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Optimizing Smart Home Energy Management with Branch and Bound Method: A Novel Model for Daily and Weekly Scheduling of Smart Appliances

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ABSTRACT

The increasing use of smart homes has led researchers to focus on load management and consumption response in the household sector. This paper proposes a method for minimizing electricity consumption costs in a smart home with programmable appliances that can be controlled. The study examines consumption management and load response in a smart home, taking into account real-time pricing. The proposed models offer a new framework for planning the time of use of appliances, taking into account the limitations and operation of household equipment. The study proposes four mathematical models of the problem, which are of the nonlinear integer programming (NLIP) and are solved using GAMS software. In addition, the Branch and Bound (B&B) algorithm developed in Python is used in the two proposed models for daily scheduling of smart appliances and for scheduling longer time periods, such as a week, a month, or even a year. In both types, one model is connected only to grid power, and the other model is connected to both the grid and photovoltaic sources. Numerical studies for the four different models show the effectiveness of the proposed models in smart home planning. Furthermore, this study investigates the potential of using B&B to solve the proposed models. The results demonstrate the effectiveness of the proposed method in reducing energy costs, while also considering the limitations and performance of household equipment. In addition, by comparing the results obtained from the proposed models, this article examines the amount of investment required to purchase solar panels in different studies.

1. Introduction

The importance of sustainable energy for economic growth and development is widely recognized; however, energy challenges persist in developing countries despite policymakers' efforts to bridge the gap between energy demand and supply [1]. With the demand for electricity increasing dramatically due to economic development, population growth, and advancements in technology, the need for more energy in the future is certain. As underdeveloped countries continue to strive for

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progress, the need for more energy in the future remains undeniable [2]. In recent years, there has been a significant shift toward urbanization, with more than 60% of the global population projected to reside in urban areas by 2030 [3]. However, rapid urbanization has led to the residential sector becoming the largest electricity consumer, resulting in a corresponding increase in fuel consumption and significant negative environmental impacts. Studies indicate that the domestic sector accounts for an average of 35% of energy demand due to the rising standard of living worldwide [4]. Energy is a crucial aspect of our daily lives, and currently, the global energy market is predominantly dominated by fossil fuels and non-renewable energy sources, which have significant economic and environmental impacts. To address this issue, researchers are focusing on reducing energy consumption, particularly in residential loads, and diversifying energy sources to include renewable energy sources [5]. Another approach being researched is demand-side participation, which involves the active involvement of consumers in managing energy use and production [6].

As electricity demand rises, meeting peak-hour demand becomes increasingly challenging, and implementing demand response programs can help manage energy supply and demand during these periods [7]. At the residential level, energy costs can be reduced by using smart price-based (demand response) control concepts [3]. The optimal use of microgrids is particularly important for the efficient and economic management of energy resources. The integration of renewable energy sources, such as solar panels and wind turbines, can help meet this demand while reducing greenhouse gas emissions. The dependence on oil and its surging prices have further accelerated the adoption of renewable energy sources in many countries over the past few decades. The urgency to reduce greenhouse gas emissions to prevent climate change adds further significance to the use of sustainable energy sources [8]. Distributed renewable energy sources can be utilized in buildings as a sustainable alternative [9]. Over the years, researchers and academics have aimed to address energy challenges by exploring the use of renewable energy sources and smart grid technology to reduce energy demand and ensure the reliability of energy supply in the building sector.

To maintain a connected and smart home, a stable, reliable, and affordable energy source is essential [10]. Therefore, the integration of renewable energy sources, such as solar panels and wind turbines, can help meet this demand while reducing greenhouse gas emissions. Home Energy Management Systems (HEMS) and smart homes have been introduced in the residential sector to reduce dependency on fossil fuels. Smart homes offer residents advanced monitoring and control of building performance through internet-connected devices. By optimizing the management of controllable household appliances and utilizing distributed production power from renewable energy sources and electric vehicles, smart homeowners can reduce their energy dependence on the power grid and lower their electricity bills [11]. Smart homes can also participate in demand-side management (DSM) programs, contributing to the decentralization of electricity. Each home can participate in the smart grid as both a supplier and a consumer of energy. Moreover, greater participation of smart homes in demand-side management (DSM) programs can further contribute to the decentralization of electricity [12]. Home Energy Management Systems (HEMS) are rapidly gaining popularity worldwide as small-scale renewable energy and energy storage become more viable [13].

Smart homes are a small but important energy sector with significant potential to implement effective energy policies, where humans are the primary decision-makers in the home energy management dilemma. Therefore, human emotions and desires play a vital role in the daily decisions of the end user [14]. Smart homes are expected to bring about significant changes in people's lifestyles. By adjusting the timing of residents' electricity consumption, smart homes can enhance electricity load flexibility and offer significant potential for electricity demand response [15]. The energy consumption of a smart home can be intelligently optimized, ensuring not only the minimum cost of energy procurement but also the convenience of the consumer [16]. Household electrical appliances can be divided into two categories in smart homes: non-programmable and programmable. Non-programmable appliances, such as televisions, computers, and lighting, are not responsive to time-varying prices. On the other hand, programmable appliances, such as washing machines, dishwashers, and clothes dryers, are responsive, and their operating times can be adjusted. The function of a smart home is to provide a schedule for the use of controllable household appliances. Smart home energy management systems help the distribution network operate more efficiently and reliably and enable the effective integration of distributed renewable energy sources. These systems rely on robust prediction, optimization, and control/scheduling algorithms that can manage the uncertain nature of renewable energy demand and generation [17]. Solar energy is the most readily accessible form of clean and renewable energy with tremendous potential worldwide. Solar home systems (SHS) utilizing solar panels on urban rooftops and in remote rural areas are rapidly expanding [18]. SHS has emerged as a popular solution for addressing energy access challenges in areas with limited or no electricity service [19]. Developing a smart home automation system with renewable energy is a sustainable approach.

It can offer several benefits, including reducing reliance on traditional fossil fuel-generated electricity, lowering the carbon footprint, and optimizing energy usage, which leads to increased energy efficiency and cost savings. By participating in demand-side management programs, homeowners can also contribute to the centralization of electricity and help balance the grid by reducing peak demand. Overall, integrating renewable energy and smart home automation systems can lead to a more sustainable and efficient energy future. Developing a smart home automation system that incorporates renewable energy is a sustainable approach. The objective of this research is to develop two types of mathematical models for a smart home. The first model utilizes only grid power, while the second model utilizes both solar energy and grid power, enabling efficient planning of home appliances and reducing energy costs.

Household electrical appliances are significant contributors to energy consumption in households, making it crucial for consumers to choose energy-efficient appliances, plan their usage effectively, and ensure their optimal energy efficiency. Most existing mathematical models provide schedules for the next 24 hours, assuming that some devices are used daily while others are used less frequently (e.g., two or three times a week). However, planning controllable devices should be investigated over a longer operational period, such as at least one week, highlighting the importance of incorporating both short-term and long-term planning approaches [20]. Therefore, in this paper, we propose two models for appliance scheduling in smart homes, which are divided into two parts: one for daily scheduling of smart appliances and the other for weekly scheduling. Both models are implemented using the CPLEX solver in GAMS software. Additionally, we propose a method that utilizes a B&B-based operational and research approach for appliance scheduling to optimize energy resource use in dynamic pricing environments and minimize total electricity consumption costs.

The development of a smart home automation system with renewable energy is a sustainable approach that offers several benefits, including reducing reliance on traditional fossil fuel-generated electricity, lowering the carbon footprint, and optimizing energy usage, ultimately leading to increased energy efficiency and cost savings.

The remainder of the paper is organized as follows. Section 2 presents a literature review relevant to the topic. Section 3 describes the problem and formulates the mathematical model. The solution algorithm is presented in Section 4. Section 5 presents the results from implementing case studies and numerical model examples. Finally, Section 6 presents the main conclusions and future research directions.

2. Literature Review

The demand for electricity increases dramatically every year. This increase in energy demand is attributed to economic development, population growth, and technological advancements in improving equipment and introducing new technologies. Therefore, in the future, more energy will definitely be needed for the development of underdeveloped countries [2]. With future demand forecasts, energy generation and distribution can be optimized to meet the needs of a growing population. However, predicting the demand of individual households is a challenging task due to the diversity of energy consumption patterns [21]. Home Energy Management Systems (HEMS) play a crucial role in regulating power flow within the smart grid. The primary goal of HEMS is to optimize energy consumption and reduce electricity costs, a mechanism that benefits both the user and the operation of appliances [22, 23]. By understanding the concept of home and people's well-being through a user-oriented approach, it becomes clear that home appliances and smart home systems should be designed as mediators between the home and energy consumption [24]. Reference [25] presents an analysis of the smart home energy management system, aiming to identify current trends and challenges for future improvement. Samadi *et al.,* presented an algorithm that maximizes the overall profit of consumers and minimizes costs, considering the limitation that consumption should be lower than the level of energy production [26]. Dieckmann *et al.,* [27] investigated potential changes in peak consumption and electricity costs caused by smart homes by developing a multi-objective smart home integrated management model, which considers the behavioral heterogeneity of household appliances and electricity consumption.

Renewable energies in today's electricity systems enhance the positive performance of energy sources while eliminating greenhouse gas emissions. To manage fluctuations in electricity production, current policies focus on expanding renewable energies and planning production capacities [27]. The Smart Home Renewable Energy Management (SHREM) system is proposed to provide high-efficiency and high-quality solar panels for power generation [28]. In Africa, where the continuous supply of electricity remains a challenge, the use of solar photovoltaic technologies as the energy source for smart homes will address this challenge and enable the development of smart homes [29]. As the final link in an integrated future energy system, the smart home energy management system (HEMS) is crucial for managing the smart use of home appliances, renewable energy sources (RES), and energy storage systems (ESS) [30].

Perhaps the research by Chen *et al.,* [31] can be considered the first study in this field to present a multi-period integer linear mathematical model. In this research, the authors considered the cost of solar cell installation as a fixed value in the objective function. In the proposed model, the energy requirement of the house is first supplied through the electricity grid and PV systems. Reference [32] of a smart residential community shows that dynamic pricing encourages household consumers to shift flexible loads from morning and evening to noon or early morning, effectively improving the matching between PV generation and residential electricity demand. Study [33] presents the conceptualization and implementation of a smart home system that uses solar panels to maximize the use of renewable energy.

This system is designed to minimize the carbon footprint and energy consumption. In 2017, AlSkaif *et al.,* [34] presented a MILP mathematical model for a house considering PV and energy storage, without selling excess PV electricity to the grid. The model was based on demand characteristics for different household classes and annual periods in Spain, resulting in a reduction of approximately 68%. In 2020, Elkazaz *et al.,* [35] presented a MIP model for managing home energy consumption that considers PV and energy storage, aiming to minimize daily energy costs and *reduce* energy loss. The model presented by Sharda *et al.,* [36] incorporates scheduling with PV integration and various constraints, ultimately developing an independent, efficient, and real-time energy scheduling system that utilizes forecasted PV power for different pricing scenarios. In the proposed model, the battery for energy storage is not considered. Khezri *et al.,* [37] provided a comprehensive and critical review of the effective parameters in the optimal planning process of solar PV and battery storage systems for grid-connected residential sectors. These parameters include economic and technical data, objective functions, energy management systems, design constraints, optimization algorithms, and electricity pricing programs.

Elazab *et al.,* [20] proposed a new offline intelligent isolated house load scheduling scheme to match the characteristics of houses in developing countries. In this work, detailed models of smart home resources and appliances are presented. A daily load scheduling scheme is proposed that considers the weekly and daily schedules of users to meet the demands of house occupants. The proposed scheme is based on the MILP (Mixed-Integer Linear Programming) optimization technique to introduce a simple and cost-effective load scheduling scheme for such remote and complex communities. Upon reviewing the literature and related sources, it becomes clear that most studies have focused on analyzing daily energy consumption, particularly in countries where energy prices fluctuate dynamically throughout the day. However, in some countries, energy prices remain constant for extended periods, such as a week, a month, or even a year. As a result, this study presents the development of two types of mathematical models to optimize the scheduling of smart home appliances, thereby reducing energy consumption and costs.

In study [38], a novel data-driven framework for smart home energy management, integrating electricity demand forecasting and user behavior recognition to maximize profit while ensuring user comfort. Using Long Short-Term Memory (LSTM) and association rule mining, the approach predicts day-ahead consumption and extracts user appliance usage patterns. A MIP model then schedules flexible appliances based on these patterns and energy demand. Simulations demonstrate the framework’s effectiveness in balancing cost savings and user preferences.

The first type is designed to optimize the daily scheduling of smart appliances, while the second type extends the approach to a weekly basis, allowing for more comprehensive planning. Typically, two main approaches to energy optimization have been observed in previous research. The first approach involves studying homes that are solely connected to the electricity grid to meet their energy requirements. The second approach focuses on homes that are connected to both the electricity grid and solar panels to supply energy. It is also noteworthy that this research considers both scenarios: homes connected only to the electricity grid and homes connected to both the grid and solar panels. This is because the growing use of solar panels for residential energy generation is becoming increasingly popular, and it is important to consider the impact of solar energy on the optimization of smart home appliance scheduling. This study incorporates both scenarios and presents a total of four models. The first model is only connected to the power grid and is responsible for optimizing the daily scheduling of smart home appliances. The second model is connected to both the power grid and solar panels and is responsible for optimizing the daily scheduling of smart home appliances. The third model is similar to the first model but is designed to optimize the schedule on a weekly basis. Finally, the fourth model is based on the weekly schedule of the second model.

3. Problem Definition

Most studies on smart homes have focused on a 24-hour time frame with real-time pricing [39]. This is largely because energy prices in most countries around the world are only provided to consumers for the next 24 hours. However, this approach assumes that all controllable appliances are turned on within a single 24-hour period, which is not a realistic representation of how households consume energy. For instance, some appliances, such as washing machines, are typically used only twice a week. Therefore, using a 24-hour program as a basis for predicting a household's annual energy consumption is not feasible. To address this limitation, a study [40] proposes a weekly pattern to reduce the energy consumption of a smart home, which can be used to predict the home's annual energy consumption. By incorporating a weekly pattern into the mathematical model, a more accurate representation of energy consumption in a household can be obtained.

Unfortunately, without knowledge of energy prices for the upcoming period, such as a week, planning for energy consumption beyond a 24-hour period is difficult. In this research, we present both a daily mathematical model and a multi-period mathematical model that provides the cost of energy consumption for an extended period, along with the scheduling of intelligent appliances for the considered periods. With the necessary data provided to the model, it is capable of scheduling smart devices and calculating the cost of energy consumption for periods ranging from one week to one year. Although obtaining the necessary data for a month or a year may be challenging, the presented model is capable of accurately calculating energy consumption costs for any given time period. Another method to reduce energy consumption is through the use of renewable energy sources, particularly photovoltaic solar cells. However, in some countries, the use of solar panels may not be cost-effective for households, as the installation costs are often prohibitively high. To address this, two models for planning smart home appliances have been presented. The first model is designed for countries where households cannot use solar panels, and it can be used to program controllable appliances.

The second model is designed for countries where solar panel installation is cost-effective, and it involves connecting the smart home to solar panels to meet the house's energy needs as much as possible. A PV module comprises several solar cells that are connected and enclosed in a stable unit. However, solar panels also come with additional costs, such as maintenance, repairs, cleaning, and depreciation, which have not been considered in the decisions made in these two models. Nevertheless, by comparing the values obtained from the two models in different scenarios, it is possible to calculate the approximate prices required for the installation and commissioning of solar panels. This paper proposes four models that combine daily and periodic models, as well as models for the use and non-use of renewable energy.

The parameters and variables used in the model are introduced in Table 1.

Table 1
Parameters and variables are used in the proposed models

	Sets and indices
I	Set of smart home appliances indexed by *i* (*i* = 1, 2, …, *15*)
J_i	Set of virtual processes for smart home appliance *i* indexed by *j* (*j* = 1, 2, …, *8*)
T	Set of time intervals indexed by *t* and *t'*(*t, t'* = 1, 2, …, 96)
d	Set of day interval indexed by d (d=1, 2, ….,7)
	Parameters
c_t	Energy price in time *t* (dollars per kWh)
Δt	The length of time intervals (i.e., 0.25 hours)
P_t^N	Total power consumption of uncontrollable appliances that must be on at time *t* (W)
P_t^C	Power consumption of the j^{th} process of the i^{th} responsive home appliances (W)
P_t^{max}	Maximum power is drawn from the grid at time *t* (W)
T_i^{off}	Maximum time delay between two consecutive processes of i^{th} responsive appliance
St_i	Time of starting the use of the i^{th} appliance
En_i	Time of ending the use of the i^{th} appliance
PV_t	Power generation capacity of the solar cell at time *t* (W)

Table 1
Continued

	Weekly parameters
c_{td}	Energy price in time t (dollars per kWh)
P_{td}^{N}	Total power consumption of uncontrollable appliances that must be on at time t (W)
P_{td}^{C}	Power consumption of the j^{th} process of the i^{th} responsive home appliances (W)
P_{td}^{max}	Maximum power is drawn from the grid at time t (W)
PV_{td}	Power generation capacity of the solar cell at time t (W)
	Variables
X_{ijt}	Binary variable determining whether the j^{th} process of the i^{th} smart appliance is on at time t (X_{ijt}= 1) or not (X_{ijt} = 0) (daily)
X_{ijtd}	Binary variable determining whether the j^{th} process of the i^{th} smart appliance is on at time t (X_{ijtd} = 1) or not (X_{ijtd} = 0) (weekly)

3.1 Daily Scheduling Models

3.1.1 Model Number 1

In model 1, the energy management system is responsible for planning the time of use of household equipment based on the real-time prices (predicted) and observing the limitations on the operation of household equipment. The objective is to minimize electricity consumption costs while ensuring that the equipment operates within the specified limits. The assumptions of the daily problem are as follows:

i. The parameters are definite.
ii. The pricing is dynamic, and the calculation of costs is based on the tariffs determined by the consumer during a 24-hour period.
iii. Both types of household appliances are considered, i.e., programmable and responsive to time-varying prices, as well as non-programmable and non-responsive to time-varying prices.
iv. The smart house is connected to the electricity grid, but when it is connected to the solar cell, it does not sell to the grid.
v. The smart house connected to the solar cell is not equipped with an energy storage system, and if the smart house is not used, the generated energy is wasted.
vi. The number of smart devices is considered to be 15, and the number of virtual processes is 8.

The planning time frame is assumed to be one day and one night. According to the time frame of announcing the price of electricity, every 24 hours of the day and night is divided into 96 equal parts (quarters of an hour). Based on these assumptions, a set of smart appliances can be programmed to minimize the consumer's payment cost. The energy management system selects the operating times of smart appliances to optimize the cost of electrical energy.

$$\min \sum_{t=1}^{96} c_t . \Delta t \ (P_t^N + \sum_{i=1}^{15} \sum_{j=1}^{8} P_t^c . X_{ijt}) \tag{1}$$

S.t

$$\sum_{t=St_i}^{En_i} X_{i.j.t} = 1 \qquad \forall \text{ i.j} \tag{2}$$

$$X_{i.j+1.t} \leq \sum_{t'=1}^{t-1} X_{i.j.t'} \qquad \forall i.j.t \tag{3}$$

$$X_{i.j.t} \leq \sum_{t'=t+1}^{t+T_{off}^{i}/\Delta t} X_{i.j+1.t'} \qquad \forall i.j.t \tag{4}$$

$$\left(P_t^N + \sum_{i=1}^{15} \sum_{j=1}^{8} P_t^c . X_{ijt}) \right) \leq \mathrm{P}_t^{\max} \quad . \ \forall \ \mathrm{t} \tag{5}$$

Equation (1) represents the objective function to minimize the electric energy cost of the smart home. Equation (2) represents the limit that the user wants the electrical device to work within a specified time range. For this reason, the user specifies the time range $[St_i \, . En_i]$ (start time and end time) for each device. It is important to note that increasing the time interval can lead to a better solution to the problem (from the perspective of cost reduction), but it can also affect the comfort of the user. To ensure the correct operation of the smart device, it is necessary (Relation 3) to arrange the virtual processes of each smart device according to its load profile. Therefore, if the jth process of smart equipment i is performed in time interval, t $\left(X_{i.j.t} = 1\right)$, the next process must be performed in a time interval greater than t$\left(X_{i.j.t'} = 1. t' > t\right)$. As stated in the definition of the objective function, $\mathrm{T}_{\mathrm{off}}^{\mathrm{i}}$ indicates the allowed interval between the virtual process j and j +1 related to the smart device i. Considering that between the processes (j) of the *i*-th smart device, there should not be a break longer than the time $\mathrm{T}_{\mathrm{off}}^{\mathrm{i}}$, so the following condition (Relation 4) should be taken into account. To prevent congestion in the distribution system, it may be necessary to limit the maximum power that can be absorbed from the network. This limit is typically set in accordance with the contract between the customer and the electricity company and is generally variable with time. Equation (5) models this limit, and the total power consumption of both intelligent and non-intelligent equipment in each time period must not exceed the maximum power that can be absorbed from the network.

This model was originally presented by [40], but in this research, we have made fundamental changes to constraints numbers 3 and 4. These changes have increased the speed of the model execution, and the order of execution of virtual activities will be properly regulated.

3.1.2 Model Number 2

To calculate the energy consumption of the smart home when using a PV solar cell, the solar cell generated power (Pv_t) is added to Model 1. The smart home is connected to the network, and if the solar cell power is insufficient to meet the energy requirements, the smart home can obtain additional energy from the network under real-time pricing. This enables the energy management system to optimize the utilization of PV solar cell power and grid power, thereby minimizing electricity consumption costs while meeting the energy requirements of the smart home. The presented model will be as follows:

$$\min \sum_{\mathrm{t}=1}^{96} \mathrm{c_t} \, .\Delta \mathrm{t} \ \left(\max\left(\left(P_t^N + \sum_{i=1}^{15} \sum_{j=1}^{8} P_t^c . X_{ijt} - Pv_t\right),0\right)\right) \tag{6}$$

S.t

(2) – (4)

$$\left(P_t^N + \sum_{i=1}^{15}\sum_{j=1}^{8} P_t^c . X_{ijt})\right) \leq \mathrm{P_t^{max}} + \mathrm{Pv_t} \qquad \forall\ \mathrm{t} \tag{7}$$

The energy management system optimizes the cost of electrical energy in the solar smart home by determining the optimal operation times for smart appliances (Equation (6)). Constraints 2, 3, and 4 are shared with this objective function, while constraint (7) is added to account for solar cell power. Since the smart house model with the solar cell is nonlinear because of the minimax form of the objective function (Equation (6)), it can be linearized by defining the new variable Z_t.

In the below model, Equation (8) represents the linear objective function by using variable Z_t which, in addition to constraints (2), (3), (4), and (7), includes two new constraints, (9) and (10), to address the problem. Variable X is a binary variable, which is expressed in Equation (11). The proposed model is a linear IP model that advanced solvers can easily solve.

Linearized of model (2):

$$\min \quad \sum_{\mathrm{t=1}}^{96} \mathrm{c_t} .\Delta\mathrm{t} . \mathrm{Z_t} \tag{8}$$

S.t

(2) – (4), (7)

$$Z_t \geq P_t^N + \sum_{i=1}^{15}\sum_{j=1}^{8} P_t^c . X_{ijt} - \mathrm{PV_t}. \quad \forall\ \mathrm{t} \tag{9}$$

$$Z_t \geq 0 \quad . \qquad \forall\ t \tag{10}$$

$$X_{i.j.t} = \{0.1\} \quad \forall\ i.j.t \tag{11}$$

3.2 Multi-periods Scheduling Models

3.2.1 Model Number 3

This model is similar to Model 1, but it assumes a planning time frame of one period, such as one week. The electricity prices are either announced for the entire week or fixed for all days of the week. Each day of the week is divided into 96 equal parts, which correspond to quarter-hour intervals. The objective remains to minimize the consumer's payment cost by optimizing the cost of electrical energy; however, in this case, only grid power is used, and no energy is sourced from solar cells or other renewable sources. Some appliances can be controlled throughout the week and are available to use on all days, while others are only usable on specific days of the week. According to the stated assumptions, a set of smart appliances can be programmed to minimize the consumer's payment cost. The energy management system selects the operating times of smart appliances to optimize the cost of electrical energy.

Based on the assumptions of the problem, the following are considered:

i. The parameters are fixed and definite.
ii. The pricing is dynamic, and the cost calculation is based on the tariffs determined by the consumer for the week.
iii. Both types of household appliances are considered, i.e., programmable and responsive to time-varying prices and non-programmable and non-responsive to time-varying prices.
iv. The model considers 15 smart devices and eight virtual processes. The planning time frame is assumed to be one week, and each day is divided into 96 equal parts (quarter hours) according to the electricity price announcement time frame.
v. Some appliances can be controlled throughout the week and are available to use on all days, while others are only usable on specific days of the week.

$$\min \sum_{d=1}^{7} \sum_{t=1}^{96} c_{t,d} .\Delta t \ (P_{td}^{N} + \sum_{i=1}^{15} \sum_{j=1}^{8} P_{td}^{c} \ .X_{ijtd}) \tag{12}$$

S.t

$$\sum_{t=St_i}^{En_i} X_{i.j.t.d} = 1 \qquad \forall\ i.j \tag{13}$$

$$X_{i.j+1.t.d} \leq \sum_{t'=1}^{t-1} X_{i.j.t'.d} \qquad \forall i.j.t.d \tag{14}$$

$$X_{i.j.t.d} \leq \sum_{t'=t+1}^{t+T_{off}^{i}/\Delta t} X_{i.j+1.t'.d} \qquad \forall i.j.t.d \tag{15}$$

$$\left(P_{td}^{N} + \sum_{i=1}^{15} \sum_{j=1}^{8} P_{td}^{c} \ .X_{ijtd}\right) \leq P_{t.d}^{max} \qquad \forall\ t\ ,d \tag{16}$$

Given these assumptions, the energy management system can select the operation times of smart appliances to minimize the consumer's payment cost by optimizing the cost of electrical energy.

Equation (12) presents the objective function for minimizing the electric energy cost of the smart home. Equation (13) represents the user's desired operating time range for each electrical device, which is specified by the start time and end time of the interval $[\mathrm{St_i}, \mathrm{En_i}]$. Increasing this interval can lead to a better solution for cost reduction, but it may also compromise the user's comfort. To ensure the correct operation of smart devices, virtual processes for each device must be arranged according to its load profile (inequality 14). If the jth process of smart equipment i is performed in time interval t $\left(X_{i.j.t.d} = 1\right)$, the next process must be performed in an interval greater than t $\left(X_{i.j.t'.d} = 1. t' > t\right)$. As defined in the objective function$\mathrm{T_{off}^{i}}$ indicates the allowed interval between virtual process j and j+1 for smart device i. To avoid breaks longer than the time $\mathrm{T_{off}^{i}}$ between the processes (j) of the i-th smart device, the following condition must be considered (inequality 15). To prevent congestion in the distribution system, the maximum power that can be absorbed from the network can be limited. This limit is determined by the contract between the customer and the electricity company and is typically variable with time. According to this limit (modeled by Equation (16)), the total power consumption of both smart and non-smart equipment in each time period should not exceed the maximum power that can be absorbed from the network.

3.2.2 Model Number 4

After calculating the weekly energy consumption of the smart home using Model 3, a solar cell will be incorporated into the model to enhance its efficiency. As a result, the smart home will be connected to the network and will be able to meet its energy requirements through the network under real-time prices if the solar cell is unable to satisfy the demand. The energy management system will plan the usage times of household equipment based on real-time prices (predicted), while also monitoring the operational limits and usage of the equipment to minimize electricity consumption costs. The proposed model will be as follows:

$$\min \sum_{d=1}^{7} \sum_{t=1}^{96} c_{t,d} .\Delta t \ (\max((\mathrm{P_{td}^{N}} + \sum_{i=1}^{15} \sum_{j=1}^{8} \mathrm{P_{td}^{c}} \ .\mathrm{X_{ijtd}} - \mathrm{Pv_{td}}),0)) \tag{17}$$

S.t

(13) – (15)

$$\left(P_{td}^{N} + \sum_{i=1}^{15} \sum_{j=1}^{8} P_{td}^{c} \ .X_{ijtd}\right) \leq \mathrm{P}_{\mathrm{t.d}}^{\max} + Pv_{td} \qquad \forall \text{ t ,d} \tag{18}$$

The energy management system optimizes the cost of electrical energy in the solar smart home by selecting the operation times of smart appliances (objective function (17)). Constraints (13, 14, and 15) are applicable to this objective function. The power generated by the solar cell added to constraint number 16 to satisfy the demand (inequality (18)).

Since the smart house model with a solar cell (Equation (17)) is nonlinear, it can be linearized by defining a new variable $Z_{t.d}$ as follows:

$$\min \quad \sum_{d=1}^{7} \sum_{\mathrm{t}=1}^{96} \mathrm{c}_{\mathrm{t,d}} \ .\Delta \mathrm{t} \ . \ Z_{t.d} \tag{19}$$

S.t

(13) – (15), (18)

$$Z_{t.d} \geq P_{td}^{N} + \sum_{i=1}^{15} \sum_{j=1}^{8} P_{td}^{c} \ .X_{ijtd} - \mathrm{P}v_{\mathrm{t,d}} \qquad \forall \text{ t ,d} \tag{20}$$

$$Z_{t.d} \geq 0 \quad . \qquad \forall \text{ t} \tag{21}$$

$$X_{i.j.t.d} = \{0.1\} \qquad \forall \text{ i,j,t,d} \tag{22}$$

The linear objective function (19) represents the linearized version of the original nonlinear objective function (17), incorporating the constraints (13), (14), (15), and (18). To solve the problem, two new constraints, (20) and (21), will also be added. Equation (21) expresses the variable X of type zero and one. Since the proposed model is an integer linear programming (ILP) model, it can be efficiently solved by advanced solvers.

3.3 Problem Data

As previously discussed, the daily scheduling assumes that all controllable appliances are turned on during a 24-hour period. Table 2 provides information on the allowed interruption time and the time for turning on and off the controllable appliances.

To obtain PV cell data for a full sunny day, Figure 1 from source [41] can be used. This normalized curve can be applied to all panels. The average value for each hour has been calculated and included after several evaluations [41]. In this study, we utilized data from a 1.4 kW solar panel system that was measured over a one-week period during the spring season (from May 15, 2022, to May 21, 2022). The source of this data is provided in the footnote. When performing smart home calculations, it is not possible to rely solely on calculations based on an ideal, sunny day due to factors such as radiation intensity, panel heating, radiation angle, and cloudy weather conditions. The measurements taken during 15-minute intervals may vary, and this is normal. Averaging is the most reliable method for obtaining consistent values for every 15-minute interval. This approach helps identify patterns or trends in energy production over time. Figures 2 and 3 display the daily and weekly production of the solar panel system.

Table 2
Parameters related to the allowed time interval in the problem

		Case 1		Case 2	
i	T_{off}^{i}	St_i	En_i	St_i	En_i
1	0.5	0	96	0	96
2	1	36	50	36	70
3	3	84	96	30	96
4	1	48	60	30	60
5	2	68	80	36	80
6	0.25	0	96	0	96
7	0.75	0	96	0	96
8	24	0	96	0	96
9	5	0	96	0	96
10	24	0	96	0	96
11	24	0	96	0	96
12	10	0	96	0	96
13	24	0	96	0	96
14	1	0	96	0	96
15	1	0	96	0	96

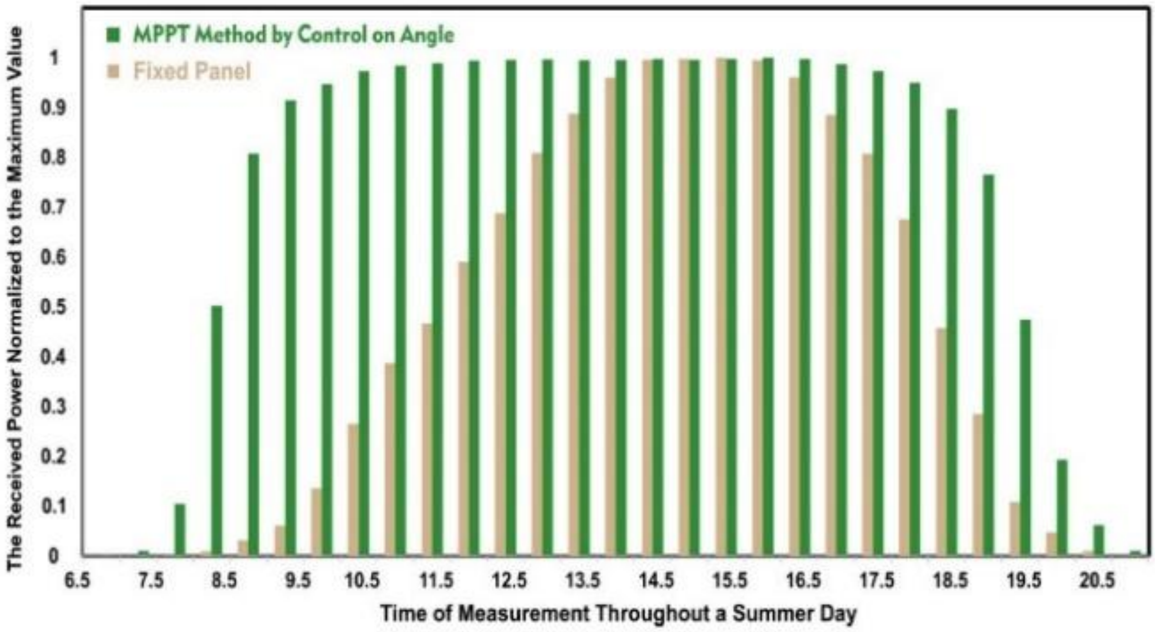

Fig. 1. Measured power for fixed and angle-compensated MPPT hourly on a summer day [41]

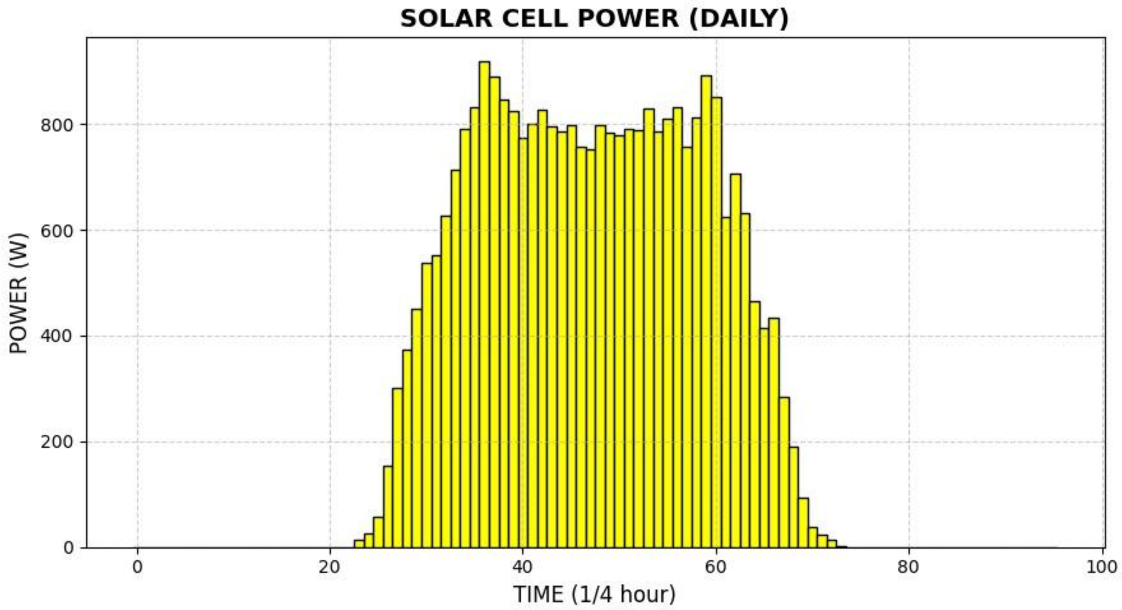

Fig. 2. Cell production capacity in 24 hours (daily)

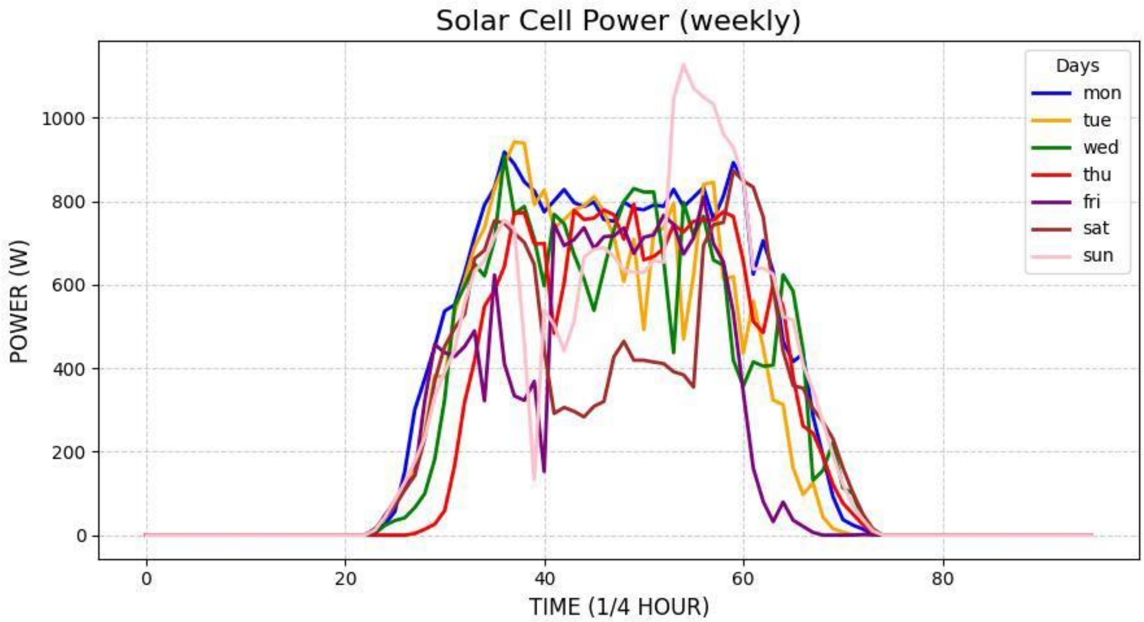

Fig. 3. Weekly solar cell production

The power consumption of the non-responsive appliances of the smart home, which is given as input to the problem, is illustrated in Figure 4.

Table 3 lists the 15 controllable home appliances that will be examined in the case studies, along with their power values for eight virtual processes. Each appliance has a power value assigned to it for each of the eight virtual processes, which represent different periods throughout the day. The load profile of any smart device can be modeled using a series of broken lines, where the load profile consists of several processes with almost constant power levels. For instance, Figure 5 illustrates the power consumption profile of a washing machine, which consists of six processes with constant power consumption. Therefore, the washing machine is assumed to be a combination of six virtual devices (processes), where each process is performed in a 15-minute interval. The utilization of appliances can be delayed between processes (in boundary processes) without compromising the appliance's quality of service. One of the advantages of this method is the high level of control that can be applied to the equipment, allowing the load to be shifted from peak times to non-peak times.

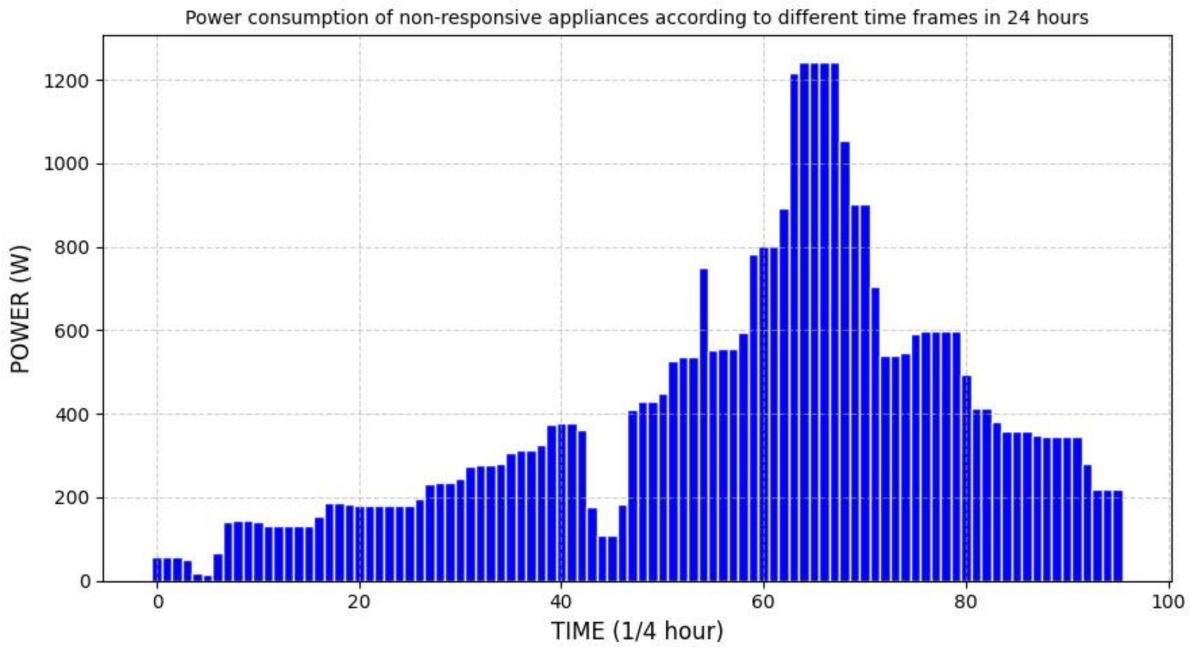

Fig. 4. Power consumption of non-responsive appliances according to different time frames in 24 hours

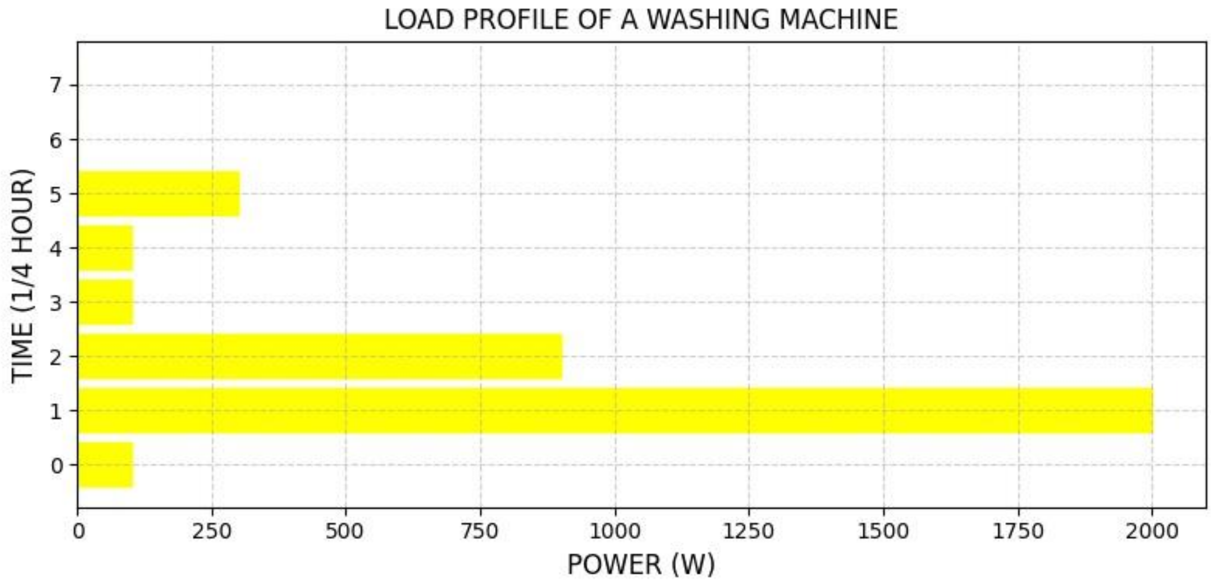

Fig. 5. Load profile of a washing machine

Table 4 displays the frequency of use for smart home appliances weekly, providing a comprehensive overview of the total number of times each appliance was used during the week.

Table 3
Power values of programmable household appliances (P_t^c)

i	The name of the smart	1	2	3	4	5	6	7	8
1	Washing machine	100	2000	900	100	100	300	0	0
2	Dish washing	200	400	1500	1200	800	400	200	200
3	Dryer	50	500	500	500	0	0	0	0
4	Vaporizer	400	400	600	300	100	0	0	0
5	Air disinfectant	200	300	500	50	100	200	0	0
6	Sprinkler 1 (greenhouse)	50	500	500	500	0	0	0	0
7	Fans	100	2000	900	100	100	300	0	0
8	Secret light	200	200	200	200	200	200	200	200
9	Slow cooker	200	400	1500	1200	800	400	200	200
10	Automatic curtain 1	100	100	100	100	100	100	100	100
11	Automatic curtain 2	100	100	100	100	100	100	100	100
12	Sprinkler 2 (garden)	50	500	500	500	0	0	0	0
13	Video recording system	100	100	100	100	100	100	100	100
14	Robot vacuum cleaner	200	400	1500	1200	800	400	200	200
15	Automatic curtain 3	100	100	100	100	100	100	100	100

Table 4
Weekly schedule for turning on controllable appliances

i	The name of the smart device	Mon	Tue	Wed	Thu	Fri	Sat	Sun
1	Washing machine	○	○	○	✓	○	○	✓
2	Dish washing	✓	✓	✓	✓	✓	○	○
3	Dryer	○	○	○	✓	○	○	✓
4	Vaporizer	○	✓	○	✓	○	✓	○
5	Air disinfectant	✓	✓	✓	✓	✓	✓	✓
6	Sprinkler 1 (greenhouse)	✓	○	○	○	✓	○	○
7	Fans	✓	✓	✓	✓	✓	✓	✓
8	Secret light	✓	✓	✓	✓	✓	✓	✓
9	Slow cooker	○	○	✓	○	○	○	✓
10	Automatic curtain 1	✓	○	✓	○	✓	○	○
11	Automatic curtain 2	✓	○	✓	○	✓	○	○
12	Sprinkler 2 (garden)	○	○	✓	○	○	○	✓
13	Video recording system	✓	✓	✓	✓	✓	✓	✓
14	Robot vacuum cleaner	○	✓	○	✓	○	✓	○
15	Automatic curtain 3	○	✓	○	✓	○	✓	○

4. Solution Algorithm

4.1 A Branch and Bound-based operational and research approach (B&B)

B&B was first presented by Land and Doig in 1960, due to their ability to decompose complex patterns and make highly accurate predictions, well known as a powerful tool in the field of operational research [42]. Among algorithms, its survey explores the space of the entire original problem based on a tree structure to generate parallel sorting solutions. This is achieved by creating children as sub-problems for unexplored nodes of the tree through branching and pruning the search space to eliminate suboptimal solutions, ultimately reaching an accurate solution suitable for solving a hard NP problem. Thus, the main cores of the algorithm are the searching strategy, branching, and pruning methods [43]. Recently, studies have focused on representing a feasible way to widely use it in optimization problems to overcome complexity in applications. In 2018, Simirnov and Voloshinov [44] implemented developed solvers in Python to address complex problems within the framework of discrete and global optimization. CBC (Coin-or- Branch and cut)[1] solver is a kind of Domain decomposition branch and bound algorithm as an open-source solver used to solve Mixed Integer - Leaner programming problems (MILP). It's developed by COIN-OR (Computational Infrastructure for Operations Research) and releases an updated version every year. Advantages of CBC solver:

i. Free and easily acceptable;
ii. High compatibility with programming problems;
iii. Extensive users;
iv. Implementable in production programming, Logistics, supply chain management, and allocation issues.

4.2 Developed CBC solver for solving the Proposed Models

The first stage involves verifying the correspondence between the proposed mathematical model and the input parameters, variables, constraints, and objective functions, which are introduced into the Python software via Pyomo. The second stage was solved within the framework of linear programming (LP), which served as the primary reference for the next stage. The third stage, based on the B&B method using CBC Solver, creates a search tree, with each node representing a sub-problem of the main problem. The process is as follows:

i. Branching: If the initial solution does not contain integer variables, the problem is split into two sub-problems. This division is performed by selecting an integer variable and adding new constraints.
ii. Prune: Any node where the solution is not an integer or has no valid solution is pruned and removed from the search. This helps to reduce the search space.

Additionally, the CBC Solver utilized cutting techniques to enhance the efficiency and speed of finding the optimal solution. These techniques introduce new constraints to the model, narrowing the search space and eliminating undesirable solutions.

i. Gomory Cuts: New constraints are added to the model to eliminate fractional solutions.
ii. CLIQUE: Cuts that are used for special problems such as assignment problems.

In the final stage, CBC seeks to find the optimal solution that satisfies all constraints and optimizes the objective function. This solution may be an integer or a mixture of integers and real numbers.

Figure 6 below depicts the steps of the B&B developed algorithm in the solved model.

Start
Input
1. Import necessary libraries:
- pandas for working with Excel data
- pyomo for mathematical modeling
- tqdm for displaying progress in loops
- time for measuring execution time
- numpy for numerical operations

2. Print the installed version of numpy to ensure compatibility.

3. Read data from Excel file:
- Load data from various sheets in the Excel file using pandas.
- Store the data from each sheet into corresponding variables.

4. Define the Pyomo model:
- Create a ConcreteModel instance in Pyomo.
- Define sets i, j, t, d for use in the model.
- Define parameters A, C, Pc, Pmax, PV using the data read from Excel.

[1] https://github.com/coin-or/Cbc

5. Process the data:
   - Convert the loaded data into the required format for use in the Pyomo model.
   - Process the data from the P sheet to extract values corresponding to each combination of (i, j, d).
6. Define variables:
   - Define variables X and W in the model, with X as binary and W as non-negative real numbers.
7. Define the objective function:
   - Set up the objective function to minimize the cost based on the variables and parameters.
8. Define constraints:
   - Implement various constraints based on the problem requirements:
     - Constraints on the values of X and W.
     - Constraints related to power consumption and production.
     - Time-related constraints for the variables.
9. Solve the model:
   - Choose the solver (CBC solver) and set it up.
   - Measure the time taken to solve the model.
   - Solve the optimization problem.
10. Process and save results:
    - Extract the values of the variables after solving.
    - Save the results to an Excel file.
    - Print the objective value and the solving time.

Finish

Fig. 6. Steps of the developed algorithm

5. Results and Analysis

5.1 Case studies

Studies 1 through 4 are based on the basic model where the solar cell is not connected to the smart home, while studies 5 through 8 compare the difference in energy costs when a solar cell is added to the home. Studies 9 through 12 use the information gathered during studies 1 through 4 for one week, while studies 13 through 16 use the information gathered during studies 5 through 8 for one week. Finally, studies 17 and 18 have been conducted to verify the accuracy of the weekly functions used. Model number 1 was run seven times a day, once on each day of the week, to verify the results of the weekly equations without solar cells (model number 3). The results of the objective function for each run are shown in Table 5. Based on the values of the two cost function results, we can conclude that the weekly function of model number 3 provides accurate forecasting.

Table 5
The amount of daily objective functions y (weekly)

Days	Amount of daily target function
Monday	1420592.75
Tuesday	1516105.25
Wednesday	1468367.75
Thursday	1569455.25
Friday	1420592.75
Saturday	1405655.25
Sunday	1395692.75
Sum of functions	10196461.8
The amount of the objective function of the ninth study	10196490

Model number 2 was run seven times a day, once on each day of the week, using solar cell data specific to that day to verify the results of the weekly equations with actual solar cell data. The results of the objective function for each run are shown in Table 6. Based on the values of the cost function results, we can conclude that the weekly equations with solar cell data (model number 4) provide accurate forecasting.

Table 6
The amount of daily objective functions according to the information of the study (weekly)

Days	Amount of daily target function
Monday	709796.031
Tuesday	875589.531
Wednesday	819389.172
Thursday	895577.474
Friday	915014.067
Saturday	813608.281
Sunday	747176.708
Sum of functions	5776151.26
The amount of the objective function of the study	5706419.644

The comparison of case studies in terms of fee amount is given in Table 7. Eight case studies were conducted in GAMS software under various conditions, including constant and variable energy prices, as well as controllable appliance turn-on and turn-off times at different intervals, as outlined in Table 2. The first to fourth case studies relate to the third model, while the fifth to eighth case studies are related to the fourth model. An attempt was made to have a sufficient number of case studies so that when the CBC method and the same initial data from the third and fourth models are run in Python, the final objective function can be compared more effectively.

Table 7
Comparison of 1st to 8th-grade case studies (weekly)

Case Study	The energy cost of the smart home (Rials) is not connected to the PV system (1&2&3&4)	Smart home energy cost (Rials) based on the proposed model that is connected to the PV system (5&6&7&8)	The difference between the two costs
1&5	10196490	5706419.644	4490070.36
2&6	995874.25	5446964.315	4548909.94
3&7	7907709.5	4886922.690	3020786.81
4&8	9520786.75	5353309.296	4167477.45

Based on the table above, if the useful life of solar cells is calculated in each case study, the cost of purchasing a solar cell system capable of producing 1400 watts of power should also be calculated using the daily lifespan. If the daily investment cost for a solar cell in case studies 1 and 5 is less than or equal to 4490070.36, in case studies 2 and 6 is less than or equal to 4548909.94, in case studies 3 and 7 is less than or equal to 3020786.81. In case studies 4 and 8 is less than or equal to 4167477.45, using the solar cell system without connecting to an energy storage system would be more economical.

5.2 Result Obtained by B&B

The B&B results in Python are shown in Table 7. The comparison between the obtained results using the GAMS software and those with the B&B with the CBC solver in Python demonstrates that, in most cases, the results are close to the optimal value of the function from the GAMS results, provided that the runtime is lower than that of the GAMS software. Furthermore, the findings, as depicted in Figures 7 and 8, demonstrate the effectiveness of using the B&B algorithm with a CBC solver as a tool to optimize household appliances in a smart home. Thus, these results hold significant promise for solving similar larger-scale smart home problems in the GAMS software, which we aim to develop to solve this proposed model with an input of 1 month in the future.

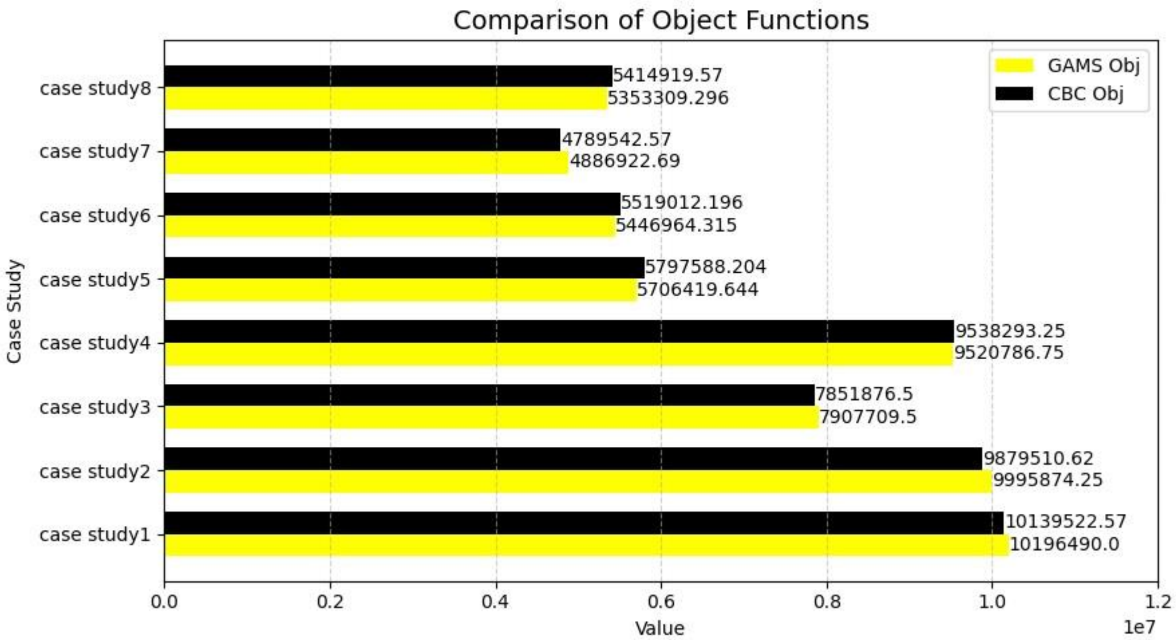

Fig. 7. Comparison of objective functions of case studies in GAMS and B&B

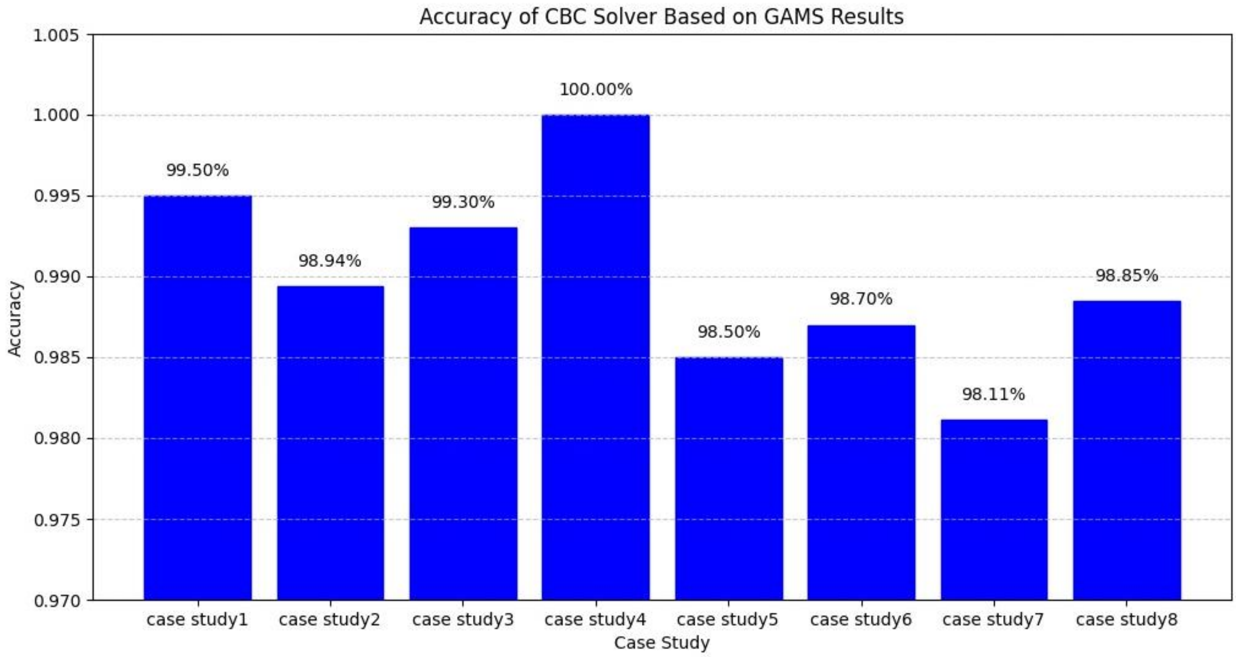

Fig. 8. The accuracy of Python and Gams programming prediction (percentage)

Table 7
Comparing results between GAMS and B&B

Case Study	Objective function in B&B method	Run time(S)	Objective function in GAMS	Run time(S)	Accuracy	Gap
1	10139522.574	538.09	10196490	16200	Near 100	0.05%
2	9879510.620	535.42	9995874.250	16200	Over 98%	1.16%
3	7851876.5	221.17	7907709.5	16200	Near 100	0.07%
4	9538293.25	539.02	9520786.75	16200	Near 100	0.001%
5	5797588.204	6859.32	5706419.644	86400	Over 98%	1. 5%
6	5519012.196	6872.14	5446964.315	86400	Over 98%	1.3%
7	4789542.570	11389.58	4886922.690	86400	Over 98%	1.99%
8	5414919.57	9931.72	5353309.296	86400	Over 98%	1.15%

6. Discussion and Conclusion

The installation of smart technology devices in homes has become increasingly popular due to the numerous benefits they offer. Planning can be done from the 20th time period onwards when the user is awake and can monitor the appliances. This also helps eliminate the afternoon peak, resulting in positive impacts on the user's time and energy costs. Home solar technology is another useful feature of home automation, as it makes homes more energy-efficient. Solar energy is both clean and abundant, and since it is renewable, it is a limitless resource. This means that the future of solar smart homes is bright. Choosing the right solar power system is not confusing, as the many benefits of home automation and solar integration provide the next step toward a more sustainable and energy-efficient residence. You can consult an expert to determine which solar panel might be right for your home.

Flexibility is one of the keys promises of the future home, with the idea that we can build solar capabilities and rely more on battery storage from the grid to achieve energy independence. Connecting to solar energy has never been easier and has become a popular option for powering the home of the future, contributing to a more sustainable world. Imagine a smart home that remains fully connected to the national grid, equipped with a backup generator to provide power when needed. This is the promise of the house of the future. The fact is that one hour of sunlight on Earth is equivalent to one year of energy for the planet. Solar energy users can greatly reduce greenhouse gas emissions and avoid the consumption of millions of barrels of fuel annually.

In conclusion, this paper proposes a method for minimizing electricity consumption costs in a smart home with programmable home equipment that can be controlled. The study focused on exploring consumption management and load response in a smart home, considering real-time pricing. The proposed mathematical models provide a new framework for planning the time of use of household equipment while considering the limitations and operation of household appliances. The mathematical models of the problem are of the nonlinear integer programming (NLIP) type, which was solved using GAMS software after linearizing the proposed models.

Moreover, the study explored the possibility of using a CBC solver for the B&B algorithm as a tool to optimize household appliances in a smart home, and its effectiveness was promising in developing a method to solve the smart home problem with large inputs (e.g., 1 month) in Python, where it could not be solved with GAMS software. Overall, this study presents a novel approach to smart home planning that can significantly reduce electricity consumption costs. The results demonstrate the effectiveness of the proposed method and highlight the potential of using B&B methods to optimize household appliances in developed models for smart homes. Further research is needed to investigate the scalability of the proposed method and its implementation in real-world settings under uncertain conditions, such as variability in the production power of photovoltaic systems. This is an important area for future research, as the performance of the proposed method may be influenced by factors such as weather conditions, shading, and panel orientation.

Acknowledgments

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Conflict of Interest

There is no conflict of interest to disclose.

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