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A COORDINATED OPTIMIZATION OF REWARDED USERS AND EMPLOYEES IN RELOCATING STATION–BASED SHARED ELECTRIC VEHICLES

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To solve the mismatch between the supply and demand of shared electric vehicles (SEVs) caused by the uneven distribution of SEVs in space and time, an SEV relocating optimization model is designed based on a reward mechanism. The aim of the model is to achieve a cost-minimized rebalancing of the SEV system. Users are guided to attend the relocating SEVs by a reward mechanism, and employees can continuously relocate multiple SEVs before returning to the supply site. The optimization problem is solved by a heuristic column generation algorithm, in which the driving routes of employees are added into a pool by column generation iteratively. In the pricing subproblem of column generation, the Shuffled Complex Evolution–University of Arizona (SCE–UA) is designed to generate a driving route. The proposed model is verified with the actual data of the Dalian city. The results show that our model can reduce the total cost of relocating and improve the service efficiency.

Keywords: shared electric vehicles, user reward mechanism, collaborative relocating, SCE–UA.

1. Introduction

In order to alleviate the low efficiency of urban road networks and the aggravation of energy consumption caused by the large number of automobiles, a more efficient mode of transportation has been explored constantly. Due to the popularization of shared electric vehicles (SEVs) in recent years, many scientists have thoroughly explored this new way of travel. The research on SEV operation mainly includes two layers: a strategic planning layer and an operation planning layer. The former refers to the medium- and long-term decision-making problems faced by the SEV operation enterprises, mainly including site selection and infrastructure layout (Fassi *et al*., 2012; Brandstatter *et al*., 2017; Bruglieri *et al*., 2017; Cao *et al*., 2022). The latter refers to the short-term decision problem faced by the SEV operation enterprises, that is, the problems faced by the enterprises in daily service management (Ciari *et al*., 2013; Jorge and Correia, 2013; Kaspi *et al*., 2014; Boyaci *et al*., 2015; Weikl and Bogenberger, 2015; Deng and Cardin, 2018).

For SEV operators, the main challenge is to rebalance the system before a decrease in customer satisfaction and a shortage of available vehicles. This is also the core of SEV relocation (Jorge and Correia, 2013). Currently, most SEV operation systems have low vehicle turnover and uneven supplies and demands of vehicles between stations, which results in high operation costs and low customer satisfaction. According to various participants, there are two ways to optimize the relocation of SEVs. One is that the enterprise hires the corresponding employee to arrange the vehicles, which is the method adopted by most enterprises at present (Almeida and Pais, 2012; Bruglieri *et al*., 2014). The other is to provide users with incentives (such as discounts, coupons, etc.) to guide them to participate in the relocation of SEVs, so as to reduce the employment

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and management costs of employees (Di Febbraro *et al.*, 2019; Wang *et al.*, 2019). The relocating method based on employees needs to pay a lot of manpower costs, and the relocation is relatively lagging behind. The relocating method based on users is developed under this background.

At present, these optimization methods aim at a single participator, and seldom consider the impact of users' travel behavior when users' satisfaction is not high, and the actual operation is not flexible and low cost. Users travel with the tide, which also led to the sharing of electric vehicles in the space-time distribution imbalance (Di Febbraro *et al.*, 2019). For operators, the mismatch between station vehicle supply and demand or the number of unreasonable inventory range will lead to lower customer satisfaction, a decline in system service levels and so on (Tian *et al.*, 2021). At the same time, the emergence of new energy vehicles put forward new requirements for vehicle relocation. Unlike traditional vehicles, the relocation of SEVs should consider the impact of battery power (Boyaci *et al.*, 2015).

An SEV user reward mechanism is established. An effective user reward mechanism can maximize the probability of user participation, so as to guide them to voluntarily choose to participate in the scheduling of SEVs. By confirming the consistency between the disaggregation model based on utility maximization theory and the target user's mental state, this paper draws the conclusion that the former can describe the residents' travel choice behavior efficiently and the latter can be used to analyze the users' choice behavior. Based on the assumption that the user is a rational person and the results of the user choice behavior analysis, this paper completes the formulation of the user reward mechanism. The optimization model of the rewarded user and employee relocation of SEV is constructed.

On the premise of satisfying the constraints of the time window, battery power and the departure station, according to the corresponding incentive rules, the user is guided to adjust the original travel plan so that the employee can complete the vehicle relocation task together, so as to achieve the goal of minimizing the total scheduling cost including the user incentive cost, the operator cost, the vehicle power consumption cost and the penalty cost for incomplete orders. The Shuffled Complex Evolution–University of Arizona (SCE–UA) is a global optimization algorithm, which combines the advantages of stochastic search algorithms, the simplex method, cluster analysis and biological competitive evolution. This method can optimize several parameters of the model at the same time, and it is an effective method for parameter optimization. Considering the characteristics of the research problem and the model, the SCE–UA is used to solve the problem.

This paper provides the following two contributions.

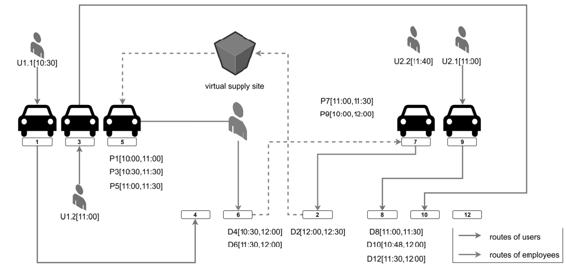

Fig. 1. Description of the optimization problem of SEV relocating.

First of all, through the investigation and analysis of the relevant factors that affect the user travel path choice behavior, this paper developed a corresponding reward mechanism. Secondly, based on certain assumptions, this paper establishes a two-agent relocation optimization model of SEVs under an incentive mechanism, and uses the SCE–UA algorithm for solution. The user-based vehicle relocation method and the employee-based vehicle relocation method are combined to establish a dual agent relocation strategy for SEVs.

The reminder of the paper is organized as follows: In Section 2, the problem of SEV relocating is described and Section 3 constructs a SEVs relocating optimization model. A column generation-based heuristic algorithm is introduced in Section 4. Then, Section 5 proposes a case study and the conclusions are discussed in Section 6.

2. Problem description

The employee-based SEV relocating optimization method requires a large amount of labor cost, while the user-based relocating scheme is less flexible. Here, we will combine the advantages of the two modes to design an SEV relocating optimization method in which both the employee and the user are involved. At the same time, on the basis of the research on the reward mechanism of SEVs, this paper formulates a corresponding reward mechanism to guide users to voluntarily accept the relocating travel scheme, and complete the inventory rebalancing of SEVs with employees.

In this paper, the SEV scheduling problem is regarded as a special vehicle routing problem with pickup-delivery and time windows. In Fig. 1, U is the required time for the user, D is the time window of pickup location, and P is the time window of parking location. In the SEV operating system, sites with inventory levels higher than the upper limit of the threshold are the supply points for SEV scheduling, and sites below the lower limit of the threshold are the SEV demand points. The absolute value of the difference between the existing SEV inventory of each site and the corresponding threshold is the number of SEVs participating in the relocating process. At the same time, each station has a time window, and a certain number of employees are configured to wait to receive tasks. After the employees complete the relocating work, they would use other vehicles such as electric bicycles to return to the departure station. Therefore, there is no relocating center in the operation system. The SEVs participating in the relocating are homogeneous, the remaining power in the initial state is known, and the residual value of the power after reaching the demand point should meet the basic requirements for power consumption in the next trip. In addition, the order information of APP users is available, that is, the pick-up/parking point, pick-up time and final destination are known, but the user may change his or her initial parking point according to the SEV scheduling to receive the reward incentives.

Under the above conditions, the questions of how to determine the travel routes and departure time of SEVs, and to minimize the sum of user incentive costs, staff costs, SEV operation costs, and penalty costs for failed orders are the main topics addressed in this paper.

3. Model development

3.1. Model hypothesis and premises. To further simplify the relocating and optimization problem of SEVs, this article makes the following assumptions based on relevant literature, professional common sense, and the results of questionnaire samples:

Scheduling tasks. This paper assumes that the current relocating requirements are known, including the proposed relocating SEV set V, SEV transfer to a site set D, and SEV transfer away for a site set O. Since there may be multiple SEVs that need to be transferred to or from some sites, in order to simplify the one-point-multi-vehicle problem, each SEV or each pair of relocating starting points are regarded as two virtual points, that is, if site 1 has three SEVs needed to be transferred out, then the physical site 1 is regarded as three SEVs being transferred out from the virtual site; thus, the one-point-multi-vehicle problem is transformed into a one-point-one-vehicle relocating problem. To solve the problem by an exchange mutation operator of the genetic algorithm, the virtual site pairs for mutation must be generated according to certain probability. At this time, the relocating task set is V, and the SEV transfer into the virtual site set is D'. The set of SEVs transferred away from the virtual station is O'.

For users and employees. Knowing that there are K travel orders, the user has a certain probability P_k to choose whether or not to participate in SEV relocating. This probability is affected by a_k, the discount on the travel plan, $\mathrm{w\_dis}_k$ the walking distance after getting off the SEV, and fee_k, the travel cost. If the user participates in the relocating, the enterprise needs to pay the corresponding incentive cost, and the user leaves the system after completing a task. Among them, a_k is determined through the statistical analysis of stated preference survey (SP survey) results of the logit model and travel plans based on the random utility multinomial logit (MNL) model to select the incentive mechanism

$$a_i = \begin{cases} \dfrac{1}{0.21821}\Big(0.69 - 0.38\,(X_{i11} - X_{i21}) \\ \quad -2.57\,(X_{i12} - X_{i22})\Big), \\ \qquad d_{\text{dis}} \le 10\,\text{km}, \\ \dfrac{1}{0.19603}\Big(0.69 - 0.48\,(X_{i11} - X_{i21}) \\ \quad -2.77\,(X_{i12} - X_{i22})\Big), \\ \qquad 10\,\text{km} < d_{\text{dis}} \le 20\,\text{km}, \\ \dfrac{1}{0.14692}\Big(0.69 - 0.38\,(X_{i11} - X_{i21}) \\ \quad -3.22\,(X_{i12} - X_{i22})\Big), \\ \qquad d_{\text{dis}} > 20\,\text{km}. \end{cases} \tag{1}$$

Here X_{i11},X_{i12}, X_{i22} are the attribute variables of the utility function corresponding to the MNL model, where the travel costs, the walking distance after disembarkation, and the discounts are represented.

The investigation is conducted to find out the selection of the original travel plan and a scheduling travel plan by the users of SEVs. The experimental situation is not experienced by the respondents, and the information of the relevant stations and routes in the questionnaire needs to be hypothesized, which belongs to the SP investigation. Survey statistics of users regarding gender, age, education, work, income and car ownership are available. In addition, according to the survey, in contrast to shared bicycle operation companies, the current SEV companies will relocate a varying number of maintainers at different sites or regions, instead of setting up a relocating center. Therefore, in order to be more in line with the actual situation, this paper sets an unlimited number of employees participating in the relocating, and there are corresponding employees waiting to accept tasks at each SEV site. After receiving the instruction, the employees of the designated site will immediately drive the SEV to the corresponding demand site, and then return to the site or area under their jurisdiction by riding an electric bicycle. At this time, the cost of employees' participating in relocating is represented by the SEV compound cost per unit distance, which includes electric bicycle power consumption, employee wages, and a potential loss of income.

System site. According to the operation conditions of SEVs, this paper considers the influence of the station service time window $\left[\mathrm{th}_n^e, \mathrm{th}_n^l\right]$, $n \in O' \cup D'$ on the choice of the SEV driving routes. For an SEV transferred from station i and an SEV transferred to station j, if the user's arrival time T_n^k or the employee's arrival time t_n^z is earlier than the service time window, there might be no car available because the previous order has not been closed; if the arrival time is later than this threshold range, it may affect the next phase of user orders, and finally cause the loss of order revenue.

SEV. In fact, the power consumption of SEVs has a certain relationship with factors such as travel distance, driving conditions, temperature, accumulated battery usage time, battery internal electrical structure and SOC characteristics. Here, in order to simplify this model, it is assumed that the battery power consumption is linearly related to electric power consumption, and the SEV participating in the relocating are all of the same type, the battery power is set to G when fully charged, and the power consumption per unit distance is the same, set to g. All SEVs run at the same constant speed denoted by s. The remaining power e of the SEV represents the remaining driving range of the SEV, and also affects whether it can participate in the relocating task of a user or an employee. When the SEV is at O', that is $n \in O'$, e_n represents the remaining power of the SEV at time th_n^e; taking into account the use of the SEV in the next relocating cycle, when the SEV is at D', that is $n \in D'$, e_n represents the minimum remaining power of the SEV at the time th_n^l. Each SEV can start charging immediately after arriving at the station with the same charging pile equipment and the charging efficiency per unit time is h. When it is used or the battery is fully charged, the charging ends. In addition, the car is fully charged at the beginning of daily operation and cannot be charged during driving.

3.2. Model symbol description. This problem is defined in an undirected network with a set of physical sites N, $N = O \cup D$. At the same time, each physical site is transformed into a corresponding number of virtual sites; then the set of virtual sites can be expressed as $N_0 = \{0, 1, 2, \dots, n\}$, $n \in N_0$, where site 0 represents a virtual distribution center. Other variables and parameters involved in the model are shown in Table 1.

3.3. Model building. This paper establishes an optimization model with the objective of minimizing the total cost of enterprise relocating and the cost is divided into three parts. One part is the cost invested by the enterprise on users and employees, which is the cost associated with people; the second part is the cost of power consumption during the relocating process, which is the cost associated with the SEVs; the third part is the loss of user order cancellation due to the uncompleted relocating task, which is the penalty cost of the uncompleted relocating task.

User and employee related cost. The user-related cost is the user incentive cost, $\sum a_k$, invested by the enterprise. The cost is determined by the amount of user incentives and the number of users participating in the relocating. Whether or not user k participates in the relocating task from site i to site j is represented by the decision variable x_{ij}^k, which is a binary variable. When the probability P_k of a user with a scheduling scheme is greater than or equal to the threshold 2/3, this can be interpreted that user k agrees to participate in the relocating task from site i to site j, where x_{ij}^k is equal to 1. The corresponding user k's incentive cost is a_k, otherwise it is equal to 0. The initial site i at which user k participates in the relocating is any point in the virtual site set converted from the physical site where user is located, that is $i \in r_k$, where r_k is the virtual initial site set of the user k. The cost associated with the employee is equal to the product of his or her travel time involved in relocating and the SEV compound cost coefficient p_z. Whether or not the employee z participates in the relocating task from site i to site j is represented by a decision variable y_{ij}^z, which is a 0-1 variable, and the initial site i at which the employee z participates in the relocating is the virtual initial site for the transformation of the site under its jurisdiction.

Electricity consumption cost of SEV. The cost is related to the mileage of SEVs. The mileage includes the mileage of users using the SEVs and the mileage of the SEVs relocated by employees.

Penalty costs for unfinished relocating tasks. Reasons such as low user participation or the number of participating relocated SEV being less than the demand may result in some relocating tasks not being completed, so that there might be no SEV available at the demand site in the future, resulting in a potential loss of order revenue. Therefore, the model should meet the known relocating requirements as much as possible and introduce penalty costs p_m caused by uncompleted tasks.

With reference to the above assumptions and requirements, the following objective function is established:

$$\begin{aligned}\min & \sum_{k=1}^{K} \sum_{j \in D'} \sum_{\in r_k} a_k x_{ij}^k \\ & + \frac{p_z}{s} \sum_{z=1}^{Z} \sum_{j \in D'} \sum_{i \in O'} y_{ij}^z d_{ij} \\ & + p_e \sum_{z=1}^{Z} \sum_{k=1}^{K} \sum_{j \in D'} \sum_{i \in O'} \left(x_{ij}^k + y_{ij}^z\right) d_{ij} \\ & + p_m \left[v - \sum_{z=1}^{Z} \sum_{k=1}^{K} \sum_{j \in D'} \sum_{i \in O'} \left(x_{ij}^k + y_{ij}^z\right) \right]\end{aligned} \tag{2}$$

Table 1. Notation.

Parameter	Definition
p_z	compound cost coefficient of enterprises
p_e	power consumption cost per unit distance
p_m	punishment costs for incomplete unit orders
G	battery capacity at full charge
g	power consumption per unit distance
h	unit time charge efficiency
e_n	remaining power of the SEV at station n
th_n^e	the earliest starting moment of Shared EV Site Service
th_n^l	the latest ending moment of Shared EV Site Service
s	average speed of the SEV
λ	an infinitely large positive number
v	the number of SEVs required or relocated
d_{ij}	distance between site i and site j
N	physical site collection, $N = \mathrm{O} \cup \mathrm{D}$
N_0	virtual site collection, $N_0 = \mathrm{O}' \cup \mathrm{D}' \cup \mathrm{O}$
O	SEV transferred from the physical site collection
D	SEV transferred to the physical site collection
O'	SEV transferred from the virtual site collection
D'	SEV transferred to the virtual site collection
V	relocating task set or participating SEV relocating set
r_k	virtual SEV off site collection converted by user k's physical site, $r_k \in \mathrm{O}'$
K	collection of users accessing SEV relocating points, $k \in K$
Z	collection of employees who govern SEV departures, $z \in Z$
x_{ij}^k	user k is 1 when participating in site i to site j SEV scheduling, otherwise equal to 0
y_{ij}^z	employee z participates in site i to site j SEV scheduling at 1, otherwise equal to 0
T_n^k	time when user k arrived at site n
t_n^z	the time that employees z arrives at site n
a_k	user k participates in SEV scheduling and gets a discount

subject to the constraints

$$a_k = f'\left(\frac{2}{3}, \mathrm{w\_dis}_{k1}, \mathrm{w\_dis}_{k2}, \mathrm{fee}_{k1}, \mathrm{fee}_{k2}\right), \quad \forall k \in \{1, 2, \dots, K\}, \tag{3}$$

$$\sum_{j \in D'} \sum_{i \in O'} x_{ij}^k \leq 1, \quad \forall k \in \{1, 2, \dots, K\}, \tag{4}$$

$$\sum_{j \in D'} \sum_{i \in O'} y_{ij}^z \leq 1, \quad \forall z \in \{1, 2, \dots, Z\}, \tag{5}$$

$$\sum_{j \in D'} \sum_{i \in \{\, i | i \in O', i \notin r_k\}} x_{ij}^k = 0, \quad \forall k \in \{1, 2, \dots, K\}, \tag{6}$$

$$\sum_{k=1}^{K} \sum_{j \in D'} x_{ij}^k + \sum_{z=1}^{Z} \sum_{j \in D'} y_{ij}^z \leq 1, \quad \forall i \in O', \tag{7}$$

$$\sum_{k=1}^{K} \sum_{i \in O'} x_{ij}^k + \sum_{z=1}^{Z} \sum_{i \in O'} y_{ij}^z \leq 1, \quad \forall j \in D', \tag{8}$$

$$y_{ij}^z d_{ij} g \leq L, \quad \forall z \in \{1, 2 \dots Z\}, \quad \forall i \in D', \quad \forall j \in O', \tag{9}$$

$$\mathrm{th}_n^e \leq T_n^k \leq \mathrm{th}_n^l, \quad \forall k \in \{1, 2, \dots, K\}, \quad \forall n \in N_0, \tag{10}$$

$$\mathrm{th}_n^e \leq t_n^z \leq \mathrm{th}_n^l, \quad \forall z \in \{1, 2, \dots, Z\}, \quad \forall n \in N_0, \tag{11}$$

$$T_i^k + \frac{d_{ij}}{s} x_{ij}^k - \lambda \left(1 - x_{ij}^k\right) \leq T_j^k, \quad \forall k \in \{1, 2, \dots, K\}, \quad \forall i \in O', \quad \forall j \in D', \tag{12}$$

$$t_i^z + \frac{d_{ij}}{s} y_{ij}^z - \lambda\left(1 - y_{ij}^z\right) \le t_j^z,$$
$$\forall z \in \{1, 2, \dots, Z\}, \quad \forall i \in O', \quad \forall j \in D', \quad (13)$$

$$t_i^z + \frac{d_{ij}}{u} y_{ij}^z - \lambda\left(1 - y_{ij}^z\right) \le t_j^z,$$
$$\forall z \in \{1, 2, \dots, Z\}, \quad \forall i \in D', \quad \forall j \in O', \quad (14)$$

$$x_{ij}^k d_{ij} g \le e_i + h\left(T_i^k - \mathrm{th}_i^e\right) \le G,$$
$$\forall k \in \{1, 2, \dots, K\}, \quad \forall i \in r_k, \quad \forall j \in D', \quad (15)$$

$$y_{ij}^z d_{ij} g \le e_i + h\left(t_i^z - \mathrm{th}_i^e\right) \le G,$$
$$\forall z \in \{1, 2, \dots, Z\}, \quad \forall i \in O', \quad \forall j \in D', \quad (16)$$

$$0 \le e_n \le G, \quad \forall n \in N_0, \quad (17)$$

$$e_j - h\left(\mathrm{th}_j^l - T_j^k\right) - \lambda\left(1 - x_{ij}^k\right)$$
$$\le e_i + h\left(T_i^k - th_i^e\right) - x_{ij}^k d_{ij} g$$
$$\forall k \in \{1, 2, \dots, K\}, \quad \forall i \in r_k, \quad \forall j \in D', \quad (18)$$

$$e_j - h\left(\mathrm{th}_j^l - t_j^z\right) - \lambda\left(1 - y_{ij}^z\right)$$
$$\le e_i + h\left(t_i^z - th_i^e\right) - y_{ij}^z d_{ij} g$$
$$\forall z \in \{1, 2, \dots, Z\}, \quad \forall i \in O', \quad \forall j \in D', \quad (19)$$

$$x_{ij}^k \in \{0, 1\}, \quad \forall k \in \{1, 2, \dots, K\}, \quad (20)$$

$$y_{ij}^z \in \{0, 1\}, \quad \forall z \in \{1, 2, \dots, Z\}, \quad (21)$$

$$a_k \ge 1.5, \quad \forall k \in \{1, 2, \dots, K\}. \quad (22)$$

Constraint (3) is the calculation formula of incentive cost derived from the user reward mechanism. Constraints (4), (5) and (6) indicate that any relocating personnel starts from the virtual relocating center and only participates in the relocating of only one car; at the same time, for users participating in the relocating, the subsequent sites of the relocating center only belong to the virtual point collection derived from the actual site where the user is located. Constraints (7) and (8) indicate that any site can only be visited once. Constraints (9) indicate that the power consumption of electric bicycle routes cannot exceed the battery capacity. Constraints (10) and (11) are arrival time constraints. They indicate that the time for any relocating personnel to arrive at a site must be within the time window of the site. Constraints (12) and (13) establish a functional relationship between the departure time and the arrival time of the user and the employee. Constraints (14) construct the relationship between the departure time of the last employee's scheduling route and the arrival time of the next employee's scheduling route. Constraints (15)–(17) are the power constraints of the SEV to ensure that the car can drive the corresponding distance; taking into account the use of the next stage of the car after the relocating is completed, Eqns. (18) and (19) define constraints on the residual value of the power after the shared car arrives at the SEV demand site. Constraints (20) and (21) represent that x_{ij}^k and y_{ij}^z are 0-1 decision variables. Constraints (22) indicate that the user incentive price (that is, the incentive cost) should be a real number no less than 1.5.

4. Column generation-based heuristic algorithm

The above-mentioned model is not practical to solve by a business solver such as ILOG CPLEX directly, even for a moderate size instance. A Dantzig–Wolfe decomposition of this model is used to obtain a master problem and a pricing subproblem. The cardinality of the variables in the master problem is extremely large, thus a column generation-based heuristic algorithm (Desrosiers and Lübbecke, 2005) is proposed.

4.1. Column generation framework. This paper transforms the above-mentioned formulation into a sets partitioning formulation (Feillet *et al.*, 2007), which is regarded as the master problem. Let Ω^E and Ω^U be the sets of users driving routes and employees driving routes, respectively. C_r is the cost of driving route r. The parameter α_r^i is equal to 1 if the driving route r visits node i, otherwise it is 0. The decision variables θ_r is equal to 1 if the driving route r is selected, otherwise it is 0. The decision variables η_i is equal to 1 if node i is not served, otherwise 0. The master problem can be formulated as follows:

$$\min \quad \sum_{r \in \Omega^E \cup \Omega^U} C_r \theta_r + \sum_{i \in D'} p_m \eta_i \quad (23)$$

subject to the constraints

$$\sum_{r \in \Omega^E \cup \Omega^U} \alpha_r^i \theta_r + \eta_i \ge 1, \quad \forall i \in D', \quad (24)$$

$$\sum_{r\in\Omega^E} \theta_r \le K, \tag{25}$$

$$\theta_r \in \{0,1\}, \quad \forall r \in \Omega^E \cup \Omega^U, \tag{26}$$

$$\eta_i \in \{0,1\}, \quad \forall i \in D'. \tag{27}$$

The objective function (23) to be minimized expresses the total cost including the transportation cost and the penalty cost. Constraints (24) mean that each virtual site should be visited at least once. Constraints (25) limit the number of available employees. Constraints (26) and (27) clarify the domain of decision variables.

Given a dual solution to the master problem, the pricing subproblem is to find a master problem variable that has the least reduced cost. Solving the pricing subproblem is essentially equivalent to enumerating all feasible driving routes. Let π_i and ρ be the dual variables of constraints (24) and (25), respectively. The reduced cost of a driving route r is given by

$$\bar{C}_r = C_r - \sum_{i\in D'} \alpha_r^i \pi_i - \rho. \tag{28}$$

The pricing subproblem is essentially an elementary shortest path problem with resource constraints (ESPPRC). The framework of the column generation algorithm is shown in Fig. 2. Since the ESPPRC is an NP-hard problem (Desaulniers *et al.*, 2008), it will consume most computing time in the process of column generation. In the next section, we propose the SCE–UA algorithm for solving the pricing subproblem.

4.2. SCE–UA algorithm. Duan (1991) proposed the SCE–UA, a global optimization algorithm based on a natural evolution process. The SCE–UA is designed with a synthesis of four concepts: (i) combination of deterministic and probabilistic methodologies; (ii) systematic evolution of a complex of points spanning the parameter space, in the direction of a global improvement; (iii) competitive evolution; (iv) complex shuffling. The SCE–UA uses a population composed of sample points. The population is partitioned into several complexes, each of which is permitted to evolve independently of the others. After a specified number of generations, the complexes are forced to mix, forming new complexes through a shuffling process. This procedure enhances survivability by sharing the information that is gained independently by each complex (Duan *et al.*, 1993). So far, the SCE–UA algorithm has been successfully applied to deal with optimal problems in research areas related to hydrology (Yapo *et al.*, 1996; 1998; Freedman *et al.*, 1998; Van Griensven and Bauwens, 2003; Yu *et al.*, 2020).

This paper attempts to solve our relocating optimization problem by the SCE–UA algorithm. SCE–UA combines some advantages from several existing methods, including random search, the genetic algorithm and the complex method. The basic idea of the SCE–UA algorithm consists in integrating the search technology with the evolution principle of competition in nature.

Thyer *et al.* (1999) compared the SCE–UA algorithm with the MSX algorithm and the genetic algorithm to test the performance of these algorithms for conceptual rainfall-runoff models. The calculation results indicated that the SCE–UA algorithm provided a better performance on robustness and convergence than the others. Thus, the SCE–UA algorithm is selected for solving the proposed problem formulation.

The calculation process of the SCE–UA can be shown as follows:

Step 1. *Initialization.* Firstly, the problem is assumed in n dimensions. Generate v $(v \ge 1)$ complexes which participate in the evolution and m $(m \ge n+1)$ samples. Accordingly, the number of points can be calculated as $s = vm$.

Step 2. *Generate a sample.* Generate randomly s sample points in the feasible space.

Step 3. *Rank points.* Evaluate the function at each point and rank these points according to the function value.

Step 4. *Partition into complexes.* Partition v complexes such that the first complex contains every $(v(j-1)+1)$-th ranked point, the h complex contains every $(v(j-1)+h)$-th ranked point, where $j = 1, 2, \dots, m$, and $h = 1, 2, \dots, v$.

Step 5. *Evolve complexes.* The competitive complex evolution (CCE) algorithm is the key component of the SCE–UA algorithm. In the CCE algorithm, every point of a complex is a potential parent which can participate in the process of reproducing offspring (Duan *et al.*, 1994). Evolve each complex according to the CCE algorithm which is introduced below.

(a) *Initialization.* Set z, λ, β, where $2 \le z \le m$, $\lambda \ge 1$, $\beta \ge 1$.

(b) *Construct a subcomplex.* Construct a subcomplex by randomly selecting z points from the complex according to the trapezoidal probability distribution which makes the best point chosen with the maximum probability.

(c) *Rank points.* Evaluate the function at each point in the subcomplex and rank these points according to the function value. Then mark the worst point in the subcomplex and calculate the centroid of other $z-1$ points except the worst point.

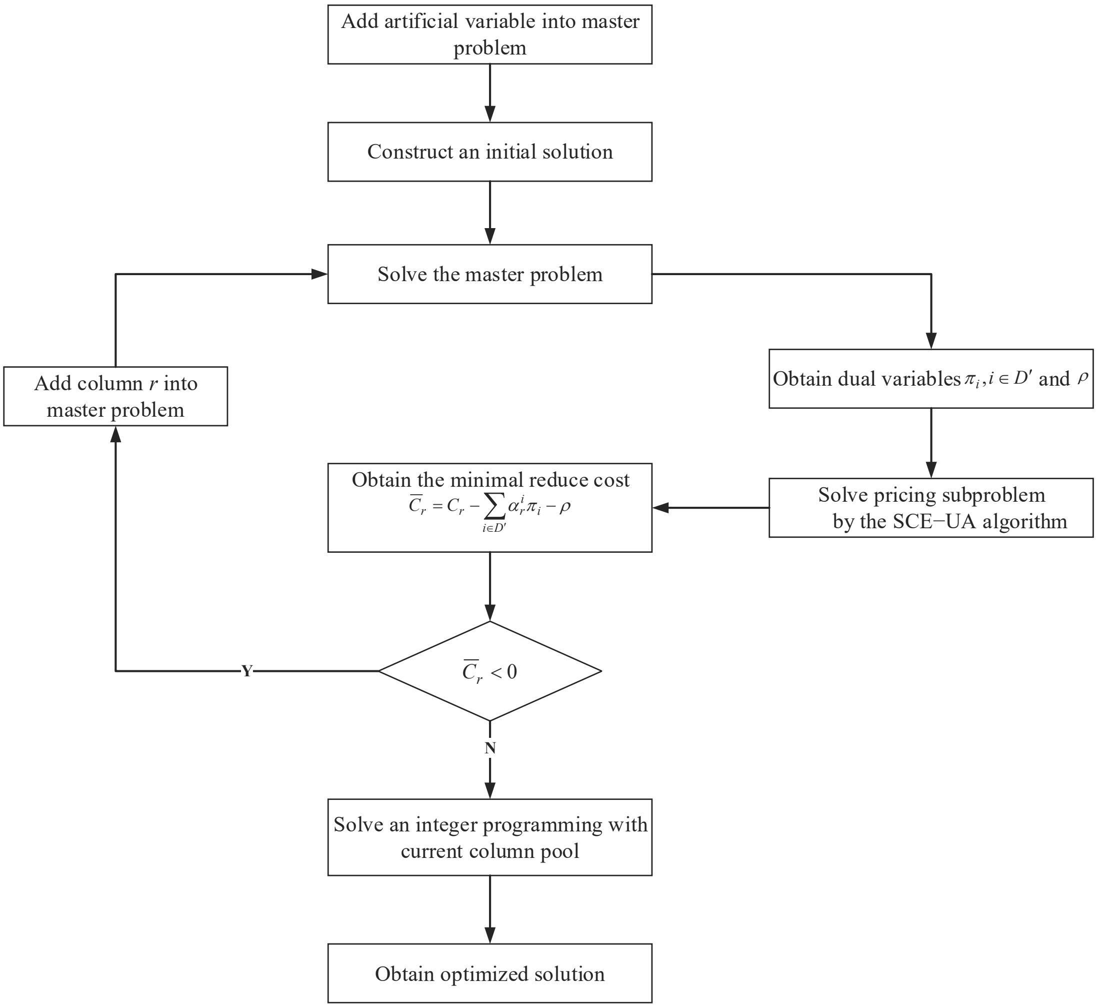

Fig. 2. Framework of column generation.

(d) *Reflection step.* Reflect the worst point through the centroid. If the newly generated point is outside the feasible space, randomly generate a point in the feasible space to replace the worst point. Then go to *Step 6*. Otherwise, if the reflected point is better than the worst point, then replace the worst point with the reflected point, go to *Step 6*.

(e) *Check convergence.* Generate the contracted point by computing a point halfway between the worst point and the centroid. If the contracted point is better than the worst point, replace the worst point with the contracted point. Otherwise, randomly generate a point in the feasible space to replace the worst point, go to (f).

(f) Repeat (b)–(e) λ times, $\lambda \geq 1$, where λ is the number of consecutive offspring generated by the subcomplex.

(g) Repeat (a)–(f) β times, $\beta \geq 1$, where β is the number of evolution steps of each complex.

Step 6. *Shuffle complexes.* Reconsolidate the points in the evolved complexes and form a new sample set.

Step 7. *Check convergence.* If all the convergence conditions are met, then stop; otherwise, go to Step 3.

5. Case studies

Consider the car-sharing service project in the Dalian High-tech Park in the Liaoning Province as an example. The operating model of the project is a single-program leasing based on the site, and the charging adopts the form of “actual mileage + actual travel time,” which is facing the problem of imbalance between the supply and demand of SEVs among the outlets.

5.1. Data collection and pre-processing. After computing preliminary statistics and screening, we selected 284 historical order data on June 20, 2018 in the

Fig. 3. Car-sharing service project in the Dalian High-tech Park.

system. In order to prevent invalid or wrong information in the original order data from affecting the results, first pre-process these historical data, and then the following specific steps are executed:

1. Delete the order data with only reservation information, which regard invalid orders because such orders do not actually take place in any trips.
2. Delete the order data with multiple duplicate records.
3. Delete the order data whose actual travel times are less than two minutes, and generally such orders do not actually have normal travel.
4. Delete the order data with actual travel mileages of more than 150 km.
5. Delete the order data lacking important information.
6. Delete different user orders at the departure station and the departure station where the relocating order is placed, and these users cannot participate in the SEV relocating and do not belong to the user set in this model.
7. Delete the orders whose pick-up or return stations are not located in Dalian.

After data cleaning, the scheduling period was set to 3 hours, and the order data were limited to the period of 15:00–18:00 p.m. on June 20, 2018, including 23 scheduling order data and 49 user order data. Further, the orders of the users whose pickup site is the above-mentioned SEV transfer site were filtered out to form a set of users participating in the relocating task. After sorting out, the above relocating orders involve a total of 10 SEV sites. The settings of other unknown parameters in the model are shown in Table 2.

Table 2. Model related parameter settings.

Parameter name	Numeric value
p_z	1.05 RMB/min
p_e	0.21 RMB//km
p_m	39.20 RMB/order
G	25.5 kWh
g	0.17 kWh/km
h	0.07 kWh/min
s	30 km/h

5.2. Solution results and analysis. The column generation based heuristic SCE–UA algorithm is used to solve the dual-agent SEV relocating optimization problem based on the reward mechanism.

In the proposed algorithm, we can generate at most 5000 driving routes before solving an integer programming problem. According to the actual data, the relevant parameters of the SCE–UA algorithm are set as follows: Generate 4 complexes which participate in the evolution and 20 samples. Accordingly, the number of points is 80. The values of the parameters z, λ and β are set as 10, 1 and 20, respectively.

The analysis of the optimization results of the relocating of SEV under the incentive mechanism can be summarized as the following steps:

(i) Preferential discounts have some influence on the user's travel plan selection, especially in areas with a high coverage of the network, and the effect of the reward amount on users is very obvious when there is less difference in walking distance after getting off the SEV.

(ii) The user cannot completely replace the employee to complete all SEV scheduling tasks, and can only relieve the pressure of the imbalance between the supply and demand of SEVs at some sites in the operating system.

(iii) The participation of SEV users lowers the number of staff relocating trips, which further reduces overall relocating costs and SEV wear and tear. The calculation results can be seen in Table 3 and Fig. 4.

It can be seen from Table 3 that there are 17 and 16 users participating in SEV relocating in the gradual travel route. However, we can find that the final total cost is the same (both are 205.62 RMB). Furthermore, the average cost per relocated SEV is 8.5 RMB. The reason for the result is that the third user at the departure station No. 5 adjusted the parking point from station 9 to station 10. Thus, it resulted in the third user at station No. 1 willing to participate in SEV relocating and adjusting the return point to station 9. At this time, the added value of the preferential discount for rewarding

Table 3. Computational results.

No.	Relocating agent	O'	D'	No.	Relocating agent	O'	D'	No.	Relocating agent	O'	D'	No.	Relocating agent	O'	D'
1	0.0	9	6	1	0.0	9	6	1	0.0	9	6	1	0.0	9	6
2	2.3	15	32	2	2.3	15	32	2	2.3	15	32	2	2.3	15	32
3	4.5	33	22	3	4.5	33	22	3	4.5	33	22	3	4.5	33	22
4	0.0	29	30	4	0.0	29	30	4	0.0	29	30	4	0.0	29	30
5	4.3	37	26	5	4.3	37	26	5	4.3	37	26	5	4.3	37	26
6	5.3	41	46	6	5.3	41	42	6	5.3	41	42	6	5.3	41	46
7	0.0	3	10	7	0.0	3	10	7	0.0	3	10	7	0.0	3	10
8	5.1	39	44	8	5.1	39	44	8	5.1	39	44	8	5.1	39	44
9	0.0	17	8	9	0.0	17	8	9	0.0	17	8	9	0.0	17	8
10	0.0	31	40	10	0.0	31	40	10	0.0	31	40	10	0.0	31	40
11	3.2	25	28	11	3.2	25	28	11	3.2	25	28	11	3.2	25	28
12	1.2	7	12	12	1.2	7	12	12	1.2	7	12	12	1.2	7	12
13	0.0	21	4	13	2.7	21	16	13	0.0	21	4	13	2.7	21	16
14	2.11	11	34	14	2.11	11	34	14	2.11	11	34	14	2.11	11	34
15	2.2	13	14	15	2.2	13	14	15	2.2	13	14	15	2.2	13	14
16	4.1	35	38	16	4.1	35	38	16	4.1	35	38	16	4.1	35	38
17	0.0	5	42	17	1.5	5	46	17	1.5	5	46	17	0.0	5	42
18	5.8	45	36	18	5.8	45	36	18	5.8	45	36	18	5.8	45	36
19	1.10	1	20	19	1.10	1	20	19	1.10	1	20	19	1.10	1	20
20	5.4	43	24	20	5.4	43	24	20	5.4	43	24	20	5.4	43	24
21	2.7	23	16	21	0.0	23	4	21	2.7	23	16	21	0.0	23	4
22	2.15	19	18	22	2.15	19	18	22	2.15	19	18	22	2.15	19	18
23	3.5	27	2	23	3.5	27	2	23	3.5	27	2	23	3.5	27	2

users of site 5 is the same as the initial value of the employee's relocating cost, and the total cost remains unchanged. In addition, the arrival time of user No. 7 at the second site can simultaneously meet the time window constraints of virtual sites 21 and 23. Therefore, in the actual scheduling process, the travel paths of the user and the designated employee can be interchanged. The calculation results can also test the effectiveness of the proposed model.

5.3. Comparison of optimization methods. In order to verify the superiority of the dual-agent relocating optimization method for SEVs under the reward mechanism, we compared it with the employee-only SEV relocating optimization methods for SEV users. The cost structures in the input data and the objective function were adjusted, and an optimization model for the relocating of SEV related to SEV employees and users was established. Then the SCE–UA was used to solve the problem. The calculation results are shown in Table 4.

It can be seen from Table 4 that the user-based SEV relocating optimization method cannot meet all relocating requirements, incurring order penalty costs and lower service levels in the system. At the same time, the total cost under the employee-based SEV relocating strategy is 345.46 RMB, which is 1.68 times higher under this method. In summary, the dual-agent relocating optimization method for SEV based on the reward mechanism can not only effectively reduce the total relocating cost, but also flexibly meet the SEV relocating requirements in the system, and further improve the service efficiency.

6. Conclusions

Based on the classification, analysis and investigation of the factors influencing the user's travel plan selection behavior, the user reward mechanism is formulated to guide users to cooperate with operator employees to complete SEV relocating optimization. An SEV relocating optimization model with the simultaneous participation of two entities was constructed to achieve the goal of minimizing the total cost of relocating. Due to the complexity of the research problems and constraints, a column generation based heuristic algorithm was used to solve the dual-agent relocating optimization problem for SEVs under the reward mechanism. We proposed the SCE–UA to solve the pricing subproblem of this column generation algorithm. Based on the historical order data of the SEV operating system in the Dalian High-tech Park, the application of this model shows that after some incentive, users may change their original planned travel paths and participate in the relocating of SEVs, but taking into account the cost minimization target, users cannot completely replace the employee to complete all

Table 4. Comparison of solution results under three SEV relocating optimization methods.

Method	Total cost (RMB)	Task completion rate	Number of users	Number of employees
relocating optimization method for SEV based on employees	345.46	100%	–	23
relocating optimization method for SEV based on users	371.19	83%	19	–
the dual-agent relocating optimization method for SEV under the reward mechanism	205.62	100%	16/17	6/7

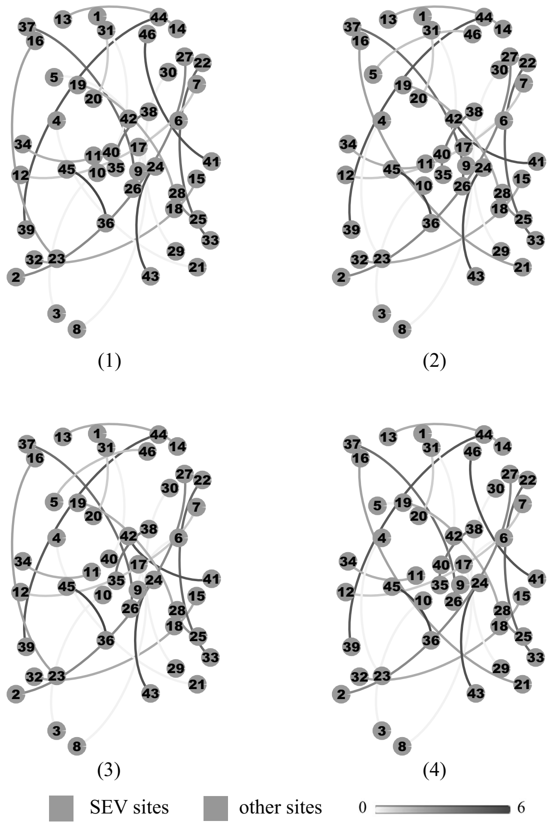

Fig. 4. Results of computations.

relocating tasks.

The overall contribution of this paper is the development of an SEV relocating optimization model with the simultaneous participation of two entities. To verify the superiority of this strategy, a comparison with the dual-agent relocating optimization method based on the reward mechanism was made in two versions. One is the SEV relocating method based only on operator employees and the other is the method only based on users. Sensitivity analyses provide some managerial insights for SEV operating service providers to help them choose the best scheme.

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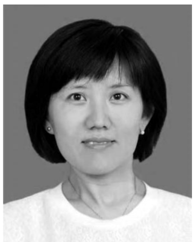

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