Behavioral–Environmental Interaction Modeling for Enhanced Voluntary Load Reduction Prediction

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Abstract—**High-impact, low-frequency events pose significant operational challenges for power system reliability, prompting transmission system operators (TSOs) to deploy emergency control actions. Before enforcing mandatory load shedding, TSOs typically issue public conservation appeals to induce voluntary load reduction (VLR). Although empirical studies show that a significant fraction of consumers respond to such appeals, VLR is not explicitly quantified or incorporated into operational decision-making, often leading to inequitable curtailment and overestimation of forced load shedding. This paper extends prior work by proposing a microscopic modeling framework to predict residential VLR during grid emergencies. The approach captures the effects of time-varying environmental stressors and the interaction of extrinsic and intrinsic behavioral drivers influencing household responsiveness. Integrating these behavioral predictions into operational planning enables more accurate net load-relief estimation, reduced unnecessary curtailment, and improved load shedding allocation. A sensitivity analysis grounded in empirical evidence and behavioral theory quantifies the influence of key VLR drivers, supporting the identification of high-leverage intervention strategies.**

Index Terms — **Agent-based modeling, extreme events, forced load reduction, human behaviors, incentives, voluntary load reduction.**

I. Introduction

The rapid growth of large-scale loads, retirement of conventional generation, and increasing penetration of intermittent resources have heightened concerns regarding power system reliability under both normal and emergency conditions. Recent extreme weather events causing widespread outages underscore the limitations of ensuring uninterrupted system operation. Consequently, emergency control actions are increasingly required across all levels of the power system. Current emergency load-shedding practices used by regional transmission operators typically allocate forced curtailments based on load ratio share [1], while often neglecting critical system-level and consumer-specific constraints.

Existing emergency operational frameworks rely on public appeals for energy conservation to mitigate grid stress. During winter storm Uri in February 2021, the Southwest Power Pool issued such appeals for the first time in its history [1]. Similarly, in January 2024, Electric Reliability Council of Texas reported effective demand reduction after requesting electricity conservation during freezing conditions [2]. These events demonstrate system operators' reliance on voluntary load reduction (VLR) to potentially avoid mandatory load curtailments. Although VLR programs traditionally target large consumers, the resulting demand reduction reflects aggregated participation across all customer classes, including residential users. Increasing adoption of distributed energy resources and flexible household loads has enabled greater residential participation, which accounted for approximately 30% of potential peak demand savings in 2022 [3].

Accurate estimation of VLR under emergency conditions requires a detailed characterization of the factors governing residential electricity conservation. While prior demand response studies consider certain determinants, existing aggregate consumer models often fail to account for heterogeneous behavioral and emotional responses. Building upon the human-behavior-based VLR model presented in [4], this work extends the framework by incorporating temporal environmental factors, including event severity and utility incentives, to quantify their influence on residential energy conservation behaviors. The proposed model is aligned with empirical observations and established behavioral theories.

The remainder of the paper is organized as follows. Section II reviews empirical studies and social science theories on factors influencing human behaviors. Section III formulates the interrelationships among internal and temporal external factors. Section IV presents the network-based model, simulation methodology, and results. Section V concludes with the main contributions and potential future extensions.

II. Related Work

According to Self-Determination Theory (SDT), intrinsic and extrinsic motivations serve as fundamental drivers of human behavior. Intrinsic motivation leads individuals to act out of personal interest or internal satisfaction, whereas extrinsic motivation prompts behavior in response to external rewards, pressures, or incentives [5]. Prior research demonstrates that human responses under uncertainty arise from the interaction between internal psychological attributes and external situational factors [6].

During power system emergencies, households may voluntarily reduce electricity demand due to intrinsic motivations, such as a sense of civic duty, and extrinsic motivations, including monetary incentives. Many demand response programs provide financial compensation for load reductions during peak periods, making utility incentives, event severity, and public conservation appeals key external triggers for participation. Empirical studies indicate that determinants influenced primarily by incentives include household criticality and perceived incentive value [5],[7],[8], whereas determinants influenced primarily by event severity include public responsibility and risk perception [6],[9]-[12].

Prospect Theory suggests that the marginal utility of gains decreases with increasing wealth and that gains are evaluated relative to a reference point [7], implying that high-income households may perceive financial incentives as less effective than lower-income households. Evidence in [8] indicates that households with children often show limited electricity reductions during demand response events despite incentives. Moreover, individuals with high-risk perception may adopt

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protective actions that increase, rather than decrease, electricity consumption [9], [10]. In contrast, a strong sense of personal responsibility for energy conservation is consistently associated with higher energy-saving intentions and behaviors [11], [12].

III. Foundational Framework for Quantifying Collective Behaviors

Human behavior may appear irrational when multiple factors interact, yet each factor follows its own internal logic. Accordingly, the internal and external influences are organized into two coherent pathways. While dependencies among internal factors exist, for instance, a household's response to event severity may depend on its criticality, each factor influences VLR through a distinct pathway. Structuring the model in this manner ensures that collective behavior is represented without double-counting or overlapping effects.

Fig.1 illustrates the interplay among these determinants and summarizes empirical evidence supporting their interactions.

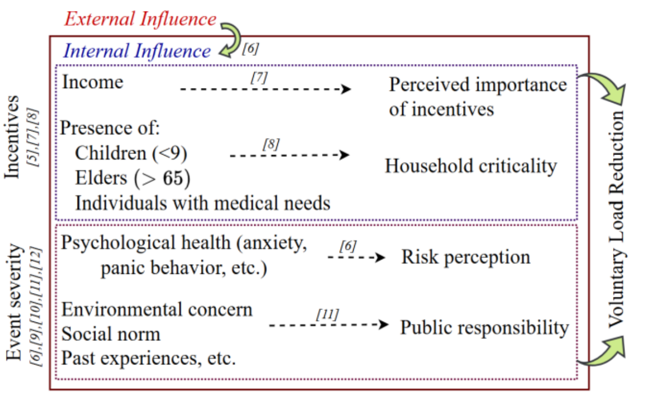

Fig. 1. Interplay among external and internal factors, along with supporting empirical studies.

To quantify the respective contributions of utility-provided incentives and event severity to VLR, we first model the dependencies among the internal behavioral factors and subsequently map these internal factors to the external drivers. Each household is represented as an autonomous agent, and the formulation applies to the i^{th} agent, at time interval t.

A. Impacts of incentives on VLR

a. *Perceived importance of incentives*

Consistent with [7], the model assumes that higher-income households perceive incentives as less important, whereas lower-income households are more sensitive to them. For higher-income households, incentives provide relatively limited benefit, resulting in lower perceived importance. Accordingly, perceived importance of incentives (PI) is modeled using a skew-normal distribution across income categories. The modified formulation based on the skew-normal probability density function (PDF) is given as follows.

$$f(PI) = \frac{2}{\omega}\phi(x)\Phi\big(K(I-0.5)(x)\big) \quad (1)$$

Where $x = \frac{PI-(1-I)}{\omega}$. Here, $I \in (0,1]$ represents the normalized income level with respect to the community's maximum and minimum income, K is a constant controlling skewness, and ω is the scale parameter. $\phi(\cdot)$ and $\Phi(\cdot)$ are standard normal PDF and corresponding cumulative distribution function (CDF), respectively.

b. *Household criticality*

Household criticality (C) is defined as weighted sum of three indictors; the presence of children (c), elders (e) and individuals with medical needs (m), each represented as a binary variable.

$$C_i = \sum_{k\in\{c,e,m\}} w_{k,i} I_k \quad (2)$$

Where $I_k \in \{0,1\}$, and $\sum w_k = 1$. Here, w_k are weight factors prioritizing each vulnerability type. For individual agents, these weights may differ based on their perceived vulnerability. Following [13], a symmetric Dirichlet distribution is used to generate these weight factors as shown in Fig. 2 (a). This approach avoids imposing prior preference among critical factors while allowing heterogeneous household-level realizations.

Fig. 2 illustrates the selection and integration of incentives influenced household parameters into behavioral distribution modeling.

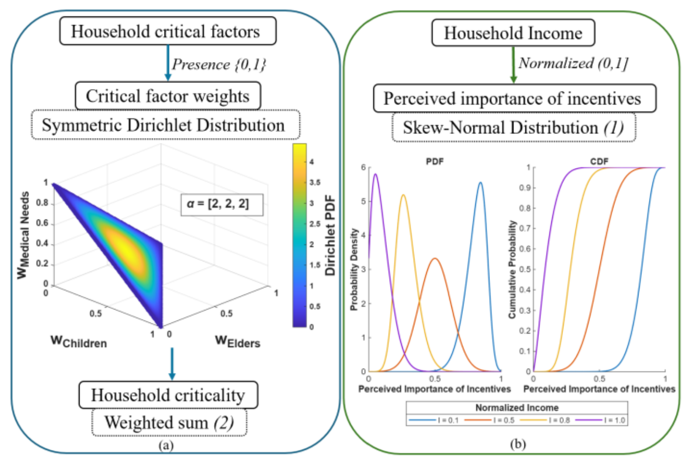

Fig. 2. Parameters affected by incentives and their corresponding behavioral distributions: (a) Household criticality, (b) Perceived importance of incentives.

The per-unit VLR variation due to incentive changes is modeled as a function of PI, C and the per-unit incentive variation (Inc) at a given time. VLR behavior is defined by modified sigmoid function which aligns with [7].

$$VLR_{PU,Inc,t,i} = \frac{PI_i(1-C_i)}{1+\exp\Big(-\beta_i\big(Inc_t-(1-PI_i)\big)\Big)} \quad (3)$$

Where $\beta_i = k_1 + k_2 PI_i$. Here, constants k_1 and k_2 control the rate at which the per-unit reduction saturates. The amplitude of the reduction is controlled by $PI_i(1-C_i)$, reflecting that households respond strongly when they perceive incentives as important and less when their household is more vulnerable.

B. Impacts of event severity on VLR

a. *Risk perception*

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Individuals with high emotional intensity perceive risk (RP) as high [6], where emotional intensity may be influenced by psychological health. Accordingly, the model assumes that, on average, households with higher psychological health issues exhibit higher risk perception, which can be represented by a skew-normal distribution as follows.

$$f(RP) = \frac{2}{\omega}\phi(x)\Phi\big(K(0.5 - PH)(x)\big) \quad (4)$$

Where $x = \frac{RP - PH}{\omega}$. Each household is assigned a psychological health index (PH) based on population-level prevalence of psychological health issues, consistent with the Patient Health Questionnaire-9 (PHQ-9). According to [14], PHQ-9 measures psychological health on a scale from 0 to 27 and exhibits an exponentially decreasing distribution from low to high scores, indicating that severe symptoms are less common. In this work, the index is treated as a continuous variable normalized to the interval [0,1].

b. *Public responsibility*

Public responsibility (PR) is a latent behavioral construction that cannot be directly observed and is commonly measured using survey-based Likert-scale responses. As reported in [11], these responses are typically skewed, with a larger proportion of individuals reporting moderate to high responsibility. Accordingly, PR is modeled using a Beta distribution based on normalized Likert-scale responses ($PR \in [0,1]$), due to its support over the unit interval and its flexibility in capturing skewed behavioral tendencies.

Fig. 3 illustrates the selection and integration of event severity influenced household parameters into behavioral distribution modeling. The distributions in both Fig. 2 and Fig. 3 are selected to reflect behavioral patterns consistent with empirical findings, social science theories and conceptual relationships summarized in Fig. 1.

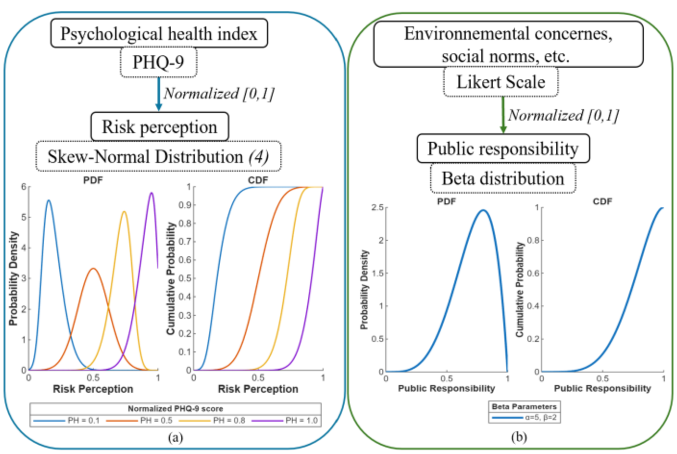

Fig. 3. Parameters affected by event severity and their corresponding behavioral distributions: (a) Risk perception, (b) Public responsibility.

The per-unit VLR variation due to changes in event severity is modeled as a function of RP, PR and the normalized event severity at time t (ES_t). The corresponding VLR behavior is defined for the case of increasing event severity, consistent with empirical studies that examine human responses as event severity escalates [6],[9]-[12].

$$VLR_{PU,ES,t,i} = PR_i\Big(RP_i\, e^{-(a_0+a_1RP_i)ES_t} + (1-RP_i)\Big(1 - ES_t^{\,b_0+b_1(1-RP_i)}\Big)\Big) \quad (5)$$

Here, the magnitude of the reduction is determined by PR. The first term of (5) captures households with higher risk perception, for which VLR decreases exponentially as event severity increases, reflecting greater protective actions. The second term of (5) represents households with lower risk perception, exhibiting smaller reductions in VLR.

The reaction time (RT) to public appeals is assumed to be dependent on PR, such that households with higher PR respond more quickly than those with lower PR.

$$RT_i = f(PR_i) \quad (6)$$

C. *Collective behavioral response*

The combined impact on VLR resulting from the interaction of external and internal factors is formulated to avoid overestimation, as both effects act on the same load. Accordingly, the per-unit VLR is defined as follows:

$$VLR_{PU,i,t} = 1 - \big(1 - VLR_{PU,Inc,t,i}\big)\big(1 - VLR_{PU,ES,t,i}\big) \quad (7)$$

The actual VLR (kW) at each time interval is modeled as a fraction of each household's controllable load (L_c), which includes shiftable demand, available backup generation and battery capacity. Load profiles may vary across households and may depend on household income.

$$VLR_{i,t} = VLR_{PU,i,t} \times L_{c_t} \quad (8)$$

In this framework, each VLR response emerges from the joint influence of two behavioral attributes. Since one attribute may inhibit participation in energy conservation while another promotes it, the observed behavior reflects a compensatory decision process, consistent with multi-attribute decision-making. This emphasizes that individual behavioral responses are multi-factorial, and modeling them based on a single attribute enforces an unrealistic assumption of rationality.

IV. Simulation and Analysis

The simulation framework models a community of 1,000 households located in Wichita, Kansas, using an agent-based modeling (ABM) approach.

A. *Demographic and other empirical dataset*

Demographic data for Wichita, Kansas are obtained using census data reporter [15] and a survey conducted by Lawrence Berkeley National Laboratory on solar PV adopters [16].

TABLE I. HOUSEHOLD LOAD AND GENERATION DATA

Income ($K)	**0 – 50**	**50 - 100**	**100 - 150**	**150 - 200**	**200 - 250**	**> 250**
Households (%)	40.1	31.3	15.9	6.3	6.6	
Solar PV (%)	12.3	32.3	23.3	13.5	7.8	10.00
Median PV size (kW)	6.2	6.7	7.0	7.3	7.8	7.8
Solar + battery (%)	6.0	7.0	8.0	10.0	14.0	14.0
Average electricity consumption (kWh)	27.5	30.4	32.7	36.5	36.5	36.5
Battery capacity (kWh)	7	7	7	10	10	10

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Demographic statistics for Wichita, Kansas indicate that approximately 17% of the population is over 65 years of age and 12% are under 9 years old, with 1% of households assumed to have medical-related electricity needs. To capture heterogeneity in residential demand behavior, four battery charging/discharging strategies and 189 distinct residential load profiles are incorporated and assigned across the household population. In the absence of distribution-specific behavioral data, empirically reported parameter ranges are adopted to represent behavioral variability. The proposed framework is data-adaptive and can be recalibrated when community-specific survey data becomes available.

B. Household clustering

To reduce the computational complexity of the simulation, households are categorized into three clusters: low, medium, and high, based on the magnitude of each relevant attribute. Within each cluster, a representative household is selected to capture the typical behavior and characteristics of that group, enabling the model to approximate population level responses while maintaining computational efficiency. Table II shows the categories and respective probabilities of occurring them in the community. $c_{11} - c_{43}$ represent clusters 1 to 12, respectively.

TABLE II. PERCENTAGE OF HOUSEHOLDS WITHIN EACH CLUSTER

Attribute	C	PR	PI	RP
Low (%)	87 (c_{11})	35 (c_{21})	10 (c_{31})	24 (c_{41})
Medium (%)	10 (c_{12})	32 (c_{22})	39 (c_{32})	49 (c_{42})
High (%)	3 (c_{13})	33 (c_{23})	51 (c_{33})	27 (c_{43})

C. Results and Analysis

The model outputs are evaluated under a series of controlled scenario analyses to assess whether the emergent behaviors are consistent with findings reported in empirical literature. Specifically, we examine:

- The influence of household criticality on VLR
- The impact of perceived incentive importance on VLR
- The impact of public responsiveness on VLR
- The impact of risk perception on VLR

Scenarios are constructed by isolating the effect of each attribute, varying one parameter at a time while keeping all others fixed. The attribute under study is perturbed by ±20% of its nominal magnitude, and the resulting VLR deviations are observed. This behavior is observed for the 8th hour from public appeal declaration. Event severity is modeled as a continuous, time-varying profile characteristic, exhibiting a rise-peak-decline pattern [6]. Midway through the public appeal, consumers are assumed to receive a 10% incentive increment to enhance VLR participation.

As illustrated in Fig. 4, household criticality exhibits a negative correlation with VLR; that is, more vulnerable households demonstrate lower willingness to reduce load, consistent with the empirical observations in [8]. Similarly, perceived incentive importance shows a positive correlation with VLR, indicating that low-income households place disproportionately high value on incentives, aligning with findings in [7]. Public responsibility shows limited marginal influence across clusters with the exception of clusters c_{23} and c_{32}, although a modest positive correlation with VLR is still observable, consistent with [11] and [12]. Furthermore, elevated risk perception leads households to adopt more protective behaviors [9], [10], which consequently reduces VLR after an initially higher response driven by public responsibility.

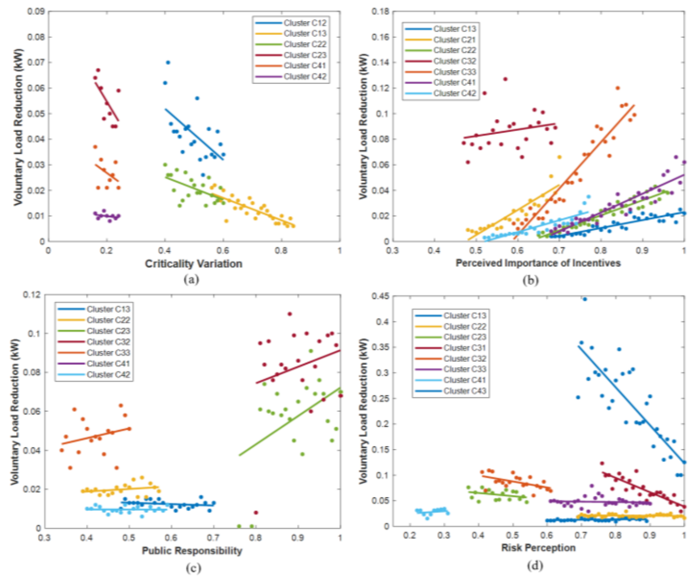

Fig. 4. VLR variation with respect to (a) household criticality, (b) perceived importance of incentives, (c) public responsibility, and (d) risk perception, with all other parameters fixed at hour 14.

TABLE III. SENSITIVITY ANALYSIS

Attributes	Cluster-wise sensitivity of VLR				
Criticality	-0.90 (c_{12})	-1.43 (c_{13})	-1.00 (c_{22})	-0.86 (c_{41})	-0.18 (c_{42})
Perceived importance of incentives	9.56 (c_{13})	13.51 (c_{21})	1.33 (c_{32})	12.35 (c_{33})	14.34 (c_{41})
Public responsibility	0.65 (c_{13})	0.59 (c_{22})	13.5 (c_{23})	6.8 (c_{32})	0.58 (c_{33})
Risk perception	-0.25 (c_{22})	-2.16 (c_{31})	-0.71 (c_{32})	-0.47 (c_{41})	-1.12 (c_{43})

Table III presents the sensitivity of VLR to selected household attributes across several clusters. The results indicate that perceived importance of incentives exhibits the highest sensitivity in all clusters, with VLR increasing as the attribute increases. Negative sensitivity values indicate an inverse relationship, where VLR decreases as attributes such as household criticality and risk perception increase. Positive values indicate a direct relationship, where VLR increases with the corresponding attribute.

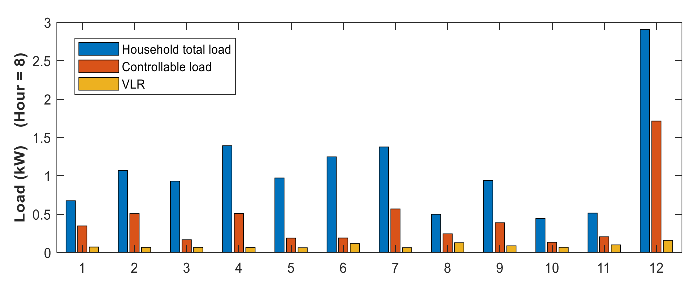

Fig. 5. Total load, controllable load and VLR across households at the 8th hour following public appeals.

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Fig. 5 illustrates that while available controllable load at each time interval is a primary determinant of potential load reduction, the realized reduction is largely governed by behavioral factors. For example, although cluster 12 has the highest controllable load, its reduction level reflects behavioral motivation rather than technical capability.

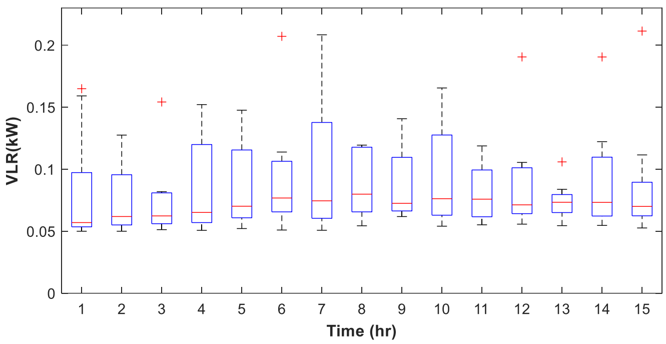

Fig. 6. VLR dynamics of all clusters throughout the declared conservation period.

Fig. 6 illustrates the hourly variation of VLR across all clusters during the conservation period. Each hour is represented by a box plot showing the range of VLR variation across the ABM simulation, along with the mean VLR. From the initiation of public conservation appeals through their conclusion, the mean VLR exhibits an initial increase followed by a slight decline toward the end of the conservation period. Overall, the magnitude of variation across the period remains small.

V. Conclusion and Future Work

This work proposes behavioral modeling framework to predict residential VLR during grid emergencies, formulated through the interaction of internal household attributes and time-varying external drivers. External drivers: event severity and incentive signals modulate consumers' intrinsic and extrinsic motivations to participate in energy conservation. The work is built upon existing empirical studies and established behavioral concepts, incorporating sensitivity analyses to ensure that the proposed behavioral model aligns with observed human behavior. Based on the observations, perceived importance of incentives shows the highest sensitivity to VLR variation across all clusters. In this study, we posit that seemingly irrational or non-modellable human actions can be decomposed into smaller, rational, and explainable behavioral components. Identifying the drivers of these component behaviors is essential for effectively leveraging residential consumer VLR and to identify how different areas would react based on their demographic characteristics. While the proposed behavioral model explains the patterns, the achievable magnitude of VLR remains constrained by household-level flexible load availability.

The current formulation treats internal attributes as fixed, though they may vary over time with changing environmental or contextual factors; incorporating temporal behavioral dynamics is therefore a key extension. The framework can also be applied across communities to compare predicted and observed reductions, supporting more equitable allocation of emergency load-reduction requirements.

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