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# Optimizing the Locations and Sizes of Solar Assisted Electric Vehicle Charging Stations in an Urban Area

**DONG JI, (Graduate Student Member, IEEE), MINGSONG LV, (Member, IEEE), JIAYU YANG, AND WANG YI, (Fellow, IEEE)**

Key Laboratory of Intelligent Computing in Medical Image, Ministry of Education, School of Computer Science and Engineering, Northeastern University, Shenyang 110169, China

Corresponding author: Mingsong Lv (lumingsong@cse.neu.edu.cn)

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**ABSTRACT** With the wide-spread adoption of electric vehicles (EVs), introducing solar energy in building EV charging stations is promising as it can reduce carbon emissions and improve air quality. The main challenges are how to decide where to build solar assisted charging stations in a city and how to size the charging stations, as the decision is affected by a broad range of factors, such as construction cost, solar energy fluctuation, and user requirements. This paper proposed an approach to efficiently decide the locations and sizes of solar energy assisted charging stations for an urban area. Experiments are conducted on real EV history data from 297 users of an EV leasing company. The results show that the proposed method can produce high quality decisions within reasonable computation time. The work of this paper will provide important information for decision makers to integrate solar energy into the EV charging infrastructure.

**INDEX TERMS** Charging station, electric vehicle, metaheuristic, solar energy.

## I. INTRODUCTION

Widespread adoption of electric vehicles (EVs) will reduce carbon emissions and improve local air quality. As the power source of the grid mainly comes from coal combustion in quite some regions [1], adopting EVs itself may not help energy conservation and emission reduction. Considering solar energy in the EV ecosystem, for example, building solar-powered charging stations, provides an opportunity for the sustainable use of electric vehicles. For example, during the daytime, employees with access to daytime plugs can charge their EVs with solar energy at their workplaces. According to a study by Oak Ridge National Laboratory, installing solar panel roofs above a parking space can produce enough electricity in one year to provide the electricity required to drive a Nissan LEAF or similar vehicle approximately 10,000 miles [2]. Solar charging systems can also help the electric grid to meet the increasing charging demand from EVs and reduce the pressure on distribution systems and transmission infrastructure.

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To adopt solar energy in EV charging stations, deciding the sizes and locations of the charging stations is challenging. First, to collect as much solar energy as possible, a large size solar power system could be designed, but this may increase construction and maintenance costs and under-utilize the solar power system. A small solar power system can be fully utilized but may fail to satisfy user requirements. An optimal design must consider both the cost and the energy supply capability of the solar power system. Second, the problem is further complicated when considering deploying solar power systems for EV charging in a city, in which the location and sizing of charging stations must consider the variations in user requirements in different regions. As the collected solar energy is affected by the weather, time of day, and surrounding environments, deciding how to construct solar energy charging stations will become even more challenging.

In this paper, we consider the problem of locating and sizing of EV charging stations that are assisted by solar energy in an urban area. The objective is to maximize the profit of utilizing solar energy in charging stations to satisfy charging requirements, in the presence of the above problems. We propose a method to jointly decide the locations of the charging stations and the size of each station. As the state space of the optimization problem is too large due to its scale, we also propose a heuristic algorithm to reduce the computation overhead. Although this work mainly focuses on servicing EV users that rent EVs from a leasing company, which is a promising business model of further EV market [3], the proposed methods can still be used for other business models or private users. The main contributions of this work are summarized as follows:

- We formulate a novel solar assisted EV charging stations planning problem. It maximizes the overall profit considering both the utilization and distribution of such charging stations in an urban area.
- We propose a complete set of methods to solve the problem, especially a technique to speed up the optimization when the scale of the problem becomes very large considering the whole urban area.
- We conducted a multi-dimensional analysis of the calculated planning results, which shows that our proposed method is effective and efficient. The rules proposed in this paper have a guiding significance for the future construction of solar assisted EV charging stations.

The rest of this paper is organized as follows: Section II presents an overview of related work. Section III presents the data set and analysis models and followed by the preliminaries and formulate the problem model in Section IV. Section V introduces the speed-up techniques and optimization solution method. Section VI conducts a case study and explains the experiment results and Section VII discusses the work and gives an outlook for future work.

## II. LITERATURE REVIEW

Various methods have been developed to help decision-makers effectively determine the location and size of charging stations. Some researchers build mathematical models by targeting different optimization objectives and combine various underlying data, such as power grid data and EV charging data, to make the proposed method more applicable to practical situations. Related works focus on finding the locations of charging stations, the sizing of charging stations or both, which will be detailed below.

### A. LOCATING CHARGING STATIONS

Concerning the optimal location of charging stations, related research works studied various application scenarios. Sreten and Pantoš [4] introduced an electric power system reliability check method into the optimal allocation of charging stations, taking into account the constraints of power system operation and EV owners' requirements. Three models in [5] were proposed to locate the charging stations by considering the spatial and temporal distribution of EV drivers' behaviors, and the model framework was verified by the actual geographic data and EV usage data. In [6], metro Boston data were used to obtain the movement patterns of individuals to find an efficient layout of charging stations to minimize overall energy overhead and EV drivers' driving distance to charging stations. From the perspective of city-scale, the authors of [7], [8] formulated an optimization problem to find the locations for installing charging stations based on large-scale taxis trajectory data and explored the potential impact of electric taxi fleet charging on the environment and power grid. Yin and Zhao [9] combined traffic flow data and Voronoi diagram to segment the map and locate the charging station. Lingfors *et al.* [10] analyzed the relationship between solar power generation and vehicle charging load from spatial and temporal domains for station construction and charging management. Yan *et al.* [11] analyzed the net costs and net profits associated with building and operating a distributed solar PV project during its lifetime in all 344 cities in China. The most valuable message is that solar generation electricity prices can compete with desulfurized coal benchmark electricity prices in 22% of those cities, which can help decision-makers to choose the right areas to build solar power charging stations. The work does not provide a method to optimize the location of charging stations.

### B. SIZING CHARGING STATIONS

Luo *et al.* [12] introduced the multi-types of charging facilities mixedly installed in the electric vehicle charging station (EVCS) during the planning stage and proposed an optimization problem to minimize the annual social cost of an EV charging system. Xu *et al.* [13] combined multiple data sources (mobile phone activity, charging sessions, and electric vehicle surveys) to understand the charging demand in residential regions which can be used to decide the size of charging stations. Some researchers [14] focused on integrating renewable energy sources into transport systems and EVCS. In [15], the charging demand and renewable energy generation were modeled and a genetic algorithm to maximize the profit measured by its net present value (NPV). Mehrjerdi and Hemmati [16] proposed a model that optimizes the rated power of charging facilities, power and capacity of battery energy storage system, hourly operation of diesel generator, and hourly operation of battery energy storage system which helps design an EVCS integrated with renewable energy. In a further study [17], the authors addressed an advanced model for dynamic capacity expansion in the micro-grid and investigated the ability of hybrid storage in the electrical networks including parametric uncertainty [18].

### C. JOINTLY LOCATING AND SIZING CHARGING STATIONS

To meet different charging requirements, Bai *et al.* [19] proposed a hybrid evolutionary algorithm that combines the non-dominated sorting genetic algorithm-II (NSGA-II) with linear programming and neighborhood search to solve the location, size, and type of charging station. Du *et al.* [20] showed that the location and sizing problem is NP-hard, and they designed a charger-based greedy solution with theoretical guarantees to maximize the satisfied charging demand. Li *et al.* [21] analyzed the real EV users' charging behavior data, and proposed a Bayesian-inference-based algorithm to solve the mixed-integer programming EVCS problem with

**TABLE 1.** A sample set of vehicle trajectory data. It includes the time stamped location, vehicle speed and gears position.

| Time | Longitude | Latitude | Speed | Gear Position |
|---|---|---|---|---|
| 2015/5/5 6:37:30 | 116.557325 | 39.916019 | 33.5 | D |
| 2015/5/5 6:37:40 | 116.558724 | 39.916042 | 53.5 | D |
| 2015/5/5 6:37:50 | 116.561982 | 39.916179 | 47.9 | D |

**TABLE 2.** A sample set of vehicle battery data. It includes the time stamped battery working information (SOC is the abbreviation of state of charge) and charging/discharging status.

| Time | Current | Voltage | Temp. | SOC | Charge Or Not |
|---|---|---|---|---|---|
| 2015/5/5 6:37:30 | 6.4 | 352.1 | 23 | 60.4 | No |
| 2015/5/5 6:37:40 | 11.5 | 349.7 | 23 | 60.4 | No |
| 2015/5/5 6:37:50 | 51.5 | 345.5 | 23 | 61.2 | No |

a flexible objective function. Zhang *et al.* [22] proposed a mixed-integer second-order cone programming model for the joint PEV charging station and distributed PV generation planning considering both transportation and electrical constraints. This was ideally convex and can be effectively addressed by off-the-shelf business solutions. A two-stage optimization model [23] was proposed to allocate and design standalone EVs charging stations on highways. The optimization model addressed the uncertainties of solar power generation, daily EV numbers, and traffic demand using a probabilistic distribution model.

To the best of our knowledge, this work presents the first practice for jointly sizing and locating EV charging stations that are assisted by solar energy for a city-wide area. Specifically, with the constraints of users' charging convenience and solar energy utilization, we optimize the overall profit of EV charging stations considering both construction and operational cost.

## III. DATA SET AND ANALYSIS

This section presents the data set used in our study, the method to use map data, the definition of user behavior, and the modeling of charging demand, which will be used in the optimization problem presented in the next section.

### A. DATA SET

#### 1) EV TRAJECTORIES

Our data set comes from an EV leasing company and contains the vehicle trajectory and battery data recorded from May 31st, 2015 to May 31st, 2017 with a 10 seconds sampling rate. The data covers 297 long-term lease customers (with a lease period of more than half a year) in Beijing, China. Examples of the data are shown in Table 1 and Table 2.

#### 2) MAP PRE-PROCESSING

We take the urban area of Beijing as the target area to locate charging stations. To extract the road network with vehicular trajectories and to reduce computational complexity, the urban area is partitioned into an $I \times J$ grid map $G$ based on the Universal Transverse Mercator [24] coordinate system. Figure 1 shows the flow of converting trajectories into grid-based map data. The specific method is to map the data analysis results to the corresponding cells at each time step according to the geographic location information of EVs.

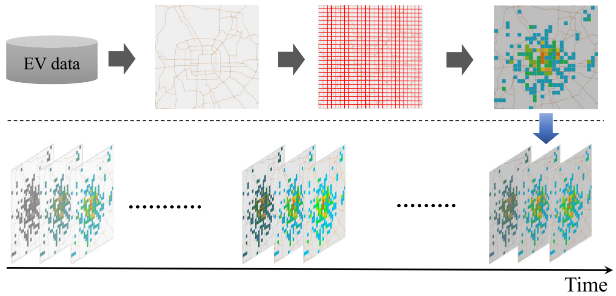


**FIGURE 1.** Converting trajectories into grid based map data. The attribute values of grid cells change with time and location.

### B. USER BEHAVIOR

EV users' parking events are the main factor the influences the charging demand. In our study, we identify a parking event if an EV stops at a location for more than 10 minutes and is in $P$ gear (means parking). The parking events partition the record of each EV into multiple trajectories. Whether a user will charge his EV is highly related to the parking time duration. Most of the short-term parking behavior is temporary and random, so it cannot effectively reflect the real charging needs. Based on the user behavior of our data set, if parking time duration is less than 20 minutes, users are not willing to charge EV, in other words, there is no charging demand. In addition, solar energy is not available roughly between 8pm and 5am. By analyzing the frequency and location information of parking behavior, we find that parking behavior often occurs in residential areas, which contradicts the goal of building stations in public places. Therefore, this paper focuses on parking behavior that lasts more than 20 minutes in non-residential areas from 5am to 8pm (daytime).

Further exploration of the SOC status of the EVs shows that EV users are willing to keep their EV at high SOC, and tend to charge the EV regardless of the current SOC status. Figure 2 shows the distribution of charging events regarding different SOC status. The green bars give the charging frequency distribution and the blue curve gives the cumulative probability for charging the EV. It can be seen that most of the time the EV is at a relatively high SOC status. Figure 3 shows the statistic histogram of start SOC when charging. The cumulative probability curve approximates a straight line. This phenomenon further indicates that EV users expect to charge their vehicles as long as there is a charging equipment when parking. In the following analysis, we assume that the users' charging decisions are not affected by the SOC status and they will charge the EVs as long as the battery is not fully charged.

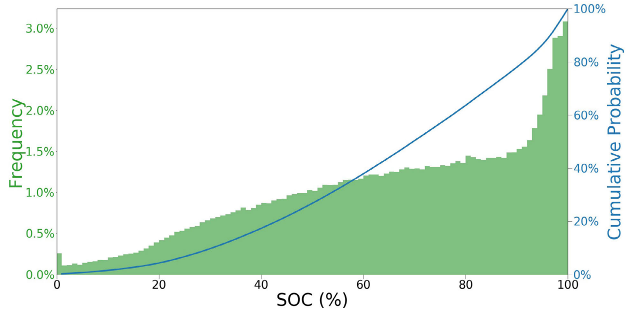


**FIGURE 2.** The initial SOC when parking. In more than 50% of parking behavior, the starting SOC when parking is nearly higher than 70%.

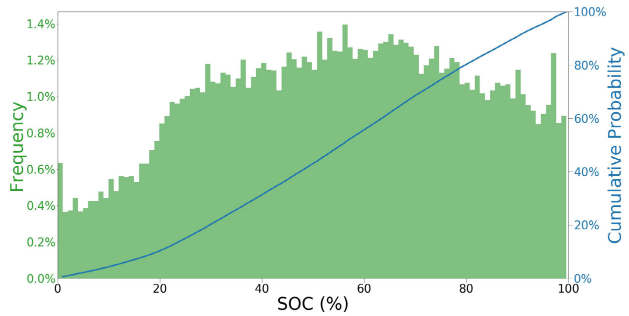


**FIGURE 3.** The initial SOC when charging. From the figure, most users are more likely to charge their EVs when SOC is between 20% and 80%.

### C. CHARGING DEMAND COMPUTATION

Estimating the charging demand for all EVs in an urban area is important for guiding the construction of charging stations. EV charging demand has spatial and temporal characteristics, and the charging demand for each grid cell also varies with time. We first simplify the charging method from constant current and constant voltage (CCCV) charging method to constant power $P_{charge}$. Given the grid map $G$, the parking events of each driver in each time slot are put into the corresponding grid cell of the map, then we can get the number of EVs in a grid cell $(i, j)$ at time $t$, denoted by $N_{i,j}(t)$, and the $n$-th EV's parking duration $T^n_{i,j}$. Then we can compute each EV's charging demand $E^n_{i,j}$, and its charging power $P^n_{i,j}$ at time $t$ by equation (1). The total charging power $P_{i,j}$ is calculated by summing all EVs' demands. $E^n_{batt}$ is the nominal capacity of the $n$-th EV. If the Energy is larger than $E^n_{batt}$, the charging will be stopped, which is specified by equation (2) and (3).

$$E^n_{i,j} = \sum_{t_0=0}^{T^n_{i,j}} P^n_{i,j}(t)\Delta t \tag{1}$$

When $E^n_{i,j} \geq E^n_{batt}$:

$$P^n_{i,j}(t) = 0 \tag{2}$$

When $E^n_{i,j} \leq E^n_{batt}$:

$$P^n_{i,j}(t) = P_{charge} \tag{3}$$

The power demand at time $t$ for the whole city can be calculated by Equation (4), and Equation (5) gives the total energy demand $E^{Dmd}_{i,j}$ of cell $(i, j)$ in time period $T$.

$$P_{i,j}(t) = \sum_{n=1}^{N_{i,j}} P^n_{i,j}(t) \tag{4}$$

$$E^{Dmd}_{i,j} = \sum_{t_0=0}^{T} P_{i,j}(t)\Delta t \tag{5}$$

## IV. PROBLEM FORMULATION

This section presents the formulation of the locating and sizing of solar assisted EV charging stations into an optimization problem which will be solved by the methods proposed in the latter section.

### A. MODELING THE LOCATING OF CHARGING STATIONS

We use a set $L = \{l_{1,1}, l_{1,2}, l_{1,3}, \ldots, l_{I,J}\}$ to model in which cells a charging station will be built. In this set, $l_{i,j} = 1$ means a charging station will be built for grid cell $(i, j)$, and $l_{i,j} = 0$ otherwise.

In this paper, charging demand can be covered if the location of demand is within a specified distance from at least one charging station. The set of the covered demands $D^{Cover}_{i,j}$ by a station at cell $(i, j)$ and the total number of the covered demands $N^{Cover}_G$ in the study area $G$ can be calculated as equation (6) and (7). The coverage rate, computed by equation (8), is to reflect whether a strategy is good or bad.

$$D^{Cover}_{i,j} = \begin{cases} \emptyset & l_{i,j} = 0 \\ \{(k, l)|(k, l) \in G, d_{i,j \to k,l} \leq R_s\} & l_{i,j} = 1 \end{cases} \tag{6}$$

$$N^{Cover}_G = |\bigcup_{i,j}^{G} D^{Cover}_{i,j}| \tag{7}$$

$$\eta^{Cr} = \frac{N^{Cover}_G}{N^{dmd}_G} \tag{8}$$

In equation (6), $d_{i,j\to k,l}$ is the distance between the vehicle parking cell $(i, j)$ and the charging station $(k, l)$ which is calculated by Chebyshev distance method [27] in equation (9); $R_s$ is the maximal distance of service on the grid map. $N^{Cover}_G$ and $N^{dmd}_G$ are the total number of charging demands covered by at least one station and the total number of charging demands in the study area.

$$d_{i,j\to k,l} = max(|i - k|, |j - l|) \tag{9}$$

### B. MODELING THE SIZING OF THE SOLAR ASSISTED SYSTEM

To make rational use of solar energy and reduce energy usage from the state grid, the size $s_{i,j}$ of solar power that integrated into the charging station should be precisely planned. In this paper, we focus on the grid-connected solar power system.

The total power of each solar assisted charging station, $P^{Solar}_{i,j}$, can be modeled by equation (10). Note that the productivity of solar energy in a region depends on solar radiance, which varies throughout the day and is influenced by location and climate. In order to reduce the impact of extreme weather events, we use the average data obtained by Meteonorm software [25] as the weather input, and use an open source simulator software PVlib [26] to simulate the solar power output. The simulation accuracy of each grid cell can be further improved by adding parameters, such as the shadow shading coefficient. In order to simplify the calculation, this paper assumes that the station will be built in a place where there is no shelter. The total power $P_{i,j}^{Solar}$ of each station can be computed as follows.

$$P_{i,j}^{Solar} = P^{SolarUnit} \times s_{i,j} \tag{10}$$

where $P^{SolarUnit}$ is the nominal power output of a single solar panel and $s_{i,j}$ is the size of the solar power system. We use a set $S = \{s_{1,1}, s_{1,2}, \ldots, s_{I,J}\}$ to represent the size of each station in the study area. The spatial-temporal charging power information affects the design of the solar assisted system and then affects the amount of solar energy that can be used to charge EVs. We assume that EV users will choose the nearest station to charge their EVs. The total charging power $P_{i,j}^{Ch}(t)$ is supplied by both the solar power $P_{i,j}^{UseSolar}$ and the grid power $P_{i,j}^{Grid}$ for station $(i,j)$. The used solar power for time $t$ is modeled as bellow:

$$P_{i,j}^{UseSolar}(t) = min(P_{i,j}^{Ch}(t), P_{i,j}^{Solar}(t)) \tag{11}$$

The used solar energy $E_{i,j}^{UseSolar}$, the total generated solar energy $E_{i,j}^{Solar}$ can be modeled by equation (12) and equation (13) respectively, and the solar energy utilization $\eta_{i,j}^{SU}$ at grid cell $(i,j)$ can be defined by equation (14).

$$E_{i,j}^{UseSolar} = \sum_{t_0=0}^{T} P_{i,j}^{UseSolar}(t)\Delta t \tag{12}$$

$$E_{i,j}^{Solar} = \sum_{t_0=0}^{T} P_{i,j}^{Solar}(t)\Delta t \tag{13}$$

$$\eta_{i,j}^{SU} = \frac{E_{i,j}^{UseSolar}}{E_{i,j}^{Solar}} \tag{14}$$

### C. PROBLEM FORMULATION

The optimization objective is to maximize the profit of building solar assisted EV charging stations with constraints to satisfy minimal efficiency of the solar assisted system.

The construction cost, denoted by $C_{co}$, is generally linearly related to the size of the solar assisted system. Equation (15) models the construction cost where $C_{assited}$ is the unit cost of install and maintenance of the solar assisted system.

$$C_{co} = \sum_{i,j \in G} s_{i,j} C_{assited} \tag{15}$$

In our model, the solar energy collected by the solar assisted system is free of charge. So the operation income $C_{op}$ is the income from providing charging service minus the cost of electricity purchased from the grid to meet the charging energy requirement that cannot be satisfied by collected solar energy, shown by equation (16). $C_{useSolar}$ is the income of charging EV with solar energy, $C_{useGrid}$ is the cost to buy electricity from the grid. $C_{ch}(t)$ is the charging price at time $t$. $C_{grid}(t)$ is the price of buying electricity from the grid at time $t$ (as grid electricity price may change over time).

$$\begin{aligned} C_{op} &= C_{useSolar} - C_{useGrid} \\ &= \sum_{i,j \in G} \sum_{t \in T} [C_{ch}(t) P_{i,j}^{UseSolar}(t) \\ &\quad - C_{grid}(t)(P_{i,j}^{dmd}(t) - P_{i,j}^{UseSolar}(t))]\Delta t \end{aligned} \tag{16}$$

The problem is to find a plan $\rho$ to maximize the profit $C_{pr}$ of building and operating the charging stations in the city, and at the same time meeting minimal requirements on charging station coverage $\alpha$ and solar energy utilization $\beta$, as shown by equation (17), where $s_{ij}^{u}$ is the upper bound of the designed size of solar power system in the station $(i,j)$. $\rho$ is defined as $\rho = \{\rho_{i,j} | \rho_{i,j} = (l_{i,j}, s_{i,j})\}$.

$$\begin{aligned} &\text{maximize } C_{pr}(\rho) = C_{op}(\rho) - C_{co}(\rho) \\ &\text{subject to } \eta^{Cr} \geq \alpha, \\ &\qquad\qquad \eta_{i,j}^{SU} \geq \beta, \\ &\qquad\qquad 0 \leq s_{ij} \leq s_{ij}^{u}. \end{aligned} \tag{17}$$

## V. METHODS

This section presents our proposed method to solve the above optimization problem. Note that the optimal solution can be found by exhaustively search all possible configurations, but this is computationally impractical. Therefore, we propose a heuristic to first decompose the big problem into several smaller ones regarding the urban regions and then search for the best location and size decision for each region.

### A. SPEED-UP TECHNIQUES

Before explaining our proposed optimization method, we first present several observations which can be used to improve the computation efficiency.

The first technique is related to partition the problem into smaller sub-problems, i.e., partition the problem of site location in the urban area into site locations for several sub-regions. We observe that the construction of a new charging station will affect the charging habits of surrounding users, that is, it will affect the spatial-temporal charging demand in a certain area, and then will affect the design of a solar assisted charging station. Two charging stations will not affect each other in providing charging services if they are far from each other. In fact, the reason is that users will not choose a farther station for charging. The observation can be specified as follows:

$$\rho^{+} = (\rho - \{\rho_{(i,j) \leq R_s}\}) \cup \{\rho_{(i,j) \leq R_s}^{+}\} \tag{18}$$

$$C_{pr}(\rho - \{\rho_{(i,j) \leq R_s}\}) = C_{pr}(\rho^{+}) - C_{pr}(\rho_{(i,j) \leq R_s}^{+}) \tag{19}$$

where $\rho^{+}$ is the new strategy in the study area. $\rho_{(i,j) \leq R_s}^{+}$ means the updated location plan of the previous plan $\rho_{(i,j) \leq R_s}$ within the $R_s$ distance range of $(i,j)$. The target value of the rest area that excludes the new planned area will not be affected.

The second observation is that users are more likely to choose the location near the destination to park for daily charging. The parking behavior of users will influence the decision-makers to choose the appropriate locations for building charging stations, but the size of the solar energy system in the charging station cannot affect the decision-making process of the station location. Once the locations of the station are determined, the optimal size of the solar assisted system can be decided according to the users' historical behaviors. The observation can be modeled as bellow:

$$\rho_{i,j}^{+} = (l_{i,j}, s_{i,j} + n_{i,j}) \tag{20}$$

$$\rho^{+} = (\rho - \{\rho_{i,j}\}) \cup \{\rho_{i,j}^{+}\} \tag{21}$$

$$\Delta\eta^{Cr} = \eta^{Cr}(\rho^{+}) - \eta^{Cr}(\rho) = 0 \tag{22}$$

where $\rho_{i,j}^{+}$ means the new plan by changing the size of the solar assisted system for the station $(i, j)$, $n_{i,j}$ is the changed amount. The coverage parameter will not be affected by the new plan $\rho_{i,j}^{+}$.

The last technique is introduced to find the optimal size of each station. Based on the equation (17) and its constraints, equation (23) can be derived as follows:

$$E_{i,j}^{Solar} \leq \frac{E_{i,j}^{UseSolar}}{\beta} \leq \frac{E_{i,j}^{Dmd}}{\beta} \tag{23}$$

where $E_{i,j}^{Dmd}$ can be obtained from the charging demand model. In the same way, based on the actual weather data and solar energy system parameters, the unit output of solar energy $E_{i,j}^{SolarUnit}$ can be obtained. The value range of the size of grid cell $(i, j)$ can be calculated by equation (24). This greatly reduces the number of iterations to find the optimal value.

$$0 \leq s_{i,j} \leq \frac{E_{i,j}^{Dmd}}{\beta E_{i,j}^{SolarUnit}} \tag{24}$$

### B. DECOMPOSING THE STUDY AREA

The non-linearity of the objective function makes it impractical to exhaustively search all possible solutions. In this work, we decompose the problem into smaller ones based on the first speed-up technique. Our approach is to use the modified grid based on density-based spatial clustering with noise (DBSCAN) algorithm [28] to cluster the candidate charging demand cells by Algorithm 1. The algorithm clusters the data points to separate the areas with high density charging demands with the areas with low density charging demands, and the clusters formed can have different shapes based on the density of data points. The algorithm can also identify data points as outliers that are in the low-density regions which help to simplify the problem size by defining outliers directly as the locations to build the station. The size design of each independent grid cell can be carried out based on the third speed-up technique.

Different clusters are captured by two parameters, the maximum distance *eps* between a pair of points and the minimum number *minPts* of points required to form a dense cluster. Algorithm 1 shows the process of clustering.

**Algorithm 1** Density Based Clustering for Spatial Features

Input: $L = \{l_{1,1}, l_{1,2}, \ldots, l_{I,J}\}$, *eps*, *minPts*
Output: Spatial features $\{cr_1, cr_1, \ldots, cr_n\}$

The set of core points $CPs \leftarrow \emptyset$;
The set of non core points $NonCPs \leftarrow \emptyset$;
cluster number $k \leftarrow 0$
**for** each $l_{i,j} \in \{l_{1,1}, l_{1,2}, \ldots, l_{I,J}\}$ **do**
  Find the points $N_{\epsilon}(l_{i,j})$ in the *eps* neighbourhood
  **if** the number of neighbors $|N_{\epsilon}(l_{i,j})| \geq minPts$ **then**
    $CPs \leftarrow CPs \bigcup \{l_{i,j}\}$
  **end if**
**end for**
**for** each $l_{i,j} \in CPs$ **do**
  Find connected components of $l_{i,j}$
  $cr_m = k + 1$
**end for**
**for** each $l_{i,j} \in NonCPs$ **do**
  **if** cluster $k$ is an *eps* neighbor **then**
    $cr_m \leftarrow k$
  **else**
    $cr_m \leftarrow -1$   // marked as an outlier
  **end if**
**end for**
**return** $\{cr_1, cr_1, \ldots, cr_n\}$

### C. MODIFIED GRASP METAHEURISTIC

The above process decomposes the big planning problem into smaller ones. Now we are to find the optimal planning for each smaller region computed in the above step. Even though, it is still not efficient to validate every solution to find the optimal one in each smaller region. Therefore, we use the modified meta-heuristic to solve the planning problem. Our approach is essentially a GRASP [29] which is a multi-start or iterative meta-heuristic. The method has two phases: a construction phase and a local search phase, and the best overall solution is kept as the final plan. The pseudo-code of Algorithm 2 depicts the GRASP procedure, where *maxIter* is the number of iterations, and $\lambda$ is used as the initial seed for the pseudo random.

#### 1) CONSTRUCTION PHASE

The traditional execution of a GRASP starts with an empty solution and the construction phase gradually builds a solution by adding a candidate element to a partial solution. In our work, the main task in this phase is to select a feasible subset of locations to build charging stations. However, if stations are built one by one, each new solution requires an assessment of all demands to determine which ones are allocated to the new station, and it is highly probable that the generated solution may not meet the constraints at the early stage. Therefore, in the modified selection method, it is assumed

**Algorithm 2** Procedure for GRASP

Input: $maxIter$, $candidates$, $Demands$, $\lambda$
Output: Best Plan $\rho$

$initLoc \leftarrow$ FilterCandidate($candidates$)
$baseLoc \leftarrow$ AssignService($initLoc$, $Demands$)
$bestPlan \leftarrow$ SizeDesign($baseLoc$, $Demands$)
$nIter \leftarrow 0$
**while** ($nIter < maxIter$) **do**
  $greedyPlan \leftarrow$ GreedyRandamConstruct($bestPlan$, $\lambda$)
  $localPlan \leftarrow$ LocalSearch($greedyPlan$, $maxLSIter$)
  **if** $C_{pr}(localPlan) < C_{pr}(bestPlan)$ **then**
    $bestPlan \leftarrow localPlan$
  **end if**
  $nIter \leftarrow nIter + 1$
**end while**
$\rho \leftarrow$ extract the planning matrix from $bestPlan$
**return** $\rho$
**end procedure**

that charging stations have been established on all candidate grid cells at the beginning of the algorithm, and the final solution satisfying the constraint conditions is computed by gradually removing the charging stations. Once the solution is determined, the potential charging demands will be assigned to the nearest stations if the demands are within its coverage distance. The advantage of removing the stations is that it reduces the computational overhead compared to select a location to build a station, as it is only necessary to reallocate the demands from the closed stations to other unclosed stations. In order to build a restricted candidate list (RCL), the potential locations to be included in the partial solution are intelligently evaluated according to a greedy evaluation function combined with the second and third speedup techniques. The limitation criteria of the list cardinality can be either based on the number of elements or based on their quality. The set $CS$ will contain the candidate plans, which will be used for the plan $\rho$. Once a feasible solution is obtained, a local optimum solution is frequently achieved by applying a local search method. The construction phase operations are shown in Algorithm 3.

### 2) LOCAL SEARCH PHASE

Given a feasible solution obtained in the construction phase, the local search phase consists of two steps. First, determine the plan that must increase the value of the target function to make a new plan. These build locations in the new plan are labeled as critical. Second, change the status of critical locations based on constraints to make the final new construction plan feasible. In our paper, a Large Neighborhood Search [30] method is deployed and a local optimal solution is obtained by investigating the neighborhood. The neighborhood action is defined as switching states between two candidate locations in different states at each time to ensure that the number of station constructions remains the same. Then, the optimal

**Algorithm 3** Greedy Randomized Construction

Input: $basePlan$, $\lambda$
Output: A greedy feasible construction plan $greedyPlan$

$CS \leftarrow \emptyset$
**for** each $l_{i,j} \in L$ **do**
  **if** $l_{i,j} == 1$ **then**
    $l_{i,j} \leftarrow l_{i,j} - 1$
    $L_{gp} \leftarrow (l_{1,1}, \dots, l_{I,J})$
    **if** $\eta^{Cr} \geq \alpha$ **then**
      $CS \leftarrow CS \cup \{L_{gp}\}$
    **end if**
    $l_{i,j} \leftarrow l_{i,j} + 1$
  **end if**
**end for**
Create $newPlan$ based on location plan $L$
$\Delta C(L) \leftarrow C_{pr}(newPlan) - C_{pr}(basePlan) \forall L \in CS$
$C^{min} \leftarrow min\{\Delta C(L) | L \in CS\}$
$C^{max} \leftarrow max\{\Delta C(L) | L \in CS\}$
$RCL \leftarrow \{L \in CS | \Delta C(L) \geq C^{min} + \lambda(C^{max} - C^{min})\}$
Select an element $L^*$ from the $RCL$ at random
Calculate the best size of $L^*$ and get the $greedyPlan$
**return** $greedyPlan$

solution of all iterations is taken as the best plan. The local search phase operations are shown in Algorithm 4.

**Algorithm 4** Local Search

Input: $localPlan$, $maxLSIter$
Output: Best local construction plan $localPlan$

initialize the set of neighborhood $N_n$, $n = 1, \dots, n_{max}$
**while** ($lsIter < maxLSIter$) **do**
  $n \leftarrow 1$
  **while** $n < n_{max}$ **do**
    random choice a neighborhood $N_m$ and generate the $N_m$ neighborhood plan $neighPlan$
    **if** $\eta^{Cr} \geq \alpha$ and $\eta^{US} \geq \beta$ **then**
      **if** $C_{pr}(neighPlan) > C_{pr}(localPlan)$ **then**
        $localPlan \leftarrow neighPlan$
        $n \leftarrow 1$
      **else**
        $n \leftarrow n + 1$
      **end if**
    **end if**
  **end while**
  $lsIter \leftarrow lsIter + 1$
**end while**
**return** $localPlan$

## VI. CASE STUDIES

In this section, we evaluate the efficiency and effectiveness of our proposed methods. The optimization methods are implemented in python and the experiments are performed on a machine with 4 Intel(R) Core(TM) i7-4790 CPU cores @ 3.6GHz and 16G main memory.

### A. EXPERIMENTAL SETUP

For the study area, EV with longitudes between [116.0486, 116.7380] and latitudes between [39.6739, 40.1936] are considered which contains the main urban area of Beijing. The GPS uses WGS-84 as the reference coordinate system. The grid cell's area is $300m \times 300m$. In such a way, the whole area is partitioned into $200 \times 200$ cells in total.

For planning parameters, the planning scheme is related to the candidate locations, the minimum coverage rate $\alpha$ and the minimum solar utilization rate $\beta$. In our data, some grid cells have only a few times of parking behaviors in a long time period. The first filter process for candidate locations is that if a grid has more than 300 parking times per year, it is selected as a candidate location to build a charging station. The time step for the demand model and the solar energy model is 15 minutes. The charging power $P_{charge}$ is 3.52 kW (220V, 16A). The values of $\alpha$ and $\beta$ in the experiments are changeable to verify that different design goals lead to different solutions and will be discussed later. The construction and maintenance cost $C_{co}$ are assigned according to the latest solar power system installation and maintenance costs [11] and the electricity price is according to the Beijing electric power policy [31]. This paper assumes that the lifetime of the solar energy system is 20 years and that both the electricity market price remains the same during the 20 year lifetime. Through the average processing, the unit cost of solar energy system $C_{assited}$ is 0.75 CNY/kWh, the charging price $C_{ch}$ is 1.65 CNY/kWh, and the grid electricity price $C_{grid}$ is 0.9 CNY/kWh.

For algorithm parameters, we assume that all charging stations have the same coverage radius $r$ =1 $km$, which is transformed to 3 cells in the grid map. This distance is in line with user habits. Too long distance will reduce the user's convenience for charging, on the contrary, if the distance is too small, the number of stations will increase, which will result in higher construction costs. So *eps* in DBSCAN is set to 3, and *minPts* is set to 1 to identify the demand location of a single grid cell. For GRASP algorithm parameters, the correct selection of the value of the RCL parameter $\lambda$ is important to achieve a good balance between the calculation time and the quality of the solution. When $\lambda$ is 1, it corresponds to pure greedy construction, while $\lambda = 0$ is equivalent to a random construction. In this experiment, the results only consider a standard value of $\lambda = 0.5$ as a trade-off between intensification and diversification. Additionally, the main parameters that affect the speed of the GRASP depend on the size of the candidate $n_{cd}$ in each spatial cluster. Specifically, the number of max GRASP iterations *maxIter* and *maxLSIter*, are both set to $n_{cd}$, and the size of RCL is at most $n_{cd}$ if the candidate plans satisfy the conditions.

### B. EXPERIMENTAL RESULTS AND EVALUATION

#### 1) CLUSTER RESULTS

The study areas after clustering are shown in Figure 4. According to the number of elements and geographical locations in each cluster, different clusters can be regrouped.

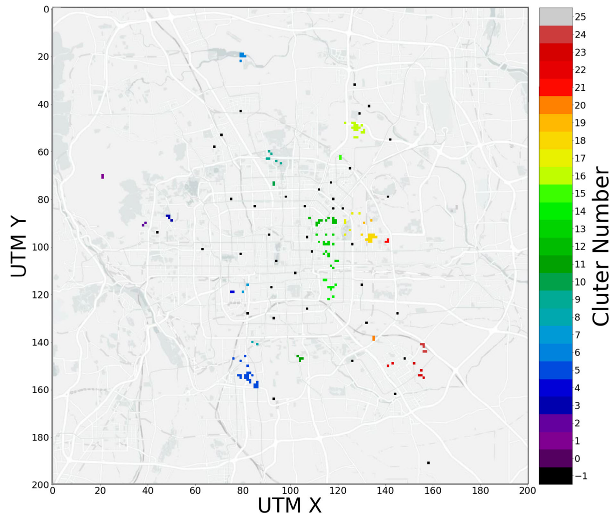


**FIGURE 4. Cluster result. There are 26 clusters with different colors, the maximum and the minimum number of each cluster are 22 and 1. The black squares indicate 39 independent charging demand cells.**

Based on the data and the information provided by Gaode Map [32], we find that parking behavior is mainly distributed near the city center, and there are several small areas in the non-central areas. Most of the high and medium density clusters are mainly public entertainment and shopping places, such as parks, golf courses, and commercial streets. The observation of outliers shows that there is no uniform way to describe parking places. The reason is that EV users have different lifestyles and different jobs, so there is no common phenomenon.

#### 2) ALGORITHM COMPARISON

The performance of the exhaustive method and metaheuristic method are compared. Both methods use speed-up techniques. Note that the exhaustive search method explores all feasible plans satisfying the constraints, while our proposed method only selectively visit a subset of the search space. Table 3 gives the profits and the computation time to find the optimal results for each method. The *cluster* column gives the ID of each cluster, and the *amount* column gives the number of candidate stations for the corresponding cluster.

From the perspective of calculation accuracy, the result obtained by the exhaustive search method is the global optimal solution. In this case, our method can find the optimal solution for all clusters. For computation time, due to the complexity of the problem, with the increase of the number of candidate cells in the cluster, the amount of computation of both methods increases. The computation time of the exhaustive search method increases much faster and fails to produce any result (within 5 days) for the big clusters 17, 13, and 5. The proposed method is able to finish within 6.5 hours. With the increase of vehicle data in the future, both the number of clusters and the number of candidate cells in the cluster will increase, our method will be more applicable.

**TABLE 3.** Algorithm comparison. Parameter $\alpha$ and $\beta$ are both 0.6.

| | | Exhaustive Method | | Our Method | |
|---|---|---|---|---|---|
| cluster | amount | $C_{pr}$ | Time(s) | $C_{pr}$ | Time(s) |
| 1 | 2 | -48639.8 | 3.5 | -48639.8 | 3.4 |
| 2 | 2 | 10612.8 | 9.3 | 10612.8 | 9.1 |
| 4 | 2 | 26346.3 | 3.1 | 26346.3 | 2.9 |
| 7 | 2 | 3050.6 | 3.0 | 3050.6 | 2.9 |
| 8 | 2 | -34770.4 | 2.7 | -34770.4 | 2.5 |
| 10 | 2 | -12183.9 | 10.2 | -12183.9 | 9.7 |
| 15 | 2 | -8464.9 | 1.3 | -8464.9 | 1.3 |
| 19 | 2 | -5713.5 | 5.5 | -5713.6 | 5.3 |
| 20 | 2 | -104294.6 | 2.5 | -104294.6 | 2.6 |
| 22 | 2 | -19710.6 | 2.6 | -19710.7 | 2.4 |
| 21 | 3 | 9858.2 | 24.8 | 9858.2 | 26.3 |
| 25 | 3 | 15374.2 | 18.2 | 15374.2 | 19.2 |
| 3 | 4 | -31718.4 | 31.1 | -31718.4 | 26.7 |
| 11 | 4 | 23306.2 | 50.4 | 23306.2 | 46.5 |
| 23 | 5 | 47205.8 | 131.1 | 47205.8 | 113.2 |
| 24 | 5 | 6008.7 | 40.1 | 6008.7 | 32.7 |
| 6 | 6 | -37937.5 | 270.8 | -37937.5 | 178.8 |
| 9 | 6 | -18833.6 | 246.2 | -18833.6 | 158.1 |
| 16 | 6 | -18754.6 | 93.6 | -18754.6 | 61.5 |
| 14 | 9 | 23019.8 | 3012.8 | 23019.8 | 800.1 |
| 12 | 13 | 99539.3 | 55694.0 | 99539.3 | 2606.1 |
| 18 | 13 | 20596.9 | 57049.0 | 20596.9 | 2798.0 |
| 17 | 17 | —— | —— | -22359.2 | 7504.8 |
| 13 | 18 | —— | —— | 276129.1 | 9419.0 |
| 5 | 22 | —— | —— | -20547.6 | 23585.6 |

When the number of candidate cells in the cluster is less than 5, the operation time is very similar.

### 3) FURTHER DISCUSSION

From the perspective of location selection, the resulted plans tend to build only one solar assisted charging station to meet the demands in a cluster, especially for a cluster with fewer candidate cells or few parking events. The reason is that the centralized construction scheme is more conducive to gathering demands and improving solar energy utilization. This phenomenon also appears in the cluster with large areas, but due to the limitation of service capacity, several locations will be selected to build charging stations. After the station locations are determined, the charging demands of each station can be obtained. We randomly select several stations and report the average power demands in Figure 5.

Figure 5(a) shows the power demand profiles when $C_{pr}$ is positive and Figure 5(b) shows the profiles when $C_{pr}$ is negative. From Figure 5(a), the curves with a higher $C_{pr}$ value fluctuate in a higher demand value range in the daytime. The demands gradually rise during the day in the morning and decrease in the afternoon. In contrast, when the $C_{pr}$ is negative as shown in the figure 5(b), the daytime demand is relatively low, generally below $2500W$, and the curves show an upward trend from morning to night. Combined with the geographic location information, the areas with high profit are located at the workplace and business center and the areas with low profit are mostly located at places such as parks.

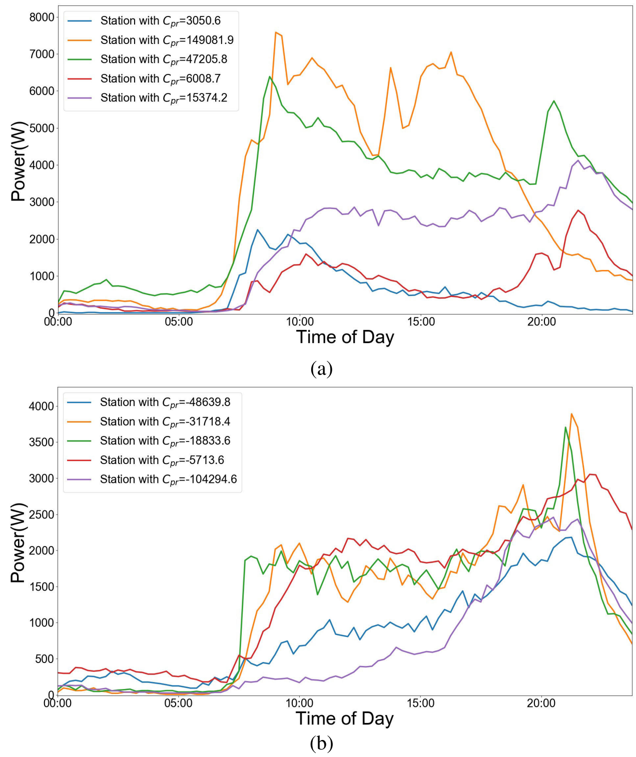


**FIGURE 5.** The profiles of charging demands. (a) Demand profile with the positive $C_{pr}$ value, (b) Demand profile with the negative $C_{pr}$ value.

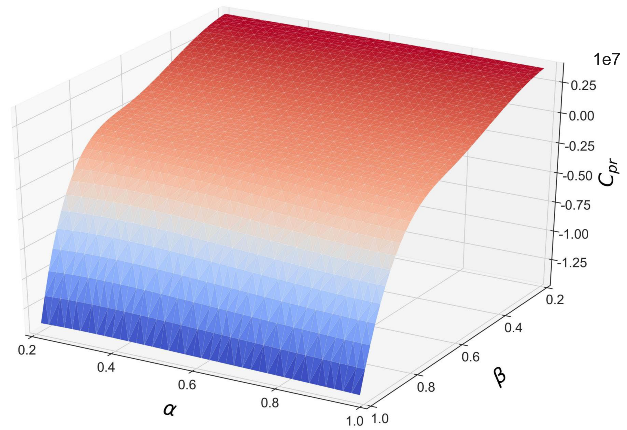


**FIGURE 6.** $C_{pr}$ of varying $\alpha$ and $\beta$. The value of $\beta$ has a greater impact on $C_{pr}$ than $\alpha$. When $\alpha$ is constant, as $\beta$ decreases, the $C_{pr}$ rises sharply between 1 and 0.8, and then gradually rises with a stable slope.

In the construction process, as the number of EVs gradually increases, the number of stations also increases. Due to the different design targets, relevant decision parameters will also change during the process. So we conducted experiments with different $\alpha$ and $\beta$ values to explore the impact of different parameters on the planning results, as shown in Figure 6.

Although different values of $\alpha$ will affect the number of stations and thus the demand value of each station, the clustering process aggregates geographically adjacent charging demands into one cluster, thereby making the number and location of charging stations in a cluster relatively stable. For $\beta$, based on existing data, excessive utilization rate setting is

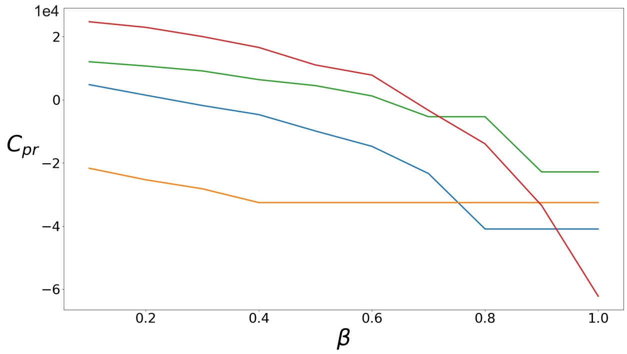


**FIGURE 7.** Oultiers' $C_{pr}$ of varying $\beta$.

not conducive to overall operations. The reason is that the different clusters or outliers have different demands, the impact of $\beta$ in each cluster is also different. Figure 7 depicts the typical cases of outliers when $\beta$ changes. From the overall trend, the curves gradually decrease with an increase of $\beta$, but the slopes are not the same. For example, the red curve shows a good parabolic state, while the orange curve remains unchanged after $\beta$ is greater than 0.4. The reason is that when $\beta$ is equal to 0.4, the constraints can only be met when the size of the solar assisted system is at the minimum. As $\beta$ continues to increase, if the system can still meet the constraints, the size will remain unchanged and $C_{pr}$ will remain constant.

## VII. CONCLUSION

This paper proposes an optimization model to plan the locations and sizes of solar assisted EV charging stations in a city area. The main novelty of this paper is that the optimization model considers the interaction between location selection and size design of charging stations. We proposed a modified metaheuristic solution with three speedup techniques to improve the computation efficiency in exploring a large state space for optimization. Experiments are conducted on real EV history data from 297 users of an EV leasing company. The results show that the proposed method can produce high quality decisions within reasonable computation time. The work of this paper will provide important information for decision makers to integrate solar energy into the EV charging infrastructure. For future work, we plan to study the influence of varying charging demands with some probability model. For the analysis of solar power generation capacity, the accuracy can be further improved by incorporating the shadow model of urban buildings and the loss model of the system. In addition, as the number of electric vehicles increases, effective strategies for charging management are also a further research direction.

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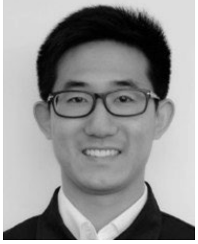

**DONG JI** (Graduate Student Member, IEEE) received the B.S. degree in electrical engineering from the Shenyang University of Technology, China, in 2012, and the M.S. degree in electrical engineering from Northeastern University, Shenyang, in 2014. He is currently pursuing the Ph.D. degree with the School of Computer Science and Engineering. His research interest includes machine learning and its various applications in renewable energy and electric vehicle.

**MINGSONG LV** (Member, IEEE) received the B.S., M.S., and Ph.D. degrees from Northeastern University, China, in 2002, 2005, and 2010, respectively. He is currently an Associate Professor with Northeastern University. His research interests include program analysis, multicore embedded systems, and new energy vehicles. He received the Design Automation, Test in Europe Best Paper Award, in 2013 (C. Song).

**JIAYU YANG** received the B.S. degree in the Internet-of-Things engineering from Northeastern University, China, in 2019. His research interests include machine learning and big data analysis.

**WANG YI** (Fellow, IEEE) received the Ph.D. degree from the Chalmers University of Technology, Gothenburg, Sweden, in 1991.

He is currently the Chair Professor with Uppsala University, Sweden, and a Professor with the Northeastern University, China. His research interests include modeling and validation of timed systems, model-checking of real-time systems, timing analysis of embedded software on multicores, and multiprocessor real-time scheduling. He received the Best Paper Awards at RTSS 2009, 2015, and 2017, DATE 2013, and ECRTS 2015. He has been an Editor of several journals, including the IEEE Transactions on Computers, the PC Chair of TACAS 2001, FORMATS 2005, EMSOFT 2006, HSCC 2011, and LCTES 2012, and the Track/Topic Chair of RTSS 2008 and DATE 2012–2014. He is also serving on the Steering Committee of FORMATS, EMSOFT (Co-Chair), LCTES, and ESWEEK.