Integrating Consumer Behavior into EENS-Based Reliability Assessment: Demand Flexibility, Peak Concentration, and Electric Vehicle Charging Scenarios

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Abstract*— Expected Energy Not Served (EENS) is a widely used reliability index for quantifying the expected amount of electricity demand that cannot be supplied under constrained system conditions. Although conventional EENS studies mainly focus on generation adequacy, outage probabilities, reserve capacity, renewable energy uncertainty, and network constraints, modern power systems are increasingly affected by demand-side dynamics. This study examines how consumer behavior influences EENS through changes in daily load profiles, peak demand formation, load factor, price responsiveness, load shifting, and electric vehicle charging behavior. A scenario-based reliability assessment framework was developed using a representative 24-hour load profile and three available capacity states: normal operation, moderate outage, and severe outage. Six consumer behavior scenarios were analyzed: reference consumption, peak-hour intensive consumption, price-responsive consumption, flexible load shifting, uncontrolled electric vehicle charging, and smart charging combined with demand-side management. The results show that consumer behavior has a substantial impact on EENS even under identical capacity conditions. In the reference scenario, EENS was calculated as 2.74 MWh/day. Peak-hour intensive consumption increased EENS to 9.32 MWh/day despite unchanged daily energy consumption, demonstrating the reliability risk of temporal demand concentration. Price-responsive consumption reduced EENS to 1.37 MWh/day, while flexible load shifting produced the lowest EENS value, at 0.91 MWh/day. Uncontrolled electric vehicle charging generated the highest reliability risk by increasing EENS to 35.84 MWh/day, whereas smart charging reduced EENS to 2.42 MWh/day despite the same additional charging demand. These findings indicate that EENS is shaped not only by supply-side adequacy but also by the timing, flexibility, and coordination of electricity demand. Demand response, load shifting, and smart charging should therefore be considered reliability-enhancing mechanisms in future power system planning.

Keywords—expected energy not served (EENS), power system reliability, demand response, consumer behavior, load shifting, peak demand, electric vehicle charging, smart charging.

I. INTRODUCTION

One of the primary objectives of electric power systems is to satisfy consumer demand in a continuous, economical, and reliable manner [1]. Achieving this objective requires the integrated consideration of generation adequacy, installed capacity, reserve margins, transmission infrastructure, renewable energy integration, and demand characteristics in both power system planning and operation. When the balance between electricity supply and demand cannot be maintained, system operators may fail to meet demand during certain periods, thereby increasing the risk of energy shortages, service interruptions, and reliability degradation. Among the quantitative reliability indices used to assess this risk, Expected Energy Not Served (EENS) is one of the most widely adopted metrics [2].

EENS represents the expected amount of electrical energy that cannot be supplied over a specified analysis period. More precisely, it expresses the probabilistic expectation of unserved energy resulting from generation inadequacy, transmission failures, renewable generation uncertainty, network constraints, or excessive demand growth [3]. Unlike interruption-based indices that primarily indicate the occurrence or duration of outage events, EENS quantifies the severity of reliability deficiencies in terms of the amount of energy not delivered to consumers. For this reason, EENS has become a critical indicator in generation adequacy assessment, reserve planning, capacity expansion studies, and long-term investment decision-making.

Conventional reliability studies generally evaluate EENS from the perspective of supply-side uncertainties [4]. In such analyses, the failure rates of generation units, variability of renewable energy resources, transmission line outages, reserve capacity availability, and overall generation adequacy are typically treated as the main determinants of unserved energy [5]. However, modern power systems are increasingly shaped not only by supply-side conditions but also by demand-side dynamics. The widespread adoption of smart meters, time-based tariffs, electric vehicles, heat pumps, flexible household appliances, and demand-side participation mechanisms has transformed consumers from passive electricity users into active actors whose behavior can influence system reliability. Residential consumption concentrated during evening hours, uncontrolled electric vehicle charging, temperature-dependent heating and cooling demand, weekday and weekend consumption variations, industrial shift schedules, and consumer responses to electricity price signals can significantly reshape daily load profiles and system operating conditions [6].

The main hypothesis of this study is that the risk of energy not served does not originate solely from supply-side deficiencies; rather, synchronized and temporally concentrated consumer consumption habits may also substantially increase the EENS value [7]. Conversely, demand-side flexibility, load shifting strategies, price-responsive consumption, and smart charging applications have the potential to reduce EENS and improve overall system reliability by mitigating peak demand conditions [8]. This perspective suggests that EENS should not be interpreted exclusively as a consequence of insufficient generation or network constraints, but also as a reliability outcome affected by the temporal structure and flexibility of electricity demand.

Demand-side management (DSM) and demand response (DR) have become fundamental mechanisms enabling electricity consumers to participate more actively in power system operation, particularly within deregulated electricity markets [9]. In general, DSM can be classified into two principal categories: energy efficiency measures and demand response programs [10]. While energy efficiency initiatives primarily aim to reduce total electricity consumption, demand response programs seek to modify the timing, magnitude, or flexibility of electricity demand in response to electricity prices, incentive mechanisms, or system reliability requirements [11]. DR programs are commonly categorized into price-based and incentive-based schemes. Price-based mechanisms include real-time pricing (RTP), time-of-use (TOU) tariffs, and critical peak pricing (CPP), whereas incentive-based programs include interruptible load agreements, direct load control, emergency demand response, and demand-side bidding mechanisms [12]. Among these approaches, real-time pricing has attracted particular attention because it encourages consumers to shift electricity consumption from high-price periods to low-price periods, thereby contributing to peak load reduction and load profile smoothing.

Existing literature has extensively investigated the economic benefits of demand response, its impact on electricity market prices, and its potential to reduce system operating costs [13]. Nevertheless, studies directly linking consumer behavioral patterns with reliability indices such as EENS remain relatively limited. Dadkhah and Vahidi incorporated demand response into a security-constrained unit commitment framework by explicitly considering consumer behavior through price elasticity matrices representing different levels of consumer rationality [14]. Their findings indicate that consumer behavior should be regarded not only as an economic variable but also as a technical factor with significant implications for power system reliability.

Similarly, Krysiak and Weigt argued that demand-side representation in energy market models is often overly simplified and fails to adequately incorporate the psychological, social, and microeconomic dimensions of consumer behavior [15]. This observation highlights the need for reliability assessment frameworks that can represent not only technical supply-side parameters but also behavioral demand-side characteristics. Accordingly, the present study extends conventional EENS-based reliability assessment by integrating representative consumer behavior scenarios into the analysis of daily load profiles, peak demand formation, load factor variation, and expected unserved energy. By doing so, the study evaluates how peak-oriented consumption, price-responsive demand, flexible load shifting, uncontrolled electric vehicle charging, and smart charging strategies influence EENS under identical system capacity conditions.

A. Objectives, Scope, and Contributions

The primary objective of this study is to examine how consumer behavior affects EENS by modifying the temporal distribution of electricity demand. While EENS is traditionally evaluated as a reliability index associated with generation adequacy, component outage probabilities, renewable generation uncertainty, and network constraints, this study approaches EENS from a demand-side perspective. In doing so, it investigates whether different consumption habits, load-shifting capabilities, price responsiveness, and electric vehicle charging patterns can increase or reduce the expected amount of unserved energy under identical generation capacity and system operating conditions.

The scope of the study is limited to a scenario-based reliability assessment framework developed around a representative 24-hour load profile. The analysis considers six consumer behavior scenarios: reference consumption, peak-hour intensive consumption, price-responsive consumption, flexible load-shifting consumption, uncontrolled electric vehicle charging, and smart charging combined with demand-side management. These scenarios are designed to represent different levels of temporal demand concentration, consumption flexibility, price or incentive responsiveness, and charging coordination. The study does not aim to reproduce the full operational complexity of a real national power system. Rather, it provides a controlled analytical framework for isolating the reliability effects of demand-side behavioral changes while keeping generation capacity conditions constant.

The study is guided by the following research questions:

RQ1: How does peak-hour intensive consumer behavior affect EENS under identical system capacity conditions?

RQ2: To what extent can price-responsive consumption reduce peak demand, improve the load factor, and decrease EENS?

RQ3: How does flexible load shifting influence the expected amount of unserved energy when total daily electricity consumption remains unchanged?

RQ4: What is the reliability impact of uncontrolled electric vehicle charging during evening peak periods?

RQ5: Can smart charging and demand-side management mitigate the adverse reliability effects of additional electric vehicle charging demand?

The central hypothesis of the study is that EENS is influenced not only by supply-side inadequacy but also by the temporal structure of electricity demand. More specifically, consumer habits characterized by synchronized and peak-oriented electricity consumption are expected to increase EENS by placing additional stress on the supply-demand balance during critical hours. Conversely, flexible consumption patterns, load-shifting strategies, price-responsive demand, and smart charging applications are expected to reduce peak demand and consequently decrease EENS, thereby improving overall system reliability.

Within this framework, consumer behavior is conceptualized through three principal dimensions. The first is temporal concentration, which refers to the tendency of

electricity consumption to accumulate during peak-load periods. The second is consumption flexibility, which reflects the capability of consumers to shift deferrable loads to alternative time intervals. The third is price or incentive responsiveness, which indicates the degree to which consumers modify their electricity usage in response to electricity price signals, demand response requests, or system reliability requirements. These dimensions are particularly important because daily electricity consumption may remain constant while its hourly distribution produces substantially different reliability outcomes. The distinction between shiftable and non-shiftable loads is also central to the proposed framework. Appliances such as washing machines, dishwashers, electric vehicle chargers, water heaters, and certain heating or cooling systems may represent shiftable loads because their operation can be postponed or transferred to off-peak periods without causing significant inconvenience. In contrast, lighting systems, essential household appliances, critical medical equipment, industrial production processes, and security systems generally constitute non-shiftable or critical loads that cannot be interrupted or deferred. From an EENS perspective, this distinction is important because shifting non-critical and deferrable loads away from congested or high-risk periods may reduce unserved energy without necessarily reducing total daily electricity consumption.

The main contribution of this study is to extend conventional EENS-based reliability assessment by integrating behavioral demand profiles into the analysis. Instead of interpreting energy not served solely as a consequence of supply-side limitations, the proposed approach explicitly accounts for demand-side risks arising from peak concentration, limited flexibility, uncontrolled charging behavior, and insufficient consumer responsiveness. This provides a more comprehensive perspective on modern power system reliability, particularly in the context of smart grids, demand response programs, flexible household loads, and increasing electric vehicle penetration.

The specific contributions of the study can be summarized as follows. First, it develops a demand-oriented EENS assessment framework that links consumer behavior scenarios with reliability outcomes. Second, it demonstrates that identical daily energy consumption may lead to different EENS values depending on the hourly distribution of demand. Third, it compares the reliability effects of peak-oriented consumption, price-responsive demand, flexible load shifting, uncontrolled electric vehicle charging, and smart charging under the same system capacity assumptions. Fourth, it evaluates EENS together with peak demand, load factor, and Energy Not Served under different capacity states, thereby providing a multidimensional interpretation of reliability performance. Fifth, it highlights demand-side flexibility as a reliability-relevant resource rather than merely an economic or market-based mechanism. The expected output of the study is a quantitative demonstration of how consumer behavior can either aggravate or mitigate reliability risks in power systems. The findings are expected to show that peak-hour intensive consumption and uncontrolled electric vehicle charging increase EENS, whereas price responsiveness, flexible load shifting, and smart charging reduce EENS by smoothing the load profile and lowering peak demand. Therefore, the study is expected to provide practical insights for system planners, distribution system operators, policymakers, and demand response program designers by showing that consumer-oriented flexibility mechanisms can contribute directly to reliability improvement.

II. METHODOLOGY

This section presents the methodology adopted to investigate the impact of consumer behavior on EENS. EENS represents the expected amount of electrical energy that cannot be supplied within a given power system during a specified analysis period. It is generally expressed in MWh/year or GWh/year and provides a comprehensive reliability measure by considering not only the occurrence of supply interruptions but also the magnitude of the corresponding unserved energy. EENS is closely related to the Loss of Load Expectation (LOLE) and Energy Not Served (ENS) reliability indices. While LOLE quantifies the probability or expected duration of supply inadequacy, ENS represents the actual or calculated amount of unserved energy associated with a specific event. EENS, on the other hand, corresponds to the probabilistic expectation of ENS over all possible operating conditions and contingency scenarios. Consequently, EENS simultaneously captures both the likelihood and the severity of supply inadequacy, making it one of the most comprehensive reliability indices used in generation adequacy assessment and system planning studies. The mathematical formulation of EENS can be expressed in Eq.1.

$$EENS = \sum_{s} P_s \times ENS_s \tag{1}$$

where P_s denotes the probability of occurrence of system state or scenario s, and ENS_s represents the amount of energy not served under that scenario. For hourly reliability analyses, the hourly amount of Energy Not Served can be calculated in Eq. 2.

$$ENS_{(t)} = \max(0, D_{(t)} - A_{(t)}) \tag{2}$$

where $D_{(t)}$ represents the electricity demand at time t, while $A_{(t)}$ denotes the available generation capacity during the same time interval. Considering the occurrence probabilities of different operating scenarios, the EENS is calculated in Eq. 3.

$$EENS = \sum_{t=1}^{24} P_s \times \max(0, D_{(t)} - A_{(t)}) \times \Delta_t \tag{3}$$

where s denotes the operating scenario, P_s represents the probability of scenario s, and Δ_t is the duration of the time interval.

In more comprehensive reliability assessments, additional factors such as generation unit outages, renewable energy generation uncertainty, transmission network constraints, and reserve capacity availability may also be incorporated into the proposed model to obtain more realistic EENS estimates.

A. Development of the Baseline Load Profile

The first stage of the proposed methodology involves constructing a baseline load profile that represents conventional electricity consumption behavior before the implementation of any demand response program, load-shifting mechanism, or electric vehicle charging coordination strategy. This baseline profile serves as the reference case against which all alternative consumer behavior scenarios are compared. The baseline load profile may be constructed using

hourly or sub-hourly electricity consumption data depending on data availability and the desired level of temporal resolution. In the present study, an hourly resolution is adopted in order to evaluate the variation of demand throughout a representative 24-hour period. The baseline profile reflects the typical daily evolution of electricity demand, including low-demand periods, daytime consumption, and evening peak-load conditions [16], [17].

The baseline load profile can be characterized by the following indicators:

- daily total electricity consumption,
- hourly peak demand,
- minimum system load,
- average system load,
- load factor,
- peak-hour consumption ratio,
- proportion of shiftable loads,
- proportion of critical or non-shiftable loads.

These indicators provide the basis for evaluating how changes in consumption timing, peak demand formation, and demand flexibility influence reliability outcomes. In this framework, total daily electricity consumption and hourly demand distribution are treated as distinct dimensions. This distinction is important because two load profiles may have the same total energy consumption but different peak demand levels, load factors, and EENS values depending on the temporal concentration of demand.

B. Consumer Behavior Modeling

To incorporate consumer behavior into the reliability assessment framework, electricity demand is represented through scenario-specific load profiles. These scenarios are designed to capture different behavioral characteristics that may influence the timing, magnitude, and flexibility of electricity consumption. Rather than modeling individual consumers separately, the study adopts an aggregate demand-side representation in which each scenario modifies the baseline load profile according to a specific behavioral assumption [18].

Consumer behavior is considered through five main dimensions. The first dimension is peak consumption tendency, which represents the inclination of consumers to concentrate electricity usage during evening hours or other system peak-load periods. A higher peak consumption tendency results in sharper demand peaks and may increase the probability and severity of unserved energy under constrained system conditions. The second dimension is load-shifting capability, which refers to the ability to transfer deferrable electricity consumption from high-demand periods to lower-demand periods. This capability is particularly relevant for flexible household appliances, water heating, certain heating and cooling loads, and electric vehicle charging. Higher load-shifting capability is expected to reduce peak demand and improve the load factor. The third dimension is price or incentive responsiveness, which reflects the extent to which consumers modify their electricity consumption in response to electricity price signals, time-of-use tariffs, real-time pricing, critical peak pricing, or demand response requests. Price-responsive consumers are expected to reduce consumption during expensive or critical periods and shift part of their demand to lower-demand intervals. The fourth dimension is comfort or behavioral constraint, which represents the practical limitations that restrict consumers' willingness or ability to change their electricity consumption habits. Even when economic incentives are available, consumers with high comfort sensitivity may be reluctant to shift electricity use if doing so causes inconvenience, disrupts routines, or affects essential activities. The fifth dimension is the critical load ratio, which denotes the proportion of electricity demand that cannot be interrupted, postponed, or shifted. Critical loads include essential household uses, medical equipment, security systems, lighting, industrial production processes, and other non-deferrable electricity uses [19], [20]. A higher critical load ratio limits the effective flexibility available for demand response and load-shifting applications.

Based on these behavioral dimensions, six representative consumer behavior scenarios are defined. Scenario S1 represents the reference consumption case, in which the baseline hourly load profile is preserved without behavioral modification. Scenario S2 represents peak-hour intensive consumption, in which demand is further concentrated during evening peak hours. Scenario S3 represents price-responsive consumption, in which consumers reduce electricity use during high-price or peak-demand periods and shift part of the reduced demand to lower-demand hours. Scenario S4 represents flexible load-shifting consumption, in which deferrable loads are transferred from peak periods to lower-demand periods while maintaining the same total daily electricity consumption. Scenario S5 represents uncontrolled electric vehicle charging, in which additional charging demand is concentrated during evening hours and increases peak demand. Scenario S6 represents smart charging and demand-side management, in which electric vehicle charging is shifted to lower-demand periods and peak demand is further reduced through coordinated demand-side actions.

III. CASE STUDY AND NUMERICAL RESULTS

A. Reference System

This section presents a scenario-based numerical analysis developed to quantify the impact of consumer behavior on EENS. The analysis is based on a representative 24-hour load profile and an hourly time resolution. For each hour, electricity demand is compared with the available generation capacity under predefined operating states in order to calculate the corresponding amount of Energy Not Served (ENS). The EENS value is then obtained by weighting the ENS associated with each capacity state by its probability of occurrence.

The objective of the case study is not to reproduce the exact operational performance of a specific real power system. Rather, the aim is to demonstrate, under controlled and identical system capacity conditions, how different consumer behavior patterns can influence EENS through changes in the temporal distribution of electricity demand. This design allows the reliability effects of demand-side behavior to be isolated from changes in generation capacity assumptions.

A representative regional power system with a daily peak demand of 100 MW is considered in the numerical analysis. The reference load profile is constructed under the assumption that residential and commercial electricity consumption gradually increases during the daytime and reaches its

maximum value during the evening peak period. The total daily electricity consumption in the reference case is assumed to be 1762 MWh. Accordingly, the average system load is 73.42 MW, and the load factor is 0.734.

The hourly reference load profile used in the numerical analysis is presented in Fig. 1.

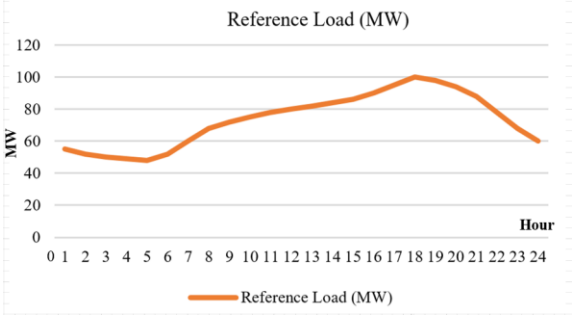

Fig. 1. The hourly reference load profile.

Three available capacity states are defined for the representative system. Under normal operating conditions, the available capacity is assumed to be 110 MW. Under a moderate outage condition, the available capacity is reduced to 95 MW. Under a severe outage condition, the available capacity is further reduced to 80 MW. The probabilities assigned to these operating states are 0.88, 0.10, and 0.02, respectively. These capacity states and probabilities are kept constant across all consumer behavior scenarios so that the resulting differences in EENS can be attributed to changes in the load profile rather than to changes in supply-side assumptions.

TABLE I. AVAILABLE CAPACITY STATES AND OCCURRENCE PROBABILITIES

System State	Probability	Available Capacity (MW)
Normal Operation	0.88	110
Moderate Outage	0.10	95
Severe Outage	0.02	80

B. *Consumer Behavior Scenarios*

.Six consumer behavior scenarios are considered in this study in order to evaluate the reliability implications of different demand-side consumption patterns. The scenarios are constructed to represent variations in peak-hour consumption tendency, price responsiveness, load-shifting capability, and electric vehicle charging behavior. Each scenario modifies the reference load profile according to a predefined behavioral assumption, while the available capacity states and their probabilities remain unchanged. This allows the effect of consumer behavior on EENS to be examined under identical system operating conditions.

Scenario S1 represents the reference case, in which the existing hourly load profile is preserved without any behavioral modification. Scenario S2 represents peak-hour intensive consumption, where demand is further concentrated during the evening peak period. Scenario S3 represents price-responsive consumption, in which consumers reduce electricity use during high-demand or high-price hours, with part of the reduced demand shifted to nighttime hours and the remaining part treated as energy savings. Scenario S4 represents flexible load-shifting consumption, where deferrable loads are transferred from peak hours to low-demand periods without reducing total daily electricity consumption. Scenario S5 represents uncontrolled electric vehicle charging, where additional charging demand is concentrated during evening hours. Scenario S6 represents smart charging and demand-side management, where electric vehicle charging demand is shifted to nighttime and midday hours, accompanied by an additional peak-period demand reduction. Table II summarizes the modeling assumptions used for the six consumer behavior scenarios.

C. *EENS Results*

For each consumer behavior scenario, daily energy consumption, peak load, load factor, and EENS were calculated. The results show that system reliability is affected not only by the total amount of electricity consumption but also by the temporal distribution of demand throughout the day. In particular, scenarios with stronger peak-hour concentration produce higher EENS values, whereas scenarios involving price responsiveness, flexible load shifting, or coordinated charging reduce the expected amount of unserved energy.

Table III presents the main reliability and load profile indicators for all scenarios. In the reference case, the daily energy consumption is 1762.00 MWh, the peak load is 100.00 MW, the load factor is 0.734, and the EENS value is 2.74 MWh/day. In Scenario S2, although the total daily energy consumption remains unchanged, the peak load increases to 112.00 MW and the EENS value rises to 9.32 MWh/day. This corresponds to a 240.15% increase compared with the reference case. Scenario S3 reduces the peak load to 94.00 MW and decreases EENS by 50.00%. Scenario S4 produces the lowest EENS value among all scenarios, with a 66.79% reduction compared with S1. Scenario S5 generates the most severe reliability impact, as uncontrolled electric vehicle charging increases the peak load to 120.00 MW and raises EENS to 35.84 MWh/day. In contrast, Scenario S6 demonstrates that smart charging and demand-side management can limit the adverse reliability effects of additional electric vehicle demand by reducing EENS to 2.42 MWh/day.

In order to demonstrate how different operating conditions contribute to the EENS value, ENS was also calculated separately under normal operation, moderate outage, and severe outage conditions. Table IV shows that scenarios with high peak concentration generate unserved energy even under less severe capacity conditions. For example, Scenario S2 produces 2.00 MWh of ENS under normal operation and 45.60 MWh under moderate outage conditions, whereas Scenarios S3, S4, and S6 produce no ENS under normal or moderate outage conditions. This indicates that demand-side flexibility can reduce exposure to reliability risk by preventing demand from exceeding available capacity during critical periods.

The most pronounced effect is observed in Scenario S5. In this case, uncontrolled electric vehicle charging produces 26.00 MWh of ENS even under normal operation, 89.00 MWh under moderate outage conditions, and 203.00 MWh under severe outage conditions. These results indicate that the reliability impact of electric vehicle integration depends strongly on charging coordination. When the same additional electric vehicle charging demand is managed through smart charging in Scenario S6, ENS occurs only under the severe outage condition, and total EENS remains lower than the reference case.

TABLE II. MODELING ASSUMPTIONS FOR CONSUMER BEHAVIOR SCENARIOS

Scenario	Description	Modeling Assumption
S1	Reference consumption	The existing hourly load profile is preserved.
S2	Peak-hour intensive consumption	The load between 18:00 and 22:00 is increased by 12%, and the corresponding energy is shifted from low-load hours to the evening peak period.
S3	Price-responsive consumption	The load between 17:00 and 22:00 is reduced by 6%; 70% of the reduced load is shifted to nighttime hours, while 30% is considered as energy savings.
S4	Flexible load-shifting consumption	The load between 18:00 and 22:00 is reduced by 15%, and the entire reduced amount is shifted to low-demand hours.
S5	Uncontrolled electric vehicle charging	An additional electric vehicle charging demand of 120 MWh/day is added between 18:00 and 23:00.
S6	Smart charging and demand-side management	The 120 MWh/day electric vehicle charging demand is shifted to nighttime and midday hours, and an additional 5% demand reduction is applied during peak hours.

TABLE III. DAILY ENERGY CONSUMPTION, PEAK LOAD, LOAD FACTOR, AND EENS BY SCENARIO

Scenario	Daily Energy (MWh)	Peak Load (MW)	Load Factor	EENS (MWh/day)	Change Compared to S1
S1 Reference consumption	1762.00	100.00	0.734	2.74	0.00%
S2 Peak-hour intensive consumption	1762.00	112.00	0.656	9.32	+240.15%
S3 Price-responsive consumption	1752.05	94.00	0.777	1.37	-50.00%
S4 Flexible load-shifting consumption	1762.00	95.00	0.773	0.91	-66.79%
S5 Uncontrolled electric vehicle charging	1882.00	120.00	0.654	35.84	+1208.03%
S6 Smart charging and demand-side management	1787.90	95.00	0.826	2.42	-11.68%

TABLE IV. ENS CONTRIBUTIONS UNDER DIFFERENT AVAILABLE CAPACITY STATES

Scenario	ENS under Normal Operation (MWh)	ENS under Moderate Outage (MWh)	ENS under Severe Outage (MWh)	Total EENS (MWh/day)
S1 Reference consumption	0.00	8.00	97.00	2.74
S2 Peak-hour intensive consumption	2.00	45.60	150.00	9.32
S3 Price-responsive consumption	0.00	0.00	68.50	1.37
S4 Flexible load-shifting consumption	0.00	0.00	45.50	0.91
S5 Uncontrolled electric vehicle charging	26.00	89.00	203.00	35.84
S6 Smart charging and demand-side management	0.00	0.00	121.00	2.42

Overall, the results confirm that the temporal concentration of electricity demand is a decisive determinant of EENS. Scenarios with the same or similar daily energy consumption may produce substantially different reliability outcomes depending on peak demand formation and load factor. Therefore, demand-side flexibility, price-responsive consumption, and smart charging should be considered reliability-relevant mechanisms, rather than only economic or operational demand management tools.

IV. DISCUSSION

The numerical results demonstrate that consumer behavior has a substantial effect on EENS, even when the available capacity states and their occurrence probabilities remain unchanged. This finding confirms the central premise of the study: reliability outcomes are influenced not only by supply-side adequacy but also by the temporal structure of electricity demand. In the reference scenario, the daily EENS value was calculated as 2.74 MWh/day. This value provides the baseline against which the reliability implications of alternative consumer behavior scenarios can be evaluated.

Scenario S2, representing peak-hour intensive consumption, illustrates the reliability risk created by temporal demand concentration. Although total daily electricity consumption remains unchanged at 1762.00 MWh, the peak load increases from 100.00 MW to 112.00 MW, while the load factor decreases from 0.734 to 0.656. As a result, EENS increases from 2.74 MWh/day to 9.32 MWh/day. This corresponds to an increase of 240.15% relative to the reference case. The important implication is that reliability deterioration may occur even without an increase in total daily energy consumption. What matters in this case is not the total amount of energy demanded, but the concentration of demand during hours when the system is more exposed to capacity limitations. Therefore, peak-oriented consumer habits should be treated as a reliability-relevant demand-side risk.

Scenario S3 shows the opposite effect. Under price-responsive consumption, peak demand decreases to 94.00 MW and the load factor improves to 0.777. The corresponding EENS value falls to 1.37 MWh/day, representing a 50.00% reduction compared with the reference case. This result suggests that price signals can contribute to reliability improvement when consumers reduce consumption during high-demand periods and shift part of their demand to lower-load hours. However, the reliability benefit observed in this scenario should not be interpreted solely as the result of load shifting, because the scenario also includes a partial reduction in total daily energy consumption. Therefore, the effect of price responsiveness reflects both temporal redistribution and demand reduction.

Scenario S4 provides a clearer indication of the reliability value of load shifting because total daily electricity consumption remains unchanged at 1762.00 MWh. In this scenario, flexible load-shifting behavior reduces peak demand to 95.00 MW, increases the load factor to 0.773, and produces the lowest EENS value among all scenarios, at 0.91 MWh/day. This corresponds to a 66.79% reduction compared with the reference case. The result demonstrates that reliability improvement can be achieved without reducing total daily energy consumption, provided that deferrable demand is moved away from peak periods. This is a central finding of the study because it indicates that demand-side flexibility can function as a reliability resource, not merely as an economic or market-efficiency mechanism.

Scenario S5 represents the most critical reliability condition. In this scenario, uncontrolled electric vehicle charging increases total daily energy consumption to 1882.00 MWh and raises the peak load to 120.00 MW. The load factor decreases to 0.654, indicating a more uneven demand profile. Consequently, EENS increases sharply to 35.84 MWh/day, which is 1208.03% higher than the reference case. This result shows that electric vehicle integration may create significant reliability challenges if charging demand is concentrated during evening peak hours. The issue is not only the additional energy required by electric vehicles, but also the timing of this additional load. When charging demand overlaps with existing peak demand, it intensifies capacity stress and increases the amount of expected unserved energy.

Scenario S6 demonstrates that the adverse reliability effects of electric vehicle charging can be mitigated through smart charging and demand-side management. Although total daily energy consumption remains at 1882.00 MWh, as in Scenario S5, the peak load decreases to 95.00 MW and the load factor improves to 0.826. The resulting EENS value is 2.42 MWh/day, which is lower than the reference case and substantially lower than the uncontrolled charging scenario. This comparison between S5 and S6 is particularly important because both scenarios include the same additional daily electric vehicle charging demand. The difference in reliability performance arises from charging coordination and peak-period demand reduction. Therefore, the results indicate that electric vehicle penetration does not necessarily increase reliability risk; rather, the risk depends on whether charging behavior is unmanaged or coordinated.

The ENS decomposition across available capacity states further supports this interpretation. In Scenarios S3, S4, and S6, no ENS occurs under normal operation or moderate outage conditions; unserved energy appears only under the severe outage condition. By contrast, Scenario S2 produces ENS even under normal operation, and Scenario S5 produces the highest ENS values under all capacity states. This pattern indicates that smoother load profiles reduce exposure to reliability risk across less severe operating conditions, whereas concentrated peak demand can create unserved energy even when available capacity is relatively high.

Taken together, the results show that EENS is sensitive to three demand-side mechanisms: peak concentration, flexibility, and coordinated charging. Peak concentration increases EENS by raising demand during critical hours. Flexibility reduces EENS by transferring deferrable consumption to lower-demand periods. Coordinated charging prevents additional electric vehicle demand from coinciding with existing system peaks. These mechanisms explain why scenarios with similar or identical total daily energy consumption can produce markedly different reliability outcomes.

From a system planning perspective, the findings suggest that demand-side behavior should be incorporated more explicitly into reliability assessment. Conventional adequacy studies often emphasize generation capacity, outage probabilities, reserve margins, and network constraints. These factors remain essential; however, the present results indicate that consumer behavior can modify the effective reliability performance of the same supply-side system. Accordingly, demand response programs, time-based tariffs, smart charging strategies, and load-shifting mechanisms should be evaluated not only in terms of cost reduction or market efficiency, but also in terms of their contribution to reducing EENS.

The results also have practical implications for the management of future power systems with increasing electrification. The expansion of electric vehicles, heat pumps, and flexible household technologies will make demand profiles more dynamic. If these loads are unmanaged, they may intensify peak demand and increase reliability risks. If they are coordinated through smart charging, demand response, and consumer-oriented flexibility mechanisms, they may improve load factor and reduce unserved energy. Therefore, the reliability impact of electrification depends strongly on the governance and coordination of demand-side resources.

It should also be noted that the numerical results are based on a representative scenario framework rather than a full-scale operational model of a real power system. The purpose of the analysis is to isolate the reliability effect of consumer behavior under controlled assumptions. Therefore, the findings should be interpreted as evidence of the directional and comparative effects of demand-side behavioral scenarios on EENS. More detailed studies using real load data, stochastic outage models, renewable generation profiles, network constraints, and market-based demand response data would be necessary to generalize the numerical magnitudes to a specific power system.

Consumer behavior affects not only the shape of the load profile but also the expected amount of unserved energy. The most important conclusion is that reliability is not determined solely by how much electricity is consumed, but also by when and how flexibly it is consumed. Demand-side flexibility, price responsiveness, and smart charging can therefore be considered reliability-enhancing mechanisms in modern power systems.

V. Conclusion

A. Key Findings

This study investigated the influence of consumer behavior on EENS by integrating demand-side characteristics into a scenario-based reliability assessment framework. Unlike conventional EENS analyses that primarily emphasize generation adequacy, component outages, reserve capacity, and other supply-side uncertainties, the proposed approach examined how different electricity consumption patterns modify daily load profiles and consequently affect the expected amount of unserved energy.

Six representative consumer behavior scenarios were evaluated: reference consumption, peak-hour intensive consumption, price-responsive consumption, flexible load shifting, uncontrolled electric vehicle charging, and smart charging combined with demand-side management. The results showed that consumer behavior has a measurable impact on system reliability even when available capacity states and their probabilities remain unchanged. In the reference scenario, EENS was calculated as 2.74 MWh/day. Under peak-hour intensive consumption, total daily energy consumption remained unchanged; however, peak load increased from 100.00 MW to 112.00 MW and EENS increased to 9.32 MWh/day. This finding confirms that the temporal concentration of demand can significantly increase reliability risk even without an increase in total daily electricity consumption.

The results also demonstrated the reliability value of demand-side flexibility. In the price-responsive scenario, EENS decreased to 1.37 MWh/day, while the flexible load-shifting scenario produced the lowest EENS value, at 0.91 MWh/day. These findings indicate that reducing or shifting demand during peak periods can improve system adequacy by smoothing the load profile and reducing exposure to capacity limitations. The comparison between uncontrolled and smart electric vehicle charging further supports this conclusion. Uncontrolled charging increased peak load to 120.00 MW and raised EENS to 35.84 MWh/day, whereas smart charging and demand-side management reduced EENS to 2.42 MWh/day despite the same additional daily electric vehicle charging demand. Therefore, the reliability impact of electric vehicle integration depends not only on the amount of additional energy demand but also on the timing and coordination of charging behavior.

B. Practical Contributions

The findings suggest that consumer behavior should be regarded as a reliability-relevant parameter in modern power system planning and operation. Demand-side flexibility, price responsiveness, and coordinated charging can reduce peak demand, improve the load factor, and decrease the expected amount of unserved energy. These mechanisms can therefore complement conventional reliability measures such as generation capacity expansion, reserve planning, and network reinforcement. From a practical perspective, the results indicate that demand response programs, time-based tariffs, load-shifting incentives, and smart charging strategies may contribute directly to reliability improvement. In particular, flexible household loads and electric vehicle charging demand should be managed in a way that prevents their concentration during critical peak periods. This is especially important for future power systems in which electrification, distributed energy resources, smart meters, and consumer-side technologies are expected to make demand patterns more dynamic. The study also highlights that demand-side management should not be evaluated only as a cost-reduction or market-efficiency tool. Its contribution to reducing EENS suggests that consumer-oriented flexibility mechanisms can function as reliability resources. Accordingly, system planners, distribution system operators, policymakers, and demand response program designers should consider the temporal structure of electricity demand when assessing system adequacy and designing reliability-oriented demand-side interventions.

C. Limitations & Future Work

The proposed analysis is based on a representative 24-hour load profile and predefined consumer behavior scenarios. Therefore, the numerical results should be interpreted as controlled scenario-based evidence rather than as the operational performance of a specific real power system. The purpose of the study was to isolate the effect of demand-side behavioral changes under identical capacity conditions. For this reason, the model does not fully represent the stochastic and spatial complexity of real power systems. Future studies may extend the proposed framework by incorporating real load data, stochastic generation outage models, renewable energy generation uncertainty, transmission and distribution network constraints, reserve dispatch, battery energy storage systems, and electricity market data. The model may also be improved by using probabilistic demand response formulations and machine learning-based consumer behavior prediction models. Such extensions would allow EENS to be evaluated under more dynamic smart grid conditions and would provide a stronger empirical basis for reliability-oriented demand-side planning.

Overall, the study demonstrates that EENS is shaped not only by supply-side adequacy but also by the timing, flexibility, and coordination of electricity demand. Peak-oriented consumption and uncontrolled electric vehicle charging increase reliability risk, whereas price responsiveness, flexible load shifting, and smart charging can reduce expected unserved energy. This confirms that consumer behavior should be explicitly integrated into reliability assessment frameworks for modern and future power systems.

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