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A Consumer Expectation-Based Multiple Satisfaction Model for Battery-Swapping Station Deployment

Abstract. *This study addresses the location problem of electric vehicle battery swap stations and considers consumer satisfaction based on expectations under multiple indicators. The problem is to determine the optimal deployment plan of electric vehicle battery swap stations in the network while saving as much investment cost as possible to maximise the desirability of demand allocation that leads to an increase in consumer satisfaction. A multiple satisfaction model incorporating cost and risk indicators is developed for this problem, with employing the accumulated range anxiety as an importance coefficient to determine the weights occupied by each indicator. In addition, an improved INSGA-II is devised to solve the model. Numerical experiments in the city of Anaheim network demonstrate the validity of the proposed model and solution method and analyse the relationship between investment costs and satisfaction based on consumer expectations. Results show that an increase in investment costs is beneficial to increase consumer satisfaction in general, but poorly located battery swap stations lead to a decrease in consumer satisfaction instead.*

Keywords: *battery swap station, flow-based location problem, multiple satisfaction, consumer expectation, INSGA-II.*

JEL Classification: R4, C6, C8.

1. Introduction

Since the 21st century, sustainable development, green energy, and carbon neutrality have become common themes for the development of countries around the world. In recent years, the topic of banning the sale of fuel vehicles has frequently appeared in official documents of various countries (Benvenutti, 2017; Weng, 2021). In March 2023, the European Council passed a bill to ban the sale of carbon dioxide-

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emitting vehicles by 2035. On March 20, 2024, the Biden administration announced strict new regulations restricting the sale of gasoline powered vehicles, aimed at gradually phasing out gasoline vehicles and ensuring that the majority of passenger cars and light trucks sold in the United States by 2032 are electric or hybrid vehicles. Compared to traditional fuel vehicles, electric vehicles (abbreviated as EVs) not only use clean energy, are environmentally friendly, and also have lower costs. They have become a focus of future transportation planning and policy formulation in many countries and regions (Shaker, 2023; Mak, 2013; Pieltain, 2011). It can be seen that EVs are gradually integrating into people's daily lives. However, due to issues with battery technology and supporting infrastructure, some consumers still have concerns when purchasing EVs. Especially, the endurance of EVs can lead to drivers experiencing "mileage anxiety". Therefore, this article proposes to consider user risk preferences and explore the optimal site selection and path planning problem for electric vehicle charging stations based on travel costs, battery depletion risk, and mileage anxiety for users.

2. Literature review

The site selection and path optimisation of electric vehicle charging facilities is a complex and multidimensional problem that involves multiple stakeholders, such as users, investors, and power grid companies. On the one hand, users hope to enjoy convenient and low-cost services. On the other hand, investors are more concerned about construction and operating costs. Therefore, the site selection and path optimisation problem of charging and swapping facilities usually faces the balance problem of multiple objectives. Most of the existing literature mainly focusses on these research objectives.

Hadian et al. (2019) propose an optimisation objective to minimise the longest working time of drivers for multi-node vehicle routing problems, while minimising total cost and carbon dioxide emissions. Li et al. (2023) establish a three-level decision model with the goal of maximising the profit of charging stations, including users, site selection, and pricing; and propose a profit maximising charging station location plan by analysing the impact of pricing strategies on user node selection behaviour. Ouyang et al. (2022) establish a hybrid charging station site selection path optimisation model that takes into account user partial charging behaviour and elastic demand, with the goal of saving budget and maximising user travel demand coverage, to determine the optimal location for fast and slow charging stations in the network. Ullah et al. (2023) established a weighted set coverage model to determine the location and capacity of fast charging stations in Aichi Prefecture, Japan, with the goal of minimising the investment cost of charging stations and the charging cost of users. Zang et al. (2020) propose a site selection optimisation model that comprehensively considers the interests and needs of multiple parties between charging stations, users, and distribution networks. The model takes into account the uncertainty of the growth rate of EVs. Yuan et al. (2020) develop a fast charging station location model based on queue theory with the goal of minimising daily total operating costs and user waiting time, to study the optimisation problem of microgrid operation for electric vehicle charging, swapping, and storage integrated stations. Based on the theory of traffic flow allocation, Wang et al. (2023) propose a site selection model for an electric bus exchange station that takes into account the departure plan and route arrangement of electric buses, in order to improve the service quality of the exchange station. Zu et al. (2022) take the service scope of charging and swapping stations as constraints and consider the service radius of charging and swapping facilities. Woo et al. (2023) consider the user's proximity preference and introduce distance constraints between sites and users in demand allocation. Kınay et al. (2021) consider the vehicle's range capability and charging station work plan, with vehicle range and charging station opening as constraints. Schettini et al. (2023) set the number of charging stations invested in the network as a constraint and considered budget constraints for investors. Akbari et al. (2018) used a genetic algorithm to calculate the minimum number and optimal location of electric vehicle charging stations based on the daily driving distance of users as constraints. Liang et al. (2020) establish a minimum total social cost model based on discrete distribution charging demand, use particle swarm optimisation algorithm to calculate the optimal location of charging stations, and determine the construction scale of charging stations based on user path planning. Loni et al. (2023) regard the charging station location path problem as a multi-objective planning problem that includes site development costs, social equity, and meeting charging needs, and use the NSGA-II algorithm to calculate the trade-off points between the three objectives.

In summary, researchers have established various goals for the charging site selection of EVs, including convenience, cost savings, maximum profit, charging efficiency, etc. In addition, different methods were adopted to solve the problem. All research is actually aimed at finding the appropriate balance of interests between investors and users, while protecting the environment, to bring convenience and benefits to our lives.

3. Model Construction

3.1 Problem Description

In order to overcome the barriers to mass acceptance of EVs, a battery swap stations (abbreviated as BSS) deployment plan that makes consumers more satisfied should be determined. Therefore, a BSS deployment problem that considers both consumer satisfaction and investment cost is studied in this paper. The problem can be expressed as a modified flow capture location model （abbreviated as FCLM) that aims to use the minimum number of BSSs to maximise the satisfaction of the consumers in the network. We call it CEMS, which is a consumer expectation （abbreviated as CE)-based multiple satisfaction model for battery swap station deployment.

Therefore, the basic assumptions for model construction are given as follows:

Assumption 1. It was assumed that the surroundings of the BSSs and paths are equally attractive to consumers. Thus, their choice only accepts cost and risk indicators.

Assumption 2. Consumers are assumed to visit the BSS passing by only if the EVs do not have enough power remaining to reach the destination.

Assumption 3. The battery performance and discharge rate are assumed to be constant during driving.

Assumption 4. It assumed that the BSS has an adequate inventory of batteries and ignore the power consumption of consumers within the BSS.

Assumption 5. The range anxiety is assumed to be affected only by remaining power, ignoring the heterogeneity of consumers.

We attribute the above problem to the travel-time problem of the OD paths between urban transportation networks. In flow-based models, the traffic flow between ODs is represented as a travel demand from a given pair of origin to destination, so consumers can be allocated to any paths between ODs that satisfy the constraints. To capture the traffic flow of consumers, it should be ensured that BSSs are deployed on at least one path between each OD that complies with the constraints. However, multiple paths exist between each OD, but not all of them can be used for demand allocation because there are limits to the tolerance of detour costs by consumers. Therefore, a multi-path generation method that considers the tolerance of detours is introduced, whose principle is to impose a length penalty on the links that make up the shortest path so that the path is no longer the shortest.

All the modelling parameters involved are shown in Table 1.

Table 1. Modelling parameters

Variables Symbol	Description
r	Index for origin node of an OD, $r \in \mathrm{O}$
s	Index for destination node of an OD, $s \in \mathrm{O}$
c	Index for candidate nodes, $c \in \mathrm{C}$
k	Index for available path between $(r,s), k \in \mathrm{K}_{(r,s)}$
m	Index of gene positions in the INSGA-II, $m \in \mathrm{A}^0 \cup \mathrm{A}^1$
C	Set of candidate nodes in network
O	Set of OD pairs in network
$\mathrm{K}_{(r,s)}$	Set of available paths between (r,s) within the detour cost constraints
A^1	Set of positions on a gene with a value of 1
A^0	Set of positions on a gene with a value of 0
α	The battery discharge efficiency
β	The remaining power of the EV
β_0	The Remaining power of the EV at the origin r
β_1	The Remaining power when the EV arrived at the BSS
β_{comf}	Comfortable range threshold above which EV drivers are free from range anxiety
CB_m	The betweenness centrality of the candidate node corresponding to the gene location
z	The adjustment factor used to align the range of the indicator
l	The distance traveled by the EV
D_1	The length of the shortest path between (r,s)

Variables Symbol	Description
D_2	The distance from the destination to the nearest BSS to the destination
D_3	Remaining mileage corresponding to βr
N_{OD}	The number of OD pairs in the network
pr_m^0	Probability that gene position m is selected
$\bar{R}(\beta_1)$	Accumulated range anxiety along a path as a function of remaining power when the EV reaches the BSS
R_{max}	Maximum value of accumulated range anxiety used in normalisation
M	A sufficiently large penalty-factor in the objective function
t	The control coefficients of the perturbation range in the algorithm
TD	The tolerance of consumers for detours
N_{BSS}	The number of BSS builds in the network
G	the consumer satisfaction
I	The importance coefficient to determine the weights
$A_{(r,s)}^{ri}$	Attractiveness of risk indicator to customers between(r,s)
$A_{(r,s)}^{ci}$	Attractiveness of travel cost indicator to customers between (r,s)
$DB_{(r,s)}^{k}$	Distance of the nearest BSS on the kth path between $(r,s)$from the origin r
DB_r	Distance of the nearest BSS to the origin r
$LP_{(r,s)}^{k}$	Length of the kth path between (r,s)
$R(\beta)$	Range anxiety profile during traveling as a function of remaining power
$S(l)$	Remaining power during travelling as a function of travel distance
X_c	Binary variable that equals 1 if a BSS is placed
$Y_{r,s}^{k}$	Binary variable that equals 1 if consumers between (r,s)travel along path k and equals 0 otherwise

Source: Authors' own creation.

3.2 CE-based Multiple Satisfaction Function

Depending on the travel plan and the remaining power at the origin, the battery swap arrangement of the consumer may be different, i.e., the consumer may be looking for a BSS during the trip or after. Therefore, based on the remaining power at the origin and the travel plan of the consumer, three possible battery swap logicare designed for the consumers.

(1) If $D_1 > D_3$, i.e. the remaining mileage of the EV at the origin is not enough to reach the destination, consumers have to find BSSs before reaching the destination.

(2) If $D_1 + D_2 < D_3$, i.e., the remaining mileage of the EV at the origin is sufficient to support its traveling to the nearest BSS after reaching the destination.

(3) If $D_1 < D_3 < D_1 + D_2$, i.e., the remaining mileage of the EV at the origin is sufficient to reach the destination but cannot travel to the nearest BSS after arrival, so that consumers have to find BSSs before reaching the destination in order to avoid the power depletion.

In the model, if consumers need to find a BSS before reaching their destination, their travel demands are allocated to the shortest path in the available set that is capable of capturing the traffic flow and receiving battery swapping at the earliest BSS encountered.

Therefore, a multiple satisfaction function is built that includes cost and risk indicators, employing range anxiety as an indicator importance coefficient to determine the weights that cost and risk occupy in consumer satisfaction. It considers two indicators, traveling cost and risk of power depletion, which are described in terms of mileage travelled to the destination and distance to the BSS, respectively. The gap between the value of the indicator and the CE in the demand allocation is described as the attractiveness of the indicator to the consumer, which becomes larger as the gap decreases. Indicator attractiveness reflects the desirable level of the indicator in the demand allocation, in order to obtain consumer satisfaction with the demand allocation, range anxiety was introduced as an indicator importance coefficient which reflects the risk attitude of consumers. The weighted attractiveness indicates consumer satisfaction with the demand allocation; the smaller the gap between the demand allocation and the CE, the greater the attractiveness and the more satisfied the consumer will be. Next, the CE-based indicator attractiveness and the range anxiety will be presented separately.

Based on the definition of indicator attractiveness above, $A_{(r,s)}^{ri}$ is formulated as:

$$A_{(r,s)}^{ri} = \begin{cases} 1, & \text{if } D_1 + D_2 < D_3 \\ \sum_{k \in K_{(r,s)}} \dfrac{DB_{(r,s)}^{k} Y_{r,s}^{k}}{DB_r}, & \text{else} \end{cases} \tag{1}$$

As Eq. (1), when consumers are allocated to path *k* of the available paths K, the distance from the nearest BSS on that path to the consumer is $DB_{(r,s)}^{k}$, and the distance from the nearest BSS from the origin *r* to consumer is DB_r, i.e. CE. $Y_{r,s}^{k}$is a binary variable that equals 1 if consumers between (*r*, *s*) travel along path *k* and equals 0 otherwise.

When $D_1 + D_2 < D_3$, consumers have the ability to travel to the most desirable BSS to receive battery swap serviceupon arrival at the destination, instead of swapping batteries along the way, so the BSSs passed by is not attractive to consumers. Conversely, they must swap batteries en route to their destinations. BSS that passed through earlier reduces the risk of power depletion of the consumers and has a greater degree of risk attractiveness to them. The degree of risk attractiveness $A_{(r,s)}^{ri}$depends on the gap to the CE, i.e., is derived from the ratio of $DB_{(r,s)}^{k}$ and DB_r.

Likewise, $A_{(r,s)}^{ci}$ is formulated as:

$$A_{(r,s)}^{ci} = \begin{cases} 1, & \text{if } D_1 + D_2 < D_3 \\ \sum_{k \in K_{(r,s)}} \frac{LP_{(r,s)}^{k} Y_{r,s}^{k}}{min\left(LP_{(r,s)}^{k}\right)}, & \text{else} \end{cases} \tag{2}$$

As Eq. (2), when a consumer is assigned to the path *k* of the available paths K, the length of the path is $LP_{(r,s)}^{k}$, and the length of the shortest path between (*r*, *s*) is $min(LP_{(r,s)}^{k})$, i.e. CE. Since consumers may choose detours only if they need to find a BSS before reaching their destination, when $D_1 + D_2 < D_3$, consumers will follow the most desirable path to their destination. Conversely, shorter paths have greater cost attractiveness to the consumer and the degree of cost attractiveness depends on the gap to the CE, i.e., the ratio of $LP^{k}_{(r,s)}$ and $min(LP^{k}_{(r,s)})$.

3.3 Range Anxiety

Range anxiety is the anxiety caused by the fear of the consumer of power depletion, the higher the range anxiety, the stronger the desire of consumers to swap batteries. As shown in Figure 1, it illustrates the changes in the remaining charge (top half) and range anxiety (bottom half) as the EVs are driven.

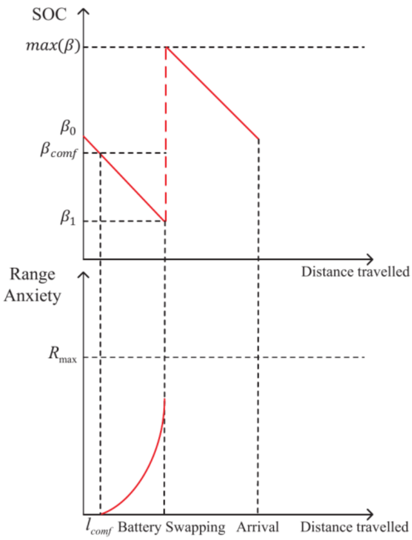

Figure 1. Accumulated range anxiety
Source: Authors' own creation.

Consumers can evaluate their satisfaction with the combined cost and risk indicators by estimating the accumulated range anxiety they may endure based on their comfort range and the remaining power in their EV when developing a plan. When the remaining power of EVs falls below the comfort range, consumers begin to experience range anxiety, which will continue to increase as the remaining power decreases.

Since the proposed satisfaction function only considers the cost and risk indicators of the consumer, the normalised range anxiety can be used as an importance coefficient to measure the weight that both indicators occupy in consumer satisfaction. The calculation is as follows:

$$S(l) = \beta_0 - \alpha \times l \tag{3}$$

$$R(\beta) = \begin{cases} 0, & \text{if } \beta \geq \beta_{comf} \\ \frac{R_{max}}{\beta_{comf}^2}\left(\beta_{comf} - \beta\right)^2, & \text{else} \end{cases} \tag{4}$$

$$\bar{R}(\beta) = \int_{\beta_0}^{s(l)} R\,(\beta) d\beta \tag{5}$$

Eq. (3) shows the remaining power β as a function of mileage l, and α is the battery discharge efficiency, in order to make comparability between power and mileage. As the remaining power decreases, the range anxiety of the consumer changes as a function of Eq. (4). According to Eqs. (3) -(4), the accumulated range anxiety over the entire trip can be expressed as the definite integral of the range anxiety function over the trip region, which is formulated as Eq. (5). In summary, the formula for the importance coefficient I of the indicators in our satisfaction function is as follows:

$$I = z + \bar{R}(\beta_1) \tag{6}$$

Based on the assumption, that consumers will have far more power than the comfort range after battery swapping, we describe the range anxiety endured by the consumers throughout the trip as accumulating when the consumers reach the BSS, i.e.$\bar{R}(\beta_1)^-$. In addition, since the cost and risk indicators have different ranges in values, a moderating factor z is introduced in Eq. (6) to eliminate the effect of differences in the range of values on the composite satisfaction. As a result, the function of CE-based multiple satisfaction is shown in Eq. (7), in which G represents the gap between the BSSs and Paths allocated by the model for the consumer and the CE in each aspect, and the importance coefficients corresponding to the risk and cost indicators are I and $1-I$, respectively.

$$G = I \times A_{(r,s)}^{ri} + (1 - I) \times A_{(r,s)}^{ci} \tag{7}$$

3.4 Mathematical Modelling of CEMS

Therefore, combining formula (1-7), we establish a model that integrates consumer satisfaction and investment costs. The details are as follows:

$$\min G = \sum_{r,s \in O} I \times A_{(r,s)}^{ri} + (1 - I) \times A_{(r,s)}^{ci} \tag{8}$$

$$\min N_{BSS} = \sum_{c \in \mathbb{C}} X_c \tag{9}$$

$$I = z + \bar{R}(\beta_1) \tag{10}$$

$$\bar{R}(\beta) = \int_{\beta_0}^{s(l)} R\,(\beta) d\beta \tag{11}$$

$$S(l) = \beta_0 - \alpha \times l \tag{12}$$

$$R(\beta) = \begin{cases} 0\,, & \text{if } \beta \geq \beta_{comf} \\ \frac{R_{max}}{\beta_{comf}^2}\left(\beta_{comf} - \beta\right)^2\,, & \text{else} \end{cases} \tag{13}$$

$$A_{(r,s)}^{ri} = \begin{cases} 1\,, & \text{if } D_1 + D_2 < D_3 \\ \sum_{k \in \mathrm{K}_{(r,s)}} \frac{DB_{(r,s)}^k Y_{r,s}^k}{DB_r}\,, & \text{else} \end{cases} \tag{14}$$

$$A^{ci}_{(r,s)} = \begin{cases} 1\,, & \text{if } D_1 + D_2 < D_3 \\ \sum_{k\in \mathrm{K}_{(r,s)}} \frac{LP^k_{(r,s)} Y^k_{r,s}}{min\left(LP_{(r,s)}\right)}\,, & \text{else} \end{cases} \tag{15}$$

$$max(\beta) > \forall LP^k_{(r,s)} \tag{16}$$

$$DB^k_{(r,s)} - \beta_0 \le \mathrm{M}\left(1 - Y^k_{r,s}\right) \tag{17}$$

$$\sum_{r,s\in O} \sum_{k\in \mathcal{K}_{(r,s)}} Y^k_{r,s} = N_{OD} \tag{18}$$

In Eq.(8), *G* is the result of multiple satisfaction, which represents the gap between CE and demand allocation. It is calculated from the attractiveness of the cost and risk indicators to consumers $\mathrm{A}^{\mathrm{ci}}_{(\mathrm{r,s})}$ and $A^{ri}_{(r,s)}$, and the accumulated range anxiety *I* of consumers. The investment cost of deploying BSSs is shown in Eq. (9), which is represented by the number of BSSs. In Eq. (10), *I* refers to the coefficient of importance of the indicator for the consumer, which is used to determine the weight occupied by the cost and risk indicators in multiple satisfaction. Eq. (11-13) presents the accumulated range anxiety of consumers in battery-swapping mode. Eq. (11) represents the calculation of the accumulated range anxiety of the consumer, which contains the remaining power β of EVs and the distance *l* travelled, as well as the function of the range anxiety $\mathrm{R}(\beta)$ of consumers, which is represented by Eq. (13). Eq. (12) represents the variation of the remaining power of EVs with the distance travelled. Eq. (14-15) are the attractiveness of the risk and cost indicators to the consumer, respectively, as components of satisfaction. Eq. (16) is the battery capacity constraint that ensures the entire trip can be completed after a single battery swapping. Eq. (17) represents the BSS accessibility constraint, which states that when consumers are allocated to the path *k* between (r, s), the distance to the nearest BSS from the origin *r* must be less than its remaining power at *r*. Eq. (18) indicates that all demands in the network must be met.

4. Case Study

As shown in Figure 2, we selected the city of Anaheim as our study area, which is the 2nd largest city in Orange County, California, USA, located 28 miles southeast of Los Angeles, and ranking as the 10th largest city in California and the 55th largest city in the United States, well-known for its theme parks, sports facilities, and convention centres. Fig. 2 illustrates the main road network in the city of Anaheim, containing 151 nodes and 414 bi-directional links, where the origin and destination of the consumers indicated by the 34 red nodes form 1122 OD pairs. The remaining 117 green nodes indicate the candidate locations for EV BSS. The proposed model and improving algorithm are used to solve the problem of BSS deployment for Anaheim in this network.

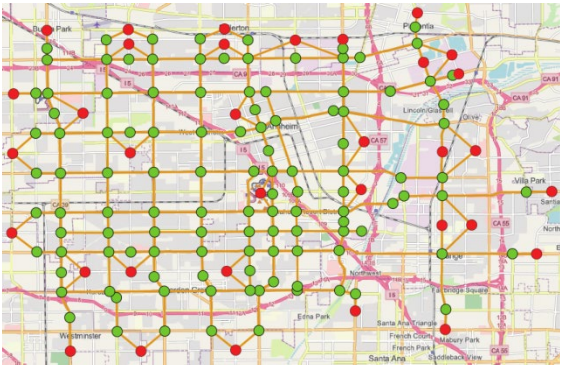

Figure 2. Anaheim transportation network
Source: https://main-anaheim.opendata.arcgis.com/.

4.1 Solving Algorithm

To efficiently address the problem in this paper, the improved strategy for NSGA-II was proposed based on the betweenness centrality of the nodes of the network, which consists of a population restoration strategy and a hybrid local search and perturbation strategy to generate new populations. The improved NSGA-II restoration strategy uses a binary coding rule where the length of genes is as many as the number of candidate nodes, and if the deployment plan contains a candidate node, the position on the gene corresponding to that node is 1, and vice versa 0. If an individual cannot meet all the demands on the network, the restoration strategy is used to select more BSSs to refine the deployment plan. The process of restoration is a roulette selection, where the probability of selecting a node $\mathrm{pr}_{\mathrm{m}}^{0}$ is given by Eq. (19).

$$pr_m^0 = \begin{cases} \frac{CB_m}{\sum_{m \in A^0} CB_m}, & \text{if} m \in A^0 \\ 0, & \text{if} m \notin A^0 \end{cases} \tag{19}$$

In roulette selection, A^0 is the set of all positions on the gene that have the value 0. With each round of roulette selection, the scale of A^0 decreases by 1, whilst the number of BSSs corresponding to genes increases by 1. In the selection process, node *m* with larger betweenness centrality CB_{m} is more likely to be selected until the individual meets all the demands in the network. To summaries, the flowchart of the improved NSGA-II algorithm is as follows:

Algorithm 1 Process of INSGA-II algorithm

Input Gene length$N$, constraints Con, population size P ,max iterationsMI,Distance matrix and traffic flow demand DT
Outputpareto frontier solutions C_{obj}
$pop_0 \leftarrow$ Initialize(N, POP)
if pop_1 meet Con=0 **then**
    Population restoration
end if
for i to MI **do**
    $F_i^1, F_i^2 \leftarrow$ Fitness Calculationpop_i // F_i^1 and F_i^2 represent the number of BSSs and consumer satisfaction respectively
    $F_i \leftarrow$ Non Dominated Sort pop_i, F_i^1, F_i^2
    $D_i \leftarrow$ Crowding Distance Sort pop_i, F_i^1, F_i^2, F_i
    $O_i \leftarrow$ Tournament Selectionpop_i, F_i, D_i
    $O_i \leftarrow$ crossoverO_i
    $O_i \leftarrow$ mutateO_i
    $R \leftarrow C_i \cup O_i$
    $F^1, F^2 \leftarrow$ Fitness Calculation R
    $F \leftarrow$ Non Dominated Sort R, F^1, F^2, F
    $D \leftarrow$ Crowding Distance SortR, F^1, F^2, F
    $C_i \leftarrow$ Elite Retention R, F, D
    $C_{obj} \leftarrow C_i$
end for

Figure 3. Algorithm process
Source: Authors' own creation.

4.2 Initial Parameters and Solution

Parameters settings for study case is shown in following table 2.

Table 2. Initial parameters

Parameters	Symbol	Value
The battery discharge efficiency	α	1
Vehicle's remaining charge at origin (converted to remaining mileage)	β_0	11.68 (km)
Adjustment factor for multiple indicators	z	0.3
Comfortable remaining power range to help drivers overcome range anxiety	β_{comf}	50 (km)
The tolerance of consumers for detours	TD	15%
The perturbation amplitude in INSGA-II	t	0.2
The perturbation probability in INSGA-II	ps	0.15
The number of OD pairs in network	N_{OD}	34×34
The number of candidate nodes in the network	N_C	117

Source: Authors' own creation.

Heuristic solutions were obtained in this paper using matlab R2021a at the above parameter levels. All numerical implementations were run in a Windows 11 environment on a desktop with 16 GB RAM and an Intel Core i7-12700@2.70 GHz processor.

4.3 Results Discussion

As shown in Figure 4, the blue line shows the average result of the proposed INSGA-II being executed thirty times. The x-axis indicates the number of BSS deployments, which represents the investment cost of the deployment plan. The Y-axis indicates the gap between the demand allocation and the CE, which reflects the satisfaction level of the consumers. On the Pareto frontier (PF) derived by INSGA-II, it can be observed that *G* decreases from 0.5922 to 0.0187 as the number of BSS deployments gradually increases from 14. The corresponding consumer satisfaction (1-*G*) increases from 40.78% to 98.13%, indicating that the allocation of consumer demand in the network becomes more desirable.

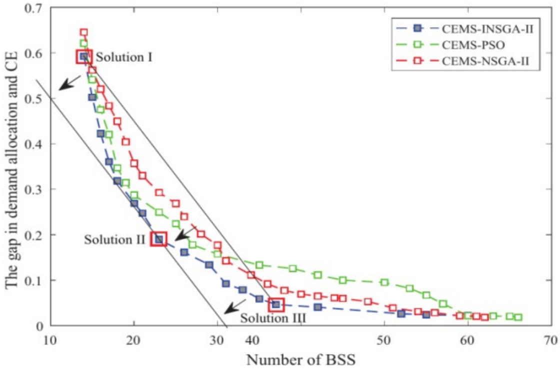

Figure 4. The Pareto front obtained through various algorithms
Source: Authors' own creation.

Observing the PF, the improvement effect of increasing the number of BSS deployments on consumer satisfaction gradually decreases as the number of BSS deployments in the network increases. Specifically, when the number of BSS deployments in the network is 14, increasing the number of BSS deployments has the most significant effect on improving consumer satisfaction. When the number of BSSs in the network is 37, increasing the number of BSSs is less effective in improving consumer satisfaction. Therefore, in order to provide the decision maker with a visual reference for decision making, as shown in Figure 4, three locations on the PF were selected as trade-off solutions (marked with red rectangles), and the selected locations were: (14,0.5922), (37,0.0492), and the point of tangency of the straight line connecting the two points to the PF (23,0.1944).

The corresponding BSS layout for solutions I, II, III is shown in Figure 5, where the red pins represent the BSS deployment locations. The performance of the three trade-off solutions in terms of investment cost and consumer satisfaction is shown in Table 3, allowing decision-makers to make choices based on their preferences and business development goals.

Table 3. Objective value of the trade-off solution

	Number of BSS	Consumer satisfaction
Solution I	14	40.78%
Solution II	23	80.56%
Solution III	37	95.08%

Source: Authors' own creation.

Additionally, in order to verify the proposed INSGA-II algorithm, two widely accepted heuristic algorithms, NSGA-II and PSO, were employed in the study case. Both algorithms were run 30 times under the same environmental parameters, and the optimisation results are shown as red and green curves in Fig. 6. Observing the overall trend, the PFs obtained by both algorithms indicate that increasing the number of BSS deployments contributes to improving consumer satisfaction.

(1) **solution I** (2) **solution II** (3) **solution III**

Figure 5. BSS layout corresponding to different solutions

Source: https://main-anaheim.opendata.arcgis.com/.

Furthermore, upon comparing solutions I, II, and III, it can be observed that the BSS deployments within the solutions steer clear of the northeastern corner of the study network, which caught our attention. As shown in Figure 6, there are four OD origins and two deployed BSSs in the area, with candidate node 57 in the centre. According to the pattern obtained above, the deployment of BSS in candidate node 57 should be helpful in improving the satisfaction of the surrounding consumers. However, the result is the opposite, and consumer satisfaction unexpectedly decreases after the addition of BSS. Thus, the CE and demand allocation of the surrounding consumers was further discussed.

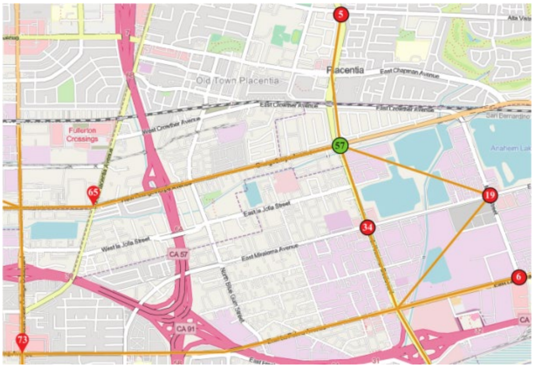

Figure 6. Partial map of the northeast corner of the study region
Source: https://main-anaheim.opendata.arcgis.com/.

Figure 7 illustrates the CE and demand allocation of the surrounding consumers, where the x-axis is the origin of the four surrounding ODs and the y-axis is the distance from the consumer to the allocated BSS.

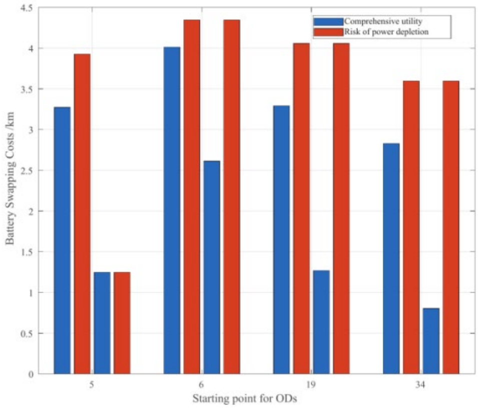

Figure 7. Changes in satisfaction due to the addition of BSS
Source: Authors' own creation.

In Figure 7, the blue bar indicates the distance from the origin to the BSS to which the consumers wish to be allocated, i.e. the CE. The red bar indicates the distance from the origin to the BSS allocated in the solution. In the context of each OD, the first two bars represent the CE and demand allocation under solution I, while the remaining two bars represent the CE and demand allocation after the addition of BSS.

The gap between the red and blue bars shows how satisfied consumers are with the BSS allocation. It can be seen that after adding BSS, consumers at origin 5 are the most satisfied as their demand allocation is in line with their expectations. However, the satisfaction of consumers from the other three origins 6, 19, and 34 has decreased. Since the BSS at 57 replaces the other BSSs in the deployment plan as the closest battery-swapping option for the consumers at the four nearby origins, their expectations are reduced to varying degrees (as shown in blue bars). However, consumers with origins 6, 9, and 34, would either have to pay excessive detour costs to bypass the BSS at candidate 57, or they would not need to swap their batteries at all on this trip, as they would have enough remaining power to drive to the nearest BSS once they reached their destination. As a result, there is no change in the allocation of the consumers except for those located at the origin 5(as shown in red bars), and the increase in *G* leads to a decrease in consumer satisfaction. In simple terms, the presence of a nearer BSS makes the BSS to which the consumer was assigned in the original deployment scenario less desirable to the consumer, even if the adding BSS is not accessible to consumers. Unlike traditional consumer satisfaction model studies, the results show that, while an increase in the number of BSS deployments generally contributes to higher consumer satisfaction, it is not a perfect positive correlation.

5. Conclusions

For the BSS deployment problem, a flow-based CEMS model for determining BSS deployment is proposed in this paper, which is a modified FCLM. First, the choices of paths and BSSs made by consumers during their travel decisions are discussed, and the expectations for shorter paths and closer BSSs are represented in the model. Also, cost and risk indicators are considered in consumer satisfaction, and the decision of consumers is described as a multiattribute process in which accumulated range anxiety is used as a weighting coefficient in the model. Finally, the proposed flow-based CEMS is implemented and validated in a semi-realistic case by the proposed improved NSGA-II, which gives the optimised BSS location layout in GIS and helps the decision makers to choose the BSS deployment location more flexibly.

The results of the PF consisting of trade-off solutions generated by INSGA-II show that cost and consumer satisfaction conflict with each other in the overall trend and that increasing the investment cost to deploy more BSSs improves consumer satisfaction and provides a more desirable battery swap service to the consumers. At the same time, the location of BSS is equally important, the travel behaviour of consumers needs to be considered in the BSS deployment, and for consumers who are used to swapping batteries along the way during their travels, the deployment of BSS in the centre of the demand-intensive area or community may not be beneficial to improve their satisfaction.

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