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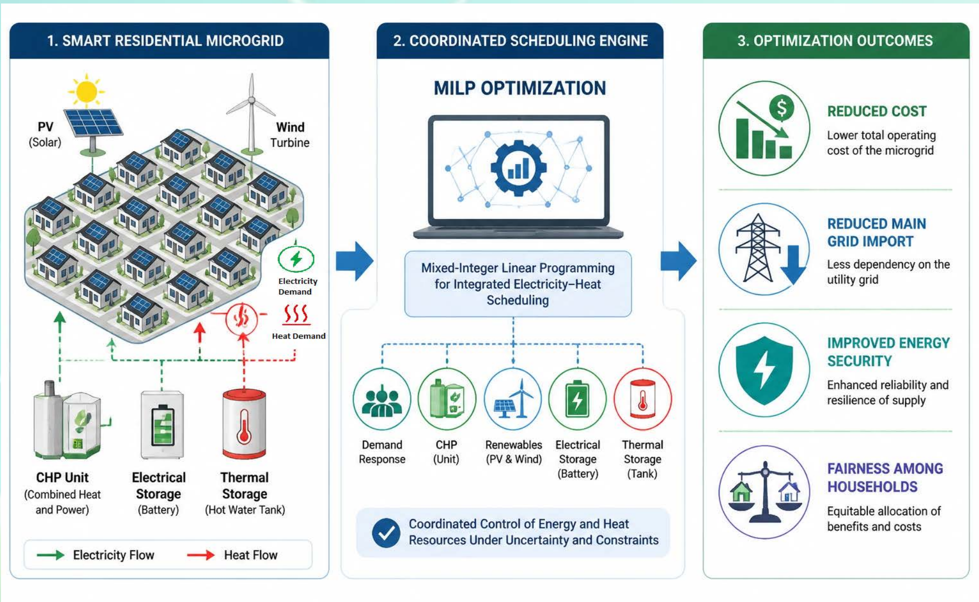
Highlights

- Comprehensive analysis of electrical and thermal energy in smart homes.
- Developed a MILP model for scheduling appliances and load shifting.
- Increasing CHP capacity significantly enhances energy distribution efficiency.
- Integrated approach reduces costs and strengthens supply security in microgrids.

Graphical Abstract



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Integrated Analysis of Electrical and Thermal Energy Distribution in Smart Homes Connected to Microgrids with CHP Sources

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A B S T R A C T

This paper presents a comprehensive analysis of the joint distribution of electrical and thermal energy in a smart home connected to a microgrid integrating renewable resources, combined heat and power (CHP) units, and storage systems. While most existing studies have primarily focused on generation planning and storage management, fewer works have examined the simultaneous optimization of electricity and heat flows in residential environments. To address this gap, a mixed-integer linear programming (MILP) model is developed to schedule household appliances and manage load shifting according to time-varying electricity prices, heating demand, and demand profiles, and the optimization is solved using MATLAB tools. The proposed framework is applied to a residential complex of 10 and 20 households under different CHP capacities and demand scenarios. Simulation results reveal that increasing CHP capacity from 5 kW to 20 kW significantly improves the coordination of electrical and thermal distribution, reduces reliance on the main grid, and lowers boiler operation, thereby enhancing overall efficiency. Additional analyses with different numbers of households confirm the scalability of the model, ensuring stable performance under varying load levels. A comparative scenario without microgrid integration further highlights the substantial benefits of the proposed system in reducing operational costs and improving resilience. To address this gap, a unified MILP jointly schedules electrical–thermal resources (CHP, renewables, and dual electrical/thermal storage) and employs a price–energy iterative scheme with explicit fairness constraints, ensuring no household is worse off than in non-cooperative operation. These results demonstrate that the coordinated consideration of both power and heat flows provides a more holistic strategy for smart home energy management than electricity-only approaches. In 24-h studies, increasing installed CHP capacity from 5 to 100 kW reduced total operating cost from \$379.68 to \$191.52 (≈49.6%). By integrating demand response (DR) programs with CHP and renewable resources, the proposed method reduces energy costs, strengthens supply security, and contributes to the sustainability of residential microgrids.

1. Introduction

The rapid growth in energy consumption, together with the global transition toward renewable energy sources and sustainable energy infrastructures, has significantly promoted the development of MGs and SHs as essential components of modern power systems. In contrast to conventional centralized generation frameworks, MGs are capable of integrating various distributed energy resources (DERs), including photovoltaic (PV) systems, wind turbine (WT) units, combined heat and power (CHP) technologies, and energy storage devices [1]. These localized energy networks can operate in both grid connected and islanded modes, thereby enhancing system reliability, operational flexibility, and economic efficiency. At the same time, smart homes, residential units equipped with advanced monitoring, control, and communication technologies, have become important platforms for implementing intelligent energy management schemes [2].

Through bidirectional information exchange between consumers and utility operators, SHs allow users to actively engage in energy management and market participation, improve the efficiency of electricity consumption, and contribute to maintaining overall grid stability. Despite these advancements, the integration of renewable energy introduces significant uncertainties due to the intermittent nature of wind and solar power. This intermittency challenges the stability of microgrids and underscores the importance of flexible demand-side management strategies [3]. To mitigate these challenges, researchers have explored various mechanisms, including storage technologies such as batteries and hydrogen-based systems [4], and distributed generation resources like CHP units, which provide simultaneous electricity and thermal energy with higher overall efficiency compared to conventional generation [5]. CHP not only reduces operating costs and emissions but also contributes to local energy autonomy. Nevertheless, the effective utilization of these resources relies heavily on advanced optimization techniques capable of handling multi-objective and multi-constraint environments.

Within this context, Demand Response (DR) has emerged as a cornerstone of modern energy management. DR programs aim to reshape the load profile by incentivizing consumers to shift or curtail their consumption in response to dynamic electricity pricing, grid signals, or other incentive mechanisms [6]. By adjusting demand rather than solely focusing on supply, DR introduces greater flexibility, improves grid stability, and supports renewable energy integration. Studies have shown that DR can reduce operating costs [7], flatten load curves [8], and improve the reliability of both standalone microgrids and interconnected systems [9].

Although considerable research has been conducted on general energy management of smart homes and microgrids, relatively fewer studies have provided an in-depth economic and operational assessment of DR programs specifically in the context of residential microgrids integrating CHP, renewables, and storage systems. Many existing works focus primarily on optimization models for cost minimization [10], heuristic algorithms for appliance scheduling [11], or the integration of storage technologies [12]. While valuable, these contributions often treat DR as an auxiliary element rather than as the central focus of analysis.

Previous studies have examined various approaches to improve the efficiency and management of modern distributed energy systems. Reference [13] analyzes the role of DR within a peer-to-peer (P2P) electricity trading framework applied to a residential smart home. The considered system includes several controllable household appliances, an electric vehicle, a battery energy storage system (BESS), and renewable-based distributed generation units such as solar photovoltaic and wind sources. The results indicate that coordinated interaction between DR programs and local energy trading mechanisms can enhance operational flexibility and improve the overall energy management of residential environments.

Paper [14] used a practical microgrid test platform to investigate system monitoring and performance assessment. The experimental setup consists of a hybrid wind–solar generation system supplying a number of domestic electrical loads. The study demonstrates that inexpensive power meters integrated with IoT communication capabilities can effectively collect detailed information about power quality indices and energy consumption patterns. Such data provide valuable insights for monitoring system behavior and can support advanced control strategies to optimize microgrid operation.

Reference [15] focuses on the economic and regulatory aspects of emerging distributed generation technologies. In this work, several policy mechanisms and incentive programs are proposed to encourage the deployment of renewable resources, CHP systems, and fuel cell units. Four different pricing frameworks for electricity generated by these technologies are developed and analyzed. Based on these scenarios, the potential tariff structures and expected financial support for electricity produced by fuel cells are determined, allowing an evaluation of their economic feasibility under different policy conditions.

A different perspective is presented in [16], which investigates the integration of solar energy with combined heat and power systems as an effective pathway for producing clean electricity while simultaneously meeting thermal energy demands. The proposed integration configuration enables the utilization of higher-temperature solar heat with minimal thermal degradation. To evaluate its effectiveness, the method is modeled and compared with three alternative integration schemes. The comparison is performed using indicators such as solar energy conversion efficiency, annual system performance, and levelized energy cost. Simulation results from the case study reveal that the proposed configuration delivers the best performance, achieving a solar heat-to-electricity efficiency of 37.1% with an integrated solar heat capacity of 54.45 MW. In addition, it provides the highest annual solar-to-electricity efficiency (21.5%) and the lowest electricity generation cost among the investigated strategies.

Under these conditions, the annual solar-generated electricity increased by 33.28 GW. In [17], various types of renewable energy sources, electric vehicles, smart homes, and IoT are considered. In addition, energy storage systems, microgrids, and the distribution network are installed to control the negative effects of the resulting operational uncertainties and load demand.

In the proposed approach, microgrids prepare their market participation bids using a fuzzy-based decision framework derived from the optimal scheduling results, with the primary objective of minimizing operational expenditures. The mathematical formulation of the model is expressed in a linear structure and evaluated on a modified IEEE 33-bus distribution system that includes three interconnected microgrids. Simulation outcomes indicate that the integration of an IoT communication infrastructure facilitates more efficient participation of microgrids in the electricity market, leading to a cost reduction of approximately 9.13%. Moreover, the results reveal that providing vehicle-to-grid related services, when coordinated through optimal scheduling, can significantly influence market dynamics; specifically, electricity prices during peak demand periods decrease by nearly 25%, while overall daily operational performance is also improved.

Reference [18] investigates the integration and optimization of energy systems using CHP technology. The study emphasizes efficient energy utilization, appropriate management of energy flows, and systematic optimization of the overall operational process in order to achieve multiple engineering objectives simultaneously. In addition to proposing an integrated framework, the work highlights several unresolved challenges in CHP research and outlines potential directions for future investigations.

In [19], a mixed-integer linear programming (MILP) model is developed to study the operational scheduling of CHP units. The research analyzes how different hydrogen blending ratios influence both energy consumption patterns and environmental performance indicators. Based on this analysis, an optimal energy exchange strategy is formulated. The findings show that electricity trading plays a dominant role in the revenue structure, mainly due to electricity sales income, generation subsidies, and carbon trading mechanisms. According to the obtained results, the proposed strategy can reduce system costs by up to 60%.

Reference [20] proposes a real-time energy management framework that integrates neural networks with an advanced control strategy. The main objective of the control mechanism is to mitigate the impact of forecasting errors while enabling real-time operational decision-making using actual generation and demand data. Simulation studies demonstrate that the proposed approach effectively prevents unnecessary power export to the upstream grid and achieves an operating cost reduction of approximately 8.75% compared with conventional offline scheduling techniques.

In paper [21], the daily energy management problem of a CHP-based microgrid is examined, where multiple types of CHP technologies are employed to simultaneously supply electrical and thermal demands. A distinctive feature of this study is the incorporation of a detailed heat-transfer loss model within the optimization framework. Furthermore, different CHP configurations are comparatively analyzed with respect to their operational characteristics. The simulation results indicate that accurate modeling of thermal losses significantly affects the optimal scheduling decisions and the total operational cost of the microgrid.

In references [22,23], a multi-objective particle swarm optimization (MOPSO) technique is applied to evaluate three renewable-based microgrid configurations designed for the climatic conditions of Shiraz, Iran. The analyzed configurations include WT, PV systems, and CHP units. The microgrid is assumed to be connected to both electricity and natural gas networks, and surplus electrical generation can be exported to the main grid. The optimization problem considers two main objective functions: the loss of power supply probability (LPSP) and the unit energy cost. The obtained results indicate that relying solely on wind turbines considerably increases dependency on the main grid. However, due to the region's high solar irradiation levels, incorporating PV units into the configuration significantly reduces the portion of electricity that must be supplied by the grid.

Reference [24] focuses on demand-side management within smart homes. In this work, household electrical loads are dynamically adjusted according to demand response signals in order to mitigate peak demand and lower consumer electricity expenses. To support this process, multidimensional data aggregation techniques are used to gather detailed power consumption information. These data enable the control center to design more effective and responsive demand response programs.

In [25], the integration of CHP units with distributed energy resources is investigated within the context of multi-carrier microgrids. The study employs a scenario-based stochastic modeling approach to represent uncertainties associated with electricity market prices. Consequently, a hybrid stochastic optimization framework is formulated for optimal energy management in the multi-carrier microgrid. Unlike conventional demand-response models that focus solely on electricity, the proposed improvement introduces a unified MILP formulation that simultaneously optimizes both electrical and thermal energy flows, determines internal energy trading mechanisms, and ensures fairness among participating households.

In this paper, an integrated framework is proposed for the joint distribution of electrical and thermal energy in smart residential microgrids, addressing a research gap where most previous studies have primarily focused on electricity management. The novelty of this study lies in the simultaneous optimization of power and heat flows through the coordinated use of DR, CHP units, renewable resources, and storage systems. A MILP model is formulated to capture the interactions between the electrical and thermal domains while accounting for household demand variability and time-varying energy prices. The framework is evaluated on a residential complex of 30 households under different CHP capacities and demand scenarios. Results demonstrate the scalability and robustness of the model and confirm its effectiveness in reducing operational costs, minimizing reliance on the main grid, and enhancing energy security. By incorporating both power and heat distributions, this work provides a more comprehensive and practical strategy for smart home energy management compared to electricity-only approaches.

The main contributions of this work are as follows:

- An integrated MILP for joint electricity–heat scheduling in residential microgrids with CHP, renewables, demand response, and dual electrical/thermal storage.
- An intra-microgrid trading mechanism based on a simple price–energy iterative procedure with a quantitative stopping criterion, resolving bilinear coupling between traded energy and internal price.
- Explicit household-level cost-fairness constraints ensuring no participant is worse off than in non-cooperative operation.
- Case studies with 10 and 20 households and multiple CHP capacities, including a no-microgrid benchmark, demonstrating reductions in total cost, grid imports, and boiler runtime.
- Reproducibility enhancements through unified notation, clarified constraints, and organized data/parameter tables.

Table 1 summarizes the main characteristics of the reviewed studies and compares them with the proposed method in this paper. The comparison is performed based on several important aspects, including the consideration of ESS, demand response capability, smart building implementation, MG integration, the use of CHP units, and the applied optimization method.

As shown in the table, previous works have investigated some of these components individually or in limited combinations. However, most of the existing studies do not simultaneously consider all key elements such as ESS, demand response, smart building environments, MG structure, and CHP units within a unified optimization framework. In contrast, the proposed method integrates all these features together and employs a MILP optimization approach, providing a more comprehensive framework for energy management and system optimization.

Table 1. Comparison of research from the last few years and current research.

Ref	Optimization Method	CHP	Microgrid	Smart Building	Demand Response	ESS
[13]	BDA	-	+	+	+	+
[14]	ILP	-	+	+	-	-
[15]	ILP	+	+	-	+	+
[17]	FUZZY	+	+	+	+	-
[19]	MILP	+	-	-	+	-
[20]	MILP	+	-	-	+	+
[21]	ICA	+	+	-	+	-
[22]	ILP	+	+	-	+	+
[23]	MOO	+	+	-	+	+
[24]	MILP	+	+	-	+	-
Proposed Method	MILP	+	+	+	+	+

2. Objective function

Renewable energy plants are being established as modern infrastructures that are simultaneously encountering two major trends: the continuous growth in electricity demand and the reduction in energy prices. Drawing on the practices of developed nations provides a valuable pathway for promoting the application of renewable energies in developing countries. This is particularly evident in two primary areas, one of which is wind energy systems. The assumed specifications for the wind turbine [26], solar panel [27], and load demand [28] are given in the references mentioned.

The problem of power consumption scheduling in a smart home is expressed as a MILP framework. In this formulation, daily operational activities are planned within specific time windows, defined by the earliest possible start and the latest permissible end time of each task. The primary objective is to minimize the overall daily energy cost while simultaneously lowering the peak load drawn from the grid. To achieve this, the time horizon is divided into discrete intervals of equal duration. The principal decision variables of the model include appliance operating states, scheduling of task initiation, and load deployment strategies. These variables must satisfy multiple constraints, such as device capacity limitations, demand requirements, thermal and electrical storage restrictions, and operational time boundaries, all while ensuring the minimization of daily costs. In optimization theory, the obtained solution can be interpreted in several ways. Typically, the goal is to determine the global optimal solution; however, in practice, a local optimum is sometimes acceptable depending on the problem complexity. For many real-world challenges (such as solving nonlinear systems, differential equations, and large-scale optimization) numerical methods serve as the most viable tools. These methods rely on an initial approximation and iteratively refine it through successive calculations until convergence toward a feasible solution is reached. More formally, numerical techniques generate a sequence, initiated from a starting guess, which gradually approaches the problem's solution. The objective function used in this study, derived from [29-31], and given in Equation (1), considers the total operational costs within a 24-hour horizon. It is composed of three main components: the cost of purchasing electricity, the cost of natural gas, and the environmental cost associated with emissions, as given in Equations (2)-(4).

$$f = \sum_{s \in S} \rho(s) \times \sum_{t \in T} \left[C_{pe}(t) + C_{pg}(t) + C_{oe}(t)\right] \tag{1}$$

$$C_{pe}(t) = \rho_e(t) \times P^{GRD}(t) \times \Delta t \qquad \forall t \in T \tag{2}$$

$$C_{pg}(t) = \rho_g(t) \times \left[P_{gas}^{PGU}(t) + P_{gas}^{AB}(t) + P_{gas}^{CAES}(t)\right] \times \Delta t = \rho_g(t) \times \left[\frac{P_e^{PGU}(t)}{\eta_e^{PGU}} + \frac{H^{HRU}(t)}{\eta_h^{PGU}} + \frac{H^{AB}(t)}{\eta_h^{AB}} + \frac{P_{CAES}^{dis}(t)}{\eta_{CAES}^{dis}}\right] \times \Delta t \,, \forall t \in T \tag{3}$$

$$C_{oe}(t) = \theta \times \left[\begin{array}{c} \varphi_{in} \times P^{GRD}(t) + \varphi_g \\ \times \left(\frac{P_e^{PGU}(t)}{\eta_e^{PGU}} + \frac{H^{HRU}(t)}{\eta_h^{PGU}} + \frac{H^{AB}(t)}{\eta_h^{AB}} + \frac{P_{CAES}^{dis}(t)}{\eta_{CAES}^{dis}}\right) \end{array}\right] \times \Delta t \;\; \forall tT \tag{4}$$

Here, $C_{pe}(t)$ denotes the electricity purchase cost from the grid at time t (in \$); $C_{oe}(t)$ represents the natural gas purchase cost at time t (in \$); and $C_{oe}(t)$ corresponds to the carbon emission cost at time t (in \$). The electricity price at time t is given by $\rho_g(t)$ in units of \$/kWh, while $\rho_g(t)$ indicates the gas price at time t in the same units. The parameter θ represents the cost associated with carbon dioxide emissions in \$/kg. Furthermore, φ_{in} and φ_g denote the equivalent emission coefficients of electricity and natural gas, respectively, measured in kg/kWh. Finally, Δt specifies the length of each time interval, assumed to be one hour. On this basis, the total daily cost minimization is expressed through the following objective function [32]:

$$\eta^{HRU} \times H^{HRU}(t) + H^{AB}(t) + P_{TESS}^{dis}(t) = H^{L}(t) + H^{AC}(t) + P_{TESS}^{ch}(t) \quad \forall t \in T \tag{5}$$

In this model, $H^{HRU}(t)$ represents the thermal output generated by the Heat Recovery Unit (HRU), while η^{HRU} denotes the efficiency of this unit, which is determined by its technical characteristics. Similarly, $H^{AB}(t)$ ndicates the heat supplied by the auxiliary boiler. The term $P_{TESS}^{dis}(t)$ corresponds to the power discharged from the Thermal Energy Storage System (TESS), whereas $P_{TESS}^{ch}(t)$ refers to the power stored within the TESS. In addition, $H^{L}(t)$ expresses the thermal demand response at time t, and $H^{AC}(t)$ defines the required heating load associated with the absorption chiller (refer to Equation (6)).

$$\mathrm{P^{ELE}(t) + P^{PV}(t) + P^{WT}(t) + P_e^{PGU}(t)} = P^{L}(t,s) + P^{ISC}(t) \quad \forall t \in T \tag{6}$$

In the given formulation, $P^{PV}(t)$ denotes the electrical output generated by photovoltaic panels, while $P^{WT}(t)$ corresponds to the power produced by wind turbine units. The term $P_e^{PGU}(t)$ represents the electricity supplied by gas turbine generators. Likewise, $P_{CAES}^{dis}(t)$ refers to the discharged power from the Compressed Air Energy Storage (CAES) system, $P^{L}(t)$ indicates the electrical demand response at time t, and $P^{ISC}(t)$ expresses the amount of stored electrical energy, as presented in Equations (7)-(12).

$$0 \leq P_{ESS}^{ch}(t) \leq P_{ESS}^{ch-max} \times U_{ESS}^{Ch}(t) \quad \forall t \in T \tag{7}$$

$$0 \leq P_{ESS}^{dis}(t) \leq P_{ESS}^{dis-max} \times U_{ESS}^{dis}(t) \quad \forall t \in T \tag{8}$$

$$U_{ESS}^{dis}(t) + U_{ESS}^{Ch}(t) \leq 1 \quad \forall t \in T \tag{9}$$

$$\mathrm{E_{ESS}(t,s) = E_{ESS}(t-1) - P_{ESS}^{dis}(t) \times \eta_{ESS}^{dis}} + \left(\frac{P_{ESS}^{ch}(t)}{\eta_{ESS}^{ch}}\right) \quad \forall t \in T, t > 1 \tag{10}$$

$$E_{ESS}^{min} \leq E_{ESS}(t) \leq E_{ESS}^{max} \quad \forall t \in T \tag{11}$$

$$E_{ESS}(0) = E_{ESS} \tag{12}$$

In the ESS model, $P_{ESS}^{ch}(t)$denotes the charging power of the storage unit at time t, whereas $P_{ESS}^{dis}(t)$represents the discharged power at the same time interval. The charging process is limited by the maximum allowable charging rate P_{ESS}^{ch-max}, while the discharging capability cannot exceed $P_{ESS}^{dis-max}$. To represent the operational state of the storage device, two binary decision variables are defined: $U_{ESS}^{ch}(t)$and $U_{ESS}^{dis}(t)$, which indicate whether the ESS is in charging or discharging mode at time t, respectively. In addition, $E_{ESS}(t)$describes the energy stored in the ESS at a given time step and reflects the state of charge of the system. The parameters $\eta_{ESS}^{ch}$and η_{ESS}^{dis}correspond to the charging and discharging efficiencies, which account for energy losses occurring during the storage and retrieval processes. Incorporating these parameters into the optimization framework allows a more realistic representation of ESS operation and ensures that the energy balance and operational constraints of the storage system are accurately maintained.

For load management, a time-based DR program is implemented, as illustrated in Figure 1. This program aims to reshape the load profile by transferring a portion of electricity consumption from peak demand periods to off-peak or medium-load intervals. Such load shifting helps reduce stress on the power system, improves the utilization of available generation resources, and contributes to lowering operational costs. Furthermore, the implementation of this strategy can enhance system flexibility and support more efficient integration of distributed energy resources within the overall energy management framework.

The mathematical model is shown in Equations (13) and (14):

$$Load(t) = (1 - DR(t)) * load(t)^{\cdot} + ldr(t) \tag{13}$$

$$load(t)^{\cdot} - Load(t) = DR(t) * load(t)^{\cdot} - idr(t) \tag{14}$$

Where:
$Load(t)$: Load considering the load demand program
$DR(t)$: Load reduction rate
$load(t)^{\cdot}$: Predicted load
ldr: Load increase rate

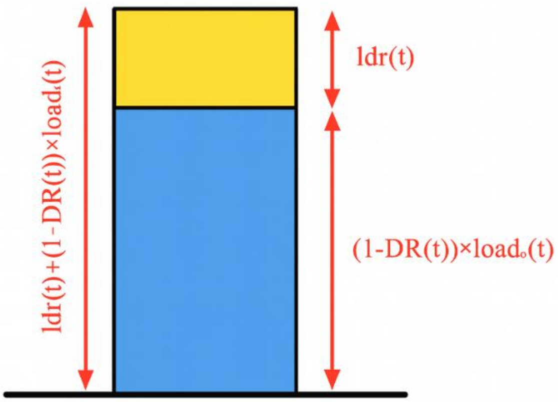

Figure 1. Load model considering load response.

Also, the load-responsive constraints can be expressed according to Equation (15):

$$\sum_{t=1}^{T} ldr(t) = \sum_{i=1}^{T} DR(t).load(t) \quad (15)$$

This equation reflects the fact that the load does not decrease or increase, but rather shifts from peak periods to medium or low load periods, in other words, the decreasing load is equal to the increasing load during the operation period. The technical limitations of the load response can also be stated as Equations (16)-(18):

$$load(t)^{inc} \leq inc(t).load(t) \quad (16)$$

$$DR(t) \leq DRmax \quad (17)$$

$$inc(t) \leq inc\ max \quad (18)$$

Where:

$load(t)^{inc}$: Maximum load that can be increased

$inc(t)$: Increaseable load percentage

$DRmax$: Maximum load percentage that can be reduced

This constraint states that the percentage of load decrease or increase must be less than a certain value.

Finally, our final objective function is written as Equation (19):

$$\emptyset = \sum_{t} \delta \mathrm{nu_t} /\propto + \sum_{t} \delta \mathrm{m^p} p_t + \sum_{t} \delta \mathrm{m^w w_t} + \frac{\sum_t \delta \mathrm{nx_t}}{\eta_t} + \sum_{t} \delta \mathrm{m^E y_t} + \sum_{t} \delta \mathrm{m^T} f_t + \sum_{t} \delta \mathrm{b_t} I_t + \sum_t (c^{dis}(d_t^- + d_t^+) + c^{reb}.reb_{\ t} - \pi_t^{DR}.r_t) - \sum_{t} \delta \mathrm{qR_t} \quad (19)$$

Which are, respectively, the operating costs of CHP, photovoltaic, wind turbine, boiler, electrical storage, thermal storage, electricity purchase from the grid, load response program, and revenue from selling electricity to the grid.

2.1. Optimization model

This section examines the problem of optimizing integrated residential energy costs in the smart grid. We begin with a simple model that incorporates household appliance characteristics, user preferences, and utility energy prices, leading to a MILP formulation. The model is then gradually expanded to include storage systems, renewable energy sources, and microgrids. In the context of microgrids, energy trading requires the model to determine both the optimal amount of energy and the optimal trading price. These aspects are represented using nonlinear expressions, which are transformed into a MILP problem. However, energy trading introduces a challenge of cost fairness among participating households. While the model minimizes the total energy purchase cost for the entire microgrid, it does not directly address cost optimization at the household level. A key issue arises when the model, relying on a single objective function (minimizing the sum of energy and non-use costs across all households), reduces costs for some households at the expense of increasing them for others. This unfair cost distribution diminishes the model's appeal to participants. To overcome this limitation, the model is extended to a multi-objective optimization framework that explicitly accounts for individual household costs. In this setting, optimality must ensure that no household experiences higher costs as a consequence of reducing costs for others. Overall, this section builds the integrated cost optimization model step by step, incorporating new components and their features. First, a complete cost optimization model is developed, capturing load and resource responsiveness as well as appliance preferences. Next, the model is extended to guarantee fairness and optimality among households participating in the microgrid.

2.2. Problem-Solving Flowchart

Consider several households within a microgrid equipped with a two-way distribution network that enables energy exchange among participants. Each household maintains access to the main power grid. When local generation within the microgrid is insufficient to meet a household's demand, additional energy is purchased from the power grid. Energy prices are announced by the utility, which may be determined based on time, demand, or any pricing scheme intended to manage consumption. Households differ in electricity consumption and generation profiles. Some may be equipped with renewable energy generation units, whose output varies with weather conditions. Appliances within each household have diverse power requirements and priority levels, while energy storage units may provide additional flexibility by shifting usage over time. Energy can also be exchanged among households within the microgrid to reduce costs or generate revenue. The objective is the minimization of total energy cost across all participating households. More specifically, given a set of appliances that must operate within a specified time horizon, the aim is to determine the optimal scheduling of consumption and resource utilization to minimize overall costs. It should be noted that this objective differs from load balancing or demand peak reduction, which are generally priorities for the utility.

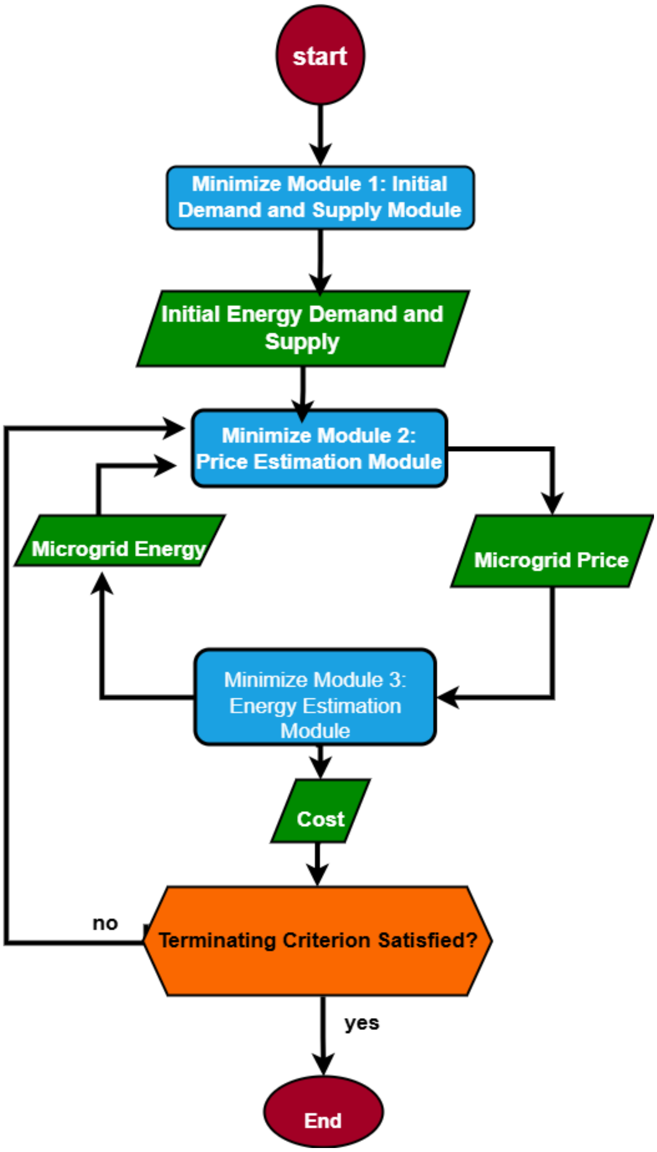

Figure 2. Problem solving flowchart.

To address the problem, a MILP model is developed. The notations required to define the input parameters and decision variables are introduced as follows. In the proposed framework, each MILP mode addresses a partial problem, while a bilinear model iteratively approximates the overall solution. Figure 2 illustrates the interaction between modes. Mode 1 generates initial estimates of energy demand and supply, which are then provided to Mode 2. Mode 2, treating these values as constants, determines the microgrid energy price. Mode 3, using the microgrid price as a constant, computes the amount of energy that can be traded. The resulting traded energy value is then passed back to Mode 2. Through this iterative process, the bilinear model updates both the microgrid energy price (Mode 2) and traded energy (Mode 3) until the stopping criterion is satisfied. The heuristic is employed solely for resolving the price–energy coupling in intra-microgrid trading; each iteration solves a structured MILP, and the core scheduling model itself is never handled by a metaheuristic. If the total cost does not improve by more than 0.1% during the final iterations, the procedure terminates. Once the termination condition is met, Mode 3 provides the final solution.

3. Simulation Results

The microgrid load is shown in Figure 3. Figures 4 and 5 show the amount of power generated from the solar system and wind turbine for the system under study. Figure 6 shows the boiler power changes. As can be seen, the amount of boiler power has also increased during times when the microgrid load has a high peak.

For the evaluation of a smart building consisting of 30 houses, the energy resources are allocated according to the total energy demand, and their capacities are determined based on this demand while considering the technical parameters and associated costs. It is assumed that the power capacity of the CHP unit can vary between 5 and 100 kW; however, in this study, the cases of 5 kW and 20 kW are specifically analyzed to illustrate the results.

For 24-hour system management, the optimal dispatch of the available resources is scheduled over a 48-hour horizon. The results of the electrical energy distribution are presented in Figure 7, while the corresponding heat distribution is illustrated in Figure 8. Furthermore, when the CHP capacity is set to 20 kW, the electrical distribution results are shown in Figure 9 and the heat distribution results are provided in Figure 10.

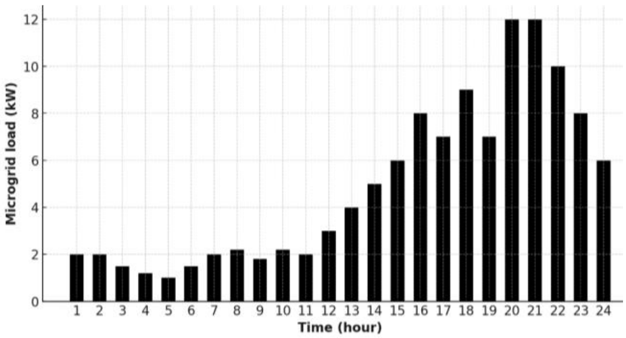

Figure 3. Microgrid load.

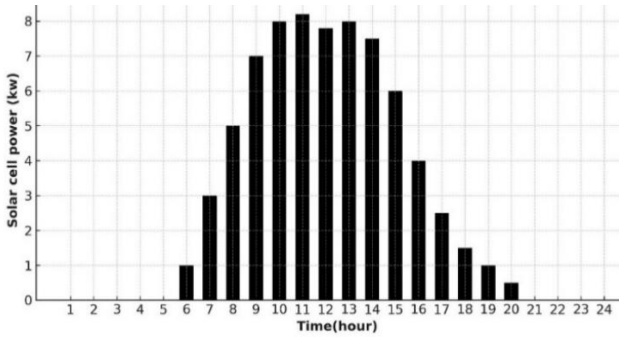

Figure 4. Solar cell output power.

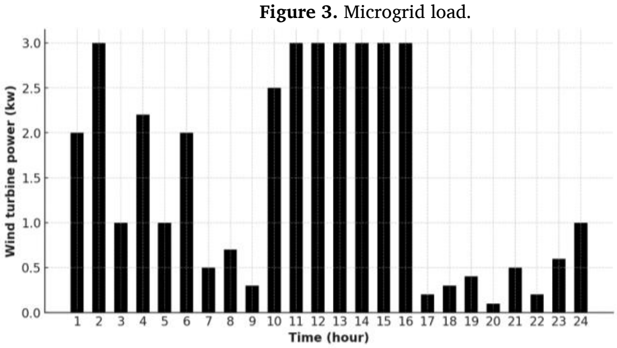

Figure 5. Wind turbine output power.

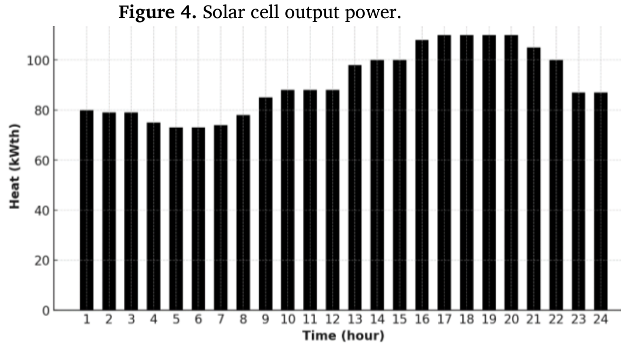

Figure 6. Boiler changes.

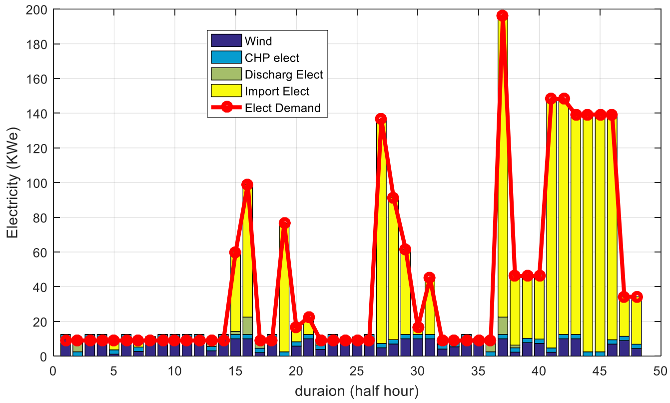

Figure 7. Electrical distribution of the studied system with CHP power and capacity of 5 kW.

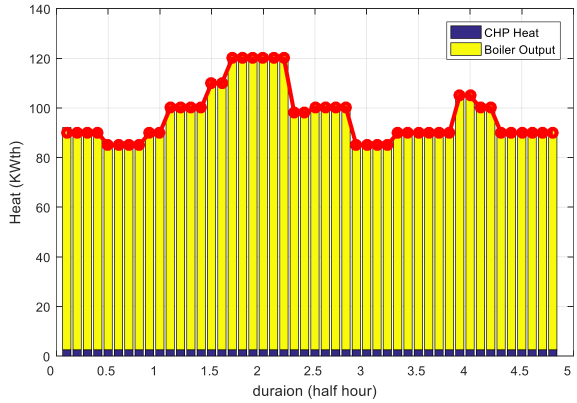

Figure 8. Heating distribution of the studied system with CHP power and capacity of 5 kW.

Figures 11 and 12 show the simulation results for 10 and 20 households, respectively

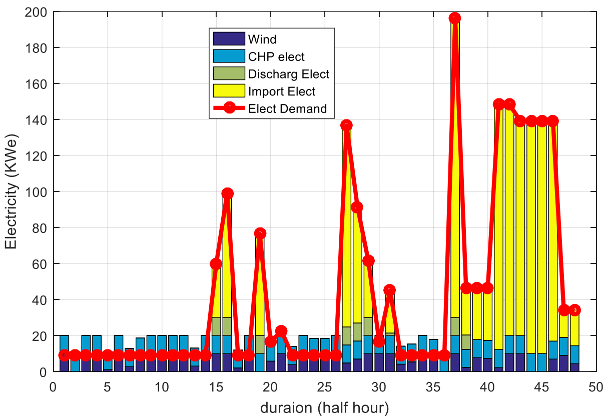

Figure 9. Electrical distribution of the studied system with CHP power and capacity of 20 kW.

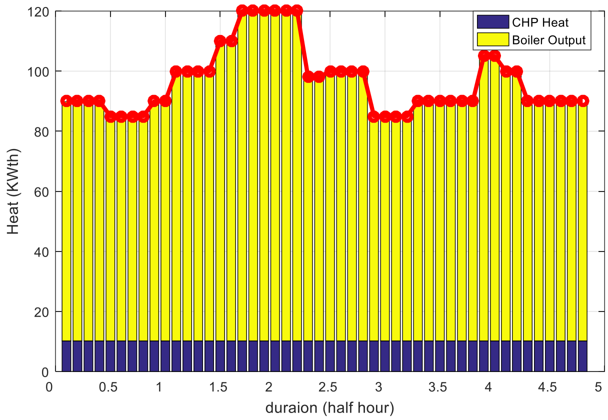

Figure 10. Heating distribution of the studied system with CHP power and capacity of 20 kW.

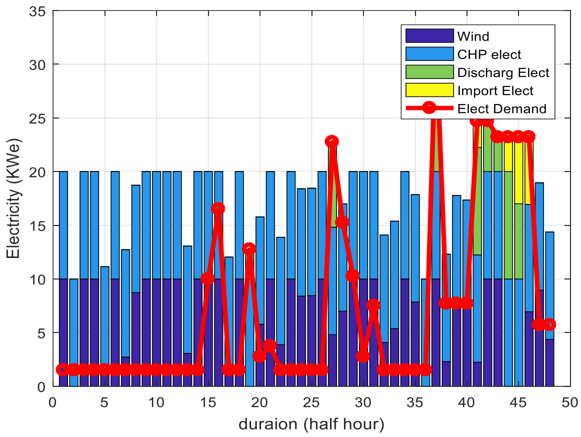

Figure 11. Electrical distribution system for 10 households.

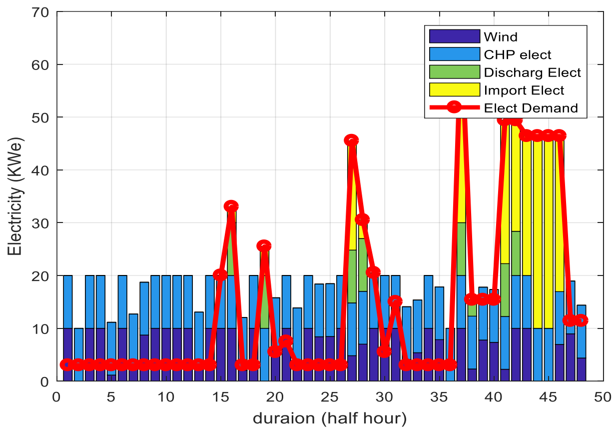

Figure 12. Electrical distribution system for 20 households.

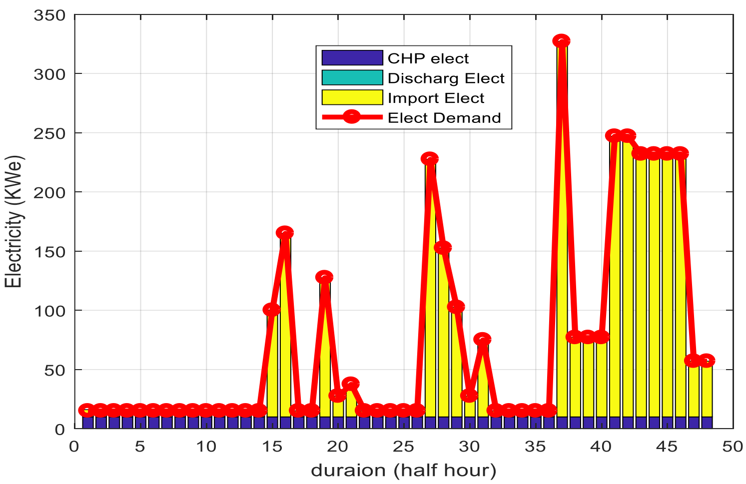

Figure 13. Electrical distribution system without the presence of a microgrid.

The electrical power distribution of the system in the absence of a MG is illustrated in Figure 13. As observed in this figure, the level of energy demand increases when the MG is not present. In addition, Table 2 presents the calculated costs for the smart house as the CHP capacity is gradually varied from 5 kW to 100 kW.

4. Results and Discussion

The simulation results provide a comprehensive overview of how different DERs and CHP capacities affect the performance of a smart home microgrid. The figures presented in the previous section illustrate the variations in load demand, renewable generation, and the corresponding behavior of the electrical and thermal distribution under different conditions.

4.1. Microgrid load and renewable generation

As shown in Figures 3-5, the electrical demand of the microgrid fluctuates significantly over time, reflecting the dynamic nature of residential consumption. Solar PV and wind turbine generation exhibit their well-known intermittency patterns, with PV output highly dependent on daylight hours and wind generation influenced by wind speed variations. These fluctuations highlight the necessity of complementary resources such as CHP and boiler units to ensure continuous supply.

The boiler output (Figure 6) shows a clear increase during peak load periods, compensating for the mismatch between renewable supply and demand. This confirms the critical role of thermal units in stabilizing the system when renewable generation is insufficient.

4.2. Effect of CHP capacity on energy distribution

The results of CHP operation at different capacities reveal a strong influence on both electrical and thermal distributions. For a small CHP unit of 5 kW (Figures 7 and 8), the system relies heavily on external resources and the boiler to meet demand. The electrical distribution shows more stress on the grid, while thermal supply requires frequent boiler adjustments. This leads to less efficient operation and higher overall costs.

In contrast, increasing the CHP capacity to 20 kW (Figures 9 and 10) substantially improves system performance. The electrical distribution becomes more balanced, with fewer fluctuations and less reliance on external supply. Similarly, the thermal distribution demonstrates smoother variations, reducing the boiler's operational burden. These results suggest that scaling up CHP capacity enhances both energy efficiency and cost-effectiveness, supporting the integration of distributed resources in smart homes.

4.3. Impact of household numbers on distribution

The simulation further evaluates the effect of varying the number of households. Figures 11 and 12 present the results for 10 and 20 households, respectively. As expected, increasing the number of consumers raises the total load and shifts the distribution profile. However, the system demonstrates scalability, with CHP and renewable sources adapting to the higher demand. Importantly, the distribution patterns remain stable, indicating that the proposed framework is robust to variations in residential scale.

4.4. Comparison with non-microgrid operation

Figure 13 depicts the distribution when the system operates without a microgrid. The demand increases significantly, and the reliance on external supply becomes dominant. This scenario clearly shows the benefits of microgrid integration, which not only reduces dependence on the main grid but also enhances the resilience and sustainability of the energy system.

4.5. Discussion of findings

The obtained results emphasize the crucial role of CHP capacity, renewable generation, and microgrid integration in achieving efficient energy management for smart homes. Increasing the CHP size leads to a more balanced distribution of both electrical and thermal energy, thereby reducing fluctuations and minimizing reliance on auxiliary resources such as the boiler or external supply.

Table 2. Obtained costs for CHP changes.

CHP capacity (kW)	Cost ($)
5	379.6838
10	379.6838
20	352.099
40	307.353
50	292.960
80	226.390
100	191.521

This indicates that higher-capacity CHP units not only improve overall efficiency but also enhance cost-effectiveness by lowering operational expenditures. Moreover, the inherent intermittency of renewable sources, including solar PV and wind turbines, highlights the necessity of stable backup systems. In this regard, CHP and boiler units act as reliable stabilizers, ensuring that the demand is continuously met despite the variability of renewable outputs.

Another key finding is the scalability of the proposed framework. The results for different household numbers confirm that the system maintains its stability and performance even as the load increases. This demonstrates the flexibility of the model, which can be effectively adapted to residential complexes of varying sizes without fundamental modifications. Finally, the comparison with non-microgrid operation clearly shows the advantages of microgrid integration. By reducing dependence on the main grid, the system enhances energy security, decreases costs, and improves sustainability.

Overall, the simultaneous analysis of electrical and thermal distributions offers a more comprehensive perspective compared to studies that focus solely on electricity. This dual consideration provides a holistic approach to residential energy management, ensuring that both power and heat demands are optimized in a coordinated manner. Consequently, the findings confirm that integrating CHP with renewable resources in microgrids represents a promising solution for the future of smart homes, combining economic, technical, and environmental benefits.

5. Conclusion

This study proposed an integrated framework for optimizing the joint distribution of electrical and thermal energy in smart homes connected to a microgrid equipped with renewable resources, CHP units, and storage systems. The developed MILP-based model coordinated power and heat flows under time-varying electricity prices and household demand profiles. Simulation results demonstrated that increasing CHP capacity from 5 kW to 20 kW improved the balance of energy distribution, reduced boiler operation, and minimized reliance on the external grid. Additional scenarios with 10 and 20 households confirmed the scalability of the framework, ensuring stable and efficient operation across different residential scales. Furthermore, comparison with a non-microgrid configuration highlighted the benefits of microgrid integration in lowering costs and enhancing resilience. Overall, the findings show that simultaneous consideration of electrical and thermal domains provides a more comprehensive strategy for residential energy optimization, and that combining demand response, CHP, and renewable resources within a unified structure enhances cost-effectiveness, strengthens energy security, and contributes to the sustainability of smart homes. Quantitatively, expanding CHP capacity from 5 kW to 100 kW reduces the 24-h operating cost from \$379.68 to \$191.52 ($\approx$ 49.6%). The most pronounced stepwise gains are observed at 20→40 kW ($\approx$ 12.7%) and 50→80 kW ($\approx$ 22.7%), highlighting where capacity additions deliver the largest marginal benefits before diminishing returns. Future research could extend this framework to larger-scale community microgrids, incorporate uncertainty modeling for renewable variability and demand fluctuations, and explore real-time control strategies to complement the optimization-based scheduling approach.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, have been completely observed by the authors.

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