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A Two-Stage Optimization Approach for Energy Pricing and Management in Smart Homes

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Abstract-- **Currently, around 30% of global energy consumption is attributed to the residential sector, and this share is projected to grow considerably in the upcoming years. This rising demand has drawn researchers' attention to optimizing energy management in smart homes. One of the most effective approaches is the development of smart homes, where internal components interact through a codified system to create a logical and compatible environment. The key innovation of this research is the introduction of a newly developed two-stage mixed-integer linear programming (MILP) framework that, unlike previous models, explicitly incorporates the uncertain nature of photovoltaic (PV) output and variations in real-time electricity prices. Unlike traditional deterministic approaches, the proposed model leverages stochastic and robust optimization techniques to handle instability in renewable energy generation and market prices, making energy scheduling more flexible and cost-effective. The proposed model is implemented in MATLAB using the CPLEX solver, enabling optimal energy scheduling in smart homes while accounting for various uncertainty scenarios. The outcomes of the simulations indicate that the proposed model significantly improves energy planning reliability and cost efficiency compared to traditional methods. Specifically, real-time pricing reduces electricity costs by 10.5% compared to day-ahead pricing.**

Index Terms- **Smart Home, Day-Ahead Pricing, Real-Time Pricing, Electric Energy Consumption Management, Uncertainty Modeling, Stochastic And Robust Optimization, Two-Stage Mixed Integer Linear Programming.**

NOMENCLATURE

HA	Home Appliances
TCA	Thermostatic Consumption Appliances
BESS	Battery Energy Storage System
EV	Electric vehicle
HEMS	Home energy management system
TSMILP	Two-Stage Mixed Integer Linear Programming
PEV	Plug-in electric vehicle
PV	Photovoltaic
REN	Renewable Energy
RTP	Real-time pricing
PD	Programmable Devices

INDICES

d	Index of PD loads
t	Index of time slots

PARAMETERS

η_{BESS}^{ch}	BESS charging efficiency
η_{BESS}^{dis}	BESS discharging efficiency
η_{PEV}^{ch}	PEV charging efficiency
η_{PEV}^{dis}	PEV discharging efficiency
C_{BESS}^{max}	BESS maximum capacity (kWh)
C_{PEV}^{max}	PEV maximum capacity (kWh)

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P_{AC}^{max} Air conditioning rated power (kW)
P_{BESS}^{chmax} Maximum charging power of BESS (kW)
P_{BESS}^{dismax} Maximum discharging power of BESS (kW)
P_{EWH}^{max} Electric water heater rated power (kW)
P_{PEV}^{dismax} Maximum discharging power of PEV (kW)
RTP_{AVG} Average electricity price ($/kWh)
$RTP_{BESS_{dis}}$ BESS discharging price threshold ($)
T Set of time slots
$RTP_{PEV_{ch}}$ Average electricity price during PEV access to the home ($/kWh)
$RTP_{PEV_{dis}}$ PEV discharging price threshold ($/kWh)
T_{AC}^{max} Upper limit of user acceptable indoor temperature (∘F)
T_{AC}^{min} Lower limit of user acceptable indoor temperature (∘F)
T_{EWH}^{max} Upper limit of user acceptable hot water temperature (∘F)
T_{EWH}^{min} Lower limit of user acceptable hot water temperature

VARIABLES

C_{PEV} PEV capacity (kWh)
P_{BESS}^{ch} BESS charging power (kW)
P_{BESS}^{dis} BESS discharging power (kW)
P_{PEV}^{dis} PEV discharging power (kW)
P_{AC} Air conditioning power consumption (kW)
P_G Interaction power between the utility and HEMS (kW)
P_{EWH} Electric water heater power consumption (kW)

I. Introduction

THE continuous rise in electricity consumption is one of the world's major challenges. With technological advancements and increased use of smart appliances, household energy consumption has surged, while many individuals lack awareness of energy-saving strategies. Power system flexibility refers to adjusting electricity generation, transmission, and consumption in response to varying demand and supply conditions, which is crucial for maintaining grid stability, reliability, and efficiency, particularly with the integration of renewable energy sources. In this context, residential customers play a key role in providing flexibility through adjusting their consumption patterns, participating in demand response programs, and adopting home energy management systems (HEMS) [3,4].

Traditional monitoring and control methods are inefficient, making intelligent scheduling and automated appliance control essential for reducing energy consumption. The household sector represents a major share of global energy demand, creating pressure on power grids. Consequently, optimal energy management has become essential, motivating the development of advanced technologies to lower costs and enhance system reliability. Smart homes equipped with energy management systems allow real-time decision-making, boosting efficiency and appliance performance. Although the smart home market is expanding rapidly, challenges such as high deployment costs and system complexity persist. The key contribution of this study is the integration of uncertainty modeling into smart home energy management. Unlike conventional deterministic approaches, this model accounts for variability in renewable energy generation, electricity prices, and household energy consumption, offering a more robust and realistic optimization framework. A dual-phase MILP framework is introduced, incorporating both day-ahead and real-time pricing schemes. Additionally, the operation of batteries in unpredictable scenarios is considered, and simulation outcomes indicate that real-time pricing reduces electricity costs by 10.5% compared to day-ahead pricing, highlighting the importance of dynamic decision-making in smart homes.

Energy management optimization in smart homes has been extensively explored through different frameworks that integrate sustainable energy generation, storage units, and electric mobility devices. HEMS utilize machine learning and artificial intelligence techniques to boost energy performance, cut expenses, and strengthen system reliability. Predictive methods, such as Markov chain modeling and supervised learning, optimize energy consumption by forecasting demand and dynamically scheduling appliances. Multi-objective optimization approaches enable bidirectional energy flow between vehicles and the home/grid, smoothing the load factor while maintaining user comfort. Off-peak scheduling strategies and the intelligent coordination of household appliances further reduce costs and lower energy consumption during peak hours. Moreover, hybrid renewable energy systems, incorporating solar, fuel cells, and storage technologies, ensure a reliable energy supply under varying weather conditions. Decision-making models leveraging data mining and AI facilitate energy trading and demand response, enhancing interactions between consumers and the grid. Within smart urban infrastructures, innovations in energy management, including IoT-based frameworks and distributed energy systems, improve sustainability, affordability, and resilience to power outages.

Furthermore, mathematical and stochastic models address the unpredictability in electricity prices, renewable energy output, and appliance operation, providing optimal scheduling strategies to balance cost and energy efficiency. Smart home energy management also considers economic factors, such as minimizing consumer costs and implementing incentive-based demand response programs, encouraging active participation in energy markets. Hybrid heating systems that integrate gas and electric sources further reduce costs and enhance efficiency compared to single-source systems. Advanced scheduling methods, including metaheuristic optimization algorithms, improve energy distribution and grid stability while lowering consumer expenses. Overall, such approaches enable more intelligent and flexible energy consumption models that balance efficiency, affordability, and environmental sustainability, while fostering greater consumer engagement in the evolving energy landscape.

In recent years, Demand Side Management (DSM) has gained significant attention as an effective strategy for enhancing energy efficiency and optimizing consumption behavior within smart grid systems. In this area, several studies have investigated the use of advanced metaheuristic optimization methods to improve DSM performance. For instance, one study utilized both the standard Beluga Whale Optimization (BWO) algorithm and its enhanced version to design an efficient DSM framework. In this model, consumers are actively involved in managing their energy usage by making decisions regarding buying, storing, or selling electricity based on real-time conditions. The system is structured around a residential microgrid that integrates photovoltaic (PV) panels, wind turbines, and an energy storage system (ESS), thereby addressing the variability of renewable energy sources. The results indicate that optimized scheduling can effectively lower electricity costs and reduce the peak-to-average ratio (PAR), while also allowing users to generate revenue under favorable conditions. These findings emphasize the role of intelligent optimization techniques in improving both economic outcomes and operational efficiency in smart home environments [9].

Another stream of research has examined how user consumption behavior and the integration of electric vehicles (EVs) affect power system reliability. In this approach, distributed generation (DG) based on renewable sources is combined with demand response (DR) programs at both the grid and consumer levels. Price-based and incentive-based DR strategies are employed to shift flexible loads according to real-time electricity prices, while certain non-essential loads may be curtailed when necessary to maintain system stability. A notable aspect of this work is the inclusion of various user behavior patterns and different EV types, providing a more realistic representation of demand. The findings show improvements not only in cost reduction but also in reliability metrics such as SAIDI and SAIFI, along with better utilization of renewable energy resources [10]. Moreover, Home Energy Management Systems (HEMS) have been extensively studied as a key element in smart homes, especially in scenarios involving local generation and storage. Previous research has introduced optimization frameworks that jointly consider PV systems, ESSs, and plug-in hybrid electric vehicles (PHEVs). One notable contribution proposes a multi-objective optimization model aimed at minimizing electricity costs, PAR, and unused PV energy. An enhanced differential evolution algorithm is applied to solve this problem. The results demonstrate that coordinated scheduling allows users to purchase electricity during low-price periods and consume or sell it during peak-price periods. This approach also significantly reduces renewable energy waste and improves overall system efficiency compared to traditional methods [11]. Despite these contributions, most existing studies rely on single-stage optimization frameworks under a fixed pricing scheme. To address this limitation, this paper proposes a bi-level (two-stage) optimal scheduling model for smart homes, where optimization is performed across two distinct stages with different pricing tariffs. This approach enhances flexibility and leads to more accurate decision-making in energy management. In addition, unlike many previous studies that adopt simplified appliance models, this work introduces a more detailed and realistic classification of household appliances based on their operational characteristics, resulting in improved modeling of energy consumption in smart homes.

In light of the preceding analysis, the key contributions of this paper are outlined below:

1. This study presents a two-step MILP model designed to reduce the energy expenses of a smart home, taking into account demand response programs, an electric vehicle that can supply power back to the home, a solar PV system, and a home battery storage system.
2. Incorporating uncertainty modeling in both renewable energy generation and electricity pricing, which is often overlooked in previous studies.
3. Comparing the electricity cost under real-time pricing and day-ahead pricing to analyze the economic benefits of real-time tariffs.
4. This study introduces a new way of grouping home appliances into three categories based on how they operate, including their energy use, timing, and temperature needs, which makes the optimization framework more realistic and applicable in practice. A comparison between the proposed method and existing approaches is presented in Table I. The comparison highlights the main differences and advantages of the proposed approach compared with previous studies.

II. Formulation

Optimizing and increasing home energy efficiency can be achieved mainly in two ways: 1) reducing total energy consumption or 2) shifting loads to off-peak periods, benefiting from domestic production and lower tariffs. While traditional approaches often rely on deterministic models, this study introduces a novel framework that incorporates uncertainty in renewable energy generation, electricity pricing, and household demand, making energy optimization more adaptive to real-world conditions. Unlike conventional models, which assume fixed electricity prices and perfect renewable energy generation forecasts, this study considers market fluctuations and stochastic variations in photovoltaic (PV) output. By including both a battery and an electric vehicle in a two-step optimization process, the system can make more flexible decisions and react to changes in energy prices and production.

The proposed MILP model helps reduce daily energy costs while considering uncertainties in solar generation, electricity prices, and household demand, and it allows energy to flow both to and from the grid as needed. The system components include a BESS, household appliances with varying levels of stimulability, a PEV, a PV system, a HEMS, and a dynamic pricing model incorporating real-time market updates. Household loads are categorized into entertainment loads (fixed and schedulable, e.g., TVs, …), bound loads (schedulable under constraints, e.g., air conditioning, water heating), and programmable loads (fully schedulable based on price variations, e.g., washing machines). The proposed model integrates real-time electricity prices, PV generation forecasts, outdoor temperature, hot water demand, and household energy consumption data into the HEMS, utilizing stochastic forecasts to mitigate uncertainty and optimize energy scheduling.

The key contributions of this research include a two-stage optimization process where, in the first stage, users submit hourly bids to the Day-Ahead (DA) market based on forecasted PV output, electricity demand, and market prices. In contrast, in the second stage, real-time energy adjustments are made every 15 minutes to correct imbalances, dynamically charging and discharging battery storage and EVs to account for deviations. Unlike traditional models that assume fixed solar power generation and electricity pricing, this study integrates probabilistic forecasts, applying stochastic methods to anticipate unexpected price fluctuations and renewable energy variations, enhancing system resilience against forecasting errors. Additionally, an intelligent charge/discharge strategy for EVs and batteries is implemented to dynamically schedule charging and discharging based on real-time pricing and household demand, ensuring sufficient EV battery charge for daily travel while maximizing cost savings, and allowing batteries to discharge when electricity prices peak or local demand exceeds supply, optimizing energy balance. Fig. 2 illustrates the operation of the proposed two-stage optimization plan, showing the decision-making process at each stage.

In managing energy consumption in a smart home, electrical devices are classified into three groups according to their usage flexibility: entertainment loads, bound loads, and scheduled loads [12,13].

1. Entertainment Loads: These appliances, like telephones, consume a fixed amount of electricity and must always be connected. They operate continuously from 08:00 to 08:00 the following day.
2. Bound Loads: These can be scheduled throughout the day without compromising comfort. They also operate from 08:00 to 08:00 the following day, but are subject to certain restrictions. Examples include air conditioning systems and water heaters.
3. Scheduled Loads: These are not mentioned explicitly in the provided text, but would be appliances that can be scheduled entirely based on optimal energy use strategies. The overall structure and main components of the smart home system are illustrated in Fig. 1. This figure provides an overview of the interactions among different elements within the proposed smart home architecture.

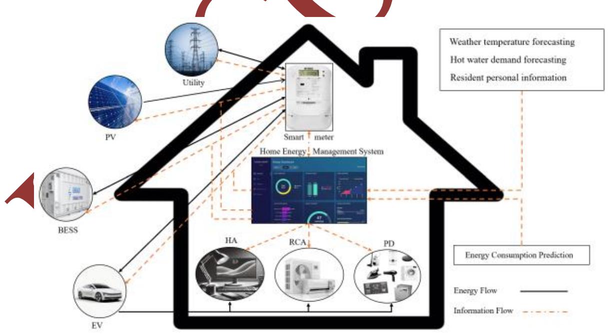

Fig. 1. The structure of a smart home Article.

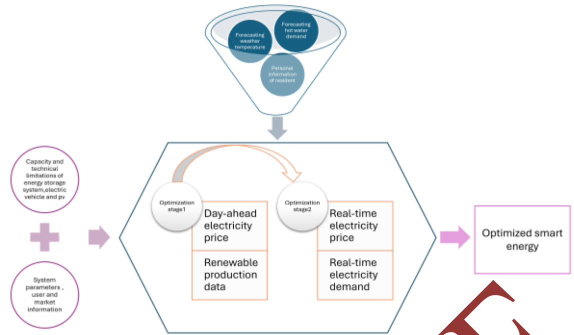

Fig. 2. Suggested two-step optimization structure – diagrammatic representation

A . Conditioning system model

In this model, the air temperature inside the building in each time period is calculated, derived from the subsequent (1):

$$\theta^{\text{in}}(t) = \theta^{\text{in}}(t-1) + \chi\left(\theta^{out}(t) - \theta^{\text{in}}(t-1)\right) + \vartheta P_{AC}(t)\Delta t \quad (1)$$

In this regard, $\theta^{\text{in}}(t)$ is the current temperature inside the building, $\theta^{\text{in}}(t-1)$ is the temperature of the previous moment, χ is the coefficient of heat transfer between the outside environment and inside the building, $\theta^{\text{out}}(t)$ is the current temperature outside the building, ϑ is the thermal efficiency of the system, which will be negative if the system is cooling and positive if the system is heating. P_{AC} is the power consumption of the conditioning, and Δt is the duration.

B. Limitations of the conditioning system

Two limitations for optimizing power consumption have been considered: Eq. (2) is related to the temperature inside the building being in the comfortable range, and Eq. (3) corresponds to the peak capacity of the conditioning system.

$$\theta_{AC}^{min} \leq \theta^{\text{in}}(t) \leq \theta_{AC}^{max} \quad (2)$$

$$P_{AC}(t) \leq P_{AC}^{max} \quad (3)$$

C. Electric water heater model

The following relationship calculates the water temperature inside the water heater at any moment:

$$\theta^{hw}(t) = \theta^{hw}(t-1)e^{-\left(\frac{1}{R'.C}\right)\Delta t} + \{G.R'.\theta^{en} + B.R'.\theta^{cw} + Q(t).R'\} \quad (4)$$

in which $\theta^{\text{hw}}(t)$ is the hot water temperature in the current period, $\theta^{\text{hw}}(t-1)$ is the temperature of hot water in the previous period, θ^{hw} is the cold water input, and θ^{en} is the temperature of the surrounding environment. Also, $Q(t) = 3.41121 * 10^{3*} P_{\text{EWH}}$ is the electric energy input of the electric water heater, and P_{EWH} is the input power electricity of the electric water heater. Other coefficients are electric water heater parameters which are defined as follows: R: Thermal resistance of the tank, SA: The area of the tank wall, V: tank volume, F: Outlet hot water flow rate, $G = SA/R$, $C = V * 8.34 * C_{\text{p}}$, $R' =$

$1/(G+B)$, $B = 8.34 * F * C_P$, where 8.34 is the density of water, and C_P is the specific heat of water.

D. Limitations Belonging to the Electrical Hot Water Generator

The two limitations of the Electrical hot water generator are the same as those of the conditioning system. Eq. (5) is considered to keep the temperature within the desired range, and Eq. (6) is used to set the maximum power of the electric water heater.

$$\Theta_{EHW}^{min} \le \Theta^{hw}(t) \le \Theta_{EHW}^{max} \quad (5)$$
$$P_{EWH}(t) \le P_{EWH}^{max} \quad (6)$$

E. *Modeling the energy storage system*

An energy storage system refers to a set of batteries that can store electricity and deliver it to other devices or the main network when needed. The power storage unit in this article is modeled in the next way by using the remaining charge at any moment, which is directly related to its charge or overall discharge:

$$C_{BESS}(t) = C_{BESS}(t-1) + P_{BESS}^{ch}(t)u_{BESS}(t)\Delta t\eta_{BESS}^{ch} + P_{BESS}^{dis}(t)\left(1-u_{BESS}(t)\right)\Delta t/\eta_{BESS}^{dis} \quad (7)$$

In this context, the first equation represents the energy storage system's capacity at the previous time step, the second equation indicates the charging power of the system, and the third equation reflects its discharging capacity.

Also, C_{ESS} represents the capacity of the energy storage system (kWh), P_{BESS}^{dis} is the discharge power of the energy storage system (kW), P_{BESS}^{ch} is the charging power of the energy storage system (kilowatts), u_{ESS} is a binary variable that indicates the charge/discharge status of the energy storage system (1 if the energy storage system is charged, 0 otherwise), η_{BESS}^{ch} is the charging efficiency of the energy storage system, and η_{BESS}^{dis} is the discharge efficiency of the energy storage system. The charging and discharging phases are divided as follows:

$$P_{BESS}(t) = P_{BESS}^{ch}(t)u_{BESS}(t) + P_{BESS}^{dis}(t)\left(1-u_{BESS}(t)\right) \quad (8)$$

In this context, the first term refers to charging the energy storage system, while the second term refers to discharging it.

F. Energy reserve system limitations

The energy Reservoir or the battery has technical limitations. The constraints belong to the energy storage unit; they are linked to the maximum filling and emptying capacities, along with the percentage range pertaining to the framework charge.

$$0.2C_{ESS}^{max} \le C_{ESS}(t) \le 0.8C_{ESS}^{max} \quad (9)$$

$$0 \le P_{ESS}^{ch}(t)\eta_{ESS}^{ch} \le P_{ESS}^{chmax} \quad (10)$$

$$P_{ESS}^{dismax} \le P_{ESS}^{dis}(t)/\eta_{ESS}^{dis} \le 0 \quad (11)$$

Eq. (9) is tied to the charging percentage range of the energy Reservoir system, which should be between 20% and 80% of the maximum storage potential of the energy unit. Eq. (10) pertains to the peak energy input linked to the storage system unit, and Eq. (11) is related to the maximum discharge power associated with the energy storage system.

G. *Electric car modeling*

The electric car also utilizes a battery with a relatively large capacity. Therefore, in this paper, the electric car is modeled similarly to the energy reserve system, with the distinction that the vehicle can only be utilized when it is at the residence. The time frame is considered from morning to the following day after midday if the energy storage battery is continuously used within the residential energy control system. Below, the power and capacity of the electric car are presented:

$$P_{PEV}(t) = P_{PEV}^{ch}(t)u_{PEV}(t) + P_{PEV}^{dis}(t)\left(1-u_{PEV}(t)\right), t \in [t_a, t_d) \quad (12)$$

The first component pertains to the power used to charge the electric vehicle, while the second component corresponds to the power used to discharge it.

$$C_{PEV}(t) = C_{PEV}(t-1) + P_{PEV}^{ch}(t)u_{PEV}(t)\Delta t\eta_{PEV}^{ch} + P_{PEV}^{dis}(t)\left(1-u_{PEV}(t)\right)\ \Delta t/\eta_{PEV}^{dis}, t \in [t_a, t_d) \quad (13)$$

The first term corresponds to the electric vehicle's capacity at the previous time step, the second term represents the charging power of the electric vehicle, and the third term reflects the discharging power of the vehicle. Here, C_{PEV} denotes the electric vehicle's capacity (kWh), P_{PEV}^{ch} is the charging power of the electric vehicle (KW), u_{PEV} is a binary variable indicating the charge/discharge status of the electric vehicle (1 if the electric car is charged, 0 otherwise), η_{PEV}^{dis} represents the discharge efficiency of the electric vehicle, η_{PEV}^{ch} indicates the charging efficiency of the electric vehicle, and P_{PEV}^{dis} is the discharge power of the vehicle (kW). Additionally, t_a is the time when the car arrives at home, while t_d represents the time the car leaves home.

H. Electric car limitations

The constraints are the same as those of the energy storage system, as described below, except that in the final period, the electric car must be fully charged before leaving the house, with a charge level of at least 80% in this case.

$$0.3C_{PEV}^{max} \le C_{PEV}(t) \le 0.8C_{PEV}^{max}, t \in [t_a, t_{d-1}) \quad (14)$$

$$0.8C_{PEV}^{max} \le C_{PEV}(t) \le C_{PEV}^{max}, t = t_d - 1 \quad (15)$$

$$0 \le P_{PEV}^{ch}(t)\eta_{PEV}^{ch} \le P_{PEV}^{chmax}, t \in [t_a, t_d) \quad (16)$$

$$P_{PEV}^{dismax} \le P_{PEV}^{dis}(t)/\eta_{PEV}^{dis} \le 0, t \in [t_{a,} n] \quad (17)$$

TABLE I. Comparison of Existing Methods in the Literature

	Reference	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	Proposed Approach
Object	Maximizing the level of user comfort	✓	✓	×	×	✓	✓	×	×	×	×	×	×	×	✓	×	×	×	×	×	×	✓
	Minimize pollution	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×
	Minimizing the ratio of peak load to the average network	×	×	×	×	✓	×	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	×
	Minimizing electricity costs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Other	×	×	×	✓	✓	×	×	×	×	✓	✓	✓	×	×	×	×	×	×	✓	✓	✓
Solution method	Mixed Integer Linear Programming	✓	✓	×	✓	✓	✓	✓	×	×	×	×	✓	✓	✓	✓	×	×	✓	✓	×	✓
	linear programming	×	×	✓	×	×	×	×	✓	×	×	×	×	×	×	×	×	×	×	×	×	×
	Non-linear programming	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×
	Heuristic and meta-heuristic algorithms	×	×	×	×	×	×	×	×	×	✓	✓	✓	×	×	×	✓	✓	×	×	✓	×
	Other	×	×	×	×	×	×	×	×	✓	×	×	×	×	×	×	×	×	×	×	×	×
The main components of the smart grid	electricity network	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	renewable resources	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Electric vehicle	✓	✓	×	×	×	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	✓	✓	✓
	Energy storage system	×	✓	×	×	✓	✓	✓	✓	×	×	×	✓	✓	✓	×	×	×	×	✓	✓	✓
	Other	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Limitations	Electricity purchase and sale tariff	×	×	×	×	×	✓	✓	✓	✓	×	×	✓	✓	✓	✓	×	×	✓	✓	✓	✓
	Energy balance	×	×	×	✓	×	×	✓	×	×	✓	×	×	×	×	✓	✓	×	×	×	×	✓
	Limitation of heating and cooling	×	×	×	×	×	✓	✓	✓	✓	✓	✓	×	×	✓	✓	✓	×	×	×	×	✓
	Restrictions on household appliances	✓	✓	✓	✓	✓	✓	✓	×	×	×	×	✓	✓	✓	✓	✓	✓	✓	×	×	✓
	Battery charge and discharge rate	✓	×	×	×	×	✓	✓	✓	✓	×	×	×	✓	✓	✓	×	×	×	×	✓	✓
	Other	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Eq. (14) is related to the allowed range of electric vehicle charging percentage in the mentioned time, which should be between 30% and 80% of the maximum capacity of the electric vehicle. Eq. (15) is related to the percentage range of electric vehicle charging at another time, which should be between 80% and 100% of the electric vehicle's maximum capacity. Eq. (16) is associated with the peak charging capacity of the electric vehicle, and Eq. (17) is associated with the peak discharging capacity of the electric vehicle. In the last relation, the value n is obtained using a special algorithm described in [12,13].

I. Three Scenario-Based Stochastic and Robust Optimization Approaches for Home Energy Management with Variable PV Generation and Electricity Prices

In this study, to account for uncertainty within the home energy management model, a stochastic optimization approach is proposed that incorporates multiple scenarios for the uncertain parameters. Instead of relying on a single deterministic value for photovoltaic (PV) generation and electricity prices, several distinct scenarios are generated to reflect varying outcomes: a Sunny Day (with high PV output and low grid dependency), a Cloudy Day (moderate PV output and moderate grid dependency), and a Rainy Day (low PV output and high grid dependency). Each scenario is assigned a probability based on historical data, allowing the optimization model to determine a schedule that minimizes the expected cost across all scenarios.
Moreover, three distinct scenarios were analyzed, in which the PV generation and real-time electricity prices vary. These scenarios account for fluctuations in solar energy production and electricity prices, allowing the optimization model to effectively minimize costs and optimize the home energy management system's performance, even under changing conditions. In this article, the amount of installed solar panel capacity and the electricity purchase price for each time period of the day are predetermined and provided as inputs to the optimization algorithm. The total power purchased during each time period is then calculated as follows:

$$P_G(t) = P_E(t) + P_{AC}(t) + P_{EWH}(t) + \sum P_d(t)u_d(t) + P_{ESS}(t) - P_{DG}(t) \quad (18)$$

In here P_d is the power consumption of the programmed appliances, P_{DG} Production of renewable energies (kilowatts), u_d is a binary variable that shows the on/off state of the programmed appliances (1 on, 0 off), P_{EWH} Electricity consumption of electric water heater(kilowatts), P_{AC} Air conditioning electricity consumption (kW), P_G The power of interaction between the power supply network and the home energy management system(kilowatts).
The goal equation of reducing the expense of buying electric power during a day is defined as follows:

$$P_G(t) = P_E(t) + P_{AC}(t) + P_{EWH}(t) + \sum P_d(t)u_d(t) + P_{ESS}(t) - P_{DG}(t) \quad (19)$$

In the end, the objective function is defined as follows:

$$Min\ cost\ = P_G(t) * \prod RTP\ *\ dt \quad (20)$$

In this article, the selling price of the additional power from the solar panel to the grid is assumed to be half of the RTP. To address uncertainty and enhance operational accuracy, a two-stage optimization framework is incorporated into the objective function. The first stage minimizes the day-ahead expected energy cost based on forecasted data, while the second stage minimizes real-time deviations and adjustment costs by adapting to actual prices and PV generation. This combined objective ensures both optimal scheduling and robust performance under uncertainties.

III. SIMULATION RESULTS

In this research, to enhance the precision of the planning model, the time frame for the first stage is set to 24 hours, with each time slot being 15 minutes long. For the second stage, while the overall time horizon remains 24 hours, each time period is extended to 60 minutes. The model encompasses a full 24-hour cycle, with the first stage consisting of 96 intervals and the second stage containing 24 intervals. In this setup, electricity sold back to the grid is priced at half the market rate, and the home can draw up to 5 kW from the grid at most. The MILP model used for managing home energy is tested on a laptop with an Intel Core i5-4200U processor, running a 64-bit version of Windows 10. The simulation utilizes MATLAB R2021, CPLEX, and YALMIP for programming and solving the model. Technical and operational details for the electric vehicle, energy storage system, electric water heater, and air conditioning system are provided in Table II. In contrast, Table III outlines the appliance scheduling strategy employed in this study.
The sources of uncertainty in this research include variations in photovoltaic (PV) generation, real-time electricity pricing, and fluctuations in load demand. PV generation is affected by weather patterns, seasonal changes, and shading, introducing unpredictability in energy availability. Electricity prices also vary due to market dynamics, demand shifts, and regulatory changes, which impact cost optimization strategies. Furthermore, household electricity consumption patterns depend on user preferences, occupancy, and appliance usage, making it crucial to account for these variations to optimize scheduling and minimize costs effectively. This case study looks at a home equipped with several technologies, including household appliances, a smart meter, rooftop solar panels, an electric vehicle, and a battery storage system. Solar generation data comes from ENTSO-E, and the analysis assumes the panels are installed on the roof. The main goal is to find the best energy trading strategies for a home that uses renewable energy, a battery, and an EV, considering both day-ahead and real-time electricity markets. In this setup, the battery and EV are the main tools for meeting the household’s energy needs. The problem is modeled as a two-step optimization that considers both energy demand and electricity prices, aiming to lower costs and reduce battery wear. The results show that by managing the EV and battery efficiently, the household can significantly increase its profitability by making the most of renewable generation. Although this study focuses on a summer scenario, the same approach could easily be applied to other seasons, such as winter, spring, and autumn.

TABLE II.

Additional Related Factors.

ESS parameters		PEV parameters	
$C_{ESS}^{max}(kWh)$	8	$C_{PEV}^{max}(kWh)$	30
$C_{ESS}^{int}(kWh)$	3.5	$C_{PEV}^{int}(kWh)$	12
$P_{ESS}^{chmax}(KW)$	3	$P_{PEV}^{chmax}(KW)$	4
$P_{ESS}^{dismax}(KW)$	-3	$P_{PEV}^{dismax}(KW)$	-4
$\eta_{ESS}^{ch}/\eta_{ESS}^{dis}$	0.92	$\eta_{PEV}^{ch}/\eta_{PEV}^{dis}$	0.92
$RTP_{ESS_{dis}}$	1.1 RTP_{AVG}	$RTP_{PEV_{dis}}$	1.18 RTP_{AVG}
Factors for calculating indoor temperature		Factors for calculating hot water temperature	
$T_{AC}^{max}(°F)$	80	$T_{EWH}^{max}(°F)$	130
$T_{AC}^{min}(°F)$	73	$T_{EWH}^{min}(°F)$	120
$T_{in}^{int}(°F)$	77	$T_{hw}^{int}(°F)$	70
α	0.9	$T^{cw}(°F)$	70
β	-11	$T^{en}(°F)$	80

TABLE III

Domestic Appliance Parameters.

Bar	Appliances	Max power (kW)	Min power (kW)	Start time	End time	Run Time (h)
HA	Light Phone Computer	1	1	08:00	08:00	24
RCA	Air Conditioning	3	0	08:00	08:00	24
	Electric Water heater	3.5	0	08:00	08:00	24
PD	Washing machine	1.5	1.5	09:00 10:00	22:00 23:00	1(wash) 2(dry)
	Dishwasher	1.2	1.2	10:00 18:00	15:00 22:00	2
	Hairdryer	1.8	1.8	08:00	23:00	0.25
	Vacuum cleaner	1.2	1.2	14:00	18:00	0.5
	iron	0.8	0.8	10:00 16:00	12:00 19:00	0.75
	Oven	2	2	10:00	19:00	2
	Humidifier	0.15	0.15	08:00	24:00	4
	Robot Vacuum cleaner	0.7	0.7	08:00	24:00	5

A. Case studies

The solar energy generation installed on the roof of the house is shown in Fig. 5. Since this research focuses on a single household, the photovoltaic output is relatively small, and the data is measured in kilowatts. Figs. 3 and 4 provide real-time and day-ahead electricity pricing data. As shown in Fig. 6, the home's indoor temperature is kept between 73°F and 80°F, and the hot water system stays within 120°F to 130°F so that all comfort requirements are met. The smart home controller then decides when appliances should run, how the EV and battery should be used, and how charging or discharging should be planned under both day-ahead and real-time electricity prices. Fig. 7 shows how the appliances are scheduled efficiently when day-ahead pricing is applied, Where the majority of appliances operate between 12:00 and 15:00, taking advantage of the peak photovoltaic output (Fig. 5) and the lowest electricity rates (Fig. 3). The system ensures that the maximum power consumption of 14 kW is met through a combination of grid electricity and solar energy, without exceeding any power limits. Fig. 8 shows that solar energy is first allocated to household appliances, followed by charging the energy storage system, with any surplus energy being sold to the grid (Fig. 9). The EV arrives at 18:30 and leaves at 07:30. Due to nearly zero solar generation at this time, it is primarily charged using grid electricity, maximizing the use of renewable energy and reducing costs. The energy storage system discharges strategically during high-price periods, such as 08:30, 09:45, and 17:00, while during high solar output periods (e.g., 12:30 and 15:30), there is no need for further discharge. By 20:00, the battery reaches its minimum capacity, ensuring that no surplus energy remains by the end of the day. Fig. 9 shows how the EV helps discharge the battery during peak periods (e.g., 20:00 and 23:00), lowering electricity costs, while its selective charging during low-price periods further optimizes overall expenses. The established charge/discharge limits for both the EV and the energy storage system minimize battery cycling, thereby extending the lifespan of the batteries.

Fig. 10 illustrates the interaction between the HEMS and the grid, where electricity is sold during high-price periods for profit and purchased during low-price periods to avoid peak demand challenges. Under real-time pricing, Fig.11 shows optimized appliance scheduling with a maximum power draw of 10 kW, reducing appliance operation overlaps and prioritizing user comfort despite slightly higher costs. Fig. 11 illustrates that at 13:00, PV output peaks (Fig.5), and electricity prices reach their lowest point (Fig.4), making it the most cost-effective time for appliance operation. However, when appliance operation time is restricted, this peak disappears. Between 19:00 and 08:00, since PV output is zero, only fixed and bound loads remain operational. Fig.12 presents the EV charge-discharge cycle, indicating that from 18:00 onwards, excess stored energy is used for household electricity, and the EV discharges until it reaches its minimum capacity. From 01:00 to 07:00, the EV charges during low-consumption hours, reducing electricity costs while ensuring full readiness for travel.

B. Importance of uncertainty modeling

To assess the effectiveness of uncertainty modeling, three distinct scenarios with varying photovoltaic (PV) generation and real-time electricity prices are examined. These scenarios encompass: (1) a Sunny Day (characterized by high PV output and low grid reliance), (2) a Cloudy Day (with moderate PV output and moderate grid reliance), and (3) a Rainy Day (featuring low PV output and high grid dependence). The findings indicate that the stochastic model yields lower expected costs compared to the deterministic approach, while the robust model guarantees enhanced reliability under extreme conditions. This highlights the crucial role of integrating uncertainty into home energy management, as it significantly improves cost-efficiency, system flexibility, and overall resilience, making it a vital consideration in developing optimal energy management strategies.

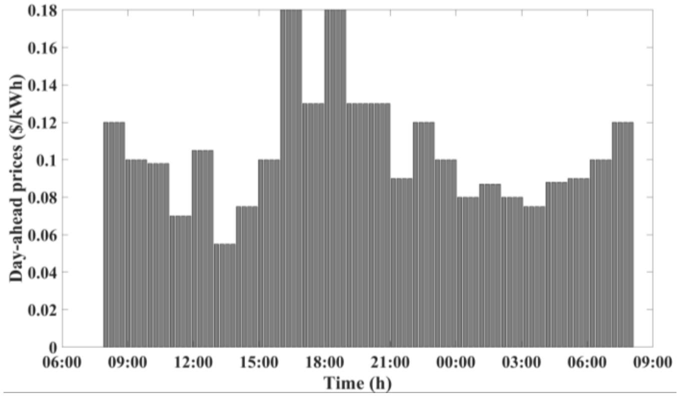

Fig. 3. Day-ahead pricing

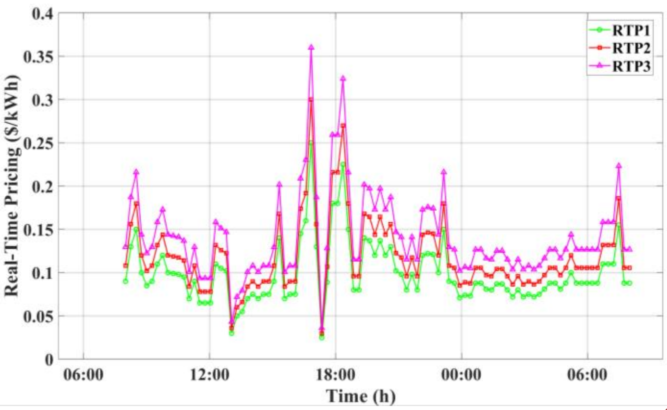

Fig. 4. Real-time pricing

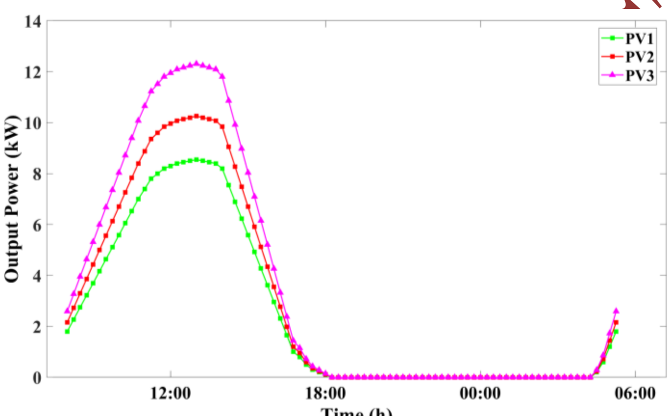

Fig. 5. PV generation

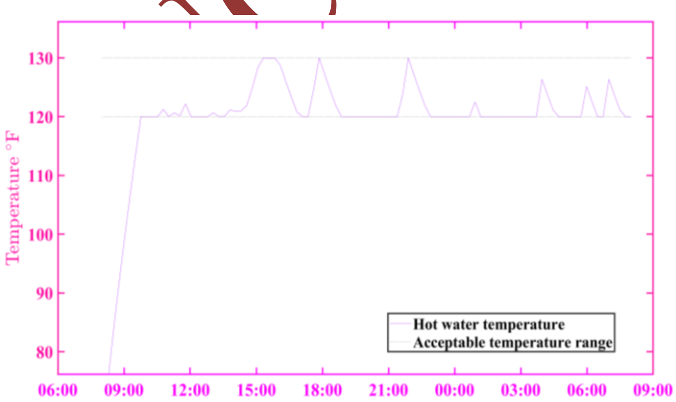

Fig. 6. The temperature of the hot water achieved through optimal scheduling

C. Simulation results under day-ahead pricing

This article examines the optimization of smart home appliances, an electric vehicle with home-connection capability, an energy storage system, and charge and discharge strategies for these systems under day-ahead and real-time pricing. Key findings include:

Fig.7 shows the optimal timing plan for Domestic devices under the next-day tariff .The optimal timing plan for domestic devices under next-day pricing shows that tasks are performed during peak photovoltaic output and low electricity price periods (12:00 to 15:00), without violating power consumption restrictions. Photovoltaic production primarily supplies household appliances, then charges the energy storage system, and any Surplus power is traded with the provider. In Figs. 7 and 8, the electric vehicle arriving home in the evening is charged primarily from the power network due to low photovoltaic production at that time. The energy storage system releases energy during high-price intervals to cover insufficient energy demand, while the electric vehicle assists during peak periods to reduce electricity costs. The discharge price threshold reduces battery cycles, extending battery life.

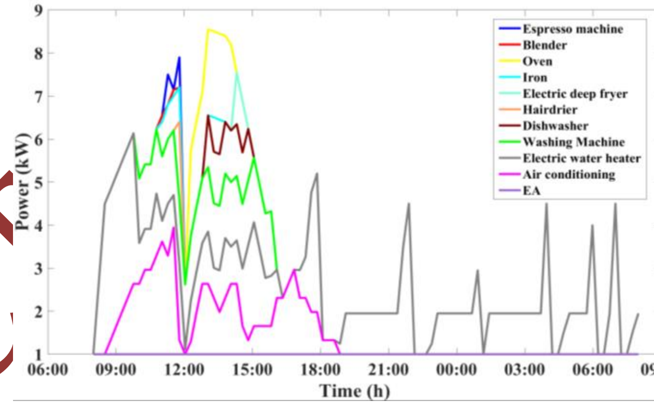

Fig. 7. The timetable for household devices in the first stage.

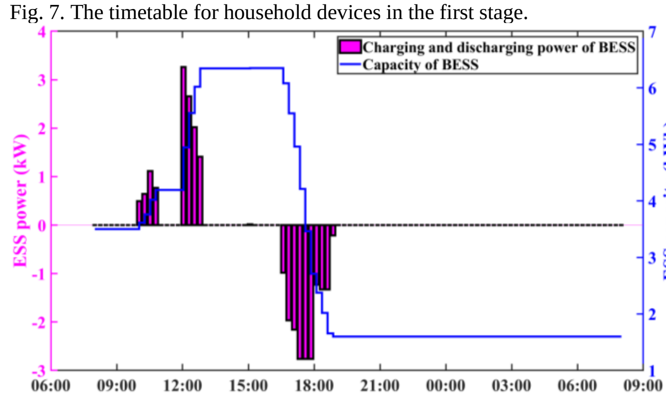

Fig. 8. Energy Incoming and outgoing power and capacity of ESS in the first stage.

The power transferred between the household energy control system and the electrical grid in the initial phase is depicted in Fig. 7. The power exchanged among the household energy control system alongside the electrical grid fluctuates with price, optimizing for profit. The model, implemented on a laptop with an Intel Core i5 processor using MATLAB, CPLEX, and YALMIP, shows that under day-ahead pricing, the cost of energy supply is 3.55$, with the optimal solution reached in approximately 13,107 seconds.

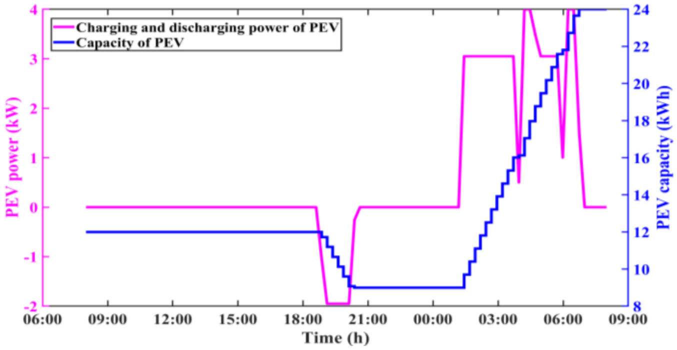

Fig. 9. Energy incoming, outgoing power, and storage capacity of plug-in electric vehicle in the first stage.

The power transferred between the household energy control system and the electrical grid in the initial phase is depicted in Fig.10. The power exchanged between the household energy control system and the electrical grid fluctuates with price, optimizing for profit. The model, implemented on a laptop with an Intel Core i5 processor using MATLAB, CPLEX, and YALMIP, shows that under day-ahead pricing, the cost of energy supply is 3.55$, with the optimal solution reached in approximately 13,107 seconds.

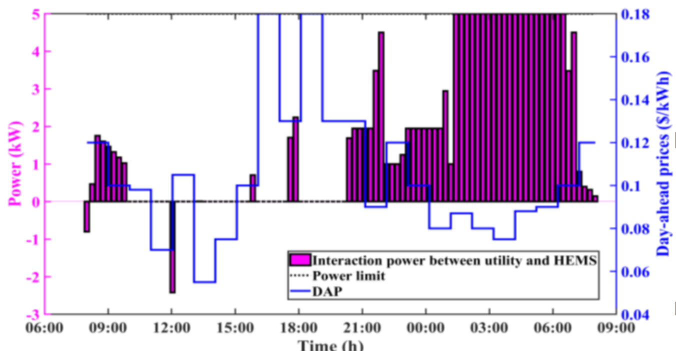

Fig. 10. Power exchange between utility and HEMS in the first stage.

D. Simulation results under real-time pricing

Fig.11 presents the optimal scheduling plan for household appliances under real-time pricing. The maximum power taken from the grid and photovoltaic system is limited to 10 kilowatts, reducing overlapping appliance usage times for consumer comfort but increasing costs. Household appliances primarily operate during peak photovoltaic output and low electricity prices at 13:00. Fig. 13 details the electric vehicle's charging and discharging schedule, starting from 18:00, optimizing home electricity supply and reducing costs by charging during low-consumption periods (01:00 to 07:00). The energy supply cost is 3.21$, with the suggested MILP framework achieving the best solution in roughly 10,997 seconds. The comparative results are presented in Table II.

TABLE IV
Comparing Results

Cost (dollars)	
Optimization under the first stage	**Optimization under the second stage**
3.5543	**3.2151**

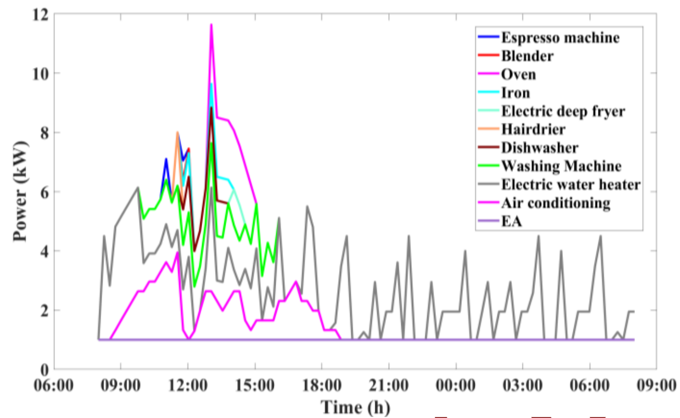

Fig. 11. The timetable for household devices in the second stage.

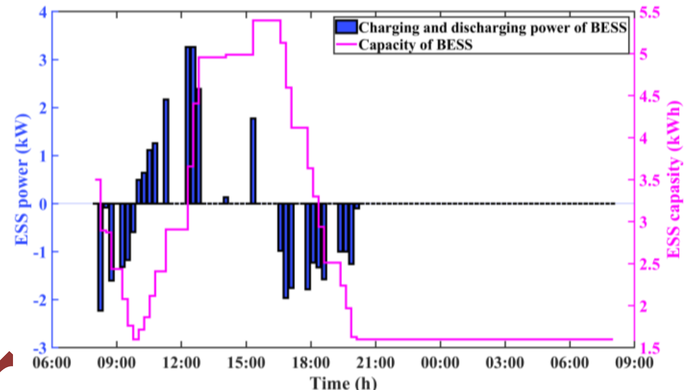

Fig. 12. Energy input and output power and storage capability of energy storage devices during the subsequent phase.

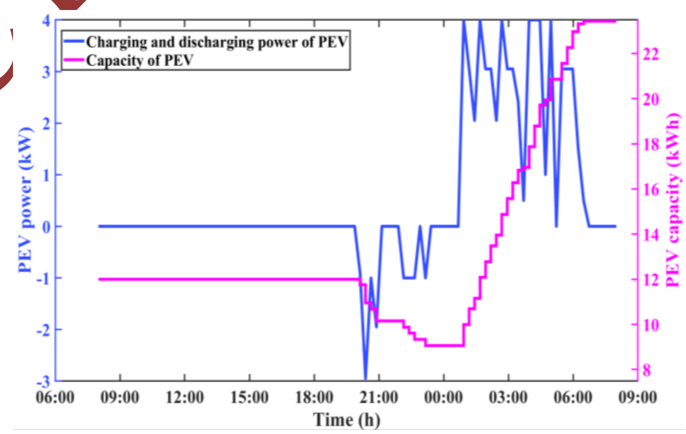

Fig. 13. Energy inflow and outflow and storage volume of PEV during the subsequent phase.

This section compares the energy costs across three distinct scenarios, each featuring varying real-time electricity prices and levels of photovoltaic (PV) generation. These scenarios are designed to test how changes in energy prices and PV output influence cost-minimization strategies. By analyzing these different scenarios, the study assesses how adaptive energy management can be while incorporating the variability of renewable power generation and the volatility of electricity market prices.The power exchange between the utility grid and the home energy management system during the second stage is illustrated in Fig. 14. This figure demonstrates the interaction between the home energy management system and the utility grid, as well as the amount of exchanged power within the second-stage optimization process.

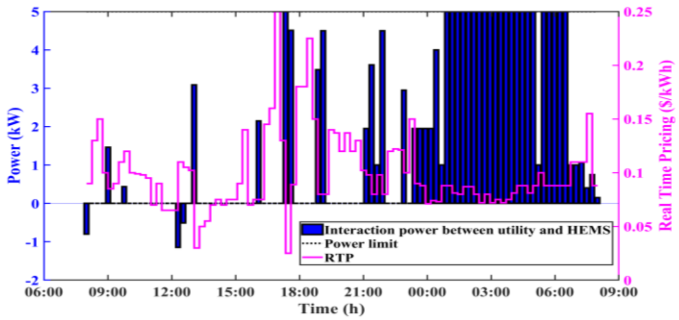

Fig. 14. Power exchange between the utility and home energy management system in the second stage.

In this study, real-time electricity pricing (RTP) is modeled using dynamic market data from the ENTSO-E platform, with prices updated at short time intervals to reflect real-time supply-demand balance and renewable generation variability. Since future electricity prices are inherently uncertain, the proposed framework adopts a two-stage optimization approach. In the first stage, scheduling decisions are made based on forecasted values of electricity prices, photovoltaic (PV) generation, and load demand. In contrast, in the second stage, these decisions are adjusted in real time using updated information. This structure enables efficient system operation without requiring perfect knowledge of future prices. Furthermore, uncertainties in PV generation, electricity prices, and demand are incorporated through scenario-based stochastic modeling, including different conditions such as sunny, cloudy, and rainy days. The effectiveness of the proposed model is evaluated by analyzing its performance across different scenarios, demonstrating improved cost efficiency and operational reliability, particularly under favorable conditions such as sunny days with higher PV generation.

IV. Conclusions and Future Research Directions

In this work, the smart home's energy behavior is examined using a two-stage MILP model that manages different household devices along with a PV unit, an electric vehicle with V2H support, and a battery system under both day-ahead and real-time electricity prices. Unlike many previous studies, the method here separates the decision process into two phases, enabling the model to respond more effectively to changes in solar generation, electricity price fluctuations, and variations in home energy use. This makes the results more practical for real-world applications. Another contribution of this study is that it organizes home appliances into clearer categories based on how they operate, how flexible they are in scheduling, and how much energy they consume. The results show that real-time pricing can reduce the total electricity bill by about 10.5% compared to day-ahead pricing, which highlights how dynamic pricing can benefit homeowners. There are also several directions for improving this work. For example, the uncertainty model can be expanded by adding factors such as changes in grid demand or by including additional distributed energy sources, such as small wind units or fuel-cell systems. Different pricing approaches can also be tested, such as TOU tariffs, event-based peak pricing, or mixed structures, to see how they influence energy costs. Finally, although this study focuses on one house, the same idea can be scaled up to groups of homes, where neighbors can share energy or coordinate their usage to improve overall efficiency. The general conclusion is that considering uncertainty in the optimization stage makes smart home energy management more flexible, reliable, and cost-effective. Future research could also examine cooperative energy trading and better forecasting methods to bring the model closer to practical deployment.

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