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Research Article

Mixed fleet sustainable facility location problem under capacity and service level constraints

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ABSTRACT

This study introduces the Sustainable Facility Location Problem with a Mixed Fleet and its mathematical model. The problem involves determining the optimal locations of facilities under budget, capacity, and service-level constraints within a mixed fleet of electric and internal combustion engine vehicles, while considering the economic, environmental, and social dimensions of sustainability. We systematically conducted computational experiments on 12 datasets and 2916 scenarios to evaluate the impact of critical parameters such as budget, emission limits, operating range of electric vehicles, and service level requirements on the solutions of the problem. Numerical results indicate that a large budget significantly improves the feasibility of solutions, relaxed emission constraints improve demand fulfillment but raise total costs, and stricter service-level requirements increase social benefits while presenting economic challenges. The model also captures regional job creation and the practical limits of switching to electric vehicles. Its results can therefore help decision makers plan facility networks during this transition.

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INTRODUCTION

Businesses today must improve supply chain performance while controlling costs and reducing environmental harm. This has become more challenging as natural resources grow scarce, and firms face increasing expectations to consider more than financial returns. As a result, many businesses are adopting strategies that also reflect environmental and social responsibility. This broader view of sustainable development has gained importance in response to climate change, air pollution, and other growing social and environmental pressures [1].

Embedding sustainability in supply chain activities can help firms strengthen their competitive position [2, 3]. Much of this performance depends on how the supply chain network is designed, particularly where facilities are located and how effectively the resulting network responds to customer needs [4]. A sustainable design, however, should not focus on efficiency alone; it must also account for economic, environmental, and social objectives.

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Facility location is major part of sustainable supply chain design, because such decisions shape a firm's operations for years. Focusing only on economic factors is no longer enough: external factors push decision-makers to consider environmental and social aspects too [5, 6]. This fits the United Nations 2030 Agenda for Sustainable Development, with 17 Sustainable Development Goals (SDGs) (Fig. 1). Firms and their decision makers both have a role in supporting these goals, yet the 2023 UN Sustainable Development Goals Report shows that progress in many areas is below target, which shows the need for more urgent action (Fig. 2).

As Figure 2 shows, the goals under "decent work and economic growth" (the 8th goal) have not been met. The status of the 13th goal also shows that current climate action plans are far from enough to address climate change (Fig. 2). Meeting these goals will take transformative action across all economies [7], not just plans and promises [8].

Logistics produces a large share of total emissions, mainly because most fleets have internal combustion engines (ICEV). This makes greener alternatives, especially electric vehicles, increasingly important [9]. Until fleets are fully electric, many companies will run a mixed fleet of internal combustion engine vehicles (ICEVs) and electric vehicles (EVs). This transition period raises critical issues within the environmental dimension of sustainability, and it brings practical challenges, particularly because EVs have a more limited driving range. In order to operate with mixed fleets, firms must make closely linked decisions on transport operations, infrastructure investment, and facility locations. These decisions matter more as emission rules get stricter and companies try to stay competitive without losing operational efficiency. Sustainable supply chain models should therefore reflect the realities of the electric and mixed fleets, balancing economic performance with environmental and social requirements.

The *facility location problem* (FLP) selects the best locations from a set of potential sites to meet customer demand at minimum total cost, including fixed opening costs and variable operational costs [10]. It is a key strategic topic with applications in logistics, supply chain management, urban planning, and public infrastructure [11–15]. Among its variants, the *uncapacitated facility location problem* (UFLP) assumes unlimited facility capacities and it is NP-hard [16-19]. Even so, very large instances have been solved; the branch-and-bound algorithm of Letchford and Miller [20], for example, handles up to 18,000 facilities. In practice, facilities have limited capacity, called *capacitated facility location problem* (CFLP). CFLP models may also include single- or multi-sourcing rules and requirements. Recent studies have also looked at dynamic and sustainable CFLPs. Ala et al. [21], for instance, study a dynamic CFLP for networks of mobile renewable energy charging stations. Combining two-stage stochastic programming, they report that suggested model deal better with uncertainty, cutting total operating cost by 7% and carbon emissions by 20%. Social sustainability still gets much less attention than the economic and environmental dimensions [22]. Models that focus on equitable job creation, regional employment, and other social factors are still needed [23], and several authors call for a more balanced treatment of the three dimensions [22, 24, 25]. Terouhid et al. [26] note in their review that existing studies rarely include social sustainability

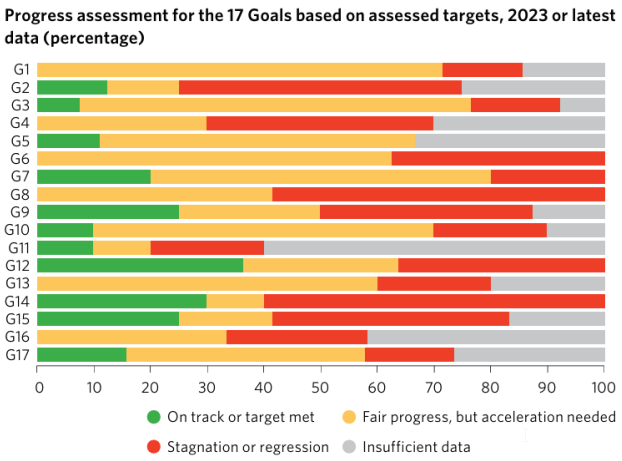

Figure 2. Status of the SDGs [7] *[Open Access]*.



Figure 1. Sustainable Development Goals [7] *[Open Access]*.

and call for frameworks with quantitative social metrics. Eskandarpour et al. [27] make a similar point for sustainable supply chain network design. Anvari and Türkay [28] approach facility location using triple-bottom-line perspective, including economic, environmental, and social criteria in the network design. Singer and Özşahin [29] build a goal programming model for facility location in the Turkish furniture industry. Dukkanci et al. [30] add welfare concerns to sustainable route planning. Brahami et al. [31] propose a multi-objective model that minimizes cost and carbon emissions in multi-mode transportation networks and solved with the non-dominated sorting genetic algorithm (NSGA-II), it shows a clear trade-off between the two objectives.

In this paper, we propose a mathematical model for the Mixed Fleet Sustainable Facility Location Problem (MF-SFLP). It covers the economic, environmental, and social dimensions of sustainability for a distribution network that uses both EVs and ICEVs, under capacity, single-source, and service level constraints. Earlier studies focus on cost and emissions and rarely address the social dimension [24, 25], and practical limitations of EVs, such as driving range, have not been fully integrated. The paper contributes in three aspects. First, we add social criteria, namely job creation weighted by regional unemployment and population density, to a sustainable location model. Second, the model represents a mixed fleet with EV range limits, an emission cap, and a minimum service level. Third, we run the model on 2916 scenarios and conduct sensitivity analyses to show the trade-offs among cost, emissions, and social benefit. The results can help decision makers align their decisions with the Sustainable Development Goals [7].

The rest of the paper is organized as follows. Section 2 introduces the problem and its mathematical model, Section 3 presents the computational results, and Section 4 concludes and suggests directions for future research.

PROBLEM DEFINITION AND MATHEMATICAL MODEL

In this section, we define the problem and give its mathematical model.

Problem Definition

We introduce the Mixed Fleet Sustainable Facility Location Problem under capacity, service level, budget, and single-source constraints. The objective is to minimize the sum of facility opening, transportation, labor, and penalty costs minus the social benefit of the opened facilities, without exceeding the budget or the legal emission limit. The model evaluates EVs and ICEVs for transportation, accounting for their distinct cost structures, environmental impacts, and social contributions due to facility opening.

The Mixed Fleet Sustainable Facility Location Problem is defined on a fully directed graph, $G = (N, A)$, in which N represents the set of nodes for the potential facility locations and customers, and A represents the set of edges (road segments) between the nodes. The assumptions of the problem are: (1) Facilities can only be opened at nodes, (2) Each facility has a capacity (W_i), (3) Vehicles have capacities (K_{ij}^v), (4) Refueling for ICEVs is possible on the routes, (5) Charging stations required for electric vehicles are available only at facilities, (6) Demand must be fulfilled at or above the specified service level where the service level (SL) represents the minimum proportion of demand that is satisfied without delays or shortages.

We have three parameter groups corresponding to the economic, environmental, and social dimensions of the mixed fleet sustainable facility location problem.

Economic Parameters

In facility location problems, the fixed opening cost parameter encompasses the expenses required for a facility to become operational. This is termed the facility opening cost in the model and is denoted as F_i. The transportation cost between facilities and customers varies depending on the distance and the type of vehicle used, where t^v represents the transportation cost per kg and km for vehicle type v. In this study, ICEVs and EVs are considered two distinct types of vehicles. Thus, the total transportation cost can be calculated as $\sum_{i \in N} \sum_{j \in N} \sum_{v \in N} t^v d_{ij} Y_{ij}^v$, where t^v is the transportation cost for vehicle type v ($v = 1$ for ICEVs and $v = 2$ for EVs), d_{ij} is the distance between nodes i and j, and Y_{ij}^v is the quantity transported between nodes i and j by vehicle type v. Each type of vehicle has different environmental impacts on the segment between two nodes in the network. EVs do not generate CO_2 emissions but require higher investment costs than ICEVs.

Labor costs are calculated based on the distance travelled d_{ij} during transportation activities. Thus, the labor cost can be calculated using the unit labor cost per distance c^v, and whether transportation occurs between i and j using vehicle v (X_{ij}^v) by $\sum_{i \in N} \sum_{j \in N} \sum_{v \in N} c^v d_{ij} X_{ij}^v$.

Due to the working environment and safety risks, drivers of EVs need to obtain special training and may have higher salary levels than those of ICEVs. Due to the training that must be provided to the drivers, we use the parameter c^v to reflect these variations based on the type of vehicle used.

Penalty costs are considered for unmet demand in the network. It represents the monetary penalty paid per unit of demand that is not fulfilled. This parameter (P) ensures that the model prioritizes meeting customer requirements. The total penalty cost can be calculated as $\sum_{j \in N} P \cdot UD_j$, where UD_j represents the quantity of unmet demand at j.

Environmental Parameters

Air pollution is a critical factor for environmental sustainability [32], and emissions from transportation activities harm the environment and human health. We consider emissions due to transportation activities in the network similar to [33]. Let e_{ij} be the emission generated

per kilometer for transporting one kilogram between nodes i and j by the ICEVs. Recall that no emissions are generated when EVs are used for transportation. Therefore, the emissions produced by ICEVs during transportation within the network can be calculated as follows $\sum_{i \in N} \sum_{j \in N} e_{ij} Y_{ij}^1$.

Social Parameters

Increasing job opportunities, ensuring equitable employment, and improving workers' income [25] are critical social dimensions within sustainable network design. In the study by [34], it is assumed that the decision to open a facility in a region will increase employment (in terms of the number of jobs) in that region by s_i. Additionally, the parameter b_i, determined based on the region's unemployment rate and population density, increases the weight of areas with high unemployment and population density in the facility location decisions. In this study, the employment growth formula used in [32] $\sum_{i \in N} s_i b_i F_i Z_i$ will be expanded and adapted as follows $\sum_{i \in N} \alpha_i s_i b_i F_i Z_i$, where α_i represents the ratio of the revenue generated to the fixed cost when a facility is established at node i. This formula is used to calculate the income generated by the facility at node i. Table 1 lists all the parameters used in the mathematical model.

Decision Variables

Decisions in the mathematical model pertain to the opening of facilities, transportation, choosing vehicle types, and meeting demands, as given below.

$$Z_i = \begin{cases} 1, & \text{if facility } i \text{ is opened} \\ 0, & \text{otherwise} \end{cases}$$

$$X_{ij}^v = \begin{cases} 1, & \text{if transportation occurs between nodes } i \text{ and } j \text{ using vehicle type } v \\ 0, & \text{otherwise} \end{cases}$$

Y_{ij}^v: Amount (in kg) transported from node i to node j using vehicle type v

UD_j: Unmet demand quantity at customer site j

Mathematical Model

The model's objective is to minimize total costs while maximizing social benefits under emission limit with service level targets and single-source constraints. The costs are fixed opening costs, transportation costs, and labor costs; carbon emissions are calculated from the vehicle type and the distance travelled. Facilities and vehicles have capacity limits. The model also decides whether the goods are carried by an EV or an ICEV. Given the ongoing transition to EVs in the logistics sector, the costs associated with establishing charging stations and developing infrastructure make selecting suitable routes for EVs and ICEVs a timely and significant challenge. Furthermore, an emission limit is imposed on the supply chain network to ensure compliance with legal standards and align with the SDGs [7]. We give the mixed integer programming model of the problem in Equations (1)–(12), and then, follow with the explanations for the objective function and constraints.

$$\textbf{Min} \sum_{i \in N} F_i Z_i + \sum_{i \in N} \sum_{j \in N} \sum_{v \in N} t^v d_{ij} Y_{ij}^v + \sum_{i \in N} \sum_{j \in N} \sum_{v \in N} c^v d_{ij} X_{ij}^v + \sum_{j \in N} P \cdot UD_j - \sum_{i \in N} \alpha_i s_i b_i F_i Z_i \quad (1)$$

Table 1. Parameters used in the mathematical model

Symbol	Description	Unit
F_i	Initial investment cost for establishing a facility at node i	Thousand TL
d_{ij}	Distance between nodes i and j	km
q_i	Demand at the facility located at node i	kg
φ	Legal upper emission limit in the supply chain	kg CO_2e
W_i	Capacity of the facility i	kg
K_{ij}^v	Capacity of vehicle v between nodes i and j	kg
t^v	Transportation cost per kg and km for vehicle type v (1 = ICEV, 2 = EV)	TL/kg×km
c^v	Labor cost for vehicle type v	TL/km
e_{ij}	Emission value per kg transported from i to j	kg CO_2e
s_i	Employment increased due to the facility opening at node i (number of jobs)	quantity
b_i	Coefficient related to unemployment and population density at node i	$0 < b_i < 1$
B	Total budget for facility establishment	Thousand TL
R	Range constraint for EVs	km
α_i	Ratio of revenue generated to fixed cost when a facility is established at node i	$0 < \alpha_i < 1$
SL	Service level parameter showing the minimum proportion of demand fulfillment across the entire supply chain	%
P	Penalty cost per unit kg for unmet demand	TL/kg

$$\text{s.t. } \sum_{j=1}^{N}\sum_{v=1}^{2} Y_{ij}^{v} \le W_i Z_i, \quad i \in N \tag{2}$$

$$\sum_{i \in N}\sum_{v \in V} Y_{ij}^{v} - UD_j = q_j, \quad j \in N \tag{3}$$

$$Y_{ij}^{v} \le K_{ij}^{v} X_{ij}^{v}, \quad i \in N, j \in N, v \in V \tag{4}$$

$$X_{ij}^{v} \le Z_i, \quad i \in N, j \in N, v \in V \tag{5}$$

$$\sum_{i \in N} F_i Z_i \le B, \tag{6}$$

$$\sum_{i \in N}\sum_{j \in N} e_{ij} Y_{ij}^{1} \le \varphi, \tag{7}$$

$$d_{ij} X_{ij}^{2} \le R, \quad i \in N, j \in N \tag{8}$$

$$\sum_{v \in V} X_{ij}^{v} \le 1, \quad i \in N, j \in N \tag{9}$$

$$\sum_{i \in N}\sum_{v \in V} X_{ij}^{v} \le 1, \quad j \in N \tag{10}$$

$$\sum_{i \in N}\sum_{v \in V} Y_{ij}^{v} \ge SL, \quad j \in N \tag{11}$$

$$Z_i, X_{ij}^{v} \in \{0,1\}, Y_{ij}^{v} \ge 0, UD_j \ge 0, \; i \in N, \; j \in N, \; v \in V \tag{12}$$

The objective function in (1) minimizes the total cost of establishing facilities, transportation, labor, and penalty due to the unmet portion of the demand as well as the negative of a revenue function that expresses social benefits in monetary terms. Constraint set (2) prevents exceeding the capacity of a facility opened at node *i*. Constraint set (3) gives the demand balance constraint for each facility. Constraint set (4) prevents exceeding vehicle capacity for the quantity transported from node *i* to node *j*. Constraint set (5) ensures that customer *j* can only be assigned to the ith facility if it is open. Constraint (6) forces the total facility opening cost to be within the allocated budget. Constraint (7) ensures that the total emissions in the designed network do not exceed the legal limit (φ). Constraint set (8) gives the range limitations on the EVs. Constraint set (9) ensures that at most one vehicle type can be used between nodes *i* and *j*. The single-source constraints given in (10) ensure that a single facility must meet demands using a single vehicle type. Constraint set (11) gives the service level constraints to ensure the minimum proportion of total demand fulfillment across the supply chain. Constraint set (12) provides the sign and type restrictions on the decision variables.

COMPUTATIONAL ANALYSIS

In this section, computational experiments were conducted to validate the proposed mathematical model and analyze the interactions between key parameters.

Data Set

In this study, we mainly use the data sets in [35] and generate other necessary data to conduct the computational analysis as explained next. In [35], 12 datasets are randomly generated for 10 potential facility locations and 50 customers. Facility locations are generated from a uniform distribution U(10, 200), while customer demands are generated from U(10, 50). Fixed costs and capacities of the facilities are obtained from the distributions U(100, 500) and U(300, 700), respectively. The different cost structures for EVs and ICEVs are reflected in the transportation cost (t^v) and labor cost (c^v) parameters. We assume that both t^2 and c^2 are 20% higher than t^1 and c^1, respectively, where $t^v \in \{1,1.2\}$ and $c^v \in \{1,1.2\}$.This study uses 12 datasets from problem p1 in [35] to conduct sensitivity analyses on budget, emissions, range of EVs, penalty cost, and service level parameters. Table 2 lists the set of parameter values used in the sensitivity analyses.

Computational Results

Based on parameter sets shown in Table 2 and defined in the study of [35], Gams Release 48.5.0 with CPLEX solver was used to run for 2916 scenarios, combining 243 distinct configurations across five key parameters: budget coefficient (ζ), range coefficient (ξ), emission coefficient (ρ), penalty cost (P), and service level (SL). Three levels are considered for each of these five parameters. These configurations were applied to 12 datasets, allowing for an extensive evaluation of feasibility and infeasibility patterns under various parameter settings (Table 3).

Results show that the budget has the biggest effect on feasibility (Table 3). As the budget increases, number of infeasible instances decreases. Relaxing the emission limit also helps, the number of infeasible instances decrease from 216 to 117 and then to 99. The EV range matters less. Going from 50% to 75% of the base range reduces the infeasible instances from 174 to 129, but a further increase to 100% changes nothing. Table 4 gives a view for the service level (SL) and the penalty cost (P). With SL = 50%, all 324 instances are feasible for every penalty level. At SL = 80%, 40 of the 324 instances become infeasible, and at SL = 100% this number rises to 104. The penalty cost has no effect on these counts. For a given service level, the number of

Table 2. Set of parameter values considered in the sensitivity analyses

Parameter	Values
$B = \zeta \cdot \sum_{i \in N} F_i$	$\zeta \in \{0.5,0.75,1.0\}$
$R = \xi \cdot Median\ (d_{ij})$	$\xi \in \{0.5,0.75,1.0\}$
$\varphi = 35000 \cdot \rho$	$\rho \in \{1.0,1.5,2.0\}$
P	$P \in \{10,50,100\}$
SL	$SL \in \{0.5,0.8,1\}$

Table 3. Number of feasible and infeasible instances under different *B, R, ρ* values

Parameter	Parameter value (% of the base level)	Number of feasible instances	Number of infeasible instances
Budget (*B*)	50	654	318
	75	858	114
	100	972	0
Range (*R*)	50	798	174
	75	843	129
	100	843	129
Emission (*ρ*)	100	756	216
	150	855	117
	200	873	99

Table 4. Number of feasible and infeasible instances under different *SL* and *P* values.

Service Level (SL)	Penalty cost (P)	Number of feasible instances	Number of infeasible instances
50%	10	324	0
	50	324	0
	100	324	0
80%	10	284	40
	50	284	40
	100	284	40
100%	10	220	104
	50	220	104
	100	220	104

infeasible instances is the same for P = 10, 50, and 100. A higher service level means more demand to be met, and in some instances, this is not possible within the limits.

Figure 3 shows how the costs change with the budget (*B*). When the budget coefficient goes from 50% to 100%, the average total cost falls from 50.41 to 33.42 thousand TL. Most of this saving comes from transportation and unmet demand. Labor costs also decrease slightly. The fixed cost, on the other hand, roughly doubles, from 2.39 to 4.83, because a larger budget allows more facilities to be opened. The social benefit grows in the same way, from 2.42 to 4.97, since each new facility creates jobs in its region. The extra money spent on facilities is thus more than recovered through lower transportation and penalty costs.

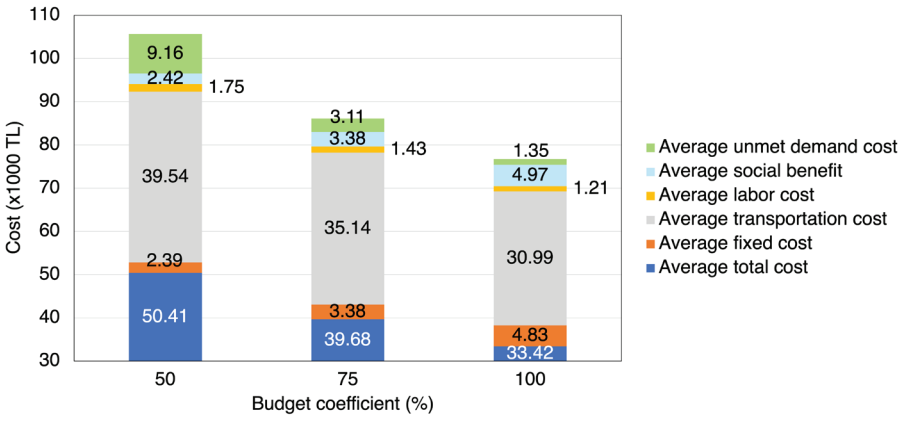

Figure 3. Effects of the budget on the costs.

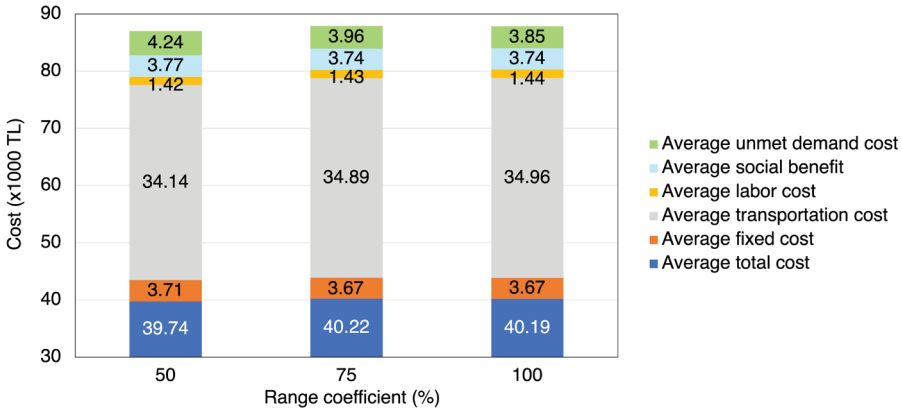

Figure 4. Effects of range on the costs.

The results of the sensitivity analysis for the range parameter (R) are presented in Figure 4. It is seen that the cost components change only slightly with the range coefficient. For the three levels, the average total cost is 39.74, 40.22, and 40.19 thousand TL, i.e., around 40 thousand TL, and the differences in the transportation, labor, and fixed costs remain below one thousand TL. The social benefit is also nearly the same. A noticeable change is observed only in the unmet demand cost, which decreases from 4.24 to 3.85, since more customers can be reached by EVs with a longer range. The values for the 75% and 100% levels are very close, in agreement with the feasibility results in Table 3. Hence, within the tested values, the EV range has only a limited effect on the cost structure.

The changes in the cost components and the social benefit under different emission coefficients are given in Figure 5. It should be noted that a higher emission coefficient corresponds to a less strict emission limit. When the coefficient is increased from 100% to 200%, the average total cost increases only slightly, from 39.78 to 40.32 thousand TL, while the transportation cost goes up from 33.40 to 35.51. The unmet demand cost, on the other hand, decreases from 5.01 to 3.45. This is because Constraint (7) limits only the flows carried by ICEVs; with a looser limit, more customers can be served by these vehicles, so more goods are transported and less penalty is paid. There is a small decrease in the fixed cost (from 3.78 to 3.63), whereas the labor cost and the social benefit remain almost unchanged. For the decision maker, the main consequence of a strict emission limit is therefore unserved demand rather than a large increase in operating costs.

The sensitivity analysis results for the penalty cost parameter (P) and the service level parameter (SL) are shown in Figures 6 and 7, respectively. As seen in Figure 6, the average total cost increases from 33.73 to 44.58 thousand TL when the penalty is raised from 10 to 100. The largest part of this increase comes from the transportation cost (from 28.98 to 39.02), because the model prefers to ship more goods when unmet demand becomes expensive. The fixed cost is 3.69 for all three penalty levels, and the labor cost changes very little. The unmet demand cost first increases from 3.46 to 4.44 and then decreases to 4.15, but this does not mean that more demand is left unmet. Since this cost is calculated as P times the unmet quantity, it may

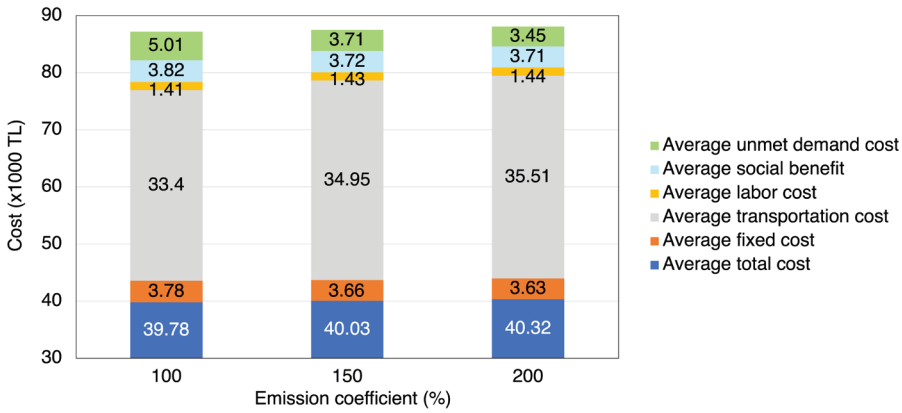

Figure 5. Effects of emission on the costs.

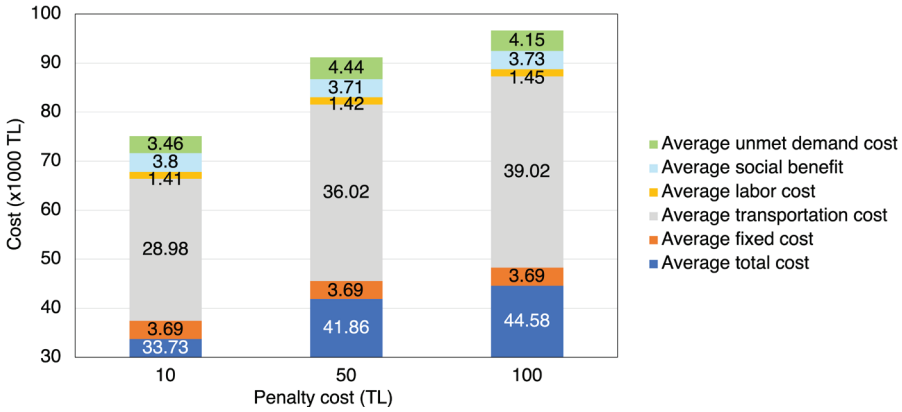

Figure 6. Effects of the penalty on the costs.

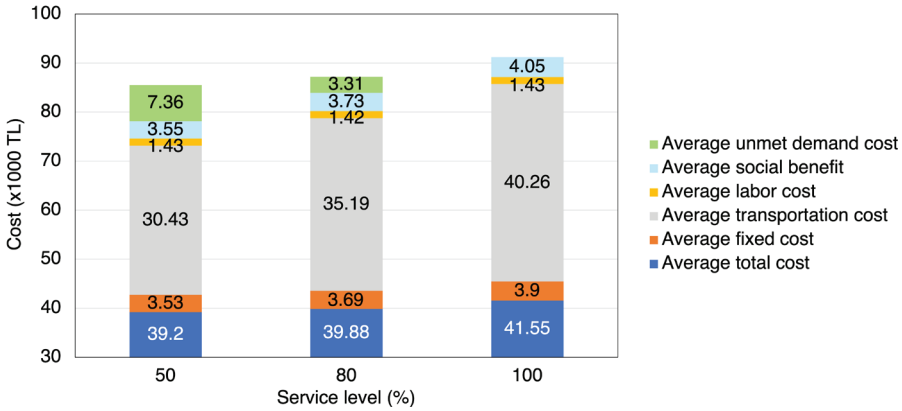

Figure 7. Effects of the service level on the costs.

increase when P becomes five times higher, even though the unmet quantity is reduced by approximately three quarters. These quantities are given in Figure 8.

Figure 7 compares the cost components for the three service levels (SL). The largest increase is seen in the transportation cost, which goes from 30.43 thousand TL at SL = 50% to 40.26 thousand TL at SL = 100%, since more demand has to be delivered. The fixed cost also increases from 3.53 to 3.90 because more facility capacity is required. The social benefit, which is linked to the investment in the opened facilities, follows the fixed cost and rises from 3.55 to 4.05. In contrast, the unmet demand cost decreases from 7.36 to 3.31 and becomes zero at SL = 100%, where all demand must be satisfied. As these changes partly compensate each other, the average total cost increases by only about 6% (from 39.20 to 41.55 thousand TL). In other words, a higher service level improves both service and social benefit at a moderate additional cost.

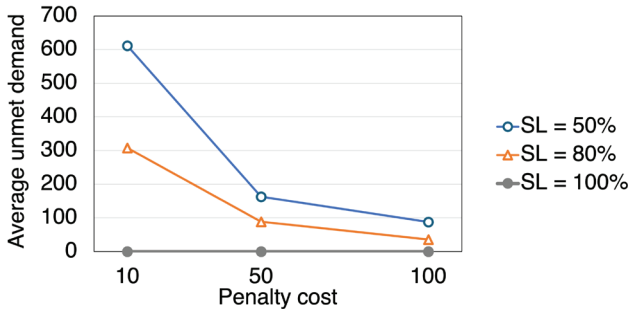

Figure 8. Effects of service level and penalty cost on average unmet demand.

In Figure 8, the average unmet demand is given for each combination of SL and P. Increasing either of the two parameters decreases the unmet demand. When SL = 50% and P = 10, the average unmet demand is about 600 kg, and it falls below 100 kg if the penalty is raised to 100. For SL = 80%, it is about 300 kg at P = 10 and less than 50 kg at P = 100, whereas for SL = 100% there is no unmet demand at any penalty level, as required by the service level constraint (11). Most of the decrease occurs between P = 10 and P = 50, and the additional reduction from 50 to 100 is smaller, which means that a moderate penalty is sufficient

Table 5. Effects of transportation cost on the solution

t_{factor}	Number of facilities opened	Total cost (thousand TL)	Fixed cost (thousand TL)	Transportation cost (thousand TL)	Labor cost (thousand TL)
0.05	6	6.72	3	2.19	1.52
0.10	6	8.91	3	4.37	1.53
1.00	10	39.46	5	33.27	1.18
10.00	10	338.89	5	332.71	1.18
20.00	10	671.60	5	665.40	1.18

Table 6. Effects of the fixed cost on the solution

f_{factor}	Number of facilities opened	Total cost (thousand TL)	Fixed cost (thousand TL)	Transportation cost (thousand TL)	Labor cost (thousand TL)
1	10	39.47	5	33.27	1.18
2	6	50.19	5	43.67	1.54
3	6	58.31	5	51.55	1.75

to eliminate most of the unmet demand. A strict service level eliminates it completely; however, as shown in Table 4, it also leads to more instances without a feasible solution.

Two more sensitivity analyses were also carried out, the first one on energy prices (fuel and electricity) and the second one on the cost of EV infrastructure. In both analyses, data set 12 of Holmberg et al. [35] was used. In the first analysis, the transportation cost was multiplied by a factor, i.e., $t_{factor}\ t^v$. Table 5 gives the effect of this factor on the optimal number of opened facilities, the total cost, and the distribution of the total cost among the fixed, transportation, and labor costs. It is seen that the total cost, and in particular the transportation cost, is highly sensitive to changes in energy prices. For a low cost factor (t_{factor}= 0.05), only six facilities are opened in the optimal solution, since transportation is relatively cheap. When energy prices increase considerably ($t_{factor} \geq 1$), however, the number of opened facilities rises to ten, and the network becomes more decentralized. In this case, each facility satisfies its own demand, which reduces the effect of the higher transportation costs.

In the second analysis, the infrastructure-related fixed costs of the first five nodes were changed in a similar way, and the fixed cost parameter was set as $f_{factor}\ F_i$ for i =1,2,…,5. For each value of the factor, Table 6 reports the number of opened facilities, the total cost, and how this cost is divided among the fixed, transportation, and labor costs.

As expected, the solutions in Table 6 are sensitive to the cost of infrastructure. When the infrastructure investment cost (F_i) is doubled or tripled, only six facilities are opened in the optimal solution instead of ten. In these cases, the higher fixed costs of the first five nodes exceed the benefits of opening additional facilities, and the operations are concentrated in fewer locations in order to limit the high initial investment in infrastructure. When Tables 5 and 6 are considered together, it can be concluded that opening more facilities to shorten the delivery distances is advantageous when transportation is expensive and infrastructure is cheap, whereas a smaller network with longer trips is preferable when energy is cheap. Given the uncertainty in future energy prices and infrastructure costs, this type of analysis can help firms to evaluate how much their network design is affected by these two factors.

The findings of this study are generally consistent with previous studies. Similar to Ala et al. [21], more instances become feasible when the operational constraints are relaxed; different from their study, however, our model considers a mixed fleet of electric and conventional vehicles during the transition period. The trade-offs obtained among the economic, environmental, and social objectives are also comparable to those reported by Anvari and Türkay [28]. In our experiments, the social benefit could be increased at a relatively small additional cost; for instance, when *SL* is raised from 50% to 100%, the social benefit increases by about 14%, whereas the increase in total cost is about 6% (Fig. 7). Studies such as [29] and [31] mainly focus on economic and environmental criteria. Since our model also includes the social dimension, the trade-offs among all three dimensions can be examined together.

CONCLUSION

In this study, a mathematical model was developed for the Mixed Fleet Sustainable Facility Location Problem with service level, single-source, and capacity constraints, considering the economic, environmental, and social dimensions of sustainability simultaneously. The model was

tested on 12 datasets and 2916 scenarios generated with different values of the budget, EV range, emission limit, penalty cost, and service level. The budget was found to have the strongest effect: all instances were feasible with the full budget, and the average total cost was approximately one third lower than half of the budget. The effect of the EV range was much smaller, and increasing the range above 75% of its base value made almost no difference. Relaxing the emission limit slightly increased transportation costs while reducing unmet demand. Higher penalties also led to less unmet demand, but with higher transportation costs. Finally, a higher service level increased the social benefit with a moderate rise in total cost, although the number of infeasible instances also increased.

The main contribution of this work is the inclusion of the social dimension. Since job creation is weighted by unemployment and population density, the model gives priority to regions with high unemployment and dense population in the facility location decisions. When this is considered together with the EV range limits and the emission cap, the problem is represented more completely than in models that consider only cost and emissions. The model can also support policymakers and logistics managers in estimating the cost of a sustainability target before such a target is adopted.

From a practical perspective, the findings can be useful for supply chain planners in retail, manufacturing, and e-commerce logistics. In our experiments, a larger budget reduced the transportation and penalty costs by more than the increase in fixed costs and also created more jobs, which shows that additional spending on facilities can be recovered through savings in other costs. Since costs and feasibility remained almost the same beyond 75% of the base range, increasing the vehicle range seems to be useful only up to a certain level for firms switching to electric fleets. A tighter emission cap resulted mostly in unmet demand rather than in higher operating costs; therefore, firms facing stricter emission regulations should check whether their EV coverage and facility locations still allow them to reach all customers. The network layout also depends on energy prices. When transportation is expensive, more facilities and shorter trips give a lower overall cost, while fewer facilities are preferable if energy is cheap.

Some limitations of this study should also be mentioned. The demand in our datasets is static, whereas in real supply chains it changes over time. As a next step, the model can be extended to a multi-period version with uncertain demand and cost parameters such as fuel prices, which would also allow changes in vehicle technology and regulations to be reflected. Renewable energy supply at the facilities could also be included. Regarding EVs, only the range limit is modeled; charging infrastructure and charging times are not considered in detail, although both are important in practice. Lastly, the social dimension is measured at the regional level through job creation weighted by unemployment and population density, and aspects such as worker welfare, occupational safety, and other effects on local communities are not included. Future studies that take these factors into account would allow social sustainability in facility location problems to be assessed more completely.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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