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A Methodology for Explicit Representation of the Stochastic Demand due to Electric Vehicles in Generation Expansion Planning Problems

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Abstract

Generation expansion planning (GEP) problems are solved to find the optimum investment decisions to satisfy the increasing electricity demand. Integration of electric vehicles (EVs) with the capability of charging from the grid will also increase the electricity demand of the grid. Depending on the charging/driving characteristics of users, demand curves for EVs will be shaped and it will be different on each day. Therefore, it is very crucial to represent this stochastic nature of EVs demand in the associated GEP problems. This paper is proposing a methodology to represent EVs demand realistically on GEP models. The proposed methodology starts with generating random demand patterns to demonstrate possibilities for the EVs demand patterns via Monte Carlo Simulation, then using an optimization-based model to select a representative set. Two stage stochastic programming model is proposed for GEP problems and solved to minimize the expected cost over the entire set, the representative set and the average EVs demand. The results show that GEP models with selected demand curves produce more realistic decisions (closer to the solutions obtained by using the entire demand patterns) than the decisions obtained by the models with average EVs demand. In most cases, the models using average EVs demand fail to capture the new peaks generated by EVs, therefore, they suggest less capacity expansion then the required amount. This results in more unmet demand in the system.

Keywords: Generation Expansion Planning, Electric Vehicles, Demand Stochasticity, Monte-Carlo Simulation
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INTRODUCTION

Generation Expansion Planning (GEP) problems are solved for optimally determining when, where and what type of generation technologies to construct in the grid to satisfy the growing electricity demand. The growth of the global electricity demand is estimated as 2.1% per year in [1]. Moreover, there is an increasing awareness for the environment and for the risk of depletion of fuels for the conventional vehicles. This leads a tendency towards increasing the proportion of the electric vehicles in the transportation sector. Introducing electric vehicles (EV) with capability of charging from the grid will contribute the electricity demand. To keep the grid reliable and sustainable, it is very crucial to incorporate the demand changes realistically in solving GEP problems to satisfy the new demand. The paper aims to provide a methodology to incorporate EVs demand in GEP and keep the GEP problem tractable.

The pattern for EVs demand is shaped based on many factors grouped as charging characteristics, driving characteristics and penetration levels. Charging characteristics includes types of chargers, battery sizes used in the vehicles and state-of-charge (capacity left in the battery) at the charging time. Driving characteristics involve the behavior of the vehicle owners such as daily driven distances, arrival and departure times to possible charging points (home, work, charge station, mall), preferences for charging places. Penetration level determine the number of the EVs. Since vehicle owners do not behave the same in each day, total demand of EV will differ from day to day as well as the distribution of the demand of EVs in each hour. Therefore, demand of EVs has a stochastic nature. Since GEP problems are long-term problems, it is very important to reflect this uncertainties in GEP problems explicitly. Another important objective of this study is to provide an approach to make it possible to realistically represent the stochastic nature of EVs demand in GEP problems.

There is vast amount of study on GEP problems. Koltsaklis and Dagoumas [2] present a review on the articles considering different perspectives of the GEP problems. They also provide a detailed survey on the GEP including the renewable energy sources in [3]. There are some studies focusing on how EVs will affect the demand curve [4-9]. There are also few studies considering the EVs together with GEP problems [10-17]. Ramirez et al. [18] solved the GEP problem where the average additional load due to the EVs is calculated for each hours and the current demand is updated to incorporate the EVs with GEP. Hajimiragha et al. [19] solves least cost GEP problem with EVs by incorporating the

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EVs via the estimated additional yearly demand. Ahmadi et al. [20] uses the EVs effects on the peal and base load when solving GEP problems. Moon et al. [21] estimates a probability density function for the EVs demand and incudes the estimated EVs demand into GEP problem. Ramirez et al. [22] also proposes a model for GEP where constraints to schedule the demand of EVs are included. de Quevedo [23] uses the total demand due to the EVs in s GEP together with renewable energy sources. Manríquez et al. [24] solves long term generation and transmission expansion planning problem under different charging schemes for EVs. Mehrjerdi [25] solves capacity expansion planning problems where EVs at charging stations thought as flexible generation units. Heuberger et al. [26] investigates the effect of EVs deployment on the capacity requirements.

The studies for GEP with EVs lack from reflecting the stochastic nature of the demand caused by EVs. The common approach is to include the estimated average EV demand for each hour. This leads to unrealistic plans since it does not consider the days with different level of EVs demands and different distribution of demand over the days. This paper provides a methodology to represent days with different demand profiles and their corresponding distribution among the year in GEP model while keeping GEP problem tractable. GEP problems are modeled as two stage stochastic programming models. By means of the methodology presented in this study, it would be possible to consider the days with new peaks (even if the probability is very low) in GEP model so that the solution suggested by the model will be more applicable to satisfy the reliability of the system.

This paper propose an approach which start with generating many numbers of random demand patterns by means of Monte Carlo simulation and then selecting a representative sets from the generated patterns to use in GEP problems. GEP problems are solved for different cases to show the effectiveness of the approach.

This paper is organized as follows: the simulation model to generate different EVs demand patterns, the mathematical model to select an appropriate subset of these patterns, and the two stage stochastic programming model for GEP to represent the demand patterns are given in Section 2. The numerical analysis and the corresponding results are given in Section 3. In Section 4, final remarks are given.

1. METHODOLOGY TO INCLUDE EVS DEMAND IN GEP

An algorithm is proposed to generate and select the representative load curves/demand patterns and use them in the mathematical model for GEP explicitly. The proposed algorithm is given in Algorithm 1.

Algorithm 1
Step 1: Generate N demand patterns which reflect any random days by using Monte Carlo Simulation.
Step 2: Use proposed optimization-based model to select the representative demand patterns (R) and to determine their corresponding probabilities.
Step 3: Minimize the expected cost by solving proposed GEP problem

1.1. Generation of EVs Demand Patterns

One could use any methods presented in the literature to generate random demand patterns. In this paper, the Monte Carlo simulation presented in [27] is used to generate the EVs demand patterns. In this simulation, all the impact factors are considered. At each iteration of the simulation, k vehicle owners for the given penetration level of EVs are generated where each owner has different driving and charging characteristics at the point of charging. The battery size, daily driving distance, departure and arrival times to the charging points, charging place decisions are assigned based on the distribution of the corresponding parameters and the policy applied. Based on these characteristics, a random demand pattern showing the amount of electricity drawn from the grid at each hour is obtained for each EV owner. By summing the demands from all the vehicle owners, the total demand for each hour is obtained. The result of one iteration is called a random demand pattern, which represents a possible day of the year.

1.2. Optimization-Based Approach for Selecting a Representative EVs Demand Patterns

In the previous step, we generated N patterns. Including all these demand patterns in GEP problems is preferable to be more realistic, but it is not computationally efficient. Therefore, a mathematical model is proposed to select a subset of the generated load curves while minimizing the deviation from the average demand for each hour.

The objective function of the models is to minimize sum of positive and negative deviations from the average demand for each hour *i*.

$$\min \sum_{h=1}^{24} (pd_h + nd_h) \quad (1)$$

The positive and negative deviations are calculated in the constraint (2).

$$\sum_{j=1}^{N} \varphi_j d_{hj} - pd_h + nd_h = \mu_h \quad \forall h = 1 \dots 24 \quad (2)$$

Here, d_{hj} represents the EVs demand for hour h in iteration j. μ_h is the average EVs demand for hour h considering all the demand patterns in N. φ_j is the decision variable for probability assigned to the demand patterns j. In this constraint, a positive probability is assigned to the demand pattern j such that the average demand is calculated by using only the patterns with positive probabilities plus the deviations are equal to the average EVs demand of hour h. The third constraint guarantees that the sum of probabilities are equal to 1 and represented as follows.

$$\sum_{j=1}^{N} \varphi_j = 1 \tag{3}$$

The non-negativity constraints are given in (4) and (5).

$$\varphi_j \geq 0, \forall j \in N \tag{4}$$

$$pd_h, nd_h \geq 0, \forall h =,\ldots 24 \tag{5}$$

1.3. Mathematical Model for GEP problems

The objective of this paper is to provide a methodology to explicitly represent the stochasticity associated with the EVs demand in GEP problems. The proposed model accomplishes it by representing the EVs demand not only by the average for each hour, but a set of EVs demand patterns for each hour with the associated probabilities. Then, the model becomes a two-stage stochastic model where the first stage variables, investment decisions, are decided with respect to the distribution of the uncertainty; and the second stage decision variables, dispatching decisions, are decided with respect to the observation of the uncertainty. The demand of the current system also differs for each day. The common approach is to select set of days to represent the different electricity demand curves in the year. We will assume that G is the set of such days and m_g is the number of days represented by the day g.

In our approach, we assume that EVs demand could be any one of the patterns in R for each day in G. Therefore, by multiplying the probabilities of EVs demand patterns by the number of days represented by g, we can obtain the number of days where the current electricity demand is as in day g and EVs demand is as in pattern j of R. The obtained parameter is called the weight, w_{gj}, and it is calculated as in Equation (9).

$$w_{gj} = \varphi_j \times m_g \tag{9}$$

The objective function of the model is to minimize the expected cost. The cost has two part, investment cost and expected dispatching cost.

$$\begin{aligned}\sum_{y}\sum_{k\in Q} c_{yk}\, s_{yk} &+ \sum_{y}\Bigg(\sum_{k\in Q}\sum_{g\in G}\sum_{j\in R}\sum_{h=1}^{24} w_{gj}\alpha_{yk}x_{ykgjh} \\ &+ \sum_{l\in L}\sum_{g\in G}\sum_{j\in R}\sum_{h=1}^{24} w_{gj}\beta_{yl}z_{ylgjh} \\ &+ \sum_{g\in G}\sum_{j\in R}\sum_{h=1}^{24} w_{gj}\gamma_y u_{ygjh}\Bigg)\end{aligned} \tag{10}$$

c_{yk} is the cost of investing generation unit type k from the possible investment options Q in year y and s_{yk} is the investment decision taking the value of 1 if the investment is done and zero if not. x_{ykgjh} is the amount of electricity produced (MWh) from the new generation unit k in year y, day g, in hour h and EVs demand follows the pattern j. α_{yk} is the cost of producing 1MWh of energy from the unit k of Q in year y. Similarly, z_{ylgjh} is the amount of electricity produced (MWh) from the existing generation unit l of the set L in year y, day g, in hour h and EVs demand follows the pattern j. β_{yl} is the cost of producing 1 MWh of energy from the unit l of L in year y. γ_y is the cost of unmet demand and u_{ygj} is the amount of energy not satisfied in year y, in day g, in hour h, and EVs demand follows the pattern j.

The first set of constraints are the demand constraints. Demand in the model represents the demand including the electricity request of EVs and it is calculated by summing the regular electricity demand plus the EVs demand as in Eq. (11).

$$D_{ygjh} = D_{ygh} + d_{hj} \tag{11}$$

D_{ygh} is the electricity demand without the EVs contribution in year y, in day g, in hour h. d_{hj} is the demand in hour h in EVs demand pattern j.

The demand constraints (12) are to guarantee that the total electricity generated from the existing and new units plus the unsatisfied demand is equal to the demand for each year, day, hour and EVs pattern.

$$\begin{aligned}\sum_{k\in Q} x_{ykgjh} + \sum_{l\in L} z_{ylgjh} + u_{ygjg} \\ = D_{ygjh} \quad \forall y, g, h, j\end{aligned} \tag{12}$$

D_{ygjh} is the demand including EVs demand in year y, in day g, in EVs demand pattern j and in hour h.

The second set of constraints (13) is the capacity constraint for the existing units. Total generation from each unit cannot be more than the available capacity.

$$z_{ylgjh} \leq \theta_l \quad \forall y, k, g, h, j \tag{13}$$

θ_k is the available capacity of unit l. It is calculated by multiplying the existing capacity with the availability factor. Availability factor could simply defined as the percentage of the time the unit available for the production.

The third set of constraints (14) is the capacity constraint for the new units. Total generation from each unit should be less than the available capacity if the investment is done before or in year y and less than zero if the investment is not done.

$$x_{ykgjh} \leq \theta_k \sum_{t=1}^{y} s_{yk} \quad \forall y, k, g, h, j \tag{14}$$

With the constraints in (15), we guarantee that each unit type investment occurs only once.

$$\sum_{y} s_{yk} = 1 \quad \forall y, k \tag{15}$$

The rest of the constraints (16-17) are binary variable constraints and non- negativity constraints for the generation amount and unmet demands.

$$s_{yk} \in \{0,1\} \quad \forall y, k \tag{16}$$
$$x_{ykgjh} \geq 0 \quad \forall y, k, g, j, h \tag{17}$$
$$z_{ylgjh} \geq 0 \quad \forall y, l, g, j, h \tag{18}$$
$$u_{ygjh} \geq 0 \quad \forall y, g, j, h \tag{19}$$

2. NUMERICAL STUDY

We consider the electricity grid of IstanbuI as a case study. The GEP problem to satisfy the increasing demand of Istanbul is solved. We assumed that wind farms are the choices for new generation units. For the current demand of the network, we pick two days from 2019 (08.01.2019 for Winter/Fall and 31.07.2019 for Spring/Summer) [28]. The selected days are the ones with the highest hourly peak demand. Selected current network demands are given in Table 1. Since the consumption of İstanbul is 16% of Turkey, we adjust the total demand to find the demand for Istanbul. We also assumed that 16% of the current installed capacity for Turkey could be used for Istanbul. The data for installed capacity and new generation units are given in Table 2.

Table 1. Selected Current Demand

	Hours					
Days	1	2	3	4	5	6
1	5208	4937	4748	4630	4578	4663
2	6127	5838	5598	5466	5366	5272
	Hours					
Days	7	8	9	10	11	12
1	4857	5318	6055	6616	6784	6934
2	5146	5435	6237	6692	6790	6960
	Hours					
Days	13	14	15	16	17	18
1	6753	6772	6832	6781	6760	6755
2	6793	6973	7188	7205	7182	7105
	Hours					
Days	19	20	21	22	23	24
1	6682	6452	6203	6036	5867	5550
2	6887	6820	6977	6922	6736	6486

Table 2: Available Capacity for Istanbul

Energy Source	Installed Capacity (MW)	Variable Cost ($/MWh)	Avail. Factor	Energy Loss	Available Capacity (MW)
Hydro	3,270	0.002	50%	8%	1504
Geothermal	172	0.011	75%	8%	119
Natural Gas	4,299	3.602	85%	8%	3362
Coal	3,187	4.474	85%	8%	2492
Stream	1,243	0.001	50%	8%	572

2.1. EVs Patterns Generation for the Case Study

To generate the extra demand from the electric vehicles, we used the impact factors presented in [27] and generate 10000 patterns. We assumed uncontrolled charging at home and public station. In this policy, people who prefer to charge at home can charge their cars at any time after arriving to home. We also assume that people using public stations can charge their cars at any time during the day. We used the distribution representing the preference of people for charging locations as presented in Table 3.

2.2. Selecting Patterns for Case Study

We used the LP model presented above to select the subset of EVs demand patterns and associated probabilities. For Case 2, 16 demand patterns are selected with the associated probabilities. 19 demand patterns are selected for Case 13. For the rest of the cases, 25 demand patterns are selected.

Table 3: Charging Location Preference Distribution

Cases	Home	Work	Public Station
1	0%	0%	100%
2	0%	100%	0%
3	10%	10%	80%
4	10%	80%	10%
5	20%	30%	50%
6	30%	20%	50%
7	30%	40%	30%
8	30%	50%	20%
9	40%	30%	30%
10	40%	40%	20%
11	50%	30%	20%
12	80%	10%	10%
13	100%	0%	0%

2.3. Results of GEP model for Case Study

The objective of this paper is to demonstrate the impact of the explicit representation of the different demand curves in the GEP model. To be able to solve the GEP problem by using the entire demand patterns, we construct a GEP model to satisfy the demand of one year in the future where 10% of vehicles in Istanbul are electrical. The daily demands selected (Table 1) are increased by 15% to reflect the future demand where 10% of vehicles in Istanbul are electric vehicles. As the investment option, we consider the wind farm. Each farm consist of 25 wind turbines each has the capacity of 2MW. The availability factor for the wind turbines are assumed to be 30% and the electricity loss is also assumed to be 8%. After applying the losses and availability factor, we computed the available wind power generation capacity from each farm as 13.8MW. We assumed 20 years for lifetime for the wind turbines to find the installation cost per year. Average cost of one wind turbine with 2MW capacity is around $3,500,000. By dividing this value to its lifetime and multiplying with 25, we found the installation cost for each farm per year $4,375,000. The unmet demand cost is assumed to be $10000 per MWh.

The GEP problem is first solved by using all the patterns (N) generated by Monte Carlo Simulation. Then the same problem is solved by only using the selected patterns (R) obtained by the optimization based model proposed before. Finally, the problem is solved by defining only one EVs pattern consists of the average demand (μ_h) of 10000 patterns for each hour and updated D_{ygjh} by using the average demand produced by EVs.

For different cases, all three problems are solved and solutions are presented in Table 4 and 5. Table 4 represents optimum objective function value if all the demand patterns are integrated to GEP and the deviations of the objective function value obtained by considering the selected demand patterns and average demand from the objective function value obtained by considering all 10000 demand patterns.

For all of the instances, using the average extra demand generated by EVs to represent the demand of EVs in GEP problem underestimate the effect of the EVs on demand. As seen in Table 4, using the selected demand patterns to integrate EVs to GEP problems produces better results for all the cases.

Table 4. Objective function value of GEPs solved

	Cost ($)	Deviation	
Cases	All	Selected	Average
1	2.77E+08	0.67%	-1.73%
2	3.6E+08	-2.57%	-4.20%
3	2.77E+08	0.09%	-2.03%
4	3.19E+08	-0.69%	-3.89%
5	2.82E+08	0.04%	-2.07%
6	2.78E+08	0.36%	-1.74%
7	2.85E+08	0.15%	-1.85%
8	2.91E+08	0.21%	-2.50%
9	2.8E+08	1.01%	-1.65%
10	2.85E+08	0.42%	-1.85%
11	2.8E+08	-0.02%	-1.45%
12	2.71E+08	0.43%	-2.41%
13	2.73E+08	-0.29%	-1.86%

To represent the results more clearly, we present the optimum investment level and total unmet demand per year. Investment represents the optimum number of wind farms invested to satisfy the demand. "All" in Table 5 represents the solution obtained by considering all of the 10000 patterns generated. "Avg" in Table 5 represents the solution obtained by considering the average of the 10000 demand patterns to reflect the extra demand of EVs. "Slc" in Table 5 represents the solution obtained by considering the selected demand patterns to integrate the EVs in GEP problems. Total unmet demand in Table 5 represents what would be the unmet demand for a year if the investment level is the one suggested by each problem and the demand might follow any one of the 10000 demand patterns generated.

The results show that the number of investments suggested by using the selected demand patterns are the same as using all the generated demand patterns in most of the instances. Using the average of the 10000 demand patterns in GEP problems causes not capturing the days where EVs increases the demand of some hours in a day drastically. Therefore, the solutions suggested by these problems suggest investing less investments, therefore, more unmet demand. Using the average is worse in the instances where new peaks might be generated as in Case 2 and 8. In those cases, more of the people charge their cars at work where the current demand of the grid is high. The highest investments are also suggested for these cases. In only two cases, using selected demand patterns suggest more investments than the problem with all demand patterns. In those cases, the unmet demand is very high for the second problem. It shows that there is a slight overestimation for the GEP with selected demand patterns.

Table 5. Optimum Investment Decisions and Total Unmet Demand for GEPs solved

	Investment			Total Unmet Demand (MWh)		
Cases	All	Slc	Avg	All	Slc	Avg
1	27	27	26	93.99	93.99	811.28
2	48	46	45	355.60	1626.12	2624.95
3	27	27	26	177.32	177.32	1056.24
4	38	37	35	85.38	474.39	2583.31
5	28	28	27	197.96	197.96	1014.64
6	27	27	26	267.29	267.29	1220.10
7	29	29	28	141.07	141.07	822.97
8	30	31	29	342.99	4.31	1493.39
9	28	28	27	79.03	79.03	722.49
10	29	29	28	140.96	140.96	962.21
11	28	28	27	19.86	19.86	521.00
12	25	26	24	267.90	0.00	1066.02
13	26	26	25	122.38	122.38	752.38

The largest number of patterns selected (R) is 25 for the cases we considered. It means that the number of demand constraints and the capacity constraints are reduced by at least (25/1000=0.0025). In addition to the reduction in the number of constraints, the number of decision variables for electricity generated by the existing units and new units, and the variables for unmet demand is also reduced by the same ratio. The solution times for the GEP model using the selected demand patterns is around one-third of the ones for the GEP model using all patterns. The same results are obtained in much shorter times with the representative sets.

It shows that we obtain GEP models which are realistic and tractable.

3. CONCLUSION

The integration of EVs into the system will increase the total demand of the grid where new investments need to be done. In order to decide the investments, GEP problems are solved. It is very important to represent the real impact of EVs in GEP problems to find solutions that are more realistic. In this paper, we propose a methodology to represent the impact of EVs on demand more realistically in the GEP problems while keeping the problems more tractable.

In this paper, we propose two stage stochastic programming models for GEP to integrate different demand patterns due to the EVs. The methodology starts with generating random days by simulation which consider the all the impact factors affecting the EVs demand. Each random days represents a possibility for a day. GEP problems with all these random days would be more realistic however; they will not be computationally efficient. Therefore, we suggested an optimization based method to select the representative set. In this optimization-based model, the deviation from the average of the generated random days is minimized. The optimization-based model suggest a subset of randomly generated demand patterns with associated probabilities.

We define cases and solve the GEP problem by using all the demand patterns generated, by the selected patterns and by the average of these demand patterns. The results show that using selected patterns suggest solution very close to the one with all the demand patterns. It is shown that our methodology provide an efficient way of integrating EVs to GEP problems while keeping the stochastic nature of the demand very close to the reality.

The electricity networks involves many stochastic parameters. The deployment of EVs into the system will increase the demand uncertainty. We provide a tool for the decision makers to help them to make proper decisions. The results shows that the methodology proposed in this study make it possible to take the days with new peaks into the account. Therefore, the capacity expansion decisions suggested are more realistic. The system operators could benefit from our study to determine best plans to design reliable power grid.

In this study, we assumed uncontrolled charging at homes and public stations. It means that drivers can charge their cars at any time depending on the arrival/departure times to these locations. However, there are incentives to influence the charging time selection of the drivers. Since with the methodology proposed here reduces the problem size, as a future study, GEP models could be developed where these incentives defined as decision variables and EVs demand patterns generated under such incentives are represented explicitly. Another improvement on the GEP models could be introducing the penetration levels for EVs as decision variables and solve GEP models to find the most suitable penetration level for the grid considered.

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