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An intelligent electric vehicle charging system for new energy companies based on consortium blockchain

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ABSTRACT

With the concerns of environment protection, electric vehicle (EV) is regarded as a promising transportation tool for green cities project. Since the amount of EV is rising shapely, the EV charging demands is also rapidly generated. However, seeking suitable charging facilities is not easy for EV users, new energy companies run charging station separately for self-interests, and charging pile information is not transparent for drivers. This dilemma is not solved until the merging of blockchain technology. In this paper, a novel EV charging system is proposed for the cooperation of new energy companies and providing convenient charging services for users. In this system, charging information is managed and recorded by the company alliance based on consortium blockchain, which is tamper-resistant and multi-centralized. Meanwhile, a new smart contract is designed to balance the allocation of company' charging users, so that the profits of different new energy companies could be fairer. To equilibrate the interest of companies and EV users, a Bio-Objective Mixed-Integer Programming model (BOMILP) is proposed as the mathematical logic of smart contracts. Furthermore, we proposed a new algorithm named Limited Neighborhood Search with Memory (LNSM) to support the implementation of smart contracts, which could make the smart contract running faster and has a better performance. At last, the proposed EV charging system and the smart contract are validated through a real case study with the EV charging data in Beijing, China.

1. Introduction

With the concern of environmental protection and the decrease of fossil fuel, the Electric Vehicle (EV) is regarded as a promising way to reduce the gas emission and relieve the tension of energy (Ahmadi, 2019; Fernández, 2018). Due to the benefits of environment and energy-saving, many governments choose to publish official policy to support the development of EV, including China, European country, and America, etc. (Qiu et al., 2019; Yan, 2018; Jenn et al., 2018). For example, in the Chinese vehicle market, the sales amount of EV is increasing sharply from 13,000 to 777,000 over the past five years (Zhang et al., 2019a, b). The main reasons for people to purchase EV are price acceptability, government subsidies, and the availability of license plates, etc. (Lin et al., 2018; Zhang et al., 2018a, b). Although plenty of people adopt the EV, the range anxiety still troubles the drivers of EV. The availability for EV charging facilities is highly concerned by users (e.g., charging station location, EV parking space, and charging price) (Yi et al., 2020; Bonges et al., 2016). In other words, with the increase of EV charging demands, the charging facilities should be well utilized and deployed synchronized.

However, the EV charging facilities are unsynchronized with the sales boom of EV. Although, there are plenty of new energy companies (NECs) run their own EV charging station (Luo et al., 2018), charging EV is not quite convenient for most drivers in real scenarios, which may be the trigger for EV users to reconsider internal combustion engine vehicles (ICEVs). There are two roadblocks of the electric vehicle charging problem (Kumar et al., 2020). Firstly, the profit of NECs is quite difficult to coordinate with each other. For different spatial distribution of charging facilities, the amount of served EV users is also unbalanced, which directly influences the revenue of companies. Due to a lack of fair allocation mechanism, companies would not be willing to cooperate and share their charging facilities' real-time information and customers. Secondly, NECs companies do not trust each other for their interest conflict, i.e., company A would provide the malicious or misleading information to company B so that the interest of A could be maximized. As a result, the charging information (e.g., real-time vacant charging pile, etc.) is separated from each company, and the users

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could not get access to the economical charging station. These problems need to be well solved, and the interest of each company as well as driver' should both be guaranteed.

Blockchain is an emerging and promising technology proposed by Nakamoto in 2008 (Nakamoto, 2008). The initial application of blockchain is the basic technology for Bitcoin which is a kind of cryptocurrency. The blockchain has the security and tamper-resistant merit, which is guaranteed by mathematics and cryptography (Li et al., 2018). Blockchain technology can build the trust link in a peer to peer network, all the nodes (e.g., companies, customers, etc.) in the network could trust each other and accelerate the business process forward. Besides in the application of the financial field, it is widely employed in the smart grid, internet of things, supply chain management, and data management, etc. (Casino et al., 2019). Due to these merits of blockchain, we could adopt the blockchain technology to handle the NECs cooperation and information sharing issue. In other words, all the charging information of drivers could be recorded on the blockchain, which is immutable and tamper-resistant. Therefore, a trustable infrastructure for real-time charging data sharing could be established and adopted by all companies.

Besides the employed blockchain to building the business trust, we still need to design a cooperation mechanism (smart contract) that adopted by the company alliance (Wang et al., 2018a, b). To solve this problem, we should focus on fair allocation problems, which are the most critical issue in the cooperation of each company. Companies always pursuit the maximum profit and the minimal cost, which may disrupt their cooperation (Ray et al., 2010). In realistic charging scenarios, the revenue of companies is generated from the payment of users, and the cost is occurred by the use of facilities (i.e., depreciation of facilities). Hence, the critical issue of NECs cooperation is to make the allocation of EV charging users more reasonable and fairer.

Based on the aforementioned discussion, a trustable and appropriate customer allocation system is desired for the cooperation of NECs. The main contribution of this paper is fourfold:

1) We proposed a new framework of EV charging system with consortium blockchain.
2) A new smart contract is designed to balance the profit of the company in an alliance.
3) A new algorithm named Limited Neighborhood Search with Memory (LNSM) is proposed to support the running of the smart contract.
4) The proposed framework and smart contract are validated through application in a real EV charging case study of Beijing, China.

The remainder of this paper is arranged as follows: Section 2 reviews the related work. Section 3 introduces an overview of the charging station sharing framework based on blockchain. Section 4 puts forward the mathematics model (smart contracts) to optimize the allocation of participants. Section 5 conducts computational experiments based on real scenario data. Section 6 draws out several managerial suggestions based on the proposed blockchain framework and experiment results. Section 7 summarizes the paper and proposes a future research direction.

2. Literature review

2.1. Electric vehicle charging problem

The electric vehicle is cleaner, cheap and noiseless, and adopted by many drivers, especially in the urban area. With the increasing amount of EV, the charging problem has emerged in the EV drivers' daily life. There are three affiliation types of charging facilities including residential, public and ultra-fast charging stations (Li et al., 2019a, b). Due to the high installation requirement of the residential charging station, the amount of residential station is not so much. Hence, the public and ultra-fast charging station domain the charging market, which could provide charging service for public EV.

There are two charging speed types, including alternating current (AC) slow charging and direct current (DC) fast charging. The fast charging point is necessary for long distance journeys, and drivers always charging EV in the evening (Bryden et al., 2018). Although the slow charging station has the charging speed drawback, it is more economic and prices cheaper for drivers. Hence, the slow charging piles are located in the urban area (Cavadas et al., 2015). Meanwhile, the travel behavior of drivers has a great influence on the selection of EV charging stations, i.e., the cost of charging, access to charging infrastructure, vehicle characteristics, etc. The price is a critical factor for drivers to choose charging stations, and most drivers tend to charge EV at a lower price (Chakraborty et al., 2019). Besides the charging fee, the parking fee is also a vital factor for drivers (Tsai et al., 2006; Khordagui, 2019), especially in first-tire cities.

In addition, the construction and investment of charging stations are also vital issues for the operations effective and profit maximized (Taherkhani et al., 2019). Due to the high maintenance cost and first investment capital, the location problem of charging stations always confused the new energy company's managers or researchers. Data-driven intelligent location is proposed to decide the right position of charging stations (Liu et al., 2019). A GIS-Based method is also effective to overlap the real maps of traffic systems and power systems and find the optimal locations for construction (Zhang et al., 2019a, b; Erbas et al., 2018). In high-density cities, the available space is limited, so that many on-street charging infrastructures are located in the urban area (Grote et al., 2019). The charging station is the most familiar facility for EV drivers in cities, and the congestion problem also frequently comes up at charging stations (Oda et al., 2018). To mitigate the congestion of charging, companies always try to adjust the charge pricing at different time periods, and the efficiency of the charging system could be well improved (Zhang et al., 2018a, b). Therefore, the operation of charging facilities is a critical issue for managers and researches, and more innovative methods should be created to promote the charging information sharing process between different companies.

2.2. Blockchain & smart contracts

The essence of the blockchain is a distributed database, which is tamper-resistant, decentralized, and peer to peer communicated (Aggarwal et al., 2019). It is an emerging technology, which has the potential to bring in a revolution for many traditional industries (Morkunas et al., 2019). Besides the application in Bitcoin, blockchain technology ensures the faithfulness of financial accounting information in the financial field (McCallig et al., 2019). With the development of blockchain and technology updated, many fields could be beneficial from the adoption of blockchain, such as decentralized energy resources (DERs), supply chain management, and carbon emission trading (Li et al., 2019a. b; Choi et al., 2019; Khaqqi et al., 2018). There are three types of blockchain, including public blockchain, private blockchain, consortium blockchain, which have different features. In the public chain, anyone can join the blockchain as a new point and perform operations (e.g., transactions or contracts). On the contrary, the private chain is a kind of permission blockchain, only the permitted nodes could join the blockchain (Fran et al., 2019). The consortium blockchain is a hybrid combination of the public blockchain and private blockchain, only the preselected nodes can perform the accounting operation rather than all nodes participate in accounting like public blockchain (Huang et al., 2019). As a result, the consortium blockchain is widely adopted by companies and employed in many real scenarios.

The smart contract is an important concept of blockchain technology field. It is an extended application of blockchain, which brings in value and information flow based on the trigger events. Different from the contract in the real world, the smart contract is completely digital and programmable (Macrinici et al., 2018). Automatic execution is another critical characteristic of smart contracts (Egelund-Müller et al., 2017). In other words, the execution of the smart contract is only related to specific events rather than participants of the blockchain. Ethereum is a widely known platform that can support the implementation of the smart contract (Guo et al., 2019). The smart contract is widely employed in various business scenarios for its prominent digital accounting ability. All the transaction information is recorded in the blockchain, and the data in the chain can be safely saved and tamper-resistant (Wang et al., 2019a, b). Therefore, smart contracts could be the basic protocol for the cooperation of the company alliance, and the profit and cost allocation can be executed automatically via smart contracts.

2.3. Profit and cost allocation

Due to the high operation cost, companies tend to cooperate with each other to reduce the cost. With the increase of participants, the gathering resource could lower the single cost and make the alliance system more economical. Before companies agree to enter the cooperation alliance, the right allocation method must be available (Yang et al., 2020). In the financial sector, profit allocation is a critical issue of investment-based crowdfunding projects. A fair allocation mechanism could support the crowdfunding platform's healthy development and protect the profit of each participant (Lozano et al., 2013). In the energy sector, the integration of distributed energy resources (DERs) can generate surplus profit compared with the summation of the individual profit (Saeed et al., 2016). In the transportation field, the airport always offers to share a part of the business profit with the airline, and the airline would give the fixed payment to the airport. Both airlines and airports benefit greatly from the cooperation (Batari et al., 2014). In the environment protection field, the carbon emission allowance is the "cost" of industrial companies, and the companies choose to collaborate with each other to share the burden of carbon taxation. Via rational allocation of an emission allowance, the total emission of the whole industrial system would be reduced in the long term (Wang et al., 2018a, b).

There are two main methodologies for allocation problems, including optimization model and game theory. 1) For solving the optimization problem, we should focus on the objective function, constraints, and decision variables. In addition, a suitable algorithm or method is also needed for the optimization of solutions (Pesaran et al., 2017). 2) Since the complexity of allocation, the game theory model is also adopted to solve the profit allocation problem. A brief summary of the representative literature about the allocation problem is presented in Table 1.

Based on the aforementioned discussion, we could know that the current researches on EV charging are fruitful and comprehensive. However, some critical issues (e.g., charging information sharing, user allocation in business cooperation, and data trustable, etc.) of EV charging are still unsolved until the emerge of blockchain technology. The information sharing of new energy companies could make it convenient for the EV user to find a satisfied charging pile, and also benefits the promotion of EV in societies. Hence, this research paper focuses on the fair and trustable cooperation of new energy companies supported by smart contract in consortium blockchain. This paper could enrich the EV charging research and provide a novel thinking for the application of consortium blockchain in real business scenarios.

3. Proposed framework

We first present the framework of the EV charging system based on blockchain, which is different from the traditional EV charging system. The application of blockchain could make the EV charging information more transparent and more reliable.

3.1. System overview

To alleviate the shortage of EV charging facilities in first-tire cities, and encourage more people to use EV for environment concerning, we proposed the collaborated operation system for new energy companies based on consortium blockchain to ensure the fairness of allocation. The employed blockchain could have a great influence on the company's information flow as Fig. 1 shows. In the traditional EV charging system (Fig. 1(a)), the EV charging station is operated separately and the real-time charging information is saved by different companies. This situation of information isolated leads to the inconvenience for EV users. Thanks to the emerging of blockchain, the collaborated operation system is proposed to handle this problem (Fig. 1(b)). No matter the charging pile affiliated to which company, the charging information could always be recorded on blockchain which is trusted and safe. Hence, the vacant EV charging pile can be maximally utilized and the EV users could get a better charging service.

The working procedure of the EV charging system is shown in Fig. 2. The working procedure could be concluded as three critical aspects. Firstly, the charging requirement of EV users should be known by the system, including the location and time. Secondly, the smart contract will be triggered according to the real-time charging information on the blockchain, and an acceptable charging solution can be generated by the system in the specific condition. Lastly, the transaction information should be packaged and added into the blockchain to make data trustable and transparent for the company member of the consortium.

3.2. Components in the system

There are four main components in the framework, including new energy company, EV user, government and blockchain system. The blockchain is the linkage of company, government and EV user side, and each side has the details components as Fig. 3 shows. Compared with the previous framework of EV charging, which only considering one or two sides of the whole EV charging system (including user side, company side, and government side). However, the three sides interact with each other, which should be considered as an integrated research object. The proposed framework solved this hard problem with the supports of blockchain technology so that the three sides could be studied jointly.

Table 1
Summary of literature for allocation problem.

Algorithm/Method	Research topic	References
Robust optimization	A decision support system for budget allocation	Jang (2019)
Multi-objective optimization	A cooperation and profit sharing mechanism for logistics companies	Defryn et al. (2018)
bidirectional-coupling optimization	An allocation approach for pollutant emission permits of industrial level	Duan et al. (2020)
Ant colony optimization	A cooperation and profit allocation method for logistics company joint distribution	Wang et al. (2017)
Dynamic optimization & Heuristics algorithm	A heuristics method to solve stochastic multi-period task-resource allocation problem	Gülpınar et al. (2018)
Random search-based optimization algorithm	An optimization schedule for Multi distributed generators allocation	Selim et al. (2019)
Epsilon-based model	A scientific allocation scheme of carbon dioxide emissions allocation	Cai et al. (2019)
Optimization & Fuzzy programming	A profit and cost allocation approach for production problem	Sakawa et al. (2001)
Game theory	A profit allocation mechanism for energy supply chains	Gao et al. (2019)
Game theory	A horizontal cooperation approach for the profit sharing of transportation system	Algaba et al. (2019)
Cooperative game theory	Fair profit allocation for serial supply chains management	Kumoi et al. (2014)
cooperative game & optimization	An equal-cost allocation for rapid-transit network of USA	Rosenthal (2017)
Evolution of game theory	A method for investment and payoff allocation in spatial public goods game	Fan et al. (2017)

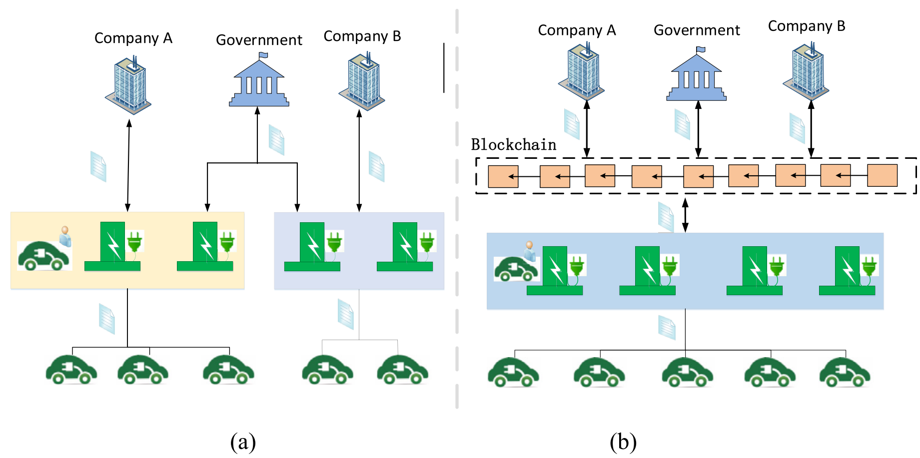


Fig. 1. The comparison of EV charging method.

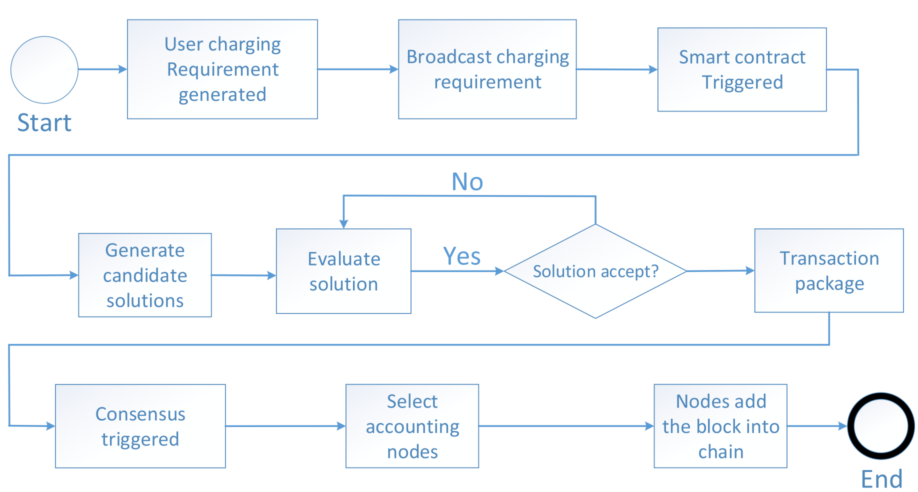


Fig. 2. The process of the system working.

- New energy company — The owner of charging stations which is responsible for the usability of charging facilities. Meanwhile, constructing new charging stations is also considered by new energy companies to meet the charging demand of EV users.
- Government—The charging service price is decided by the local government as well as the real-time electricity price. In addition, the license plate for EV is also regulated by government as well as the subsidy policies. What should be noticed is that the electricity price is fluctuant at different time segments.
- EV users— The users of charging station who prefer the nearby charging station. According to the SOC condition, the users can decide when and where to charge the EV. Each EV belongs to the

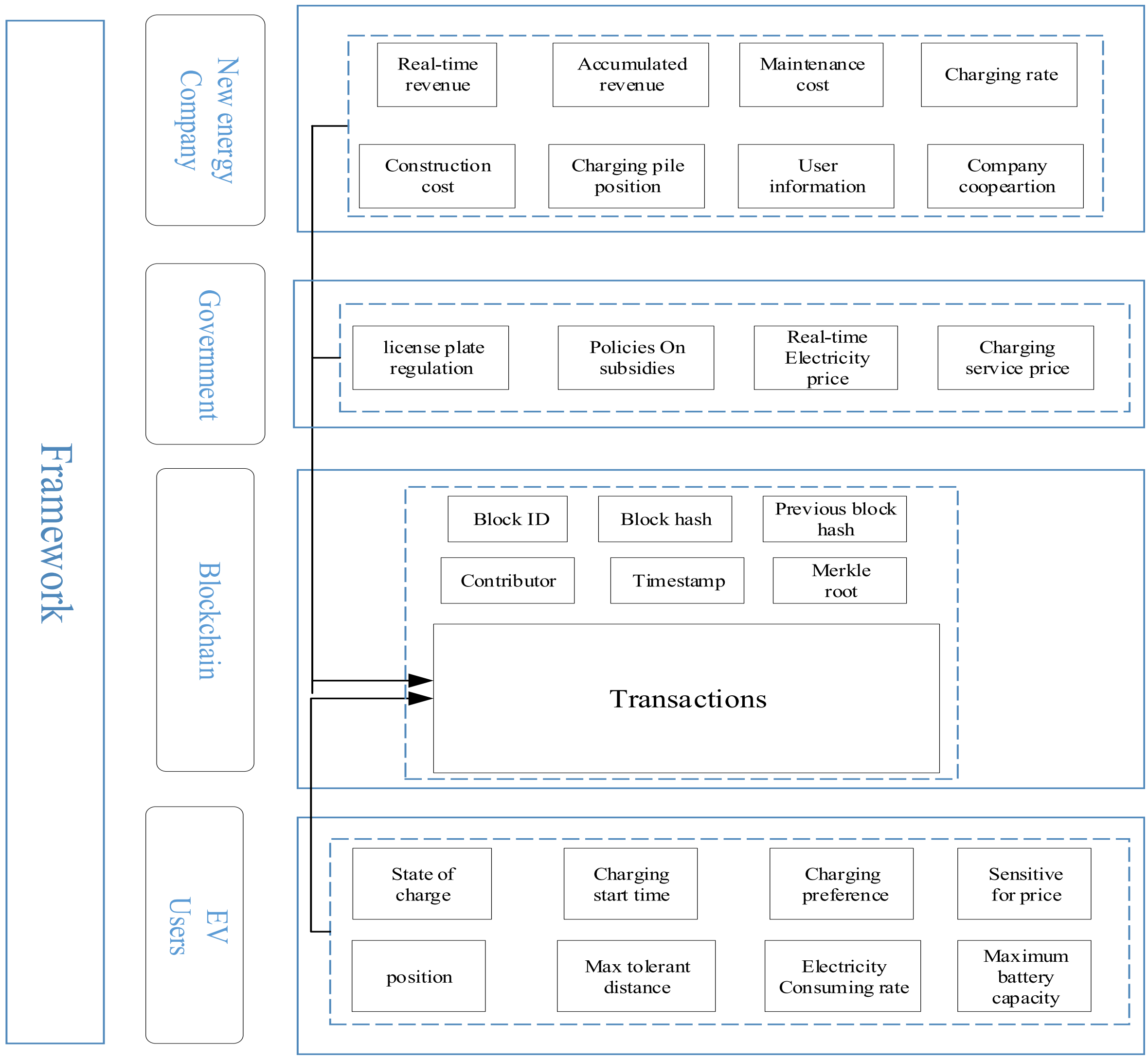


Fig. 3. The framework of EV charging system.

specific EV company for the user's choice of vehicle brand. The maximum tolerant distance for charging vehicles is a critical index for users to seek the appropriate EV charging stations.

- Blockchain —The data blocks which is linked by the previous block hash value to ensure the reliability of the accounting system. Considering the application scenario in this paper, we choose the consortium blockchain to build the trustable linkage between companies and users. The information which is related to the EV charging process (e.g., charging price, charging start time, SOC condition, etc.) will converge in the block body (transactions). Companies could generate the charging bill of users based on the data saved on the blockchain.

4. Design & implementation of smart contract

The essence of smart contacts is computer code which embedded previously on the blockchain system (Swan, 2015). Before generating the program code, we should clearly define the mechanism and rules about the specific smart contract. In other words, propose the mathematical model is the first step for the design of smart contracts. In the mathematic model, we should put our emphasis on optimal objection and constraints. Then, we could start the coding work according to the previous model. We constructed a Bio-Objective Mixed-Integer Programming model (BOMILP) to solve charging facilities' dynamic allocated problem.

4.1. Assumptions & notations

To make the model more easily understood, reasonable assumptions is needed. The assumptions and the features used for formulation are as follows:

- Once the EV finished charging operation, the user drive away from the charging station immediately.
- During the charging period, all the equipment of EV is power off, including air-conditioner, music system, etc.
- The electricity fee is charged by EV charging station as a part of profit.

Nomenclature	
Indices & Sets	
n	Index of companies (n $\in N$)
u	Index of EV users (u $\in$ U)
t	Index of time segments (t $\in$ T)
b	Index of block number in consortium blockchain
p	Index of charging station (p $\in P$)
p_n^F	Index of fast charging stations belong to company n ($p_n^F \in PF$)
p_n^S	Index of slow charging stations belong to company n ($p_n^S \in PS$)
N	Set of companies
U	Set of EV users
T	Set of time segments
PF	Set of fast charging station
PS	Set of slow charging station
P	Set of total charging station
T_c^u	Set of charging time of each user u
Parameters	
Cap	The maximum battery capacity of EV
ω	Unit kilometer power consumption (kW•h/km)
L_{max}	Maximum serving times of station before maintenance
d_{max}^u	Maximum tolerant distance of user u from requiring position to charging station
μ_t	The electricity price at time t per kW•h.
γ^F	The fast charging service price decided by government
γ^S	The slow charging service price decided by government
c_1	The construction cost of one fast charging station per time segment
c_2	The construction cost of one slow charging station per time segment
τ	The subsidy ratio for the cost of station decided by government
SOC_u^t	State of charge of EV user u at time t
δ_f	Fast charging rate
δ_s	Slow charging rate
Δt	The span of each time segment
Variables	
$x^t_{(p_n^f,u)}$	1, if the fast charging station p of company n is occupied by user u at time t , 0, otherwise
$x^t_{(p_n^s,u)}$	1, if the slow charging station p of company n is occupied by user u at time t , 0, otherwise
A_n^{Ft}	The amount of available fast charging station of company n at time t
A_n^{St}	The amount of available slow charging station of company n at time t
O_n^{Ft}	The amount of occupied fast charging station of company n at time t
O_n^{St}	The amount of occupied slow charging station of company n at time t
d_{pu}^t	The charging distance of EV user u to charging station p at time t

4.2. Objective function

The objective of the optimization model is to minimize the unbalance of revenue and operation costs for different companies. Meanwhile, the EV users' satisfaction for charging EV should also be considered in the model. Most users prefer to the nearest charging station (i.e., the distance between charging station and start position to charge EV is highly related.) Hence, the bi-objective function can be expressed as Eq. (1) and Eq. (2). To make the expression concise and clear, the calculation methods of P_n^t and $\overline{P}_t$ are described in Eq. (3) and Eq. (4).

$$\min f_1 = \frac{\sum_{n\in N}(P_n^t - \overline{P_t})}{N} \qquad \forall t \in T \tag{1}$$

$$\min f_2 = \sum_{u\in U} d_u^t \qquad \forall t \in T \tag{2}$$

$$P_n^t = x^t_{(p_n^f,u)} \cdot \left[\mu_t + \gamma^F - (1-\tau)c_1\right] + x^t_{(p_n^s,u)} \cdot \left[\mu_t + \gamma^S - (1-\tau)c_2\right] \forall t \in T \tag{3}$$

$$\overline{P_t} = \frac{\sum_{n\in N} P_n^t}{N} \tag{4}$$

4.3. Constraints

The constraints define the scope of feasible solutions in the optimization model. These constraints can be categorized into three parts. Firstly, the characteristic of the charging system should be abstracted into the model, e.g., one charging pile only serves 1 EV at a time segment. Secondly, the resources constraint of charging facilities also should be considered. Lastly, the characteristics of EV users are also needed to fulfill the model.

- Charging characteristics constraints

$$\sum_{u\in U} X^t_{(p_n^f,u)} \le 1 \qquad \forall \quad p_n^f \in PF \qquad t \in T \tag{5}$$

$$\sum_{u\in U} x^t_{(p_n^s,u)} \le 1, \forall \quad p_n^s \in PS \qquad t \in T \tag{6}$$

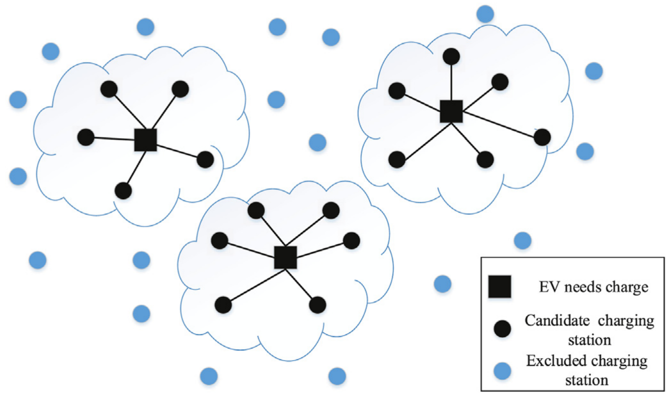


Fig. 4. The limited strategy of neighborhood search.

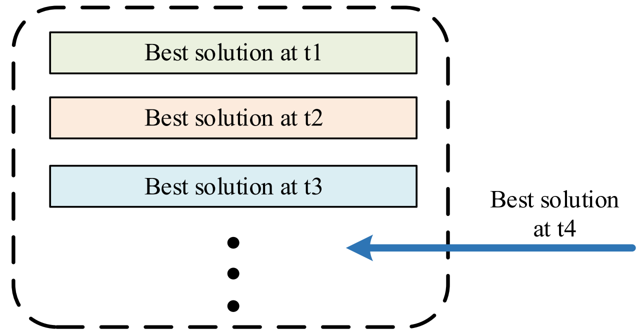


Fig. 7. Adopted solution add into the memory pool.

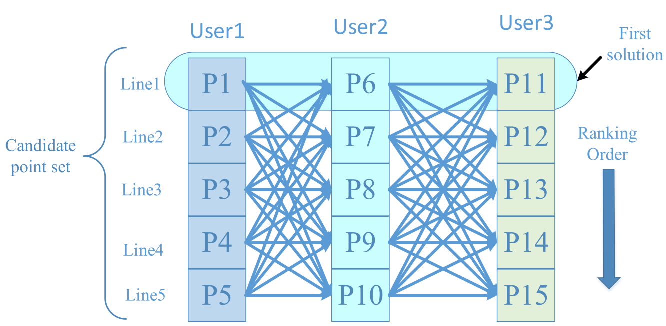


Fig. 5. The search mechanism of Algorithm.

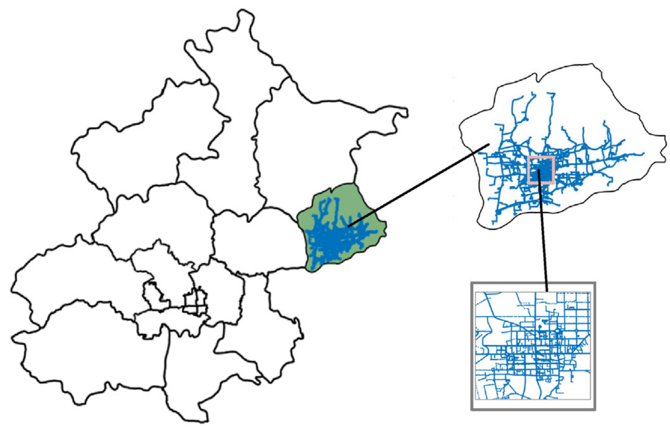


Fig. 8. The data visualization of EV in Beijing.

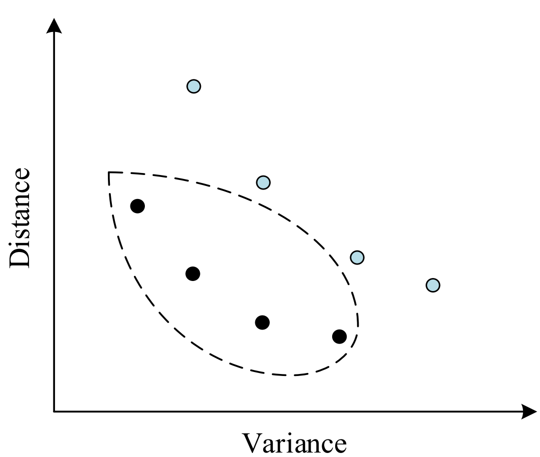


Fig. 6. The generation of Pareto-set.

Step 3: Calculate the equilibrium degree of each solution. Equilibrium degree is introduced to describe the unbalanced profit of each solution and equals the variance of solution matrix. Hence, we could calculate the real-time accumulated profit of each solution based on the previous best solution (memory pool), and get the value of variance. If the solution is not satisfied, go back to Step 2 to regenerated solution. As a result, we can always get a Non-inferior solution at each iteration.

$$\sum_{n\in N}\sum_{u\in U} x^t_{(p^f_n,\ u)} + \sum_{n\in N}\sum_{u\in U} x^t_{(p^s_n,\ u)} = \sum_{n\in N} O^{Ft}_n + \sum_{n\in N} O^{St}_n \qquad \forall t\in T \tag{7}$$

$$\sum_{t\in T^u_c} \delta_f \cdot x^t_{(p^f_n,u)} + Cap \cdot SOC^t_u \le Cap \qquad \forall u\in U \tag{8}$$

$$\sum_{t\in T^u_c} \delta_s \cdot x^t_{(p^s_n,u)} + Cap \cdot SOC^t_u \le Cap \qquad \forall u\in U \tag{9}$$

Constraint (5) and (6) state that each charging pile could serve at most 1 EV at a time segment. Constraint (7) guarantee that all the EV users who require charging services are assigned to the respective charging station. Constraint (8) and (9) ensure that the charged electricity could not surpass the maximum battery capacity of EV.

- Charging facility resource limits

$$\sum_{u\in U}\sum_{p^f_n\in PF} x^t_{(p^f_n,\ u)} \le \sum_{n\in N} A^{Ft}_n \qquad \forall t\in T \tag{10}$$

$$\sum_{u\in U}\sum_{p^s_n\in PF} x^t_{(p^s_n,\ u)} \le \sum_{n\in N} A^{St}_n \qquad \forall t\in T \tag{11}$$

The constraint (10) and (11) guarantee that the fast and slow charging demand of EV users could be met at any time segment.

- Users charging distance limited

$$\frac{Cap \cdot SOC_u^t}{\omega} > d_u^t \qquad \forall t \in T, u \in U \tag{12}$$

$$d_{pu}^t \le d_{max} \qquad \forall t \in T, u \in U \tag{13}$$

Constraint (12) guarantee the remaining electricity of EV could support the vehicle sailing to the charging station. Constraint (13) ensures that the EV users would not choose the charging station over the maximum tolerant distance.

- Non-negativity constraints

$$x_{(p_n^f,u)}^t \in \{0,1\}, x_{(p_n^s,u)}^t \in \{0,1\}, d_{pu}^t > 0 \tag{14}$$

Constraint (14) enforces the binary and non-negativity restriction for the variables.

4.4. Implementation of smart contract

To solve the problem and transfer the solution into an executable smart contract, we should find an appropriate algorithm to get the feasible solution. Different from the traditional optimization method, the smart contract embedded in blockchain requires a faster and lighter algorithm to meet the nodes' demands. Neighborhood search algorithm (NSA) is a kind of approximate algorithm to solve combinatorial problems. The NSA is convenient for implementation and improvement so that the NSA could be a candidate algorithm for smart contracts. Due to the various scenario of optimization problems, some researchers improved and fulfilled the NSA for getting better performance (e.g., variable neighborhood search, large neighborhood search, etc.) (Olender et al., 2019; Hintsch et al., 2018). Meanwhile, the EV charging dispatch is dynamic and timely, we should also take variation of system into consideration (Hintsch et al., 2018).

Based on the aforementioned discussion, we proposed Limited Neighborhood Search with Memory (LNSM) algorithm to solve the BOMILP problem so that the smart contract of blockchain could work more efficiently and intelligently. There are two critical strategies in the LNSM:

i) Limited the candidate solution set to improve the searching efficiency.
ii) Dynamic changes the solution based on the previous decision.

The concrete steps of LNSM are as follows:

Step 1: Limit the candidate charging point. Firstly, denotes D_{up}^t is the charging distance of user u at time t to point p. Based on the charging demand of EV user u_c , we can calculate the distance between EV position and charging station position, if the charging distance D_{up}^t is lower than the maximum tolerant distance d_{max}^u , and also lower than EV remaining range considering SOC capacity as Eq. (15) shows, the point is selected as a feasible point (Fig. 4).

$$D_{up}^t < \min\left(d_{max}^u, \frac{Cap - Cap \bullet SOC_u^t}{w}\right) \qquad \forall u \in U, t \in T \tag{15}$$

Proposition 1. *The limitation of feasible points could lower down the invalid search and accelerate the convergence of LNSM.*

Proof of Proposition 1. *Denote n_u is the number of selected nodes set U, and N is the number of all nodes ($n_u < N, \ \forall u \in U$). The total combinational solution before limited is larger as* Eq. (16) *shows.*

$$\left\{\underbrace{n_1 \times n_2 \times \cdots \times n_{u-1} \times n_u}_{u} = \prod_{u \in U} n_u\right\} < \left\{\underbrace{N \times N \times \cdots \times N \times N}_{u} = N^u\right\} \tag{16}$$

Accordingly, the comparison times would also descend as a result of $\prod_{u \in U} n_u < N^u$, and the algorithm complexity is also minimized.

Proposition 2. *There is always a Non-inferior set (Pareto set) at each iteration.*

Proof of Proposition 2. *To prove* Proposition 2, *we denote $P_{(u,i)}$ as the match of line i in candidate set $k_u \in K_u$, $f_1(x)$ as the variance of solution, and $f_2(x)$ as the distance function. As a result of distance ranking, the distance of each user u is ascent. This means that:*

$$f_2(P_{(k_u,i)}) \le f_2(P_{(k_u,i+1)}) \qquad \forall u \in U \tag{17}$$

We could transform Eq. (17) *to* Eq. (18) *for calculating total distance. Apparently, with the ascending of i , the total distance is not less than the previous solutions. So that, the result in small number of i is non-inferior to the larger number of j.*

$$\sum_{u \in U} f_2(P_{(k_u,i)}) \le \sum_{u \in U} f_2\left(P_{(k_u,j)}\right) \qquad \forall i,j \in I \tag{18}$$

As the definition of Pareto set, and the optimization issue of this paper (i.e., minimization problem both of two objections), the bottom left area is the best target area as Fig. 6 *shown. Based on the* Eq. (18), *we could know that the minimized result of total distance is in a small number of i. Hence, we can draw the conclusion that no less than one solution owns the best result of one objection, so we Proof the* Proposition 2.

Step 2: Rank operation & generate solutions. Based on the candidate point set of **Step 1**, we could rank the distance from small value to large value (Fig. 5). After ranking operation finished, we could select the candidate point from sets, so that the objective function (2) could be first satisfied. The generate solution order is from the top line to the end line. For example, we first select the line 1 as the newly generated solution (P1, P6, P11), which total distance is the least. If the solution is not satisfied, we could regenerate the new solution in the neighborhood solutions, e.g., (P2, P6, P11), (P1, P7, P11), etc.

Step 4: Select the best solution & Update the memory pool. According to the result of **Step 3**, we can get the best solution, which satisfied our requirements. After selecting the best solution, we should add the solution into the memory pool. Therefore, the memory pool could integrate the whole solutions of different time segments (Fig. 7).

The executed details of smart contract for allocating EV to different charging station is shown in **Algorithm 1**.

Algorithm1: Smart contact for allocation EV charge

Input: d^u_{max} ,$Cap, SOC^t_u, D^t_u, k_u,\ f_1, f_2, T.$
Output: Solution S
$S \leftarrow \emptyset$
$k_u, \leftarrow \emptyset$
for $t \in T$
    for $u \in U$
        if $D^t_{up} \le \min(d^u_{max}, \frac{Cap - Cap \bullet SOC^t_u}{w})$
            $k_u \leftarrow p$
        end if
    end for
    $k_u \leftarrow ranking\ k_u$
    While stop condition not met **do**
        $f_1 \leftarrow$ calculate the variance of *s from* k_u
        $f_2 \leftarrow$ calculate the distance of *s from* k_u
        if *s is* accepted of time segment *t*
            $S \leftarrow$ s
        end if
    end while
end for
Return S
End algorithm

5. Case study

This section discusses the EV charging issue on blockchain method. Through analyzing the real data from one of the biggest cities of China, we could verify the efficiency of EV allocation system. The performance of the smart contract is also examined in real data scenarios.

5.1. Case introduction & data pre-processing

The case study is conducted based on the real EV charging data of Beijing, China. Beijing is one of the biggest cities in China, and the environmental condition of Beijing is concerned by the government (Wang et al., 2019a, b). The EV is seemed a promising transportation vehicle to mitigate environmental pollution, and the Chinese government provided plenty of policy to support the development of EV. Hence, the EV market is a boom in recent years, and many people choose to buy EV for travel, especially in Beijing (Zhuge et al., 2019). Due to the high amount of EV in Beijing, the convenience and economics for charging vehicles are highly concentrated by EV users. Although, there are lots of charging facilities in city, the charging information is isolated from each EV charging company. As a result, EV users always could not get real-time information of charging pile situation (occupied or vacant). So, the introduction of charging facility recommend system is very desired for users. To make the information system more transparent of different companies, the consortium blockchain is employed in the system.

The EV charging data published by national EV data federation involves two parts, including 3 electric vehicle charging data, and traveling information of about 60 days. There are more than 200 million EV travel data records and 5000 charging data records in the row data set. The position data of EV is recorded by GPS equipment, and the interval of collection is 10 s. The GPS data of EV is shown in Fig. 8, each point means the position of one EV in a specific time. The charging needs are shown in Fig. 9.

The details information of data is shown in Table 2.

We could know the information (Table 3) from the aforementioned data set. The battery capacity is calculated according to Eq. (19), and the power consumption derived from Eq. (20). In addition, the calculation of charging rate of EV follows Eq. (21). Lastly, we average the values for the concern of random error.

$$Cap = \frac{\Delta Electricity}{\Delta SOC} \qquad \forall u \in U \tag{19}$$

$$Cons = \frac{\Delta Mileage}{\Delta SOC} \qquad \forall u \in U \tag{20}$$

$$Rate = \frac{\Delta Electricity}{\Delta t} \qquad \forall u \in U \tag{21}$$

Next, we set the charging pile information for experiments. The charging pile of Beijing area is dominated by four companies, includes State Grid Corporation of China (SGCC), Teld of BAIC., Potevio New Energy Co., Ltd, and StarCharge. After collecting data from these companies' website, we can get the comparison for charging pile number located in Beijing (Fig. 10(a)). The detailed information

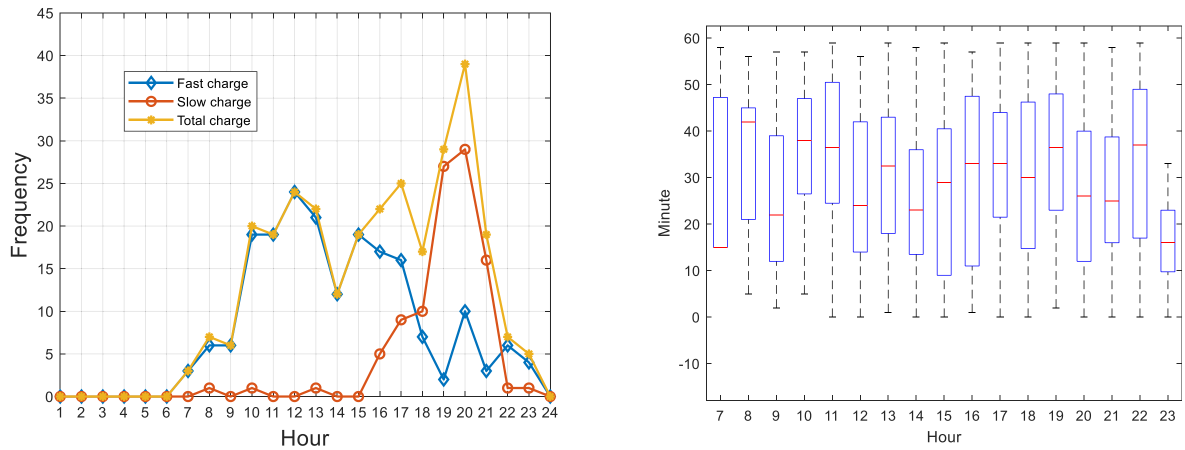


Fig. 9. The distribution of EV charging needs during a day.

Table 2
Data description.

Data fields	Description
Data set 1 (EV Charging)	
Electric vehicle ID	Vehicle number
Charging start time	Start charging time
Current SOC	The remains electricity of battery
Current mileage	The total mileage of current
Data set 2(EV travel)	
EV position	The latitude and longitude of EV
Timestamp	Current time
Charge state	Charging in process or not

Table 3
The parameter of EV charging.

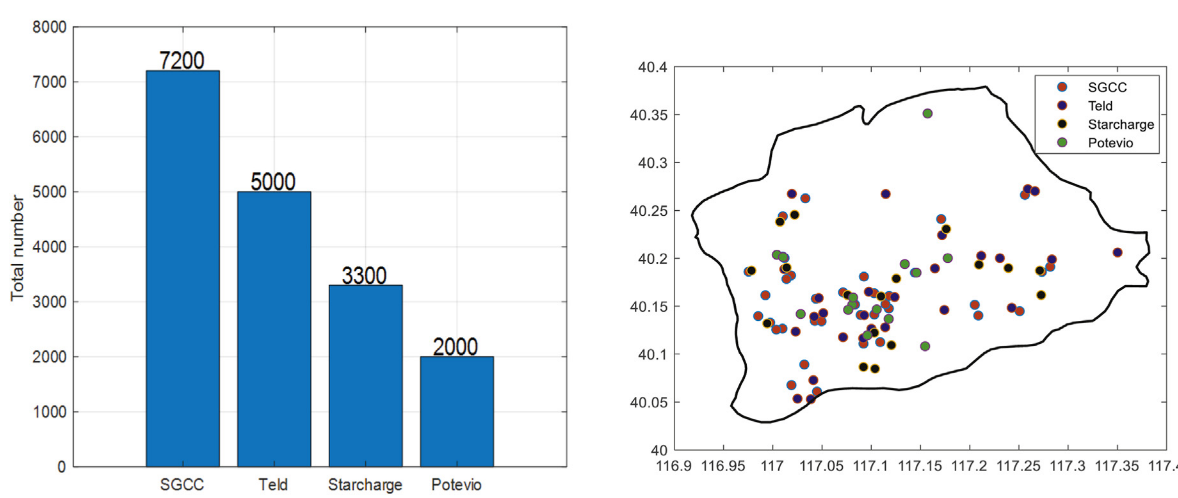
Battery capacity/kWh	Power consumption per kilometer/kWh	Fast charging rate (kW)	Slow charging Rate(kW)	Maximum tolerant distance for charging (Km)
32	0.1554	13.99	2.84	2

of charging station is shown in Fig. 10(b). We assume that each charging station has one fast charging pile and two slow charging piles.

At last, we collect the charging price data according to the government website of Beijing Development and Reforming Office (published in 2015). The periodic electricity of Beijing is shown in Fig. 11, and the service price charged by the station is 0.8 RMB/kWh. In addition, the construction price of fast and slow charging pile is 5 RMB/day and 0.5 RMB/day, according to the charging pile sales price (50,000 RMB/5,000RMB), the government subsidy ratio is 80% for each charging pile, the lifecycle of charging pile is 3 years (about 1000-day).

5.2. The implementation of blockchain system

There are two steps to make the charging system work well. The first step is the critical data collection, including the real-time charging needs of EV user, and the vacant charging pile of companies. After data collection, the system will generate an account node (i.e., contributor of the block) to record the data on the



(a) (b)

Fig. 10. Charging pile compassion and spatial distribution.

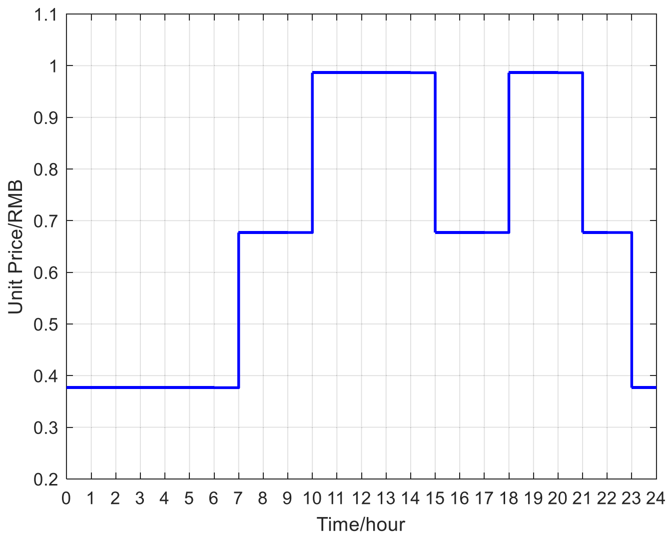


Fig. 11. The periodic electricity price of Beijing.

consortium blockchain. After data recorded, the smart contract will be triggered to realize the dynamic allocation of the charging pile. Each time segment, the Smart contact would be triggered once to build the linkage between EV users and charging piles.

For the user side, there is an App embedded in the user' smartphone or EV control panel to seek the appropriate charging pile. Firstly, when the charging demands generated by EV users, they should log into the system as Fig. 12(a) shows. Secondly, the system will generate a recommended charging station according to the result of smart contact as Fig. 12(b) shown. Next, when the users agree and start to navigate to the station, the system would connect the map system and generate an appropriate route for users (Fig. 12(c)).

For the company side, the consortium blockchain system is constructed to record the transaction information as Fig. 13 shows. The transaction information is maintained by all the companies in the consortium so that the data is trustable and adoptable by companies at any time. First of all, the system gathers the transaction information and package it into a data block, the block hash value and Merkle tree are generated via the hash function (e.g., 'MD5', 'SHA-1', 'SHA-256', etc.). Next, there will be a contributor (accounting nodes) generated in the consortium to put the data block into the blockchain. In this system, the generating mechanism is by turn, for example, if the previous block is recorded by SGCC, and the next block should be recorded by StarCharge. By this way, the block chain would be extended orderly and the consortium blockchain is well maintained.

5.3. The performance of the system

To evaluate the performance of the proposed system, two numerical experiments are conducted in this section. i) The first experiment is to verify the effect of the memory operation in the LNSM algorithm, which is proposed in Section 4. We compare LNSM algorithm with LNS (non-memory) algorithm and check the different results in the profit equilibrium of the system. ii) The second experiment is to do the parameter sensitivity analysis of the algorithm, via altering the limitation leverage, neighborhood search time to view the difference of results.

Experiment 1: We fix the candidate station as 5 stations, EV number as 3, then adopt LNSM and LNS algorithm respectively as the core mechanism for the smart contract to carry out this experiment. The accumulated profit of each company is shown in Fig. 14(a) and Fig. 14(b) in 61 days, the LNSM shows a better equilibrium of company alliance compared with LNS, which is the non-memory method. In addition, the profit variance of

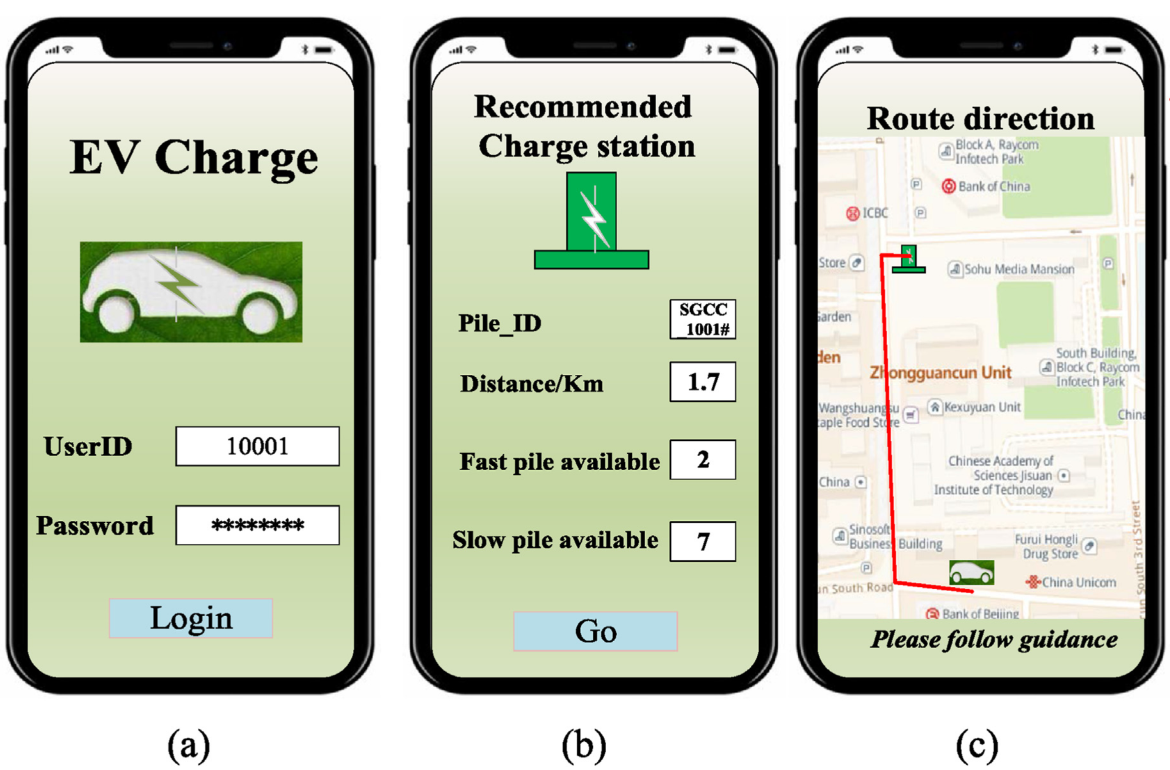


Fig. 12. The graphic user interchange of EV charging system.

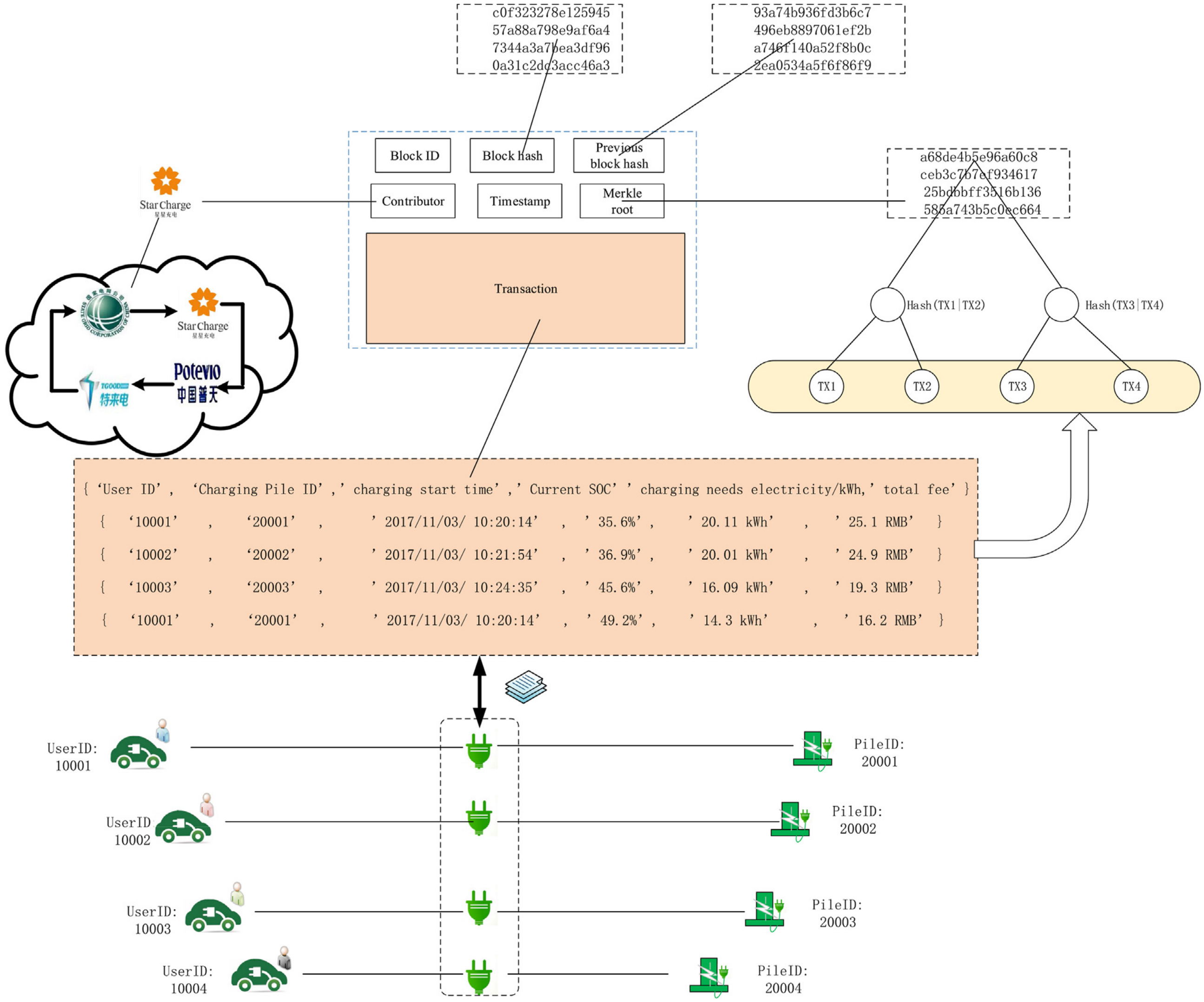
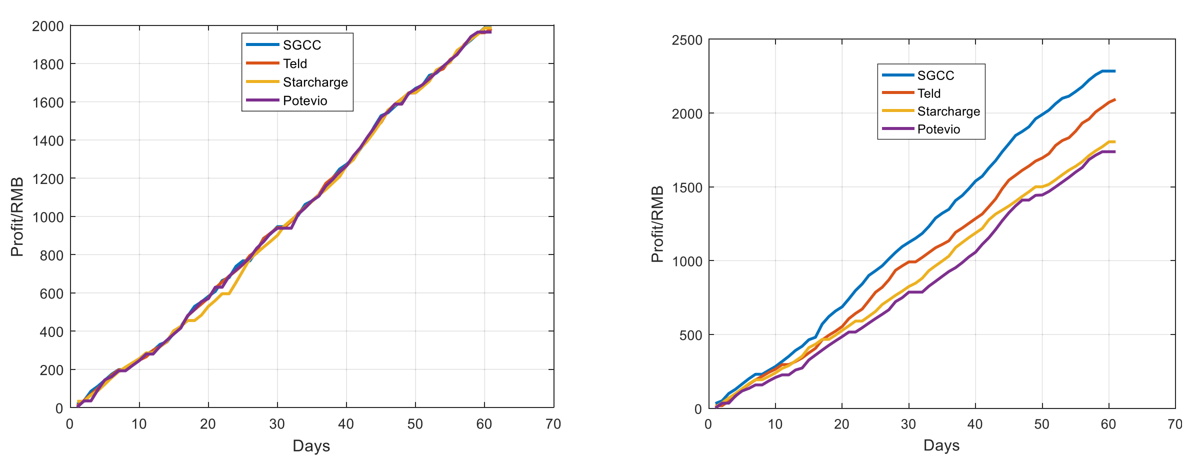


Fig. 13. The framework of consortium blockchain.



(a) LNSM (b)LNS

Fig. 14. The profit comparison between LNSM and LNS.

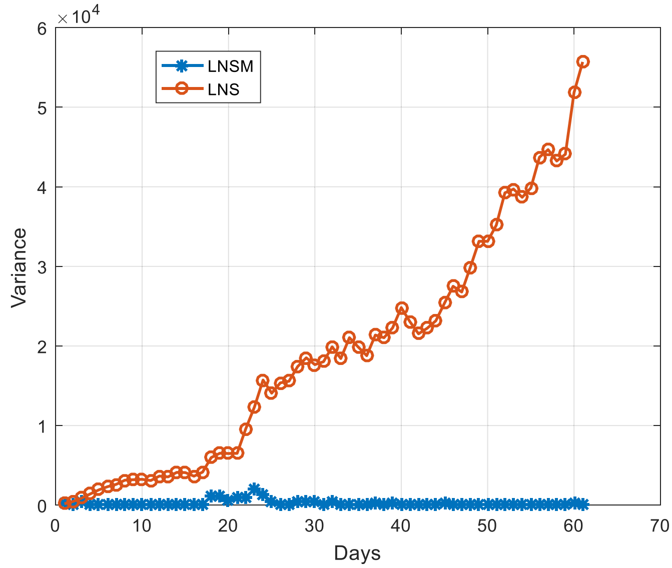


Fig. 15. The variance comparison between LNSM and LNS.

companies is shown in Fig. 15, and we could see that the variance of companies in LNSM algorithm is quite stable and low, but the variance of LNS algorithm is much higher than LNSM.

Experiment 2: We employed LNSM algorithm for the smart contract and alter the candidate EV charging station for users. The profit variance of new energy company alliance is shown in Fig. 16. With the candidate restrictions relax, the smart contract could make the profit of new energy companies more equilibrium. Therefore, the variation of the number of candidate charging stations has a great influence on the equilibrium of the profit of new energy companies. Furthermore, we could deserve from the experiment result that there is a threshold of the candidate station. When the candidate station number increases from 8 to 9, the variance of companies still has great change. Yet, with the candidate station number increase from 9 to 10, the variance of companies almost has no change.

It can be observed that the employed of memory method is quite useful for the equilibrium of the new energy company alliance, and should be adopted in the EV station recommend the system for EV users.

6. Managerial insights

Several useful managerial insights and suggestions could be derived from the proposed consortium blockchain framework and experiment results. It is related to the real-business operation and has the potential to put the EV industry move forward.

1) Effectively using the vacant resource is critical for business operation, and could make companies save a lot of extra costs. In this EV charging system of blockchain, all the EV charging facilities, which belong to different new energy companies, are management synergistically through the transparent information sharing. Hence, EV users could be linked to the vacant charging facilities as soon as possible. In this way, the charging facilities could be maximized used and EV users could also conveniently get real-time information about vacant charging facilities.
2) The cooperation of companies could be more operable and implemented by a reliable and trustable blockchain system. The cooperation of companies is a difficult and troublesome problem in the management field for a long period, and the most important issue of cooperation is the profit allocation mechanism. EV charging framework proposed in this paper could handle the profit allocation of company alliance via the autonomous executed smart contract, which is independent running and could not be dominated by any company. Hence, companies have the motivation to maintain the fairer system, and market monopoly problems could be mitigated to a large extent.
3) The users' preference for service or products has a great impact on the business operation of companies, and there could be a threshold value of users' preference in the business system. With the increase of users' candidate station, which means that the users would accept the more faraway station to charge EV, and the profit of companies could be more balanced through the dynamic allocation by smart contracts. Furthermore, the relationship between users' preference and the balance of companies' profit is no-linear. Once over the threshold value, the change of users' preference would have less impact to the companies' cooperation. To better manage the company

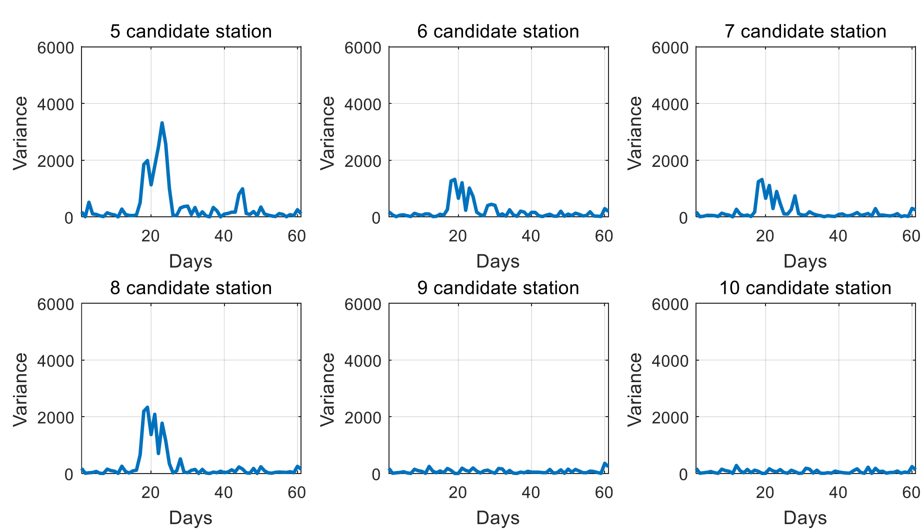


Fig. 16. Sensitivity analysis for different candidate station of EV user.

alliance, we should take care of the users' preference for charging service.

7. Conclusion and future works

This paper proposed a cooperation system for new energy companies based on consortium blockchain technology. In this system, companies connected with their customer via the trigger of smart contracts, which could maintain the fairness of customer allocation and balance the profit of the company alliance. Companies trust with each other via the support of consortium blockchain, which is tamper-resistant and data transparent. Meanwhile, a practicable business framework is built for companies, and a concise application method is designed for EV users. Further, we put forward a new algorithm named LNSM to enhance the performance of the allocation smart contract. Through mathematics Proof, we could draw the conclusion that the LNSM could lower the computational complexity. Through the numerical experiments, we observed that the performance of LNSM algorithm is better than the non-memory LNS algorithm.

For future research, we could add user preference to the mathematic model. Due to preference is various between different EV users, e.g., the location environment of the charging station, the company brand of charging station, the price of parking vehicle, etc. In addition, the incentive of accounting nodes for consortium blockchain could be further studied, EV charging token could also be a good idea for the joint operation of new energy companies. Lastly, to provide a more suitable charging station for EV users, the single blockchain system would require more data from the other blockchain. Hence, the research of cross-chain could be a promising method to link more data and build a more intelligent society.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Zhengtang Fu: Methodology, Software, Writing - original draft. **Peiwu Dong:** Conceptualization, Funding acquisition. **Yanbing Ju:** Methodology, Validation.

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