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Smart Home Power Management in The Presence of Electric Vehicle to Reduce Operating Costs

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Abstract

In recent years, the increase in electricity consumption in the household sector and the increase in the purchase price of electricity have led to the creation of an energy management system in smart homes. The smart home energy management system schedules the equipment for the next 24 hours. This paper examines a smart home that incorporates new technologies like interruptible loads, electric vehicles, energy storage systems, renewable energy sources, and smart devices. In this paper, the smart home energy management system, knowing its consumption needs and the current price of electricity in the electricity market, provides the power it requires by purchasing from the power grid or using the production power of renewable energy resources. Additionally, the smart home energy management system can sell its excess production power to the grid in a few hours. This paper aims to reduce the operating costs of a smart home during the day, and it has done so in several different scenarios. The effect of charging and discharging electric vehicle, energy storage system, and renewable energy resources in reducing costs has been investigated in these scenarios. The effectiveness of the proposed plan is checked in a typical house during 24 hours. With the implementation of smart home energy management programs, the operating cost decreased from 2.575 to 0.492 during 24 hours. Also, by checking the performance of the equipment at the time of planning, the efficiency of the model is proven.

Keywords: optimization, smart home energy management system, electric vehicle, renewable energy resources
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1. Introduction

Environmental concerns, fossil fuel limitations, and pollution are among the most important challenges facing today's society. Transitioning from traditional distribution networks to smart grids is considered a solution to these challenges. The adoption of smart homes as components of smart grids has been accelerating in recent years. Ideally, a smart home includes a Smart Home Energy Management System (SHEMS), renewable energy sources (RES), controllable and uncontrollable loads, an electric vehicle, an energy storage system (ESS), a smart meter, and communication infrastructure [1].

However, energy management in a smart home poses an optimization problem with extensive technical and economic constraints that must be properly modeled and solved. Furthermore, local electricity markets are developing rapidly within the smart grid. Consumers can purchase electricity from these markets at varying prices throughout the day. Given that a smart home consists of various controllable and uncontrollable loads, the amount of electricity purchased from the local market or grid depends on the controllability of these loads and common economic and non-economic motivations. Consumers can also sell the electricity produced by their renewable energy sources back to the grid.

Reducing the operational costs of a smart home and increasing income from electricity sales are important objectives in smart home energy management. The SHEMS plays a crucial role in the smart grid by managing demand on the consumer side and optimizing energy usage[2].

The integration of a SHEMS with household appliances allows interruptible loads to be scheduled for use during off-peak hours when electricity prices are lower, thereby reducing household electricity costs. Given their important role in serving both consumer interests and the power grid, SHEMS are tasked with making decisions and coordinating the operation of household appliances.

SHEMS is an ideal system that monitors and manages electricity output, storage, and consumption in smart homes. By utilizing home network communication and sensing technologies, SHEMS can collect energy consumption data from home appliances and provide real-time remote monitoring and control of smart home devices. Furthermore, SHEMS can provide energy storage and management services for RES and ESS.

Extensive research has been conducted on the use of SHEMS for various purposes, including design, operation, market participation, communication infrastructure, and the utilization of renewable resources. Each of these topics is examined below:

- Operation of the Smart Home:
    - Optimization of Energy Consumption: Research on methods to reduce energy consumption.
    - Data Analysis: Use of data to improve performance and increase the comfort of residents [3].
- Participation in Local Markets:
    - Load Flexibility and Energy Trading: Investigating how smart homes can participate in local energy markets to sell excess electricity produced or reduce load during peak consumption times.
    - Energy Management Systems: Developing systems for better management of energy resources at home [4].
- Communication Infrastructures:
    - Internet of Things (IoT): Research utilizing IoT technologies to connect and coordinate devices in smart homes.
    - Cybersecurity: Examining methods to secure data and devices in smart home environments [5].
- Smart Home Design:
    - Ergonomics and Design: Developing solutions to enhance the comfort and efficiency of smart homes.
    - Continuous Evolution: Exploring the evolution of smart home technologies and their impact on design and performance [6].
- Renewable Energy Resources in the Smart Home:
    - New Technologies: Implementing solar, wind, and other renewable resources in homes.
    - Systems Integration: Research on integrating these resources with existing systems to increase efficiency and reduce environmental impacts [7].

These research topics contribute significantly to the advancement of smart home technologies and play an important role in improving the quality of life while reducing environmental impacts. Each of these fields presents exciting and important opportunities for researchers and scientists. Overall, the main contributions of this paper can be outlined as follows:

- Integration and coordination of equipment, including interruptible and non-interruptible loads, and RES, by the SHEMS.
- Development of an optimal schedule using a SHEMS for a smart home equipped with various types of residential appliances, which involves determining the on/off status of loads and scheduling the charging and discharging times for electric vehicle and energy storage system.
- Considering the comfort of smart home residents during the scheduling process.
- Utilizing the charging and discharging capabilities of EVs and ESS to supply the electricity needed by homes during specific time intervals.
- Enabling the smart home to buy electricity from or sell electricity to the utility company.
- Achieving optimal operational cost for the smart home by prioritizing cost minimization.

The paper is organised as follows: Section 2 reviews similar works; Section 3 discusses the modelling and formulation of the problem; Section 4 presents and analyses the modelling results; and Section 5 concludes the study.

2. Related Work

Reference [8] proposes a model that connects an EV to a smart home to minimize costs while maximizing the efficiency of the EV. This model consists of a PV system and an EV with Vehicle to Home (V2H) and Home to Vehicle (H2V) capabilities. The results indicate that effective peak consumption reduction is achievable through the use of an EV with V2H technology, along with a significant reduction in the total energy bill. However, this study does not model an ESS.

In [9], home loads are categorised into three kinds according to their controllability. The planned smart home incorporates a photovoltaic system, a wind turbine, and an energy storage system. A bi-objective function is established to reduce the disparity between generation and consumption, along with power procurement. The suggested load control technique identifies the appropriate temporal distribution for each load. The algorithm indicates that charging or discharging the battery improves the smart home's operation. Furthermore, the system uses less electricity, resulting in lower losses and transmission costs. This study does not simulate an electric vehicle.

Reference [10] examines the optimal functioning of a smart home integrated with photovoltaic systems, energy storage systems, and electric vehicles under a dynamic pricing model. A SHEMS utilising a mixed integer linear programming (MILP) model is presented to optimise energy output and consumption. A 24-hour case study illustrates substantial reductions in energy expenses with the ideal approach.

Reference [11] illustrates the scheduling issue for residential appliances in the presence of an EV. The home load scheduling problem is solved by taking into account consumer preferences. The study looks at the elements that influence the timing of residential loads and examines the performance of the best model under different scenarios. The goal is to reduce power expenditures by getting appropriate incentives and minimizing scheduling hassle.

In [12], household energy management is focused on using various assets such as home appliances, EVs, ESS, and PV systems. The ESS and PV are used to supply household appliances, and excess energy can be fed back into the grid. The SHEMS optimization problem is formulated as an MILP problem. Consumers indicate their participation in demand response programs based on real-time prices provided by the utility. Simulation results demonstrate significant cost benefits for users while minimizing the peak to average ratio for the utility provider.

In [13], researchers examine various methodologies for simulating distinct elements of a smart house, encompassing photovoltaic systems, electric vehicles, and heat pumps. The methodologies are simulated, executed, and juxtaposed with actual measured data from a single-family residence. The merits and drawbacks of each method are examined, illustrating the circumstances in which the methods can yield a dependable and precise representation of the dynamics of the smart home.

Reference [14] offers a SHEMS with EV, PV, and ESS. The smart home system takes a hybrid approach, combining optimization and prioritizing. The suggested algorithm prioritizes EV, ESS, and grid power based on energy pricing. The energy management algorithm tries to reduce total energy costs while meeting residential electricity demand and the ESS's charging demands. The algorithm's performance over 24 hours is examined using electricity pricing data.

A SHEMS is proposed in [15] to facilitate demand response applications for residential consumers. This paper introduces a pricing-based demand response program for a smart house equipped with diverse home appliances while taking consumer satisfaction into account. The design may adapt to accommodate various appliances, including energy storage devices, electric vehicles, and photovoltaic systems. The SHEMS offers diverse adaptable solutions that yield varying degrees of customer pleasure for an array of appliances. This framework aims to reduce energy expenses while considering user preferences and the lifestyles desired by residents. The numerical findings indicate the efficacy of the proposed design.

Reference [16] employs a scheduling technique that utilizes intelligent algorithms to manage energy in smart houses within a residential microgrid. Smart houses include domestic appliances, solar systems, electric vehicles, and programmed devices. Real-time pricing is viewed as a price-driven demand response program. The proposed method is tested for efficiency by applying it to a smart microgrid with 20 smart homes. Quantitative studies show that the home energy management technique reduces electricity costs and peak demand inside residential microgrids.

Reference [17] presents a building energy management method considering ESS, RES, and EVs. However, the EV's power exchange with the grid is modeled in a unidirectional manner.

The reviewed studies can be summarized as follows:

Reducing Costs and Increasing Efficiency: Most studies focus on optimizing energy use to reduce consumption costs and enhance the efficiency of energy systems in smart homes. Proposed solutions include using EVs as energy storage devices, integrating PV systems and ESS to provide sustainable energy, and reducing dependency on the central power grid.

Optimization of Electricity Consumption: Various strategies have been explored to schedule household loads and minimize energy consumption during peak periods. Advanced models such as MILP have been utilized to achieve these goals while considering consumer preferences.

Flexibility and Demand Response: Demand response programs that encourage consumers to adjust their consumption based on lower energy costs are gaining attention. These programs enable smart homes to automatically adapt their energy consumption according to real-time tariffs.

Limitations and Challenges: Some studies have identified weaknesses such as the lack of consideration for aspects like battery life or user well-being. Additionally, attention must be paid to the environmental and economic impacts of energy management decisions.

This summary indicates that the development of smart homes and energy management technologies is progressing. Integrating new technologies and advanced modeling can lead to improved energy efficiency and reduced consumption costs.

A comprehensive framework for the operation of a smart home should include an EV with the ability to charge and discharge under different conditions, an ESS for enhanced efficiency, and RES for purposes such as providing power or selling excess energy. The proposed model, based on MILP, can achieve an optimal energy plan for the smart home, ensuring the lowest cost and maximum convenience for users.

3. Problem Formulation

This section illustrates the modeling of different equipment within a smart house, encompassing photovoltaic systems, wind turbines, controllable loads, uncontrollable loads, electric vehicles, and energy storage systems. The SHEMS schedules the operational timings of domestic appliances and the charging/discharging intervals for the EV and ESS. Furthermore, the smart house is capable of purchasing power from or selling power to the utility grid.

To coordinate the performance among these devices, detailed modeling of each component is required. The modeling of smart home equipment is based on the following assumptions:

A) Objective function

The primary goal of power management in a smart home is to minimize the customer's payments to the grid. To achieve this objective, household appliances are programmed to turn on and off in a manner that reduces electricity costs. The decision variables in the optimization issue are power purchased from the grid, power sold to the grid, and the charging/discharging power of the EV and ESS.

$$Min\, C\left(\sum_{t\in T}\lambda_t^{Buy}\, P_t^{Buy} - \lambda_t^{Sell} P_t^{Sell}\right).\forall t \tag{1}$$

Eq. (1) represents the objective function of the problem. The utility grid sets and communicates to the SHEMS the current electricity purchase and sale prices, denoted by λ_t^{Buy} and λ_t^{Sell} respectively, as shown in Fig. 1.

B) Power Balance

Eq. (2) is referred to as the power balance equation, which asserts that the aggregate power consumption in the smart home must be equivalent to the total power generation. During specific intervals, the energy consumption surpasses the energy generated by RES, necessitating the smart home to procure power from the grid to offset this shortfall.

$$P_t^{Buy} + P_t^{PV.Used} + P_t^{WT.Used} + P_t^{EV.Used} + P_t^{ESS.Used} = P_t^{Sell} + P_t^{PV.Sold} + P_t^{WT.Sold} + P_t^{EV.Sold} + P_t^{ESS.Sold} + P_t^{App.Constant} + P_t^{App.UIL} + P_t^{App.IL}.\forall t \tag{2}$$

C) Energy Storage System Model

In a smart home, the energy storage system functions as both a power source and an energy consumer, contingent upon its operational mode (charging or discharging). During charging, the ESS operates as a load, and the SHEMS has the capability to halt the charging operation and defer it to a later time. Consequently, the ESS is classified as an interruptible load. The mathematical formulation of the ESS restrictions is as follows:

$$P_t^{ESS.dch} \times \eta^{ESS} = P_t^{ESS.Used} + P_t^{ESS.Sold}.\forall t \tag{3}$$

$$0 \le P_t^{ESS.ch} \le P_R^{ESS.ch} \times b_t^{ESS}.\forall t \tag{4}$$

$$P_R^{ESS.dch} \times (1 - b_t^{ESS}) \le P_t^{ESS.dch} \le 0.\forall t \tag{5}$$

$$SOC_t^{ESS} = SOC_{t-1}^{ESS} + \frac{\eta^{ESS} \times P_t^{ESS.ch}}{E^{ESS}} - \frac{P_t^{ESS.dch}}{\eta^{ESS} \times E^{ESS}}.\forall t \tag{6}$$

$$SOC^{ESS.min} \le SOC_t^{ESS} \le SOC^{ESS.max}.\forall t \tag{7}$$

$$SOC_{t=0}^{ESS} = SOC^{ESS.init}.if\;\; t = 0 \tag{8}$$

$$SOC_{t=T}^{ESS} = SOC^{ESS.finally}.if\; t = T \tag{9}$$

The ESS can either consume the discharged electricity at home or sell it to the grid, according to Eq. 3. Eqs. 4 and 5 show that an ESS cannot charge or discharge more than its rated capacity. Eq. 6 shows that the ESS capacity at time t is dependent on the previous moments. Eq. 7 shows that the minimum and maximum capacity of the ESS cannot exceed the specified value. Eq. 8 shows the ESS initial capacity at the start of the day, and Eq. 9 indicates it at the end of the day.

D) Electric Vehicle Model

The electric vehicle is capable of both vehicle-to-grid (V2G) and grid-to-vehicle (G2V) operations. The electricity discharged per hour from the EV is equivalent to the power consumed by household loads and the power sold to the grid. An electric vehicle links to the residence at designated intervals and participates in Smart Home Energy Management System activities. Due to their comparatively high capacity, EV batteries are regarded as equivalent to ESS models in this research. The equations of the EV are presented in (10)–(16).

$$P_t^{EV.dch} \times \eta^{EV} = P_t^{EV.Used} + P_t^{EV.Sold}.\forall t \in \left[T^{arrive}.T^{exit}\right] \tag{10}$$

$$0 \le P_t^{EV.ch} \le P_R^{EV.ch} \times c_t^{EV}. \forall t \in [T^{arrive}. T^{exit}] \quad (11)$$

$$0 \le P_t^{EV.dch} \le P_R^{EV.dch} \times (1 - c_t^{EV}). \forall t \in [T^{arrive}. T^{exit}] \quad (12)$$

$$SOC_t^{EV} = SOC_{t-1}^{EV} + \frac{\eta^{EV} \times P_t^{EV.ch}}{E^{EV}} - \frac{P_t^{EV.dch}}{\eta^{EV} \times E^{EV}}. \forall t \in [T^{arrive}. T^{exit}] \quad (13)$$

$$SOC^{EV.min} \le SOC_t^{EV} \le SOC^{EV.max}. \forall t \in [T^{arrive}. T^{exit}] \quad (14)$$

$$SOC_{t=0}^{EV} = SOC^{EV.init}. IF\ t = 0 \quad (15)$$

$$SOC_{t=T}^{EV} = SOC^{EV.finally}. IF\ t = T \quad (16)$$

The equations of the EV closely resemble those of the ESS. The sole distinction is that these equations are applicable only when the vehicle is connected to the home. ($\forall t \in [T^{arrive}. T^{exit}]$).

E) Solar panel and wind turbine Model

The installation and use of RES, such as solar panels and wind turbines, offer significant economic benefits for smart home residents. Residents can utilize electricity generated by renewable energy sources instead of buying it from the utility and may also sell surplus power back to the grid. In this study, both solar panels and wind turbines are considered. The modeling of the solar panel and wind turbine is based on the relations expressed in references [18],[19], and [20], respectively.

After satisfying the household's energy needs, the solar panel and wind turbine can sell surplus electricity to the grid. Eqs (17) and (18) represent the power produced by the solar panel and wind turbine, which can be either consumed or sold to the grid.

$$P_t^{PV} = P_t^{PV.Used} + P_t^{PV.Sold}. \forall t \quad (17)$$

$$P_t^{WT} = P_t^{WT.Used} + P_t^{WT.Sold}. \forall t \quad (18)$$

F) Household appliances Model

Home appliances are classified into two primary categories depending on their intrinsic properties: controllable and non-controllable loads. Non-controllable appliances, like refrigerators and lighting fixtures, possess predetermined functioning times and cannot be scheduled or optimized. The SHEMS must satisfy these loads whenever required by the consumer; thus, they do not contribute to energy management.

Controllable household appliances are classified into two kinds: Uninterruptible Loads (UIL) and Interruptible Loads (IL). The SHEMS can schedule these appliances, considering user preferences, to participate in energy management programs and achieve the smart home's desired objectives.

Uninterruptible loads loads can have their start times altered by the SHEMS but cannot be interrupted once in operation; they must run continuously from start to finish. Examples include washing machines, dishwashers, and clothes dryers. The mathematical equations for UILs are as follows:

$$\sum_{t \in T_c} S_{(i.t)} = G_i. \forall i \quad (19)$$

$$S_{i.t} = S_{i.t-1} + X_{i.t} - Y_{i.t}. \forall t. i \quad (20)$$

$$X_{i.t} + Y_{i.t} \le 1. \forall t. i \quad (21)$$

$$\sum_{ts} S_{(i.ts)} \ge MUT \times X_{i.t}. \forall : i.ts > t \quad (22)$$

$$\sum_{i} P_{i.t}^{UIL} \times S_{i.t} = P_t^{App.UIL}. \forall t. i \quad (23)$$

Eq. 19 specifies the total operating time required for each device within 24 hours. Eq. 20 manages the state of the device (on or off) over time. Eq. 21 prohibits the device from being turned on and off simultaneously. Eq. 22 enforces the minimum up time (MUT) required for the device to remain on once it has started. Eq. 23 shows the power consumed by uninterruptible loads.

Interruptible loads may be interrupted during operation and subsequently resumed without affecting user comfort. Owing to electricity costs and other limitations, the SHEMS can adjust the operational schedules of these loads and defer them as necessary.

The equations for interruptible loads in household appliances are as follows:

$$\sum_{t} L_{(j.t)} = H_t. \forall j \quad (24)$$

$$L_{j.t} = L_{j.t-1} + M_{j.t} - N_{j.t}. \forall t. j \quad (25)$$

$$M_{j.t} + N_{j.t} \le 1. \forall t. j \quad (26)$$

$$\sum_{ts} (1 - S_{(j.ts)}) \le MDT \times Y_{j.t}. \forall\ : j.ts > t \quad (27)$$

$$\sum_{i} P_{j.t}^{IL} \times L_{j.t} = P_t^{App.IL}. \forall t. j \quad (28)$$

The equations for ILs are similar to those for UILs, with the exception that MUT is not considered. Instead, Eq. 27, which represents the maximum downtime (MDT) of a device, is modeled.

Uninterruptible for fixed loads, the appliance equations are as follows:

$$P_t^{App.Constant} = \sum_{i} (I_{k.t} \times P_{k.t}^{App}) \quad (29)$$

$$I_{k.t} = \begin{pmatrix} T_{1.k1} & \cdots & T_{1.km} \\ \vdots & \ddots & \vdots \\ T_{24.k1} & \cdots & T_{24.km} \end{pmatrix}_{24 \times km} \quad (30)$$

$$P_{k.t}^{App} = \begin{pmatrix} P_{k1} \\ \vdots \\ P_{km} \end{pmatrix}_{km \times 1} \quad (31)$$

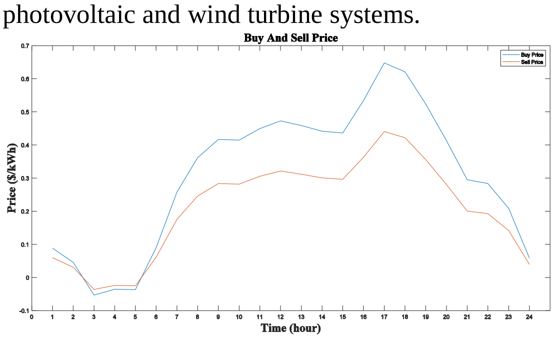
Eq. 29 Represents the power consumption of fixed appliances, which should be included in the power balance constraint. Eqs. 30 and 31 considered as inputs, detailing the time indices and power ratings of the fixed appliances.

4. Simulation and Results

The previous section introduced the mathematical models of the SHEMS designed to reduce users' costs. This system calculates the power consumption of various components in each planning period by considering price signals and other input parameters. It accounts for three types of loads (fixed, interruptible, and uninterruptible), as well as EV charging and discharging, ESS, and the electricity produced and consumed from PV panels and WT. This section evaluates the proposed algorithm through several scenarios in a smart home setting. The optimization problem was modeled using the MILP method with IBM ILOG CPLEX Optimization Studio 12.8.0, running on an AMD A12-9720P @ 2.70 GHz computer with 12 GB RAM.

A) Input data and assumption

The efficacy of the suggested model is evaluated by a simulated example covering a complete day (24 hours). Fig. 1 depicts the electricity tariffs established by the main grid, whereas Fig. 2 presents an overall power usage of non-controllable loads. Table 1 delineates specifics regarding the EV and ESS, whereas Table 2 enumerates non-controllable loads along with their pertinent information. The electric vehicle leaves the residence at 7 AM and returns at 6 PM, promptly reconnecting to the grid upon arrival. It is capable of charging, discharging, and engaging in energy management programs until 7 AM the subsequent day. Table 3 provides data on controllable loads, whereas Fig. 3 illustrates the output power of the photovoltaic and wind turbine systems.



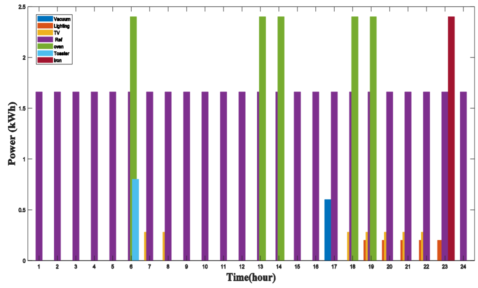


Table.1.
The ESS and EV parameters.

	ESS	***EV***
SOC^{init}	0.65	0.8
$SOC^{finally}$	0.65	0.8
P_R^{ch} (KWh)	2.5	6.6
P_R^{dch} (KWh)	2.5	6.6
η	0.95	0.95
E^{max} (KWh)	7	50
SOC^{min}	0.2	0.3
SOC^{max}	1	1

Table.2.
Non-controllable loads.

Appliance	***User's preferred time for usage time***	***Time of use (hours)***	***Power (KW)***
electric iron	23	1	2.4
toaster	6	1	0.8
electric oven	6 13-14 18-19	3×1	2.4
refrigerator	1-24	24	1.66
television	7-8 18-22	5	0.28
lighting	19-23	5	0.2
Vacuum cleaner	17	1	0.6

Table.3.
Controllable loads.

	Uninterruptible loads			***Interruptible loads***
	Washing machine	***dishwasher***	***Clothes dryer***	***air conditioner***
power (kw)	1.4	1.32	3.8	1.75

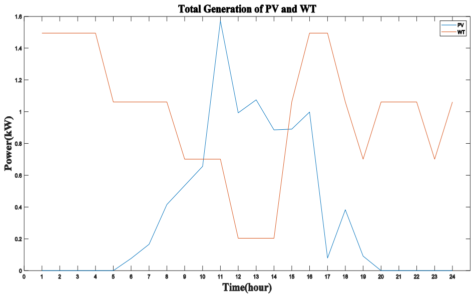


Fig. 3. The output power produced by PV and WT.

B) Scenarios of operation the smart home

Scenario 1: Without considering ESS, EV and RES

In this scenario, the smart home lacks RES, ESS, and EV. Instead, it schedules its loads solely based on user preferences. Fig. 4 depicts the hourly electricity purchases and sales to the grid. As expected, without ESS, RES, and EV, the grid supplies electricity continuously throughout the day. The total cost for purchasing electricity in this scenario is $2.575.

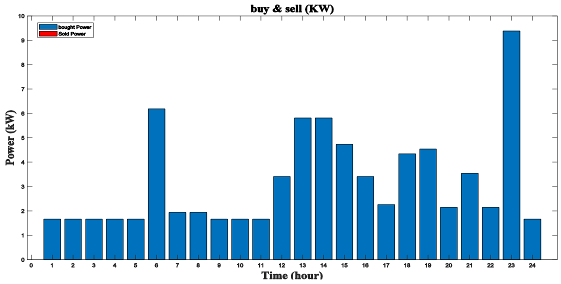


Fig. 4: The amount of buying and selling electricity per hour in scenario 1

Scenario 2: With the presence of RES

only RES are integrated into the smart home. Fig. 5 illustrates the electricity bought from and sold to the grid. A significant portion of the generated power is allocated for home consumption, and excess power is sold back to the grid during certain hours. The presence of RES reduces the grid's electricity purchases, resulting in a total payment of $1.544, a substantial decrease compared to Scenario 1.

Scenario 3: With the presence of ESS

In this scenario, only ESS is incorporated into the smart home. The Energy Storage System charges when electricity costs are low and discharges when prices are high. When discharging, the ESS first supplies household loads and then sells any excess electricity to the grid. Fig. 6 shows the electricity transactions with the grid, indicating that the ESS fully meets the house's electricity needs during two hours, eliminating grid dependency during those times. The total payment cost for one day in this scenario is $1.886, slightly higher than in Scenario 2.

Scenario 4: With the presence of EV

This scenario includes only the EV as part of the SHEMS plan. The electric vehicle charges during periods of cheap pricing and discharges during periods of high pricing. The EV is not present at home for certain hours of the day. Fig. 7 displays the electricity transactions, showing

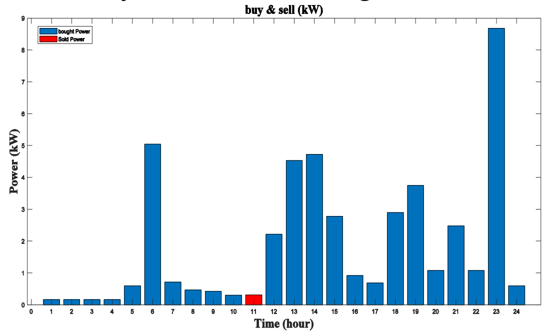


Fig.5: The amount of buying and selling electricity in the scenario 2

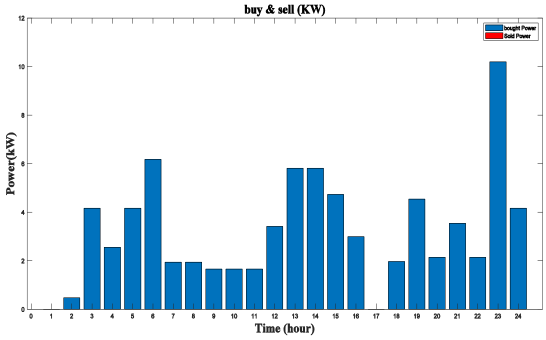


Fig.6: The amount of buying and selling electricity in the scenario 3

periods when the house does not draw power from the grid and instances where it sells electricity back. The EV, with a larger battery capacity than the ESS, leads to improved results compared to Scenario 3, reducing the payment fee to $1.659. The difference in cost between Scenarios 3 and 4 is attributed to the EV's greater discharge capacity compared to the ESS.

Scenario 5: With the presence of RES and ESS

In this scenario, both RES and ESS are present in the smart home. RES can store energy and sell excess power to the grid during high-price hours. Fig. 8 shows the electricity transactions, indicating that the smart home does not purchase more electricity from the grid compared to previous scenarios. Fig. 9 demonstrates that the ESS fully utilizes its power for domestic purposes without selling any back to the grid. Additionally, Fig. 10 shows that RES can sell power to the grid during two hours. The total payment fee for this scenario is $1.231.

Scenario 6: with the presence of RES, ESS and EV

The final scenario integrates RES, ESS, and EV into the smart home. Fig. 11 illustrates that SHEMS does not receive electricity from the grid for many hours, while Figs. 12, 13, and 14 confirm that RES, EV, and

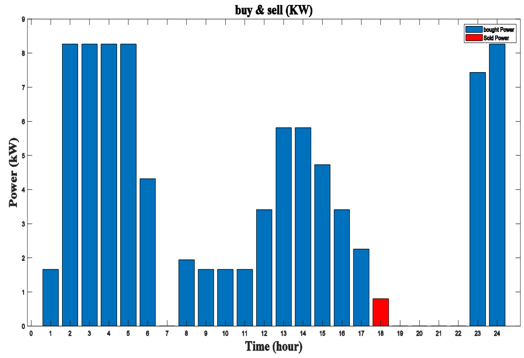


Fig. 7: The amount of buying and selling electricity in the scenario 4

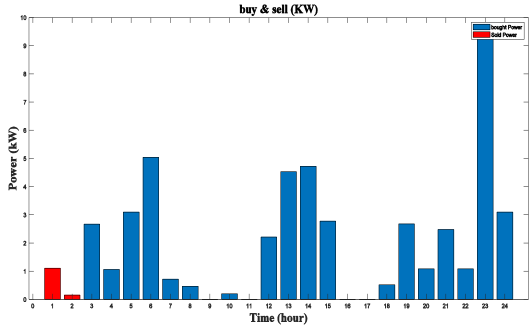


Fig. 8: The amount of buying and selling electricity in the scenario 5

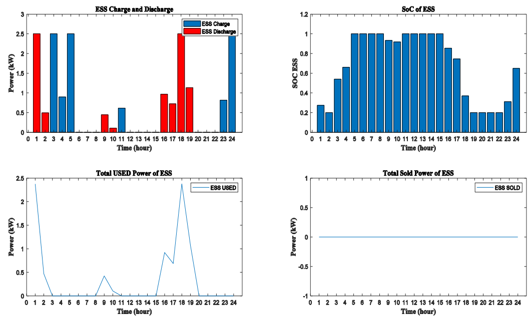


Fig. 9: a) charge/discharge rate, b) SOC, c) consumption rate, d) electricity sales rate of the ESS in the scenario 5

ESS provide the necessary power during these times. The smart home sells excess electricity to the grid during one hour, as shown in Figs. 12 and 14. The operating cost in this scenario is $0.492, a significant reduction compared to all previous scenarios. Fig. 15 illustrates the consumption of uninterruptible household appliances, and Fig. 16 shows the consumption of appliances subject to hourly interruptions.

Table 4 compares the aforementioned scenarios, highlighting a substantial reduction in operating costs from Scenario 1 to Scenario 6. This reduction is primarily due to the integration of RES, ESS, EV, and interruptible loads.

5. Conclusion

This study presents a planning model that analyzes the consumption of household appliances, the charging and discharging of EVs and ESS, and the management of electricity consumption and sales from RES across six different pricing scenarios, both with and without the availability of these resources in the smart home. The results demonstrate that integrating RES, ESS, and EV significantly reduces the operating costs of a smart home, decreasing from $2.575 to $0.492 within a 24-hour period. In high electricity price periods, ESS and EV utilize their stored power to supply household loads and sell excess power to the grid. Additionally, PV and WT systems allocate their production power for domestic use and sell any surplus to the grid. SHEMS optimally manages both interruptible and uninterruptible loads during low electricity price periods, based on user preferences. The optimal SHEMS program effectively reduces the operating costs in the smart home. This paper proposes a scalable model that is open to further enhancements and improvements.

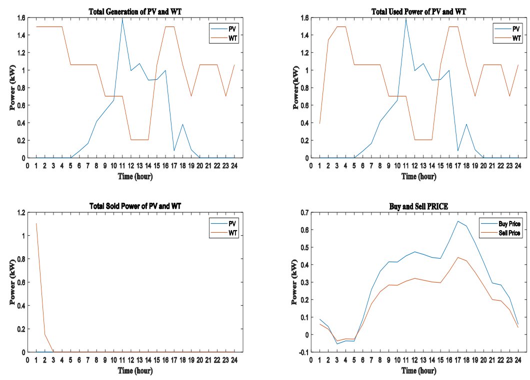


Fig. 10: amount of a) production, b) consumption, c) electricity sales in the scenario 5, d) electricity price

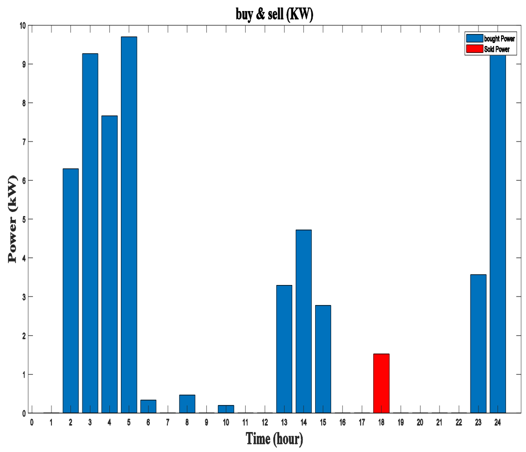


Fig. 11:The amount of buying and selling electricity from/to the grid in the scenario 6

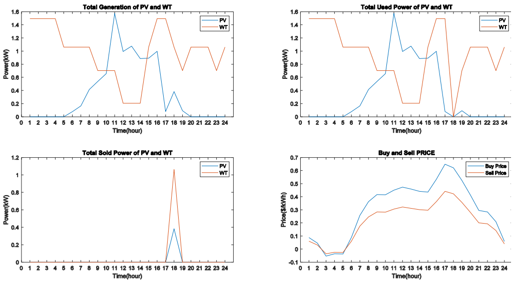


Fig. 12: amount of a) production, b) consumption, c) WT and PV electricity in the scenario 6, d) electricity price

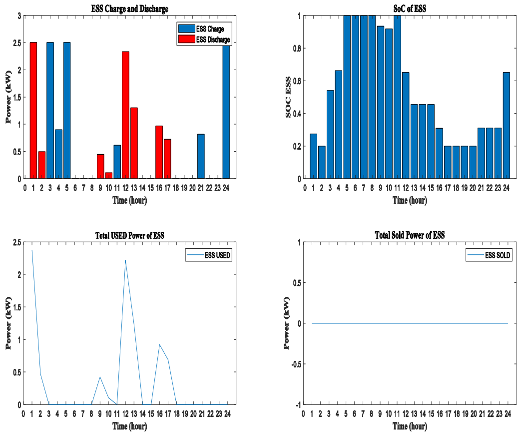


Fig. 13: a) charge/discharge rate, b) SOC, c) consumption rate, d) electricity sales rate of the ESS in the scenario 6

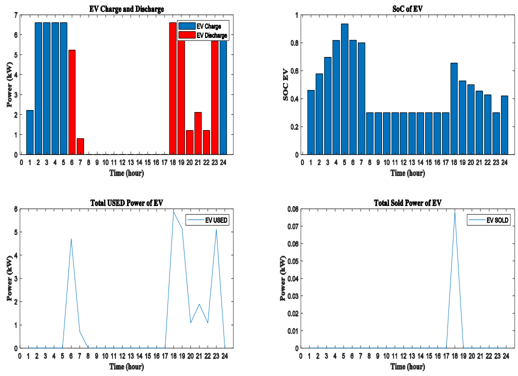


Fig. 14: a) charge/discharge rate, b) SOC, c) consumption rate, d) EV sales rate in the scenario 6

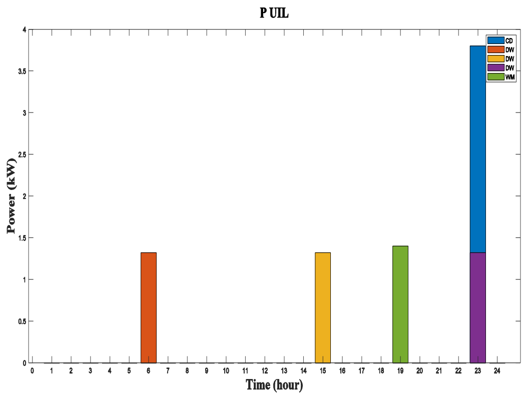


Fig. 15: Uninterruptible load consumption in the scenario 6

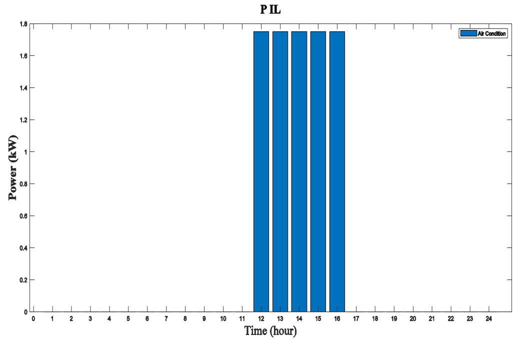


Fig. 16: Consumption of interruptible loads in the scenario 6

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