Impacts of Managed Charging and Other Innovative Rates for Electric Vehicle Charging on EV Customer Load and Utility System Grid

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Project Overview

Project Scope:
- The effects of innovative rates on EV charging behavior & utility grid dynamics

Phase 1: Literature Review (COMPLETE, now revising for policy- and decision-makers)
- Reviewed industry and academic studies of EV innovative rates.
- Investigated managed charging's impact on customer & utility load, especially at the local distribution level.

Phase 2: Development of Analytical Model and Proof-of-Concept (Today's presentation)
- Customer effects: Difference in Differences (DiD) method
- Grid Impacts: Time Series Power Flow and Monte-Carlo Analysis with Stochastic Inputs for North Carolina

Phase 3: Case Study
- Utilize Duke Energy data on EV pricing pilots
  - Impact of Time-of-Use (NC) & Off-Peak Credit rates (FL, SC, IN) on customer load & utility system
    - Current and forecasted

Innovative Rate Study

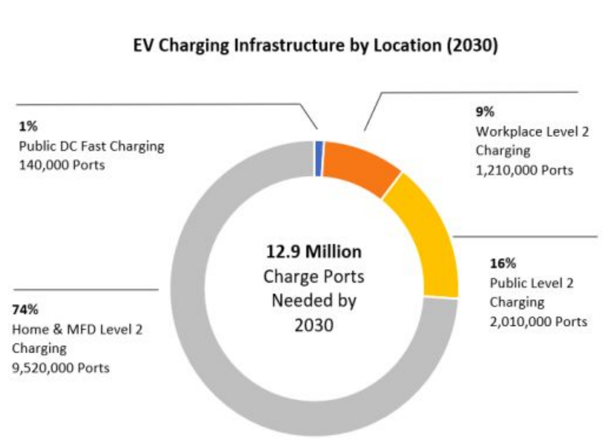
Optimizing Residential Electric Vehicle Charging
The Empirical Gap in Residential EV Charging Literature

Charging Patterns:
- ~75% of EV Charging will occur at home

Research Gap:
- Few Empirical Studies on Residential EV Charging
- Simulation Data vs Real-World Behavior

Challenges:
- Potential amplification of peak loads, leading to power losses, reduced power quality, and the risk of exceeding the grid's capacity (Muratori, 2018).

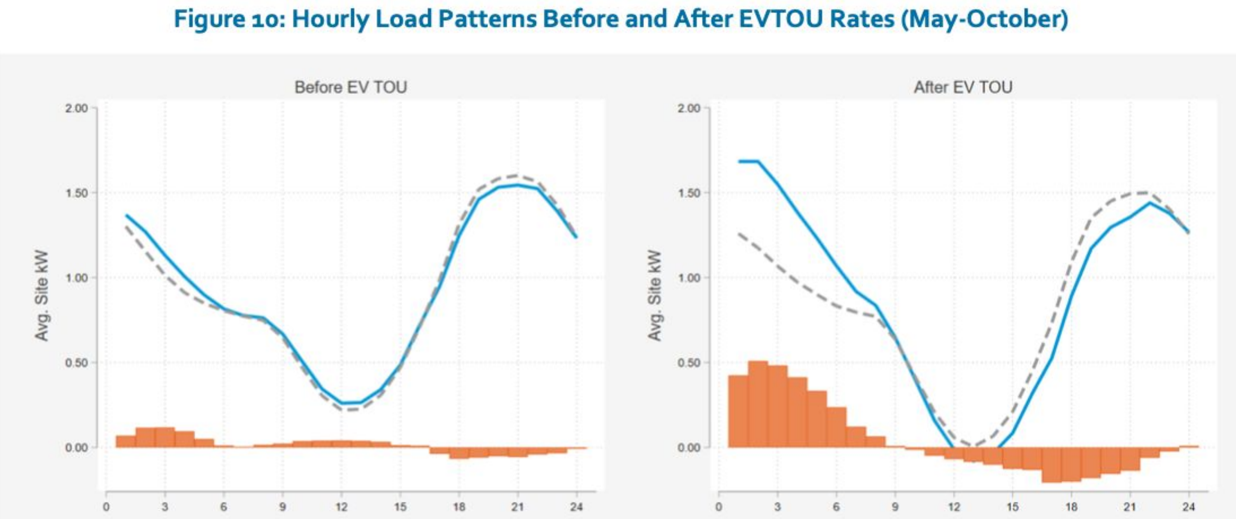
Critical Efforts:
- Understand Psychological Drivers
- Interventions, Incentives & Educational Campaigns
- Develop Strategies for Sustainable EV Charging



Satterfield, C., & Schefter, K. (2022, June). Electric Vehicle Forecast & Infrastructure Report. Prepared for Edison Electric Institute.

Bridging the Divide: Innovations in EV Charging Research
A Difference-in-Differences (DiD) Approach to Evaluate Causal Impact

Figure 10: Hourly Load Patterns Before and After EVTOU Rates (May-October)



*The dependent variable is difference between differences after the EV TOU rate and before the EV TOU rate

Reference: Bode, J. et al. Load Impact Evaluation of San Diego Gas and Electric's Electric Vehicles Time-of-Use (TOU) Rates: Final Report CAMAC ID: SDG0337, Demand Side Analytics, LLC, April 1, 2022

Innovative Rate Study

Empirical Grid Impact of In-Home EV Charging Differs From Predictions Made *(Qiu et. al, 2022)*

Model:

$$kWh_{ith} = \alpha_i + \sum_{H=1}^{24} \beta_H EV\_Charging_{ith} * I_H + \gamma p_{ith} + f(HDD_{ith})\theta + f(CDD_{ith})\eta + Dayofsample + Hourofday + \varepsilon_{ith}$$

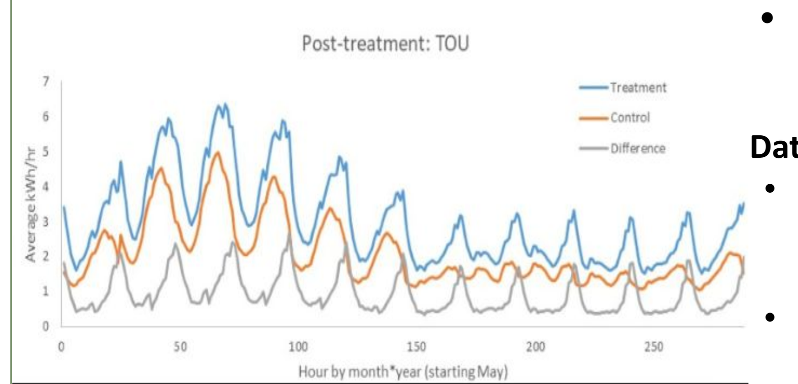


Fig. 1. Average hourly load profiles of the treatment and control groups one year before and after the adoption of EV charging.

Central Position:
- In-home EV charging differs from predictions made by simulation models.

Data & Methods:
- 1600 homes in Phoenix, AZ served by Salt River Project from 2014 to 2019.
- DiD approach to analyze causal impact of residential charging programs.

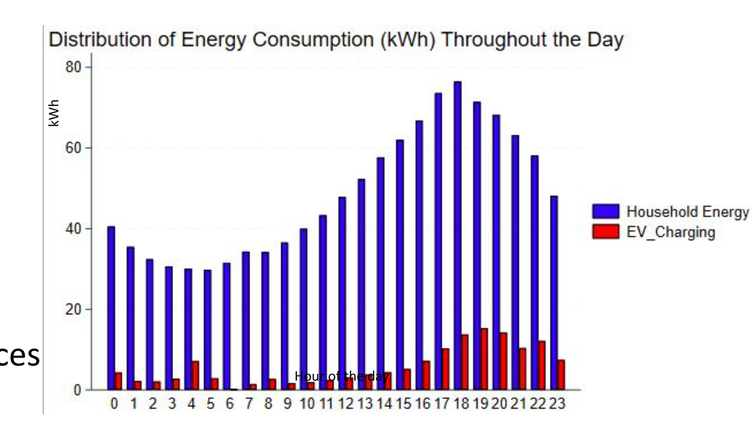
Results:
- Unmanaged home charging increases system load during peak hours.
- TOU pricing successfully incentivizes charging during off-peak hours.
- Rebound effects are observed for EV customers on increasing block rate.
  - EV owners use less energy midday as they increase their driving due to the lower cost of operating EVs.

Phase II: Pecan Street Proof-of-Concept

Dataset:
- 2018 load profiles of 25 households in Austin, TX.

Methodological Significance:
- Utilizes Florida Off-Peak Credit program to determine peak times.
- Placebo Difference-in-Differences (DiD) regression analysis
- Isolated confounding factors and assessed robustness.

Insights:
- A baseline for model operation
- Revealed typical unmanaged charging behavior.

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. xtdidreg (Off_Peak_period EV_Charging grid) (did_term), group(treatment) time(numer_date)

                          Robust
Off_Peak_p~d  Coefficient std. err.      t    P>|t|     [95% conf. interval]

ATET
    did_term
   (1 vs 0)    -.0108116   .000877   -12.33   0.052    -.021955    .0003318

Note: ATET estimate adjusted for covariates, panel effects, and time effects.
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Phase III: Assessing the Influence of Pricing Strategies on Behavior: *A case study of Duke Energy's Residential Charging Programs*

Research Questions:
- Does participation in residential EV charging programs lead to reduced peak electric use?
- Does it lead to new "timer" or "rebound" peaks outside of the specified peak hours?

Data:
- 400 EV homes served by Duke Energy in four U.S. states from 2021 (pre-EV rate) to 2023.
- Empirically overcome simulation limitations by observing actual data (Lee et al., 2020).
- Explore the influence of various pricing plans on charging behaviors
  - (Bode et al., 2022; Qiu et al., 2022).

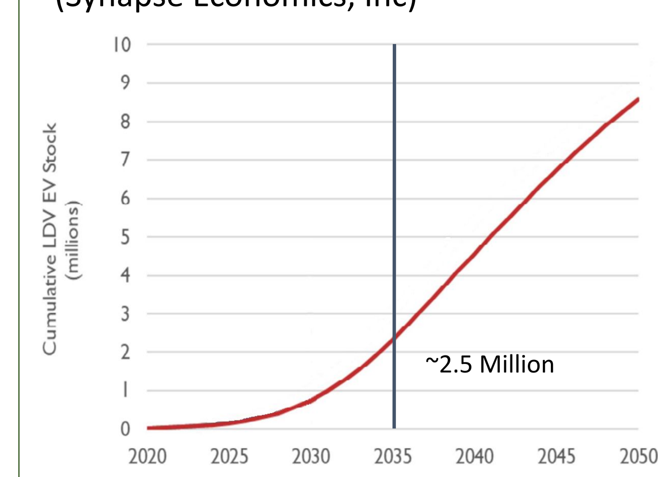
Method:
- DiD approach to evaluating the *causal* impact of EV charging (Qiu et al., 2022).

Objectives:
- Provide more representative regional estimates of EV adoption and charging behaviors.
- Make causal inferences from the data to provide recommendations regarding the program.

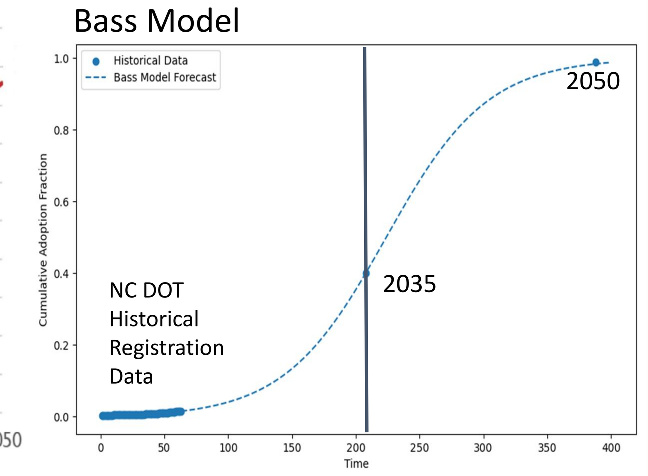
Estimate EV Penetration Levels

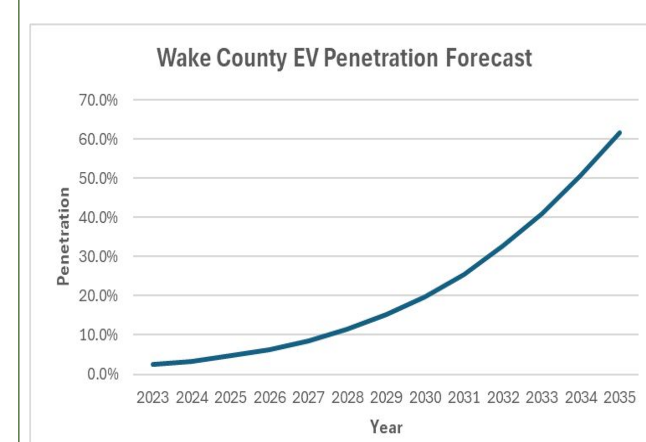
Goal: Estimate EV Penetration Levels by Circuit for the Planning Period (2035)

Source: Transforming Transportation in NC (Synapse Economics, Inc)

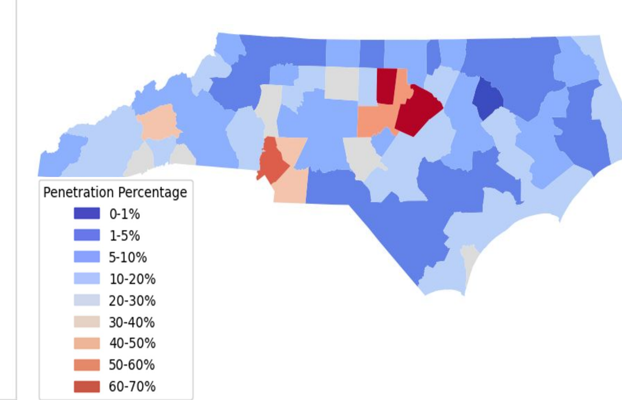


Sources: North Carolina Department of Transportation, Bass Model





North Carolina By-County EV Forecast 2035



Allocate EVs to Customer

Step 1	Step 2
Lookup/Return House Tax Value from County Property Tax Database	**Convert House Tax Values to Relative Probabilities of Obtaining an EV**

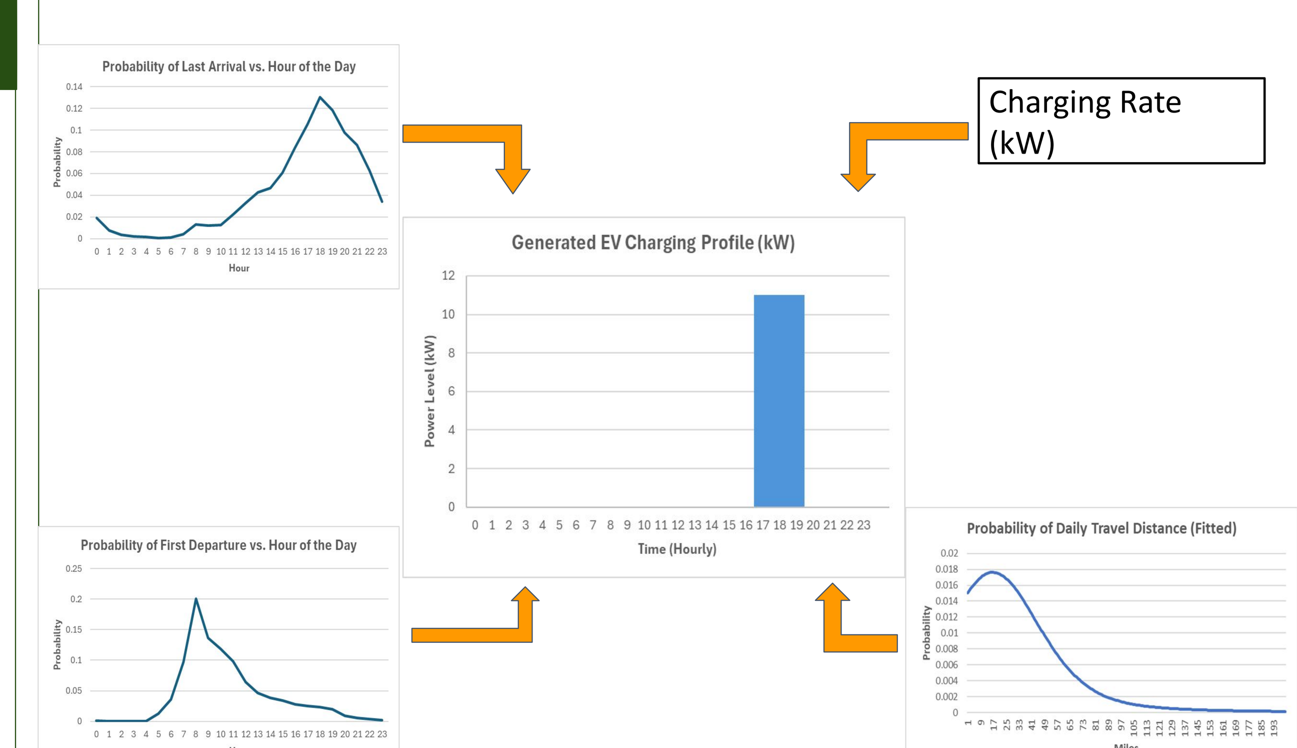
Household	Latitude	Longitude	Street Number	Street Name	City	County	Tax Value	Probability of Obtaining an EV
A	35.775497	78.673175	100	Wolfpack Ln	Raleigh	Wake	300,000	0.25
B	35.776497	78.674175	200	Wolfpack Dr	Raleigh	Wake	200,000	0.17
C	35.777497	78.675175	300	Wolfpack Cir	Raleigh	Wake	700,000	0.58

Assumption: Higher Home Tax Value = Higher Chance of Household Obtaining an EV

Determine Residential EV Charging Profiles

Unmanaged Charging Case

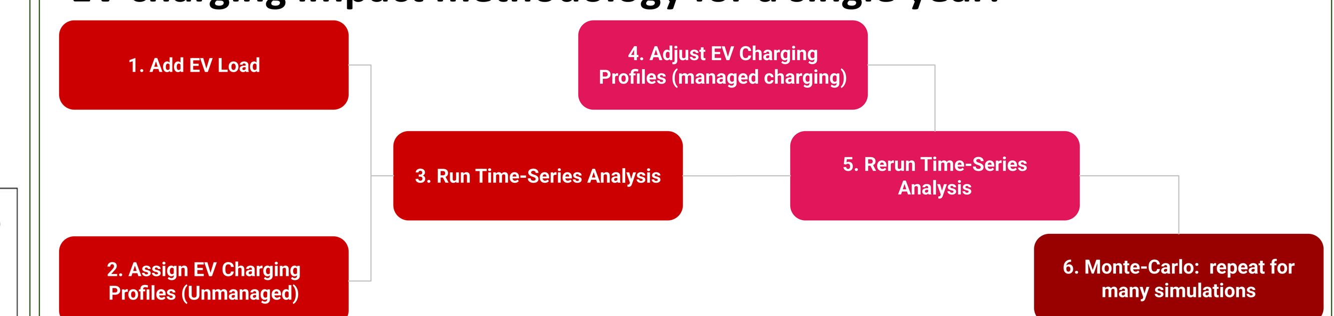
Source: North Carolina Travel Data



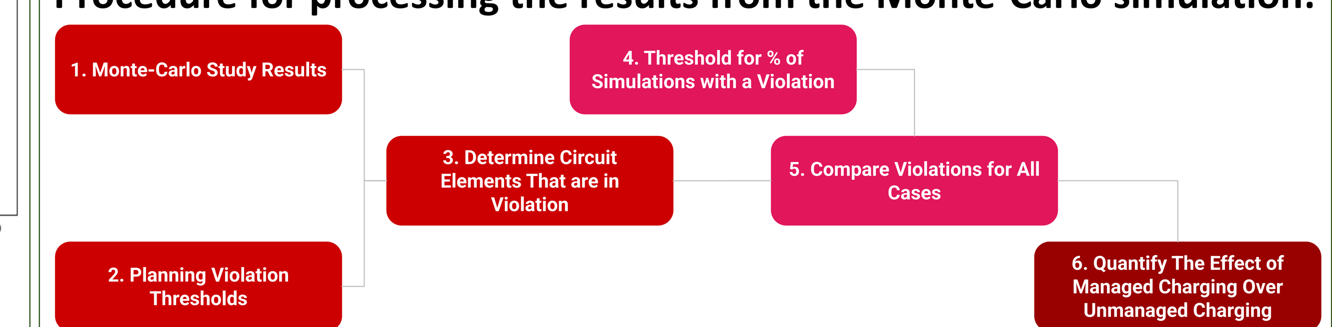
Source: National Household Travel Survey (2017)

Combined Impact of Innovative Rates and Grid Impact

EV charging impact methodology for a single year:



Procedure for processing the results from the Monte-Carlo simulation:



Software tools:
- CYME Steady State Analysis with Load Profiles Module
- CYME Python Scripting Tool Module

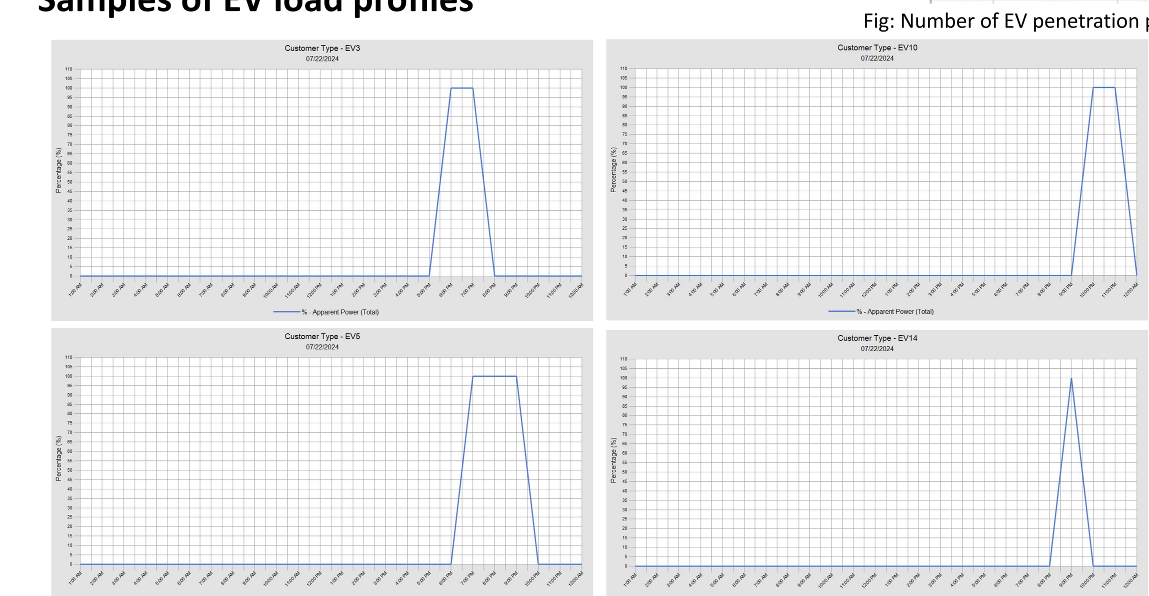
Phase II Example Impact Study

IEEE 34 bus system:
- Estimate the number of residential customer
- Estimate the number of total vehicle (2 Vehicle/HH)
- Estimate the number of EVs based on penetration %

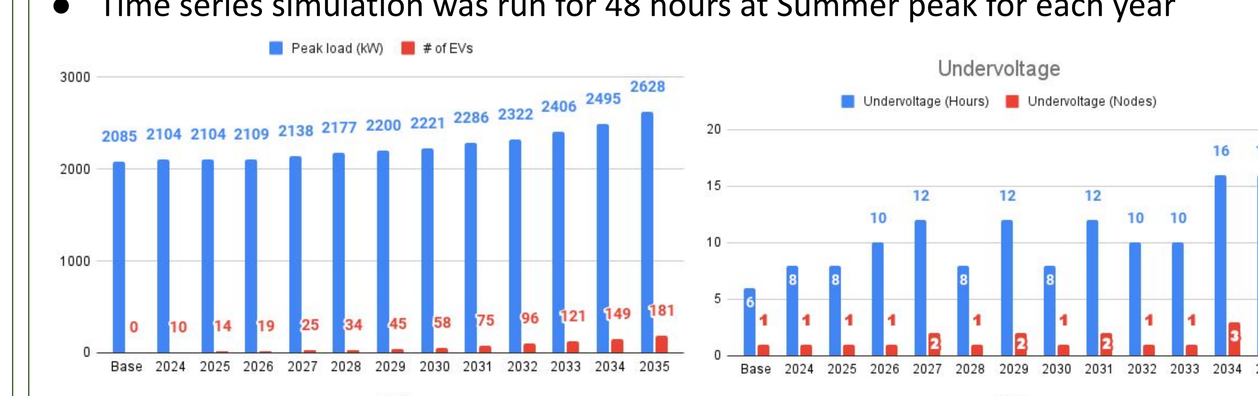
Year	Penetration %	# of EVs
2023	2.4	7
2024	3.4	10
2025	4.7	14
2026	6.4	19
2027	8.6	25
2028	11.5	34
2029	15.2	45
2030	19.8	58
2031	25.6	75
2032	32.6	96
2033	41.0	121
2034	50.8	149
2035	61.7	181

Fig: Number of EV penetration per year

Samples of EV load profiles



Results:
- Time series simulation was run for 48 hours at Summer peak for each year



Other impacts to be considered for Phase III
- **Transformer overloading**
- **Conductor overloading**
- **Phase imbalance**

Takeaways

We successfully completed Phase II Proof-of-Concept

1. Using Pecan Street Austin TX data, demonstrated feasibility of DiD Method to estimate EV customer response to innovative rates
2. Estimated EV penetration levels for each county of North Carolina
3. Established stochastic method for EV load allocation based on house tax values
4. Established method for generating stochastic EV Charging Profiles for the unmanaged case using NC travel data
5. Developed CYME framework for Impact Analysis combining grid impacts and innovative rates