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A design and analysis of computer experiments based mixed integer linear programming approach for optimizing a system of electric vehicle charging stations

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A R T I C L E I N F O

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A B S T R A C T

This paper formulates a mixed integer linear programming (MILP) model to optimize a system of electric vehicle (EV) charging stations. Our methodology introduces a two-stage framework that integrates the first-stage system design problem with a second-stage control problem of the EV charging stations and develops a design and analysis of computer experiments (DACE) based system design optimization solution method. Our DACE approach generates a metamodel to predict revenue from the control problem using multivariate adaptive regression splines (MARS), fit over a binned Latin hypercube (LH) experimental design. Comparing the DACE based approach to using a commercial solver on the MILP, it yields near optimal solutions, provides interpretable profit functions, and significantly reduces computational time for practical application.

1. Introduction

The energy shortages of the 1970 s spurred the exploration of alternative energy sources for vehicles, leading to the initiation of electric vehicle (EV) research. In the present times, the increasing demand for sustainability has greatly elevated the significance of electric vehicles EVs. A recent environmental evaluation conducted by the Electric Power Research Institute and the Natural Resource Defense Council has indicated that opting for electricity in place of gasoline/petroleum has the potential to substantially decrease emissions of greenhouse gases and other airborne pollutants (He et al., 2015). To bolster the usage of EVs, some governments have taken a variety of initiatives. Norway is one of the countries working towards the goal of having all new car sales be electric vehicles by 2025, to meet their emission reduction targets (Lambert, 2016). By endorsing both current and forthcoming technologies in electric power-based vehicular products, the transportation industry anticipates transitioning from its oil-dependent design to a cleaner and more environmentally sustainable electric-based design. One of the critical factors that requires attention when it comes to EV charging infrastructure is the driving range and accessibility of charging stations. This limitation has led to a constrained adoption of electric vehicles. One of the solutions to this problem is installation of EV charging stations, which minimizes operational cost for EV charging stations and maximizes the profit in running the stations. Through the generation of electricity using renewable sources, charging stations could actively engage in the electricity market. This additional dynamic provides even more motivation for the U.S. transportation sector to seek out cleaner alternatives.

1.1. Literature review

Several papers in the literature have studied optimal planning for EV charging stations, Plug-in Hybrid vehicles (PHEVs), charging pads, and battery swapping.

1.1.1. EV charging station literature review

Some papers proposed using heuristics for optimal planning of charging station locations. Tang et al. (2013) proposed a Particle Swarm Optimization for the planning of EV charging stations. This model considered an initial fixed investment cost, charging cost, operating

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costs, service radius and capacity of charging station, etc., to determine the layout of EV charging stations. Lin & Hua (2015) proposed a flow capturing location model that uses Particle Swarm Optimization for selecting locations for EV charging stations. This study considered 25 nodes with 42 arcs for setting up EV charging stations while accounting for initial construction costs of facilities, the maximum charging distance, and the cost of power network loss. Awasthi et al. (2017) proposed a hybrid algorithm based on a Genetic Algorithm and an improved version of a conventional Particle Swarm Optimization to find an optimal placement of charging stations while accounting for initial investment cost and distribution grid power quality. Vazifeh et al. (2019) developed a data-driven approach for EV charging stations employing a Genetic Algorithm applied to a geographical grid to minimize total excess driving distance to charging stations, energy overhead, and the number of charging stations. Yang et al. (2021) presented a hybrid approach of differential evolutionary algorithm and Particle Swarm Optimization, which was applied to solve a charging station location model while considering charging station capacity and total charging costs. In this research, a Voronoi diagram was used to partition the service coverage area of the charging stations. Li et al. (2023) proposed multimodal multi-objective problems, where solutions with similar objective values are often distant in the decision space. It reviews two decades of related work and compares the performance of 15 state-of-the-art multimodal multi-objective evolutionary algorithms that employ a variety of diversity-maintaining techniques on existing test suites.

Biesinger et al. (2017) presented an urban station-based car-sharing approach where the users can rent and return publicly available EV cars from charging stations. In this research, a heuristic algorithm for finding and designing charging stations was formulated as a bi-level model in which the first level is to decide the station location, the number of charging slots per station, and the total number of cars using a variable neighborhood search algorithm. A path-based heuristic was used in the second level to determine which trips are accepted by the system. To solve the dynamic control of a system of plug-in hybrid vehicle charging stations problem, Kulvanitchaiyanunt et al. (2015) proposed and formulated a finite horizon stochastic program. The objective of the study was to maximize profit, which is the revenue from selling power back to the power grid and the charging of vehicles minus the cost of buying electricity from the power grid. This research considered wind energy, solar power generation, total demand at each station and market price at each node. Paganini et al. (2022) proposed applying a spatial supply infrastructure to serve a distributed demand for EV charging facilities. To address the issue of sparsity, a mixed integer linear programming (MILP) formulation for a facility location problem is used. Sadeghi et al. (2022) proposed a bi-objective MILP model to determine optimal locations for charging stations while taking into consideration the number of chargers to be set up at each station and their types. This model aimed to minimize the total cost as well as users' dissatisfaction. This study used Lagrangian Relaxation to handle the complexity of the model. Arslan & Karasan (2016) presented a charging station location problem with plug-in hybrid vehicles as a generalization to the flow recapture location problem to maximize the vehicle miles traveled using electricity and thereby minimize the total cost of transportation under the existing structure between electricity and gasoline. The authors proposed an arc-cover formulation and Benders decomposition algorithms as exact solution methods. Mirheli & Hajibabai (2022) proposed a bi-level optimization framework for the design and operational management of EV charging infrastructure, incorporating user-equilibrium decisions. The upper-level component is focused on reducing the overall deployment costs of charging facilities and maximizing revenue from EV charging fees. In contrast, the lower-level component aims to minimize travel time and charging expenses for EV users. The suggested bi-level model is capable of efficiently identifying the ideal charging facility locations, their physical capacities, and implementing demand-responsive pricing strategies.

Brandstatter et al. (2017) proposed a robust integer linear optimization method to determine optimal locations for charging stations of electric car-sharing systems. Sánchez et al. (2022) proposed a mixed-integer linear programming model to solve the electric location routing problem with time windows considering the state of charge, freight, battery capacities and customer time windows in the decision model. A clustering strategy based on k-means is used to divide the set of vertices into small areas and define the potential sites for recharging stations. Battistelli et al. (2012) developed a stochastic programming framework that considered uncertainty associated with vehicle-to-grid and wind power scenarios. Khosrojerdi et al. (2012) presented a linear mathematical model to optimize the cost of power trading, which used auto regressive methods to forecast wind power output and market clearing price for energy. Ma & Zhang (2018) proposed a queuing theory model to optimize the sizing and the location of charging stations and solved it using an exhaustion search method. This research used a Bass model developed by Frank Bass to predict the total number of EVs and to calculate the size of the charging stations. Gorbunova & Anisimov (2020) developed a model for optimal selection of the limited number of charging stations to meet maximum demand while minimizing the total cost of operating the charging infrastructure. This model considered characteristics of the road network, traffic flow at nodes and places of attractions for the population. Tan & Lin (2014) proposed a stochastic model for back-up flow capturing demand to ensure stability in service coverage. Soltani et al. (2014) developed a similar stochastic model to maximize profit based on price responsiveness of customers.

Gerding et al. (2013) presented a two-sided market for advanced reservation to reduce the queue faced by customers and uncertainty over the availability of a charging facility. In this method, the EV owners reported their preference of time and charging location, while charging stations reported their availability and cost. Park et al. (2014) proposed a reservation recommendation algorithm to select the charging stations based on distance and route. It provided recommendations of three charging stations based on: (i) desired amount of charge without waiting time, (ii) desired amount of charge with waiting time, and (iii) the limited amount of charge with waiting time. It also helped in time slot management if there was a need to reserve a charging station slot. Yudovina & Michaildis (2015) proposed a decentralized policy of assigning electric vehicles to a network of charging stations with the goal to achieve little to no queue for optimal location deployment of the charging infrastructure. Lamontagne et al. (2022) proposed a model for determining optimal locations of EV charging stations to maximize the number of EVs while considering user-specific characteristics, which represented the decision of the user to purchase EVs. This study focused on supporting a plan for maximizing EV adoption. Chang et al. (2014) proposed an extension to the Flow Refueling Location Model, which considered the allocation of both charging stations and charging pads to optimize the flow of recharged EVs. This study proposed deploying charging pads on the road network to capture more traffic than captured by charging stations alone. Li et al. (2022) presented a series of optimization problems, which included the global transport cost from demand points to supply stations with bounded capacity and model demand elasticity, with the goal of minimizing the detour mileage. The paper describes an optimal charging station location problem for intercity highway networks and developed two approaches for modeling and solving. The first one is node-link network topology and the second is station-sub path meta network topology.

You et al. (2015) proposed a novel cooperative charging strategy for an intelligent charging station. This strategy was designed to operate effectively in a dynamically shifting electricity pricing context. In this system, EVs shared energy stored in their batteries amongst each other under the supervision of an aggregator. This collaborative approach granted the aggregator enhanced flexibility in managing schedules. This problem was formulated as a scheduling MILP model to capture discrete states of the battery (charging, idle, and discharging). Zhang et al. (2023) presented a day-ahead optimized dispatching technique for a distribution network that incorporates a fast-charging station (FCS). This FCS is integrated with photovoltaic systems and energy storage mechanisms, aiming to alleviate the adverse effects of the FCS on the distribution network. Initially, historical vehicle travel data served as the foundation for employing a Monte Carlo simulation method to replicate the fast-charging load. Finally, the uncertainties associated with photovoltaic power were managed through the implementation of a robust optimization model that pertained to the economic operation of the distribution network. Li et al. (2018) proposed a two-stage robust optimization model for micro-grid energy management including EV charging stations. In this study, the authors proposed an optimization scheduling strategy based on a combination of day-ahead scheduling (first stage) and model predictive control (second stage). Some researchers proposed battery swapping, either as an alternative to charging pads or in addition to charging stations, for greater reach. Mak et al. (2013) proposed a robust optimization model for deploying battery-swapping infrastructure where a depleted battery can be exchanged for a recharged one in the middle of long trips. Kang et al. (2016) proposed a centralized charging approach for EVs incorporating battery swapping. This strategy factored in optimal charging precedence and charging site selection based on real-time electricity prices at specific locations. In this study, a population based heuristic approach was used to minimize the total charging cost, as well as to reduce the power loss and voltage deviation of the power network. To minimize the cost and land use, Chen & Hua (2014) proposed a new location model based on set covering. This model hinged on the use of existing gas stations as potential locations to determine the potential set of charging and battery swapping stations. Jatschka et al. (2022) proposed a multi-objective battery swapping station location problem focused on optimizing the setup of stations for exchanging depleted electric scooter batteries. The goal is to minimize a three-part objective while meeting expected demand. An MILP is solved using Large Neighborhood Search. Wu et al. (2015) proposed using a Genetic Algorithm to solve an optimization model to maximize the number of batteries in stock and minimize the cost due to different charging schemes He et al. (2023) proposed a bi-level planning framework where a collaborative location optimization approach is developed at the upper level to optimize the location of charging stations. Furthermore, a collaborative capacity optimization approach is formulated at the lower level to optimize the capacity of truck mobile chargers and fixed chargers at candidate stations. In this study, the big-M method is applied to linearize and convert the nonlinear problem into a MILP model.

1.1.2. *Design and analysis of computer experiments literature review*

In this paper, we develop a two-stage framework, which addresses the design of a system of EV charging stations using a design and analysis of computer experiments (DACE) based system design optimization approach. DACE based optimization was first conducted for continuous-state stochastic dynamic programming (SDP) by Chen et al. (1999) and Chen (1999) and has since been applied for numerous high-dimensional dynamic optimization applications, including airline optimization (Chen et al., 2003, Siddappa et al., 2007), water resources (Tsai et al., 2004, Cervellera et al., 2006), environmental quality control strategies (Yang et al., 2009, Sule et al., 2011, Fan et al., 2018, Ariyajunya et al., 2021), and pain management (Lin et al., 2014). The concept of DACE based optimization for two-stage stochastic programming was first proposed by Chen (2001) and first demonstrated by Pilla et al. (2008) and Shih et al. (2014) using an airline fleet assignment case study.

1.2. *Research gap and contribution*

Although the aforementioned papers proposed different approaches and implemented several algorithms for the optimization of locations for EV charging stations, an approach to find a globally optimal set of stations to be opened, with the corresponding number of slots, has never been found while considering factors such as the customer demand obtained from the city population (hotspots) of EVs, the distances from hotspots to the stations, and available solar energy and wind energy generation. This represents a significant gap, and to address these issues, we propose a deterministic MILP model to obtain a globally optimal set of stations to be opened that maximizes profits. In this research, we consider 11 possible locations for charging stations for 140 demand hotspots in multiple time periods. Throughout our experiments, leveraging the advanced Integer Programming MILP tool, GUROBI, we identified opportunities to enhance computational efficiency in finding solutions. Consequently, we developed a DACE based system optimization approach, marking a significant methodological contribution within this study.

DACE based optimization for system design is a two-stage framework that integrates the first-stage system design problem with a second-stage control problem of the EV charging stations. Specifically, the first stage specifies the design of the system that maximizes expected profit, and the second stage solves the system control problem. The first-stage design optimization incorporates both the operational costs of stations and the revenue from a system control problem in the second stage. The "design" part of the DACE approach uses design of experiments to organize a set of feasible system designs of EV charging stations. In this paper, we develop a new design of experiments approach, referred to as a binned Latin Hypercube (LH), to sample points in the system design space. Although the binned LH experimental design is developed specifically for the EV charging station problem, it has the potential to be used in other capacity planning applications where both the decisions to open and determine capacity are considered simultaneously. For each of these system designs, we execute a second-stage control problem to obtain the corresponding expected revenue. The "analysis" part of the DACE approach uses the expected revenue data to build a metamodel that approximates expected revenue as a function of the first-stage system design using multivariate adaptive regression splines (MARS). The obtained MARS model is then optimized by subtracting the cost component to predict the profit to obtain a best system design. In other words, we employ this expected revenue approximation in the profit objective of the first stage to enable a more computationally efficient and interpretable method to optimize the system design. The results that we obtain from the DACE based system design optimization approach, when compared to solutions of the MILP model from a commercial solver, provide a near optimal solution with a loss of less than 1 % of profit. Furthermore, the DACE approach reduces the computational time from several hours to roughly 18 min, making it a much more suitable option for practical use. In addition, the DACE approach yields highly interpretable profit functions allowing us to analyze the marginal profits as a function of the number of slots opened at each station with the help of the MARS model.

We organize the rest of this paper as follows: In Section 2, we present the system design problem formulation, including system design modeling assumptions, formulation of the problem using MILP and the DACE approach in detail. In Section 3, we describe system design experiments where we discuss the results. Finally, we present conclusions in Section 4.

2. System design problem formulation

2.1. *System design layout*

The EV charging station depicted in Fig. 1 is devised to harness energy from both wind and solar sources, as well as the conventional power grid. The stored energy within the charging station is subsequently utilized for recharging electric vehicles (EVs). The system has the capability to store excess energy for future requirements through a battery storage unit. The surplus stored energy can serve as a reserve for meeting demand in case the generated energy falls short. Should the energy produced by wind/solar sources and the battery storage prove inadequate to meet the demand, the system will procure the necessary

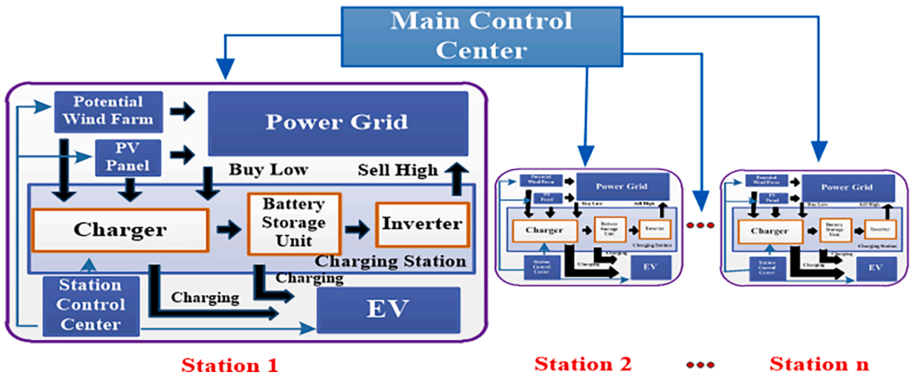

Fig. 1. EV Charging station Layout.

energy from the power grid. Additionally, any surplus energy stored in the unit can be sold back to the power grid, contributing to increased profits.

Fig. 2 displays the positioning of 11 possible station sites across the Dallas/Fort Worth area in Texas. Surrounding these stations are 140 hotspots (cities) distributed at predetermined distances from each station.

2.2. System design modeling assumptions

The model assumes that decisions are optimized over a fixed reoccurring time horizon, such as a day. In addition, there is a fixed cost, which we refer to as an operational cost, to open a charging station and charging slots at an opened station for the entire time horizon. Moreover, we discretize the time horizon into a fixed set of discrete time periods.

The demand model assumes that the demand at charging stations is based on their proximity to the hotspots. The closest station to a hotspot captures a fraction of the total hotspot demand, which is a linear function of the distance between them. All other stations do not capture any demand from the hotspot. We also assume that stations that are sufficiently far away from a hotspot are unable to fulfill any demand of that hotspot. The capacity of a charging station is determined by the number of open slots. We assume each station can open at most a fixed maximum number of slots. In instances where the demand at a charging station surpasses its capacity, a portion of customers display a willingness to wait for service in a subsequent time interval. This willingness is expressed as a recapture rate, while the remaining demand will be lost. We use piecewise linear functions for the nonlinearity in the constraints associated with the recaptured demand. Moreover, we assume that the amount of electricity purchased from the grid at a station in a time period is no larger than the nominal demand.

The subsequent MILP formulation is designed to optimize the selection of charging stations and the allocation of slots while simultaneously maximizing total profits. While providing an optimal solution, it is important to note that the proposed MILP formulation's drawback lies in its demand for extensive computational time when utilizing a commercial solver. Hence, we develop the DACE based optimization approach to determine the system of EV charging stations.

In this paper, the following notations are introduced for the MILP formulation and the DACE based system design optimization problem formulation.

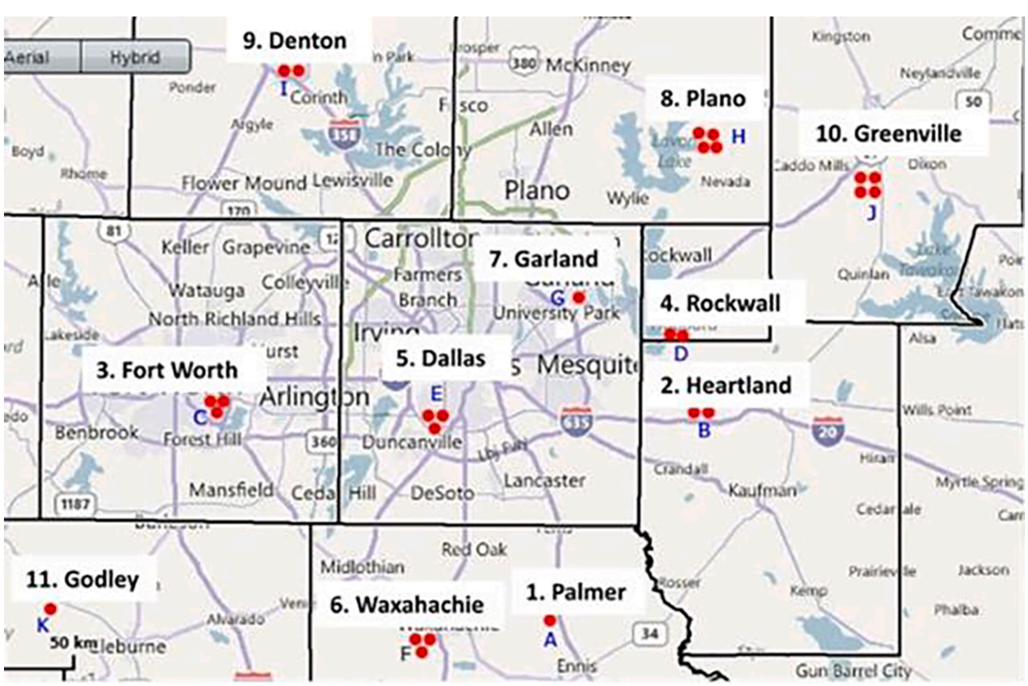

Fig. 2. The distribution of the station locations.

Sets.

J	set of potential station locations indexed by j
I	set of demand hot spots indexed by i
$I(j)$	set of demand hot spots within the max-mile radius of station j
T	set of time periods in the time horizon indexed by t
K	set of basis functions in a multivariate adaptive regression splines (MARS) function indexed by k
N	set of LH experimental design points
Parameters	
m_{ij}	Distance from hotspot i to station j (in miles)
φ	Maximum mile radius between the hotspots and the station
p_i	Population of EVs at hotspot i
d_t	Demand percentage in time period t
e	Charging efficiency of the battery
dc	Discharge rate of the battery
ϕ	Recapture rate
θ	First time period in the time horizon
ρ	Last time period in the time horizon
r_t	Electricity retail price in time period t
cr	Battery charge capacity
c_j	Operational cost of station j
Nc_j	Operational cost of a slot at station j
v	Minimum battery level
u	Maximum battery level
$\beth$	Maximum number of slots opened per charging station
sc	Slot capacity
W_t	Wind generation (Mwh) in time period t
S_t	Solar production (Mwh) in time period t
M_t	Market price in time period t
β_0	Y-intercept of the MARS function
β_k	Least squares estimators for basis function k of the MARS function
LH_j	Traditional LH design value between 0 and 1 of station j
Variables	
$x_j \in \{0,1\}$	Binary variable, if station j is operational
$y_{ij} \in \{0,1\}$	Binary variable, if hotspot i is assigned to station j
$\alpha_{tj} \in \{0,1\}$	Binary variable, if the solar production in time period t is allocated to station j
ω_{tj}	Fraction of the total wind generation in time period t allocated to station j
g^+_{tj}	Electricity bought from the power grid by station j in time period t
g^-_{tj}	Electricity sold to the power grid from direct charge from station j in time period t
B^-_{tj}	Electricity sold to the power grid from the battery at station j in time period t
D_{tj}	Total demand in time period t at charging station j
D^1_{tj}	Demand satisfied by direct charge of station j in time period t
D^2_{tj}	Demand satisfied by the battery at station j in time period t
L_{tj}	Battery level of station j in time period t
Bc_{tj}	Battery charge of station j in time period t
Ns_j	Number of operational slots at station j
Tc_j	Total capacity of slots at station j
Nd_{tj}	Nominal demand in time period t at station j
R_{tj}	Recaptured demand from time period $t-1$ at charging station j
a_{tj}, b_{tj}	Binary decision variables used for the piecewise linear formulation in time period t at station j
Z_{MILP}	Objective function of the MILP formulation
$(\overline{x}, \overline{Ns})$	System station design
$Z_{MILP}(\overline{x}, \overline{Ns})$	Objective function of a system station design
$Rev(\overline{Ns})$	Revenue of a system station design
BF_k	The value of basis function k in the MARS model

2.3. MILP formulation

The objective function in the MILP is given as Eq. (1).

$$\max\sum_{t\in T}\sum_{j\in J}\left[\left(M_t\left(g^-_{tj}+B^-_{tj}-g^+_{tj}\right)+r_tNd_{tj}\right)\right]-\sum_{j\in J}\left(c_jx_j+Nc_jNs_j\right) \tag{1}$$

The first three terms in objective (1), with the market price (M_t) coefficient, are revenue from selling energy to the power grid both from the direct charge and the battery across all the stations minus the cost of buying energy from the power grid. The fourth term is the revenue from meeting the demand at the electricity retail price (r_t). The last two terms subtract the operational cost of an EV station at a potential location and the cost of opening slots. Consequently, objective (1) is the profit from these six components of the EV charging system.

The constraints of the MILP are as given below in Eqs. (2)–(34).

$$\sum_{i\in I(j)} p_i * d_t\left[\frac{(\varphi-m_{ij})}{\varphi}y_{ij}\right] = D_{tj};\ \forall j\in J,\ \forall t\in T \tag{2}$$

The constraints in Eq. (2) guarantees that the total demand in time period t at charging station j is the product of the distance function, which is the percentage of the demand of hotspot i assigned to station j with the population of hotspot i and the general demand percentage in time period t.

$$y_{ij} \le x_j;\ \forall i\in I(j),\ \forall j\in J \tag{3}$$

$$\sum_{j\in J} y_{ij} \le 1;\ \forall i\in I \tag{4}$$

The constraints in Eq. (3) ensure that demand hotspot i can be assigned to station j only if station j is opened. The constraints in Eq. (4) ensure that each hotspot i is served by at most one station.

$$x_j + y_{i\hat{j}} \le 1;\ \forall i\in I,\ \forall j, \hat{j}\in J, m_{ij} < m_{i\hat{j}} \tag{5}$$

The constraints in Eq. (5) ensure that if station j is closer than $\hat{j}$, then the hotspot will be assigned to the closer one.

For the piecewise linear function for the recaptured demand, $\forall j\in J, \forall t\in T$, let ε be an upper bound (very large number, $+\infty$) and a_{tj} be such that

$$a_{tj} = \begin{cases} 1 & \text{if } D_{tj}+R_{tj} \geqslant Tc_j \\ 0 & o.w. \end{cases}$$

$$\varepsilon\left(1-a_{tj}\right) + D_{tj} + R_{tj} \geqslant Tc_j \tag{6}$$

$$D_{tj}+R_{tj} \leqslant Tc_j + \varepsilon\ a_{tj} \tag{7}$$

$$-\varepsilon\left(1-a_{tj}\right) + Tc_j \leqslant Nd_{tj} \leqslant Tc_j + \varepsilon\left(1-a_{tj}\right);\ \forall j\in J,\ \forall t\in T \tag{8}$$

$$-\varepsilon\ a_{tj} + D_{tj} + R_{tj} \leqslant Nd_{tj} \leqslant D_{tj}+R_{tj}+\varepsilon\ a_{tj};\ \forall j\in J,\ \forall t\in T \tag{9}$$

The constraints in Eqs. (6)–(9) represent a piecewise linear formulation ensuring that if the sum of the total demand and the recaptured demand in time period t at station j is greater than or equal to the total capacity of the station j, then total nominal demand in time period t at station j is equal to the total capacity of the charging station j; otherwise, it is equal to the sum of the total demand and recaptured demand in time period t at station j.

When the demand for a time period exceeds the total capacity, it is assumed that a proportion ϕ of customers are amenable to waiting for service in a subsequent time period. Specifically, $\forall j\in J, \forall t\in T\backslash\{\theta\}$, let b_{tj} be such that

$$b_{tj} = \begin{cases} 1 & \text{if } \phi\left[D_{(t-1)j}+R_{(t-1)j}-Tc_j\right] \ge 0 \\ 0 & o.w. \end{cases}$$

$\forall j\in J$ let $b_{\theta j}$ be such that

$$b_{\theta j} = \begin{cases} 1 & \text{if } \phi\left[D_{\rho j}+R_{\rho j}-Tc_j\right] \ge 0 \\ 0 & o.w. \end{cases}$$

$$\varepsilon\left(1-b_{tj}\right) + \phi\left[D_{(t-1)j} + R_{(t-1)j} - Tc_j\right] \geqslant 0;\ \forall j\in J,\ \forall t\in T\backslash\{\theta\} \tag{10}$$

$$\varepsilon\left(1-b_{\theta j}\right) + \phi\left[D_{\rho j} + R_{\rho j} - Tc_j\right] \geqslant 0; \forall j\in J \tag{11}$$

$$\phi\left[D_{(t-1)j}+R_{(t-1)j} - Tc_j\right] \leqslant \varepsilon\ b_{tj};\ \forall j\in J,\ \forall t\in T\backslash\{\theta\} \tag{12}$$

$$\phi\left[D_{\rho j}+R_{\rho j} - Tc_j\right] \leqslant \varepsilon\ b_{\theta j}; \forall j\in J \tag{13}$$

$$-\varepsilon\ (1-b_{tj}) + \phi[D_{(t-1)j} + R_{(t-1)j} - Tc_j] \leqslant R_{tj} \leqslant \phi[D_{(t-1)j} + R_{(t-1)j} - Tc_j]\ +\ \varepsilon\ (1-b_{tj});\ \forall j \in J,\ \forall t \in T) \tag{14}$$

$$-\varepsilon\ (1-b_{\varepsilon j})\ + \phi[D_{\rho j} + R_{\rho j} - Tc_j] \leqslant R_{\varepsilon j} \leqslant \phi[D_{\rho j} + R_{\rho j} - Tc_j]\ +\ \varepsilon\ (1-b_{\varepsilon j});\ \forall j \in J \tag{15}$$

$$\varepsilon\ b_{tj} \leqslant R_{tj} \leqslant \varepsilon\ b_{tj};\ \forall j \in J,\ \ \forall t \in T \tag{16}$$

The piecewise constraints in Eqs. (10)–(16) ensure that if the total demand and recaptured demand from time period t-1 at station j is greater than or equal to the total capacity of the station j, then the recaptured in time period t at station j is ϕ of the demand and recaptured demand in time period t-1 minus the total capacity of the charging station j. Otherwise, there will be no recaptured demand. We assume that the recaptured demand at the last time period is taken into consideration to calculate the recaptured demand of the demand at the first time period. Observe that $\forall j \in J, \forall t \in T \setminus \{\theta\}$, $a_{tj} = b_{t-1j}$, and $a_{\theta j} = b_{\rho j}$ by definition, so we can reduce the number of binary variables in the model.

$$Ns_j = \frac{Tc_j}{sc};\ \forall j \in J \tag{17}$$

The constraints in Eq. (17) guarantee that the count of opened slots at charging station j is determined by dividing the total capacity of charging station j by the capacity of each individual slot.

$$Nd_{tj}\ = (D^1_{tj} + D^2_{tj});\ \forall j \in J,\ \forall t \in T \tag{18}$$

The constraints in Eq. (18) ensure that the total nominal demand in time period t at charging station j is equal to the demand satisfied by the direct charge of station j in time period t and the demand satisfied by the battery at station j in time period t.$\forall j \in J, \forall t \in T$, let α_{tj} be such that

$$\alpha_{tj} = \begin{cases} 1 & \text{if solar production } t \text{ is allocated to station } j \\ 0 & o.w \end{cases}$$

$$L_{tj} = L_{(t-1)j} + Bc_{tj} - eD^2_{tj} + eB^-_{tj};\ \forall j\ \in J,\ \forall t\ \in T \tag{19}$$

$$L_{\theta j} = L_{\rho j} + Bc_{\theta j} - eD^2_{\theta j} + eB^-_{\theta j};\ \forall j\ \in\ J \tag{20}$$

$$Bc_{tj} = W_t\omega_{tj} + S_t\alpha_{tj} + g^+_{tj} - g^-_{tj} - D^1_{tj};\ \forall j \in J, \forall t \in T \tag{21}$$

The set of energy balance constraints include the battery level transition as Eq. (19), the energy balance for the battery charge as Eq. (21). Moreover, the constraints in Eq. (20) ensure the battery level at the first time period is calculated using battery level transition equation and the battery level at the last last time period.

$$g^-_{tj} \leq W_t\omega_{tj} + S_t\alpha_{tj} + g^+_{tj};\ \forall j \in J, \forall t \in T \tag{22}$$

$$g^+_{tj} \leq Nd_{tj};\ \forall j \in J,\ \forall t \in T \tag{23}$$

The constraints in Eq. (22) ensure that the electricity sold to the power grid from the direct charge of station j in time period t should be less than or equal to the sum of the total wind purchased by station j in time period t, the solar production of station j in time period t, and the electricity bought from the power grid by station j in time period t. However, because there is no reason to purchase and sell back to the power grid from the same station in the same time period, the purchase term g^+_{tj} in (22) can be omitted. Similarly, the constraints in Eq. (23) ensure that the electricity bought from the power grid by station j in time period t should be no more than the total nominal demand in time period t at charging station j.

$$B^-_{tj} + D^2_{tj} \leq dc{*}e{*}x_j;\ \forall j \in J, \forall t \in T \tag{24}$$

$$Bc_{tj} \leq cr{*}x_j;\ \forall j \in J, \forall t \in T \tag{25}$$

$$v{*}x_j \leq\ L_{tj} \leq u{*}x_j;\ \forall j \in J,\ \forall t \in T \tag{26}$$

The constraints in Eq. (24) ensure that the sum of the electricity sold back to the power grid from the battery at station j in time period t and the demand satisfied by the battery at station j in time period t cannot be higher than the product of discharge rate and storage efficiency of station j. Similarly, the constraints in Eq. (25) ensure that the battery charge of station j in time period t should be within the battery charging capacity. The constraints in Eq. (26) ensure that the battery inventory is between minimum and maximum battery level for each station. Moreover, (24) - (26) are only considered when station j is operational.

$$\sum_{j \in J}\omega_{tj}\ \leq 1;\ \forall t \in T \tag{27}$$

The constraint in Eq. (27) ensures that the fraction of the allocated wind generation to all the stations is no more than 1.

$$\omega_{tj} \leq x_j;\ \forall j \in J,\ \forall t \in T \tag{28}$$

$$\alpha_{tj}\ \leq x_j;\ \forall j \in J,\ \forall t \in T \tag{29}$$

Constraints in Eqs. (28) and (29) ensure that the total wind purchased by station j in time period t, and the solar production of station j in time period t are only considered if the station is operational.

$$0 \leq\ Nsj\ \leq \beth\, x_j;\ \forall j \in J \tag{30}$$

The constraints in Eq. (30) ensure that the number of slots opened is between zero and the maximum possible number of slots opened per charging station j. Moreover, no slots are open if the station is not operational.

$$Nd_{tj},\ D_{tj},\ D^1_{tj},\ D^2_{tj,}\ \ \omega_{tj},\ Tc_j,\ L_{tj},\ g^+_{tj},\ \ g^-_{tj},\ \ B^-_{tj},\ Bc_{tj},\ \ R_{tj}\ \geq\ 0;\ \forall j \in J,\ \ \forall t \in T \tag{31}$$

$$x\ \in \mathbb{B}^{|J|} \tag{32}$$

$$y \in \mathbb{B}^{|I|*|J|} \tag{33}$$

$$\alpha, a,\ b \in \mathbb{B}^{|T|*|J|} \tag{34}$$

The constraints in Eqs. (31)–(34) ensure that the given variables are nonnegative, and x, y, α, a and b are binaries of appropriate dimension. Furthermore, the constraints in Eqs. (4), (5), and (27) create a dependent relationship between the stations and prevent the problem from being separable by station.

2.4. DACE based system design optimization approach

DACE is a statistical technique designed to efficiently carry out computer experiments, particularly suited for exploring applications governed by intricate computer models (Sacks et al., 1989). These types of computer models find widespread use in engineering domains, often seen in applications like finite element simulations (Furushima & Manabe, 2011). Chen et al. (2006) provided a review of DACE methods, including the adaptation to DACE based optimization. In the conventional approach of DACE, an experimental design is employed to structure a series of computer experimental runs. This arrangement facilitates the creation of a statistical "metamodel" that serves as an approximation for the performance output simulated by an intricate computer model. The metamodel is a mathematical surrogate that can be employed to study the simulated system more efficiently. In DACE based optimization, the computer model is an optimization algorithm instead of the traditional computer simulation model. Specifically, in this paper, we develop the following DACE based optimization approach using the steps below.

1. Using an experimental design (binned LH), a set of sample points, each representing a system design in the design parameter space, is generated.

2. The performance (revenue) of each system design point is then determined by fixing the system design variables and solving the MILP to obtain the solution to a control subproblem.

3. A multivariate adaptive regression splines (MARS) model is fit to the experimental design obtained by the binned LH experimental design in step 1 and the corresponding revenues generated by step 2.

4. The obtained MARS model in step 3 is then optimized by subtracting the cost component to predict the profit to obtain a best system design.

5. True profit is calculated using the system design point from step 4, with the help of the MILP. The obtained result is the solution to our first-stage system design problem. Using this step, we optimize the design of the EV charging stations. A more detailed explanation is provided in Sections 2.4.1–2.4.4.

2.4.1. Binned LH design

As described in the MILP formulation, the system design variables are given by the vectors $(\overline{x}, \overline{Ns})$, where vector $\overline{x}$ includes binary variables, indicating which stations are operational, and vector $\overline{Ns}$ gives the number of open slots. A traditional LH experimental design yields independent values between given limits. However, due to constraint set (30), the vectors $\overline{x}$ and $\overline{Ns}$ are dependent in that slots can only be opened at operational stations. Consequently, we develop a binned LH, which consists of a traditional LH experimental design along with a mapping that determines a feasible system design $(\overline{x}, \overline{Ns})$ from a traditional LH experimental design point. Moreover, traditional LH experimental designs fill the space, but optimal solutions tend to reside in very small portions of the feasible decision space, so the mapping needs to be intelligent to include "good" system design points so that the MARS model can accurately model this part of the space. For example, opening 8 or more stations usually yields more capacity than needed to meet demand, whereas opening fewer than 3 stations will be insufficient to fulfill demand. Consequently, we need an experimental design where many of the system design points have between 4 and 7 operational stations. Specifically, we used a traditional LH experimental design to generate 325 11-dimentional experimental design points between 0 and 1 using the MATLAB R 2016a function "*lhsdesign*". The fractional values obtained from the first 20 points of the traditional LH experimental design are as indicated in Table 1 below. The mapping is shown as the step function given in Fig. 3, which can be defined as follows for a station *j*:

$$(\overline{x}_j, \overline{Ns}_j) = \begin{cases} (0,0) & \text{if } LH_j < \frac{9}{19} \\ \left(1, \left\lceil 19\left(LH_j - \frac{9}{19}\right)\right\rceil\right) & o.w. \end{cases}$$

Here LH_j refers to the traditional LH design value between 0 and 1. The mapping translates the traditional LH experimental design in Table 1 into the binned LH experimental design in Table 2, which indicates the locations of the charging stations and the number of slots at each charging station $(\overline{x}, \overline{Ns})$. Fig. 4 also shows the distribution of the number of operational stations in the binned LH experimental design. Observe that 80 % of the system design points have between 4 and 7 operational stations, which will appropriately capture demand without too much excess capacity. The 325 binned LH experimental design points were split into 250 training data points and 75 testing data points.

2.4.2. Second-Stage control problem

For each system of charging stations $(\overline{x}, \overline{Ns})$ in the experimental design, the corresponding second-stage control problem revenue $Rev(\overline{Ns})$ is determined using MILP as shown in Eq. (35).

$$Rev(\overline{Ns}) = max\sum_{t\in T}\sum_{j\in J}\left[\left(M_t\left(g_{tj}^- + B_{tj}^- - g_{tj}^+\right) + r_tNd_{tj}\right)\right] \tag{35}$$

s.t. Eqs. (2)–(34) and $Ns = \overline{Ns}$.

As depicted in Fig. 5, each row serves as input for the control subproblem formulation. This problem is addressed using the MILP presented in Eq. (35), resulting in the derivation of the respective revenues denoted as $Rev(\overline{Ns})$.

2.4.3. MARS model

To forecast the revenue for the EV charging station system, the second-stage model calibrates a MARS statistical model (Friedman, 1991, Chen, 1999). This specific model demonstrates notable proficiency in predicting revenue by considering the count of available charging slots across diverse locations. MARS is trained using the

Table 1
20 points LH Design using MATLAB (Partial).

LH_1	LH_2	LH_3	LH_4	LH_5	LH_6	LH_7	LH_8	LH_9	LH_{10}	LH_{11}
0.74	0.28	0.45	0.17	0.45	0.31	0.78	0.64	0.23	0.51	0.50
0.84	0.02	0.66	0.70	0.32	0.62	0.53	0.79	0.76	0.52	0.61
0.24	0.09	0.19	0.46	0.10	0.29	0.42	0.05	0.89	0.68	0.00
0.51	0.76	0.53	0.63	0.11	0.82	0.07	0.85	0.85	0.91	0.58
0.46	0.67	0.63	0.96	0.86	0.82	0.24	0.42	0.63	0.94	0.76
0.33	0.74	0.03	0.32	0.54	0.99	0.59	0.43	0.72	0.88	0.67
0.83	0.58	0.47	0.07	0.96	0.47	0.44	0.34	0.93	0.58	0.52
0.99	0.78	0.89	0.79	0.99	0.49	0.90	0.57	0.46	0.90	0.83
0.59	0.04	0.14	0.38	0.41	0.61	0.06	0.31	0.30	0.12	0.97
0.18	0.37	0.44	0.56	0.36	0.86	0.48	0.40	0.69	0.34	0.30
0.12	0.22	0.67	0.19	0.22	0.04	0.57	0.36	0.30	0.03	0.79
0.57	0.44	0.32	0.08	0.46	0.20	0.15	0.68	0.68	0.50	0.26
0.31	0.84	0.96	0.14	0.27	0.97	0.58	0.71	0.06	0.72	0.03
0.25	0.26	0.70	0.84	0.48	0.98	0.87	0.99	0.99	0.19	0.10
0.54	0.56	0.23	0.31	0.44	0.48	0.22	0.95	0.20	0.42	0.32
0.18	0.02	0.56	0.40	0.26	0.84	0.17	0.37	0.66	0.09	0.29
0.66	0.15	0.88	0.62	0.10	0.96	0.07	0.16	0.37	0.30	0.03
0.06	0.80	0.57	0.82	0.42	0.70	0.71	0.94	0.74	0.80	0.17
0.03	0.18	0.77	0.74	0.52	0.40	0.02	0.30	0.02	0.49	0.44
0.27	0.79	0.90	0.38	0.33	0.44	0.30	0.57	0.10	0.78	0.75

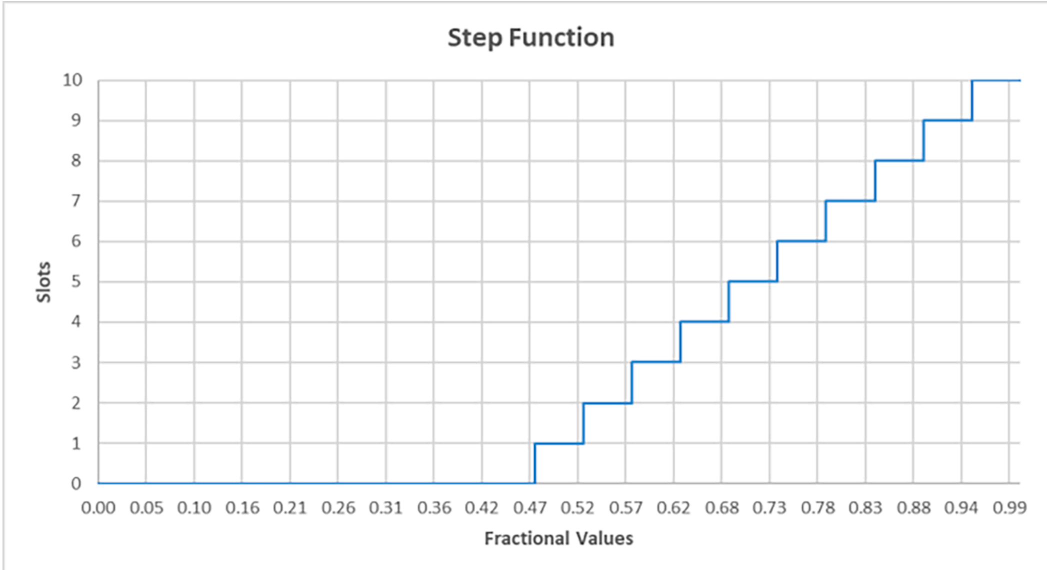

Fig. 3. Step Function.

Table 2
20 points Binned LH Design (Partial)$\boldsymbol{Ns_1}$.

	Ns_2	Ns_3	Ns_4	Ns_5	Ns_6	Ns_7	Ns_8	Ns_9	Ns_{10}	Ns_{11}
5	0	0	0	0	0	6	3	0	1	0
7	0	4	5	0	3	1	6	6	1	3
0	0	0	0	0	0	0	0	8	4	0
1	6	1	3	0	7	0	8	8	9	2
0	4	3	10	8	7	0	0	3	9	6
0	5	0	0	1	10	2	0	5	8	4
7	2	0	0	10	0	0	0	9	2	1
10	6	8	6	10	0	9	2	0	8	7
2	0	0	0	0	3	0	0	0	0	10
0	0	0	2	0	8	0	0	4	0	0
0	0	4	0	0	0	2	0	0	0	6
2	0	0	0	0	0	0	4	4	1	0
0	7	10	0	0	10	2	5	0	5	0
0	0	4	7	0	10	8	10	10	0	0
1	2	0	0	0	0	0	10	0	0	0
0	0	2	0	0	7	0	0	4	0	0
4	0	8	3	0	10	0	0	0	0	0
0	7	2	7	0	5	5	9	5	7	0
0	0	6	5	1	0	0	0	0	0	0
0	6	8	0	0	0	0	2	0	6	5

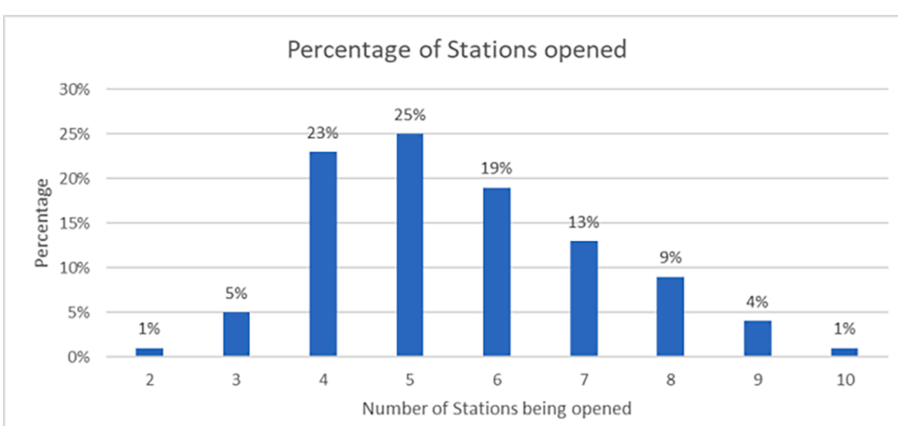

Fig. 4. Percentage of Stations opened.

Ns_1	Ns_2	Ns_3	Ns_4	Ns_5	Ns_6	Ns_7	Ns_8	Ns_9	Ns_{10}	Ns_{11}	Control Problem → Solve
5	0	0	0	0	0	6	3	0	1	0	$Rev(Ns^1)$
7	0	4	5	0	3	1	6	6	1	3	$Rev(Ns^2)$
0	0	0	0	0	0	0	0	8	4	0	$Rev(Ns^3)$
1	6	1	3	0	7	0	8	8	9	2	$Rev(Ns^4)$
0	4	3	10	8	7	0	0	3	9	6	$Rev(Ns^5)$
0	5	0	0	1	10	2	0	5	8	4	$Rev(Ns^6)$
7	2	0	0	10	0	0	0	9	2	1	$Rev(Ns^7)$
10	6	8	6	10	0	9	2	0	8	7	$Rev(Ns^8)$
2	0	0	0	0	3	0	0	0	0	10	$Rev(Ns^9)$
0	0	0	2	0	8	0	0	4	0	0	$Rev(Ns^{10})$
0	0	4	0	0	0	2	0	0	0	6	$Rev(Ns^{11})$
2	0	0	0	0	0	0	4	4	1	0	$Rev(Ns^{12})$
0	7	10	0	0	10	2	5	0	5	0	$Rev(Ns^{13})$
0	0	4	7	0	10	8	10	10	0	0	$Rev(Ns^{14})$
1	2	0	0	0	0	0	10	0	0	0	$Rev(Ns^{15})$
0	0	2	0	0	7	0	0	4	0	0	$Rev(Ns^{16})$
4	0	8	3	0	10	0	0	0	0	0	$Rev(Ns^{17})$
0	7	2	7	0	5	5	9	5	7	0	$Rev(Ns^{18})$
0	0	6	5	1	0	0	0	0	0	0	$Rev(Ns^{19})$
0	6	8	0	0	0	0	2	0	6	5	$Rev(Ns^{20})$

Fig. 5. Computing revenues solving control problem.

experimental design data points extracted through binned LH, along with the associated revenues resulting from solving the second-stage control problem (35) as a response variable. The resultant fitted model, as shown in Eq. (36), serves as a predictor for revenue.

$$\widehat{Rev}(Ns) = \beta_0 + \sum\nolimits_{k=1}^{K} \beta_k BF_k(Ns) \tag{36}$$

In our paper, we fit two different MARS models, one with basis interaction terms and the other with no interaction.

2.4.4. First-Stage EV system master problem

The system of charging stations (x^*, Ns^*) is obtained by maximizing profit using the optimization problem given by (37),

$$\widehat{Z}_{MILP}(x^*,\ Ns^*) = \max \widehat{Rev}(Ns)\ -\ c_j x_j -\ Nc_j Ns_j \tag{37}$$

s.t. Eqs. (30) and (32).

To evaluate the quality of (x^*, Ns^*), $Z_{MILP}(x^*, Ns^*)$ is then calculated using Eq. (38).

$$Z_{MILP}(x^*, Ns^*) = max \sum\nolimits_{t\in T} \sum\nolimits_{j\in J} \left[\left(M_t \left(g_{tj}^- + B_{tj}^- - g_{tj}^+ \right) + r_t Nd_{tj} \right) \right] - \sum\nolimits_{j\in J} \left(c_j x_j + Nc_j Ns_j \right) \tag{38}$$

s.t. Eqs. (2)–(34), and $x_j = x^*$,$Ns_j = Ns^*$

The obtained $Z_{MILP}(x^*, Ns^*)$ and (x^*, Ns^*) are the profit and solution of the DACE approach, respectively.

3. System design experiments

3.1. MILP experiments

For experimental purposes, all experiments were conducted on a workstation equipped with an Intel Core i7 CPU @2.60 GHz, featuring 2 physical cores, 4 logical processors, and 8 GB RAM. The optimization procedures were executed using CPLEX 12.6.3 (CPLEX, 2015), and GUROBI 9.5 (GUROBI Optimization, 2022). The data utilized for this investigation encompasses wind generation (W_t) (National Renewable Energy Laboratory, 2012), solar generation (S_t) (Miller & Lumby, 2012), market price (M_t) (Electric Reliability Council of Texas, 2002), and demand profiles (d_t) (Khosrojerdi et al., 2012). The fixed retail price (r_t) of electricity is 10.24 cents per kilowatt-hour per time periods (U.S. Department of Energy, 2012). The maximum (v) and minimum (u) battery levels are 3.6 MWh and 720 kWh per slot. The charging rate (cr) and discharging rates (dc) are 600 kW and 75 kW per slot. The capacity of every slot (sc) is 18.75 kWh. In our study, the storage efficiency (e) is assumed to be 79.8 % (Wetz, 2010). For convenience, we assumed that a station (j) more than a 20-mile (φ) radius from a hotspot (i) is unable to fulfill the demand of that hotspot. The cost to open a slot (Nc_j) at a station (j) is assumed to be 10 % of the operational cost of the station (c_j). The maximum allowable number of slots (ℶ) that can be opened is 10. Given market price fluctuations every 15 min (t), our formulation encompasses a daily control problem spanning 96 15-minute periods. In instances where the demand for a given time period surpasses capacity, it is assumed that 50 % (recapture rate (ϕ)) of the customers are willing to wait for service in a subsequent time slot, while the remaining customers are lost.

Table 3 below illustrates the ideal operational station setup, the available open slots, and the individual profits generated by each station across different operating cost scenarios. It also outlines the computational time if the experiment is conducted within a 6-hour time limit.

We employed CPLEX to solve the MILP for a range of operating cost values. It has been noted that the best integer solution typically materializes within a span of 20 min to 1 h and 55 min, although verifying its optimality necessitates approximately 5 additional days of computational effort. Consequently, a maximum runtime of 6 h is applied to all scenarios except the one involving an operational cost (c) of $100 per day. This specific cost value is selected as the baseline, as it mirrors a probable operating expense for a charging station compared to the other scenarios. The foundational station cost of $0 per day is observed to render all stations operational, yielding a higher count of opened slots and overall profit relative to the other scenarios. As operational costs escalate, more stations remain closed, and the quantity of slots per station diminishes correspondingly. However, during the transition from a cost of $70 to $100, the number of slots (Ns) in Garland increases from 2 to 3. This alteration occurs because Garland absorbs the demand previously served by Rockwall (which remains closed at an operational cost of $100 per day).

Table 3
Optimal charging station slot capacities across cost scenarios

Cost		Station Location (Individual Profits and # of Slots)											Total Open	Total Profit	Duration	Status
Station	Slot	Palmer	Heartland	Fort Worth	Rockwall	Dallas	Waxahachie	Garland	Plano	Denton	Greenville	Godly				
$ -	$ -	$160.64	$ 168.80	$1,373.42	$179.46	$ 411.99	$ 167.34	$453.14	$162.96	$ 221.59	$ 163.85	$170.66	11	$3,633.83	6 Hrs	Stopped
		1	5	6	1	5	1	3	1	4	1	1	29			
$ 40.00	$ 4.00	$116.64	$ 124.80	$ 845.72	$142.69	$ 971.90	$ 147.54	$219.44	$118.96	$ 174.08	$ 119.85	$126.79	11	$3,108.39	6 Hrs	Stopped
		1	1	5	1	5	1	2	1	2	1	1	21			
$ 50.00	$ 5.00	$118.20	$ -	$ 398.59	$151.60	$1,157.51	$ -	$220.31	$424.87	$ 399.27	$ -	$122.38	8	$2,992.73	6 Hrs	Stopped
		1	0	5	1	5	0	2	1	1	0	1	17			
$ 60.00	$ 6.00	$ -	$ -	$ 866.69	$355.60	$ 543.56	$ -	$454.75	$ -	$ 684.76	$ -	$ -	5	$2,905.34	6 Hrs	Stopped
		0	0	5	1	5	0	2	0	1	0	0	14			
$ 70.00	$ 7.00	$ -	$ -	$ 704.60	$295.34	$ 424.65	$ -	$415.07	$ -	$1,003.91	$ -	$ -	5	$2,843.57	6 Hrs	Stopped
		0	0	5	1	4	0	2	0	1	0	0	13			
$ 100.00	$ 10.00	$ -	$ -	$2,072.21	$ -	$ 293.96	$ -	$201.76	$ -	$ 121.45	$ -	$ -	4	$2,689.38	4 Days 23 Hrs	Complete
		0	0	5	0	4	0	3	0	1	0	0	13			
$ 200.00	$ 20.00	$ -	$ -	$1,869.73	$ -	$ 405.68	$ -	$ -	$ -	$ -	$ -	$ -	2	$2,275.42	6 Hrs	Stopped
		0	0	5	0	4	0	0	0	0	0	0	9			
$ 300.00	$ 30.00	$ -	$ -	$2,067.06	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	1	$2,067.06	3 hrs 23 min	Complete
		0	0	5	0	0	0	0	0	0	0	0	5			
$ 400.00	$ 40.00	$ -	$ -	$1,925.83	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	1	$1,925.83	5 hrs 33 min	Complete
		0	0	4	0	0	0	0	0	0	0	0	4			
$2,000.00	$200.00	$ -	$ -	$ 51.53	$ -	$ -	$ -	$ -	$ -	$ -	$ -	$ -	1	$ 51.53	6 Hrs	Stopped
		0	0	1	0	0	0	0	0	0	0	0	1			

Based upon our demand assumptions, there is no need to activate 8 or more stations to meet demand. Conversely, opening fewer than 3 stations would be inadequate to fulfill demand. As depicted in Table 3, operational costs of $60, $70, and $100 yield 5, 5, and 4 opened stations, respectively. For the $100 per day cost scenario, it took CPLEX approximately 4 days and 23 h of processing time to attain an optimal solution. The optimal solution's objective value stands at $2689.38 ($Z_{MILP}$), with operational stations encompassing Fort Worth, Dallas, Garland, and Denton. Their respective daily profits are $2072.21, $293.96, $201.76, and $121.45. Furthermore, the count of opened slots at each of these locations is 5, 4, 3, and 1, respectively.

In addition to solving the baseline scenario (operational cost of $100) with CPLEX, we also solve it with GUROBI with the lp file generated from CPLEX OPL. Given that the generation of the lp file is negligible, GUROBI required 2 h to provide the same optimal solution as CPLEX, which is used as the baseline method and is utilized for comparison against the DACE approach for this specific research purpose.

Fig. 6 portrays the temporal distribution of demand (D_{tj}) across stations from time periods 1 to 96. Notably, the total demand distribution for Fort Worth takes the lead, Dallas follows as the second highest, trailed by Garland and Denton. In terms of daily consumption per station, the values are 4.61 MWh, 3.89 MWh, 1.97 MWh, and 1.12 MWh, respectively. Furthermore, the demand is lowest between time periods 12 and 20, encompassing the early morning hours from 3 am to 5 am. Subsequently, a gradual upswing unfolds, culminating in peak demand between time periods 52 to 68, spanning the afternoon from 1 pm to 5 pm. This heightened demand is succeeded by a gradual decline.

In Fig. 7, the distribution of opened slots across various cost scenarios is presented. The illustration highlights that at an operational cost (c) of $0, Fort Worth and Dallas exhibit a substantial slot count of 6 and 5, respectively, while Denton and Garland closely follow with slot counts of 4 and 3, respectively. Interestingly, Fort Worth and Dallas maintain their high slot counts despite cost escalation, whereas Garland and Denton experience a reduction in slots as costs rise. This visual

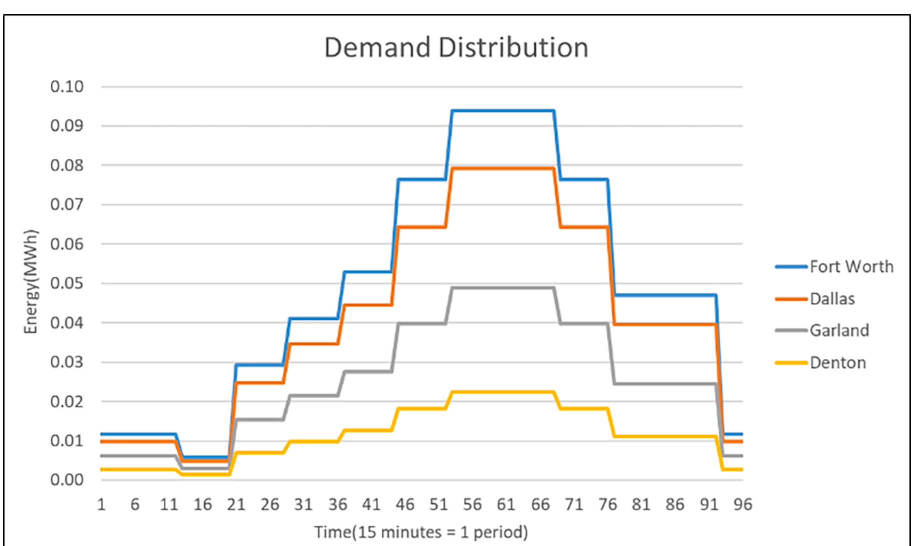

Fig. 6. Demand distribution at an operational cost of $100.

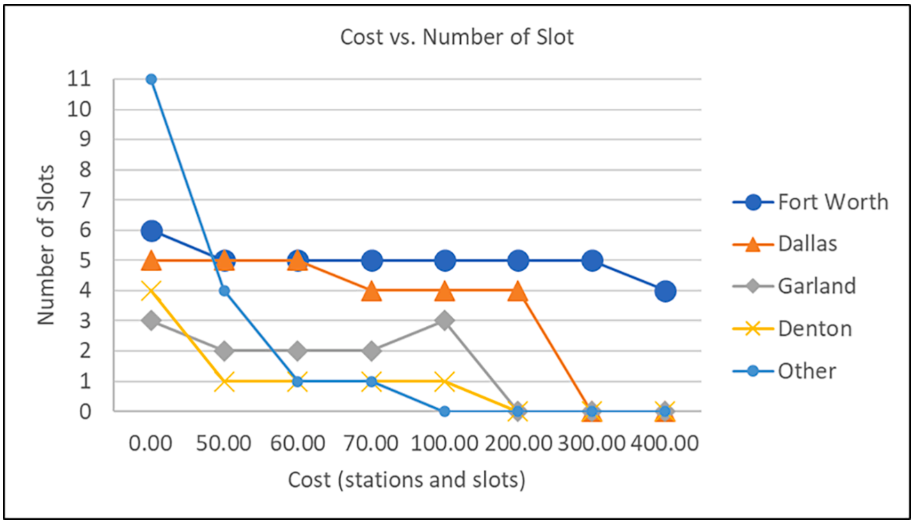

Fig. 7. Major stations: different cost vs. number of slots.

representation mirrors real-world dynamics, where, beyond a certain threshold, the feasibility of opening higher-cost slots diminishes due to insufficient demand. In essence, when the cost reaches $200 per day, the generated profits from Garland and Denton no longer cover their costs, resulting in their closure.

3.2. DACE based system design optimization experiments

In all our experiments utilizing the DACE based system design optimization, a baseline operational cost (c) of $100 per station per day is upheld. We generate four MARS revenue models utilizing two software tools: MATLAB 8.6 with the ARESLAB toolbox (Jekabsons, 2016) and Salford Predictive Modeler (SPM) 8.0 (Minitab, 2016). Each software package calibrates one MARS model with basis interaction terms and another with no interactions. For the SPM non-interaction MARS model, we set the maximum basis functions to 100 and consider the minimum observation between knots as 1. Subsequently, the optimized MARS models are produced using three distinct software programs: CPLEX CP Optimizer (CPLEX, 2015), AMPL 11.2 (Fourer et al., 1990) with the Couenne solver (Belotti et al., 2009), and MINOS solver (Murtagh et al., 2006). The charging station systems derived from CPLEX CP and Couenne are identical, thereby generating 8 distinct systems through the DACE approach, as depicted in Table 4. The coefficient of determination (R-squared) for each MARS model is computed, as displayed in the table. Additionally, the percentage difference (% Diff) between the objective solutions $Z_{MILP}(x^*, Ns^*)$ and Z_{MILP} is enclosed in parentheses in the table. Initial analysis indicates that the DACE approach utilizing the non-interaction MARS metamodel from the SPM software exhibits superior performance, with a percentage difference of $Z_{MILP}(x^*, Ns^*)$ of 0.4 % and has the highest testing R-squared. In this study, charging station systems generated through the DACE approach with non-interaction metamodels exhibit slightly higher accuracy than those with interaction terms. This implies that minimal demand shifts occur due to the stations being widely dispersed. Consequently, the distribution of demand (e.g., Eqs. (4) and (5)) and the allocation of wind power across stations (e.g., Eq. (27)) exert limited influence on the solution in this specific case.

The system design build (x^*, Ns^*) derived from our optimal model (CPLEX CP/Couenne, MINOS) is further dissected and juxtaposed against the MILP, as demonstrated in Table 5 below.

It is noticeable that each system design builds features identical operational stations, positioned in Fort Worth, Dallas, Garland, and Denton. Furthermore, the cumulative count of open slots is 13 for the MILP, CPLEX CP, and AMPL – Couenne approaches, while the AMPL – MINOS solution involves 12 open slots.

Table 4
Comparisons of the DACE MILP objective solutions.

Software for MARS Design	Interaction allowed or not	Testing R^2	$Z_{MILP}(x^*, Ns^*)$	
			CPLEX CP /Couenne (% Diff)	MINOS (% Diff)
ARESLAB	Yes	97.0	2406.8 (3.1)	2566.8 (4.6)
ARESLAB	No	97.7	2670.0 (0.7)	2674.6 (4.3)
SPM	Yes	97.2	2414.0 (2.8)	2555.8 (5.0)
SPM	No	**98.7**	**2678.5 (0.4)**	2629.5 (2.2)

3.3. Interpretable profit functions

One of the major benefits of the DACE based system design optimization approach is that the MARS models with no interaction yield highly interpretable profit functions. These functions allow decision makers to analyze the marginal profits as a function of the number of slots opened at each station. Graphs portraying the relationship between marginal profits and open slots are presented in Fig. 8. Prominent basis functions are linked with Fort Worth, Dallas, Garland, and Denton. All other basis functions connected to different stations possess coefficients of zero in the projected revenue function, indicating that, as per MARS analysis, these stations hold negligible marginal profits. Consequently, the DACE optimization phase maintains them in a closed state. Notably, the interpretable profit function for the Fort Worth station reveals an increase in profit from 1 to 4 slots, followed by a decrease beyond this point. This indicates that the optimal number of slots for Fort Worth is 4, whereas for Dallas, the optimal count is 5, as indicated by a similar trend. Similarly, for Garland and Denton, the optimal count is 2 slots per station. These findings mirror the outcomes (x^*, Ns^*) derived from

Table 5
Number of Slots (MILP vs. DACE).

	Number of slots per opened Stations (cost $100)				
	Fort Worth	Dallas	Garland	Denton	Total
MILP	5	4	3	1	13
CPLEX CP/Couenne	4	5	2	2	13
MINOS	3	5	2	2	12

Fig. 8. Profit Functions at Four charging Stations.

CPLEX CP and AMPL – Couenne. Furthermore, the optimal profits achieved by Fort Worth, Dallas, Garland, and Denton are \$904.55, \$1543.95, \$35.67, and \$194.71 respectively, summing up to \$2678.88, mirroring the $Z_{MILP}(x^*, Ns^*)$ results obtained from the non-interaction MARS model using SPM software, as presented in Table 4. Observe that by using these profit functions, we can construct an optimal solution without the use of a commercial optimization solver.

3.4. CPU time Comparisons

To further substantiate the utilization of the DACE based system design optimization approach, the process run times of the interaction and non-interaction models are computed and tabulated in Table 6. After generating the binned LH experimental design via MATLAB, the revenue data is collected employing GUROBI, culminating in a total runtime of 18 min. Once the revenue data is assembled, it is employed to construct the MARS model through SPM software. Ultimately, optimization of the MARS model is carried out utilizing CPLEX CP, with the resultant outcomes provided. The swiftest comprehensive process time is recorded as 18 min and 40 s, attributed to the non-interaction model.

Table 6
CPU Time Comparisons (MILP vs. DACE).

Task			Time
Binned LHS Design			1 sec
Revenue Function (250 Training and 75 Testing – 3.3 sec average) – GUROBI			18 min
Interaction		No interaction	
Process	*Times*	*Process*	*Times*
SPM	12 sec	SPM	6 sec
CPLEX CP	1 min 20 sec	CPLEX CP	34 sec
DACE - Total	**19 min 32 sec**	**DACE - Total**	**18 min 40 sec**
Original MILP (Gurobi) — 2 h			

Due to the efficiency with which this MARS model discerns station revenues, the DACE approach can swiftly reoptimize across diverse cost scenarios, obviating the need for reacquiring responses from the binned LH design. Specifically, variations in operational cost (c) lead only to shifts in the profit functions depicted in Fig. 8, while alterations in the slot-opening cost (Nc) solely induce tilting, thus permitting optimization across distinct cost scenarios without resorting to a commercial optimization solver. In comparison to the original 2-hour computational requirement for the MILP from the baseline method, the DACE approach exhibits enhanced computational feasibility.

4. Conclusion

An optimized model using mixed-integer linear programming (MILP) is developed to determine optimal EV charging station locations, the quantity of slots to activate at each station, and the resulting overall profit. Given that this particular issue remains unaddressed in existing literature, no established method serves as a baseline. However, utilizing the provided MILP formulation, the most direct approach involves employing the GUROBI branch-and-bound solver, which is considered as the baseline method. The result indicates that Fort Worth should have the highest number of slots, trailed by Dallas, Garland, and Denton. However, this method's drawback lies in its extended computational time, taking several hours to complete, despite giving an optimal solution. To address this limitation of our baseline method, a two-stage framework and a system design optimization approach rooted in DACE (Design and Analysis of Computer Experiments) are introduced for solving the EV charging station network problem. In this investigation, the DACE approach reveals that systems without interaction terms yield superior results compared to those with interaction terms, implying minimal demand shifts due to the considerable station separation. Furthermore, the DACE strategy generates highly interpretable profit functions, facilitating the analysis of marginal profits in relation to the number of slots open at each station. These profit functions allow decision makers to optimize profit under different cost scenarios without the use of a commercial solver. Prominent basis functions are linked to Fort Worth, Dallas, Garland, and Denton. Remarkably, the DACE approach streamlines the solution process, requiring only about 18 min to achieve a solution within 1 % of optimality, in contrast to the several hours taken by the MILP approach.

In terms of future prospects, there is a plan to explore solving the problem with stochastic input variables related to wind and solar power generation, as well as market pricing fluctuations.

CRediT authorship contribution statement

Ukesh Chawal: Methodology, Software, Visualization, Formal analysis, Investigation, Validation, Writing – original draft. **Jay Rosenberger:** Conceptualization, Methodology, Supervision, Validation, Data curation, Writing – review & editing. **Victoria C.P. Chen:** Conceptualization, Methodology, Supervision, Validation, Data curation, Writing – review & editing. **Wei J. Lee:** Data curation, Supervision. **Mewan Wijemanne:** Visualization, Writing – original draft. **Raghavendra K. Punugu:** Software, Validation, Writing – original draft. **Asama Kulvanitchaiyanunt:** Data curation.

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.

Data availability

Data will be made available on request.

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References

Ariyajunya, B., Chen, Y., Chen, V. C. P., Kim, S. B., & Rosenberger, J. (2021). Addressing state space multicollinearity in solving an ozone pollution dynamic control problem. *European Journal of Operational Research, 289*(2), 683–695. https://doi.org/10.1016/j.ejor.2020.07.014

Arslan, O., & Karaşan, O. E. (2016). A Benders decomposition approach for the charging station location problem with plug-in hybrid electric vehicles. *Transportation Research Part B: Methodological, 93*, 670–695. https://doi.org/10.1016/j.trb.2016.09.001

Awasthi, A., Venkitusamy, K., Padmanaban, S., Selvamuthukumaran, R., Blaabjerg, F., & Singh, A. K. (2017). Optimal planning of electric vehicle charging station at the distribution system using hybrid optimization algorithm. *Energy, 133*, 70–78. https://doi.org/10.1016/j.energy.2017.05.094

Battistelli, C., Baringo, L., & Conejo, A. (2012). Optimal energy management of small electric energy systems including V2G facilities and renewable energy sources. *Electric Power Systems Research, 92*, 50–59. https://doi.org/10.1016/j.epsr.2012.06.002

Belotti, P., Lee, J., Liberti, L., Margot, F., & Wächter, A. (2009). Branching and bounds tightening techniques for non-convex MINLP. *Optimization Methods & Software, 24* (4–5), 597–634. https://doi.org/10.1080/10556780903087124

Biesinger, B., Hu, B., Stubenschrott, M., Ritzinger, U., & Prandtstetter, M. (2017). Optimizing charging station locations for electric car-sharing systems. *Evolutionary Computation in Combinatorial Optimization*, 157–172. https://doi.org/10.1007/978-3-319-55453-2_11

Brandstätter, G., Kahr, M., & Leitner, M. (2017). Determining optimal locations for charging stations of electric car-sharing systems under stochastic demand. *Transportation Research Part B: Methodological, 104*, 17–35. https://doi.org/10.1016/j.trb.2017.06.009

Cervellera, C., Chen, V. C. P., & Wen, A. (2006). Optimization of a large-scale water reservoir network by stochastic dynamic programming with efficient state space discretization. *European Journal of Operational Research, 171*(3), 1139–1151. https://doi.org/10.1016/j.ejor.2005.01.022

Chang, S., Li, H., & Nahrstedt, K. (2014). In *December). Charging facility planning for electric vehicles* (pp. 1–7). IEEE.

Chen, C., & Hua, G. (2014). A new model for optimal deployment of electric vehicle charging and battery swapping stations. *International Journal of Control and Automation, 7*(5), 247–258.

Chen, V. C. P. (1999). Application of orthogonal arrays and MARS to inventory forecasting stochastic dynamic programs. *Computational Statistics and Data Analysis, 30*(3), 317–341. https://doi.org/10.1016/s0167-9473(98)00084-x

Chen, V. C. P., Ruppert, D., & Shoemaker, C. A. (1999). Applying experimental design and regression splines to high-dimensional continuous-state stochastic dynamic programming. *Operations Research, 47*(1), 38–53. https://doi.org/10.1287/opre.47.1.38

Chen, V. C. P. (2001). Measuring the goodness of orthogonal array discretizations for stochastic programming and stochastic dynamic programming. *SIAM Journal on Optimization, 12*(2), 322–344. https://doi.org/10.1137/s1052623498332403

Chen, V. C. P., Günther, D., & Johnson, E. L. (2003). Solving for an optimal airline yield management policy via statistical learning. *Journal of the Royal Statistical Society Series C: Applied Statistics, 52*(1), 19–30. https://doi.org/10.1111/1467-9876.00386

Chen, V. C., Tsui, K. L., Barton, R. R., & Meckesheimer, M. (2006). April). A review on design, modeling and applications of computer experiments. *IIE Transactions, 38*(4), 273–291. https://doi.org/10.1080/07408170500232495

CPLEX, IBM ILOG. (2015). *International Business Machines Corporation v12.6.3 (Version 12.6.3)*. http://www-01.ibm.com/software/commerce/optimization/cplex-optimizer/.

Electric Reliability Council of Texas. (2002). ERCOT History Accessed August 2, 2016 http://www.ercot.com/about/profile/history/.

Fan, H., Tarun, P. K., Chen, V. C. P., Shih, D. T., Rosenberger, J. M., Kim, S. B., & Horton, R. A. (2018). Data-driven optimization for dallas-fort worth airport deicing activities. *Annals of Operations Research, 263*(1–2), 361–384. https://doi.org/10.1007/s10479-017-2747-1

Fourer, R., Gay, D. M., & Kernighan, B. W. (1990). A Modeling Language for Mathematical Programming. *Management Science, 36*(5), 519–554. https://doi.org/10.1287/mnsc.36.5.519

Friedman, J. H. (1991). Multivariate adaptive regression splines. *The annals of statistics, 19*(1), 1–67. https://doi.org/10.1214/aos/1176347963

Furushima, T., & Manabe, K. (2011). Superplastic micro-tubes fabricated by dieless drawing processes. *Superplastic Forming of Advanced Metallic Materials* (327–360). Elsevier. https://doi.org/10.1533/9780857092779.3.327.

Gerding, E., Stein, S., Robu, V., Zhao, D., & Jennings, N. R. (2013). May). Two-sided online markets for electric vehicle charging. *Proceedings of the 2013 international conference on Autonomous agents and multi-agent systems*.

Gorbunova, A., & Anisimov, I. (2020). Optimizing the Location of Urban Charging Stations: Case study of the City of Tyumen, Russian Federation. *WIT Transactions on the Built Environment*. doi: 10.2495/ut200021.

GUROBI Optimization, LLC. (2022). *GUROBI Optimization Reference Manual v9.5 (Version 9.5)*. https://www.gurobi.com.

He, F., Yin, Y., & Zhou, J. (2015). Deploying public charging stations for electric vehicles on Urban Road Networks. *Transportation Research Part C: Emerging Technologies, 60*, 227–240. https://doi.org/10.1016/j.trc.2015.08.018

He, K., Jia, H., Mu, Y., Yu, X., Dong, X., & Deng, Y. (2023). Coordinated Planning of Fixed and Mobile Charging Facilities for Electric Vehicles on Highways. *IEEE Transactions on Intelligent Transportation Systems*.

Jatschka, T., Rauscher, M., Kreutzer, B., Okamoto, Y., Kataoka, H., Rodemann, T., & Raidl, G. R. (2022). *February). A Large Neighborhood Search for Battery Swapping Station Location Planning for Electric Scooters*. Cham: Springer Nature Switzerland.

Jekabsons, G. (2016). ARESLab: Adaptive regression splines toolbox for Matlab/Octave, 2011. *URL http://www. cs. rtu. lv/jekabsons.*

Kang, Q., Wang, J., Zhou, M., & Ammari, A. C. (2016). Centralized Charging Strategy and Scheduling Algorithm for Electric Vehicles Under a Battery Swapping Scenario. *IEEE Transactions on Intelligent Transportation Systems, 17*(3), 659–669. https://doi.org/10.1109/tits.2015.2487323

Khosrojerdi, A., Allen, J., Lee, W. J., & Mistree, F. (2012). September). Designing an Electric Charging Station for Plug-In-Hybrid-Electric-Vehicles in the Face of Uncertain Demand. *12th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference and 14th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*.

Kulvanitchaiyanunt, A., Chen, V. C., Rosenberger, J., Sarikprueck, P., & Lee, W. J. (2015, May). A linear program for system level control of regional PHEV charging stations. *2015 IEEE Industry Applications Society Annual Meeting*. (2046-2052). IEEE.

Lambert, F. (2016). *Norway keeps electric vehicle tax exemption until 2020, positions itself to stay EV leader*. Electrek. https://electrek.co/2016/11/09/norway-keeps-electric-vehicle-tax-exemption-until-2020-positions-itself-to-stay-ev-leader/. Accessed September 16, 2017.

Lamontagne, S., Carvalho, M., Frejinger, E., Gendron, B., Anjos, M. F., & Atallah, R. (2022). Optimising Electric Vehicle Charging Station Placement using Advanced Discrete Choice Models. ArXiv:2206.11165 [Math]. http://arxiv.org/abs/2206.11165.

Li, J., Xie, C., & Bao, Z. (2022). Optimal en-route charging station locations for electric vehicles: A new modeling perspective and a comparative evaluation of network-based and metanetwork-based approaches. *Transportation Research Part C: Emerging Technologies, 142*, Article 103781.

Li, W., Zhang, T., & Wang, R. (2018). In *May). Energy management model of charging station micro-grid considering random arrival of electric vehicles* (pp. 29–34). IEEE.

Li, W., Zhang, T., Wang, R., Huang, S., & Liang, J. (2023). Multimodal multi-objective optimization: Comparative study of the state-of-the-art. *Swarm and Evolutionary Computation, 101253*.

Lin, C.-F., LeBoulluec, A. K., Zeng, L., Chen, V. C. P., & Gatchel, R. J. (2014). A Decision-Making Framework for Adaptive Pain Management. *Health Care Management Science, 17*(3), 270–283. https://doi.org/10.1007/s10729-013-9252-0

Lin, W., & Hua, G. (2015). In *July). The flow capturing location model and algorithm of electric vehicle charging stations* (pp. 1–6). IEEE.

Ma, J., & Zhang, L. (2018). A Deploying Method for Predicting the Size and Optimizing the Location of an Electric Vehicle Charging Stations. *Information, 9*(7), 170. https://doi.org/10.3390/info9070170

Mak, H. Y., Rong, Y., & Shen, Z. J. M. (2013). Infrastructure planning for electric vehicles with battery swapping. *Management science, 59*(7), 1557–1575. https://doi.org/10.1287/mnsc.1120.1672

MATLAB. (2016). The Math Works, Inc., 2016. (Version 2016a) https://www.mathworks.com/.

Miller, A., & Lumby, B. (2012). *Utility scale solar power plants: A guide for developers and investors*. World Bank Group, New Delhi, India: Guidelines book written for IFC.

Minitab, LLC. (2016) *Salford Predictive Modeler v8.0 (Version 8.0)*. https://www.salford-systems.com/products/.

Mirheli, A., & Hajibabai, L. (2022). Hierarchical optimization of charging infrastructure design and facility utilization. *IEEE Transactions on Intelligent Transportation Systems, 23*(9), 15574–15587.

Murtagh, B. A., & Saunders, M. A. (1977). *MINOS*. A large-scale nonlinear programming system (for problems with linear constraints): User's guide. Defense Technical Information Center. https://doi.org/10.21236/ada044906.

National Renewable Energy Laboratory. (2012). National solar radiation data base Accessed July 26, 2016 http://rredc.nrel.gov/solar/old_data/nsrdb/.

Paganini, F., Espíndola, E., Marvid, D., & Ferragut, A. (2022). December). Optimization of spatial infrastructure for EV charging. In *In 2022 IEEE 61st Conference on Decision and Control (CDC)* (pp. 5035–5041).

Park, C. J., Lee, J., Park, G. L., & Hyun, J. S. (2014). Development of reservation recommendation algorithms for charging electric vehicles in smart-grid cities. *International Journal of Smart Home, 8*(1), 113–122. https://doi.org/10.14257/ijsh.2014.8.1.12

Pilla, V. L., Rosenberger, J. M., Chen, V. C. P., & Smith, B. (2008). A statistical computer experiments approach to airline fleet assignment. *IIE Transactions, 40*(5), 524–537. https://doi.org/10.1080/07408170701759734

Sacks, J., Welch, W. J., Mitchell, T. J., & Wynn, H. P. (1989). Design and analysis of computer experiments. *Statistical science, 4*(4), 409–423.

Sadeghi Ahangar, S., Abazari, S. R., & Rabbani, M. (2022). A region-based model for optimizing charging station location problem of electric vehicles considering disruption - A case study. *Journal of Cleaner Production, 336*, Article 130433. https://doi.org/10.1016/j.jclepro.2022.130433

Sánchez, D. G., Tabares, A., Faria, L. T., Rivera, J. C., & Franco, J. F. (2022). A Clustering approach for the optimal siting of recharging stations in the electric vehicle routing problem with time windows. *Energies, 15*(7), 2372.

Shih, D. T., Kim, S. B., Chen, V. C. P., Rosenberger, J. M., & Pilla, V. L. (2014). Efficient computer experiment-based optimization through variable selection. *Annals of Operations Research, 216*(1), 287–305. https://doi.org/10.1007/s10479-012-1129-y

Siddappa, S., Günther, D., Rosenberger, J. M., & Chen, V. C. P. (2007). Refined experimental design and regression splines method for network revenue management. *Journal of Revenue and Pricing Management, 6*(3), 188–199. https://doi.org/10.1057/palgrave.rpm.5160086

Soltani, N. Y., Kim, S. J., & Giannakis, G. B. (2014). Real-time load elasticity tracking and pricing for electric vehicle charging. *IEEE Transactions on Smart Grid, 6*(3), 1303–1313.

Sule, N. V., Chen, V., & Sattler, M. (2011). A decision-making framework for assessing control strategies for ground level ozone. *Atmospheric Environment, 45*(28), 4996–5004. https://doi.org/10.1016/j.atmosenv.2011.05.070

Tan, J., & Lin, W. H. (2014). In *October). A stochastic flow capturing location and allocation model for siting electric vehicle charging stations* (pp. 2811–2816). IEEE.

Tang, Z. C., Guo, C. L., Hou, P. X., Fan, Y. B., & Jia, D. M. (2013). Optimal planning of electric vehicle charging stations location based on hybrid particle swarm optimization. *Advanced Materials Research, 724–725*, 1355–1360. https://doi.org/10.4028/www.scientific.net/amr.724-725.1355

Tsai, J. C. C., Chen, V. C. P., Beck, M. B., & Chen, J. (2004). Stochastic dynamic programming formulation for a wastewater treatment decision-making framework. *Annals of Operations Research, 132*(1–4), 207–221. https://doi.org/10.1023/b:anor.0000045283.86576.62

U.S. Department of Energy. (2012). *Electric Power Monthly March 2012 (with Data for January 2012)*. http://www.eia.gov/cneaf/electricity/epm/epm_sum.html. Accessed August 12, 2016.

Vazifeh, M. M., Zhang, H., Santi, P., & Ratti, C. (2019). Optimizing the deployment of electric vehicle charging stations using pervasive mobility data. *Transportation Research Part A: Policy and Practice, 121*, 75–91. https://doi.org/10.1016/j.tra.2019.01.002

Wetz, D. (2010). *Energy storage needs and options*. Renewable Energy Sources: The University of Texas at Arlington.

Wu, T. H., Pang, G. K., Choy, K. L., & Lam, H. Y. (2015). In *June). An optimization model for a battery swapping station in Hong Kong* (pp. 1–6). IEEE.

Yang, L., Chen, J., Li, W., & Wen, Z. (2021). Research on optimizing the location and capacity of electric vehicle charging stations. lecture notes of the institute for computer sciences. *Social Informatics and Telecommunications Engineering, 76–90*. https://doi.org/10.1007/978-3-030-77569-8_6

Yang, Z., Chen, V. C. P., Chang, M. E., Sattler, M. L., & Wen, A. (2009). A decision-making framework for ozone pollution control. *Operations Research, 57*(2), 484–498. https://doi.org/10.1287/opre.1080.0576

Yudovina, E., & Michailidis, G. (2015). Socially optimal charging strategies for electric vehicles. *IEEE Transactions on Automatic Control, 60*(3), 837–842. https://doi.org/10.1109/tac.2014.2346089

You, P., Yang, Z., Chow, M. Y., & Sun, Y. (2015). Optimal cooperative charging strategy for a smart charging station of electric vehicles. *IEEE Transactions on Power Systems, 31*(4), 2946–2956.

Zhang, C., Peng, K., Zhang, X., Jiang, Y., Liu, Y., & Cai, Y. (2023). A robust optimal dispatching strategy of distribution networks considering fast charging stations integrated with photovoltaic and energy storage. *Frontiers in Energy Research, 11*. https://doi.org/10.3389/fenrg.2023.1126295