Using Electric Vehicle Charging Load Elasticity To Augment Grid Reliability Indices

Nipun Popli†, Dhananjay Anand†, Casey Quinn†, John Smart†, Timothy McJunkin†

Abstract—**In this paper we introduce a non-linear logistic model to represent incentive-driven aggregate electric vehicle (EV) charging behavior. We use this model to quantify non-linear price elasticity and assess its reinforcing impact on grid reliability. We present proof-of-concept demonstration on IEEE 24-bus Reliability Test System (RTS), where a Monte Carlo Simulation of the logistic model is employed to quantify improvements in probabilistic resource adequacy. Our findings highlight the potential of real-time incentive-based managed EV charging as a cost-effective strategy to augment bulk-system adequacy.**

Index Terms—**expected energy not served (EENS), effective load carrying capability (ELCC), electric vehicle (EV), loss of load expectation (LOLE), loss of load probability (LOLP), nonlinear price sensitivity, Monte Carlo Simulation (MCS).**

I. Introduction

Ensuring reliable and affordable energy remains a top priority for the U.S. Department of Energy [1]. In bulk power systems, these goals hinge on resource adequacy planning under capacity expansion cost constraints. Grid reliability is evaluated using probabilistic indices that measure the risk of generation shortages, summarized in TABLE I. While adding firm capacity improves reliability, it also raises electricity costs, as discussed next. The Effective Load Carrying Capability (ELCC) is a key reliability metric (see TABLE I). Variable resources like wind and solar reduce ELCC, adversely impacting the grid adequacy [2]. For example, Southwest Power Pool's 33.79 GW of wind provides 5.15 GW ELCC in summer and 8.62 GW in winter [3]. Federal Energy Regulatory Commission (FERC) has stated that overestimating ELCC for intermittent sources during peak hours can distort capacity markets [4]. With electricity demand rising, firm capacity expansion is essential but faces delays from permitting, construction, and supply chain constraints for technologies like nuclear and gas [5]–[7]. PJM's latest auction cleared at FERC's cap of 329.17 per megawatt-day (MW-day), a 600% increase since 2022 [8]. Managed EV charging can help ease capacity stress and improve reliability. U.S. light-duty EVs are projected to reach 30-42 million by 2030 and up to 50 million by 2040 [9]. Unmanaged charging at this scale could create concentrated peak loads, straining firm generation. However, flexible charging can shift demand away from evening peaks. Effective national-scale management could double simultaneous EV charging without affecting user needs [10]. With advances in modeling and control, EVs can become *non-wire* and *non-plant* assets that enhance grid reliability.

† Idaho National Laboratory, 1955 Fremont Ave, Idaho Falls, ID 83415, (email: {nipun.popli, dhananjay.anand, casey.quinn, john.smart, timothy.mcjunkin@inl.gov}@inl.gov).

TABLE I: Key Reliability Indices and Definitions

Reliability Index	Definition	Units
ELCC: Effective Load Carrying Capability	a measure of average power a variable or non-controllable generation resource can be relied on to meet electricity demand during peak hours	MW
LOLP: Loss of Load Probability	probability of system's daily peak or hourly load being greater than available generation capacity in a year	Probability
LOLE: Loss of Load Expectation	expected number of days per year when system's generation capacity is insufficient to meet load at least once during the day.	Days
EENS: Expected Energy Not Served	expected energy that will not be supplied due to generation insufficiency.	MWh/year

II. Main Contributions and Paper Structure

Before presenting our research contributions, we first outline the major EV charging strategies in Fig. 1, with varying levels of automation and centralization:

1) *Direct Control of EV Charging*: Utility or centralized operator directly controls EV charging in real time.
2) *Aggregator-Managed Charging Load*: Third-party manages charging across multiple EVs for grid services.
3) *Customer Response to Dynamic Incentives*: Users adjust charging in response to real-time price incentives.
4) *Static Time-of-Use (ToU) Charging*: Charging is scheduled during off-peak hours based on fixed utility rates.
5) *On-Vehicle Grid-Aware Charging*: Charge scheduling based on expected times of grid stress, subject to opt-in by user or preset on the vehicle.

Our focus is on *customer response to dynamic/real-time incentives*. It enables real-time flexibility without requiring direct control or full automation. We model its impact on grid reliability indices under different levels of user responsiveness. Our proposed approach can be envisioned as a more granular and dynamic alternative to static ToU pricing.

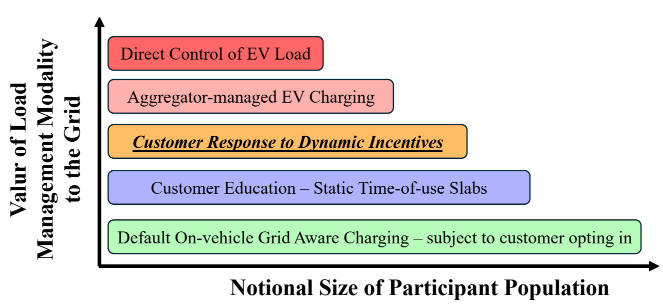

Fig. 1: Strategies for managed EV charging in support of grid.

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A. Research Gap and Contributions

We propose integrating managed aggregate EV charging as a deferrable load into grid reliability assessments. The viability of real-time incentive-driven charging is higher due to the advent of connected vehicles, with the ability to optimize charging profiles. Yet, the impact of large-scale managed EV charging on key reliability indices (TABLE I), specifically in capturing non-linear, incentive-driven user behavior, remains under explored. To fill this research gap, our paper:

1) proposes logit curve to represent non-linear elasticity of the aggregate EV charging demand in response to financial incentives for a realistic non-linear representation of user behavior, and,
2) integrates model proposed in 1) into a rigorous Monte Carlo Simulation (MCS) to probabilistically assess its impact on grid reliability indices, highlighting contribution of managed charging to grid resource adequacy.

B. Paper Organization

In this paper, our overarching objective is to establish method viability. The empirical calibration, parametric sensitivity analysis, and additional granularities and details are deferred to ongoing partnerships with industry to source field data. In Section III, we begin by introducing the logit curve and its suitability for modeling aggregate user behavior. In Section IV, we cover system component modeling approach for simulations. In Section V, we provide proof-of-concept examples. Lastly, in Section VI, we conclude with recommendations for future research.

III. The S-Curve as a Model for Aggregate Response

Our work is focused on a real-time incentive-driven EV load elasticity to reinforce grid reliability. This capability is presumed to be enabled with the proliferation of vehicles and charging infrastructure communicating in real-time with data services. This is in contrast to current ToU pricing, where users respond to fixed rate tiers [11]. Our approach evaluates the nonlinear price elasticity of EV charging demand by leveraging methodologies developed for other incentive-driven markets. Although this paper focuses specifically on EV users responses to real-time incentives, it is possible to extend this framework with additional operational constraints such as how long vehicles remain parked and the degree to which their charging can be deferred without compromising driver mobility. In Section III-A, we provide the motivation to look beyond linear price-elasticity models to capture the aggregated EV charging flexibility. This is achieved by considering the use of reverse S-shaped curve. Then, in Section III-B, we provide the mathematical characterization of the modified S-shaped curve to represent EV load as a function of incentives provided to end users.

A. Nonlinear Aggregate Behavior

In practice, the aggregate behavior can be categorized under three phases, as highlighted in Fig. 2:

- **Initiation Phase:** aggregated response reflects minimal to no sensitivity at low incentives until a tipping price point or a rebate is offered,
- **Responsive Phase:** a region of high elasticity towards incentives, achieved post tipping price-point, leading to increased participation and a steep rise in aggregate response, and,
- **Saturation Phase:** second zone of inelasticity, as the end user's willingness to adjust is diminished or exhausted, thereby saturating the aggregate response.

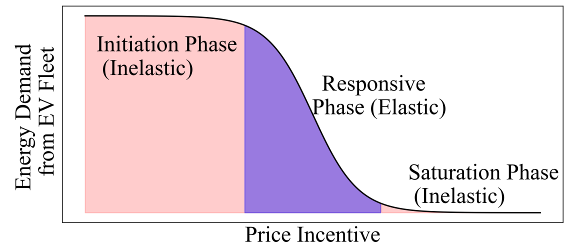

Fig. 2: Expected aggregate EV behavior, resembling a decaying S-curve as incentives to shift charging increase.

The efficacy of real-time incentive-driven managed EV charging depends on identifying two key price points: $a)$ threshold at which most users are willing to defer charging, and $b)$ price beyond which higher incentives yield diminishing returns. This behavior is well captured by reverse S-shaped demand response curves. As a case in point, the consumer response to day-ahead electricity prices in the Central Western European market follows reverse and decaying S-shaped curve, reflecting non-linear price elasticity (refer to Fig. 2 in [12]). The reverse and decaying S-shaped curve has also been used to model transformer aging with rising EV adoption [13], to forecast EV uptake [14], and to predict the diffusion of innovations and price-driven supply-demand dynamics [15].

B. A Modified S-curve for Aggregate EV Charging Behavior

We now present a modified mathematical form of the decaying S-curve, inspired by one leveraged in [16], as:

$$P\left[c_i\right] = P^{\min} + \frac{P_{\text{EV}}^{\text{BL}} - P^{\min}}{1 + e^{\alpha(c_i - c_o)}}, \tag{1}$$

where EV fleet's power consumption $P\left[c_i\right] \in \mathbb{R}_+$ is a function of the real-time incentive $c_i \in \mathbb{R}$. Then, $P_{\text{EV}}^{\text{BL}}, P^{\min} \in \mathbb{R}_+$ represent baseline or maximum possible demand when there are no incentives, or, $c_i = 0$, and minimum demand as price/incentive is large, i.e., $c_i \to \infty$, respectively. Effectively, c_o can be envisioned as a point of inflection between initiation phase and responsive phase. For cases where $c_o < c_i$, the average EV user's behavior tends to curtail the charging in response to real-time incentives c_i to alleviate the grid stress. The parameter α drives the slope in the responsive phase/region once the inflection point c_o is exceeded with a larger incentive c_i. While individual responses to incentives will vary, the aggregate behavior of large EV populations will mimic a reverse S-curve, where participation accelerates after a threshold and eventually saturates to a minimum value. The interpretation of the S-curve in Eq. (1) is summarized in TABLE II.

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TABLE II: Interpretation of the Decaying S-Curve Model

Variable or Parameter	**Description**
$P[c_i]$	EV load at incentive level c_i
$P^{\min}$	Minimum EV load - nonelastic, or, essential charging
$P^{\mathrm{BL}}_{\mathrm{EV}}$	Baseline or maximum EV load - full charging with no incentives, or, $c_i = 0$
c_o	Inflection point before which EV users are non-responsive to real-time incentives
c_i	Incentive normalized with respect to inflection point c_o
α	Curve's steepness - higher value signifies increased sensitivity to real-time rebates or incentives

IV. System Model and Underlying Assumptions

For proof-of-concept simulations, we will rely on IEEE Reliability Test System (RTS) [17]. It is a benchmark model for comparing reliability evaluation techniques. RTS includes 24 buses, 17 load buses with time varying hour-by-hour demand for a year (APPENDIX F in [18]), peak load of 2850 MW, 32 generating units at 10 buses (see Chap.3 in [18] for capacities and forced outage rates). For Monte Carlo simulations, we probabilistically model system components to capture their stochastic behavior, as described next.

A. Composite Load Modeling

The net load is a key input for estimating LOLP, which is defined as the likelihood that net load will exceed net generation capacity, i.e., $p(\text{Net Load}>\text{Net Generation Capacity})$ where probability $p(.)$ numerically represents chances or likelihood of grid failure. To compute LOLP with incentive-driven managed EV charging, aka demand response, we divide RTS system's net load into three components:

$$P^{\mathrm{net}} = \underbrace{P^{\mathrm{Base}}_{\text{non-EV}}}_{\text{Inelastic non-EV Load}} + \underbrace{P^{\mathrm{BL}}_{\mathrm{EV}} - P^{\mathrm{DR}}_{\mathrm{EV}}}_{\text{EV Load}}, \tag{2}$$

where $P^{\mathrm{Base}}_{\text{non-EV}}, P^{\mathrm{BL}}_{\mathrm{EV}}, P^{\mathrm{DR}}_{\mathrm{EV}} \in \mathbb{R}_{+}$. The term $P^{\mathrm{Base}}_{\text{non-EV}}$ is the non-EV load, $P^{\mathrm{BL}}_{\mathrm{EV}}$ is the baseline or the maximum possible EV load on the RTS system when no incentives ($c_i = 0$) are provided to the EV users to temporally shift their charging behavior. $P^{\mathrm{DR}}_{\mathrm{EV}}$ is the aggregate EV demand response, or, incentive c_i driven reduced power consumption for EV charging. Next, we mathematically characterize $P^{\mathrm{Base}}_{\text{non-EV}}$ on hourly basis as:

$$P^{\mathrm{Base}}_{\text{non-EV}} = P_{\text{Hourly}}\left(1 + \beta \mathrm{w}\right), \tag{3}$$

where P_{Hourly} is the hourly load of the RTS system based on the typical daily, weekly - weekend and weekday, and seasonal variations in electricity demand for 52 weeks of the year [18]. Now, utilities plan net generation capacity around peak load with a 10–20% reserve margin to accommodate demand uncertainty. To model this, we introduced Gaussian noise w to the hourly base load with an attenuating factor of $\beta = 0.125$. Fig. 3 depicts the resulting net load profile without EVs. Notice that most hours exhibit moderate demand. Yet, there are infrequent but pronounced peak load events (exceeding 3000 MW). These rare peak-demand hours disproportionately impact grid reliability indices. Next, we describe the characterization of the baseline EV load and its subcomponents as:

$$P^{\mathrm{BL}}_{\mathrm{EV}} = x.P^{\mathrm{Peak}}_{\mathrm{Yearly}}, \tag{4a}$$

where baseline EV load $P^{\mathrm{BL}}_{\mathrm{EV}}$ is modeled as a fraction of yearly peak load $P^{\mathrm{Peak}}_{\mathrm{Yearly}}$ with $x \in [0, 1)$. In the unmanaged charging scenario, baseline EV load can be modeled as an additional, inelastic hourly demand profile to be superimposed onto the base load $P^{\mathrm{Base}}_{\text{non-EV}}$. Finally, elastic or incentive-driven component of the EV load, i.e., $P^{\mathrm{DR}}_{\mathrm{EV}}$ is calculated by subtracting the incentive-driven charging pattern, as characterized in Eq. (1), from the baseline EV load, as:

$$P^{\mathrm{DR}}_{\mathrm{EV}} = P^{\mathrm{BL}}_{\mathrm{EV}} - P\left[c_i\right]. \tag{4b}$$

It must be noted that while evaluating the LOLP, we used non-randomized or deterministic characterization of baseline EV load in Eq. (4a). The goal was to explicitly quantify the direct impacts of incentive-driven managed EV charging.

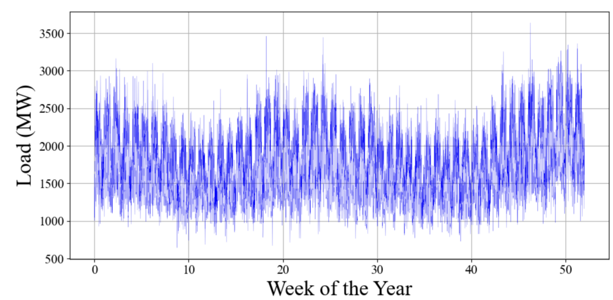

Fig. 3: IEEE RTS network's hourly load profile (52 Weeks).

B. Generator Modeling

The IEEE RTS network includes 32 generators, as a mix of coal-fired steam, gas turbines, and hydro units. Their capacities range from 12 MW to 400 MW. For LOLP estimation, generator availability is modeled using a binomial distribution, where each unit is either available or unavailable based on its Forced Outage Rate (FOR). It is a reliability metric defined as the probability of unplanned outages as:

$$\mathrm{FOR} = \frac{\mathrm{MTTR}}{\mathrm{MTTF} + \mathrm{MTTR}}, \tag{5}$$

where MTTF is the mean time to failure and MTTR is the mean time to repair. If a generator or a site has n identical units, each with a probability $p = 1-\mathrm{FOR}$ of being operational, then the probability of exactly k units being available at a given time is quantified as $P(K = k) = \binom{n}{k} p^k (1-p)^{n-k}$. For instance, a site may have multiple identical units. The binomial probabilistic characterization allows for modeling partial outages and variability in generator availability.

V. Proof-of-Concept Simulations

In this section we present Monte Carlo Simulation results under three scenarios. In Section V-A we assume full generator availability to investigate the impact of incentive-based EV charging on reliability. In Section V-B we introduce

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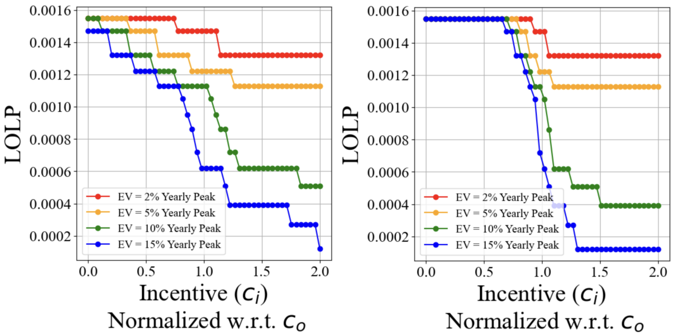

(a) α = 3 (b) α = 10

Fig. 4: LOLP versus normalized incentive c_i for four EV uptake scenarios (x=2%,5%,10%,15%) under fixed generation capacity. Left (Right) subplot depict results for α = 3 (α = 10).

generator outages to reflect realistic grid conditions. Lastly, in Section V-C we replace 7% of firm capacity with non-firm resources to assess renewable integration effects.

A. with Fixed Generation Capacity

As a first step, we simulated the impact of incentive-driven EV charging behavior under the assumption of no generator outages. We considered four EV uptake scenarios where the baseline EV load $P_{\text{EV}}^{\text{BL}}$ was set to 2%, 5%, 10%, and 15% of the yearly peak load $P_{\text{Yearly}}^{\text{Peak}}$ = 2850 MW, i.e., $x \in \{0.02, 0.05, 0.10, 0.15\}$ in Eq. (4a). The inelastic part of EV load, representing non-participating users, was modeled as $P_{\text{EV}}^{\min} = 0.2 P_{\text{EV}}^{\text{BL}}$. For the logistic demand response model, we assumed the inflection point as $c_o = 1$ and sampled the incentive from a uniform distribution $\mathcal{U}[0, 2]$, signifying sampling of c_i between no incentive (0) to twice of the inflection point c_o (2). To simulate variability in base/non-EV load, we drew $100,000$ samples from a pre-generated hourly load dataset. For each sample, net demand was computed by adjusting incentive-driven flexible EV demand. The simulations were performed across a range of incentive levels c_i. Then, LOLP was calculated as the fraction of scenarios where net demand exceeded generation capacity. Fig. 4a and Fig. 4b depict the impact of EV adoption on grid reliability for steepness parameter $\alpha \in \{3, 10\}$ in Eq. (1). In both instances, increased incentive (x-axis) to manage or flex aggregate EV charging improves LOLP index (y-axis). As expected, the enhancements in grid reliability is more pronounced/larger at higher EV uptake levels. Our preliminary results contrast with the common expectation that large-scale EV integration may adversely impact grid reliability, as charging would take place in evening hours, which are typically the peak hours.

B. with Constrained Generator Availability

We now relax the assumption of unimpeded availability of total generation of 3135 MW throughout the operating year. As described in Section IV-B, each generator availability is modeled as a discrete random variable using a binomial distributions. Rest of the parameters, as described in preceding subsection, were maintained at the same values/distributions for simulation purposes. Fig. 5 illustrates LOLP simulations across all EV uptake scenarios for α = 10. As expected, for constrained generation with plausible outages, the LOLPs are elevated in contrast to the estimates in Fig. 4b.

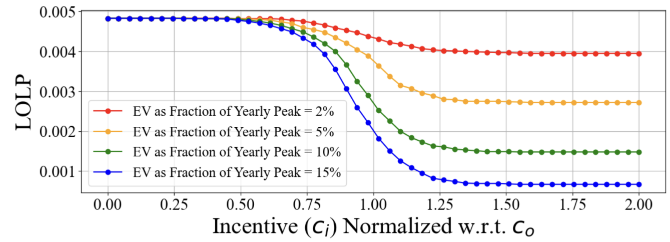

Fig. 5: LOLP versus c_i with α = 10, and for the same EV uptake scenarios as in Fig. 4 by relaxing the assumption of no generator outages.

C. with Intermittent Resources Displacing Firm Capacity

We now displace 140 MW firm generation with renewable resources of net nameplate capacity (360 MW). A total of 9 generating units with lowest nameplate capacities (5 units of 12 MW each, 4 units with 20 MW each) are replaced by wind-based resources with an average ELCC of 33% (based on [3] and as confirmed by utility engineers we reached out to). The plots are included in Fig. 6. As expected, the LOLP increased from a base level of 0.005 in Fig. 5 to 0.009 in Fig. 6, due to reduced ELCC of renewables compared to conventional oil- and gas-fired turbines. Finally, we highlight the reinforcing impact of the incentive-driven managed charging on loss of load expectations (LOLE) and expected energy not served (EENS) in Fig. 7a and in Fig. 7b, respectively. For brevity, we used averaged mathematical expressions [19]. LOLE is estimated as the product of average LOLP and the number of hours (T=8760). It is then scaled to the unit of days per year. EENS is computed as the unserved MW during hours when supply shortages were observed, i.e., EENS = $\sum_{t=1}^{T} \max(0, \text{Net Load - Net Generation})$. In summary, incentive-based managed EV charging can defer the need for new peak capacity investments and also help utilities avoid FERC penalties imposed for non-compliance with reliability standards [20], [21].

VI. Conclusions and Future Work

In this paper, we demonstrated the viability of managed EV charging to reduce key risk indices namely LOLP, LOLE, and EENS. By modeling non-linear aggregate user behavior through a reverse and decaying S-shaped curve, and integrating it into Monte Carlo simulations, we show that EV charging, if managed at scale, can offset the reliability challenges without firm-capacity expansion. In ongoing collaboration with utilities, the following avenues will guide improvements to our methodology for practical relevance.

An important future work is computation of distributions for parameters in the decaying S-shaped curve. These distributions will be shaped by features such as operating hour of

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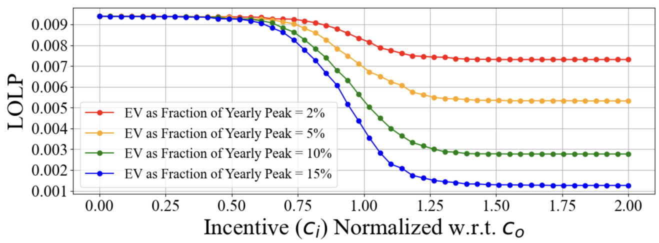
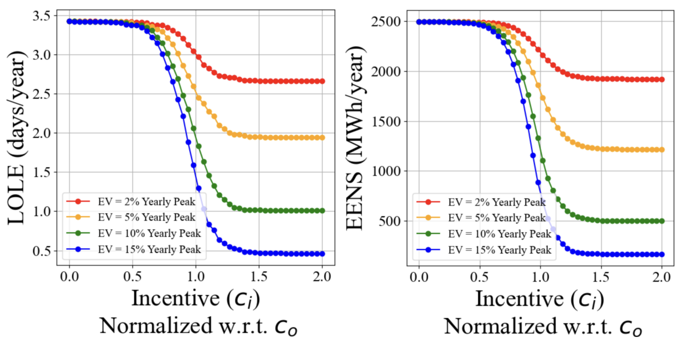


Fig. 6: Re-simulating cases in Fig. 5 by replacing 140 MWs of firm capacity generation with 360 MW of wind.



(a) LOLE (b) EENS

Fig. 7: LOLE and EENS estimates for scenario with intermittent resources displacing firm capacity with LOLP in Fig. 6.

the day, season, weekday/weekend, dwell time and minimum state-of-charge for vehicles. For instances, estimating $P^{\min}$ requires capturing features like battery health and minimum state-of-charge requested by end-users, and c_o may depend on geographic factors. Although feeder constraints, local congestion, and voltage issues at the distribution level are beyond the scope of this paper, they represent critical factors influencing the effectiveness of managed EV charging strategies, as these constraints can limit managed charging. Future granularity improvements will also incorporate diversity in the incentive response of diverse vehicle and driver groups. Lastly, we also plan to employ sequential Monte Carlo simulation (SMCS) techniques to incorporate generator failure and repair characteristics, and sub-hourly data for renewable outputs such as wind and solar. This integrated approach will enable precise estimation of reliability indices under realistic operating conditions. Though, the inputs to integrated approach are very utility-specific and will depend on empirical field data. To conclude, following is the summary of future directions we plan to pursue in collaboration with utilities.

- *Empirical Calibration and Parametric Sweep:* Leverage utility-shared datasets to infer distributions for (α, c_0, $P^{\min}$, $P_{\mathrm{EV}}^{\mathrm{BL}}$) and perform expansive parameter sweep.
- *Accommodate Tail Events:* Perform sampling of c_i by using skewed or gamma distributions to mimic plausible pricing strategy during scarcity events.
- *Temporal Granularity:* Incorporate sub-hourly time-varying renewable generation profiles and their correlations with pricing and load to highlight efficacy of managed charging to balance intermittent renewables.
- *Sequential MCS:* Perform sequential Monte Carlo simulations to account for generator outages and repair times.
- *Diversity in User Behavior:* Model heterogeneity in EV user response across diverse vehicle classes (light, medium, heavy).

References

[1] U.S. Department of Energy. (2025, Feb.) Secretary Wright Acts to "Unleash Golden Era of American Energy Dominance". Accessed: 2025-11-17.
[2] PowerGEM, "Effective Load Carrying Capability Study," *ERCOT*, February 2025.
[3] Southwest Power Pool, Inc., "2024 ELCC Wind Solar and ESR Study Report," Southwest Power Pool, Tech. Rep., Sep. 2024, accessed: 2025-11-17.
[4] *Commissioner Christie's Dissent from Order Concerning PJM's proposed ELCC.* FERC, 2021.
[5] IAEA, "Project Management in Nuclear Power Plant Construction: Guidelines and Experience," 2012.
[6] X. Fishman, "Licensing and Permitting Reforms to Accelerate Nuclear Energy Deployment," 2024.
[7] U.S. Chamber of Commerce, "U.S. Chamber Comments on EPA's Combustion Turbine Proposal," U.S. Chamber of Commerce, Tech. Rep., Aug. 2023, accessed: 2025-11-17.
[8] E. CX, "Understanding the Surge in Capacity Rates and Its Impact on Energy Costs," March 2025.
[9] W. et. al., "The 2030 National Charging Network: Estimating U.S. Light-Duty Demand for Electric Vehicle Charging Infrastructure," National Renewable Energy Laboratory, Tech. Rep., 2023.
[10] M. e. a. Kintner-Meyer, "Electric vehicles at scale–phase I analysis: High EV adoption impacts on the western US power grid," Pacific Northwest National Laboratory, Tech. Rep. PNNL-29894, 2020.
[11] PG&E, "Electric Vehicle (EV) rate plans."
[12] Y. Wan, T. Kober, and M. Densing, "Nonlinear inverse demand curves in electricity market modeling," *Energy Economics*, vol. 107, p. 105809, 2022.
[13] S. Powell, E. C. Kara, R. Sevlian, G. V. Cezar, S. Kiliccote, and R. Rajagopal, "Controlled workplace charging of electric vehicles: The impact of rate schedules on transformer aging," *Applied Energy*, 2020.
[14] EV Curve Futurist. (2024, Dec.) The S-Curve of EV Adoption. Accessed: 2025-11-17.
[15] D. Kucharavy and R. De Guio, "Application of S-shaped curves," *Procedia Engineering*, 2011, proceeding of the ETRIA World TRIZ Future Conference.
[16] W. Wang, L. Jiao, T. Dong, Z. Xu, and G. Xu, "Simulating urban dynamics by coupling top-down and bottom-up strategies," *International Journal of Geographical Information Science*, vol. 33, no. 11, pp. 2259–2283, 2019.
[17] R.Billinton, *Reliability Assessment of Electric Power Systems Using Monte Carlo Methods.*
[18] J. Wuijts, "Implementation of Methods for Generation Adequacy Assessment with Wind Considerations," Master's thesis, Norwegian University of Science and Technology (NTNU), July 2024.
[19] E. Preston, "A Simple Calculation Procedure for LOLE, LOLH, and EUE, Calculation of Probabilistic Transmission Line Flows, and Study Results for Extreme Renewables in ERCOT," Presentation at the IEEE LOLE Working Group Meeting, July 2015.
[20] "FERC Orders PacifiCorp to Respond to Allegations of Reliability Violations," April 2021.
[21] Federal Energy Regulatory Commission. (2025) All Civil Penalty Actions – 2025. Accessed: 2025-11-17.

979-8-3315-8138-1