

Electric Vehicle Charging Station Expansion Plans Under Uncertainty

By

Mohammad Marufuzzaman

Department of Industrial and Systems Engineering

Mississippi State University (MSU), Miss. State, 39762

Phone: (662)-312-5987

Email: maruf@ise.msstate.edu

John M. Usher

Department of Industrial and Systems Engineering

Mississippi State University (MSU), Miss. State, 39762

Phone: (662) 325-7624

Email: usher@ise.msstate.edu

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ABSTRACT

With the advancement of battery technologies, more electric vehicles are expected to get introduced in the market. The energy needed to run those batteries is enormous. This calls for developing optimization models that help governments plan for energy expansion and to coordinate the efforts between energy suppliers and charging station investors. To supply this need, in this paper we propose a two-stage stochastic mixed-integer programming (MIP) formulation to establish a dynamic multi-period plan that maximizes the expected monetary return from expanding power cells to electric vehicle charging stations over a pre-specified planning horizon. We propose a Sample Average Approximation (SAA) algorithm to solve our proposed optimization model. We choose Washington, DC as a testing ground to visualize and validate the modeling results.

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INTRODUCTION

Nowadays, electric vehicles (EV) are shaping the future of transportation, as the advances in batteries storage capabilities allow a car like the Tesla S model to travel almost 300 miles on a single charge, compared to the more popular Nissan leaf, which can travel only 85 miles. This breakthrough makes electric cars more realistic and feasible than ever before. It is one of the alternatives that is hoped to become the substitute for fossil fuel, which is scarce and harmful to the environment. The use of EV leads to an increase in the the energy requirements, which call for plans to expand the infrastructure. According to Washington State's Department of Transportation, a total of 228,725 kWh of energy were supplied to charge EV cars between 2012 and 2015, which is equivalent to 22,397 gallons of gas [1].

As the adoption rate of EV is expected to increase, the need for more charging stations is apparent. In 2029, it is expected that the load from EVs will reach 107 aMW [2]. Hence, preparations should be made in advance to be ready to cover the power requirements. The main reason of this work is to provide decision makers at electric utilities and charging stations' investors a tool that helps in coordinating the efforts and to better plan for the imminent increase in EV cars. It makes decisions regarding where to expand power, and based on that it decides where to locate charging stations. Several papers in literature addressed the problem of locating charging stations. Wang & Lin [3] propose a mixed integer program that locates charging stations using a flow-based set covering. The objective is to minimize costs of locating the charging stations. They are located at the shortest paths to cover all demand from traveling flow of cars. Using grid partition method, the location and size of each charging station is determined and the location of each partition is found using Genetic Algorithm by Ge, Feng, & Liu [4]. The aim is to minimize the direct and indirect travel losses to the charging station while considering traffic density and station's capacity limitations. MirHassani & Ebrazi [5] present mixed integer linear programming based on the flow refueling location model (FRLM) that developed by Kuby & Lim [6]. The main idea of FRLM is to locate several charging stations in a long round trip using maximum cover. The paper extends on the FRLM by considering more assumptions like driver behavior, which produced solutions faster than FRLM. Likewise, Chung & Kwon [7] develop a multi period planning of constructional plan of charging stations based on the FRLM using three different methods: a multi period optimization, a forward myopic method, and a backward myopic method. He, Venkatesh, & Guan [8] present two schemes: a global optimal schedule that minimizes the costs of for all EVs in a day by deciding the optimal charging and discharging of power, and a local optimal schedule to minimize total EV costs within a sub group. Bayram et al. [9] considers charging stations provided with power storage units to alleviate stochastic demand. The main goal is to

provide electricity from grid to the storage units and reroute customers to different stations. Stochastic models are proposed to achieve these objectives. A simulation-optimization model is proposed by Xi, Sioshansi, & Marano [10] to locate charging stations so as to maximize their utilization. There are three steps presented to attain this objective. The first is to get the volume of flow for EV cars. Then a simulation model is utilized to determine the number of cars successfully finishing a charge at a station. Finally, a linear programming model is given to decide the sizing and location of each charging station. Wang & Lin [11] extends the work of Watson & Woodruff [12] by taking into consideration several constraints, like facility budget, types of stations, and possible rerouting of EVs. In [13], an optimal control strategy for a charging station equipped with a power storage, integrated EVs, and sources of renewable energy is provided using a multi period mixed linear integer programming model. The objective is to maximize economic benefits by determining power levels in storage units and charging and discharging power of EV. A stochastic chance-constrained programming model is also given assuming uncertainty in demand and power generation, EV state of charge, and the times of connection and disconnection.

To the best of the author's knowledge, none of the prior studies modeled the feasibility of locating EV charging stations based on electricity grid power availability. Moreover, there are very limited studies that consider system uncertainties such as EV adoption rates, EV flow rate, and charging capacity that often impact the location and routing decisions of electric vehicles. To fill this gap in the literature, this paper introduces a novel two-stages stochastic programming model that helps governments in planning for power expansion in anticipation of the imminent growth in EV adoption rates, which will lead to an increase in the demand of energy from charging stations. The model decides in the first stage the areas where it is best to expand power at based on the flow of cars per year at the roads in that area, and in the second stage, the decisions for locating the charging stations are made. The outcome of this study provides a number of managerial insights such as optimal expansion decision of power grid and deployment of charging stations decision under limited budget availability, which can effectively aid decision makers to design a robust network to adopt electric vehicles in a given region.

OBJECTIVE

This study develops a two-stage stochastic programming model which takes into account the uncertainty in both the adoption rates and charging behavior of geographic regions. Further, we consider the important links between the power and transportation systems by ensuring that electric vehicle charging stations are only installed where there is a sufficient power support. In addition to proposing the general model, another important contribution of this paper is applying this model to a real-world case study. We use Washington, DC as a testing ground in our case study. This region possesses a number of favorable factors (e.g., high income and dense population) that are likely to attract intensive electric vehicle infrastructure investment in the future. We solve the two-stage stochastic program using a Sample Average Approximation algorithm and present the computational efficiency to solve the proposed model by using this algorithm.

METHODOLOGY

This section presents a two-stage stochastic programming model formulation to establish a dynamic multi-period plan that maximizes the expected monetary return from expanding power cells and electric vehicle charging stations over a pre-specified planning horizon under electricity demand uncertainty. For the convenience of the readers, the mathematical notation is summarized in Table 1.

Table 1 Description of the sets, parameters and variables used in this study

Notation	Description
Sets	
I	Set of rows
J	Set of columns
I_i	Set of neighboring rows of row $i \in I$
J_j	Set of neighboring columns of column $j \in J$
T	Set of time periods
S	Set of capacities for charging stations
Ω	Set of scenarios
Parameters	
ξ_{ijt}	Fixed cost of expanding power in cell $(i, j) \in (I, J)$ in time period $t \in T$
μ_{ijt}	Expected profit from car traffic in dollars for cell $(i, j) \in (I, J)$ in time period $t \in T$
M_t^p	Budget availability for expansion in time period $t \in T$
f_{ijt}	Flow (cars/time period) at cell $(i, j) \in (I, J)$ in time period $t \in T$
φ_{st}	Cost of opening a charging station of size $s \in S$ in time period $t \in T$
M_t^c	Budget availability for locating charging stations in time period $t \in T$
c_{ijklt}^r	Cost of reallocating power to a charging station located at cell $(i, j) \in (I, J)$ from cell $(k, l) \in (I_i, J_j)$ in time period $t \in T$
ψ_{ijklt}	Expected income (in \$/kWh) obtained from reallocating power to a charging station located at cell $(i, j) \in (I, J)$ from cell $(k, l) \in (I_i, J_j)$ in time period $t \in T$
d_{ijt}^ω	Power demand (in kWh) at a charging station located in cell $(i, j) \in (I, J)$ in time period $t \in T$ under scenario $\omega \in \Omega$
\bar{c}_{ijs}	Capacity (in kWh) of a charging station of size $s \in S$ located in cell $(i, j) \in (I, J)$
γ_{ijt}	Minimum utilization required for a charging station located at cell $(i, j) \in (I, J)$ in time period $t \in T$
\bar{r}_{ijt}	Amount of residual power available at cell $(i, j) \in (I, J)$ in time $t = 1$
α_t	Percentage of car charged in time period $t \in T$
β	Unit power requirement for each car
ρ_ω	probability of scenario $\omega \in \Omega$
Decision variables	
A_{ijt}	1 if cell $(i, j) \in (I, J)$ is selected for power expansion in time period $t \in T$; 0

	otherwise
Y_{ijst}^ω	1 if a charging station of size $s \in S$ is open at cell $(i, j) \in (I, J)$ in time period $t \in T$ under scenario $\omega \in \Omega$; 0 otherwise
B_{ijklt}^ω	Amount of power transferred from cell $(k, l) \in (I_i, J_j)$ to cell $(i, j) \in (I, J)$ in time period $t \in T$ under scenario $\omega \in \Omega$
R_{ijt}^ω	Amount of power remaining at cell $(i, j) \in (I, J)$ in time period $t \in T$ under scenario $\omega \in \Omega$

Model Formulation

In the two-stage stochastic programming model formulation, the first stage decides the electric power capacity expansion decision to support the installation of charging station in the second stage. We consider the area for this study is divided into a square grid and the parameters of the mathematical model are defined for each cell in the grid. The cells are referred to through their respective row and column number. Due to the nature of the problem's constraints, dummy rows and columns are added above, below, to the right, and to the left of the grid. This is done to insure the validity of some constraints. The values of parameters in those cells are set so that they do not affect the solution of the model. We define $I = \{2, \dots, |I| - 1\}$ as the set of candidate rows and $J = \{2, \dots, |J| - 1\}$ as the set of candidate columns for possible power expansion of electric vehicle charging stations over a set of time periods $t \in T$. Each cell $(i, j) \in (I, J)$ referred to by its respective row i and column number j . We further define I_i (indexed by $k \in I_i$) and J_j (indexed by $l \in J_j$) be the neighboring cells of a selected cell $(i, j) \in (I, J)$ where $(l, k) \neq (i, j)$. For each cell $(i, j) \in (I, J)$, f_{ijt} denote the expected number of cars that will in a given time period $t \in T$. We assume that this flow generates a profit of μ_{ijt} for the charging stations, if a station is located at cell $(i, j) \in (I, J)$ in time period $t \in T$. We represent ξ_{ijt} as fixed investment cost of locating a charging station at $(i, j) \in (I, J)$ in time $t \in T$. We assume that M_t^p define as the budget availability to select cells for expanding power for electric vehicle charging stations in a given time period $t \in T$. The model is designed so that if a cell is selected, a set of surrounding cells to the selected cell are prohibited from being chosen for power expansion to ensure the sparsity of the charging stations. We feel this is necessary at the early stages of building the infrastructure for EV, since the adoption rate of EV cars increase steadily. Sparsity insure that the covering of demand will not be exaggerated. It is assumed that if a cell is selected, the expanded power is enough for the expected flow of cars.

The objective of the second stage is to maximize the expected profits of reallocating power from adjacent cells. The stochastic element in the second stage is demand denoted by d_{ijt}^ω (in kWh), and this is due to the uncertainty in the amount of energy drawn by EV owners at the charging stations. Let Ω be the set of scenarios of different realization of power demand for the charging stations located in cell $(i, j) \in (I, J)$ at a given time period $t \in T$ and $\omega \in \Omega$ defines a particular realization. Let φ_{st} denote the cost of opening a charging station of size

$s \in S$ in time period $t \in T$, and at that time period, we are given a budget M_t^c to open the charging stations. Since decisions for power expansion are based on the current observed flow, the demand may increase when the charging stations are built. In that case, we assume that the amount of power may transfer from cell $(k, l) \in (I_i, J_j)$ to cell $(i, j) \in (I, J)$ in time period $t \in T$ under scenario $\omega \in \Omega$ by incurring a reallocation cost of c_{ijklt}^r . This in turn will increase the income (in \$/kWh) of a charging station by serving additional customers visited at cell $(i, j) \in (I, J)$ in time period $t \in T$ and is denoted by ψ_{ijklt} . It is worth to note here that the cells will also have the option to retain their excess energy which they can use in remaining time periods. Additionally we make following assumptions to simplify our modeling approach without the loss of generality:

- Demand is assumed to be equal or larger than the demand from flow of cars at the first stage.
- Demand is increasing at all cells as time periods increase.
- Grid power is available all the time.
- All charging stations will be of fast charging DC chargers. This assumption is made to ensure the ability to meet the demand.

We now introduce the following first and second-stage decision variables for our two-stage stochastic programming model formulation. The first-stage decision variables $\mathbf{A} := \{A_{ijt} | (i, j) \in (I, J), t \in T\}$, select the set of cells for possible power expansion of electric vehicle charging stations in a given time period t . The first set of second-stage decision variables $\mathbf{Y} := \{Y_{ijst} | (i, j) \in (I, J), s \in S, t \in T, \omega \in \Omega\}$ select the size, cell, and time to open a charging station in a given scenario.

The other second-stage decision variables include $\mathbf{B} := \{B_{ijklt}^\omega | (i, j) \in (I, J), (k, l) \in (I_i, J_j), t \in T, \omega \in \Omega\}$ denote the amount of power transferred from cell $(k, l) \in (I_i, J_j)$ to cell $(i, j) \in (I, J)$ in time period $t \in T$ under scenario $\omega \in \Omega$ and $\mathbf{R} := \{R_{ijt}^\omega | (i, j) \in (I, J), t \in T, \omega \in \Omega\}$ denote the amount of power remaining at cell $(i, j) \in (I, J)$ in time period $t \in T$ under scenario $\omega \in \Omega$. The following is a two-stage stochastic mixed-integer linear programming (MILP) model formulation of the problem referred to as model [EVC]:

$$[\text{EVC}] \underset{\mathbf{A}}{\text{Maximize}} \sum_{(i,j) \in (I,J)} \sum_{t \in T} \mu_{ijt} A_{ijt} + \sum_{\omega \in \Omega} \rho_\omega Q(\mathbf{A}, \omega) \quad (1)$$

Subject to

$$\sum_{(i,j) \in (I,J)} \xi_{ijt} A_{ijt} \leq M_t^p \quad \forall t \in T \quad (2)$$

$$A_{ijt-1} \leq A_{ijt} \quad \forall (i, j) \in (I, J), t \in T \quad (3)$$

$$\sum_{k=i-1}^{i+1} \sum_{l=j-1}^{j+1} A_{klt} \leq 1 \quad \forall (i, j) \in (I, J), t \in T \quad (4)$$

$$A_{ijt} \in \{0,1\} \quad \forall (i, j) \in (I, J), t \in T \quad (5)$$

With $Q(A, \omega)$ being the solution of the following second-stage problem:

$$Q(A, \omega) = \underset{B, Y, R}{\text{Maximize}} \sum_{(i,j) \in (I,J)} \sum_{(k,l) \in (I_i, J_j), (k,l) \neq (i,j)} \sum_{t \in T} (\psi_{ijklt} - c_{ijklt}^r) B_{ijklt}^\omega \quad (6)$$

Subject to

$$\sum_{(i,j) \in (I,J)} \sum_{s \in S} \varphi_{st} Y_{ijst}^\omega \leq M_t^c \quad \forall t \in T, \omega \in \Omega \quad (7)$$

$$Y_{ijst-1}^\omega \leq Y_{ijst}^\omega \quad \forall (i, j) \in (I, J), s \in S, t \in T, \omega \in \Omega \quad (8)$$

$$\frac{d_{ijt}^\omega A_{ijt}}{c_{ijs}} \geq \gamma_{ijt} Y_{ijst}^\omega \quad \forall (i, j) \in (I, J), s \in S, t \in T, \omega \in \Omega \quad (9)$$

$$\sum_{k=i-1, k \neq i}^{i+1} \sum_{l=j-1, l \neq j}^{j+1} B_{ijklt}^\omega \leq R_{ijt}^\omega \quad \forall (i, j) \in (I, J), t \in T, \omega \in \Omega \quad (10)$$

$$R_{ijt-1}^\omega - \sum_{k=i-1, k \neq i}^{i+1} \sum_{l=j-1, l \neq j}^{j+1} B_{ijklt}^\omega = R_{ijt}^\omega \quad \forall (i, j) \in (I, J), t \in T, \omega \in \Omega \quad (11)$$

$$R_{ijt}^\omega = pr_{ijt} \quad \forall (i, j) \in (I, J), t = 1, \omega \in \Omega \quad (12)$$

$$\max\{d_{ijt}^\omega - \beta \alpha_t f_{ijt}, 0\} A_{ijt} \geq \sum_{k=i-1, k \neq i}^{i+1} \sum_{l=j-1, l \neq j}^{j+1} B_{ijklt}^\omega \quad \forall (i, j) \in (I, J), t \in T, \omega \in \Omega \quad (13)$$

$$\sum_{s \in S} Y_{ijst}^\omega \leq 1 \quad \forall (i, j) \in (I, J), t \in T, \omega \in \Omega \quad (14)$$

$$Y_{ijst}^\omega \in \{0,1\} \quad \forall (i, j) \in (I, J), s \in S, t \in T, \omega \in \Omega \quad (15)$$

$$B_{ijklt}^\omega \geq 0 \quad \forall (i, j) \in (I, J), (k, l) \in (I_i, J_j), t \in T, \omega \in \Omega \quad (16)$$

$$R_{ijt}^\omega \geq 0 \quad \forall (i, j) \in (I, J), t \in T, \omega \in \Omega \quad (17)$$

In [EVC], the objective function (1) is the sum of the first-stage profits and the expected second-stage profits. The first-stage profits maximize the monetary return from flow that the charging stations may get by expanding power in a given cell $(i, j) \in (I, J)$ in time period $t \in T$. Budget is an important aspect in any project. Constraints (2) is given here because it is usually necessary to be accounted for. It limits the number of cells that can be selected in a given time period $t \in T$ with a pre-specified budget M_t^p . Constraints (3) ensure that if power is expanded into a cell at time period $t - 1$ then it will still be selected in the subsequent periods $t \in T$. Constraints (4) ensure that the distribution of charging stations around a selected cell $(i, j) \in (I, J)$ is sparse and prevents a set of surrounding cells to the selected cell from being chosen for power expansion. Constraints (5) set the binary restrictions for the first-stage decision variables.

In the second-stage, the objective function (6) maximizes the monetary return of rerouting power to cover extra demand. Constraints (7) limit the number of charging stations that can be opened in a given time period $t \in T$ with a pre-specified budget M_t^c . Constraints (8) indicate that if a charging station is opened in an earlier time period, it will still remain open in the subsequent time periods. Constraints (9) indicate that a charging station is open only if the expected utilization is attractive for the investors. Constraints (10) ensure that the power rerouted is no more what is available. Since power can be drawn from adjacent cells as necessary, the remaining amount should be monitored. Constraints (11) assign the remaining power after reallocation to the next time period. Constraints (12) indicate that the residual power at the first period is initialized with the parameter \bar{p}_{ij1} , which is the amount of residual power available at the beginning. If the demand is more than the expected flow, power from adjacent cells $(k, l) \in (I_i, J_j)$ can be rerouted to the selected cell $(i, j) \in (I, J)$ to fulfill the unaccounted for increase in demand which is denoted by constraints (13). Constraints (14) indicate that at most one charging station of size $s \in S$ is opened in a given cell $(i, j) \in (I, J)$ in time period $t \in T$ under scenario $\omega \in \Omega$. Finally, constraints (15) set the binary restrictions and (16), (17) are the standard non-negativity constraints.

Solution Algorithm

This section presents the solution technique used to solve the model [EVC]. Note that by setting $|\Omega| = 1$ and $|T| = 1$ i.e., a single scenario and a single time period, we can show that the problem [EVC] is a special case of a capacitated facility location problem which is known to be an *NP*-hard problem [14]. When the number of scenarios in our stochastic program model are too large, commercial solvers, such as CPLEX, cannot solve the large-scale instances of this problem. To overcome this computational challenging problem, in this section we propose a sampling based algorithm which is known as Sample Average Approximation method (SAA) to solve the problem. The aim is to generate high quality solution for the problem in a reasonable amount of time.

Sample Average Approximation

The two-stage stochastic program is challenging to solve by exact solution techniques and commercial solvers, such as CPLEX fails to solve even a moderate size of this problem. Therefore, SAA method is employed to reduce the computational burden to solve our problem. With the SAA approach, the objective function is approximated through a random sample of scenarios. SAA is used extensively to solve large scale supply chain network flow related problems, such as [15], [16] and others. Interested readers may refer to review the works from Kleywegt et al. [17] for the proof of convergence properties of SAA. In SAA, a sample $\omega^1, \omega^2, \dots, \omega^N$ of N realization of the random vector ω is generated from Ω according to a probability distribution P and they are solved repeatedly until a pre-specified tolerance gap is achieved. After the scenarios are generated (e.g., N scenarios), problem [EVC] is estimated by following SAA problem:

$$\underset{a \in A}{\text{Maximize}} \quad \{\hat{g}(A) := \sum_{(i,j) \in (I,J)} \sum_{t \in T} \mu_{ijt} A_{ijt} + \frac{1}{N} \sum_{n=1}^N Q(A,n)\} \quad (18)$$

As the sample size increases the optimal solution of (18), \tilde{A}_N , and the optimal value v_N , converges with probability one to an optimal solution of the original problem [EVC] [17]. The following steps briefly summarize the Sample Average Approximation (SAA) technique to solve problem [EVC].

1. Generate M independent demand scenarios of size N i.e., $\{d_m^1(\omega), d_m^2(\omega), \dots, d_m^N(\omega)\}, \forall m = 1, \dots, M$ where $d = \{d_{ijt}^\omega, \forall (i,j) \in (I,J), t \in T, \omega \in \Omega\}$ and solve the corresponding SAA:

$$\underset{a \in A}{\text{Maximize}} \quad \{\hat{g}(A) := \sum_{(i,j) \in (I,J)} \sum_{t \in T} \mu_{ijt} A_{ijt} + \frac{1}{N} \sum_{n=1}^N Q(A,n)\} \quad (20)$$

The optimal objective value is denoted by v_N^m and the optimal solution by $\hat{A}_N^m, m = 1, \dots, M$.

2. Compute the average of the optimal solutions obtained by solving all SAA problems, \bar{v}_M^N and variance, $\sigma_{\bar{v}_M^N}^2$:

$$\bar{v}_M^N = \frac{1}{M} \sum_{m=1}^M v_N^m \quad (21)$$

where, \bar{v}_M^N provides a statistical upper bound on the optimal objective function value v^* for the original problem defined by (1)-(17). Since M samples are generated and $v_N^1, v_N^2, \dots, v_N^M$ are independent, the variance of \bar{v}_M^N is given by:

$$\sigma_{\bar{v}_M^N}^2 = \frac{1}{(M-1)M} \sum_{m=1}^M (v_N^m - \bar{v}_M^N)^2 \quad (22)$$

3. Pick a feasible first-stage solution $\tilde{A} \in A$ obtained from **Step 1** of the SAA algorithm, i.e., one of the solutions from \hat{A}_N^m and estimate the objective function value of the original problem [EVC] using a reference sample N' as follows:

$$\tilde{g}_{N'}(\tilde{A}) := \sum_{(i,j) \in (I,J)} \sum_{t \in T} \mu_{ijt} A_{ijt} + \frac{1}{N'} \sum_{n=1}^{N'} Q(A,n) \quad (23)$$

The estimator $\tilde{g}_{N'}(\tilde{A})$ serves as a lower bound for the optimal objective function value of problem [EVC]. We now generate a large set of power demand scenarios (N') i.e., $\{d^1(\omega), d^2(\omega), \dots, d^{N'}(\omega)\} \forall n = 1, \dots, N'$. Typically, sample size N' is chosen much larger than the sample size N in the SAA problems i.e., $N' \gg N$. We can estimate the variance of $\tilde{g}_{N'}(\tilde{A})$ as follows:

$$\sigma_{N'}^2(\tilde{A}) := \frac{1}{(N'-1)N'} \sum_{n=1}^{N'} \left\{ \sum_{(i,j) \in (I,J)} \sum_{t \in T} \mu_{ijt} \tilde{A}_{ijt} + Q(A,n) - \tilde{g}_{N'}(\tilde{A}) \right\}^2$$

4. Compute the optimality gap ($gap_{N,M,N'}(\tilde{A})$) and its variance (σ_{gap}^2) using the estimators calculated in **Steps 2** and **3**.

$$gap_{N,M,N'}(\tilde{A}) = \bar{v}_M^N - \tilde{g}_{N'}(\tilde{A})$$

$$\sigma_{gap}^2 = \sigma_{N'}^2(\tilde{A}) + \sigma_{\bar{v}_M^N}^2$$

The confidence interval for the optimality gap is then calculated as follows:

$$\bar{v}_M^N - \tilde{g}_{N'}(\tilde{A}) + z_\alpha \{ \sigma_{N'}^2(\tilde{A}) + \sigma_{\bar{v}_M^N}^2 \}^{1/2}$$

with $z_\alpha := \Phi^{-1}(1 - \alpha)$, where $\Phi(z)$ is the cumulative distribution function of the standard normal distribution.

DISCUSSION OF RESULTS

This section conducts numerical studies to test the proposed model and draw relevant managerial insights. We have chosen Washington DC as a testing ground for this study. The following subsections first describe the input parameters used in this study, then conducts a computational study on model [EVC] and present results from the case study and draw managerial insights and finally we present the performance of the algorithms.

We selected Washington DC for our case study in which we apply the model. The reason behind choosing Washington DC is that the city offers incentives to own EV cars and the adoption rate is high. The map is divided into a grid of size 50×46 cells (i.e., $|I| = 50, |J| = 46$) including the dummy ones mentioned earlier. Each cell is approximately 0.5 mile² in area. We have considered five time periods for this study, and they are measured in years starting in 2017 and ending in 2021. All costs are calculated based on 2017 dollars and then adjusted for inflation. The data for cell-specific parameters were obtained only for those that have a road passing through them. The values for parameters for other cells were given a value of zero. The cost of expanding power (ξ_{ijt}) in a given cell $(i, j) \in (I, J)$ is set to \$700,000 [18] and we assume that we are given an annual budget ($M_t^p = \$5M, \$6M, \$7M, \$8M, \text{ and } \$9M$) to expand power for years 2017 - 2021 [18]. Similarly, the construction cost for locating a fast electric vehicle charging station (φ_{st}) in a new location is set to \$50,000 [19]. We investigate three different electric vehicle charging station capacities ($s = 100 \text{ kWh}, 200 \text{ kWh}, \text{ and } 300 \text{ kWh}$). We further assume that we are given an annual budget ($M_t^c = \$400, \$550, \$700, \$850, \text{ and } \$1000$) (in thousand dollars) to build infrastructures for electric vehicle charging stations in our tested region for years 2017 – 2021 [20]. The cost of reallocating power (c_{ijklt}^r) to a charging station located at cell $(i, j) \in (I, J)$ from cell $(k, l) \in (I_i, J_j)$ in time period $t \in T$ is set to \$0.12/kWh [21]. Finally, we set $\mu_{ijt} = \$0.5/\text{kWh}$, $\gamma_{ijt} = 40\%$, $\beta = 10 \text{ kWh}$, and $\alpha_t = 20\%$ for our base case experimentations.

The first experiment studies the impact of budget on power expansion and installing charging station decisions. We conduct four sets of experiments: a) base budget for both M_t^p and M_t^c , (b) M_t^c is increased by 50% while keeping the budget M_t^p fixed, (c) M_t^p is increased by 50% while keeping the budget M_t^c fixed, and (d) both M_t^p and M_t^c are increased by 50%. Figures 1-2 show the deployment of power expansion cells A_{ijt} (represented by “square” symbol in Figures 1-2) and charging stations Y_{ijst}^ω (represented by symbol “circle” in Figures 1-2) for the experiments (a) and (d). From these figures it is observed that the decisions of A_{ijt} and Y_{ijst}^ω are highly impacted by the budgets M_t^p and M_t^c set by the decision makers. It is

observed that the results for experiment (b) show a little progression of selecting charging stations over the base case scenario (shown in Figure 1). This is obvious because in experiment (b) the budget is fixed for the power expansion decision, so the model gets less options to establish the charging station in the second stage. Now, if we increase the power expansion budget by 50% and fixed the charging station budget, then the number of cell for power expansion shows a significant increasing trend, where the charging stations show a little increasing trend (experiment (c)). However, it is important to note that many of the cells selected in the first-stage are eventually not picked for locating charging stations in the second-stage. Finally, Figure 2 shows the results when the budget for both power expansion and charging station increases by 50% over years 2017 - 2021. It is seen that increasing both budgets show a rapid expansion of the number of cells for power expansion and charging stations. We observe some additional charging stations being located far away from the original cluster of stations primarily due to serving the high density of population, hospitals, and colleges located near the stations.

In summary, it is observed that depending on the values of M_t^p and M_t^c set by the decision maker many more cells and charging stations are opened to provide a broader coverage for the electric vehicles. These results provide an insightful ground for decision makers to invest in power expansion to certain regions to maximize profit.

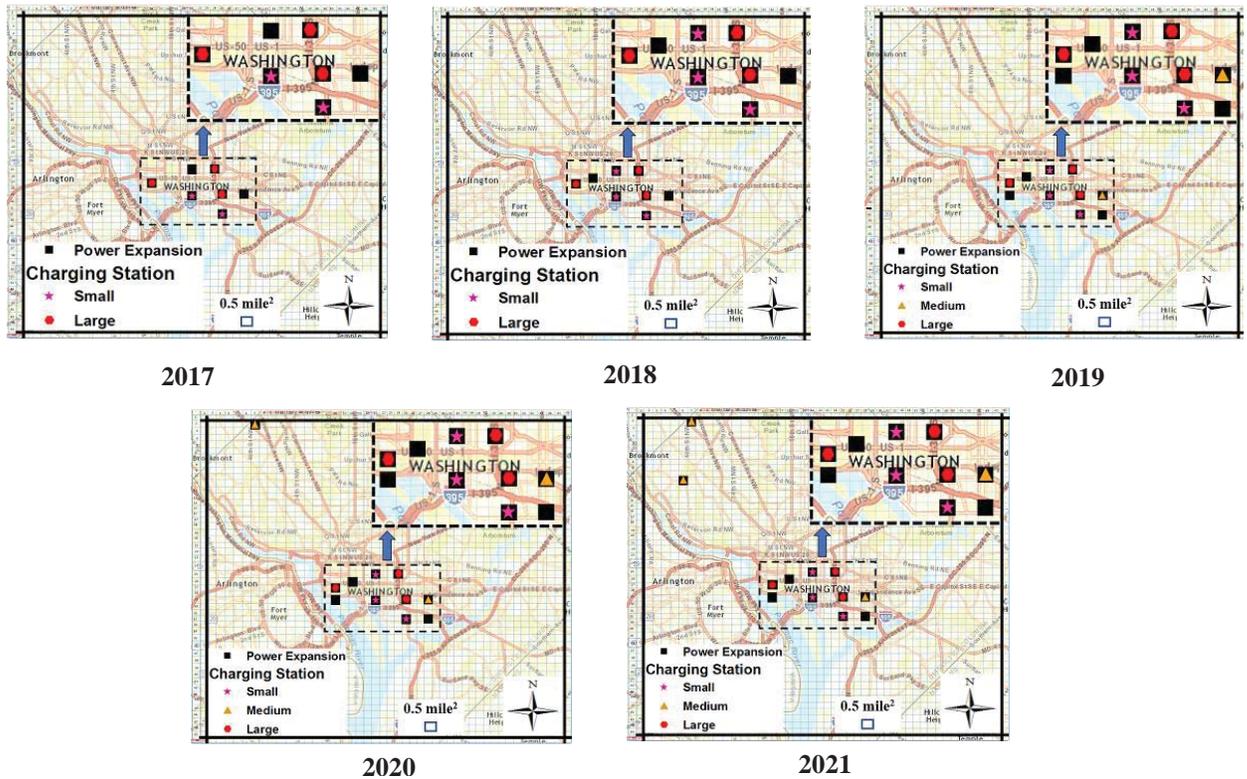


FIGURE 1 Electric vehicle charging station expansion planning under base case scenario.

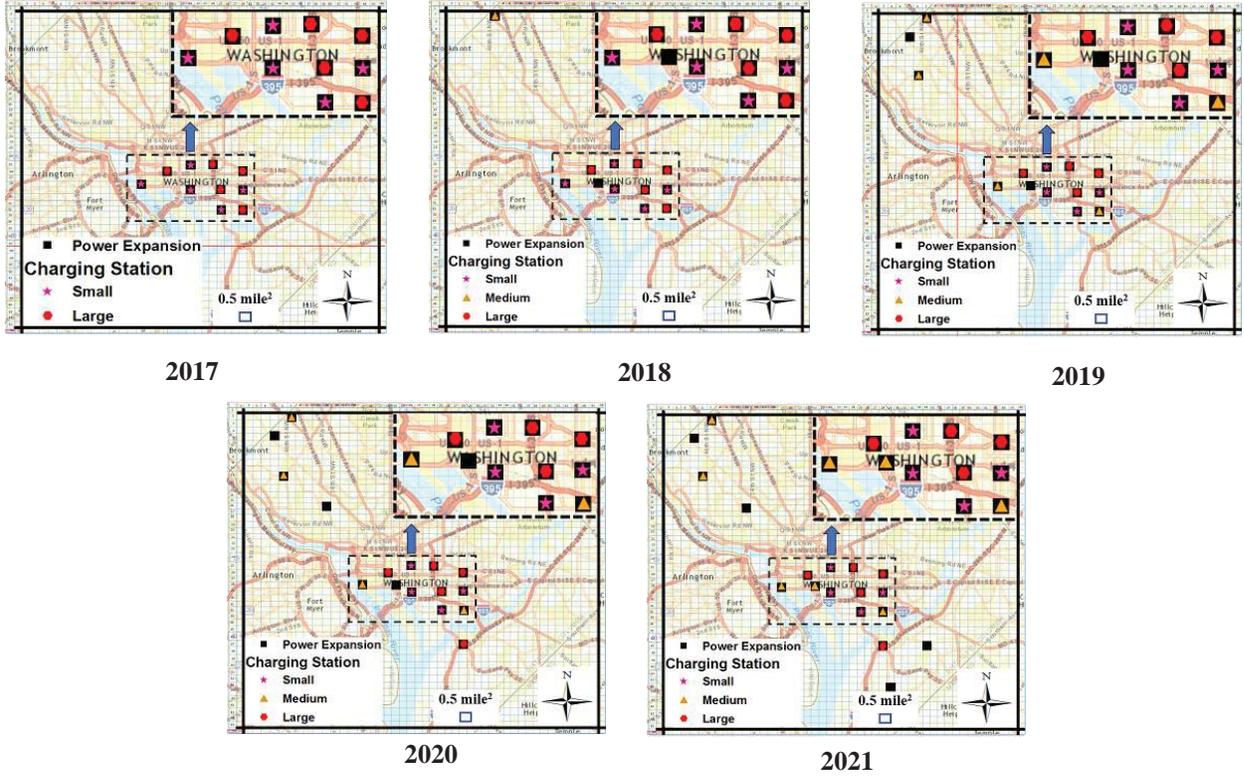


FIGURE 2 Electric vehicle charging station expansion planning under experiment (d).

This section presents the impact of power demand (d_{ijt}^ω) variation on the number of cell selection for power expansion and installing charging station decisions. For our experiment we assume that the power demand follow normal distribution at each cell $(i, j) \in (I, J)$ in time period $t \in T$. We conduct two set of experiments: (a) low power demand variation and (b) high power demand variation. The standard deviation (SD) of power demand is set equal to 0.15 for low power demand variation and 0.50 for high power demand variation. Results indicates that as the level of power demand increases, the number of cell for power expansion and number charging station increases under a specified budget limit. More specifically, the model decides to select more cell for power expansion and charging station of different sizes to cope against the power demand variability and on average the number of cell for power expansion increases by 18.75% and charging station by 35.89%. Figure 3(a) summarizes the number of power expansion cells (PE) and charging stations (CS) opened under low and high demand variabilities. This in turn will have an impact on the amount of power transferred from cell $(i, j) \in (I, J)$ to cell $(k, l) \in (I_i, J_j)$ under scenario $\omega \in \Omega$, as illustrated in Figure 3(b). This implies that the power demand variability level highly impacts the power expansion and establishing charging station decisions.

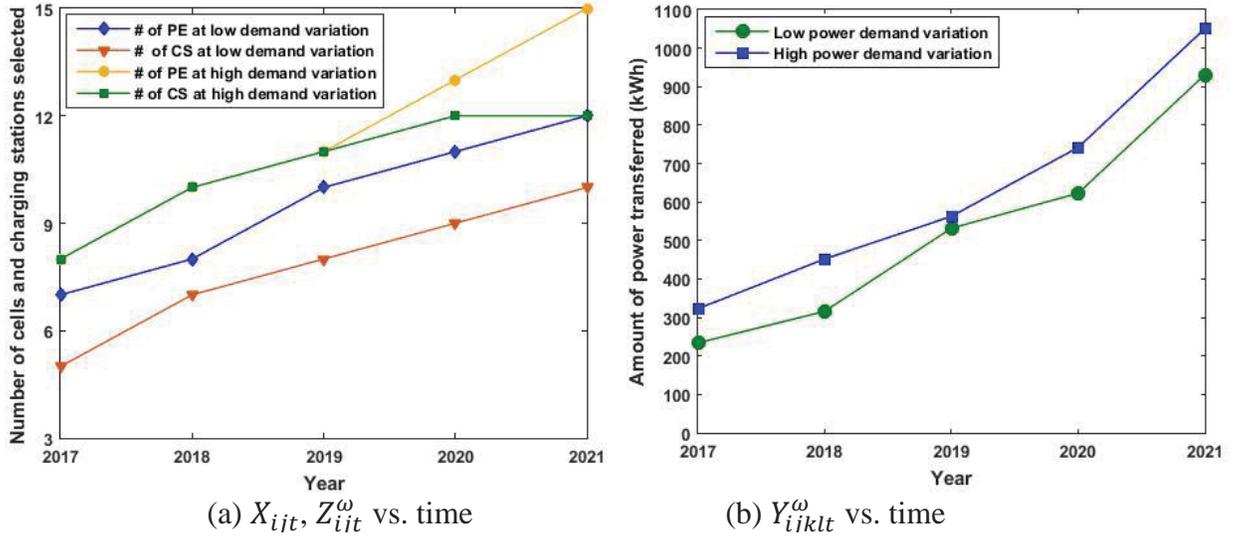


FIGURE 3 Impact of power demand variability on system performance.

We now analyze the impact of car traffic flow, f_{ijt} , on system performance. Figure 4 provides a relationship between charging station opening decisions Y_{ijst}^ω under different f_{ijt} values. Clearly, increasing the flow (f_{ijt}) at each cell $(i, j) \in (I, J)$ in time period $t \in T$ impacts the charging station opening decisions Y_{ijst}^ω under a pre-specified budget restriction. For instance, a 50% increase in f_{ijt} increases the average number of charging stations $|Y|$ by 31.4%.

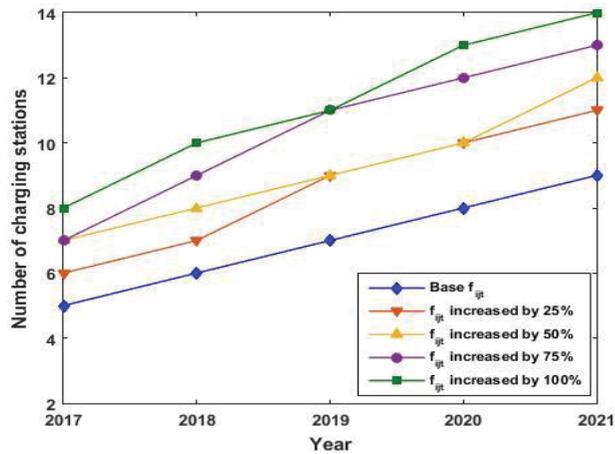


FIGURE 4 Impact of f_{ijt} on locating charging station decisions.

CONCLUSIONS

This study develops a novel optimization framework that can be used to design widespread adoption of electric vehicle charging stations for a pre-specified planning horizon subjected to stochastic power demands. The model can be computationally very challenging depending on the size of the cells, time periods, and scenarios set by the decision maker. To alleviate these challenges and to solve real scale problem instances, we have used Sample Average Approximation (SAA) algorithm.

By using Washington, DC as a testing ground, we conducted thorough computational experiments to test our model and to draw managerial insights. Our computational experiments reveal some insightful results about the impact of cell expansion (M_t^p) and charging station budgets (M_t^c) on electric vehicle adoption performance. We further conduct sensitivity analysis on the impact of power demand (d_{ijt}^ω) variability and vehicle flow rate (f_{ijt}) on system performance. It is observed that the model decides to open an additional 18.75% power expansion cells and 35.89% charging stations to counter high power demand variability over the base case scenario. Moreover, we observe that a 50% increase in vehicle flow f_{ijt} will open an additional 31.4% charging stations in our tested region under a specified budget constraint. We believe our results will be used by energy distribution agencies as well as charging stations investors to understand the growth pattern of EV cars on the road, and take action towards providing services and exploit the economic benefits that comes with it and eventually help to develop a future sustainable transportation system.

RECOMMENDATIONS

This research opens up a number of future research opportunities. Our study makes several assumptions, such as fast charging stations, known electric vehicle traffic volume, no power failure, and fixed charging capacity over time. High fidelity models will be developed in the future to relax these assumptions. Further, it is interesting to integrate renewable energy sources into the optimization framework and assess the robustness of the model in a situation where a disruption (e.g., hurricane, tornado) impacts the system. These issues will be addressed in future studies.

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