Estimating the Impact of Utility Rate Structures on Electric Vehicle Loading in Distribution Systems

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***Abstract*—This paper presents a method to estimate the impact of utility rate structures on electric vehicle (EV) loading in distribution systems. This framework is divided into two phases (1) the effect of rate structures on EV charging behavior and (2) the effect of this EV charging behavior on the distribution feeder. The approach implements the Monte Carlo (MC) method to determine the average circuit loading and violations for each evaluated rate scenario, which can then be compared. The MC simulations rely on a combination of static inputs, such as the circuit model, baseload, and EV penetration, as well as probabilistic inputs, specifically the spatial allocation of EV customers and the EV charging profiles for each rate structure scenario. Additionally, this paper provides a novel method for estimating the EV penetration at the county-level based on the county-level historical EV registration data with reconciliation to the state-wide forecast. Lastly, this paper provides a realistic utility case study implementing this framework with the EV charging results of a real utility rate pilot study combined with a real utility circuit and base loading data. This case study evaluated ten rate structure scenarios. The results show certain non-standard rate scenarios reduce overall circuit loading and voltage impacts compared to the standard rate; however, distribution transformers experience significant overloading for all rate structure scenarios.**

***Index Terms*—Electric vehicle charging, coordinated charging, grid integration, demand forecasting, power system analysis.**

I. Introduction

As electric vehicle (EV) adoption increases, utilities must prepare for rising demand on residential distribution circuits, which can potentially lead to component overloading and voltage violations. Traditional planning philosophy calls for upgrading or reconfiguring grid infrastructure to mitigate local distribution system issues; however, there is potential for using managed charging to help mitigate these issues without capital investments, which can be costly. Managed charging can either be active (directly reducing charging of a customer) or passive (rate incentives). While active managed charging may be the most effective, it requires additional equipment or systems to implement. In contrast, non-standard utility rate structures, such as time-of-use (TOU) and critical-peak-pricing (CPP), are a more readily deployable mitigation technique with the potential to shift charging away from peak hours and defer infrastructure investments [1]. Subsequently, evaluating the effectiveness of these non-standard rate structures in mitigating localized loading and voltage issues caused by EV charging is a critical task for utilities.

A. EV Adoption Forecasting

The rate of EV adoption has slowed in 2025 for the United States (U.S.) but is still expected to increase significantly in the next decade. Longer term forecasts still show EVs with a 26% share of new car retail sales by 2030 despite this slowdown [2]. In [3], it points out that today's demand dip in the U.S. is creating battery overcapacity, which could accelerate price competition and potentially leading to a spike in EV adoption. These market research group forecasts typically focus on global, entire U.S., and state-level EV adoption, while only a handful of literature focuses on the more granular level of county or zip-code.

In North Carolina (NC) for example, EV adoption has increased exponentially through 2024, reaching over 112,000 registered total battery electric vehicles (BEVs) and plug-in hybrids (PHEVs) in February 2025 from approximately 50,000 registered total BEVs and PHEVs at the beginning of 2023 [4]. In this study, the term "EV" incorporates both BEVs and PHEVs unless otherwise noted.

Our previous work in [5] forecasts EV adoption for the entire state of NC from 2024-2035 using a Bass Diffusion model [6], historical state-wide EV registration data, and an existing market research outlook predicting 2.5 Million EVs in NC by 2035.

The researchers in [7] also utilized a Bass Diffusion model, a mix of public and non-public customer financial data, and an 85% market share of EVs in 2050 to forecast annual EV adoption of a single California distribution feeder from 2020-2050. While this forecast is highly granular at the circuit level, this forecast method uses non-public data and does not reconcile to state-level forecasts.

The Brattle Group, on behalf of ERCOT, used a vehicle stock turnover model applying Bloomberg market share forecasts to Texas-level vehicle sales projections from the EIA Annual Energy Outlook, then spatially allocated these forecasts to substations based on sociodemographic propensity scores

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[8]. While this approach achieves substation-level granularity and does reconcile to the state-level forecast, it relies on a single year value of ZIP-code EV registrations (2022) as an allocation weight rather than leveraging a multi-year historical trend.

Lastly, the researchers in [9] forecast EV adoption at the ZIP-code level using logistic growth curves based on historical EV penetration levels from 2011-2019 and other logistic predictors, such as demographic, employment, land-use intensity, and charging-station data. While this approach is granular, it does not reconcile the ZIP-code level estimates to state-wide forecasts.

B. Spatial Allocation of EVs on Distribution Feeders

There are few studies that spatially allocate EVs using non-uniform probabilities. Notably, the researchers in [7] use the results of their EV adoption forecast to spatially allocate EVs to specific addresses based on a binary choice (logit) model that uses income, housing type (single vs. multifamily), property value, and access to charging infrastructure to determine address-level purchase probabilities.

The previous work in [5] provides a simplified methodology for using only property tax values to determine customer-level purchase probabilities with the assumption of a higher property tax value will equate to a higher probability of obtaining an EV. The framework presented in this paper follows this methodology for spatially allocating the EV loads.

C. EV Charging Impacts on Distribution Feeders

Early studies considered only uncoordinated EV charging (i.e. no special rate structures) with the typical conclusion that residential distribution transformers are the most affected [10]. Notably, Muratori [11] used bottom-up household consumption-time load/demand models and found significant thermal violations for customer transformers with a 6.6 kW charging rate at penetration above 50%, though without circuit-level modeling. The researchers in [7] concluded that uncoordinated charging mainly stresses transformers, with conductor and voltage impacts only arising at higher EV penetrations (after approximately 71%). The study in [5] found that over 65% of transformers are overloaded at a penetration of 36.5%, with peak loading rising about 33% from the baseline penetration of 1.4%, voltage violations steadily increasing, and conductor impacts only occurring at the highest evaluated penetration levels.

In contrast to uncoordinated charging, there are very few studies that have examined the effect of rate structures on EV loading for distribution systems. The authors of [7] considered a smart charging case with randomized charging between 10 pm and 6 am, though not tied to an actual rate structure. The researchers in [1] simulated ten California distribution feeders at 13% EV penetration under three rate scenarios: TOU-immediate (all customers start at off-peak time) and TOU-random (staggered starts within the off-peak window). These scenarios were also not based on real rates.

D. Impact Assessment Methods

The traditional method of distribution system analysis has been largely deterministic. Historically, utility planners have relied on steady-state "snapshot" simulations of extreme loading conditions, typically peak and low demand, to assess system adequacy and identify potential violations. These analyses assume fixed load profiles, providing a single outcome rather than a range of possible scenarios. While effective for identifying worst-case conditions and guiding infrastructure upgrades, this approach does not capture the variability and uncertainty introduced by modern technologies such as electric vehicles, distributed generation, and demand response.

In contrast to deterministic methods, stochastic methods incorporate variability and uncertainty in load, generation, and customer behavior by using probabilistic simulations, allowing utilities to assess a wide range of possible operating conditions and quantify the likelihood of system constraint violations rather than relying on a single deterministic outcome. The Monte Carlo method is a common stochastic method used to model and analyze power systems that exhibit inherent uncertainty or randomness by running a large number of simulations based on random sampling. Several papers, including [5] and [7], have implemented the Monte Carlo method to study EV impacts on power systems. Due to the probabilistic nature of EV charging start time, duration, magnitude, and location, the framework presented in this paper utilizes the Monte Carlo method.

E. Research Gap

Despite extensive research on EV impacts to distribution systems, there are still gaps for a comprehensive assessment method for estimating the effectiveness of rate structures on the EV charging loading and the resulting impact on a distribution system. Some of the main gaps identified and addressed in the paper are the following (i) a framework for evaluating the impact of different rate structures on EV loading for distribution systems based on real customer responses to the rate structures, (ii) a framework for county-level EV adoption estimation using only publicly available county-level historical registration data with reconciliation to state-wide forecasts, and (iii) a realistic utility case study evaluating the impact of various rate structure scenarios on EV loading for a distribution system. By filling these gaps, this paper provides guidance for utility distribution planners weighing the relative merits of employing non-standard rates to mitigate the impact of residential EV charging.

In summary, this paper provides several key contributions:

- A new framework for estimating the impact of utility rate structures on EV loading in distribution Systems.
- A new method for estimating the county-level EV adoption using historical EV registration data with reconciliation to a state-wide forecast.
- A realistic case study using actual utility data that quantifies and compares the thermal and voltage impacts of EV adoption across ten distinct rate structure scenarios.

The paper is organized as follows. Section II provides an overview of the impact of rate structures on EV charging behavior. Section III presents the novel proposed framework for assessing the impact of rate structures on EV loading in distribution systems. Section IV provides an overview and the results of the realistic utility case study. Finally, Section V concludes the paper by summarizing the main contributions.

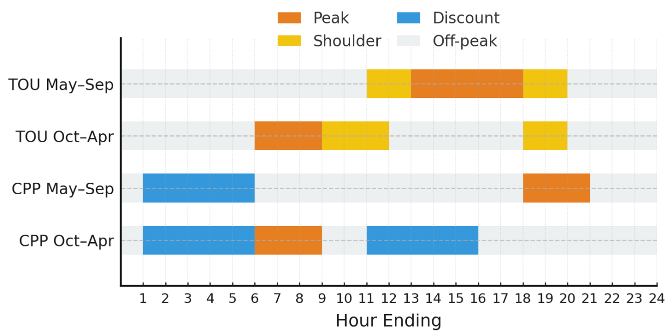

Fig. 1. TOU and CPP Daily Rate Periods

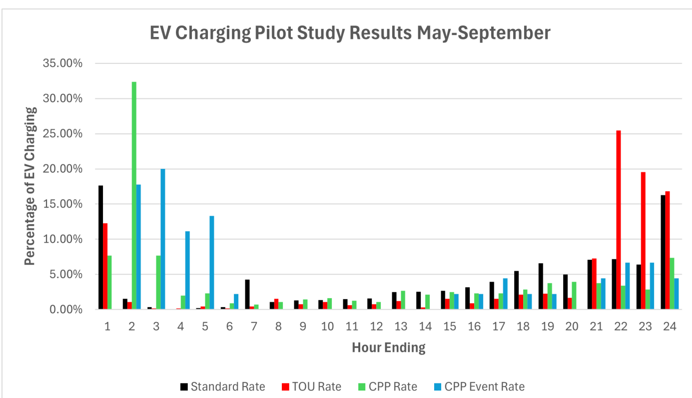

Fig. 2. EV Charging Pilot Study Results (May-September)

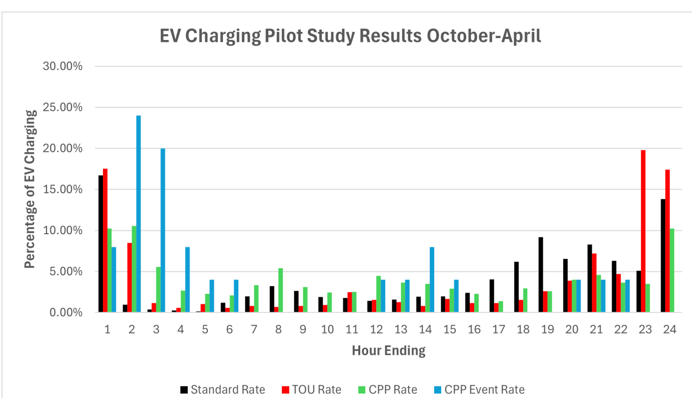

Fig. 3. EV Charging Pilot Study Results (October-April)

II. Impact of Rates on EV Charging Behavior

The first step of the proposed framework involves determining the impact of rates on EV charging behavior. This section summarizes the EV charging pilot study conducted by a utility in NC and provides an overview of the rate structures considered for the case study.

The NC pilot study comprised of 41 residential EV-owning households that were subjected to three rate structure types (standard, TOU, CPP) for each of the May-September and October-April rate seasons over a three year period from 2021-2023. The CPP rate was separated into all days ("CPP Rate") and only the CPP Event days ("CPP Event Rate"), which represent the top 20 days of the year with the highest system-wide peak demand. Hourly consumption data was provided and a methodology, which will be described in the separate publication, was implemented to record and process the times of the customer charging sessions for all of the rate structures. It is notable that the results showed that 85% of charging sessions concluded in less than one hour.

The results show that the standard rate results show low charging in the daytime with a gradual increase in the evening with an eventual maximum from 12-1am. The results also show that the non-standard rates move the charging distribution to the off-peak periods, which vary by rate type and season as depicted in Figure 1. Figures 2 and 3 compare the charging distribution (percentage of EV charging) over a 24 hour period for the four rate structures for each rate season.

For both the TOU and CPP rates, customers are charged differently based on the periods of the day. In addition to the differences in the times of the low pricing periods, the CPP rate has a significantly lower energy cost for all three time periods of the day during the majority of the year except for the CPP event days. During the CPP event days, the energy cost significantly increases from an hour before to an hour after the normal peak period time. The CPP event days will not necessarily align with the individual circuit peak days but will nevertheless likely coincide with high loading on the circuit. Since the methodology presented in this paper focuses on evaluating the EV impacts during peak demand days, it is logical to evaluate a rate scenario inclusive of both normal CPP days and event CPP days (CPP Rate) and a rate scenario of only CPP event days (CPP Event Rate). A more in-depth analysis of the pilot studies summarized here will be provided in a future publication.

III. Method to Estimate EV Load Impact

This section provides the framework for estimating the impact of EV loading on a distribution system by using the EV charging distributions obtained in the previous section.

To assess the EV charging load impact on a given feeder, we adopted the common approach of performing a time series simulation using power flow analysis software. Simulations consider the planning horizon years, typically 5-10 years. To reduce the computations, we focused on the peak loading conditions on the feeder and considered a summer peak day and a winter peak day, which also allows the use of traditional loading and voltage limits. The main EV data needed for the impact study is an estimation of: (i) customers who will have EVs at each year, (ii) their charging time profiles over a day. Hence, the first challenge for the impact assessment is

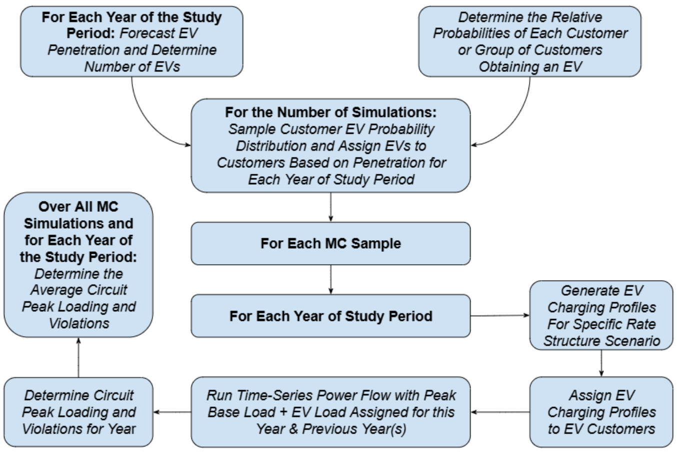

Fig. 4. Circuit Impact Assessment Method Overview

obtaining this data. The method adopted to estimate this data is given in the next subsection and provides us the likelihood of EV adoption for a customer; hence, the MC method is used to incorporate the uncertainties in the EV data. Figure 4 provides an overview of the method.

As the figure shows, first the EV penetration is forecasted over the study period and the number of EVs for each year is determined. Section B describes the method for estimating the county level EV penetration, which provides a more realistic EV penetration for a particular circuit. Next, the total new EVs for each year are allocated to customers on the circuit, which is outlined in Section C. Importantly, these customers are predetermined across the MC simulations to remain consistent for all rate cases.

A. Monte Carlo Simulation

To account for the uncertainties in the EV adoption locations on a system and the EV charging profiles, the MC method is implemented. System simulation involves time-series power flow analysis for the two peak days of the year and for each of the planning years over the many simulation instances. This process is repeated for each rate case considered.

For MC simulations, 24-hour EV charging profiles are generated and assigned for all customers. The process for generating these profiles is provided in Section D.

Note that in order to have a fair comparison between the rate cases, the system and EV customer data need to be kept the same between the rate cases except for the EV charging profiles. MC simulations should be run for many iterations (typically at least 100 or higher) for each rate case to obtain accurate results.

The MC simulations ultimately provide us the estimated sample average values of the quantities we are interested in: equipment overloads and voltage violations. These results can then be processed based on the specific traditional utility planning criteria to determine circuit peak loading and violations due to the addition of EVs under a specific rate case. Subsequently, the loading and violations for each rate case are compared to one another to determine their relative effectiveness in mitigating the impact of increased EV charging.

B. EV Penetration Forecasting

Given the limited EV adoption data available from EV registration records, it is quite challenging to estimate the EV adoption levels on a given distribution system over the next planning period (5-10 years). Our proposed approach aims at getting an estimate of EV adoption on a distribution system based on the county the system is located. To address the limited data issue, the proposed method uses both the county level data as well as the state-wide data. This method provides three concrete benefits over existing methods: (1) hierarchical reconciliation of lower-level forecasts to a higher-level forecast often reduces forecast error [12], (2) it prevents unconstrained county forecasts from cumulating to unrealistic state-wide total forecasts, and (3) it allows matching of individual county adoption goals to state-wide legislative targets and planning scenarios.

The requirement for the county-level EV registration data is that the trend of each county must be increasing, which logically should hold true. The requirements for the state-wide forecast is that, with a high correlation, the forecast must fit to a 3$^{\text{rd}}$ order polynomial regression that is strictly increasing for $x \geq 0$, which is typical of EV adoption forecasts as a 3$^{\text{rd}}$ order polynomial matches the first half of an "S" curve adoption model (including Bass Diffusion). For demonstration, this method is applied to the state of NC using county-level vehicle registration data provided by the NC Department of Transportation [4] and the monthly NC state-wide EV adoption forecast from [5] (shown in Figure 5). The EV registration data from September 2018 to November 2023 for NC was utilized and this data shows 98 of 100 counties having increasing EV adoption rates. The other two counties are have remained stagnant but only have a few EVs and therefore, are insignificant and have been excluded. The following are the steps for this proposed method:

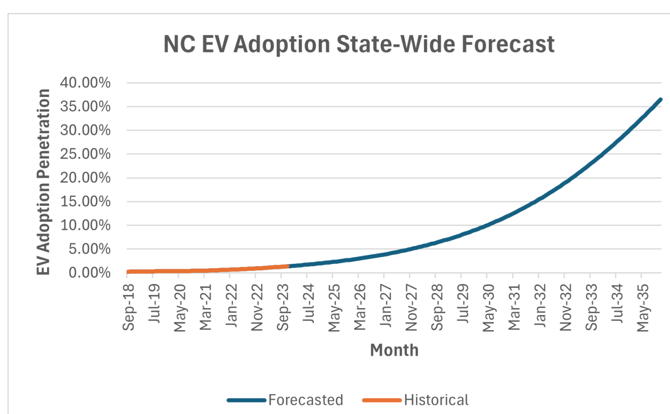

Fig. 5. NC State-Wide EV Adoption Forecast [5]

Step 1 (Initial forecast of county EV adoption) Each county of the state is initially forecasted separately using a 2$^{\text{nd}}$ order polynomial regression. This results in each county having unique "a", "b", and "c" coefficient values based on the trend of its individual historical EV registration data. The reason for using an initial 2nd order polynomial regression, is that it will provide a simple, increasing forecast for all lower-level forecasts as to allow reconciliation with the higher-level 3rd order forecast.

There are now N lower-level series $i = 1, \dots, N$ with original 2nd order regressions

$$\hat{y}_i(x) = a_i x^2 + b_i x + c_i,$$

where historical observations are in discrete time steps $x \in \{1, 2, \dots, T_h\}$. The forecast period is defined as $x \in \{T_h + 1, \dots, T_f\}$, where $T_f > T_h$ denotes the forecast horizon. This process seeks to adjust the growth exponent "2" so that the sum of forecasts at $x = T_f$ matches T_f for the state-wide forecast.

Step 2 (Adjust exponent and match to T_h) The quadratic exponent "2" is replaced for each county forecast by a common exponent $d \in (1, 3)$ (e.g., $1.8, 1.9, 2.1, 2.2, \dots$), while keeping a_i and b_i fixed. The adjusted forecast model is defined as

$$\tilde{y}_i(x; d) = a_i x^d + b_i x + \tilde{c}_i(d), \tag{1}$$

where the intercept $\tilde{c}_i(d)$ is updated to ensure the adjusted model exactly matches the last historical observation:

$$\tilde{c}_i(d) = y_i(T_h) - a_i T_h^d - b_i T_h \tag{2}$$

Because the intercept is matched to T_h, the adjusted forecast for any $x > T_h$ can be rewritten as:

$$\tilde{y}_i(x; d) = y_i(T_h) + a_i\big(x^d - T_h^d\big) + b_i\big(x - T_h\big) \tag{3}$$

Step 3 (Formulate total forecast at T_f). The total adjusted forecast sum at the final time step T_f is

$$\begin{aligned} S(d) &= \sum_{i=1}^{N} \tilde{y}_i(T_f; d) \\ &= \underbrace{\sum_{i=1}^{N} y_i(T_h)}_{C} + \underbrace{\sum_{i=1}^{N} a_i}_{A} \left(T_f^d - T_h^d\right) \\ &\quad + \underbrace{\sum_{i=1}^{N} b_i}_{B} \left(T_f - T_h\right) \end{aligned} \tag{4}$$

The value of d is chosen such that the sum of the T_f for the county forecasts matches the T_f for the state-wide forecast (denoted $S^\star$):

$$S(d) = S^\star \implies S(d) - S^\star = g(d) = 0, \tag{5}$$

$$g(d) = C + A\big(T_f^d - T_h^d\big) + B(T_f - T_h) - S^\star = 0 \tag{6}$$

Step 4 (Solve for d using Newton-Raphson) If $A \neq 0$, the derivative of $g(d)$ with respect to d is unchanged by the linear term, since $B(T_f - T_h)$ is constant:

$$g'(d) = A\Big(T_f^d \ln T_f - T_h^d \ln T_h\Big). \tag{7}$$

Given an initial guess d_0 (e.g., $d_0 = 2$), the iterative update becomes

$$\begin{aligned} d_{k+1} &= d_k - \frac{g(d_k)}{g'(d_k)} \\ &= d_k - \frac{C + A\big(T_f^{d_k} - T_h^{d_k}\big) + B(T_f - T_h) - S^\star}{A\big(T_f^{d_k} \ln T_f - T_h^{d_k} \ln T_h\big)} \end{aligned} \tag{8}$$

Step 7 (County forecasts after solving for d) Once d satisfies $g(d) = 0$ and solving for $\tilde{c}_i$ by setting $x = T_h$ with $y_i(T_h)$, a_i, and b_i known; the following is provided for each county:

$$\tilde{y}_i(x) = a_i x^d + b_i x + \tilde{c}_i, \qquad x = T_h + 1, \dots, T_f. \tag{9}$$

Step 8 (Hierarchical Reconciliation) Now that the sum of the T_f values for the county forecasts match the state-wide forecast T_f value, each discrete value of the county-level forecasts in the interval $x \in \{T_h + 1, \dots, T_f - 1\}$ should be proportionally adjusted separately but simultaneously for all counties so that the resulting sum of the counties equals the state-wide forecast. To accomplish this, the required sum of the counties was divided by the initial fitted sum of the counties at each time step and then each value was multiplied by this adjustment factor, as provided in (10).

$$\tilde{y}_i(x) = \hat{y}_i(t)\, \frac{\hat{Y}(t)}{\sum_{j=1}^{m} \hat{y}_j(t)}\ (\forall\, i, t). \tag{10}$$

Where

- $\tilde{y}_i(x)$ is the reconciled lower-level forecast for series i at time t
- $\hat{y}_i(t)$ is the original (unadjusted) forecast for series i at time t.
- $\hat{Y}(t)$ is the higher-level (aggregate) forecast at time t.
- $\sum_{j=1}^{m} \hat{y}_j(t)$ is the total of all lower-level forecasts across m series at time t.
- m is the total number of disaggregated lower-level series.
- i indexes the individual lower-level series.
- t indexes discrete time steps over the forecast horizon.

Ultimately, this process results in the sum of all of the county-level forecasts exactly matching the aggregate state-wide forecast for every value while maintaining the existing historical EV adoption trends for each county. Note that to convert the discrete number of EVs per year to peneration percentages, the total number of light-duty vehicles for each county will need to be forecasted.

The results of this process applied to NC are shown in Figure 6 for 2030 and Figure 7 for 2035. Additionally, the results for Wake County, which yielded the highest adoption percentage by 2035, is shown in Figure 8.

C. Spatial Allocation of EVs

After obtaining an estimate on the EV penetration level for the distribution system, this next step involves allocating the total new EVs to customers on the feeder. This method uses relative probabilities to stochastically assign EVs to customers. One notable technique for determining these probabilities

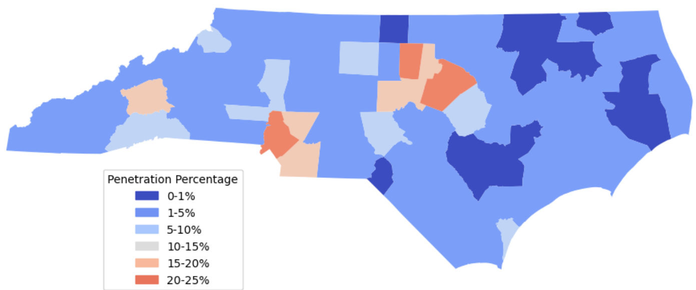

Fig. 6. NC EV Adoption Forecast Map By County 2030

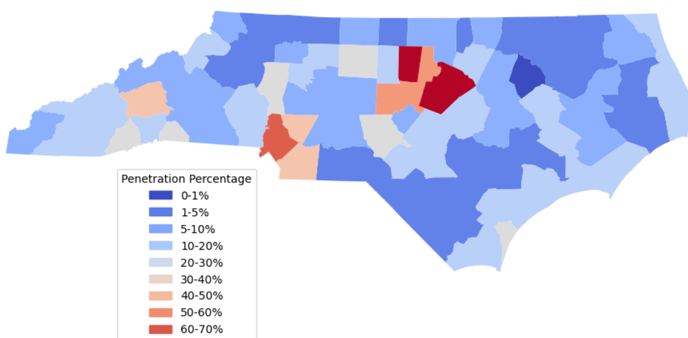

Fig. 7. NC EV Adoption Forecast Map By County 2035

follows the methodology of [5] by linking county property-tax records to customer transformers via GPS coordinates. For this method, it is assumed that higher property tax value correlates with a higher likelihood of EV ownership. From the circuit model, each transformer's ID, latitude/longitude, and associated customer count are obtained. Then from the county property tax database (typically publicly available online), the parcel latitude/longitude and tax values are imported and filtered to single-family residential with a structure. For each distribution transformer from the circuit model, the property tax value of the nearest residential parcel is assigned (nearest-neighbor matching). To reflect the multiple customers per transformer, an adjusted property tax value can be calculated as the assigned property tax value multiplied by the number of customers on the transformer. Lastly, these adjusted values are normalized over all transformers yielding a relative probability distribution for EV adoption across the circuit. This resulting probability distribution can then be sampled to allocate EVs to customers each year based on the penetration rates. To ensure fair comparison across rate structure scenarios, it is important that the customer allocations are predetermined for each year of each simulation before running the rate structure scenario simulations.

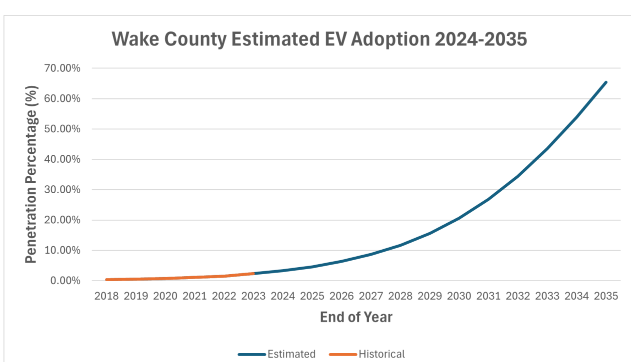

Fig. 8. Wake County Forecasted EV Adoption 2024-2035

D. Generation of Stochastic EV Charging Profiles

For each of the rate structure scenarios, the EV charging profiles need to be stochastically generated and assigned to each allocated EV customer, which requires the sampling of multiple probability distributions. There are four components that must be considered to generate the EV charging profiles: charging loadshape, charging start time, charging deadline, and charging time. The charging loadshape refers to the signal appearance of the charging profile, which includes the charging power during both charging and not charging times. The charging start time is the time that the customer starts the charging session. The charging deadline is when the charging must end. Lastly, the charging time is the length of time that the vehicle charges, which is a function of energy and charging power.

1) Charging Loadshape: A logical assumed charging loadshape is a constant power "On/Off" (rectangular) profile as the level 2 residential charging is not limited by the batteries but by the internal AC/DC power electronic converter and can charge to its power limit. EV batteries are typically rated to handle much higher power due to their capability to charge "on-the-go" with DC fast charging. This constant "On/Off" (rectangular) profile was validated by the NC State University FREEDM Center 9kW EV charger (charging an unknown Tesla) as shown in Figure 9.

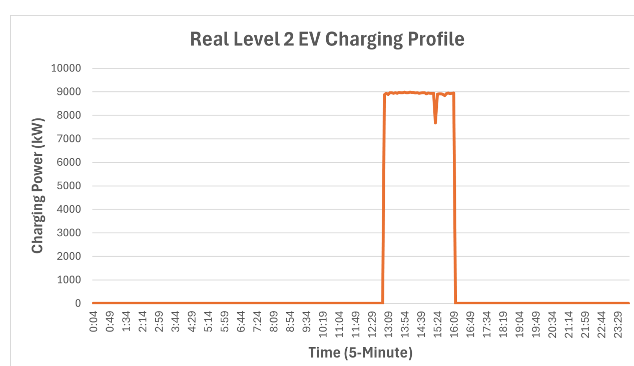

Fig. 9. Real Level 2 EV Charging Profile from NCSU FREEDM Center

This assumed charging loadshape requires a peak charging power for the "On" state. For electric-only EVs (PEVs), a reasonable charging power is 11 kW and for plug-in hybrid electric vehicles a reasonable charging power is 7 kW. These values are based on the US Department of Energy published PEV and PHEV level 2 charging ratings for PEVs and PHEVs in 2024, respectively [13], and may need to be updated in the future. When the EV charging profiles are generated, a particular profile will have a percent chance of being a PHEV with a peak charging power of 7 kW and a percent chance of being a PEV with a peak charging power of 11 kW. These percentages can be based on the existing or future split of PHEV/PEV for a particular region. For example, NC shows an existing approximate 25%/75% PHEV/PEV distribution [4]. These charging loadshapes are kept consistent between the different rate structure scenarios.

2) Charging Start Time: The charging start times for all rate structures are assumed to be different from one another. These start-times can be drawn from a utility's EV charging pilot study as shown for NC in Figures 2 and 3. These distributions capture real-world behavior among early adopters. Since these are early adopters and may not reflect the general driving population, these results should be supplemented with broader travel statistics from the NHTS [14] or another reputable source for travel statistics. Since the early adopter EV customers on the pilot program showed that 85% of charging sessions concluded in less than an hour, using these distributions is a valid proxy for the charging starting time distributions. As the level of adoption increases, the reliance on supplemental travel statistics will need to be reevaluated.

3) Charging Deadline: The charging deadline for each charging profile dictates when the vehicle is unplugged and ends the charging session. It is assumed that rates do not affect a driver's daily home/away schedule so the charging deadline distribution should be the same for all rate structure scenarios. This charging deadline distribution should be obtained from travel statistics as a probability distribution of the times when drivers left their home for a trip. For each generated charging profile, the charging start time should be determined first so that a valid charging deadline can be established. The deadline must occur at least one hour after the start time to ensure the session qualifies as a valid charging event.

An example charging deadline distribution is shown in Figure 10, which was taken from [5] and is based on the travel statistics from [14]. This distribution was an input for the case study in Section V.

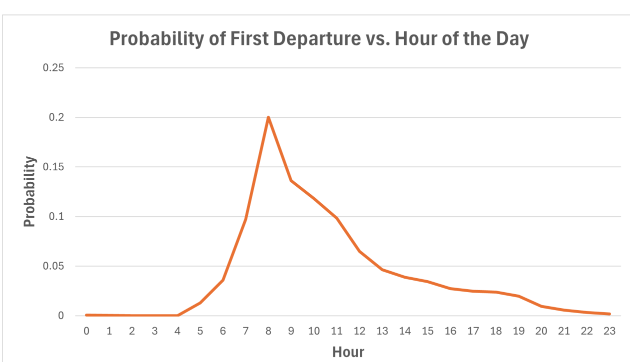

Fig. 10. 24-Hour Departure Distribution from the NHTS [5] [14]

4) Charging Time: The charge time can be calculated from:

$$T = \min\left\{ \left\lceil \frac{E}{P} \right\rceil ,\ t_{\text{deadline}} - t_{\text{start}} \right\} \tag{11}$$

Where

- T is the actual charging duration used in the simulation.
- E is the energy requested for the session (kWh).
- P is the charging rate (kW).
- t_{start} is the charging start time (h).
- t_{deadline} is the charging deadline (h).
- $\lceil \cdot \rceil$ is the ceiling operator (smallest integer $\geq$ the result).
- $\min\{\cdot, \cdot\}$ returns the smaller of its two arguments.

E was calculated using the following equation. This charging energy equation was taken from [5].

$$E = \frac{D \cdot \frac{1}{\text{kmpkwh}}}{\eta} \tag{12}$$

Where,

- E is the requested charging energy for a charging session
- D is the daily driving distance in km
- kmpkwh is the assumed average km per kWh for all EVs
- η is the assumed charging efficiency

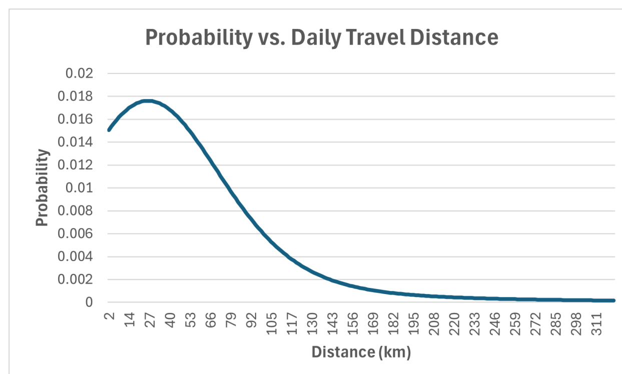

Fig. 11. Daily Travel Distance [5]

D for each generated profile is sampled from a distribution of driving distances. An example driving distance distribution is shown in Figure 11, which was taken from [5] and is based on the daily driving distance statistics from [14].

IV. Utility Case Study

A. Utility Data and Circuit Overview

This section provides a realistic utility case study implementing the method in Section III on a real 24 kV voltage class radial circuit in an urban setting. This circuit comprises of 1,799 single-family residential customers served by 208 residential transformers (all single phase with a rating of 15-100 kVA). The total circuit length is approximately 4.6 km of overhead conductor backbone consisting of primarily 477 AAC conductor. Lastly, this circuit includes two 1200 kVAR capacitor banks, which are switched on for both peak scenarios due to high load, but does not include any voltage regulators or distributed energy resources.

For the time-series analysis non-EV base load, the customers are assigned a set 24-hour peak load profile provided by the utility, which is scaled based on the individual customer peak load determined during initial peak load allocation.

Figures 12 and 13 provide the total circuit peak base load (without EV charging) for the summer and winter peak days, respectively. The utility has a higher winter peak as reflected in the base load.

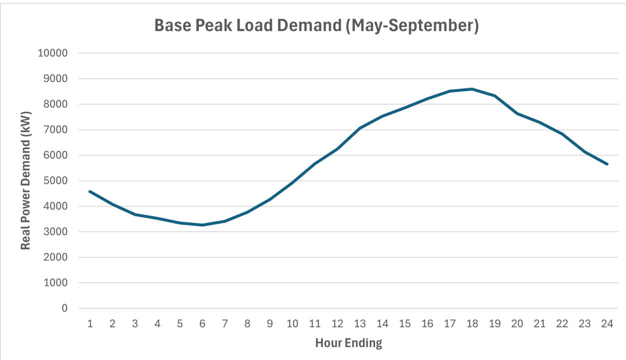

Fig. 12. Summer Base Peak Load Demand

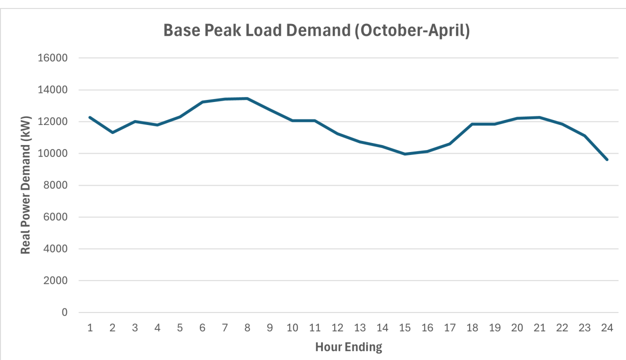

Fig. 13. Winter Base Peak Load Demand (October-April)

B. Utility Planning Criteria and System Impact Metrics

The following includes the specific evaluated metrics and the associated utility-specified planning criteria:

- Peak feeder head loading (kW)
- Percentage of transformers exceeding 130% rated capacity for summer and 160% rated capacity for winter.
- Bus voltage allowed range: 1.017pu to 1.05pu.
- Conductor overloading: 50% of rated capacity for summer and 66% of rated capacity for winter.

Note that the allowed bus voltage window is greater than the U.S. minimum delivery standard of 0.975pu and the conductor loading threshold is significantly lower than rated capacity to ensure reliability during abnormal system configurations.

C. Input Parameters

This case study uses the EV penetration forecast for Wake County (shown in Figure 8) as it is the county with the highest number of estimated EVs for NC in 2035.

The EV customers for this circuit were spatially allocated using the method provided in Section III. The actual nearest-neighbor property taxes for each transformer were utilized to determine the relative EV adoption probabilities of each transformer.

When generating the EV charging profiles, five rate structure scenarios were considered for both summer and winter (ten total): (1) all EV customers on standard rate, (2) all EV customers on CPP rate, (3) all EV customers on CPP Event response rate, (4) all EV customers on the TOU rate, and (5) customers on a mixed rate consisting of 50% on the standard rate, 40% on CPP rate, and 10% on the TOU rate. This mixed rate scenario provides a realistic future mixture of customers on the different rates, which is based on guidance from the NC utility.

D. Simulation

The case study time-series simulation was performed for 100 iterations over the study period of 2024-2035 for each of the five rate structure scenarios for both the summer and winter 24-hour peak load periods. The circuit loading, transformer loading, bus voltages, and conductor loading were recorded and processed based on the utility planning metrics.

E. Results

1) Feeder Loading: Figures 14 and 15 show the circuit peak loading results for summer and winter, respectively.

Figure 14 shows that all rate scenarios for the summer lead to similar circuit loading until the EV penetration reaches approximately 34.4%. After this penetration level the the circuit peak loading for the TOU rate scenario increases much quicker compared to the other rate scenarios, eventually reaching nearly 170% of the base load. Similarly, the CPP rate scenario increases much quicker after the 53.9% penetration level, reaching nearly 150% of the base load. The mixed rate scenario and CPP event rate scenario show the lowest circuit peak at the highest evaluated penetration levels, even lower than the standard rate scenario.

Figure 15 shows that all rate scenarios for the winter have a minimal increase in peak load until 26.8% EV penetration. After this penetration level the rate scenarios diverge with the TOU and CPP event rate scenarios having the highest circuit peak loading, reaching nearly 150% of the base load, and the CPP and mixed rate scenarios showing the lowest circuit peak loading, even lower than the standard rate scenario.

2) Transformer Overloading: Figures 16 and 17 show the percentage of transformers overloaded for summer and winter, respectively. For summer, the TOU rate scenario clearly shows the highest number of overloads with approximately 65% of transformers overloaded by 65.4% EV penetration. For winter, all rate scenarios show comparable customer transformer overloads, reaching approximately 65-70% overloads by the highest evaluated EV penetration. It is notable that all rate scenarios for both summer and winter show significant negative impacts to customer transformers.

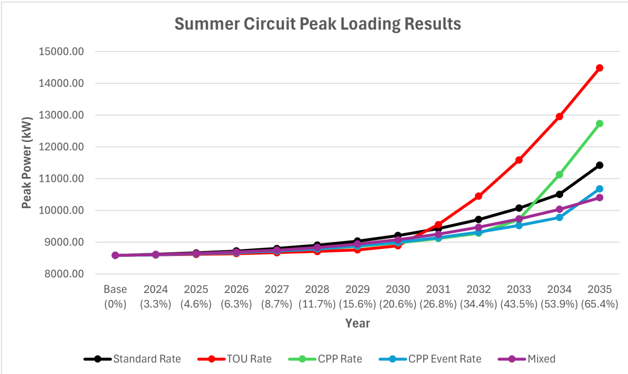

Fig. 14. Summer Circuit Loading

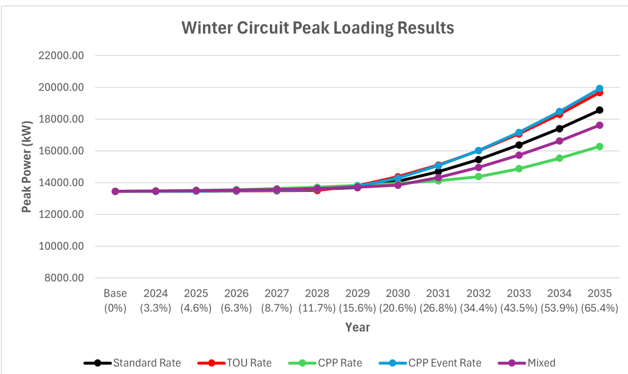

Fig. 15. Winter Circuit Loading

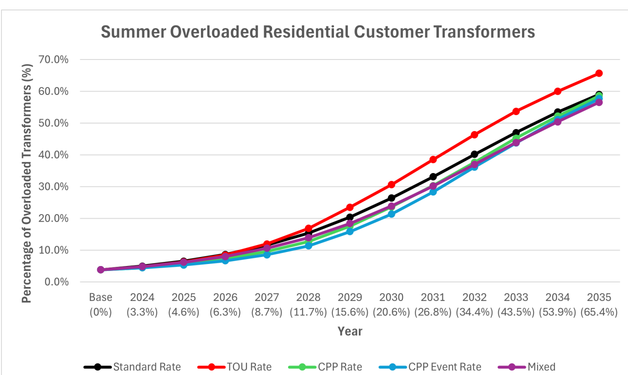

Fig. 16. Summer Transformer Overloading

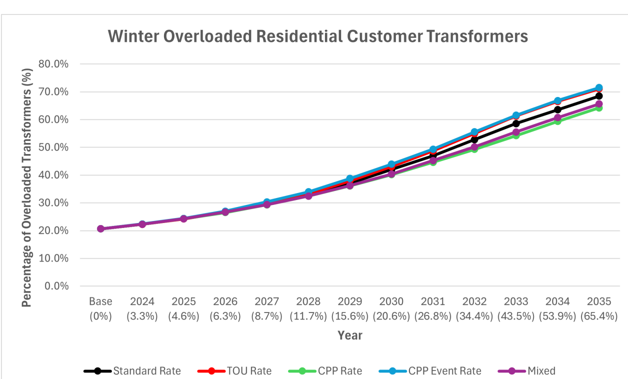

Fig. 17. Winter Transformer Overloading

3) Bus Voltage Impacts: Figures 18 and 19 show the number of nodes out of 947 total nodes on this circuit with voltage violations.

For the summer, the voltage violations are minimal with only the TOU rate scenario showing a significant increase in node violations in the highest evaluated EV penetration levels.

For the winter, all rate scenarios show minimal voltage violations until 20.6% EV penetration, in which all rates start to increase. The CPP rate shows the worst impacts with 180 unique nodes followed by TOU at 140 unique nodes for the highest evaluated EV penetration. The mixed and CPP Event rate scenarios show a slight improvement over the standard rate.

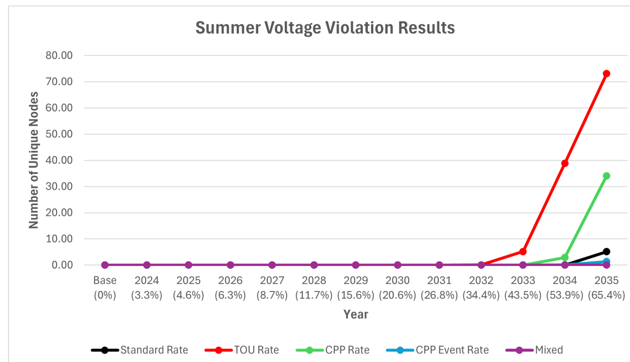

Fig. 18. Summer Bus Voltage Violations

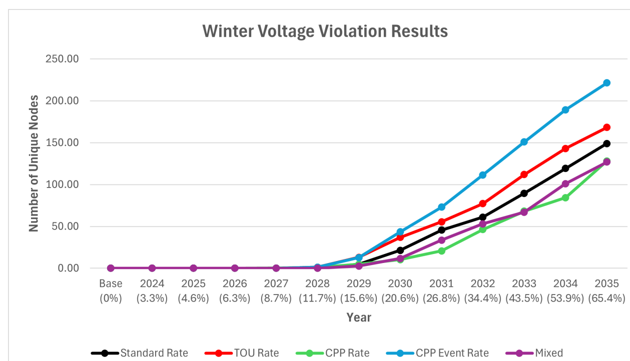

Fig. 19. Winter Bus Voltage Violations

4) Conductor Overloading: The conductor overloading for both Summer and Winter is provided in Figures 20 and 21, respectively. The conductor overloading does increase with EV penetration but is limited overall for all rate structure scenarios.

V. Conclusion

This paper provides comprehensive framework for analyzing the impacts of different utility rate structures on EV loading in distribution systems. This framework can be implemented as a planning tool by utilities to make decisions on whether to promote particular rate structures for adoption by EV customers.

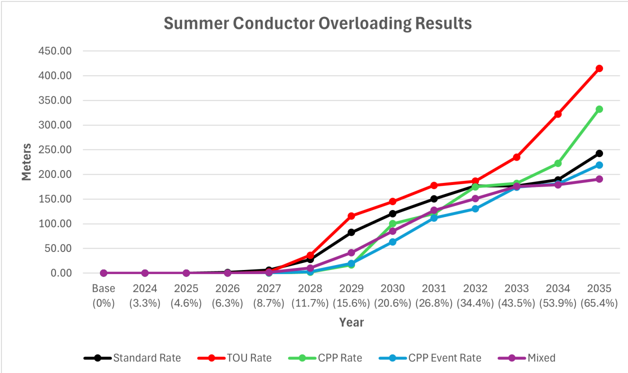

Fig. 20. Summer Conductor Overloading

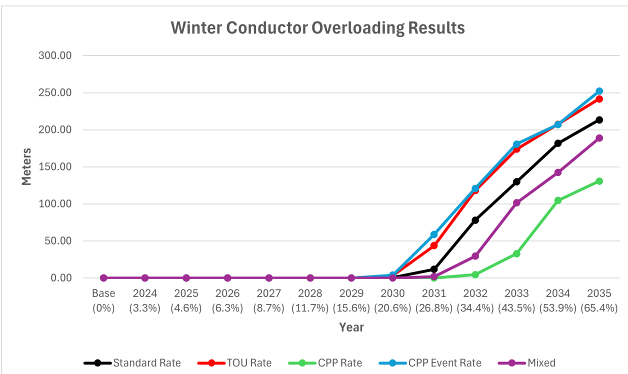

Fig. 21. Winter Conductor Overloading

In addition to this comprehensive framework, a novel method is provided for estimating the county-level EV penetration based on the historical county-level EV registration data and a state-wide forecast. This method provides the advantage of reconciliation of the lower-level county forecasts to the state-wide forecast. The limitation of this method is that it depends on the accuracy of the state-wide forecast and the rate of EV adoption may change over time for each county compared to the historical adoption rates. Ultimately, the forecasts will need to be updated as more EV registration data becomes available.

Lastly, a realistic case study is performed on a real utility circuit in NC using real utility data. The results of the utility case study show that the circuit peak load (for both summer and winter) and undervoltage impacts (for winter only) only begin to increase for an EV penetration of greater than 20.6%, which will likely not occur for several more years at a minimum. Additionally, the summer mixed and CPP rate scenarios and the winter mixed and CPP Event rate scenarios show improvement for the circuit peak and undervoltages compared to the standard rate scenario, potentially delaying the need for other mitigation techniques. However, it is notable that there are significant impacts to customer transformer overloads for all ten rate scenarios even at low penetration levels suggesting that customer transformers may require direct capacity upgrades or the use of direct managed charging.

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