0	44,616-30,116-22,716-9,816	
		E4	U2-M4-U2	1,000-0	44,616-35,216-26,116	

Table A5. Optimum Solution Results According to The Change in Battery Capacities for Data Set 2

Change in Battery Capacity	Total Cost (TL)	Vehicle No	Optimal Route	Amount of Product Transported in Arcs (kg)	Battery Power of Vehicles at Nodes (m)	Change (%)
-20%	14,788,300	K2	D-U2-D	3,400-0	-	0
		K3	D-U1-D	1,700-0	-	
		E2	U2-M6-M5-M7-U2	1,700-800-500-0	42,744-35,844-28,744-19,044-12,244	
		E3	U1-M4-M1-U1	1,700-1,200-0	42,744-26,344-20,044-8,544	
		E5	U2-M3-M2-B3-M8-U2	1,700-700-400-400-0	42,744-27,844-17,044-42,744-33,944-21,044	
-10%	14,788,300	K2	D-U1-D	1,700-0	-	0
		K3	D-U2-D	3,400-0	-	
		E1	U1-M4-M1-U1	1,700-1,200-0	48,087-31,687-25,387-13,887	
		E2	U2-M6-M5-M7-U2	1,700-800-500-0	48,087-41,187-34,087-24,387-17,587	
		E4	U2-M3-M2-B3-M8-U2	1,700-700-400-400-0	48,087-33,187-22,387-48,087-39,287-26,387	
+10%	14,782,700	K1	D-U1-D	3,400-0	-	-0.037
		K2	D-U2-D	1,700-0	-	
		E1	U1-M2-M3-M8-U1	1,700-1,400-400-0	58,773-40,773-29,573-21,573-3,273	
		E2	U1-M4-M1-U1	1,700-1,200-0	58,773-42,373-36,073-24,573	
		E5	U2-M6-M5-M7-U2	1,700-800-500-0	58,773-51873-44,773-35,073-28,273	
+20%	14,782,700	K1	D-U2-D	1,700-0	-	-0.037
		K3	D-U1-D	3,400-0	-	
		E1	U1-M2-M3-M8-U1	1,700-1,400-400-0	64,116-46,116-34,916-26,916-8,616	
		E4	U2-M6-M5-M7-U2	1,700-800-500-0	64,116-57,216-50,116-40,416-33,616	
		E6	U1-M4-M1-U1	1,700-1,200-0	64,116-47,716-41,416-29,916	

Table A6. Optimum Solution Results According to The Change in Battery Capacities for Data Set 3

Change in Battery Capacity	Total Cost (TL)	Vehicle No	Optimal Route	Amount of Product Transported in Arcs (kg)	Battery Power of Vehicles at Nodes (m)	Change (%)
-20%	13,430,350	K1	D-U3-D	1,700-0	-	0.010
		K4	D-U2-D	3,150-0	-	
		E2	U2-M8-M5-M4-U2	1,700-1,300-300-0	75,192-58,292-51,892-38,892-34,692	
		E4	U3-M1-M2-M7-M10-B4-M11-U3	1,700-1,200-500-250-150-150-0	75,192-65,292-40,892-17,492-7,592-75,192-72,692-63,992	
		E7	U2-M9-M6-M3-U2	1,450-550-200-0	75,192-65,092-62,992-46,692-40,792	
-10%	13,428,950	K1	D-U3-D	1,700-0	-	0
		K3	D-U2-D	3,150-0	-	
		E2	U3-M1-M2-M7-M10-M11-U3	1,700-1,200-500-250-150-0	84,591-74,691-50,291-26,891-16,981-12,091-3,391	
		E3	U2-M8-M5-M4-U2	1,700-1,300-300-0	84,591-67,691-61,291-48,291-44,091	
		E7	U2-M9-M6-M3-U2	1,450-550-200-0	84,591-74,491-72,391-56,091-50,191	
+10%	13,428,950	K2	D-U2-D	3,150-0	-	0
		K4	D-U3-D	1,700-0	-	

		E1	U2-M8-M5-M4-U2	1,700-1,300-300-0	103,389-86,489-80,089-67,089-62,889	
		E3	U2-M9-M6-M3-U2	1,450-550-200-0	103,389-93,289-91,189-74,889-68,989	
		E5	U3-M1-M2-M7-M10-M11-U3	1,700-1,200-500-250-150-0	103389-93,489-69,089-45,689-35,789-30,889-22,189	
+20%	13,428,950	K1	D-U2-D	3,150-0	-	0
		K3	D-U3-D	1,700-0	-	
		E2	U3-M1-M2-M7-M10-M11-U3	1,700-1,200-500-250-150-0	112,788-102,888-78,488-55,088-45,188-40,288-31,588	
		E4	U2-M9-M6-M3-U2	1,450-550-200-0	112,788-102,688-100,588-84,288-78,388	
		E8	U2-M8-M5-M4-U2	1,700-1,300-300-0	112,788-95,888-89,488-76,488-72,288	