

Prediction of Electric Vehicle Penetration and Its Impacts on Distribution Systems: A Real-World Case Study in Maryland

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Abstract—With the growing penetration of electric vehicles (EVs) in power distribution networks, electric utilities are facing many challenges. For example, the growing EV charging load may cause degradation in voltage quality, higher network losses, and overloading of equipment. The distribution grid infrastructure needs to be upgraded to handle these problems. In this study, we develop an integrated data-driven planning framework for electric utilities to predict EV adoption and analyze their impacts on distribution feeders. This planning framework consists of two modules. In the first module, we design a generalized Bass diffusion model (GBM), which utilizes historical adoption data, EV availability, incentives, cost, and demographic information to predict EV adoption at the zip code or feeder level. Subsequently, in the second module, we combine the EV adoption prediction and the representative EV charging load profiles to analyze the impacts of EVs on distribution feeders such as voltage violations and equipment overloading. The proposed solution framework was tested in a case study in Maryland, U.S. using real-world data and distribution circuit models. The results feature accurate predictions of EV adoption and reveal when, where, and how severe the voltage violations and overloading issues will be with the growing EV penetration. The proposed framework serves as a valuable tool for system planners to determine distribution system upgrade plans.

Index Terms—Electric vehicle, transport electrification, EV adoption prediction, diffusion models, EV impact analysis.

I. INTRODUCTION

The penetration of EVs in the U.S. has been surging. Alongside this fast adoption, the EV charging network has been expanding rapidly as well [1], [2]. In the State of Maryland, Baltimore Gas and Electric has the fastest growing EV charging network, with 250 existing charging stations and plans to install another 250 by 2025. Meanwhile, Pepco Holdings, another prominent local utility, is on track to operate 350 chargers across Maryland by the third quarter of 2024.

However, electric utilities are facing difficulties in accommodating the growing EV load. For example, during peak EV charging times, the power distribution system may experience deteriorated voltage quality, higher network losses, and overloaded transformers, leading to reliability issues [3], [4]. The grid infrastructure may need to be upgraded to handle the

increasing load from EVs. However, upgrading the distribution system is a time-consuming and expensive process [5]. These challenges underscore the need for effective planning tools to address the impacts of EV integration on power distribution systems.

For electric utilities, a pivotal task in preparing for the surge of EVs is accurately forecasting their adoption within their service territories, a subject extensively explored in existing literature [6], [7]. The adoption rate of EVs is influenced by multiple factors such as vehicle cost, fuel prices, the availability of charging infrastructure, local demographics, and government incentives. To enhance prediction accuracy, several advanced modeling techniques have been developed. The discrete choice model [8], [9], for instance, evaluates individual consumer decisions, taking into account their preferences and the varying attributes of available options. The agent-based model [10], on the other hand, simulates individual agent interactions to gauge their collective impact on the system. Additionally, the Bass diffusion model (BM), a prevalent tool for forecasting new product adoption, analyzes the adoption trajectory based on previous adopters and the potential market size [11], [12]. The generalized Bass diffusion model (GBM) further enhances the traditional Bass framework by integrating external influences such as model availability, costs, and incentives, thereby providing a more refined and accurate depiction of adoption trends [13], [14]. However, it is worth noting that despite the advancements in modeling techniques, there is a scarcity of studies that handle EV predictions at the feeder level — a granularity that is critical for utilities to develop actionable strategies for feeder upgrades.

Once the EV adoption prediction is performed, the focus shifts to understanding its impacts on power distribution systems, especially on each specific feeder. The extent of these impacts depends on factors such as the number of EVs, their charging patterns, and the existing distribution infrastructure's capacity. An obvious challenge is the risk of overloading distribution transformers, especially during peak charging periods

[15]. This scenario could also lead to increased losses, reduced efficiency [16], and necessitate expensive equipment upgrades or replacements [17]. Uncoordinated EV charging further risks voltage instability [18] and power quality issues [19], affecting both EV owners and other consumers on the distribution network. Addressing these issues necessitates a comprehensive analysis at the feeder level. This includes evaluating each feeder’s unique characteristics and constraints while factoring in the anticipated EV charging patterns. Such an analysis will enable utilities to pinpoint potential bottlenecks, and then facilitate necessary infrastructure enhancements [3] and the implementation of intelligent demand response programs [4].

In this paper, we propose a solution that can provide the utilities with an integrated, data-driven planning framework for predicting EV adoption and analyzing their impacts on the distribution network at the feeder level. This framework consists of two modules. In the first module, we design a GBM, which utilizes historical adoption data, EV availability, incentives, cost, and demographic information to predict EV adoption at the zip code or feeder level. Then, in the second module, we combine the outputs of the EV adoption and the representative EV charging load profiles to analyze impacts such as voltage violations and equipment overloading on distribution feeders using power flow simulations. The proposed solution framework is validated using a case study in Maryland, U.S. using real-world data and circuit models. The results showed that the proposed solution has enhanced prediction accuracy and can reveal when, where, and how severe the voltage violations and overloading issues will be with the growing EV penetration. The proposed approach can be a helpful tool for system planners to design the circuit upgrades.

The rest of the paper is summarized as follows. Section II explains the overall framework and data preparation. Section III elaborates the technical details of the two modules in the solution framework. Section IV demonstrates the case study results from Maryland. Section V states the conclusion.

II. OVERVIEW OF THE SOLUTION FRAMEWORK AND DATA PREPARATION

A. Overview of the Solution Framework

Our proposed solution framework consists of two modules, as illustrated in Figure 1. Module 1 predicts EV adoption at the state, county, zip code, and feeder levels by utilizing historical adoption data, EV incentives, and demographic information. Module 2 uses the outputs of module 1 (the EV adoption) and real-world charging load profiles to analyze the impacts on distribution feeders.

B. Data Summary and Preparation

The datasets used in this work are summarized in Table I, by the module they are applied to. The details of the datasets, their sources, and how they were prepared are explained as follows.

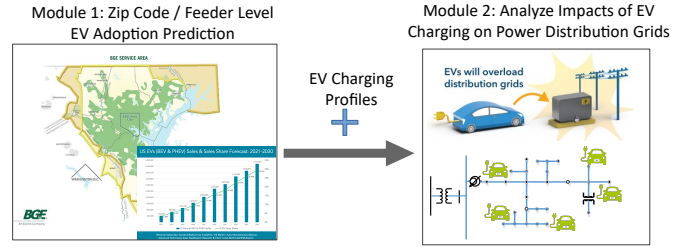


Fig. 1: The proposed framework for EV penetration prediction and impact analysis.

TABLE I: Summary of the Dataset

	Data Type
Module 1	Historical EV adoptions.
	EV availability.
	Average EV price.
	Average EV incentive from federal government.
	Average Maryland State EV incentive.
Module 2	Demographic data of counties and zip codes in Maryland.
	EV charging profiles.
	Distribution circuit model.
	Distribution circuit demographic data.

1) *Historical EV Adoptions*: The historical EV adoption data contain the cumulative EV registration numbers in Maryland, U.S., and each of its counties. These data were collected from two sources. The yearly data from 2011 to 2020 are collected from Exelon Corporation and the monthly data from July 2020 to April 2023 are collected from Maryland’s open data portal [20].

2) *EV Availability*: The EV availability is the number of available EVs in the market for sale. We use the monthly EV sales number in the U.S. from January 2011 to April 2023 to estimate EV availability. These data are collected from Argonne National Laboratory [21].

3) *Average EV Price*: Given the extensive duration of this study, we collected the average EV prices in the U.S. from two resources. The monthly average EV prices from July 2014 to April 2023 are collected from Kelly Blue Book press releases [22]. The yearly price data are calculated by using the data from the International Energy Agency (IEA) [23].

4) *Average U.S. Federal EV Incentive*: We prepared the average U.S. federal EV incentive data by year from 2011 to 2019, and by month from January 2020 to April 2023. The U.S. federal EV incentive program was initiated in 2009, offering a \$7,500 tax credit for each EV purchased. On the other hand, each EV manufacturer had a cap of 200,000 EVs to receive this credit and the incentive would gradually decrease to zero for this manufacturer after reaching the cap.

According to this guideline, the EVs from Tesla and General Motors stopped receiving the federal incentive in December 2019 and March 2020, respectively. In August 2022, the U.S. government renewed the incentive program and the cap has been removed since then. In this work, we used the EV sales and qualified incentive values of each manufacturer to calculate the weighted average incentive values. The EV sales data by manufacturer were collected through [24].

5) *Average Maryland State EV Incentive*: Starting from 2010, the Maryland State provides EV incentives in terms of tax credits. The incentive value varies each year due to changes in policies and funding caps. We estimated the yearly and monthly average state incentive by dividing the funding cap by the number of EV sales in Maryland. The funding cap can be found in Maryland government bills such as [25].

6) *Demographic Data at County and Zip Code Levels in Maryland*: For this study, we incorporated demographic information, specifically the population numbers at both the county and zip code levels in Maryland. These data were collected from the Maryland census data portal [26].

7) *EV Charging Profiles*: The EV charging profiles consist of the hourly EV charging load across various types of chargers in Maryland. These data were provided by Exelon. In total, there are 4,046 individual chargers, operated by seven different service providers. Depending on the chargers' locations, they are categorized as residential, multifamily, and public chargers.

8) *Distribution Circuit Model*: The distribution circuit models featured in this study represent distribution circuits in Maryland, supplied by Exelon. Each model is a complete description of the electric circuit, including the circuit topology, parameters of circuit elements/equipment, and load profiles of electricity customers, which enable us to run power flow analysis.

9) *Distribution Circuit Demographic Data*: To enhance the precision of EV charging simulations at the distribution circuit level, we gathered additional data on the corresponding geographic location, including population number and the customer type (residential, commercial, and mixed-use) data were collected from Exelon.

III. METHODOLOGY

A. Methodology for EV Adoption Prediction (Module 1)

In module 1, to predict the EV adoption numbers by year and month, we designed a generalized Bass model (GBM) [27] by incorporating both the EV availability data and EV cost data into the prediction model. GBM has been successfully used to perform prediction for other types of distributed energy resources such as rooftop solar photovoltaic systems [28]. GBM was developed on top of the basic Bass diffusion model (BM), which is described by (1).

$$\frac{f(t)}{1 - F(t)} = p + qF(t) \quad (1)$$

Here $F(t)$ is the cumulative adoption function. $F(t) \rightarrow 1$ as $t \rightarrow \infty$. $f(t) = \frac{dF(t)}{dt}$ is the adoption rate. The left-hand

side of the function describes the conditional adoption rate at time t , and it is controlled by two factors: p and q . p is the innovation factor, describing innovative adopters who are willing to adopt the product themselves, and q is the imitation factor, describing the adopters who follow other adopters' use of the product. Both p and q are positive [29]. In this model, EV adoption is modeled as a function of time t and $F(t)$ has a closed form solution as in (2):

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \quad (2)$$

The model of GBM can be described by (3)

$$\frac{f(t)}{1 - F(t)} = [p + qF(t)]x(t) \quad (3)$$

Here, $x(t)$ is a variable at time t to represent the market influential factors. $F(t)$ has a closed form solution as in (4), in which $X(t) = \int_0^t x(\tau)d\tau$.

$$F(t) = \frac{1 - e^{-(p+q)X(t)}}{1 + \frac{q}{p}e^{-(p+q)X(t)}} \quad (4)$$

In the proposed approach, we introduce two influential factors ϕ_{avail} and ϕ_{cost} . ϕ_{avail} represents the influential factor of EV availability and ϕ_{cost} represents the cost of purchasing an EV. Let β_{avail} and β_{cost} be the corresponding coefficients. Then the aggregated market influential factor $x(t)$ is defined by (5). In this proposed model, EV adoption is not only determined by time but also the EV availability and cost.

$$x(t) = 1 + \beta_{\text{avail}}\phi_{\text{avail}}(t) + \beta_{\text{cost}}\phi_{\text{cost}}(t) \quad (5)$$

$\phi_{\text{avail}}(t)$ is calculated by (6). Here $SI(t)$ is the number of available EVs in the U.S. market at time t , which is estimated following the approach described in Section II-B2.

$$\phi_{\text{avail}}(t) = \ln \frac{SI(t)}{SI(0)} \quad (6)$$

Similarly, $\phi_{\text{cost}}(t)$ is calculated by (7). Here $C_{s_{\text{total}}}(t) = C_{s_{\text{price}}}(t) - Inc_{\text{fed}}(t) - Inc_{\text{state}}(t)$ is the average net cost of purchasing an EV at time t . $C_{s_{\text{price}}}(t)$ is the average EV price described in Section II-B3. $Inc_{\text{fed}}(t)$ is the federal incentive calculated in Section II-B4. $Inc_{\text{state}}(t)$ is the Maryland State incentive calculated in Section II-B5.

$$\phi_{\text{cost}}(t) = \ln \frac{C_{s_{\text{total}}}(t)}{C_{s_{\text{total}}}(0)} \quad (7)$$

Both BM and GBM models are trained by minimizing the error between the estimated EV adoptions and the actual EV adoptions in each time interval, as shown in (8). Here m is the eventual adoption number, $S(t_i)$ is the actual EV adoption number at time t_i . In BM, the parameters of p and q will be estimated; in our proposed GBM model, p , q , β_{avail} , and β_{cost} will be estimated. We use the number of existing light-duty vehicles in the corresponding area as the value for m .

The parameters are estimated using the nonlinear least squares (NLS) method.

$$\min \sum_{i=1}^N \{m[F(t_i) - F(t_{i-1})] - [S(t_i) - S(t_{i-1})]\}^2 \quad (8)$$

The proposed approach is designed to perform EV adoption predictions in four levels: Maryland State, county, zip code, and feeder levels. To perform Maryland State-level and county-level predictions, we used the historical EV adoption data by the state and its counties as described in Section II-B1. To perform zip code-level predictions, we first predict the adoptions of the county that a zip code belongs to, then we estimate the zip code's adoption through multiplying the county adoption by the ratio of the zip code's population to the county's population. The feeder-level prediction is calculated in a similar approach as zip code-level prediction.

B. Methodology for EV Impacts Analysis (Module 2)

In module 2, we analyze the impacts of charging load of the predicted future EV adoptions by using power flow analysis. This is performed in three steps.

1) *Step 1: Determine the number of EVs to Analyze:* The number of EVs to analyze depends on the predicted number of EV adoptions for a distribution feeder using the approach in Module 1. For example, to analyze the circuit for the next 5 years or 10 years, we use the corresponding predicted EV adoptions in the next 5 or 10 years.

2) *Step 2: Determine the Load Profile:* The load profile contains two components: the existing historical load profile of a feeder in year x , and the added EV charging load profile. The historical load profile is constructed by aggregating the actual load profiles of each user in a feeder as recorded by smart meters, and it represents the baseline load in the year x . To model the EV charging profile, we first calculate the number of added EVs F_{add} compared with year x . This is calculated by $F_{\text{add}} = F_{\text{pred}} - F_{\text{year}_x}$, in which F_{pred} is the predicted future EV adoptions of the feeder determined in Step 1 and F_{year_x} is the actual historical EV adoptions of the feeder in year x . Second, we assign each added EV randomly to a distribution transformer in the distribution feeder. Third, we assign each EV a real-world charging profile, which is randomly selected from the pool of actual representative EV charging profiles (see Section II-B7), ensuring that the selected profile corresponds to the transformer type that the EV belongs to.

3) *Step 3: Power Flow Analysis and Result Collection:* In this step, we perform power flow analysis using the feeder's circuit model and the load profiles prepared in Step 2. The voltage level of the circuit and the load level of each distribution transformer are collected for the EV impacts analysis.

IV. CASE STUDY

In this section, we will demonstrate the case study results using the proposed two-module approach and the real-world data and circuit models for the State of Maryland.

A. Case Study of Module 1: Prediction of EV Adoptions

In this case study, we tested four different EV prediction models: BM as a baseline, GBM with EV availability only, GBM with EV cost only, and the proposed GBM with both EV availability and cost. In GBM with EV availability only, we assume $x(t) = 1 + \beta_{\text{avail}}\phi_{\text{avail}}(t)$. In GBM with EV cost only, we assume $x(t) = 1 + \beta_{\text{cost}}\phi_{\text{cost}}(t)$.

In both BM and GBM models, we define t as the number of months since the year 2012. Thus, $t = 0, 1, 12$, and 120 correspond to December 2011, January 2012, December 2012, and December 2021 respectively. Since there were only yearly EV adoption data from 2011 to 2020 and monthly adoption data is available from July 2020 to April 2023 (see Section II-B1), when fitting the NLS problem in (8), we only use the t_i that has the corresponding data. Thus, t_i corresponds to the December of the year 2011 to 2019 for $i = 0, \dots, 8$, and t_i corresponds to each month from July 2020 to April 2023 for $i = 9, \dots, 42$. We use the data from 2012 to April 2022 to train the prediction models, and evaluate their performance by calculating the mean squared error (MSE) when predicting the adoptions from May 2022 to April 2023. The monthly historical EV adoption data from July 2020 to April 2023 were smoothed using the moving average method with a window of 3 months, which can mitigate the spikes that interfere with the model estimation.

The prediction MSE of the Maryland State-level EV adoptions by each model is compared in Table II. Here we show both the fitting MSE (Train MSE) in the training data and the prediction MSE (Test MSE) in the testing data. It is not surprising that by introducing more explanatory variables, the GBM models have lower train MSE. The important thing is that the GBM models have significantly lower Test MSE than BM, which shows their higher accuracy when predicting unseen data. We can see that using either EV availability or EV cost can improve the prediction accuracy, and the proposed GBM that includes both availability and cost has the lowest prediction errors.

TABLE II: EV Adoption Prediction MSE of the Models

Model	Train MSE	Test MSE
BM (baseline)	2.07E+05	1.53E+05
GBM (with EV availability only)	1.90E+05	1.24E+05
GBM (with EV cost only)	1.99E+05	9.21E+04
GBM (with both EV availability and cost)	1.85E+05	7.35E+04

Figure 2 shows the EV adoption prediction of Maryland by the BM and proposed GBM. From these two figures, we can see that BM can only predict a smooth adoption curve, while the proposed GBM can predict adoption better by considering the changing market conditions.

We also performed long-term adoption prediction extending up to the year 2040. Figure 3 shows the prediction of two zip code areas' EV adoptions by the proposed GBM with both EV availability and cost. The two zip code areas correspond to the zip codes of 20723 in Howard County and 21901 in

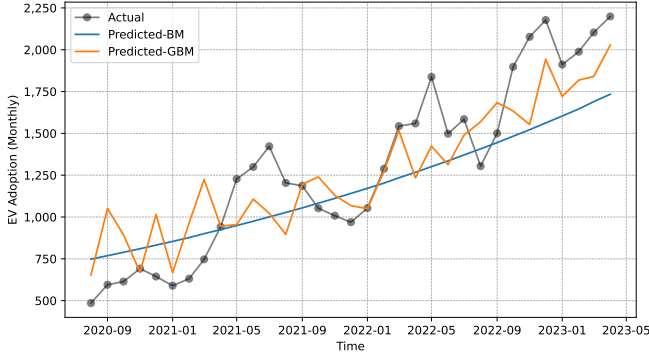


Fig. 2: The monthly EV adoption prediction of Maryland by BM and GBM compared with the actual values.

Cecil County. The EV availability data from 2024 to 2040 was estimated by [30]. The EV cost from 2024 to 2040 is estimated by assuming the incentives will end in 2032; the prices between 2024 and 2028 are predicted by [31] and we assume the price will gradually drop to \$40,000 in 2040. From Figure 3 we can see the trend and level difference of different zip code areas, which shows the importance of more granular segmentation in EV adoption prediction.

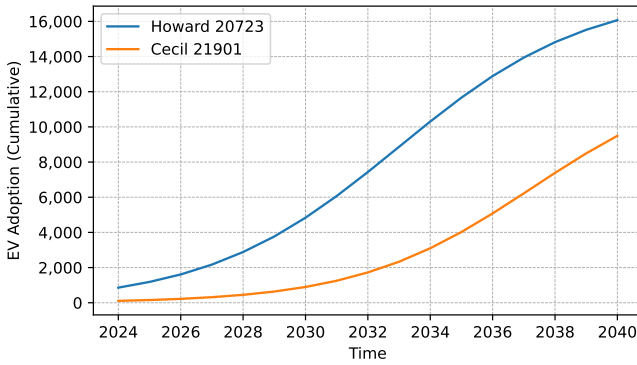


Fig. 3: The prediction of cumulative EV adoptions by year in two zip code areas.

B. Case Study of Module 2: Analyzing Impacts of EV Charging on Power Distribution Systems

We applied the EV adoption prediction to a real-world distribution circuit in Maryland to analyze their impacts. The circuit has 294 distribution transformers and serves 1,411 customers; about 88% of them are residential customers, 7% are mixed-use customers, 2.5% are commercial users, and 2.5% are unknown-type users. The real-world EV charging profiles were collected from three types of chargers: residential, multifamily, and public. Based on the customer type distribution of the circuit, we assumed that 80% of the EVs use residential chargers (assigned randomly to residential transformers), 15% use multifamily chargers (assigned randomly to mixed-use and

residential transformers), and 5% use public chargers (assigned to commercial, mixed-use, and unknown-type transformers). The historical customer load profiles are derived from hourly smart meter data in 2022.

TABLE III: Results of EV Impacts Analysis

Year	2022	2025	2030	2035	2040
Predicted/estimated EV adoptions	65	173	706	1703	2346
Max volt (p.u.)	1.079	1.081	1.0794	1.083	1.083
Min volt (p.u.)	0.889	0.887	0.882	0.850	0.817
Over-voltage count	1223	1362	1098	1636	988
Under-voltage count	10234	10793	13854	20836	27206
Overloading count	217	225	444	1031	1490

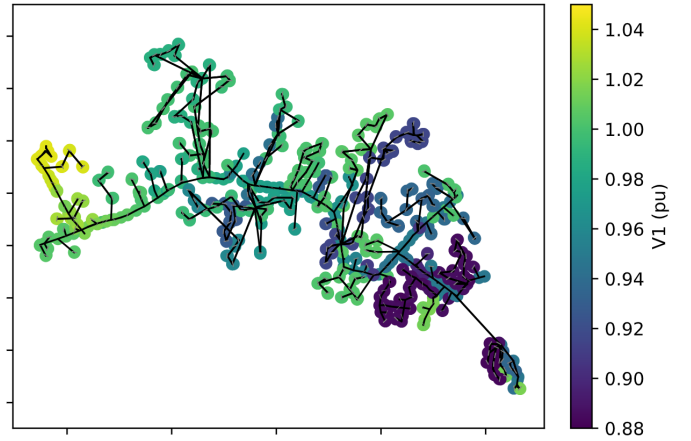


Fig. 4: The predicted heat map of voltage in the summer evening hour of 2030.

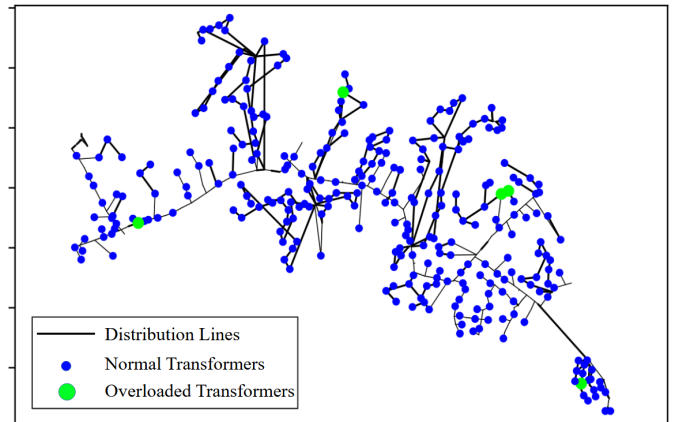


Fig. 5: The predicted location of overloaded distribution transformers in the summer evening hour of 2030.

We performed power flow analysis with OpenDSS using the customer load profile from Aug 1st, 2022, to Aug 14th, 2022. These two weeks represent the summer peak periods when electricity usage was higher. We estimated the impacts of EV charging load to the circuit using module 2 between

the years 2022 and 2040. The results are shown in Table III. Using module 1, we estimated that from the year 2022 to 2040, the EV adoptions in this circuit will grow from 65 to 2346. We collected the maximum and minimum voltage among all distribution transformers in these two weeks' simulation. We also counted how many over/under voltage incidents will happen. When a distribution transformer is over-voltage (> 1.05 p.u.) or under-voltage (< 0.95 p.u.) in an hour, then it is an over/under voltage incident. In two weeks' time range, there are $24 \times 14 = 336$ hours and 294 transformers, so there are at most $336 \times 294 = 98784$ possible incidents. Similarly, we counted how many overloading incidents happen for distribution transformers, in which when a distribution transformer is overloaded in an hour, it is counted as one incident. We can see that under the current circuit design, the minimum voltage keeps dropping, and the circuit will have more and more severe under-voltage issues and transformer overloading in the next few years. These results show an urgent need for circuit upgrading and we can see that the proposed method can be a useful tool for system planners to develop system upgrade strategies.

In addition to quantitatively analyzing the impacts of EV charging loads, we also use module 2 to show where these incidents in Table III might happen. Figure 4 shows the predicted voltage levels in the circuit at 17:00 on August 9, 2030. Figure 5 shows the location of the overloaded distribution transformers in the same hour. This analysis can help system planners to design specific upgrades on the circuit.

V. CONCLUSION

In this paper, we developed a two-module solution to predict EV penetration and analyze its impacts on the distribution system through a case study in Maryland. In module 1, we proposed a GBM approach with both the EV availability and cost data. This approach enables us to consider more complicated market factors in EV adoption, which yields a more accurate EV adoption prediction. In module 2, we used the predicted EV adoption and actual EV charging profiles to analyze the voltage levels and equipment overloading. This was performed on a real-world distribution circuit in Maryland using power flow analysis. The results showed that the proposed method can reveal when, where, and how severe the under-voltage and overloading issues might be with the growing EV penetration. The proposed approach can be a helpful tool for system planners to develop circuit upgrade plans.

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