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AN AI-BASED FRAMEWORK FOR BEHAVIORAL RESIDENTIAL LOAD MODELING AND DISTRIBUTION GRID ANALYSIS

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ABSTRACT

Increasing electrification and AI-driven energy management are changing the magnitude and timing of residential electricity demand, creating new challenges for distribution system planning. Traditional power system studies typically rely on predefined load profiles that do not explicitly represent human behavioral dynamics. In this paper, we develop an AI-based framework that integrates behaviorally generated residential demand with distribution feeder power-flow analysis. The framework combines AI-driven household demand generation, feeder-level load injection, and OpenDSS-based time-series simulation within a unified experimental platform. Using IEEE distribution feeders, controlled experiments are conducted to examine the effects of feeder topology, household behavioral archetypes, electric vehicle (EV) adoption, weekday-weekend variation, and demand aggregation on voltage behavior. Results show that the framework produces behaviorally interpretable load profiles with distinct temporal patterns across household types and day types, and that these differences propagate to feeder-level voltage responses. Besides, EV charging increases peak demand and worsens voltage depressions, while large-scale replication of plausible household demand patterns produces substantial feeder stress. The primary contribution of this work is a flexible simulation platform for studying how behavioral demand formation and electrification interact with distribution grid performance, providing an initial foundation for future research on AI-assisted demand modeling and grid resilience.

Keywords: AI agents, residential electricity demand, distribution feeder, EV charging, smart grid.

1 INTRODUCTION

The United States electric grid is entering a period of structural stress driven by converging technological, climatic, and economic forces [1, 2]. Much of the nation's distribution infrastructure was constructed decades ago under assumptions of predictable unidirectional electricity flows and relatively stable residential demand. These systems were designed for passive consumers whose consumption patterns followed consistent daily and seasonal cycles. Today, however, that paradigm is rapidly challenged. Electrification of transportation and heating, accelerating deployment of distributed energy resources, and the expansion of artificial intelligence (AI)-intensive data centers are collectively altering both the magnitude and temporal structure of load profiles [3]. Recent industry assessments project substantial increases in electricity demand associated with AI and cloud computing infrastructure within this decade [2, 3]. For example, AI applications require substantial computing power, projected to contribute to a national capacity shortfall of 13–44 GW by 2028 [2, 4]. At the same time, electric vehicle (EV) adoption is creating geographically clustered, high-power charging events that strain local transformers and feeders [5, 6]. Extreme weather events linked to climate change further stress already aging infrastructure [7, 8], exposing vulnerabilities at the distribution level where voltage limits, line thermal ratings, and

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transformer capacities define operational resilience [9].

These trends challenge several long-standing assumptions in distribution system planning. Distribution networks were originally designed for relatively stable and weakly correlated residential demand rather than highly synchronized or rapidly changing loads [10]. Historically, household electricity use was diversified across time, resulting in limited coincidence at the feeder level [11]. However, the growing adoption of EVs, automated energy management systems, and digital technologies increases the probability of coincident charging events, coordinated load shifting, and rapid rebound peaks [12]. In this context, the grid is increasingly exposed to more active and dynamic demand patterns. Although long-term infrastructure expansion remains necessary, it is capital-intensive and slow to deploy [13]. As a result, near-term resilience increasingly depends on how electricity demand is coordinated and managed at scale.

This challenge has motivated a substantial body of research on grid modernization, optimization, and control. Centralized economic dispatch models incorporate renewable variability and storage scheduling [14, 15]. Distributed optimization techniques coordinate DERs and demand response resources [16, 17]. Hosting capacity analyses quantify feeder limits under high photovoltaic or EV penetration [18, 19]. These advances have strengthened the physical modeling of distribution systems and improved forecasting accuracy. However, a key assumption persists across much of this literature: electricity demand is typically treated as an externally specified input rather than an endogenous outcome of household behavior and decision-making.

In practice, demand representations typically rely on either historical consumption data or statistical load modeling approaches [20–22]. Historical datasets contain implicit information about household behavior, but they often reflect the specific locations, infrastructures, and socioeconomic conditions where the data were collected, limiting their generalizability to new regions or emerging consumption patterns. Moreover, detailed high-resolution consumption datasets are frequently difficult to obtain due to privacy restrictions, limited data-sharing policies, or incomplete monitoring infrastructure. Statistical or Monte Carlo–based load models provide greater flexibility for scenario generation, but they frequently rely on simplified assumptions and may not explicitly represent the behavioral mechanisms that drive electricity consumption.

These limitations become more consequential as AI-mediated decision tools actively shape consumption. Smart thermostats, EV charging platforms, and home energy management systems do not merely respondent to demand; they actively structure it by determining when loads are shifted, scheduled, or deferred[12]. In this sense, AI-assisted households are no longer passive stochastic loads, but they are adaptive agents making structured decisions based on shared signals, common training data, and similar optimization objectives [23, 24]. This shift suggests that electricity demand should not be modeled solely as an external input to the grid, but also as the outcome of interactions among human behavior, automated decision tools, and physical network constraints.

Despite rapid advances in AI-driven demand response research [23, 25] , few studies systematically integrate agent-level decision logic with high-fidelity feeder constraints in a unified framework. Instead, the behavioral adaptation layer and the physical grid layer are typically modeled separately. This gap creates an opportunity to rethink how electricity demand is represented in grid studies. Rather than treating demand solely as an external input to the power system, it can also be viewed as the outcome of interactions between human behavior, automated decision tools, and the physical constraints of the grid [26, 27]. Understanding these interactions is important for maintaining grid resilience. On the one hand, coordinated demand management enabled by automated decision tools may help reduce system stress through peak shaving and flexible scheduling [28]. On the other hand, highly uniform control strategies may introduce new vulnerabilities. If large populations of devices respond simultaneously to identical price signals or carbon intensity indicators, coincident demand peaks may lead to voltage violations, thermal overloads, or accelerated transformer aging [12]. Under certain network conditions, synchronized load shifts may also contribute to feeder-level instability [29]. As a result, coordinated demand response can either mitigate or amplify grid stress depending on feeder topology, load density, and the diversity of user behaviors. Evaluating these outcomes requires modeling frameworks capable of capturing nonlinear interactions between digital control mechanisms and the physical power infrastructure.

To address the challenge identified above, this paper introduces an AI-based research framework that integrates generative AI-driven demand modeling with distribution feeder power-flow analysis. The proposed framework is intended to capture the interaction between behaviorally adaptive electricity demand and the operational constraints of distribution networks. It consists of three main modules: 1) selection and configuration of the distribution test feeder, 2) development of an AI-driven behavioral demand generation framework, and 3) design of a prototype AI-agent-based grid simulation platform. In particular, the behavioral demand generation module offers a flexible and comprehensive approach for representing household decision-making and generating high-resolution, dynamic consumption profiles. More broadly, the framework integrates agent-level behavioral modeling with high-fidelity feeder constraints in a unified simulation environment. This integration enables the analysis of how coordinated behavioral responses, such as synchronized household routines and EV charging, which can influence distribution feeder performance under different electrification scenarios.

The **key contributions** of this paper are threefold: 1) we develop a research framework for studying how behaviorally generated residential electricity demand interacts with distribution feeder dynamics. The framework integrates AI-driven demand generation with distribution power-flow simulation, enabling controlled experiments on the relationship between household consumption patterns and feeder-level grid responses. 2) We build a prototype simulation platform that realizes this framework through an end-to-end workflow, linking AI-based demand generation with OpenDSS feeder simulations in a reproducible experimental environment. 3) We present experiment studies on IEEE distribution feeders that illustrate how AI-influenced demand profiles can affect feeder-level system behavior, providing an initial empirical foundation for future studies that incorporate richer behavioral diversity, adaptive decision mechanisms, and broader scenario exploration.

The remainder of this paper is organized as follows. Section 2 introduces the overall modeling framework. Section 3 then describes the experimental design, including the scenario settings used in the simulation study. Section 4 presents the simulation results and analyzes feeder responses under different AI-driven demand conditions. Section 5 discusses the limitations of the current approach, and Section 6 concludes the paper with directions for future research.

2 METHODOLOGY

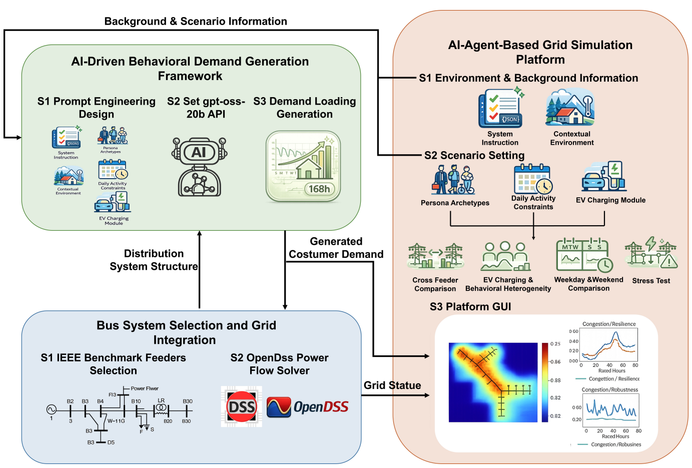


FIGURE 1: An overview of the proposed AI-based research framework integrating generative AI-driven demand modeling with distribution feeder power-flow analysis.

The proposed research framework integrating generative AI-driven demand modeling with distribution feeder power-flow analysis is given in Figure 1. Additional details for each module are provided in the following subsections.

2.1 Bus System Selection and Grid Integration

In the first module, power system analysis is conducted using standard IEEE distribution feeder models. These benchmark feeder systems provide realistic representations of distribution network topology and electrical characteristics and are widely used for evaluating new grid analysis methods [30, 31]. Rather than focusing on the detailed structure of a specific feeder within the methodology description, the proposed framework is designed to be compatible with multiple standard feeder models. The specific feeder systems used in the experiments are described later in the experimental design section.

To integrate AI-generated residential demand into the distribution system model, for each selected feeder load node, the original baseline demand is replaced by the aggregated demand generated by N AI-driven households. The resulting load at time t is defined as

$$P_i^{\text{new}}(t) = N \times P_{\text{AI}}(t), \tag{1}$$

where $P_{\text{AI}}(t)$ represents the hourly electricity demand profile generated by the AI agent for a single household, and N denotes the number of aggregated households assigned to feeder node i. This formulation replaces the original feeder load with an aggregated AI-driven demand trajectory while keeping the feeder topology and other system parameters unchanged. This formulation assumes that the AI-generated household profile represents a typical individual residential demand pattern that can be replicated across multiple households.

Once the aggregated electricity demands are obtained, they are fed into OpenDSS, a widely used tool for distribution system simulation and analysis [32, 33], where power flow calculations are then performed. Specifically, simulations are conducted in hourly time-series mode without modifying original topology, voltage bases, or equipment ratings. Baseline feeder operation is first validated under default load conditions to establish reference voltage and loading metrics. Then, at each simulation step, the AI-generated load profiles are injected into the feeder model and the resulting system state is obtained through OpenDSS power flow solutions. This integration enables the evaluation of how behavior-driven residential demand patterns propagate through the electrical network and influence feeder voltage dynamics while preserving the underlying electrical topology and network parameters.

2.2 AI-Driven Behavioral Demand Generation Framework

In the second module, residential electricity demand is generated using an AI-driven behavioral demand formation framework designed to translate contextual conditions and household activity patterns into time-resolved electricity consumption trajectories. Instead of relying on predefined load curves or purely statistical demand models, the framework represents residential electricity consumption as the outcome of behaviorally defined agents operating within a structured environmental context. In this work, we use a large language model (LLM) as the generative AI agent engine to produce household demand trajectories. However, the overall framework is intentionally designed to remain model-agnostic and compatible with other AI-based or traditional behavioral simulation approaches. Within this structure, the AI agent receives contextual information and behavioral constraints and generates an electricity demand profile with a predefined time step (e.g., hourly/daily) that satisfies both household activity requirements and basic physical feasibility conditions. To standardize the the electricity demand generation process, a structured prompt architecture is proposed to organizes the input information provided to the AI agent. This architecture separates information into multiple conceptual layers to ensure consistency across scenarios while allowing controlled variation in behavioral parameters.

In particular, the prompt architecture consists of three conceptual components: a *system instruction layer*, a *shared contextual layer*, and *persona-specific behavioral definitions*. The *system instruction layer* defines the task of the AI demand agent, which is to generate a residential electricity demand trajectory over a defined time horizon at a given temporal resolution. Several operational constraints are embedded in this layer to ensure realistic demand formation, including non-negativity of electricity demand, plausible residential consumption levels, and the ability to differentiate between different daily and weekly (e.g., weekday and weekend) activity patterns. The generated output is required to follow a structured data format containing temporal electricity demand values. The *shared contextual layer* provides environmental conditions that remain consistent across all agents within a given experimental scenario. These contextual parameters include geographic location, seasonal conditions, representative weather assumptions, and electricity tariff structures such as time-of-use pricing. By isolating environmental variables within a dedicated context block, the framework enables controlled sensitivity analysis. For example, modifying tariff schedules or temperature conditions—without altering the behavioral definitions of residential agents.

The *persona behavioral descriptions* specify household activity patterns that influence electricity demand timing and flexibility. These behavioral inputs describe factors such as daily occupancy schedules, work routines, appliance usage patterns, and responsiveness to external signals such as electricity prices. Because these behavioral characteristics are defined through structured prompt parameters rather than fixed deterministic load curves, the framework can generate diverse yet interpretable demand trajectories across different scenarios. It should be noted that these persona behavioral descriptions are not intended to represent statistically accurate demographic distributions but instead provide structured variation in demand timing and flexibility. Because behavioral attributes are defined through editable parameters rather than fixed narrative descriptions, additional archetypes or refinements can be introduced without modifying the underlying simulation pipeline. This design supports extensibility while maintaining internal consistency across experimental scenarios.

Additionally, EV charging is modeled as a separable demand module rather than being embedded directly within the behavioral personas. Although certain archetypes may logically include EV ownership, the charging demand itself is parameterized independently to preserve experimental control. This separation enables direct comparison between identical behavioral archetypes with and without EV integration and allows systematic analysis of synchronization effects under increasing adoption levels. Finally, the generated demand profiles based on the proposed prompt architecture are subsequently validated through a lightweight post-processing stage to ensure physical plausibility, including non-negative consumption values and realistic residential energy ranges. Profiles that violate these constraints are regenerated using the same behavioral parameters to maintain comparability across scenarios. Overall, by structuring demand generation around AI-based behavioral agents operating within controlled contextual environments, the framework provides a scalable foundation for studying how behavioral variability interacts with distribution system constraints.

2.3 AI Agent-Based Grid Simulation Platform

In the third module, a prototype AI agent-based grid simulation platform is built using Streamlit [34]. The platform integrates the behavioral demand generation module presented in Section 2.2 with the feeder modeling approach introduced in Section 2.1, thereby forming a unified end-to-end simulation workflow. In the current implementation, demand trajectories are generated using gpt-oss-20b (open-source model from OpenAI) [35] accessed via the Ollama API[36]. The platform architecture is designed to flexibly support different AI models, allowing future substitution or comparison across alternative models. As shown in Figure 2, the prototype interface comprises three main panels. The first panel contains three interactive input boxes through which users specify AI agent prompt information for residential demand generation. These inputs enable the customization of load-profile characteristics and behavioral assumptions. Upon clicking the "Run Simulation" button, the user-defined information is passed to the AI-based behavioral demand generation module, which produces dynamic electricity consumption profiles for individual households. The generated single household-level demand profiles are subsequently transferred to the bus-system selection and grid-integration module, where they are aggregated and assigned to selected feeder load nodes. The aggregated demand replaces the baseline load at the corresponding nodes while preserving the feeder's original topology and electrical parameters. After the updated load profiles are incorporated into the feeder model, time-series power-flow simulations are performed in OpenDSS. At each simulation time step, the feeder state is updated and key operational variables, such as bus voltage magnitudes, are calculated. The resulting outputs, together with visualizations of the single household-level demand profiles, are presented in the results panel. To improve transparency and usability, the platform also includes a monitoring panel that provides users with real-time information on background execution processes. This panel enables users to follow the progress of the overall simulation procedure and inspect the status of individual computational steps.

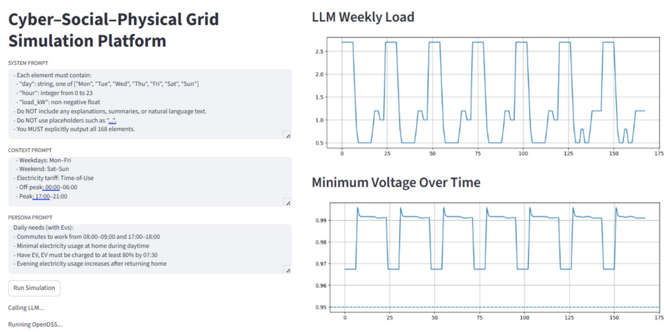


FIGURE 2: AI agent grid simulation platform prototype.

3 EXPERIMENT DESIGN

To evaluate how behaviorally AI generated residential electricity demand interacts with distribution system constraints, a structured set of simulation experiments is designed across multiple dimensions, including feeder topology, residential behavior patterns, EV charging presence, and demand aggregation levels. All simulations are conducted over a one-week horizon with hourly resolution, resulting in 168 time steps per scenario. The AI-generated residential demand profiles described in Section 2.2 are integrated into the distribution feeders through the load replacement scheme implemented in OpenDSS. The experimental design aims to systematically examine how different demand formation mechanisms propagate through distribution networks and influence feeder-level operational conditions such as voltage variation and loading levels.

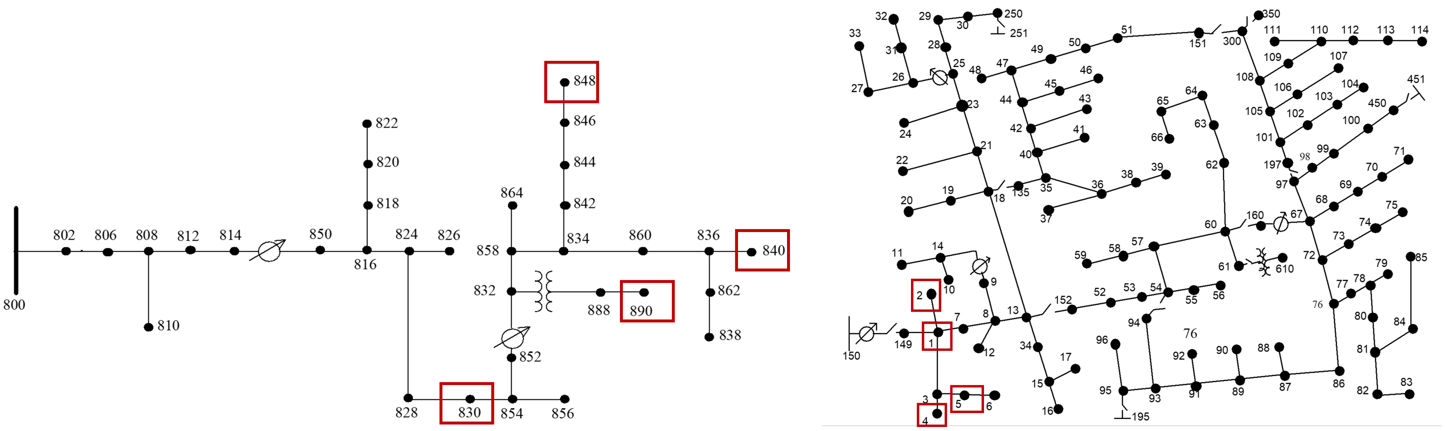
3.1 Feeder Systems and Load Injection Nodes

As shown in Figure 3, two IEEE benchmark feeders are considered in this study, which are IEEE 34-bus and IEEE 123-bus systems [30].These feeders represent increasing levels of network scale and structural complexity and are widely used in distribution system research [37, 38]. The IEEE 34-bus feeder serves as the primary experimental testbed. Its long radial structure and relatively high line impedance make it particularly sensitive to load concentration and temporal demand shifts. These characteristics make the feeder well suited for observing voltage variations caused by behaviorally generated residential demand patterns. The IEEE 123-bus feeder is included as a larger and more complex network. Compared with the 34-bus feeder, the 123-bus system contains a greater number of buses and a more spatially distributed load structure. This feeder therefore allows the evaluation of how behavior-driven demand patterns propagate across larger networks and whether spatial load distribution mitigates or amplifies localized demand effects.By using feeders with different structural characteristics, the experiments can isolate how network topology influences the propagation of behaviorally generated demand within distribution systems.

Specifically, to integrate AI-generated residential demand profiles into the feeder simulations, a subset of spatially separated load nodes is selected in each bus feeder (highlighted in Figure 3). Selecting multiple injection points allows the simulation setup to better represent the spatially distributed character of residential electricity demand while preserving experimental control. Besides, replacing loads at several separated nodes, rather than at a single location, reduces unrealistic load concentration and enables the analysis to capture how behaviorally generated demand propagates across different portions of the feeder network. At each selected node, the baseline residential load is replaced in accordance with the load aggregation scheme described in Section 2.1. The same set of injection nodes is maintained across all experimental scenarios to ensure that differences in feeder behavior are attributable to the demand profiles themselves, rather than to changes in the spatial placement of loads.

3.2 Costumer Behavioral Archetypes and Background Information Setting

To represent heterogeneous residential electricity consumption behaviors, four representative household archetypes are defined in this study through the AI-driven demand generation framework. To be specific, these archetypes are commuter households, remote workers, stay-at-home residents, and flexible urban users, as summarized in Table 1. These archetypes represent different occupancy patterns and daily routines that influence when electricity consumption occurs during the day. Commuter households represent residents who leave home during daytime working hours and return in the evening. As a result, their electricity consumption tends to be relatively low during the daytime and increases significantly during evening hours after returning home. Remote workers represent households with home-based work activities, leading to higher electricity consumption during daytime hours due to the use of computers, lighting, and heating systems. Stay-at-home residents represent households with relatively stable daily occupancy patterns, re-



(a) IEEE 34 Bus system

(b) IEEE 123 Bus system

FIGURE 3: Distribution bus system structure.

sulting in more evenly distributed electricity demand throughout the day. Flexible urban users represent residents with irregular schedules and greater responsiveness to external signals such as electricity prices or daily activity changes. All behavioral scenarios are generated under a consistent set of environmental assumptions to ensure comparability across experiments. These shared conditions include the geographic location of Fort Collins, Colorado (USA), winter seasonal conditions with representative cold temperatures. By keeping these environmental parameters consistent across behavioral scenarios, the experiments isolate the effects of household activity patterns and electricity usage flexibility on feeder operation.

3.3 Scenario Configuration

Based on the feeder systems and behavioral archetypes described above, a structured set of simulation scenarios is designed to evaluate how behaviorally generated residential demand interacts with distribution system constraints. The scenarios are organized into three groups: baseline experiments, behavioral experiments, and stress-test experiments. The detailed scenrio setting is shown in Table 2. Unless otherwise specified, each AI-generated demand profile represents a single household and is aggregated to represent 50 households connected to each selected load node. This aggregation level approximates a small residential cluster while maintaining interpretability of feeder responses. The aggregated demand is injected into the feeder using the load replacement scheme described in Section 2.1.

The baseline experiments characterize the original operating conditions of the IEEE benchmark feeders without AI-generated demand or EV charging. These simulations are primarily intended to ensure that the experimental setup functions properly. Therefore, the results will not be displayed in the subsequent section. The behavioral experiment group evaluates how different demand formation mechanisms influence feeder operation. Several variations are considered within this group. First, cross-feeder comparisons apply the same commuter-type residential behavior to different IEEE feeders in order to isolate the influence of network topology on demand propagation. Second, EV charging is introduced as a modular demand component that can be activated while keeping other behavioral parameters unchanged. This configuration enables direct observation of how EV charging affects feeder voltage conditions. Third, behavioral heterogeneity is examined by comparing the four residential archetypes defined in Section 3.2 under otherwise identical feeder and aggregation conditions. Temporal variation between weekday and weekend demand patterns is incorporated within behavioral experiment group rather than treated as an independent experiment group. Because day type is specified directly in the AI demand generation context, demand profiles can be regenerated under both weekday and weekend conditions for representative cases. This approach avoids redundant experimentation while still allowing examination of how daily activity shifts influence feeder performance. The stress-test experiment group evaluates feeder robustness under increasing levels of coordinated demand behavior. In these scenarios, the number of aggregated households represented by the AI agent demand profile is progressively increased from 50 to 100 and 1000. This represents higher adoption levels of synchronized residential behavior. Such stress tests help identify conditions under which operational constraints such as voltage limits become more likely to be violated. Together, these scenarios provide a controlled experimental framework for evaluating how AI-generated residential demand interacts with distribution system constraints across different feeder structures, behavioral assumptions, and adoption intensities.

TABLE 1: AI Agent Prompt Structure for Residential Demand Generation.

Component	Description
System Instruction	Defines the task of the LLM agent to generate a residential electricity demand profile over a 7-day horizon with hourly resolution. The output must be a JSON array containing 168 elements, each including day, hour, and load (kW). Constraints include non-negative electricity demand, realistic household consumption levels, and distinct weekday and weekend behavior patterns.
Contextual Environment	Shared environmental conditions for all agents within a scenario. Includes geographic location (Fort Collins, Colorado is used in this study), winter season, representative cold temperature conditions, and time-of-use electricity tariff structure with peak and off-peak pricing periods.
Persona Archetypes	Four behavioral archetypes describing different residential electricity usage patterns: (1) Remote Worker — high daytime occupancy and steady electronics usage, (2) Commuter — low daytime demand with concentrated evening usage, (3) Stay-at-home Resident — continuous occupancy and stable daily routines, (4) Flexible Urban User — irregular schedules with higher flexibility and responsiveness to price signals.
Daily Activity Constraints	Operational conditions describing household routines such as commuting schedules, home occupancy periods, appliance usage, and indoor comfort needs. These constraints guide the temporal distribution of electricity demand generated by the LLM.
EV Charging Module	Electric vehicle charging demand is modeled as an optional load component that can be enabled or disabled independently from behavioral personas. This allows controlled comparison between scenarios with and without EV integration.

4 RESULT

This section presents the simulation results obtained from the experimental setup described in Section 3. The results are organized into several components. We first compare system behavior across different IEEE feeder models. We then examine the influence of EV charging on residential demand formation and voltage stability. Next, differences among household behavioral archetypes are analyzed to evaluate how user behavior shapes aggregate demand patterns. Weekday–weekend dynamics are subsequently examined to assess whether the framework captures temporal variability in residential energy use. Finally, a stress-test experiment evaluates feeder performance under increasing levels of aggregated residential electrification.

4.1 Comparison Across Different Bus Systems

The weekly residential demand profiles generated by the AI agent are shown in Figure 4 (a) and Figure 5 (a). Both profiles reflect typical daily residential patterns characterized by relatively low nighttime consumption, elevated daytime demand associated with home-office activities, and evening peaks corresponding to household appliance and comfort loads. The prompt uesd at this phrase to generate demand profile explicitly incorporates contextual information such as season, electricity tariff structure, and day type (weekday versus weekend). As a result, some variability between weekday and weekend demand patterns emerges. In the IEEE 34-bus case, weekend electricity consumption is slightly lower than weekday levels, reflecting reduced daytime work-related electricity usage. In contrast, the profile generated for the IEEE 123-bus experiment exhibits slightly higher weekend peaks, indicating that discretionary household activities are sometimes shifted toward weekend periods. Because the AI agent-based demand generator is probabilistic, small variations in weekly demand profiles can arise across simulation runs. We therefore interpret cross-feeder comparisons cautiously, recognizing that feeder response is influenced both by network topology and by the specific demand realization generated by the AI agent. Nevertheless, the overall temporal structure of the profiles remains consistent, with similar daily peak timing and comparable average demand levels, enabling qualitative comparison of feeder responses.

Voltage distributions for representative hours are illustrated in Figure 4 (b)-(d) for the IEEE 34-bus feeder and Figure 5 (b)-(d) for the IEEE 123-bus feeder. In the 34-bus system, bus voltages remain largely within the acceptable operating range (0.95–1.05 p.u.) [39] , with only moderate voltage drops observed near the feeder extremities where accumulated line impedance increases sensitivity to load injections. Despite the concentrated residential demand peaks, the feeder maintains rel-

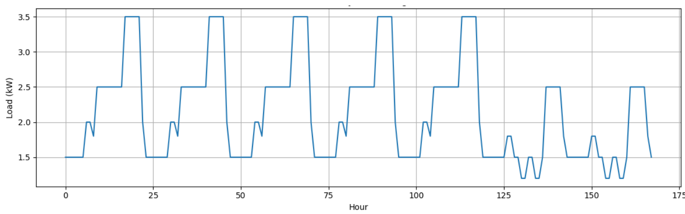
TABLE 2: Scenario Configuration for AI-driven Demand Simulation.

Scenario ID	Feeder	User Type	EV Option	Households	Purpose
		Baseline Experiments			
B1	IEEE 13	Baseline	Off	0	Baseline system behavior
B2	IEEE 34	Baseline	Off	0	Baseline system behavior
B3	IEEE 123	Baseline	Off	0	Baseline system behavior
		Behavioral Experiments			
S1	IEEE 34	Remote Worker	Off	50	Cross-feeder comparison
S2	IEEE 123	Remote Worker	Off	50	Cross-feeder comparison
S3	IEEE 34	Commuter	Off	50	EV ablation reference
S4	IEEE 34	Commuter	On	50	EV charging impact
S5	IEEE 34	Remote Worker	On	50	Behavioral comparison
S6	IEEE 34	Commuter	On	50	Behavioral comparison
S7	IEEE 34	Stay-at-home	On	50	Behavioral comparison
S8	IEEE 34	Flexible Urban	On	50	Behavioral comparison
		Stress Test Experiments			
S9	IEEE 34	Commuter	On	50	Stress test baseline
S10	IEEE 34	Commuter	On	100	Increased adoption
S11	IEEE 34	Commuter	On	1000	Extreme synchronization

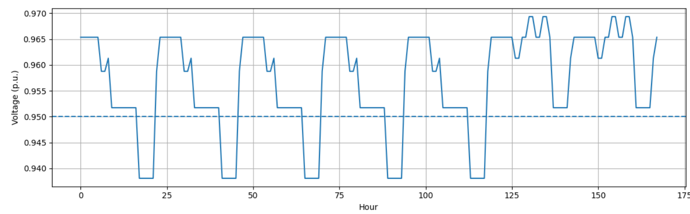
atively stable voltage conditions throughout the observed time periods. In contrast, the IEEE 123-bus feeder exhibits more pronounced localized voltage deviations. As shown in Figure 5 (c) and (d), several buses experience deeper voltage drops, with some nodes approaching or crossing the lower operational bound of 0.95 p.u. These deviations are concentrated in specific feeder segments where multiple loads are electrically close and interact through shared line impedances. The larger network size and more heterogeneous load distribution increase the likelihood of localized voltage sensitivity, even when the aggregate demand profile remains comparable. The temporal evolution of minimum bus voltage over the full 168-hour simulation horizon further highlights these differences. In the IEEE 34-bus feeder (Figure 4 (b)), minimum voltage values generally remain near or slightly above the 0.95 p.u. threshold, with occasional short-duration dips during peak demand periods. By comparison, the IEEE 123-bus system (Figure 5 (b)) shows more frequent and deeper voltage excursions, with several hours falling below the acceptable voltage limit. These voltage drops typically coincide with evening demand peaks in the generated residential load profiles. Overall, these results suggest that feeder topology and load distribution strongly influence how behaviorally generated residential demand propagates through the distribution network. While the IEEE 34-bus feeder exhibits relatively stable voltage behavior under the tested demand conditions, the IEEE 123-bus feeder demonstrates greater localized sensitivity to the same class of residential demand patterns. To isolate the impact of network topology, The following scenarios will all operate on the IEEE-34 system.

4.2 Impact of EV Charging on Distribution Grid Performance

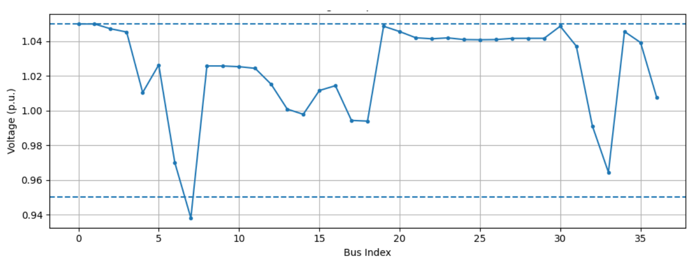
To further evaluate how emerging electrification trends influence distribution system performance, we introduce EV charging into the residential demand profiles. Two scenarios (S3 and S4) are compared using the IEEE 34-bus feeder under identical conditions. The AI generated weekly household load profiles for the two scenarios are illustrated in Figure 6 and Figure 7. In the non-EV scenario, the generated demand follows a relatively typical residential pattern characterized by moderate daytime usage and a gradual evening increase associated with household activities after work. Peak household demand remains within a range of approximately 3–3.5 kW, and the weekly pattern exhibits relatively stable daily cycles. When EV charging is introduced, the load trajectory changes noticeably. As shown in Figure 7 (a), the presence of EV charging produces significantly higher evening demand peaks, with household loads exceeding 6 kW during charging periods. As a result, the late-night valley observed in the non-EV scenario is replaced by a pronounced nighttime peak driven by EV charging demand. This shift ef-



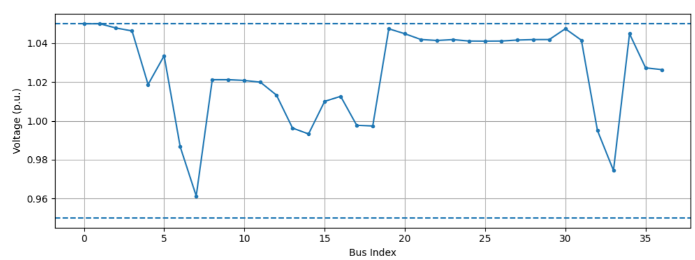
(a) Weekly load generated by AI agent



(b) Minimum bus voltage over 168 hours

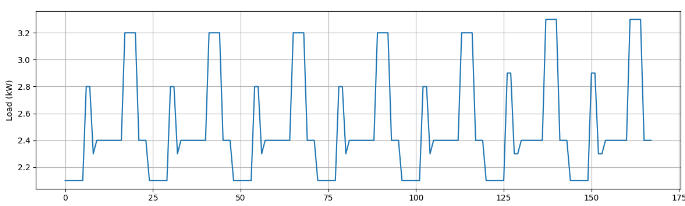


(c) Voltage snapshot (Hour 20)

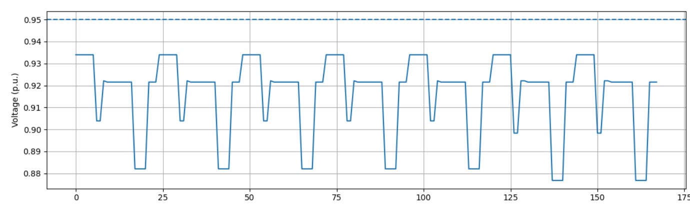


(d) Voltage snapshot (Hour 80)

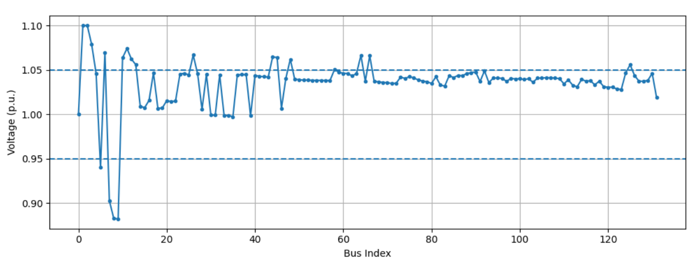
FIGURE 4: Scenario S1 (IEEE 34-bus, Remote worker, 50 households, Without EV): AI generated load and feeder voltage response. (a) Weekly load profile generated by the AI agent for a representative household; (b) minimum bus voltage across the feeder over the 168-hour simulation; (c) and (d) voltage snapshots across all buses at representative time points (Hour 20 and Hour 80), illustrating spatial voltage variations along the feeder. The dashed horizontal lines in the voltage plots indicate the standard operational voltage limits (0.95–1.05 p.u.) [39] used to assess voltage regulation performance. The same voltage bounds and subplot structure are used throughout subsequent figures unless otherwise noted.



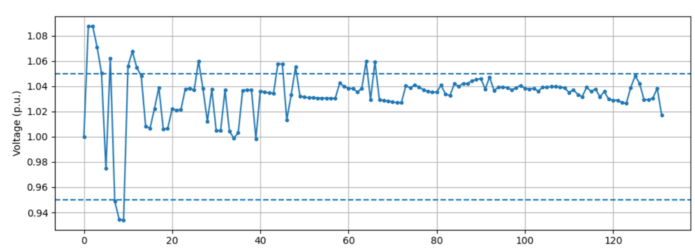
(a) Weekly load generated by AI agent



(b) Minimum bus voltage over 168 hours



(c) Voltage snapshot (Hour 20)



(d) Voltage snapshot (Hour 80)

FIGURE 5: Scenario S2 (IEEE 123-bus, Remote worker, 50 households, Without EV): AI generated load and feeder voltage response.

fectively redistributes the timing of peak demand, moving the highest load levels from evening household activity periods to nighttime charging intervals. These results highlight how EV charging can significantly reshape the temporal distribution of residential electricity demand rather than simply increasing the overall magnitude of household load.

The impact of these modified demand profiles on distribution system voltage behavior can be observed in the bus voltage snapshots shown in Figure 6 (c), (d) and Figure 7 (c), (d). In the non-EV scenario, the feeder maintains relatively stable voltage levels across most buses. Although localized voltage drops occur at certain buses during peak demand hours, the overall system operates close to the acceptable voltage range, with most bus voltages remaining near 0.95 p.u. or above. The minimum voltage trajectory over the full 168-hour simulation horizon (Figure 6 (b)) exhibits periodic fluctuations that correspond to daily load cycles but remains relatively stable overall. When EV charging demand is introduced, the voltage behavior changes in several notable ways. First, the magnitude of voltage drops becomes more pronounced during peak demand periods. Second, the minimum bus voltage over time shows deeper and more frequent depressions, with several hours experiencing values approaching 0.90–0.92 p.u.. These voltage reductions coincide with the evening charging peaks observed in the household demand profile, indicating that EV charging introduces additional stress on the feeder during already high-demand periods.

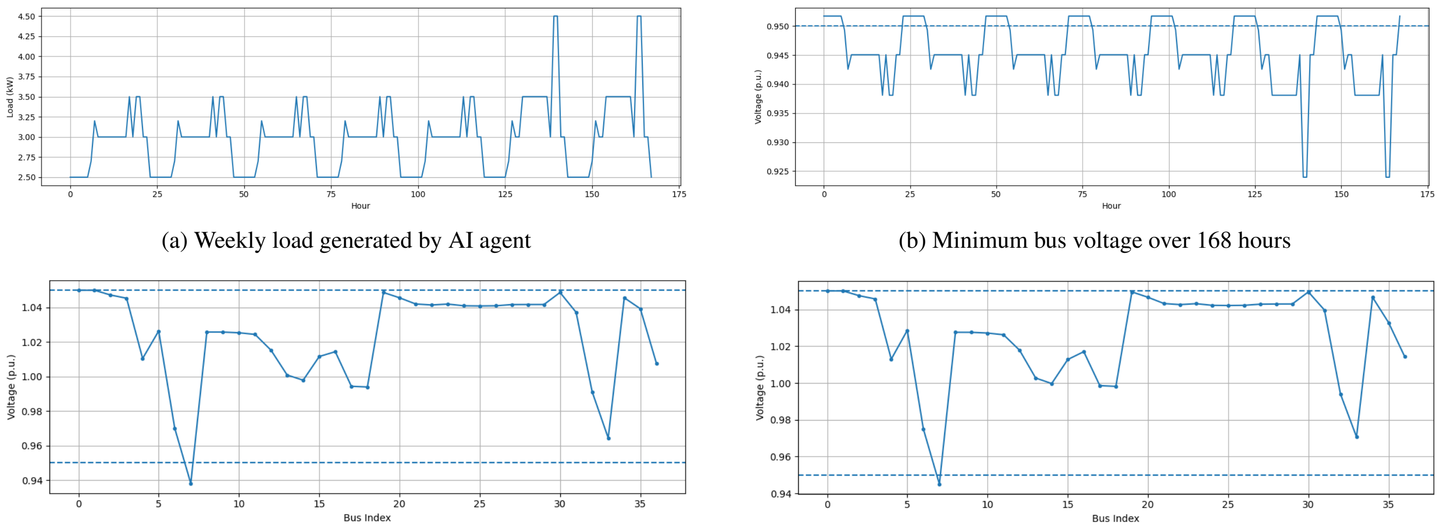
Despite these differences, the overall spatial structure of the voltage profile across buses remains largely consistent between the two scenarios. This suggests that the feeder topology and electrical characteristics continue to determine the locations where voltage drops are most severe, while the EV charging demand primarily amplifies the magnitude of these variations rather than fundamentally changing their spatial distribution. It is important to note that the observed differences between the two scenarios are unlikely to be driven solely by variability in the AI agent-generated demand patterns. Both simulations use the same behavioral persona and contextual constraints, differing only in the inclusion of EV charging requirements. The generated load profiles maintain comparable daily patterns, with the primary difference being the additional charging-related demand. Therefore, the increased voltage stress observed in Scenario 4 can reasonably be attributed to the introduction of EV charging rather than stochastic variation in the LLM output. Overall, the results suggest that even moderate levels of EV adoption among commuter households can significantly increase peak residential demand and exacerbate voltage stability challenges in distribution feeders. The interaction between synchronized evening charging behavior and existing residential load patterns may therefore represent an important operational consideration for future grid planning, particularly as EV adoption continues to grow.

4.3 Impact of Different User Types

To further investigate how behavioral heterogeneity influences electricity demand formation and grid response, four scenarios (S5-S8) corresponding to the defined representative residential user types are compared. According to the results, we observe that the AI-generated weekly load profiles exhibit distinct temporal patterns across the four user types. As shown in Figure 8, the Remote Worker scenario produces relatively stable daytime demand due to continuous home occupancy and moderate appliance usage during working hours. Evening load increases (approx. 3.2 kW) are present but remain less pronounced compared to commuter households where peak load surpasses 6 kW. Consequently, the overall load profile displays smoother daily cycles with limited sharp peaks. In contrast, the Commuter scenario (Figure 7) demonstrates stronger evening load concentration. Electricity consumption remains relatively low during daytime hours when occupants are away from home, followed by rapid demand increases after typical commuting hours. The addition of EV charging further amplifies this evening peak, producing synchronized charging periods that significantly elevate residential load levels. The Stay-at-Home Resident scenario (Figure 9) generates a comparatively stable demand trajectory throughout the day. Because occupants remain at home and maintain consistent routines, electricity usage is distributed more evenly across daytime and evening periods. As a result, the feeder experiences smaller short-term load spikes compared with commuter-driven demand patterns. The Flexible Urban User scenario (Figure 10) exhibits the highest level of temporal variability. In this case, the AI agent introduces more dynamic and irregular electricity usage patterns, reflecting flexible daily schedules and higher responsiveness to contextual conditions. The resulting load profile contains intermittent high-demand spikes associated with EV charging and opportunistic electricity consumption.

These behavioral differences translate directly into distinct feeder voltage responses. In the Remote Worker and Stay-at-Home scenarios, voltage profiles remain relatively stable across buses, with most voltages staying within acceptable operating limits. Although localized voltage reductions appear at certain buses, the overall spatial structure of voltage variation remains consistent with the baseline feeder characteristics. In contrast, the Commuter and Flexible Urban User scenarios produce more pronounced voltage fluctuations. Concentrated evening demand, particularly when EV charging coincides with household activity peaks, leads to deeper voltage drops at several downstream buses. The Flexible Urban scenario shows the most severe voltage depressions, with minimum bus voltages approaching the lower operational threshold more frequently than in other cases. Despite these differences in magnitude, the spatial pattern of voltage variation across buses remains largely consistent among all user types. This suggests that feeder topology and electrical characteristics continue to determine the locations where voltage drops are most likely to occur, while behavioral demand patterns primarily influence the severity and frequency of these voltage deviations.

Overall, the results demonstrate that residential behavioral diversity plays a significant role in shaping distribution grid stress. Even under identical system conditions, variations in occupancy patterns, daily schedules, and charging flexibility can produce markedly different load trajectories and voltage stability outcomes. These findings highlight the importance of incorporating behavioral heterogeneity into AI-driven demand modeling and future distribution system planning.



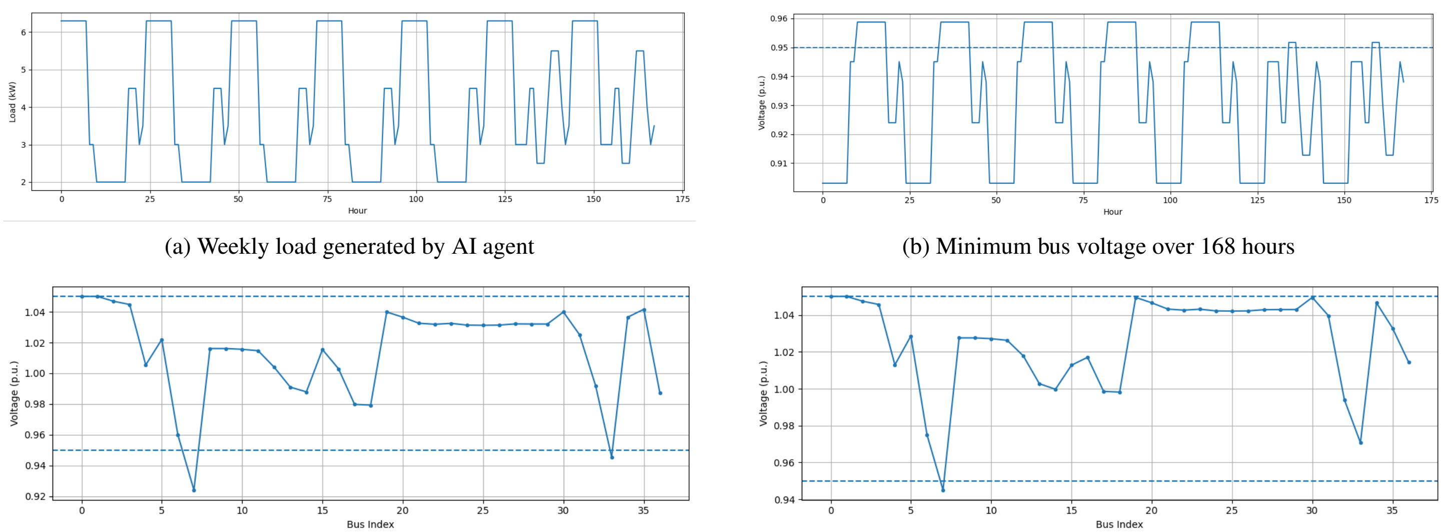
(a) Weekly load generated by AI agent

(b) Minimum bus voltage over 168 hours

(c) Voltage snapshot (Hour 20)

(d) Voltage snapshot (Hour 80)

FIGURE 6: Scenario S3 (IEEE 34-bus, Commuter, 50 households, Without EV): AI generated load and feeder voltage response.



(a) Weekly load generated by AI agent

(b) Minimum bus voltage over 168 hours

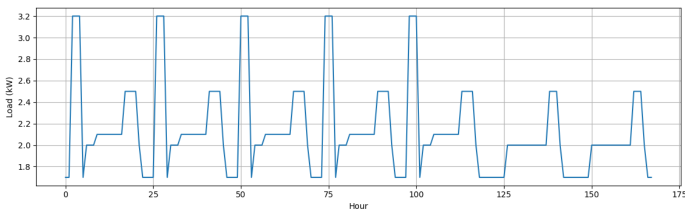
(c) Voltage snapshot (Hour 20)

(d) Voltage snapshot (Hour 80)

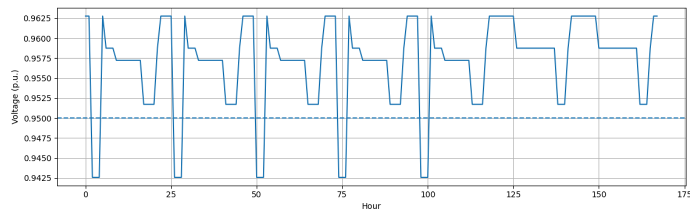
FIGURE 7: Scenario S4/S6/S9 (IEEE 34-bus, Commuter, 50 households, With EV): AI generated load and feeder voltage response.

4.4 Weekday and Weekend Behavioral Differences

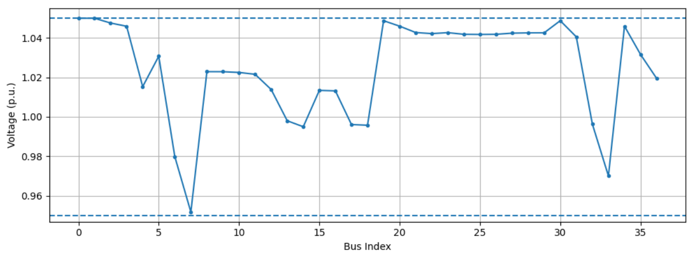
To evaluate whether the AI-driven demand generation framework can capture temporal variations in household behavior, we further examine differences between weekday and weekend electricity consumption patterns. The prompt structure explicitly specifies the day type (Weekday is Monday to Friday and Weekend is Saturday to Sunday), allowing the AI agent to adjust household activity schedules accordingly while keeping environmental and system parameters unchanged. The generated weekly demand profiles reveal noticeable differences between weekday and weekend electricity usage. As illustrated in Figure 9 (a), the demand profile for commuter households exhibits a structured weekday routine characterized by relatively low daytime consumption and pronounced evening demand peaks. These peaks typically occur after typical commuting hours, when occupants return home and engage in electricity-intensive activities such as cooking, appliance usage, and EV charging. Consequently, weekday electricity demand shows a highly synchronized evening peak pattern that repeats across multiple days of the week. In contrast, weekend electricity usage displays a more



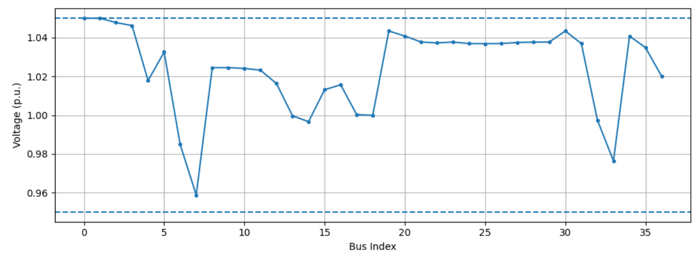
(a) Weekly load generated by AI agent



(b) Minimum bus voltage over 168 hours

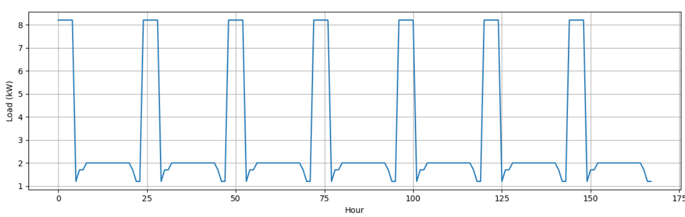


(c) Voltage snapshot (Hour 20)

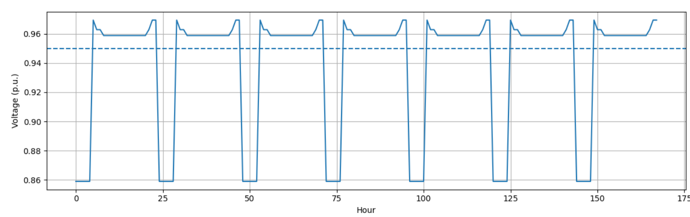


(d) Voltage snapshot (Hour 80)

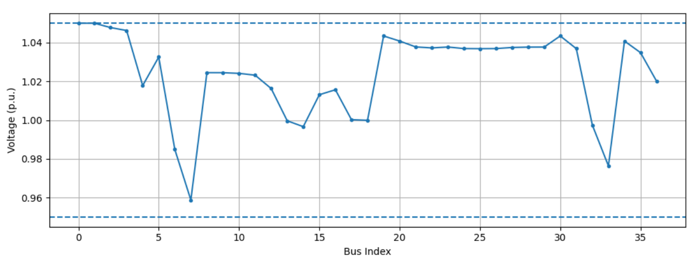
FIGURE 8: Scenario S5 (IEEE 34-bus, Remote Worker, 50 households, With EV): AI generated load and feeder voltage response.



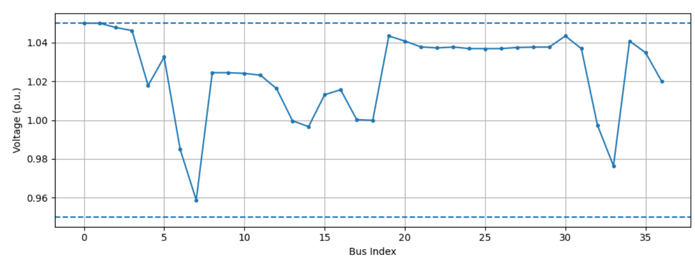
(a) Weekly load generated by AI agent



(b) Minimum bus voltage over 168 hours



(c) Voltage snapshot (Hour 20)

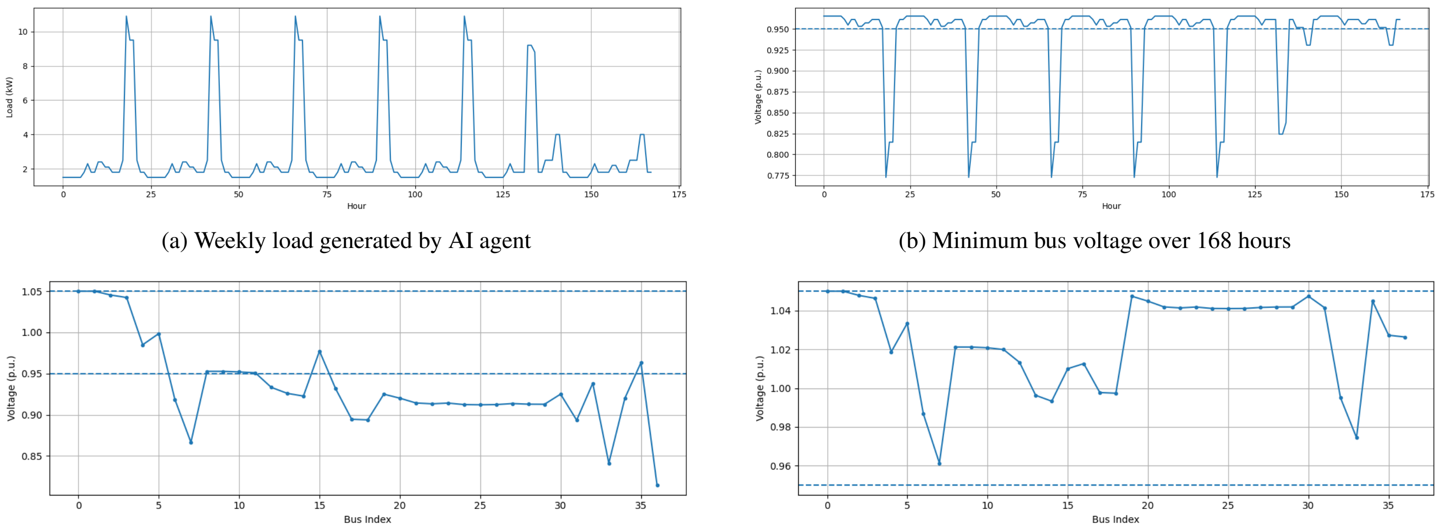


(d) Voltage snapshot (Hour 80)

FIGURE 9: Scenario S7 (IEEE 34-bus, Stay-at-Home Resident, 50 households, With EV): AI generated load and feeder voltage response.

flexible and distributed demand pattern. Because occupants are more likely to remain at home throughout the day, electricity consumption tends to increase during late morning and afternoon hours rather than being concentrated exclusively in the evening. This behavioral shift produces a flatter daily demand curve compared with the sharper weekday peaks observed for commuter households.

A different pattern can be observed for remote worker households. As shown in Figure 10 (a), electricity consumption remains relatively higher during daytime hours even on weekdays due to home-based work activities such as computer usage, lighting, and heating. Compared with commuter households, the difference between weekday and weekend demand patterns is therefore less pronounced for remote workers, since occupancy conditions remain relatively similar across the week. These behavioral differences propagate to the feeder-level voltage dynamics. Figures 9(b) and Figures 10(b) illustrate the minimum bus voltage trajectories over the 168-hour simulation horizon. For commuter households, the strong synchronization of evening electricity consumption during weekdays produces deeper short-



(a) Weekly load generated by AI agent

(b) Minimum bus voltage over 168 hours

(c) Voltage snapshot (Hour 20)

(d) Voltage snapshot (Hour 80)

FIGURE 10: Scenario S8 (IEEE 34-bus, Flexible Urban User, 50 households, With EV): AI generated load and feeder voltage response.

term voltage depressions that align with evening demand peaks. In contrast, the more distributed electricity usage observed during weekends reduces the degree of temporal load synchronization, resulting in milder voltage fluctuations. Voltage snapshot comparisons further illustrate this effect. As shown in Figures 9(c)(d) and Figures 10(c)(d), the spatial distribution of voltage variations across buses remains largely consistent at different time periods. This indicates that feeder topology primarily determines the locations where voltage drops occur. However, the magnitude of voltage deviations varies depending on the temporal concentration of residential demand. Periods with highly synchronized evening demand typically exhibit deeper voltage depressions, while more evenly distributed load patterns lead to smaller voltage deviations

Overall, these results demonstrate that the proposed AI-based demand generation framework is capable of capturing realistic weekday to weekend behavioral differences in residential electricity consumption. By translating contextual information about daily schedules into time-resolved demand profiles, the platform enables the analysis of how routine behavioral cycles propagate from individual households to distribution grid performance.

4.5 Stress Test

To further examine the resilience of the distribution system under large-scale electrification scenarios, a set of stress test experiments is conducted using the IEEE 34-bus feeder. In these experiments, the number of aggregated commuter households with EV charging is progressively increased from 50 households (S9,Figure 7) to 100 households (S10,Figure 11) and 1000 households (S11,Figure 12). All other contextual parameters, including behavioral profiles, weather conditions, and electricity tariff structures, remain unchanged. This design allows the analysis to isolate the effect of increasing electrified residential demand on feeder performance.

As shown in Figs. 7(a), 11(a), and 12(a), the underlying weekly load profile generated by the AI agent remains behaviorally consistent across the stress test scenarios. The profile reflects the expected commuter pattern, with relatively low daytime electricity consumption and pronounced evening peaks associated with return-home activities and EV charging. Because the same single-household demand structure is used in all three scenarios, differences in feeder response can be attributed primarily to the scaling effect introduced by aggregating this profile across larger numbers of households. The feeder voltage response changes substantially as the aggregation level increases. In the baseline stress-test case with 50 households (S9,Figure 7), the system already experiences repeated voltage depressions during daily peak periods, but the minimum voltage trajectory remains within a range (0.95–1.05 p.u.) [39] that still preserves partial operational feasibility. When the aggregation level increases to 100 households (S10, Figure 11), the temporal structure of the voltage curve remains similar, but the magnitude of the voltage drops becomes more severe. The minimum bus voltage decreases to approximately 0.87–0.89 p.u., indicating that the feeder is operating closer to its stability limits under the higher aggregated load. Under the extreme scenario of 1000 households (S11, Figure 12), the system experiences severe voltage collapse-like behavior. The minimum bus voltage trajectory drops dramatically to values as low as approximately 0.12–0.15

p.u., far below acceptable operating thresholds. The voltage snapshot results shown in Fig. 12(c) and Fig. 12(d) further indicate that multiple downstream buses experience voltages below 0.95 p.u.In this case, the feeder is no longer able to support the aggregated demand represented by the synchronized commuter-EV load pattern.

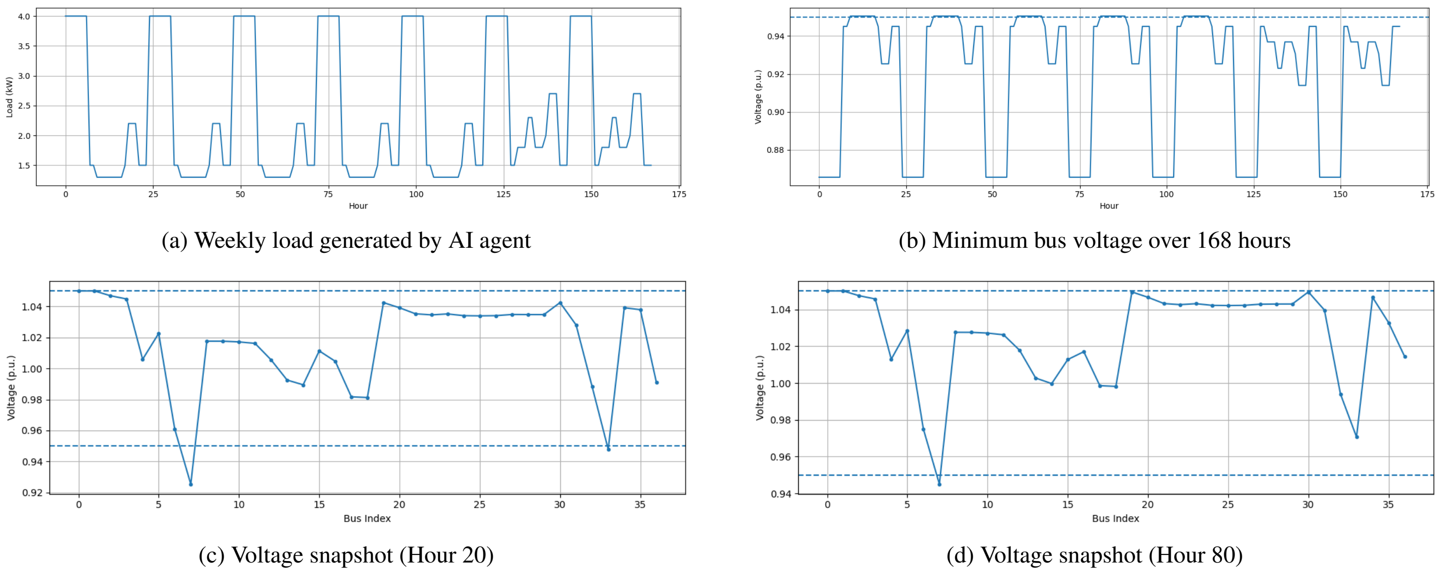
These results highlight that the stress test is driven not by changes in individual household behavior, but by the collective scaling of otherwise plausible residential demand patterns. In other words, a behaviorally realistic single-household load profile may remain harmless at low adoption levels yet become highly disruptive when replicated across a sufficiently large population. This finding is particularly important for studying future electrification pathways, where the challenge may lie less in any one household's behavior than in the synchronized adoption of similar charging and consumption practices across many users. Overall, the stress test demonstrates that aggregation scale is a key factor in determining distribution grid resilience. Even when the underlying AI-generated behavior remains fixed, increasing the number of coordinated electrified households can drive the feeder from manageable stress to severe voltage instability. This result underscores the importance of evaluating not only individual demand behavior, but also large-scale adoption effects in future AI-driven and electrified residential energy systems.

5 DISCUSSION

The results presented in this study highlight the potential of AI-driven behavioral demand modeling for analyzing the interaction between residential electricity consumption and distribution grid performance. By linking behavioral demand generation with feeder system simulations, the proposed framework provides a new perspective for studying how household activities, electrification technologies, and large-scale adoption patterns may influence grid stability. The experiments demonstrate that AI-generated demand profiles can capture meaningful behavioral structures such as daily activity cycles, behavioral heterogeneity among users, and temporal differences between weekday and weekend consumption. These behaviorally driven demand patterns propagate through the distribution system and produce measurable voltage responses, illustrating the importance of incorporating human behavioral dynamics into future power system studies.

Despite these promising results, the current implementation of AI agents also has several limitations. In this study, residential electricity demand is generated using prompt-based AI agents. While this approach enables flexible and intuitive behavioral modeling, the controllability and precision of such agents remain limited. Because the demand profiles are generated through natural language prompts rather than calibrated behavioral models, the resulting electricity consumption patterns may not fully reflect the complexity of real-world household behavior. In particular, factors such as regional lifestyle differences, socioeconomic conditions, appliance ownership, and building characteristics are not explicitly represented in the current prompt-based framework. In addition, LLM-based AI agents may introduce numerical inconsistencies in the generated demand trajectories. For example, in scenarios that include EV charging, the Stay-at-Home Resident profile occasionally produces a higher peak demand than the commuter profile. Given that EV charging typically represents the largest electricity load and occurs during nighttime charging periods in the modeled scenarios, the peak demand levels of these profiles would be expected to be similar. Such discrepancies reflect the tendency of LLM-based generation to produce plausible behavioral patterns while not strictly preserving quantitative relationships between loads. Furthermore, due to the stochastic nature of generative models, identical prompt configurations do not always produce identical demand trajectories. This effect can be observed in repeated simulations such as the stress-test experiments, where individual runs vary slightly in absolute values while still exhibiting consistent aggregate trends. Future work will therefore focus on incorporating empirical behavioral data into the AI-driven behavioral demand modeling. Survey-based data collection and real-world residential energy datasets can be used to better characterize household activity patterns and electricity usage behaviors. Such datasets may enable the training or calibration of localized AI agents that more accurately represent specific populations and geographic regions. In addition, future research will compare AI-generated demand trajectories with conventional demand modeling approaches commonly used in power system studies, such as Monte Carlo–based load simulation and empirical demand extraction from measured consumption datasets. Systematic comparisons between these methods will help evaluate the accuracy, variability, and behavioral realism of AI-generated demand profiles. Through these comparisons, the role of AI-driven behavioral simulation can be more clearly positioned relative to traditional stochastic and data-driven demand modeling techniques.

It is important to emphasize that the primary objective of this work is not to provide a fully calibrated behavioral demand model, but rather to establish a flexible simulation platform that connects AI-based behavioral modeling with power system analysis. The experimental results presented here serve as initial demonstrations of how such a platform can be used to explore emerging research questions related to electrification, demand synchronization, and behavioral diversity. More broadly, the study reveals the potential of AI agents as a tool for simulating residential electricity consumption behaviors in power system research. As AI technologies continue to evolve and richer behavioral datasets become available, this platform may support a wide range of future investigations into the dynamic interactions between human behavior, electrified technologies, and distribution grid stability.



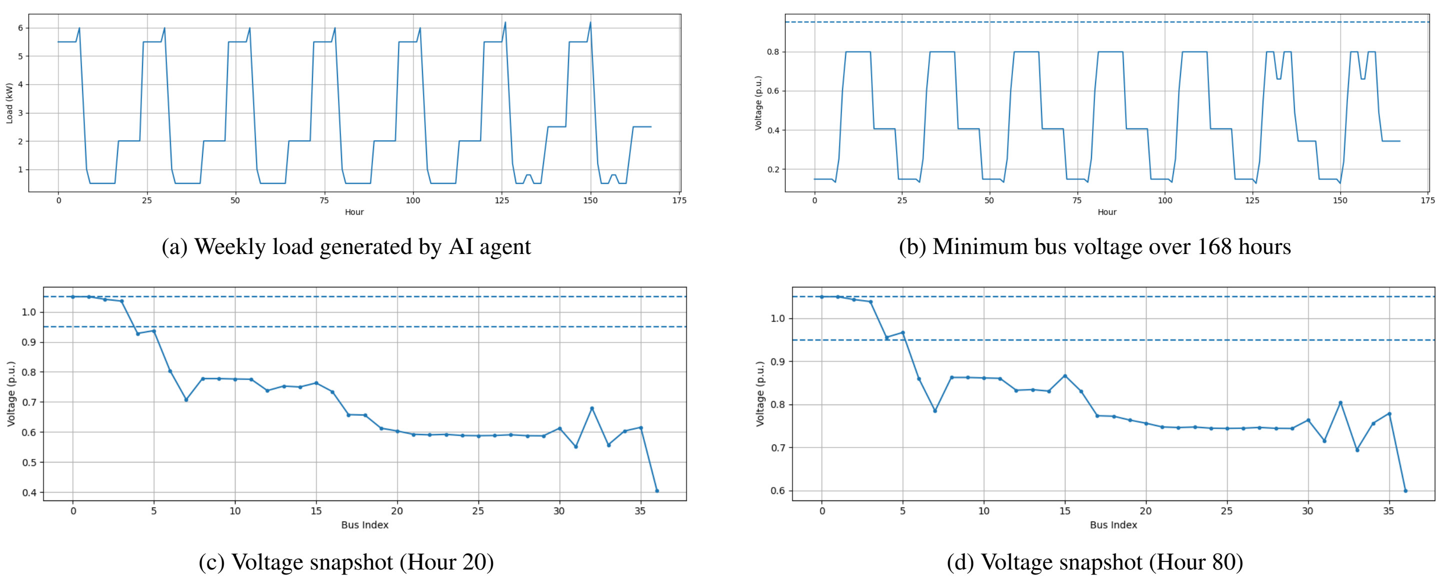
(a) Weekly load generated by AI agent

(b) Minimum bus voltage over 168 hours

(c) Voltage snapshot (Hour 20)

(d) Voltage snapshot (Hour 80)

FIGURE 11: Scenario S10 (IEEE 34-bus, Commuter, 100 households, With EV): AI generated load and feeder voltage response.



(a) Weekly load generated by AI agent

(b) Minimum bus voltage over 168 hours

(c) Voltage snapshot (Hour 20)

(d) Voltage snapshot (Hour 80)

FIGURE 12: Scenario S11 (IEEE 34-bus, Commuter, 1000 households, With EV): AI generated load and feeder voltage response.

6 CONCLUSION

This paper presents a generative AI-based framework for modeling residential electricity demand as a behaviorally generated and dynamically varying input to distribution grid analysis. By integrating AI-driven household demand generation with OpenDSS-based feeder simulation, the proposed approach enables a unified examination of how household activities, electrification technologies, and large-scale adoption patterns influence distribution system stability. Through experiments on standard IEEE distribution feeders, the study showed that the framework can generate behaviorally interpretable residential load profiles that reflect daily activity structure, differences across household archetypes, and weekday–weekend variation. When these profiles are injected into feeder models, they produce distinct voltage responses that depend not only on household behavior but also on feeder topology and spatial load distribution. The results further showed that EV charging significantly increases peak demand and worsens voltage depressions, especially when charging behavior is temporally synchronized with existing residential evening peaks. In addition, the stress test analysis demonstrated that even individually plausible household demand patterns can create significant distribution-level stress when replicated across large populations, highlighting aggregation scale and behavioral synchronization as important drivers of grid vulnerability.Taken together, these findings support the central premise of this work: residential electricity demand should be studied not only as a fixed exogenous profile, but also as an endogenous outcome of behavioral routines, AI-mediated decision processes, and network constraints. The primary contribution of this paper is therefore not a fully calibrated behavioral load model, but a flexible research platform that connects behavioral demand formation with physics-based power system analysis in a reproducible simulation environment.

Future work will focus on improving behavioral realism and quantitative reliability by incorporating empirical household energy data, calibrating agent behavior against observed consumption patterns, and comparing AI-generated demand trajectories with conventional stochastic and data-driven load models. The framework can also be extended to explore adaptive demand response, coordinated charging control, and AI-assisted energy management in larger and more heterogeneous distribution systems. In this way, the proposed platform provides a foundation for future research on the evolving interaction between human behavior, electrification, and distribution grid resilience.

ACKNOWLEDGMENT

This study used a large language model (LLM), gpt-oss-20b (open-source model from OpenAI) [35], aaccessed locally via API from Ollama platform [36], to generate residential electricity demand trajectories under structured prompt constraints for the research workflow described in Section 2.The model was used during the research period from November 2025 to March 2026.

In addition, ChatGPT (OpenAI, GPT-5.4 model) accessed via the web interface was used for limited editorial assistance, including spelling correction and language polishing of the manuscript text. No scientific claims, analytical results, data generation, or conclusions were produced by this tool.

The authors reviewed, validated, and take full responsibility for the integrity, accuracy, and interpretation of all content, analyses, and conclusions presented in this manuscript.

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