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Research Paper

Improving the Resilience of a Smart Microgrid Based on Energy Interactions Between Smart Homes

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Abstract— *The development of smart energy microgrids (MGs) and the influence of various types of distributed energy resources (DERs) on the demand side have increased the importance of addressing technical issues within MGs. In addition, the expansion of smart homes can improve issues related to the resilience of MGs during a disaster event. Therefore, this paper presents an efficient model for the optimal planning of energy management in a smart MG, taking into account the optimal energy interactions between smart homes and aiming to improve the MG's resilience in a disrupted state, specifically with the integration of smart homes. In the suggested framework, interactions between smart homes and the microgrid operator (MGO) are considered. Through this model, the MGO obtains oversight of home energy management (HEM) systems, which enables it to improve resilience against MG disruptions. By facilitating energy management and interaction among smart homes, supported by DERs, the MGO can effectively bolster system resilience. In the mathematical modeling, smart homes include responsive loads (RLs), non-RLs, a bath-heating system (BHS), air-conditioning (AC), plug-in hybrid electric vehicles (PHEVs), energy storage systems (ESSs), and photovoltaic (PV) systems. Simulation analysis shows that operating the HEM system effectively, together with interlinked smart home energy exchanges, boosts the resilience of microgrids by 63.59%, using the General Algebraic Modeling System (GAMS). The results obtained are promising.*

Keywords—Smart microgrid, home energy management system, distributed energy resource, resiliency.

1. INTRODUCTION

1.1. Motivation

Electric smart microgrids (MGs) act as the final link in the energy supply chain for end users [1]. Their peak technical performance ensures a dependable future for the electricity sector. Recently, improving the resilience and protection of smart MGs that incorporate distributed energy resources (DERs) has garnered considerable interest [2]. These MGs operate as cohesive control systems, allowing them to connect to or disconnect from the main grid, functioning in either grid-connected or island mode [3]. The deployment of MGs is vital for improving DER integration, tackling network challenges such as peak demand, and reducing energy not supplied (ENS) and increasing the network resilience [4]. Microgrids, by having the property of modularity, can lead to improved resilience of the electric distribution network [5]. To maximize the effectiveness of smart MGs, it is essential to incorporate DERs on the demand side and encourage energy interactions among users. This collaboration, along with strategic energy planning, can greatly enhance the overall objectives of the MG [6].

Energy interactions among consumers can enhance resilience in MGs during high-impact, low-probability (HILP) events [7]. When disruptions occur, the MG disconnects from the main distribution network, creating isolated islands of power. This capability to form independent islands with both generation and consumption boosts resilience over traditional networks. By deploying smart grid technologies and forming smart microgrids, the resilience of distribution systems is improved. To this end, a novel resource allocation model based on the modularity feature of MGs has been proposed in [8]. Additionally, smart MGs offer improved services, ensure better power availability, and enhances security for consumers [9].

The home energy management (HEM) system is a key solution for managing DERs in smart homes [10]. It includes a smart meter (SM) and a home controller (HC) that are connected to household devices. The HC addresses load-sharing challenges from the user's perspective [11]. Smart homes also incorporate local energy storage systems (ESS), photovoltaic (PV) systems, and plug-in hybrid electric vehicles (PHEVs) in the load planning process. To motivate smart home users to engage in consumption management programs, the MG operator (MGO) provides incentives, such as reduced tariffs. Consumers can respond to the MG control center's requests through the HEM system [12].

This study defines smart homes as those equipped with responsive loads (RLs), non-responsive loads (non-RLs), a bath heating system (BHS), air conditioning (AC), PHEV, ESS, and PV systems. These intelligent devices can engage in two-way communication with the HEM system. Such interactions depend on telecommunication networks and the Internet of Things (IoT) across various home area networks (HAN) and local area networks (LAN). By automating the control of smart home devices, the MGO and HEM systems enhance resilience and motivates consumers to participate in managing energy demand. As a result, the HEM

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system is vital for effective energy planning and strengthening resilience in energy MGs.

1.2. Literature review

In [13], the enhancement of smart home appliance usage alongside electric vehicles and a small rooftop PV system is explored by focusing on their influence on energy consumption and cost savings. The methodology emphasizes strategic scheduling of smart appliances, leveraging real-time pricing to minimize energy expenses. Results indicate a potential cost reduction of up to 80.6% compared to baseline scenarios across various conditions. However, this study demonstrates how household energy scheduling can benefit energy management. This study has not considered the role of optimal household load planning in studies of the average pressure level of the distribution network and has not studied the effect of household load management in optimal planning of the MG. Also, the interaction of consumers in energy management in the MG in order to improve the resilience of the MG has not been considered. In [14], a stochastic programming strategy is proposed for optimizing energy consumption in a grid-connected smart HEM system, which integrates PV panels, batteries, and diesel and gas heating/cooling systems. A demand response program is utilized under time-of-use pricing in Syria to enhance efficiency. The main goal is to minimize expected costs and improve consumer comfort by optimizing controllable DERs. To address the uncertainties in PV generation and potential electrical rationing, the conditional value-at-risk approach is applied, using two methods for modeling the uncertainty, interval bands and interval-based scenarios. However, the technical constraints of MGs, particularly regarding their resilience and the role of energy exchanges in mitigating these challenges, remain underexplored. Additionally, analyzing various scenarios to determine the optimal choice from either the MG's perspective or that of the consumers has not been addressed. In [15] a novel method for enhancing the efficiency of HEM systems is proposed by focusing on achieving financial and operational goals while improving the power factor. It involves managing flexible loads, adjusting thermostatic loads based on user preferences, and accurately assessing power for energy storage and electric vehicles. The model addresses uncertainties in user behavior and renewable energy generation using a Markov decision process and incorporates deep reinforcement learning for real-time load scheduling. However, in this study, PV and AC equipment by the MG operator have not been identified. By identifying the equipment that responds to price signals, load response programs can be used to better improve the load curve and reduce costs. Also, examining various types of smart homes and their energy interactions can enhance the objectives of MGs and improve energy availability during disruptions. In [16], an optimization method for energy management systems is developed to integrate renewable DERs with independent diesel generators. The system features a wind turbine, PV system, a diesel generator, and an ESS, designed to support both flexible and fixed loads connected to the network. Validation through simulations confirms the method's practicality. Compared to other strategies, this approach enhances efficiency, improves resource allocation, optimizes load scheduling, and adapts well to demand and supply fluctuations, ultimately achieving significant cost savings and maximizing energy utilization. This study thoroughly analyzes energy management in MGs with various DERs but fails to consider the impact of consumer involvement and two-way interactions on enhancing MG objectives. It also does not address scenarios where the MG operates independently from the main grid. In [17], the challenges of energy management in an isolated hybrid MG are explored to integrates three renewable energy sources solar, geothermal, and biomass along with an ESS. This study employs intelligent management techniques aimed at minimizing energy production costs through cost function optimization, ensuring efficient operation despite variable weather. Although this study has studied the case of MG disconnection from the main grid, it did not consider the HEM system's integration with electrical devices and DERs through the HAN, nor its connection to MGO via the LAN for bidirectional information exchange. In [18], a detailed framework for developing an emergency response plan for power outages is presented. This study highlights the need for a specialized team with clear roles, including coordinator and safety personnel. However, it didn't examine how the involvement of smart homes and their energy exchanges contribute to strengthening resilience and optimizing performance from the viewpoints of both smart homes and MG. Also, the effects of these interactions on the resilience and performance metrics have not been adequately explored.

In [19] a statistical framework is created to evaluate the resilience of grid-connected MGs during islanding events, focusing on their ability to maintain essential loads. It defines MG survivability as the probability of meeting critical load demands in such scenarios. The research also presents an optimized control algorithm for isolated MG operations and conducts sensitivity analyses to identify key parameters that improve survivability, reduce fuel usage, and minimize disruptions to critical loads. This study provides a thorough examination of MGs in an island environment; however, it overlooks the energy exchanges among consumers, which could significantly enhance MG research. Additionally, the study does not incorporate other energy sources like ESS and PHEV. The research outlined in [20] focuses on transforming traditional electricity distribution networks into resilient, autonomous smart MGs that optimize the integration of DERs. This paper examines management strategies for connecting and disconnecting these DERs and their effects on MG performance and resilience. The study also addresses technical challenges, such as voltage fluctuations, and proposes adding energy sources to improve resilience. However, the research does not consider the impact of optimal consumer planning or demand-side participation on MG efficiency. In paper [21], the exploration of energy management in smart grids is approached through two scenarios: one where the microgrid is integrated with the main grid and another where it functions autonomously. This study predominantly aims to optimize economic outcomes from the perspective of smart homes while also enhancing the technical performance of the microgrid when connected, placing less emphasis on reliability enhancements. Additionally, the research employs half-hour intervals for data analysis; utilizing shorter intervals could further elevate accuracy. In [22], the improvement of resilience in a distribution system is investigated, with a focus on the deployment of both fixed and portable ESSs to maintain network stability. The study prioritizes the supply of critical loads as the primary metric for achieving resilience, formulating the problem as a mixed-integer linear optimization model. The objective function aims to minimize costs, while constraints are imposed to ensure operational feasibility under both normal and resilient network conditions. Although the research effectively addresses the resilience of distribution networks, but incorporating energy interactions on the demand side could significantly improve the operation of ESSs, an aspect that remains unexplored in this study.

In [23], the authors emphasized the value of incorporating smart homes into microgrid energy management, enabling optimized scheduling of decentralized energy sources, storage solutions, and domestic appliances to minimize operational costs. They introduced efficient planning methods for household energy system usage, emphasizing the integration of solar thermal ESS, and gauged its influence through comparative scenarios analyzing operational costs both with and without their inclusion in the residential energy system. However, the research did not consider collaborative energy interactions between smart homes, which could potentially improve the efficiency of the DERs. In [24], a novel optimization strategy is introduced, featuring a dual objective: decreasing energy losses during normal operation and system load shedding in disrupted conditions after the occurrence of natural disasters.

This is accomplished by strategically positioning DG and ESS within a smart microgrid. While the authors aim to highlight the resilience-boosting impact of DERs on the smart microgrid during natural disasters, they overlook the potential of data and energy interactions among consumers to further improve resilience indexes in disrupted mode. In Paper [25], a new approach to resilience in the energy IoT is presented, featuring a new multi-dimensional method. The study explores the layered vulnerabilities of smart microgrids within the energy IoT framework, examining the interplay between the " physical, perception, communication, and application layers." It formulates a new model that consider the various stages of smart microgrid operation and introduces a multi resilience strategy that accounts for different operational phases. However, the research does not address how different DERs on the demand side contribute to improve the resilience.

After reviewing the related literature, a comparison of recent literature with the proposed model can be summarized in Table 1. As shown in this table case-by-case research on MGs shows several key deficiencies, including inadequate engagement of demand-side participation and load response programs, poor planning for smart home equipment usage, and neglecting the impact of ESS, AC and BHS on HEM. Additionally, there is often insufficient consideration of HEM systems in MG planning, limited participation of smart home devices and DERs in resiliency efforts, and suboptimal use of MG energy interactions for resilience enhancement. Lastly, improvements in technical functions during disruptions to increase the resilience of a smart microgrid based on energy interactions between smart homes are frequently ignored.

1.3. Contributions

This paper aims to introduce a comprehensive model for optimizing electrical energy management in a smart MG, drawing insights from existing research. The main focus is on facilitating bidirectional communication and energy interactions among smart homes to enhance the MG's resilience. The key contributions of this study are as follows:

1) Maximizing the use of different home energy resources: Device implementation, including PV, PHEV, ESS, and smart appliances enables optimized energy usage which improves MG resilience through effective energy control.

2) Fostering active participation in demand-side management: Encouraging smart home users to actively manage their energy consumption through HEM systems; The demand response requires users to engage with incentives along with the MGO for enhancing grid resilience.

3) Efficiently scheduling smart home appliances while prioritizing user comfort: The control system operates appliances efficiently to reduce energy usage while maintaining comfort standards for smart home residents. The implementation requires finding models that strike an optimal balance between energy efficiency and user satisfaction to deliver an acceptable quality of living.

4) Assessing energy transactions both purchases and sales within a HEM framework: Evaluating the energy bought from and sold back to the microgrid by smart homes and energy interaction between them using HEM systems impacts on MG resilience.

5) Strengthening overall MG resilience by presenting an innovative mathematical model to optimize electrical energy planning, emphasizing the importance of energy interactions between smart homes to improve resilience during disruptions: The proposed model with new mathematical modes allows smart homes to collaborate with each other for energy-sharing purposes that improves microgrid disturbance responses and recovery mechanism to enhance system resilience.

1.4. Manuscript structure

This research is structured in the following manner. Section 2 outlines the core principles of the suggested model along with its mathematical formulation. Following that, Section 3 then presents numerical findings along with validations and analyses of performance. Finally, Section 4 contains the concluding observations.

2. Proposed Strategy

2.1. Core principles of the proposed model

The essential integrated framework is depicted in Fig. 1. HEM systems can concurrently link to smart home electrical devices and the MG operator (MGO) via the home area network (HAN) and local area network (LAN), respectively. These HEM systems collect data such as consumption details through both networks simultaneously [26, 27]. Information obtained from electric loads, including smart appliances, non-RLs, ESS, PHEV, BHS, AC units, and PV systems is leveraged to optimize the management of RLs and DERs in energy oversight. Subsequently, the HEM systems within each smart residence transmit this data to the MGO through smart meters installed in every smart home.

Power system resilience refers to the ability of the system to withstand disasters and recover quickly to normal conditions [28, 29]. Measures to improve resilience are divided into three phases: pre-disaster (preventive proactive actions), during the disaster (corrective active actions), and post-disaster (restorative reactive actions). [30]. To achieve equilibrium in energy usage and boost resilience during disruptions within a MG, the MGO should explore optimal strategies for energy exchange among smart homes [31]. In standard operational mode, individual smart homes manage all HEM systems. Conversely, during a disruption, the MGO takes control of all HEM systems to enhance the overall functionality of the MG and improve system resilience against disturbances. As illustrated in the resilience curve in Fig. 1, the MG's efficiency during the disturbed mode declines from P1 to P3. Subsequently, after entering the recovery mode, the system reverts to its original performance level (P1). By facilitating bidirectional energy interactions among smart homes within the HEM system, we can enhance the resilience of the MG, elevate the efficiency during disturbed conditions to point P2, and reduce the ENS for the MG in this mode.

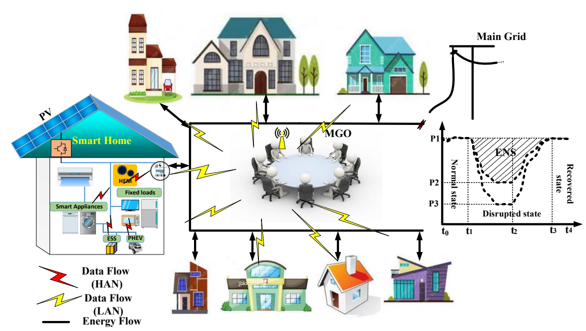


Fig. 1. Fundamental integrated strategy.

Based on the illustrated figure, this study primarily aims to develop an effective mathematical framework for the optimal management of electrical energy within a MG. The model will consider energy exchanges and data transactions between smart homes, with the overarching objective of enhancing the MG's resilience.

2.2. Mathematical representation of the proposed model

The aim is to enhance the resilience of the smart MG by strategically planning energy interactions among smart homes. These interactions will demonstrate its positive impact on resilience. The modeling assumes that if the MG faces a disruption lasting half an hour due to any HILP event, how well it can still

Table 1. Comparison of recent literature with the proposed model.

	[13] (2024)	[14] (2024)	[15] (2024)	[22] (2024)	[24] (2025)	[25] (2025)	Proposed model
PV	*	*	-	*	*	*	*
ESS	-	*	*	*	*	-	*
PHEV	*	-	*	-	-	-	*
AC	-	-	-	-	-	-	*
BHS	-	-	-	-	-	-	*
RL	*	*	*	*	*	*	*
Non-RL	-	-	*	*	*	*	*
HEM System	-	-	*	-	-	-	*
Resiliency	-	-	-	*	*	*	*
Energy Interaction	-	-	-	-	-	-	*

supply power to smart homes should be assessed. This assessment focuses on the energy-sharing infrastructure among smart devices. Ultimately, the key question is whether smart homes can lower the expected ENS of the MG by sharing energy with one another.

In this equation, the system's ENS is modeled in a disrupted state. This occurs when the MG is disconnected from the main grid, preventing energy interaction between smart homes. In this modeling, each home's DERs provide energy solely to that specific smart home.

$$\begin{array}{l} MG\_ENS^{EI=NO} = \\ \left|\sum_{t}^{N_T}\left[\sum_{h}^{N_H}\left[HE^{DER}_{h,t}-HTE_{h,t}\right]\right]\right| \\ s.t \quad \left\{\left[HE^{DER}_{h,t}-HTE_{h,t}\right]>0 \quad \Downarrow \right. \\ MG\_ENS^{EI=NO}=0 \quad \forall h,t \end{array} \tag{1}$$

In this equation, $MG\_ENS^{EI=NO}$ indicates the ENS for a smart MG over a day without energy interaction between smart homes. N_T denotes the length of the planning period, while N_H refers to the number of smart homes. Each smart home generates its own energy during disruptions, specifically when the MG is disconnected for half an hour, with no energy interaction between smart homes. If the total energy produced by DERs in these smart homes exceeds their total energy consumption, then all equipment needs are met, resulting in zero ENS for that period. This state must be included in the model. $HE^{DER}_{h,t}$ represents the total energy from ESS, PHEV, and PV systems available during disruptions. Lastly, $HTE_{h,t}$ signifies the total energy consumption of each smart home's equipment for every time interval, as detailed in the equations below.

$$\begin{array}{l} HE^{DER}_{h,t}=\left(\eta_h^{ESS_{disch}}\times HE^{ESS_{disch}}_{h,t}\times I^{ESS_{disch}}_{h,t}\right)+ \\ (\eta_h^{PHEV_{disch}}\times HE^{PHEV_{disch}}_{h,t}\times I^{PHEV_{disch}}_{h,t})+ \\ \left(\eta_h^{PV,DC-AC}\times HE^{PV,expected}_{h,t}\right) \qquad \forall h,t \end{array} \tag{2}$$

$$\begin{array}{l} HTE_{h,t}=HE^{NRL}_{h,t}+\sum\limits_{j\in J}\left(HE^{RL}_{h,j}\times I^{RL}_{h,j,t}\right)+ \\ (HE^{BS}_{h}\times I^{BS}_{h,t})+(HE^{AC}_{h}\times I^{AC}_{h,t}) \qquad \forall h,t \end{array} \tag{3}$$

In this context, $\eta_h^{ESS_{disch}}$ denotes the conversion factor from DC to AC for the ESS. $HE^{ESS_{disch}}_{h,t}$ represents the total energy discharged by the ESS during the time period t for each smart home, while $I^{ESS_{disch}}_{h,t}$ is a binary variable indicating the discharge status of the ESS from the h-th home in the t-th interval. $\eta_h^{PHEV_{disch}}$ indicates the DC to AC conversion factor for PHEV in the h-th home, and $HE^{PHEV_{disch}}_{h,t}$ signifies the total energy discharged by the PHEV during time interval t for each smart home. $I^{PHEV_{disch}}_{h,t}$ is a binary variable reflecting the discharge mode of the PHEV from the h-th home in the t-th interval. $\eta_h^{PV,DC-AC}$ identifies the DC to AC conversion factor for PV systems in every smart home, while $HE^{PV,expected}_{h,t}$ estimates the expected energy output from PVs for time interval t. $HE^{RL}_{h,j}$ and $HE^{NRL}_{h,t}$ correspond to the energy demand of the j-th RL and the overall energy consumption of non-RL household loads during interval t, respectively. $I_{h,j,t}$ is a binary variable for the j-th load in interval t; if it equals 1, it indicates that the j-th load is consuming energy during that period. HE^{BS}_{h} reflects the energy consumed by BHS, and $I^{BS}_{h,t}$ is a binary variable for interval t. Additionally, HE^{AC}_{h} quantifies the energy used by the AC system, with $I^{AC}_{h,t}$ serving as a binary variable related to it; if this variable equals 1, it indicates that the AC system is actively regulating indoor temperature.

The quantity of energy supplied by DERs in smart homes is contingent upon their state of energy (SOE). Consequently, the volume of energy that can be released from ESS and PHEV during each time period can be determined by evaluating the SOE using the equations outlined below.

$$\left\{\begin{array}{l} SOE^{ESS}_{h,t}<HE^{ESS^{\min}_{disch}}_{h,t} \quad \Downarrow \\ HE^{ESS}_{h,t}=0 \qquad \forall h,t \\ SOE^{ESS}_{h,t}\geq HE^{ESS^{\max}_{disch}}_{h,t} \quad \Downarrow \\ HE^{ESS}_{h,t}=HE^{ESS^{\max}_{disch}}_{h,t} \ \forall h,t \\ HE^{ESS^{\min}_{disch}}_{h,t}\leq SOE^{ESS}_{h,t}<HE^{ESS^{\max}_{disch}}_{h,t} \quad \Downarrow \\ HE^{ESS}_{h,t}=SOE^{ESS}_{h,t} \quad \forall h,t \end{array}\right. \tag{4}$$

$$\left\{\begin{array}{l} SOE^{PHEV}_{h,t}<HE^{PHEV^{\min}_{disch}}_{h,t} \quad \Downarrow \\ HE^{PHEV}_{h,t}=0 \qquad \forall h,t \\ SOE^{PHEV}_{h,t}\geq HE^{PHEV^{\max}_{disch}}_{h,t} \quad \Downarrow \\ HE^{PHEV}_{h,t}=HE^{PHEV^{\max}_{disch}}_{h,t} \ \forall h,t \\ HE^{PHEV^{\min}_{disch}}_{h,t}\leq SOE^{PHEV}_{h,t}<HE^{PHEV^{\max}_{disch}}_{h,t} \quad \Downarrow \\ HE^{PHEV}_{h,t}=SOE^{PHEV}_{h,t} \quad \forall h,t \end{array}\right. \tag{5}$$

In this context, $SOE^{ESS}_{h,t}$ and $SOE^{PHEV}_{h,t}$ represent the SOC of ESS and PHEV at the conclusion of the time period t for each smart home h. Meanwhile, $HE^{ESS^{\min}_{disch}}_{h,t}$, $HE^{ESS^{\max}_{disch}}_{h,t}$, $HE^{PHEV^{\min}_{disch}}_{h,t}$, and $HE^{PHEV^{\max}_{disch}}_{h,t}$ indicate the minimum and maximum discharge rates for the ESS and PHEV during each time interval.

During disruption mode, and without taking energy interactions into account, the DERs available in each smart home solely deliver the energy necessary for that specific residence. As a result, the proportion of home energy supply (HES) for each household in each time interval can be determined using a designated equation.

$$HES_{h,t}^{EI=NO} = \frac{HE_{h,t}^{DER}}{HTE_{h,t}} \qquad \forall h,t$$
$$s.t \begin{cases} HES_{h,t}^{EI=NO} < 1 \Rightarrow \%HES_{h,t}^{EI=NO} = HES_{h,t}^{EI=NO} \times 100 \quad \forall h,t \\ HES_{h,t}^{EI=NO} \geq 1 \Rightarrow \%HES_{h,t}^{EI=NO} = 100 \quad \forall h,t \end{cases} \tag{6}$$

Based on the criteria established in this equation, during the intervals when the overall energy output from the DERs in smart homes exceeds the total energy demand of household appliances, the value of $HES_{h,t}^{EI=NO}$ will exceed 1 for that interval. Because the goal of calculating the home energy percentage is to assess this situation, $HES_{h,t}^{EI=NO}$ is assigned a value of 100% during these intervals, indicating that the entire energy requirement of the home is met by the DERs.

The improvement of MG resilience has been simulated by factoring in energy interaction between the smart homes. The assessment of ENS for these homes, specifically when energy is bought and sold among them, is outlined in the following equation. This method provides a deeper insight into how energy trading influences the overall availability and reliability of energy within the MG system.

$$MG\_ENS^{EI=YES} = \left| \sum_{t=1}^{N_T} \left[\sum_{h=1}^{N_h} \left[HE_{h,t}^{DER} - ((1 - MGES_t) \times HTE_{h,t}) \right] \right] \right|$$
$$s.t \begin{cases} \left[\sum_{h=1}^{N_h} \left[HE_{h,t}^{DER} - ((1 - MGES_t) \times HTE_{h,t}) \right] \right] > 0 \ \Downarrow \\ MG\_ENS^{EI=YES} = 0 \quad \forall t \end{cases} \tag{7}$$

In this equation, $MG\_ENS^{EI=YES}$ indicates the percentage of energy supplied to homes by all smart homes after they have shared their DERs, resulting in a consistent value for each home. It is essential to recognize that, in this method, some homes may experience a decrease in ENS, while others may see an increase. Viewed from the MG's perspective, all HEM systems are available during disruptions, especially when the MG is disconnected from the main grid. This availability helps to reduce the ENS for the MG and bolsters its resilience. The following equation outlines the percentage of MG energy supply (MGES).

$$MGES_t = \frac{\sum_{h=1}^{N_H} HE_{h,t}^{DER}}{\sum_{t=1}^{N_T} HTE_{h,t}} \qquad \forall t$$
$$s.t \begin{cases} MGES_t < 1 \Rightarrow \%MGES_t = MGES_t \times 100 \quad \forall h,t \\ MGES_t \geq 1 \Rightarrow \%MGES_t = 100 \quad \forall h,t \end{cases} \tag{8}$$

As stipulated in this model, the parameter $MGES_t$ will exceed 1 when the cumulative energy output of DERs in smart residences surpasses the overall energy demand of household appliances. This determination is crucial for assessing the home's energy contribution. Therefore, in such intervals, a value of 100% is assigned to indicate that all household energy is sourced from DERs. Consequently, considering all relevant equations, the main objective function of this research, which focuses on enhancing resilience, can be articulated as follows:

$$OF = Maximize\,(MG\_RI) = \frac{\left(MG\_ENS^{EI=NO} - MG\_ENS^{EI=YES}\right)}{MG\_ENS^{EI=NO}} \times 100 \tag{9}$$

In this analysis, MG_RI illustrates the enhancement in resilience by contrasting the advancements in ENS when energy interactions among smart homes are either included or excluded. This section of the paper outlines the essential constraints for modeling the examined issue on a case-by-case basis. The energy acquired by each smart home during the time interval t is comprised of two components: $HE_{h,t}^{buy,MG}$, representing the energy procured from the main grid, and $HE_{h,t}^{buy,neighbor}$, which denotes the energy sourced from neighboring smart homes within the MG.

Consequently, the comprehensive energy bought by each smart home, along with the energy sold by each one, is represented by the following equations, respectively.

$$HE_{h,t}^{buy} \times I_{h,t}^{buy} = HE_{h,t}^{buy,MG} + HE_{h,t}^{buy,neighbor} \qquad \forall h,t \tag{10}$$

$$HE_{h,t}^{sell} \times I_{h,t}^{sell} = HE_{h,t}^{sell,neighbor} \ \forall h,t \tag{11}$$

In this context, $I_{h,t}^{buy}$ and $I_{h,t}^{sell}$ are binary variables associated with the energy transactions of smart home h at time t, where a value of 1 indicates that the smart home is engaged in buying or selling energy. Additionally, $HE_{h,t}^{sell,neighbor}$ represents the quantity of energy sold by each smart home to other homes within the MG.

It is important to note that while there is a framework for modeling energy purchases and sales, the total discharge energy from ESS and PHEV, as well as the total energy generated by PV systems, is not fully delivered to the homes; rather, a portion of this energy is allocated for sale within the MG. The mathematical representation of the total energy sold by each smart home, which is distributed among other homes in the MG, is formulated in the following equation. In this equation, the total electrical energy sold by ESS, PHEV, and PV for each smart home is denoted as $HE_{h,t}^{ESS_{disch}^{MG}}$, $HE_{h,t}^{PHEV_{disch}^{MG}}$, and $HE_{h,t}^{PV_{disch}^{MG}}$ for each respective interval.

$$HE_{h,t}^{sell} \times I_{h,t}^{sell} = HE_{h,t}^{ESS_{disch}^{MG}} + HE_{h,t}^{PHEV_{disch}^{MG}} + HE_{h,t}^{PV_{disch}^{MG}} \ \forall h,t \tag{12}$$

Smart homes cannot engage in both energy buys and sales simultaneously within the same time interval; Therefore, it is essential to include the following equation in the modeling process.

$$I_{h,t}^{buy} + I_{h,t}^{sell} \leq 1 \qquad \forall h,t \tag{13}$$

In this research, the MG is designed such that it cannot sell energy to the main grid; all energy exchanges occur solely among smart homes within the MG. Consequently, the total energy acquired by smart homes within the MG must equal the total energy sold by other smart homes within the same system. This condition is essential and must be satisfied for every time interval considered in the analysis.

$$\sum_{h} HE_{h,t}^{sell,neighbor} = \sum_{h} HE_{h,t}^{buy,neighbor} \ \forall t \tag{14}$$

Each smart home acquires energy to meet the demands of its electrical appliances and DERs. Therefore, to achieve equilibrium in the energy consumption of every smart home, a mathematical framework must be developed to quantify the total energy acquired for each designated time period.

$$HE_{h,t}^{buy} \times I_{h,t}^{buy} = HE_{h,t}^{NRL} + \sum_{j \in J} \left(HE_{h,j}^{RL} \times I_{h,j,t}^{RL} \right) + \left(HE_{h}^{BS} \times I_{h,t}^{BS} \right) + \left(HE_{h}^{AC} \times I_{h,t}^{AC} \right) + \left(\frac{1}{\eta_h^{ESS_{ch}}} \times \left(HE_{h,t}^{ESS_{ch}} \times I_{h,t}^{ESS_{ch}} \right) \right) + \left(\frac{1}{\eta_h^{PHEV_{ch}}} \times \left(HE_{h,t}^{PHEV_{ch}} \times I_{h,t}^{PHEV_{ch}} \right) \right) - \left(HE_{h,t}^{ESS_{disch}^{\text{home}}} \right) - \left(HE_{h,t}^{PHEV_{disch}^{\text{home}}} \right) - \left(HE_{h,t}^{PV_{disch}^{\text{home}}} \right) \quad \forall h,t \tag{15}$$

In this context, the variables representing the quantities of energy injected by ESS, PHEV, and PV systems to each smart home during the specified time interval t are denoted as $HE_{h,t}^{ESS_{disch}^{\text{home}}}$, $HE_{h,t}^{PHEV_{disch}^{\text{home}}}$, and $HE_{h,t}^{PV_{disch}^{\text{home}}}$, respectively. Subsequently, the mathematical models for these energy sources will be detailed through their respective equations. The state vector associated with load j and the energy consumption of the BHS is presented in the equation that follows.

$$I_{h,t}^{BS} = \left[I_{h,1}^{BS},\ I_{h,2}^{BS},\ \cdots\ I_{h,N_T}^{BS} \right] \quad \forall h \tag{16}$$

$$I_{h,t}^{BS} = \left[I_{h,1}^{BS},\ I_{h,2}^{BS},\ \cdots\ I_{h,N_T}^{BS} \right] \quad \forall h \tag{17}$$

Smart home owners should recommend the timing for utilizing RLs and the periods for employing the BHS, taking into account consumer comfort and the energy usage trends of their residences. These elements should be structured in the following manner.

$$\sum_{t=s_j}^{f_j} I_{h,j,t}^{RL} = U_j^{RL} \qquad \forall h,j \tag{18}$$

$$\begin{aligned} &\sum_{t=ts}^{t=tf} I_{h,t}^{BS} = U_{h,t}^{BS} \qquad \forall h \\ &s.t \begin{cases} t < t_s & I_{h,t}^{BS} = 0\ \forall h \\ t > t_f & I_{h,t}^{BS} = 0\ \forall h \end{cases} \end{aligned} \tag{19}$$

In this context, s_j and f_j delineate the initiation and end periods for employing the j-th controllable RL within the h-th smart home. It is important to highlight that these timeframes are proposed by proactive homeowners to optimize energy management. U_j^{RL} represents the duration necessary for the j-th respondent to utilize the specified load. Based on the aforementioned framework, any binary variable associated with each household's controllable load that falls outside the designated interval is assigned a value of zero. Furthermore, t_s and t_f indicate the commencement and cessation periods for utilizing the BHS, as recommended by the homeowners of each smart residence. $U_{h,t}^{BS}$ encompasses the intervals advised by these homeowners for BHS usage. Consequently, total energy consumption for the BHS should be confined to this specified timeframe; any consumption occurring outside this recommended period is deemed negligible. To effectively model uninterrupted operation whenever a home responder activates a load, it is essential that the designated interval remains continuous.

$$y_{h,j,t}^{RL} - z_{h,j,t}^{RL} = I_{h,j,t}^{RL} - I_{h,j,t-1}^{RL} \qquad \forall h,j,t \tag{20}$$

$$\sum_{t=1}^{N_T} y_{h,j,t}^{RL} = 1 \qquad \forall h,j \tag{21}$$

$$y_{h,j,t}^{RL} + z_{h,j,t}^{RL} \le 1 \quad \forall h,j,t \tag{22}$$

In these formulations, $y_{h,j,t}^{RL}$ and $z_{h,j,t}^{RL}$ denote the binary indicators for the activation and deactivation of the RLs. $y_{h,j,t}^{RL} = 1$ signifies the initiation of RL j at time t, while $z_{h,j,t}^{RL} = 1$ indicates its cessation during the time interval t.

Within the context of modeling energy consumption in a smart home, the duration for which the AC system operates to regulate indoor temperature is treated as a manageable electrical load. In this section, the binary variable associated with the AC system is structured as follows:

$$I_{h,t}^{AC} = \begin{cases} 1 & \theta_{h,t}^{home} > \ \theta_{h,t,set}^{AC} \\ 0 & \theta_{h,t}^{home} \le \ \theta_{h,t,set}^{AC} - \theta^{margin} \qquad \forall h,t \\ I_{h,t-1}^{AC} & otherwise \end{cases} \tag{23}$$

$$\theta_{h,t}^{home} = \theta_{h,t-1}^{home} + \left[k_\theta^{room} \times (\theta_{h,t-1}^{amb} - \theta_{h,t-1}^{home}) \right] + \left[k_{human} \times n_{t-1}^{human} \times (\theta_{human} - \theta_{h,t-1}^{home}) \right] + \left[k_{AC}^{eff} \times \theta_{AC}^{g} \times I_{h,t-1}^{\theta} \right] \qquad \forall h,t \tag{24}$$

In this context, $\theta_{h,t}^{home}$ represents the temperature of the h-th residence during the t-th time segment. $\theta_{h,t,set}^{AC}$ denotes the desired temperature setting for that same interval, while θ^{margin} refers to the constant that dictates temperature reduction. k_θ^{room} signifies the thermodynamic property of the room, and $\theta_{h,t-1}^{amb}$ reflects the external ambient air temperature from the previous interval (t-1). k_{human} describes the heat exchange coefficient between individuals and their surroundings, whereas n_{t-1}^{human} counts the number of occupants in the room during the prior time segment (t-1). θ_{human} indicates the body temperature of a person, and k_{AC}^{eff} represents the cooling system's temperature effect coefficient. θ_{AC}^{g} is associated with the operational temperature margin and the temperature reduction constant. Lastly, $I_{h,t-1}^{\theta}$ serves as a binary variable indicating whether the cooling system was active during the previous interval (t-1).

In the framework of energy usage modeling for smart homes, $HE_{h,t}^{ESS_{ch}}$ and $HE_{h,t}^{PHEV_{ch}}$ denote the energy needed to recharge the ESS and PHEV during the time period t for each household. Meanwhile, $\eta_h^{ESS_{ch}}$ and $\eta_h^{PHEV_{ch}}$ represent the conversion coefficients from AC to DC for the ESS and PHEV, respectively. Additionally, $I_{h,t}^{ESS_{ch}}$ and $I_{h,t}^{PHEV_{ch}}$ indicate the binary indicators for the charging states of ESS and PHEV during the specified time interval t, where a value of 1 signifies that the ESS and PHEV are in charging mode.

ESS store energy during off-peak times and release it during high-demand periods, helping to lower energy costs and smooth out consumption patterns. In economic contexts, the variation of prices across markets plays a crucial role in boosting profitability and efficiency. Consequently, charging ESS when energy prices are low and discharging them during high-price periods can significantly reduce expenses for smart homes [32]. When these systems are managed effectively, they not only meet household energy needs but can also enable the sale of surplus energy back to the MG. Additionally, PHEVs enhance home energy management by working with HEM systems to optimize their charging and discharging schedules. However, if PHEVs are not used thoughtfully, they may contribute to peak demand spikes that disrupt the overall load balance, potentially causing technical challenges for the grid [33]. Thus, the energy stored in PHEVs can be utilized for home energy management while the vehicles are stationary. The following equations outline the constraints on the discharge capacity of both ESS and PHEV systems.

$$HE_{h,t}^{ESS_{disch}^{\text{home}}} + HE_{h,t}^{ESS_{disch}^{MG}} = \left(\eta_h^{ESS_{disch}} \times HE_{h,t}^{ESS_{disch}} \times I_{h,t}^{ESS_{disch}}\right) \quad \forall h,t \tag{25}$$

$$HE_{h,t}^{PHEV_{disch}^{\text{home}}} + HE_{h,t}^{PHEV_{disch}^{MG}} = \left(\eta_h^{PHEV_{disch}} \times HE_{h,t}^{PHEV_{disch}} \times I_{h,t}^{PHEV_{disch}}\right) \quad \forall h,t \tag{26}$$

In this context, $HE_{h,t}^{ESS_{disch}^{MG}}$ and $HE_{h,t}^{PHEV_{disch}^{MG}}$ represent the quantities of energy released by the ESS and the PHEV, respectively. It is important to note that the ESS and the PHEV cannot undergo charging and discharging simultaneously within the same timeframe. Consequently, the subsequent modeling approaches will take this limitation into account.

$$I_{h,t}^{ESS_{ch}} \times I_{h,t}^{ESS_{disch}} \leq 1 \quad \forall h,t \tag{27}$$

$$I_{h,t}^{PHEV_{ch}} \times I_{h,t}^{PHEV_{disch}} \leq 1 \quad \forall h,t \tag{28}$$

The SOE for the ESS and PHEV within each smart home is represented by the following formulas, which reflect their respective charging and discharging rates.

$$SOE_{h,t}^{ESS} = HE_h^{ESS,initial} + \sum_{m}^{t} \left[\left(HE_{h,m}^{ESS_{ch}} \times I_{h,m}^{ESS_{ch}}\right) - \left(HE_{h,m}^{ESS_{disch}} \times I_{h,m}^{ESS_{disch}}\right)\right] \quad \forall h,t \tag{29}$$

$$SOE_{h,t}^{PHEV} = HE_h^{PHEV,initial} + \sum_{m=1}^{t} \left[\left(HE_{h,m}^{PHEV_{ch}} \times I_{h,m}^{PHEV_{ch}}\right) - \left(HE_{h,m}^{PHEV_{disch}} \times I_{h,m}^{PHEV_{disch}}\right)\right] \quad \forall h,t \tag{30}$$

In this context, m represents the time interval index, while $HE_h^{ESS,initial}$ and $E_h^{PHEV,initial}$ denote the initial values of the SOE for the ESS and PHEV at the outset of the planning phase for smart home h. The discharge rates and capacity constraints for both the ESS and PHEV are articulated through the subsequent equations.

$$\begin{cases} \left(HE_{h,m}^{ESS_{disch}} \times I_{h,m}^{ESS_{disch}}\right) \leq SOE_{h,t-1}^{ESS} \quad \forall h, t \geq 2 \\ \left(HE_{h,m}^{ESS_{disch}} \times I_{h,m}^{ESS_{disch}}\right) \leq E_h^{ESS,initial} \quad \forall h, t = 1 \end{cases} \tag{31}$$

$$SOE_{h,t}^{ESS} \leq HE_h^{max,ESS} \quad \forall h,t \tag{32}$$

$$\begin{cases} \left(HE_{h,m}^{PHEV_{disch}} \times I_{h,m}^{PHEV_{disch}}\right) \leq SOE_{h,t-1}^{PHEV} \\ \forall h, 2 \leq t \leq t_o \\ \left(HE_{h,m}^{PHEV_{disch}} \times I_{h,m}^{PHEV_{disch}}\right) \leq HE_h^{PHEV,initial} \\ \forall h, t = 1 \end{cases} \tag{33}$$

$$\left(HE_{h,m}^{PHEV_{disch}} \times I_{h,m}^{PHEV_{disch}}\right) \leq \left[SOE_{h,t-1}^{PHEV} - HE_{O-H,h}^{PHEV}\right] \quad \forall h, t \geq t_R \tag{34}$$

In this modeling, spanning from t_0 to t_R, the PHEV is positioned away from the residence and is unable to either charge or discharge during this period. These timeframes are designated by PHEV owners for effective energy management. $HE_{O-H,h}^{PHEV}$ shows the energy consumption of the PHEV while it is outside the home, which varies across different smart homes. The SOE of the PHEV battery prior to and following its departure from the residence is represented as follows.

$$SOE_{h,t}^{PHEV} \leq HE_h^{max,PHEV} \quad \forall h, t \leq t_0 \tag{35}$$

$$\left[SOE_{h,t}^{PHEV} - HE_{O-H,h}^{PHEV}\right] \leq HE_h^{max,PHEV} \quad \forall h, t \geq t_R \tag{36}$$

Where, $HE_h^{max,PHEV}$ denotes the peak capacity accessible for the PHEV at smart home h. It is crucial that the PHEV battery possesses adequate energy to enable its departure from the home. Taking into account the energy usage patterns specified by smart home owners while the PHEV is away, the SOE of the PHEV battery just before it leaves the residence can be represented as follows.

$$HE_{O-H,h}^{PHEV} \leq SOE_{h,t_0-1}^{PHEV} \quad \forall h \tag{37}$$

The energy transfer cycle for each ESS and PHEV need to occur within specified timeframes. Consequently, the minimum and maximum rates for both charging and discharging of ESS and PHEV are represented in the equations below.

$$\begin{cases} HE_{h,t}^{ESS_{ch}^{\min}} \leq HE_{h,t}^{ESS_{ch}} \leq HE_{h,t}^{ESS_{ch}^{\max}} \\ \forall h,t \\ HE_{h,t}^{ESS_{disch}^{\min}} \leq HE_{h,t}^{ESS_{disch}} \leq HE_{h,t}^{ESS_{disch}^{\max}} \\ \forall h,t \end{cases} \tag{38}$$

$$\begin{cases} HE_{h,t}^{PHEV_{ch}^{\min}} \leq HE_{h,t}^{PHEV_{ch}} \leq HE_{h,t}^{PHEV_{ch}^{\max}} \\ \forall h,t \\ HE_{h,t}^{PHEV_{disch}^{\min}} \leq HE_{h,t}^{PHEV_{ch}} \leq HE_{h,t}^{PHEV_{disch}^{\max}} \\ \forall h,t \end{cases} \tag{39}$$

In the architecture of advanced residential environments, the inclusion of PV systems is an essential factor. The electricity generated by these systems is harnessed to enhance energy management within smart homes. The solar energy available at the PV installation site during various time periods is represented using a beta probability distribution function, informed by solar radiation data specific to that location. The mathematical framework of PV systems is detailed in previous studies [34, 35]. Subsequently, the expected energy from the PV system is examined, with the cumulative energy produced in each time segment for each smart home being modeled in a specified manner.

$$HE_{h,t}^{PV_{disch}^{\text{home}}} + HE_{h,t}^{PV_{disch}^{MG}} = \left(\eta_h^{PV,DC-AC} \times HE_{h,t}^{PV,expected}\right) \quad \forall h,t \tag{40}$$

The formula indicates that the projected energy generated by the solar PV system ($HE_{h,t}^{PV,expected}$) is either consumed within the smart home ($HE_{h,t}^{PV_{disch}^{\text{home}}}$) or transferred to the MG ($HE_{h,t}^{PV_{disch}^{MG}}$), where it can be shared among other residences. Furthermore, η^{PV} signifies the efficiency metric of the PV system.

The equations involved include those for modeling adjustable household energy demands, BHS, and AC units aimed at regulating indoor temperatures, as well as equations related to the charging and discharging processes of ESS, PHEVs, and PV. An essential consideration in this modeling is the limitation on energy flow from the MG to smart homes and vice versa. The following equation specifies the minimum and maximum volumes of energy that can be exchanged between smart homes and the MG.

$$\begin{cases} 0 \leq HE_{h,t}^{buy} \times I_{h,t}^{buy} \leq HE_{h,t}^{maxBuy} \\ \forall h,t \\ 0 \leq HE_{h,t}^{sell} \times I_{h,t}^{sell} \leq HE_{h,t}^{maxSell} \\ \forall h,t \end{cases} \tag{41}$$

Here, $HE_{h,t}^{maxBuy}$ and $HE_{h,t}^{maxSell}$ represent the peak quantities of energy that can be transacted within the time frame t for each smart home, which must be factored into the modeling based on the MG's stipulations. Additionally, various elements that need to be addressed in the modeling are examined, particularly the constraints on energy transfer from the main grid to the smart MG. The subsequent equation delineates the thresholds for the minimum and maximum energy that can be exchanged between the smart MG and its upstream counterpart.

$$0 \leq \sum_{h=1}^{N_h} HE_{h,t}^{buy} \leq TE_t^{\max Buy,MG} \times I_t^{\max Buy,MG} \\ \forall t \tag{42}$$

Here, $TE_t^{\max Buy,MG}$ denotes the peak quantity of smart MG energy that can be acquired from the main grid during the specified time frame t. $I_t^{\max Buy,MG}$ serves as the binary variable associated with the procurement of smart MG energy from the main grid; a value of 1 signifies that energy is indeed being purchased from this source. It is crucial to recognize in this model that the energy transmitted from the main grid to the target MG must adhere to a cap on energy injection. The lack of such a restriction on energy consumption can lead to numerous technical challenges, such as the emergence of peak loads or even fluctuations in load density at various times throughout the day.

3. Simulation Studies: Numerical Results and Performance Validations

3.1. Input data

The methodology presented in this paper features a sophisticated MG comprising 500 smart homes, categorized into four unique types. Each type varies in the quantity of responsive and non-responsive electrical loads, as well as DERs. Specifically, 20% of the homes are classified as type 1, 10% as type 2, 40% as type 3, and 30% as type 4. Table 2 details the RLs available in each category, considering the comfort of the inhabitants and their recommended timeframes. This strategy entails a comprehensive examination of the smart residential MG throughout a 24-hour period, divided into 96 intervals of 15 minutes each.

The table illustrates that a washing machine is among the identified RLs. This appliance requires approximately six cycles, totaling around ninety minutes each day. Its energy usage is estimated at 1.5 kWh per day, translating to roughly 0.25 kWh per cycle. Washing machines are commonly found in various smart home setups, while other responsive devices, like slow cookers, may only be present in select smart homes.

In this work a table is presented illustrating the timeframes proposed by homeowners, focusing on the comfort levels of residents within various types of smart homes, each accompanied by its unique recommendations. Utilizing GAMS software, the suggested intervals for each smart home are analyzed to optimize the timing for every RLs effectively. The time intervals proposed by the inhabitants of smart homes for the HEM system are illustrated in the Table 3. It is essential for smart home occupants to notify the HEM system regarding their usage patterns of the BHS beforehand. Consequently, as indicated in this table, each smart home utilizes the BHS with an energy consumption rate of 0.325 kWh per interval throughout every designated period.

The Table 4 illustrates the AC systems and various DERs evaluated for smart homes. As indicated, not every smart home incorporates all available DERs. To ensure diversity among these homes, the table details the inclusion or exclusion of AC systems and other DERs for each category of smart home.

The Fig. 2 illustrates the count of smart home inhabitants throughout various intervals on a summer day in a tropical locale. Based on the modeling developed for the AC system, the quantity of occupants significantly influences the system's efficiency in maintaining the home's temperature.

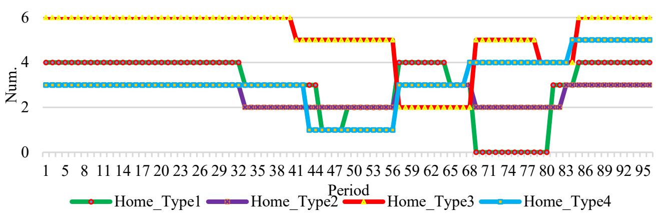


Fig. 2. The number of residents of smart homes.

In the outlined simulation, the energy usage of the AC system is 0.225 kWh per interval for smart home type 1, 0.25 kWh per interval for type 2, and 0.275 kWh per interval for type 3. The variable $\theta_{t,set}^{cooler}$, representing the AC temperature during the time frame t, is set at 25C. The variable θ^{margin}, denoting the fixed temperature decrease, is established at 10C. Additionally, k_{θ}^{room}, reflecting the room's thermodynamic constant, is uniform at 0.1 across all types. Lastly, θ_{t-1}^{amb} pertains to the external air conditions surrounding the smart home, as illustrated in the accompanying figure below.

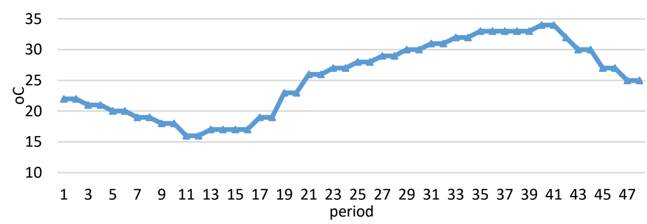


Fig. 3. Ambient air temperature outside the smart home.

In the ongoing exploration of AC system simulation, k_{human} represents the thermal exchange coefficient between individuals and their surroundings, fixed at 0.005. Meanwhile, n_{t-1}^{human} denotes the count of occupants in the room during the previous time period (t-1). θ_{human} reflects the average human body temperature, standardized at 37 degrees Celsius. k_{cooler}^{eff} signifies the cooling system's temperature impact factor, set at -0.9, while θ_{cooler}^{g} represents the temperature decrement constant, valued at 2.

The modeling incorporates ESSs and PHEVs within each smart home, as detailed in the following tables. This analysis assumes uniformity in the type and capacity of ESS units across all smart homes, albeit with varying initial charge levels. Additionally, the minimum charge and discharge rates for both ESSs and PHEVs are estimated at 26% of their maximum capabilities for each time interval.

The PV system allocated for each smart home delivers a uniform capacity of 1000 watts and is constructed from five solar panels, each producing 200 watts. The η^{PV} panels boast an efficiency rating of 18.6%, and the space required for installation in every smart home is 6 square meters. Solar irradiance varies between 22 and 78, influencing the energy yield for all smart homes. The diagram below depicts the power output generated by the PV systems in these smart homes.

In the analysis of the examined issue, the inclusion of fixed loads from smart homes, which do not adjust in response to demand, is taken into account. The figure illustrating the behavior of these fixed loads for each category of smart home is presented in Fig. 5.

Table 2. Pseudo code for shuffled bat optimization algorithm.

List of smart appliances	Energy consumption		Necessary time (h)	Recommended intervals for using smart appliances			
	kWh/day	**kWh/period**		**Type1**	**Type2**	**Type3**	**Type4**
Laundry	1.5kWh/day	0.25kWh/period	1.5	32-96	40-96	50-88	32-96
Dish Washer	1kWh/day	0.25kWh/period	1	76-96	-	80-94	72-88
Clothes dryer	1.4kWh/day	0.35kWh/period	1	-	1-32	-	6-60
Slow cooker	1.2kWh/day	0.2kWh/period	1.5	-	36-50	-	36-76
Microwave	0.8kWh/day	0.2kWh/period	1	64-84	60-96	68-96	-
Robot vacuum cleaner	0.9kWh/day	1.5 0.15kWh/period	1.5	1-96	1-96	1-96	-
Kitchen Hood	0.5kWh/day	0.25kWh/period	0.5	80-96	-	76-96	68-92

Table 3. Suggested periods for smart homes to use the BHS.

Energy consumption	Type1	Type2	Type3	Type4
0.325 kWh/day	72-96 6 period	60-80 6 period	56-96 8 period	40-88 10 period

Table 4. AC system and DERs for smart homes.

	Type1	Type2	Type3	Type4
AC	√	√	√	-
PHEV	√	√	-	
ESS	√	-	√	√
PV	-	√	√	√

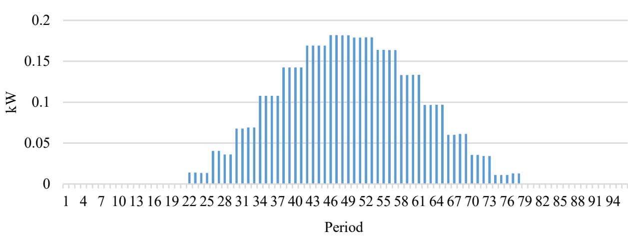


Fig. 4. The generated power of the PV system.

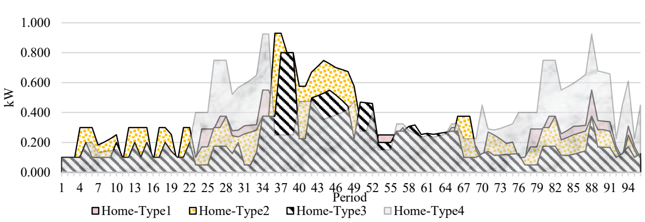


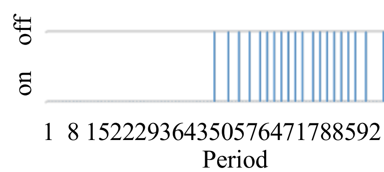
Fig. 5. Fixed loads curve of smart homes.

Table 5. ESS's information.

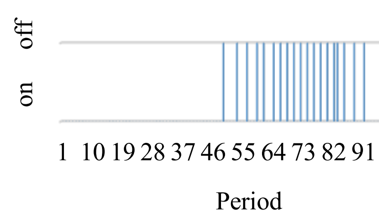
Information	Type1	Type2	Type3	Type4
$HE_h^{ESS,initial}$	0.531 kWh	-	0.7965 kWh	1.062 kWh
$HE_h^{max,ESS}$	4.25 kWh			
$HE_{h,t}^{ESS_{ch}^{max}}$, $HE_{h,t}^{ESS_{disch}^{max}}$	0.2655 kWh/period			
$HE_{h,t}^{ESS_{disch}^{min}}$	0.2655*%26=0.06903 kWh/period			
$\eta_h^{ESS_{disch}}$, $\eta_h^{ESS_{ch}}$	0.96			

Table 6. PHEV's information.

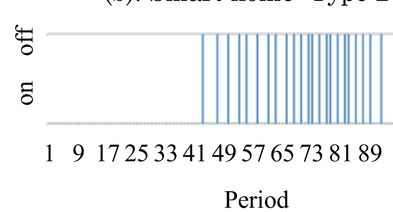
Information	Type1	Type2	Type3	Type4
$HE_h^{PHEV,initial}$	0.85 kWh	0.425 kWh	-	0.425 kWh
Out of home intervals	36-56	28-60	-	32-52
$HE_{O-H,h}^{PHEV}$	4.25 kWh	5.1 kWh	-	5.95 kWh
$HE_h^{max,PHEV}$	6.8 kWh			
$HE_{h,t}^{PHEV_{ch}^{max}}$, $HE_{h,t}^{PHEV_{disch}^{max}}$	0.425 kWh/period			
$HE_{h,t}^{PHEV_{ch}^{min}}$, $HE_{h,t}^{PHEV_{disch}^{min}}$	0.426*%26=0.1105 kWh/period			
$\eta_h^{PHEV_{disch}}$, $\eta_h^{PHEV_{ch}}$	0.96			



(a): Smart home-Type 1



(b): Smart home -Type 2



(c): Smart home -Type 3

Fig. 6. Optimal planning of AC system.

The subsequent analysis explores the outcomes of the modeling, considering the input data.

3.2. Numerical results and performance validation

A key function of the HEM system is to strategically schedule the efficient functioning of DERs and smart appliances. Table 7 illustrates the ideal timing for utilizing RLs across various categories of smart homes.

The effective scheduling of the BHS usage, reflecting the timeframes proposed by smart home proprietors, is outlined in Table 8. These designated periods are structured to guarantee that energy expenses are kept to a minimum for smart homes. This prompts owners to engage the BHS during these advantageous times. Utilizing IoT technology, smart home systems can seamlessly relay these optimal timeframes to homeowners, empowering them to undertake essential measures within the specified intervals to optimize energy efficiency.

Strategizing the most efficient operation of the AC system involves considering factors such as ambient temperature, the household's population, and all elements outlined in the AC system's model, as illustrated in Fig. 6 for various categories of

Table 7. Optimum planning of smart home RLs.

Smart home	Laundry	Dishwasher	Clothes dryer	Slow cooker	Microwave	Robot vacuum cleaner	Kitchen hood
Type1	75-80	77-80	-	-	77-80	91-96	95-96
Type2	75-80	-	24-27	45-50	93-96	24-29	-
Type3	75-80	91-94	-	-	93-96	57-62	90-91
Type4	75-80	76-79	57-60	57-62	-	-	90-91

Table 8. Optimum planning of BHS.

	Type1	Type2	Type3	Type4
BHS planning	80,90,91,92,95,96	61,62,77,78,79,80	62,63,75,76,77,78,79,80	57,58,60,61,74,75,76,77,79,80

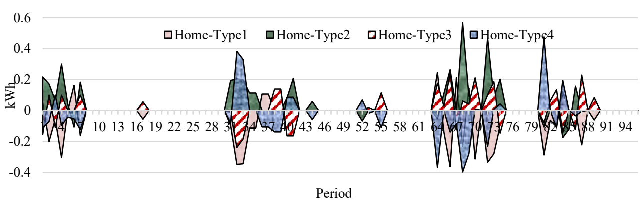


Fig. 7. Energy interactions between smart homes.

smart homes.

Fig. 7 illustrates the level of energy interactions among smart homes within the MG for various time intervals. As depicted, certain periods exhibit no energy transfers between the smart homes, indicating that, during these times, the smart homes lack surplus energy to share with others. Conversely, in other intervals, energy interactions are evident, reflecting the dynamics of energy trading within the MG. Notably, the total energy consumed by the homes matches the total energy supplied, highlighting a balanced system of energy distribution among the smart homes.

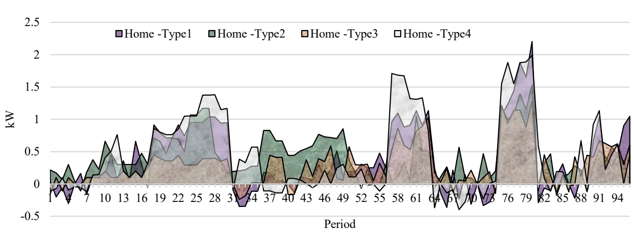


Fig. 8. Energy consumption curve of smart homes.

The energy profile for each smart home, as managed by HEM, is illustrated in Fig. 8. This illustration reveals that during certain intervals, energy is transferred among the smart homes because the energy consumption dips into negative values.

The illustrations in Fig. 9 depict the suitable timeframes for charging and discharging ESS and PHEV within smart homes. Based on the parameters analyzed, ESS is excluded from consideration in home type 2, while PHEV is not factored into home type 3.

In the illustration depicting the functionality of PHEVs, it is evident that charging and discharging do not occur while the vehicles are away from their smart homes. Furthermore, prior to departing from home, PHEVs must acquire the necessary energy, which is stored in the EV's battery, based on the predetermined strategy established by the HEM system tailored for each smart household.

The findings indicate that the HEM systems in each smart home have successfully optimized energy usage in alignment with the objectives established for smart MGs. It is important to highlight that the data illustrated in Figs. 5 to 9 and Tables 6 and 7 is valid under conditions where HEM systems function independently

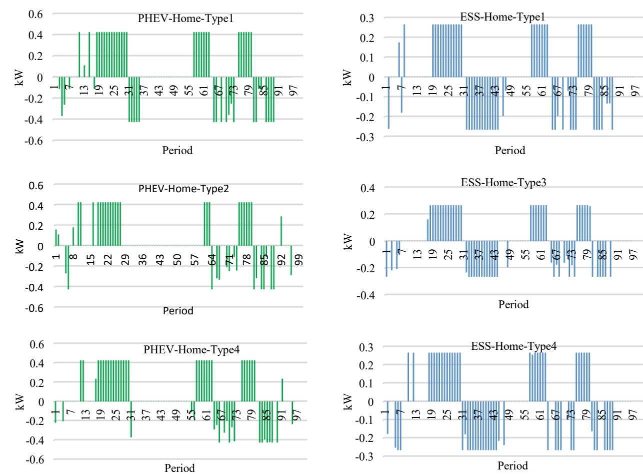


Fig. 9. Optimal charging and discharging of ESS and PHEV.

to achieve effective energy management within individual homes. Specifically, when the control of energy loads and DERs is managed by HEM, the outcomes depicted in those figures and tables hold true. However, this study acknowledges that the MG is currently operating in a disrupted state, with all loads and DERs being managed by the MGO. Consequently, to enhance the MG's resilience and maximize the distribution of available energy, the MGO aims to allocate resources equitably among all smart homes.

Table 9. Results of smart MG resilience.

$MG\_ENS^{EI=NO}$	7221.7 kWh
$MG\_ENS^{EI=YES}$	2629.3 kWh
MG_RI	63.59%

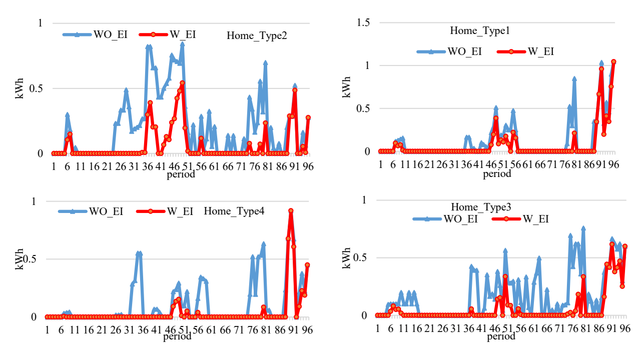


Fig. 10. ENS of smart homes.

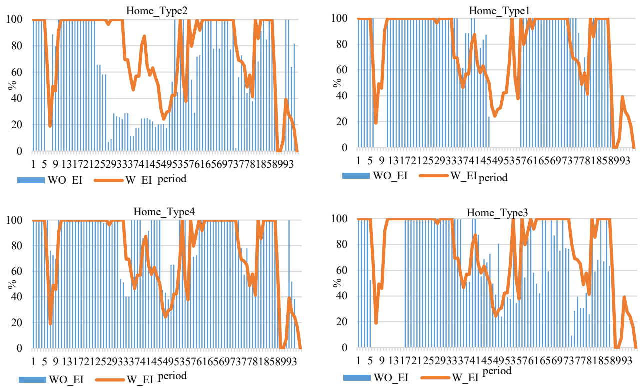


Fig. 11. The percentage of supplied energy.

The examination of electrical energy strategies within a MG aims to bolster its resilience. When the smart MG becomes disconnected from the main grid for any reason, the functionality of DERs in smart homes, combined with the HEM system, can significantly lower the ENS. As illustrated in Table 9, a comparison is made between scenarios where smart homes do not participate in energy interactions (EI=NO) and those where they do (EI=YES), showcasing the improvement in MG resilience. The findings reveal that ENS decreases from 7221.7 kWh to 2629.3 kWh, representing a 63.59% enhancement. This underscores the importance of strategically planning DERs to maximize their effectiveness within the MG before any disruptions take place.

The information in this table highlights how the sharing of energy among smart homes allows for the harnessing of surplus energy from DERs to fulfill the energy needs of other households. This collaboration boosts the share of energy supplied by MGs. It is essential to recognize that if there is a disruption in the MG, the energy management systems of smart homes are managed by the MGO. All HEM systems are set up to function under the direction of this operator, focusing on enhancing the resilience of the MG.

The data reflected in the previous table pertains to the durability of the MG and lacks insights into the effects of energy interaction during a MG disruption. Fig. 10 depicts the ENS values for different categories of smart homes over various time frames. It is evident from this figure that when smart homes are capable of engaging in energy interactions (W_EI) with one another, their ENS levels in each period are lower compared to situations where they cannot interact (WO_EI).

According to Fig. 10, the ENS value reaches zero during certain periods, regardless of whether energy interactions occur. This indicates that DERs in smart homes can completely meet their energy demands. However, in other time frames, an increase in the ENS value suggests active energy exchanges among the smart homes. When the MG is isolated from the main grid, all consumers and DERs fall under the jurisdiction of the MGO. To enhance resilience and minimize ENS levels, the operator uniformly manages all DERs across the smart homes. The outcomes of this enhanced energy management strategy are illustrated in the figure above.

To facilitate a deeper analysis, Fig. 11 presents a comparison of the load distribution percentages affected by disruptions in the MG, examining two cases: one involves energy collaboration among smart homes, and the other does not. When smart homes are capable of sharing energy generated by DERs, the MGO regulates the HEM systems, ensuring an equitable load allocation to bolster the MG's resilience. By evaluating these load distribution percentages over various intervals, it becomes evident that efficient energy coordination and collaborative sharing among smart homes can enhance the load distribution for each home during disturbances within the MG and increase the MG's resilience.

The data indicates that the percentage of energy supplied diminishes during specific timeframes, even as energy is exchanged among smart homes. This phenomenon occurs when the MG becomes isolated from the main grid, placing all HEM systems under the control of the MGO. In this state, the operator focuses on enhancing the MG's performance to minimize ENS. Consequently, during these periods, while some smart homes experience a drop in energy supply, others see an increase, balancing out at a certain level. Under normal conditions, each HEM system operates independently; however, in disrupted situations, they collectively serve the MGO's goals, primarily aimed at bolstering the MG's resilience.

The assessment of energy supply ratios among smart homes with energy interactions demonstrates particular advantages, depending on house type. Among the three smart home types—Type 1, Type 2, and Type 3—energy interaction ratios are 1.04, 1.19, and 1.26, respectively. A ratio of 0.91 represents the energy dynamics of Type 4 smart homes, as these homes receive little benefit from these interactions, thus releasing more energy into the system. Some homes may experience a reduction in ENS, while others may notice an enhancement of ENS levels. These energy interactions lead to increased resilience of the MG.

4. CONCLUSION

Strategic energy management at the demand level and active participation are vital elements for reaching the technical goals of upcoming distribution networks. This research examines smart homes that encompass both responsive and non-responsive loads, including bath-heating systems (BHS), air-conditioning (AC), plug-in hybrid electric vehicles (PHEVs), energy storage systems (ESSs), and photovoltaic (PV) installations. Results from the simulation were thoroughly evaluated based on the implemented modeling framework using relevant tables and figures. Each result was carefully analyzed and compared with others. As the microgrid operator oversees all energy assets alongside smart residences, the operator ensures the implementation of optimal energy strategies that utilize available resources from homes. The simulation findings illustrate that an optimized home energy management (HEM) framework, coupled with improved energy exchanges, can substantially lower the Energy Not Supplied (ENS) in a microgrid (MG) and enhance its overall resilience. In conclusion, the topology development in this research provides an autonomous MG system independent of the main grid while focusing on the resilience requirements of isolated systems and energy management strategies. By integrating advanced strategies for smart homes and DERs, the proposed framework not only enhances the resilience of the energy supply in the face of potential disruptions but also promotes sustainable practices through the optimized utilization of DERs. The model results demonstrate that implementing HEM technology in smart homes alongside energy trade among them in a smart MG leads to exceptional enhancements in MG resilience. The implementation of demand-side management (DSM) achieves a maximum resilience improvement of 63.59%, which reflects its significant role in enhancing the technical performance of smart MGs. Empowering communities through innovative solutions will enable the effective use of local DERs, leading to a more independent, sustainable energy future. As fully discussed in the article, the main focus of this study is on how the MG's resilience can be improved through energy interactions between smart homes when the MG becomes disconnected from the main grid for any reason (natural disasters, physical attacks, cyber-attacks, etc.). The proposed modeling assumes that if the MG faces a disruption due to any high-impact, low-probability (HILP) event, its ability to continue supplying power to smart homes must be assessed. This assessment focuses on the energy-sharing infrastructure among smart devices. The impact of HILP disasters on the main components of the system will be addressed in future studies due to the large volume of cases examined in this study.

REFERENCES

[1] N. Afsari, S. SeyedShenava, and H. Shayeghi, "A milp model incorporated with the risk management tool for self-healing oriented service restoration," *J. Oper. Autom. Power Eng.*, vol. 12, no. 1, pp. 1–13, 2024.

[2] R. Aghapour, M. Zeraati, F. Jabari, M. Sheibani, and H. Arasteh, "Cybersecurity and data privacy issues of electric vehicles smart charging in smart microgrids," in *Electric Vehicle Integration via Smart Charging: Technology, Standards, Implementation, and Applications*, pp. 85–110, Cham: Springer Int. Publ., 2022.

[3] H. Shayeghi and A. Rahnama, "Frequency regulation of a standalone interconnected ac microgrid using innovative multistage tdf(1+fopi) controller," *J. Oper. Autom. Power Eng.*, vol. 12, no. 2, pp. 121–133, 2024.

[4] S. Panjeie, A. Fakharian, M. Sedighizadeh, and A. Sheikhi fini, "Robust scheduling of unbalanced microgrids for enhancing resilience by outage management strategy," *J. Oper. Autom. Power Eng.*, vol. 13, no. 2, pp. 110–120, 2025.

[5] S. Mousavizadeh, T. Bolandi, M. Haghifam, M. Moghimi, and J. Lu, "Resiliency analysis of electric distribution networks: A new approach based on modularity concept," *Int. J. Electr. Power Energy Syst.*, vol. 117, p. 105669, 2020.

[6] F. Moazzen, O. Shahhoseini, H. Arasteh, S. Mirsadeghi, and F. Jabari, "Emerging business models for iot-based smart distribution systems," in *Synergy Development in Renewables Assisted Multi-Carrier Systems*, pp. 461–495, Cham: Springer Int. Publ., 2022.

[7] M. Miah, R. Shah, N. Amjady, T. Surinkaew, and S. Islam, "Resiliency assessment and enhancement of renewable dominated edge of grid under high-impact low-probability events—a review," *IEEE Trans. Ind. Appl.*, 2024. Early Access.

[8] S. Mousavizadeh, A. Alahyari, T. Bolandi, M. Haghifam, and P. Siano, "A novel resource allocation model based on the modularity concept for resiliency enhancement in electric distribution networks," *Int. J. Energy Res.*, vol. 45, no. 9, pp. 13471–13488, 2021.

[9] B. Mohammadi-Ivatloo and F. Jabari, *Operation, Planning, and Analysis of Energy Storage Systems in Smart Energy Hubs*. Cham: Springer Int. Publ., 2018.

[10] T. Sattarpour, D. Nazarpour, and S. Golshannavaz, "A multi-objective hem strategy for smart home energy scheduling: A collaborative approach to support microgrid operation," *Sustain. Cities Soc.*, vol. 37, pp. 26–33, 2018.

[11] K. Ren, J. Liu, Z. Wu, X. Liu, Y. Nie, and H. Xu, "A data-driven drl-based home energy management system optimization framework considering uncertain household parameters," *Appl. Energy*, vol. 355, p. 122258, 2024.

[12] D. Wang, R. Fan, P. Yang, K. Du, X. Xu, and R. Chen, "Research on floating real-time pricing strategy for microgrid operator in local energy market considering shared energy storage leasing," *Appl. Energy*, vol. 368, p. 123412, 2024.

[13] V. Juyal and S. Kakran, "Smart home energy management and active power loss analysis of a residential community," *J. Build. Eng.*, vol. 91, p. 109548, 2024.

[14] H. Issa, M. Abedini, M. Hamzeh, and A. Anvari, "Day-ahead multi-criteria energy management of a smart home under different electrical rationing scenarios," *Renew. Energy Focus*, p. 100647, 2024.

[15] J. Aldahmashi and X. Ma, "Real-time energy management in smart homes through deep reinforcement learning," *IEEE Access*, 2024.

[16] M. Majeed, S. Phichisawat, F. Asghar, and U. Hussan, "Optimal energy management system for grid-tied microgrid: An improved adaptive genetic algorithm," *IEEE Access*, 2023.

[17] F. Szilagyi, D. Petreus, M. Paulescu, T. Patarau, S. Hategan, and N. Sarbu, "Cost-effective energy management of an islanded microgrid," *Energy Rep.*, vol. 10, pp. 4516–4537, 2023.

[18] N. Shibu, A. Devidas, S. Balamurugan, S. Ponnekanti, and M. Ramesh, "Optimising microgrid resilience: Integrating iot, blockchain, and smart contracts for power outage management," *IEEE Access*, 2023.

[19] J. Nelson, N. Johnson, K. Fahy, and T. Hansen, "Statistical development of microgrid resilience during islanding operations," *Appl. Energy*, vol. 279, p. 115724, 2020.

[20] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, "Benefits of demand response on operation of distribution networks: A case study," *IEEE Syst. J.*, vol. 10, pp. 189–197, 2016.

[21] H. Mokhtarzadeh, J. Olamaei, S. Abedi, H. Siahkali, and A. Akhavein, "Energy interactions between in-home energy management (i-hem) systems for enhancing resilience in smart residential microgrid," *Electr. Eng.*, vol. 105, no. 6, pp. 3929–3949, 2023.

[22] M. Sheibani, M. Zeraati, F. Jabbari, and E. Heydarian-Forushani, "Portable energy storage systems expansion planning to improve the power systems resilience," *Trans. Electr. Eng.*, 2024.

[23] A. Najafi-Ghalelou, S. Nojavan, M. Majidi, F. Jabari, and K. Zare, "Solar thermal energy storage for residential sector," in *Operation, Planning, and Analysis of Energy Storage Systems in Smart Energy Hubs*, pp. 79–101, Springer, 2018.

[24] S. Behzadi, A. Bagheri, and A. Rabiee, "Resilience-oriented operation of micro-grids in both grid-connected and isolated conditions within sustainable active distribution networks," *J. Oper. Autom. Power Eng.*, vol. 13, no. 1, pp. 38–51, 2025.

[25] H. Dui, H. Li, X. Dong, and S. Wu, "An energy iot-driven multi-dimension resilience methodology of smart microgrids," *Reliab. Eng. Syst. Saf.*, vol. 253, p. 110533, 2025.

[26] X. Wang, X. Mao, and H. Khodaei, "A multi-objective home energy management system based on internet of things and optimization algorithms," *J. Build. Eng.*, vol. 33, p. 101603, 2021.

[27] M. Zeraati, F. Jabari, and S. Salarkheili, "Blockchain-based transaction platform for peer-to-peer energy trading," in *Demand-Side Peer-to-Peer Energy Trading*, pp. 77–97, Springer, 2023.

[28] A. Kahnamouei, T. Bolandi, and M. Haghifam, "The conceptual framework of resilience and its measurement approaches in electrical power systems," in *Proc. IET Int. Conf. Resilience Transm. Distrib. Netw.*, pp. 1–11, IET, 2017.

[29] A. Dadashzade, H. Bagherzadeh, M. Mottaghizadeh, T. Bolandi, M. Amirioun, M. Majidzadeh, and F. Aminifar, "Electricity distribution networks resilience in area exposed to salt dust: Fragility curve modeling of insulators, monte carlo-based resilience assessment, and enhancement measures," *Heliyon*, vol. 10, no. 16, 2024.

[30] S. Modaberi, S. Tohidi, S. Zadeh, and T. Bolandi, "A review of power system resilience assessment and enhancement approaches by focusing on wind farms and wind turbines," *IET Renew. Power Gener.*, vol. 17, no. 9, pp. 2391–2410, 2023.

[31] F. Qayyum, H. Jamil, N. Iqbal, and D. Kim, "Iot-orchestrated optimal nanogrid energy management: Improving energy trading performance and efficiency via virtual operations," *Int. J. Electr. Power Energy Syst.*, vol. 155, p. 109668, 2024.

[32] B. Chreim, M. Esseghir, and L. Merghem-Boulahia, "Recent sizing, placement, and management techniques for individual and shared battery energy storage systems in residential areas: A review," *Energy Rep.*, vol. 11, pp. 250–260, 2024.

[33] S. Vakili, A. Naminezhad, M. Mehregan, and S. Malbosi, "Home energy management system with plug-in hybrid electric vehicles, energy storage system, and photovoltaic system commitment by considering different incentive and price-based demand response programs in smart grids," *Energy Equip. Syst.*, vol. 12, no. 1, pp. 63–77, 2024.

[34] Z. Solatidehkordi, J. Ramesh, A. Al-Ali, A. Osman, and M. Shaaban, "An iot deep learning-based home appliances management and classification system," *Energy Rep.*, vol. 9, pp. 503–509, 2023.

[35] R. Khezri, S. Bahramara, and A. Mahmoudi, "Cloud energy storage in power systems: Concept, applications, and technical challenges," *IET Gener. Transm. Distrib.*, vol. 7, no. 8, pp. 1690–1706, 2023.