



Genetic-Based Optimized Energy Management at Smart Home Considering the Increase Consumer Convenience and Priority

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Abstract

In recent years, as household energy use has risen, there has been a greater emphasis on intelligent energy management within smart homes. The energy crisis is now one of the world's most pressing issues. With fossil fuel limitations and escalating electricity costs due to increased demand, there is a pressing need for research and effective solutions in this field. Building smart homes is one approach to reducing energy usage. In these homes, consumers can not only control their energy consumption but also sell excess energy back to the grid using renewable sources like solar and wind. This dissertation aims to create a smart home energy management system (HEMS) to efficiently operate residential electrical appliances. The model prioritizes optimizing energy use to enhance user comfort, thermal comfort levels, and profitability of smart home energy management, aligning with consumer preferences. The results demonstrate the model's effectiveness. It uses consumption data and current U.S. electricity market prices, running simulations on an Intel Core i5-6200U processor system with 64-bit Windows 10, Matlab R2017b, and Genetic Algorithm (GA) optimization.

Key words: Energy Management System, HEMS, Smart Home, Consumer Priority

1- Introduction

A smart integration of smart meters and intelligent energy management systems in smart homes is pivotal in enhancing energy efficiency and consumer convenience. According to Page (2018), the adoption of smart meters has significantly increased, setting a foundation for more sophisticated home energy management systems [1]. Zhou et al. (2016) elaborate on the concepts and configurations of smart home energy management systems (SHEMS), highlighting the importance of scheduling strategies that adapt to the dynamic nature of energy prices and user preferences [2]. These systems are designed to optimize energy consumption while ensuring user comfort, leveraging technologies such as machine learning and genetic algorithms to forecast and adjust to energy usage patterns effectively. Corno and Razzak (2012) discuss the implementation of intelligent energy optimization in smart homes, which utilizes user-intelligible goals to configure energy consumption [3]. This



approach not only enhances energy efficiency but also improves the user's ability to interact with and understand the system's decisions. Vojdani (2008) adds that the integration of renewable energy sources into smart grids is essential for the development of self-healing systems that promote sustainability and reduce reliance on traditional energy sources [4]. The role of genetic algorithms in optimizing energy management in smart homes is particularly notable. Bharathi et al. (2017) describe the use of genetic algorithms for demand-side management in smart grids, which can efficiently schedule appliances and manage loads to minimize costs and maximize energy savings [43]. This method reflects a significant shift towards adaptive, responsive energy management systems that not only respond to grid demands but also anticipate and act in the consumer's best interest based on learned consumption patterns. Moreover, the integration of renewable energy sources is crucial in advancing smart home energy management. Al-Ali et al. (2011) demonstrate a renewable energy management system in smart homes that effectively balances energy consumption with production from renewable sources, optimizing the overall energy usage while ensuring that energy is available when most needed [17]. The genetic algorithm approach in this context allows for a more dynamic and efficient handling of unpredictable renewable energy outputs and varying consumer demands. Continuing from the established importance of genetic algorithms in the management of smart home energy systems, Arif et al. (2014) explore the integration of renewable energy dispatch with demand-side management in micro-grids, utilizing genetic algorithms to achieve an optimal balance between energy supply and demand [44]. This approach exemplifies the potential of genetic-based optimization techniques to not only enhance energy efficiency but also to accommodate the variable nature of renewable energy sources like solar and wind power.

Additionally, the research by Nguyen et al. (2015) on energy management for households incorporating solar-assisted thermal load demonstrates the capabilities of genetic algorithms to handle complex, multi-variable optimization problems within smart grids. They show that such systems can effectively manage both the consumption and production of energy, accounting for uncertainties in renewable energy outputs and price fluctuations [45]. This is critical in ensuring that smart homes can operate independently as much as possible, reducing their reliance on external power sources and enhancing their sustainability. The practical application of these genetic-based optimization strategies in real-world scenarios is further evidenced by Anvari-Moghaddam et al. (2015), who present an optimized smart home energy management system that considers both energy savings and a comfortable lifestyle [51]. Their study highlights how genetic algorithms can be fine-tuned to reflect the priorities of the consumers, balancing cost, comfort, and energy efficiency. This user-centered approach is vital for the acceptance and effectiveness of smart home technologies. In terms of technological implementation, Shao et al. (2013) discuss the development of physical-based demand response-enabled residential load models that incorporate genetic algorithms to optimize the scheduling



and operation of home appliances [46]. This detailed modeling is crucial for predicting and managing the energy usage in smart homes, providing a reliable basis for making energy-saving decisions that do not compromise the homeowner's comfort. The combination of genetic algorithms with other technological advancements in smart homes, such as the use of ZigBee for wireless communication and infrared remote controls, further enhances the capability of these systems to provide efficient and user-friendly solutions. Han et al. (2011) demonstrate how these technologies can be integrated into an energy management system, allowing for more granular control and monitoring of energy usage [13]. Building upon the effective use of genetic algorithms in smart home energy management, there is also an increasing focus on enhancing user engagement and system intelligibility. For instance, Mesarić and Krajcar (2015) emphasize the integration of electric vehicles and renewable energy sources with home demand-side management systems, showcasing how genetic algorithms help in creating a more interconnected and efficient household energy ecosystem [16]. This integration allows for the intelligent scheduling of appliance use and vehicle charging, which minimizes energy costs and maximizes the use of on-site generated renewable energy. Furthermore, the potential of genetic algorithms extends beyond mere optimization to facilitate real-time operational decisions. Hu and Li (2013) detail the hardware design of a smart home energy management system that utilizes dynamic price response—a concept where genetic algorithms play a pivotal role in adjusting home energy consumption in response to fluctuating electricity prices [23]. This capability is crucial for leveraging periods of lower energy prices or reduced grid demand, enhancing the economic benefits of smart home systems. The evolution of smart home energy management also incorporates significant improvements in the algorithms' ability to predict and adapt to user behavior and environmental variables. For instance, Zhang et al. (2014) review various home energy management systems in the context of the smart grid, noting that genetic algorithms are instrumental in refining the systems' responsiveness and adaptability to changes in energy demand and supply conditions [20]. This continuous improvement in algorithmic performance is essential for developing systems that not only manage energy efficiently but also anticipate future energy patterns and adapt accordingly. Moreover, the work of Asare-Bediako et al. (2012) highlights the evolutionary trends in home energy management systems, where genetic algorithms contribute to the progression from basic automated systems to highly sophisticated frameworks that actively learn and predict household energy behaviors [19]. These systems are increasingly capable of integrating with broader smart grid functionalities, offering a holistic approach to energy management that extends beyond individual homes to entire communities or regions. In the broader scope of demand response and grid interaction, Mohsenian-Rad et al. (2010) demonstrate how autonomous demand-side management, based on game-theoretic energy consumption scheduling, can benefit from the strategic capabilities of genetic algorithms [36]. These algorithms optimize individual and collective energy decisions within the smart grid, promoting a balance between energy consumption, cost, and environmental impact. The strategic



application of these algorithms ensures that smart homes can effectively respond to grid demands while maintaining user comfort and convenience. Continuing further into the impacts and developments in smart home energy management, the role of genetic algorithms is crucial in adapting to user-specific needs and environmental conditions. For instance, Han et al. (2011) discuss how green home energy management systems can benefit from the comparison of energy usage between similar home appliances, employing genetic algorithms to optimize energy efficiency without compromising user convenience [12]. This type of tailored optimization is essential in promoting widespread adoption and satisfaction with smart home technologies. The efficiency of genetic algorithms in managing the variability of renewable energy sources is well-documented by Batista et al. (2013). Their work on monitoring photovoltaic and wind energy systems within smart grids, utilizing ZigBee devices, highlights how these algorithms help in dynamically managing energy flows, thus enhancing the reliability of renewable sources in smart homes [48]. Research by Huang et al. (2018) on chance-constrained optimization in home energy management systems also illustrates the sophistication of current models [42]. Here, genetic algorithms are used to deal with the uncertainty of renewable outputs and electricity pricing, optimizing energy consumption strategies to minimize costs while maintaining a high level of reliability and user satisfaction. Moreover, the flexibility and adaptability of genetic algorithms are evident in the work of Du and Lu (2012), where appliance commitment strategies for household load scheduling are developed [47]. These strategies, enabled by genetic algorithms, allow for real-time adjustments based on immediate energy consumption needs and availability, further illustrating the practical benefits of these technologies in everyday life. Lastly, the educational aspect of smart home energy management systems is covered by Milam and Venayagamoorthy (2014), who detail U.S. initiatives in smart meter deployment and the associated consumer education on energy savings and efficiency [25]. This highlights another critical role of genetic algorithms: not only do they optimize energy use, but they also contribute to consumer awareness and engagement, which are vital for the long-term sustainability of energy management practices.

2- Problem statement

In this section, the basic concepts of a smart home are introduced.

2-1- HEMS concept

This device provides an opportunity for energy management in smart homes by residents, which will have a significant effect on reducing the price of electricity consumption [11]. Smart HEMS, as an optimal system, provides energy management services in order to monitor and efficiently manage production, storage and provides energy consumption in smart homes [12]. With the communication techniques in the HAN home network, the collection of energy consumption information from all household appliances is provided. Real-time remote monitoring and control of various operating



modes of smart home appliances can be achieved by a personal computer or smart phones from any place and time [13]. In addition, HEMS can provide the optimal use status of home appliances and also provide energy storage and management services for distributed energy resources (DER) and HEMS [14].

2-2- HEMS architecture

The general structure of a smart HEMS is shown in Fig. 1-2. The HEMS center includes a centralized intelligent controller to provide monitoring modules and control functions to the home owner based on the home communication network [15]. The real-time data of programmable and non-programmable home appliance electricity consumption can be collected by the smart HEMS main panel and implement the optimal demand message. The electric vehicle (EV) is a special type of programmable load. This device provides energy from electric networks for the transportation of residents and emergency power for other household loads in a smart collective environment [16].

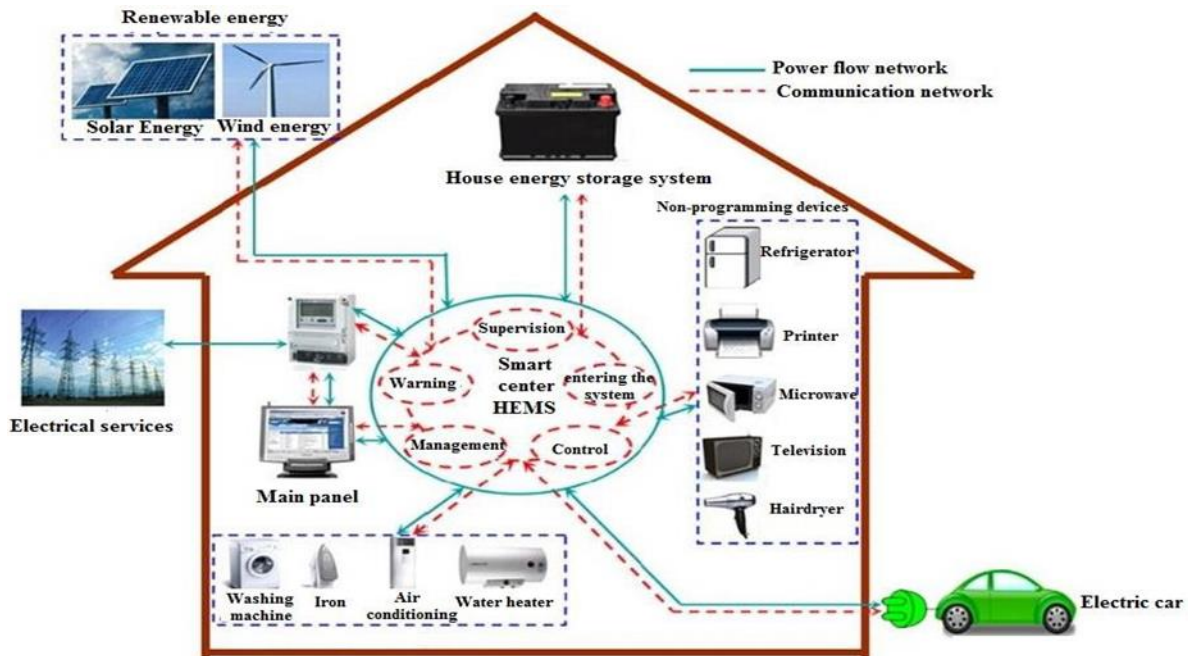


Fig. 2-1: Architecture of the smart home energy management system [2].



3- Proposed method

In this section, the studied system is described, and modeling of its various components including electric water heater, heating system, solar panels, and battery is presented. Furthermore, the proposed method is introduced and explained.

3-2 Problem Modeling

The objective of this paper is to design a controllable Home Energy Management System (HEMS) and to utilize it in a residential house equipped with a 5 kW solar system and battery storage for storing electrical energy and using it allowed required hours.

The controllable appliances in this study are categorized into two groups. The first category includes appliances such as washing machines, dishwashers, clothes dryers, irons, vacuum cleaners, microwaves, electric stoves, electric kettles, and toasters, which require specifying a start time for their operation. Each appliance begins functioning at this specified time and completes its task within a predetermined duration. The second category comprises electric water heaters and heating/cooling systems, for which minimum and maximum temperatures are determined to decide their on/off status during each hour or time interval (quarter-hour in this paper). The subsequent sections of this section present the modeling of various components of the system.

3-2-1 Water Heater Modeling

The consumer specifies their desired minimum and maximum temperatures for the water heater. To model this, it is assumed that, according to reference [54], the heating section of the electric water heater can be represented as a first-order system.

$$C_w = \frac{dT_{hw}}{dt} = Q_{elec} - mC_p(T_w - T_{inlet}) + (T_{amb} - T_w) \quad (3-1)$$

In this formula:

T_{hw} : Hot water temperature as a function of (°F)

T_{inlet} : The ambient temperature of the water heater as a function of (°F)

: The specific heat of water in terms of $\frac{Btu}{lb \cdot ^\circ F}$ is equal to 1.

$1b \cdot ^\circ F$



The thermal resistance of the tank is denoted by R and depends on $\overline{h_r(f_t)}^{2 \cdot ^\circ F}$. Also, SA is the surface area of the

Btu

water heater tank.

Q_{elec} is the heat energy absorbed by the tank in one hour, calculated in Btu , is determined as follows:

$$Q_{elec} = 3412P \quad (3-2)$$

Where (P) is the power in kilowatts (Kw) of the water heater

In the Eq. (3-1), m is the volume of hot water output from the tank can be obtained in terms of output water in onehour (f) as follows:

$$m = 8.34 \left(\frac{1b}{gal} \right) \times f \left(\frac{gal}{hr} \right) \quad (3-3)$$

The term C_w in the equation (3-1) is based on the volume of the water tank and can be determined from the relationship provided by the following formula:

$$C_w = V(gal) \times \frac{1ft^3}{7.48gal \times 62.4} \times \frac{1b}{ft^3} \times 1 \times \frac{Btu}{1b^\circ F} \quad (3-4)$$

Here, V represents the volume of the tank in gallons.

Based on the model proposed for the water heater tank, the ambient temperature around the water heater changes depending on the amount of hot water exiting the water heater. Typically, the control system for this device is considered such that the user sets a minimum and maximum temperature for the hot water. When the hot water temperature falls below the minimum value, the water heater turns on and remains on until it reaches the maximum temperature. If the hot water temperature is within the range of the minimum and maximum temperatures, the water heater remains in its current state (either on or off). In other words, when the hot water temperature is between the minimum and maximum values, the state of the water heater (on or off) depends on its previous state.

In this paper, to improve the total energy consumption cost and to ensure that the water heater operates more during times of low electricity prices, an intelligent control system determines two temperatures: a minimum (T_{min}) and a maximum (T_{max}). Based on the user-defined setpoint temperature (setpoint), the water heater's operation is expressed as follows:

$$\left\{ \begin{array}{l} \text{if } T < T_{min} \Rightarrow \text{State} = ON \\ \text{if } T > T_{max} \Rightarrow \text{State} = OFF \\ \text{if } T_{min} \leq T \leq T_{max} \Rightarrow \begin{cases} \text{if } T_{max} + T_{min} - 2T > u \Rightarrow \text{State} = On \\ \text{if } T_{max} + T_{min} - 2T > u \Rightarrow \text{State} = OFF \end{cases} \end{array} \right.$$



(3-5)

Based on the above algorithm, if the water temperature is less than T_{min} , the water heater turns on. If the water temperature exceeds T_{max} , the water heater turns off. However, when $T_{min} \leq T \leq T_{max}$, the decision to turn the water heater on or off depends on which temperature limit (T_{min} or T_{max}) is closer to the current temperature T . In explaining Eq. (3-5), the value of u is considered to be 20% of the difference T_{min} and T_{max} , meaning: $u = 0.2(T_{max} - T_{min})$. For a better understanding, assume the system predicts the previous performance of the water heater. Consider a scenario where the water heater is on in the fifth interval, and its temperature is approaching T_m . Despite not yet reaching that temperature, the system predicts that the water heater will remain on in the next interval as well. However, shortly after, the control system will turn off the water heater. This indicates that the system did not accurately predict the water heater's behavior and allocated the sixth interval to the water heater, whereas another appliance could have been turned on during that time.

With this explanation, if the proposed system is used, this issue and similar ones are solved by approaching the temperature to T_{min} . Where the water heater is off and T is bringing close to T_{min} , the traditional control method cannot be possibly predicted to turn on the water heater in the next interval and the water heater will still turn on. If the system correctly predicted this situation, it could have turned off another appliance that has been issued a command to prevent its activation, thereby avoiding penalties resulting from the system.

3-2-2 Air Conditioning System Modeling

Based on [55], and considering that the air and water data are for January 2, 2018 (winter season), we assume that the air conditioning system is responsible for heating. The thermal model for room temperature is formulated as shown in Fig. 3.

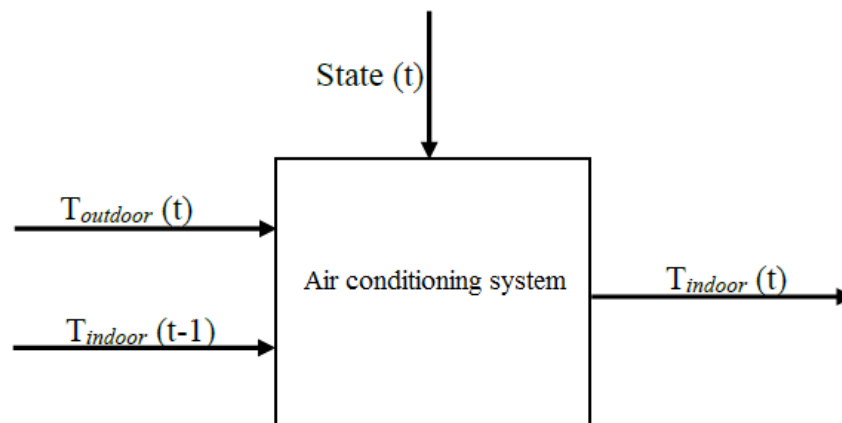


Fig. 3-1: Air Conditioning System Modeling



Based on the current room temperature, outside temperature, and the status of the heating system (on/off), the room temperature is updated. The model used in this paper is presented as a model implemented in MATLAB software, based the following equations:

$$\left(\frac{dQ}{dt}\right) = (T_{heater} - T_{room}) \cdot M_{dot} \cdot C$$

(3-6)

$$\left(\frac{dQ}{dt}\right)_{losses} = \frac{(T_{heater} - T_{outdoor})}{R_{eq}}$$

(3-7)

$$\left(\frac{dT_{room}}{dt}\right) = \frac{1}{M_{dot} \cdot C} \left(\frac{dQ_{heater}}{dt} - \frac{dQ_{losses}}{dt} \right)$$

(3-8)

In these equations:

$\left(\frac{dQ}{dt}\right)$: represents the heat flow into the room by the HVAC system,

C : is heat capacity of air in $(1012 \text{ J/kg} \cdot ^\circ\text{C})$.

M_{dot} : denotes the air volume flow rate moved into the room by the HVAC system, measured in kg/hr.

T_{heater} is the temperature of the air exiting the HVAC system.

T_{room} is the current temperature of the room air.

$\left(\frac{dQ}{dt}\right)_{losses}$ represents the heat flow losses from the building, derived from Eq. (7). In this equation, the thermal resistance R_{eq} equivalent for the building can be determined using the following equation:

$$R_{eq} = 0.0180 \frac{^\circ\text{C}}{\text{J}} \times \frac{1 \text{ hr}}{3600 \text{ s}}$$

(3-9)

and the value of C is equal to $(1012 \text{ J/kg} \cdot ^\circ\text{C})$

The emphasis here is that the value of (T_{heater}) is defined by the equations from 3-6 to 3-8.

3-2-2-1- Determining the Electrical Heating System Power

The value of (T_{heater}) mentioned in equations 3-6 to 3-8 represents the temperature of the heated air by the electrical heating system. In this paper, it is assumed that the HVAC system increases the inlet air temperature to 10 degrees Celsius (50 degrees Fahrenheit).

$$T_{heater} = T_{room} + 50^\circ\text{F}$$

(3-10)

Now, the question arises: How much electrical power is required by the HVAC system to achieve a



temperature increase of 10 degrees Celsius)? According to the reference (source), this can be determined using Eq. 3- 11, where the power P required by the HVAC system will be in kilowatts (kW).

$$P_{kw} = \frac{Temp\ Rise \times CFM}{3193} \quad (3-11)$$

In this equation:

The TempRise is the amount of increased temperature (in °F)

CFM is transfer volume in a certain interval of time in terms of $\frac{(ft)^3}{min}$

For example, if the building area is 100 square meters with a height of 3 meters, the building volume will be 300cubic meters or 10594(ft)³.

$$\left(300 \times \left(1_m \times \frac{100_{cm}}{1_m} \times \frac{1_{inch}}{2.54_{cm}} \times \frac{1_{ft}}{12_{inch}} \right)^3 \right) \quad (3-12)$$

Now, if we want the building temperature to increase by 10 degrees Celsius (50 degrees Fahrenheit) in one hour, we will have:

$$CFM = \frac{10594}{60_{min}} \approx 177 \frac{(ft)^3}{min} \quad (3-13)$$

Based on Eq. (3-11), the required amount of kw is determined as:

$$P_{kw} = \frac{50(^{\circ}F) \times 177 \frac{(ft)^3}{min}}{3193} \approx 2.75kw \quad (3-14)$$

Based on the CFM value, the air volume flow rate M_{dot} considering the air density is selected of approximately 388 kg/h,.

3-2-2-2 Air Temperature Control System

The air temperature control system predicts the room temperature similar to the water heater temperature control system, with the difference that the room temperature takes on a different value. Thus, the same advantage mentioned applies to T_{min} and T_{max} based on u . With appropriate prediction of the indoor air temperature control system performance, the operating time of the devices can be accurately determined and adjusted.



2-3-2-3 Energy Storage System Model

The energy storage system essentially refers to a battery bank capable of storing energy and delivering it to other devices or even the main grid when needed. In a smart home environment where operational periods are scheduled, the charge and discharge cycles of the storage system are also determined by the energy management system. To maintain battery efficiency, the power discharge and charge (SOC) states must be limited to specific ranges as described below:

$$P_{batt.ch}(q) \leq P_{ch.max} \cdot \eta_{ch} \cdot u_{batt}(q) \quad (3-15)$$

$$P_{batt.ch}(q) \leq \left(\frac{P_{dch.max}}{\eta_{dch}} \right) \cdot (1 - \mu_{Batt}(q)) \quad (3-16)$$

$$(SoC_{min} \leq SoC \leq SoC_{max}) \quad (3-17)$$

$P_{ch.max}$ and $P_{dch.max}$ are the maximum power limits of battery charge and discharge.

SoC_{min} and SoC_{max} are the top and bottom limits SOC of the battery.

η_{ch} and η_{dch} are binary variables indicating the charging and discharging status of the battery. Since the battery cannot simultaneously charge and discharge, the following constraint must be considered:

$$\mu_{ch}(q) + \mu_{dch}(q) \leq 1$$

The advantage of using two variables $\mu_{ch}(q)$ and $\mu_{dch}(q)$ compared to the state of the battery with a certain variable is that with two variables, we can represent a state where the battery is neither charging nor discharging. Consequently, the battery's lifespan increases compared to a scenario where it is always either charging or discharging. Updating the SoC based on the battery's previous state and its charging or discharging within the q interval is according to Eq. (18) [51].

$$(SoC(q + 1) = SoC(q) + \frac{(P_{batt.ch}(q) - P_{batt.dch}(q)) \cdot \Delta h_{step}}{E_{batt}} \quad (3-18)$$

E_{batt} is the battery energy capacity is expressed in kWh and Δh_{step} is time interval [51] which its value is considered one-quarter (1/4) of an hour.

3-2-4-Photovoltaic (PV) Generator Modeling

A photovoltaic (PV) generator is a system that directly converts sunlight into electrical energy. The electrical power output of the generator is a function of solar radiation intensity and ambient temperature. For this purpose, the power of the PV modules is measured under standard test conditions and calculated under various environmental conditions. The data on solar radiation



intensity is known based on [56] and is plotted at specified time intervals. Additionally, the ambient temperature T_c varies throughout the day according to the Fig. 2-4 . The values are assumed according to [57]:

$$P_{pvt} = P_{STC} \frac{G}{G_{STC}} [1 - K_{T.PV}(T_{Ct} - T_r)] \quad (3-19)$$

G_{STC} = is the solar radiation level measured in standard test conditions in W/m². G = Solar radiation is expressed in W/m²

$K_{T.PV}$ = Photovoltaic generator power temperature coefficient

P_{STC} =Maximum power under standard test conditions in photovoltaics (w)

T_{Ct} =Environment temperature in degrees Celsius

T_r =Reference temperature of the photovoltaic module (degrees Celsius)

P_{pvt} =The power generated by the photovoltaic module at time t (w)

3-4-Combination of real-time pricing (RTP) and inclining block rate (IBR)

In an intelligent cost-minimizing electricity control system, it is possible for most devices to enter circuits during low-cost moments, causing the grid to experience peak loads at these times. This situation, when considering a large number of smart homes connected to the power grid, can pose challenges, and solutions must be considered to reduce the peak to average ratio (PAR) of the load. In other words, the intelligent optimization problem aimed at minimizing costs from the consumer's perspective should be such that both parties (consumer and utility company) are satisfied. One suitable solution to address this issue is to consider inclining block rate (IBR), where if the electrical power received by the consumer exceeds a predetermined threshold, the electricity price increases significantly for that period. Consequently, the smart system decides to distribute loads at different times to mitigate peak-to-average ratio (PAR) night and day. The relation contributed to the IBR is as follows:

$$Pr c_i(s_i) = \begin{cases} a_i & 0 \leq s_i \leq c_i \\ b_i & s_i > c_i \end{cases} \quad (3-20)$$

a_i represents the Instant price of electricity in i time interval.

b_i is the second-tier level of the electricity price , which must also be larger than a_i .

s_i represents the total consumed power the time interval during i time interval.

Based on this equation, after identifying s_i as the consumed power, if s_i exceeds a threshold c_i , the price of electricity is calculated with b_i instead of a_i . It is usual that b_i is considered as a coefficient of : $b_i = \lambda a_i$



3-5 - Objective Function

In the optimization problem of interest, the objective function to be optimized consists of three main components. The first part relates to the electricity cost resulting from the consumption of electrical power by equipment, whereby there is a natural inclination for devices to be used more during periods of lower electricity prices. However, users of these devices still prefer to activate them at their desired times to perform their tasks, which constitutes the second part of the objective function. The third part of the objective function pertains to user satisfaction with the ambient temperature, defined as the level of comfort or thermal well-being.

In the following, sections of this objective function will be expressed mathematically.

3-5-1 Electricity Cost

Each electrical device consumes a certain level of electrical power, and for every unit of time that the device operates, it will consume energy. By multiplying this amount by the energy consumption (in kilowatt-hours) and the electricity price, the cost of electrical energy consumption will be determined. The following equation describes this relationship.

$$J1 = MinCost = Min \sum_{q=1}^T Prc_q(Pq) \times Pq \times \Delta t(q)$$

s.t: (3-21)

$$Pq = Min \sum_{i=1}^v P_i \times u_i(q)$$

In this expression, P_i represents the power consumption of device i , and (q) indicates the on/off state of device i during the time interval q (if $u = 1$, the device is on, and if $u = 0$, the device is off). Here, q denotes a period of time, typically 15 minutes, proposed in this paper. After calculating the energy consumed in a period for all specified devices Pq , the electrical energy cost for that period $Prc_q(Pq)$ is determined based on the electricity price using the pricing pattern combination (IBR and RTP). This cost is computed by summing the values obtained for different time periods to calculate the total electricity cost for a day. Pq in each time interval represents the net power consumption of devices, meaning that the power received from the grid and the power generated by solar panels or the power that batteries may provide due to charging or discharging must be considered in this relation. Therefore, Pq is modified:



$$P_q = \sum_{i=1}^N P_i \times u_i(q) + P_{batt}(q) - P_{pv}(q) \quad (3-22)$$

Where $P(q)$ is the amount of power obtained from solar energy.

$P_{ba}(q)$ represents the battery power, which can be positive (charging) or negative (discharging).

$$P_{batt}(q) = P_{batt.ch}(q) - P_{batt.dch}(q) \quad (3-23)$$

$P_{batt.ch}(q)$ represents the battery charging power, and $P_{batt.dch}(q)$ represents the battery discharging power.

3-5-2- Resident Comfort Level

In addition to cost reduction, the user desires to have their preferred device turned on at any hour they choose and to perform the assigned task. For this purpose, before starting the planning process, the user must specify time categories for each device. The first category is the permissible operating time for devices, meaning that equipment should operate within that interval. The second category is the user's preferred time interval for device operation, indicating that the user strongly prefers devices to operate during their desired time period. Additionally, each device has different prioritization criteria that must also be specified. The details of user-entered information will be discussed in Section Four.

Suppose for device i , if the permissible time interval is defined as $[h_{s,i}, h_{e,i}]$ and the preferred interval $[h', h']$,

then the preference function (J_2) can be considered as follows:

$s.i \ e.i$

$$s.t \begin{cases} \text{if } t_{s,i} \geq h'_{s,i} \ \& \ t_{e,i} \leq h'_{e,i} \Rightarrow x_q = 0 \\ \text{otherwise} \Rightarrow \begin{cases} t_{s,i} < h'_{s,i} \Rightarrow x_q = \alpha_1(h'_{s,i} - t_{s,i}) \\ t_{e,i} < h'_{e,i} \Rightarrow x_q = \alpha_2(t_{e,i} - h'_{e,i}) \end{cases} \end{cases} \quad (3-24)$$

This relationship indicates that if a device operates within the user's preferred time interval, the satisfaction level will be 100%. Since the goal is to minimize the objective function, x_q will be equal to 0. Otherwise, x_q will be increased by the distance from the preferred time period.

3-5-3 Thermal Comfort

The third part of the objective function is dedicated to the thermal comfort of the residents, such that if the temperature falls within the desired range, $y_3 = 0$. Also, If it is out of range, J_3 can be;



$$\text{Min } J_3 = \sum_{q=1}^T y_q \quad (3-24)$$

$$y_q = \begin{cases} 0 & \text{if } T_{\min} \leq T \leq T_{\max} \\ \beta_H \times (T - T_{\min}) + y_H & \text{if } T > T_{\max} \\ \beta_C \times (T_{\min} - T) + y_C & \text{if } T < T_{\min} \end{cases}$$

T demonstrates the environmental temperature. $T_{\min}$ and $T_{\max}$ are the lower and upper temperature limits, respectively. The objective is to optimize J_3 . Therefore, if T is in the range of $T_{\min}$ and $T_{\max}$, $y_q = 0$. Otherwise, the value of y_q will be increased. Total y_q s in all eras of time, will be resulted in J_3 .

4- Results and Analysis

In order to reduce consumer costs, enhance user comfort, and increase HEMS efficiency, a model for planning thermal comfort levels was presented in the previous section. In this section, the performance of the proposed system will be evaluated under various scenarios. It is noteworthy that all simulation stages were conducted in the Matlab R2017b software and using the genetic optimization algorithm.

4-2 Input Data

The input data includes information about responsive loads (plannable devices) and their power consumption, as well as the power consumption of non-responsive loads (non-plannable) and the predicted daily hot water usage based on the references [42,51]. Additionally, information regarding electricity real time pricing on an hourly basis from reference [58] is considered for specific regions in New York on January 2, 2018, as shown in Fig. 4-1.

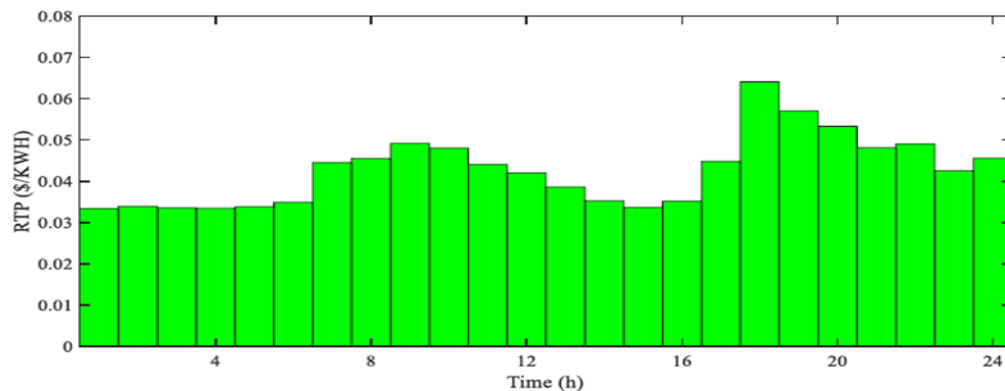


Fig. 4-1: Electricity real time pricing



The air temperature data for New York City on January 2, 2018, is provided based on reference [55]. See Fig. 4-2 for details.

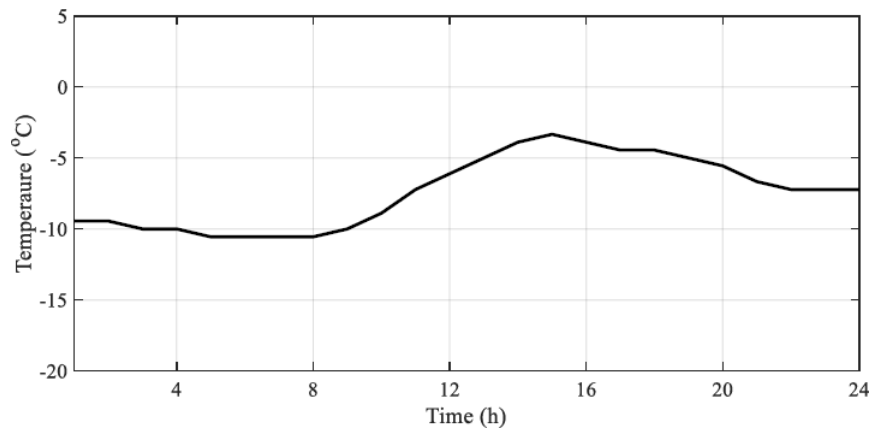


Fig. 4-2: The solar irradiance levels on January 2, 2018.

Figs. 4-3 and 4-4 based on reference [56], show solar irradiance levels and ambient temperature, the extractable power capacity from solar panels with 5kw capacity for residential homes, as presented in models provided in Section3.

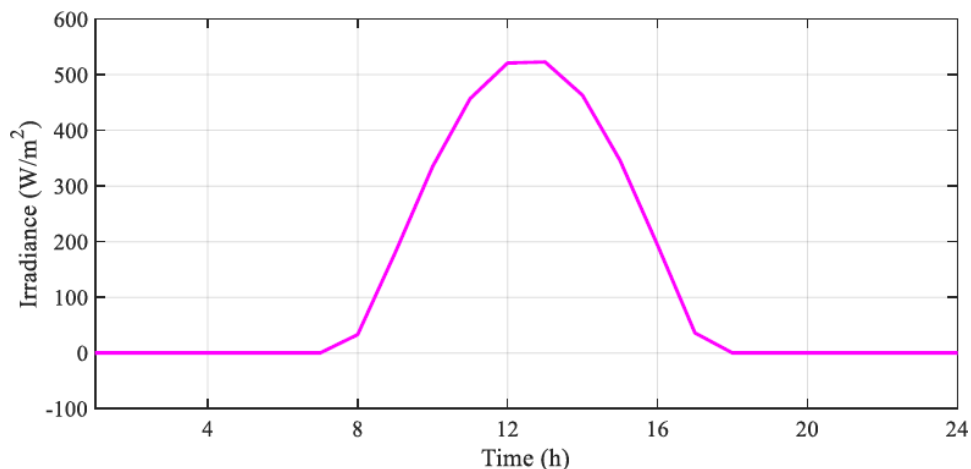


Fig. 4-3: Solar Radiation Levels, January 2, 2018.

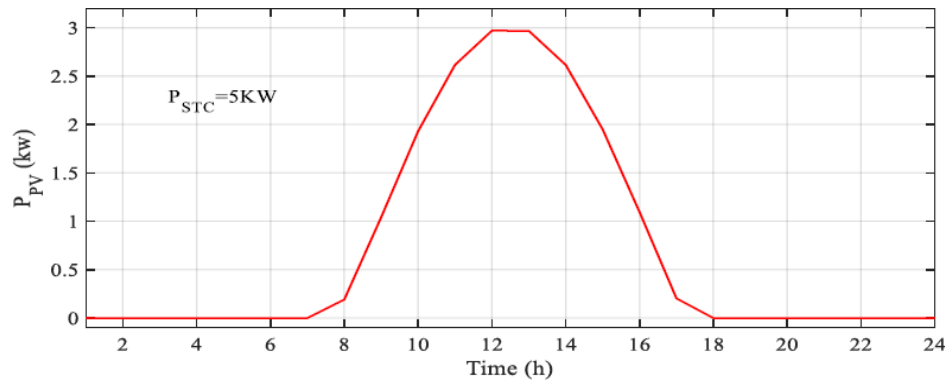


Fig. 4-4: Amount of Extractable Power from Solar Panels

In Table 4-1, the information on smart devices used in the model is provided. This table includes the nominal power of each device, along with the allowable operating time intervals, user-preferred operating intervals, and the predicted duration of device operation. For example, according to [51], the nominal power of a washing machine is 1

kW, and it should operate for a maximum of 2 hours. The allowable operating interval for this device is considered from 7 AM to 9 PM, while the user prefers this device to operate preferentially between 8 AM and 2 PM.

An important point to note about this table is that the performance information of devices is presented on an hourly basis, and the planning for them is also done on an hourly basis. However, it is possible that some of these devices may complete their tasks in less than an hour. Nevertheless, the scheduling system, based on hourly time intervals, is forced to allocate a full hour for the operation of each device. For example, in this table, two one-hour intervals are allocated for the washing machine's operation, even though the machine may complete its task in one hour and 15 minutes, the system's prediction necessitates reserving two one-hour intervals for operation. This issue becomes prominent when the electricity price is lower during the second interval, where the device operates for only 15 minutes. Because, the scheduling prediction allocates the two-hour interval for the device's operation, missing the opportunity for another device to operate at a favorable price during this time interval. In other words, in a one-hour interval where the electricity price was low, only 15 minutes of electricity consumption occurred, and the devices remained off for the remaining 45 minutes.

To address this issue, instead of planning on a 24-hour basis, scheduling is carried out in intervals of 15 minutes, meaning decisions about device activation are made four times per hour. Therefore, it is necessary to update the information from Table 4-1 to Table 4-2, accordingly.



Table 4-1: The performance of household appliances on an hourly basis [51].

Household Appliances	nominal power (kW)	Permissible Operating Interval	Preferred Operating Interval	Duration of Operation per Hour	Priority weighting of Performance
Washing Machine	1	07:00-21:00	08:00-14:00	2	1
Dishwasher	1.6	06:00-18:00	14:00-18:00	2	2
Clothes Dryer	1.8	09:00-21:00	11:00-17:00	1	1
Iron	1.2	01:00-13:00	05:00-07:00	1	2
Vacuum Cleaner	0.8	08:00-20:00	09:00-12:00	1	2
Microwave	1	08:00-19:00	11:00-14:00	1	3
Electric Stove	0.6	10:00-18:00	14:00-17:00	2	3
Electric Kettle	1	04:00-12:00	06:00-07:00	1	3
Roast	0.8	01:00-10:00	06:00-08:00	1	3

Second table: In Table 4-2, it is assumed that appliances operate in intervals of 15 minutes. Table 4-2: Operation of household appliances in 15

Household Appliances	nominal power (kW)	Permissible Operating Interval	Preferred Operating Interval	Duration of performance (15 minutes)	Priority weighting of Performance
Washing Machine	1	29-84	33-56	7	1
Dishwasher	1.6	25-72	57-72	6	2
Clothes Dryer	1.8	37-84	45-68	3	1
Iron	1.2	5-42	21-28	2	2
Vacuum Cleaner	0.8	33-80	37-48	2	2
Microwave	1	33-76	45-56	3	3
Electric Stove	0.6	41-72	57-68	7	3
Electric Kettle	1	17-48	25-28	3	3
Roast	0.8	5-40	25-32	2	3

Another point regarding Tables 4-1 and 4-2 is the priority weighting of appliance functions. The scheduling system must consider that appliances with higher weights have greater priority in the preferred operational time interval. For example, between a toaster and an iron, the toaster is more important for timely operation. Other system details are listed in Table 4-3.



Table 4-3: Parameters and Assumed Values in the Simulation

Model			Model		
Name	Parameter	Quantity	Name	Parameter	Quantity
Solar panel model	PSTC	5 kw	Air conditioning system	Req	1.6e-5
	GSTC	1000 w/m ²		C	1012.4
	Tr	25 °C		Mdot	388
	KT,PV	0.0045			
Energy storage system	EBatt	4 kwh	Energy storage system	hstepΔ	0.25h
	ηch	0.87		ηch	0.9
	Pch,max	2 kwh			

4-3- Information on Simulation Algorithm

To optimize the problem under study, the Genetic Algorithm (GA) algorithm in MATLAB software was employed.

4-3-1- Introduction to Genetic Algorithm

The Genetic Algorithm is an adaptive exploratory search method based on genetic population. The algorithm begins with a set of solutions called a population. In each generation, the fitness of each chromosome is evaluated, and then chromosomes are selected for the next generation possibly based on their fitness values.

A genetic algorithm is a search method used in computation to find approximate or exact solutions for optimization and search problems. In genetic algorithms, initially, several solutions for the problem are generated randomly or algorithmically. This set of solutions is called the initial population, where each solution is termed as a chromosome. Then, using genetic algorithm operators, better chromosomes are selected, combined, and subject to mutation. Finally, the current population is combined with a new population resulting from the combination and mutation of chromosomes.

Before a genetic algorithm is executed for a problem, a method for encoding genomes into computer language is employed. One common method of encoding is using binary strings, consisting of strings of zeros and ones, which is the method used in this paper for solving optimization problems [59].

Information about the parameters of the genetic algorithm (GA) used in this paper is provided in Table 4-4.

Table 4-4: Parameters of the Genetic Algorithm

Parameter	Quantity	Parameter	Quantity
Chromosome string type	Bit strings	Coefficient(Crossore r)	0.8
String size	543	Mutation percentage	0.3
population size	3000		
maximum number of iterations	100		

4-3-1- Explanation of Chromosome or Bit String Size

As indicated in Table 4-1, the studied system is equipped with 9 adjustable and programmable appliances. To determine the start time for each appliance based on the number of time intervals ($24 * 4 = 96$), 7 bits are required, resulting in a total of 63 bits for all 9 appliances. Additionally, to determine the minimum and maximum temperatures for two appliances (such as water heaters and air conditioning systems) in each interval, 3 bits per interval are considered, resulting in a total of 1152 bits ($96 * 4 * 3$), which is a large number of bits. To reduce the number of bits, given the dynamic nature of the ventilation system and water heating, it is possible to define the minimum and maximum temperatures for each hour. In this case, ($24 * 4 = 96$), 228 bits are required for defining two minimum and maximum temperatures per hour, using 3 bits each. Furthermore, to determine the charging and discharging status of the battery, two 96-bit vectors are required, where the first vector will specify the charging status and the second vector will specify the discharging status of the battery. It is important to note that two bits indicating battery charge and discharge status within a time interval cannot be simultaneously 1. Therefore, a total of 543 bits are required overall, as illustrated in Fig. 4-5.

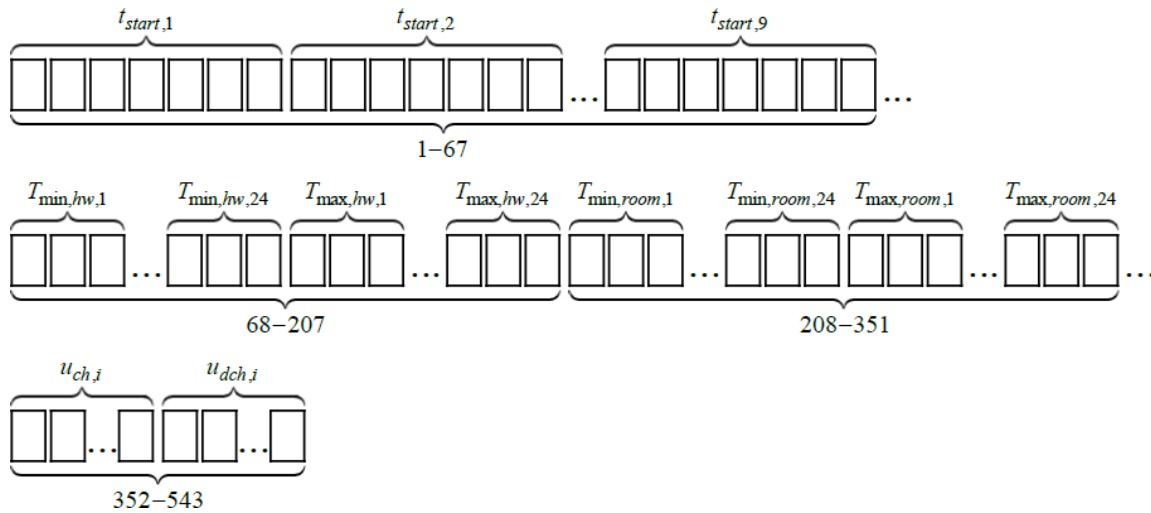


Fig.4-5: Chromosome Size (Bit String)

4-4 First Section of Simulation

After introducing the specifications of the studied system and all parameters, including the algorithm parameters for a 24-hour period with 15-minute time intervals, the GA planning process is conducted as follows.

Fig. 4-6 illustrates the change in the defined objective function value, which has converged to a constant value after approximately 30 iterations.

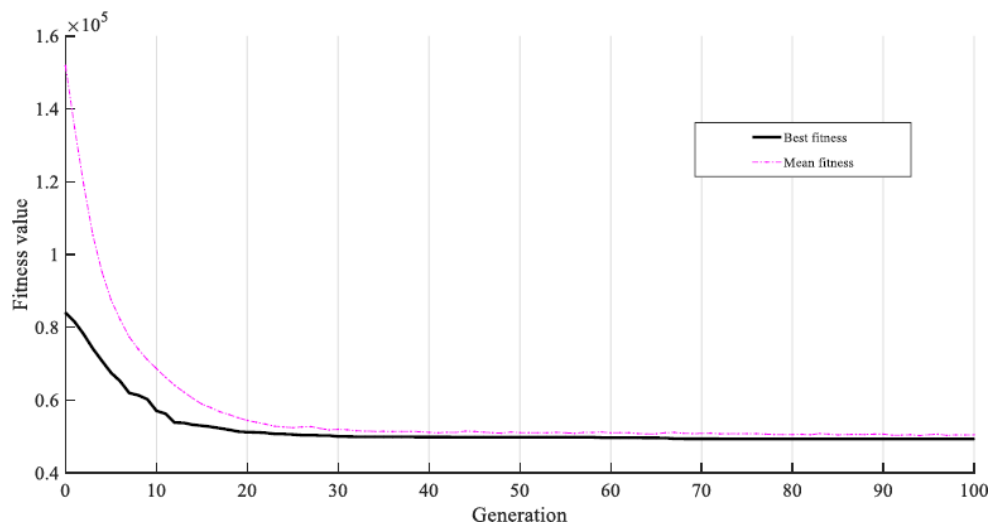


Fig. 4-6: The process of changing the value of the defined objective function after 100 iterations



Table 4-5 illustrates the performance intervals determined by HEMS for the next day, which, upon comparison with Table 4-3, indicates that all 9 devices are appropriately weighted within the user comfort section of the objectivefunction during the preferred user time interval.

Table 4-5: HEMS performance intervals for the next day

Household Appliances	Start time of operation	End time of operation
Washing Machine	11:30	13:00
Dishwasher	14:15	15:30
Clothes Dryer	13:30	14:00
Iron	6:00	6:15
Vacuum Cleaner	11:30	11:45
Microwave	12:45	13:15
Electric Stove	15:00	16:30
Electric Kettle	6:15	6:45
Roast	7:00	7:15

In Fig. 4-7, the operational time is presented in a stair-step manner.

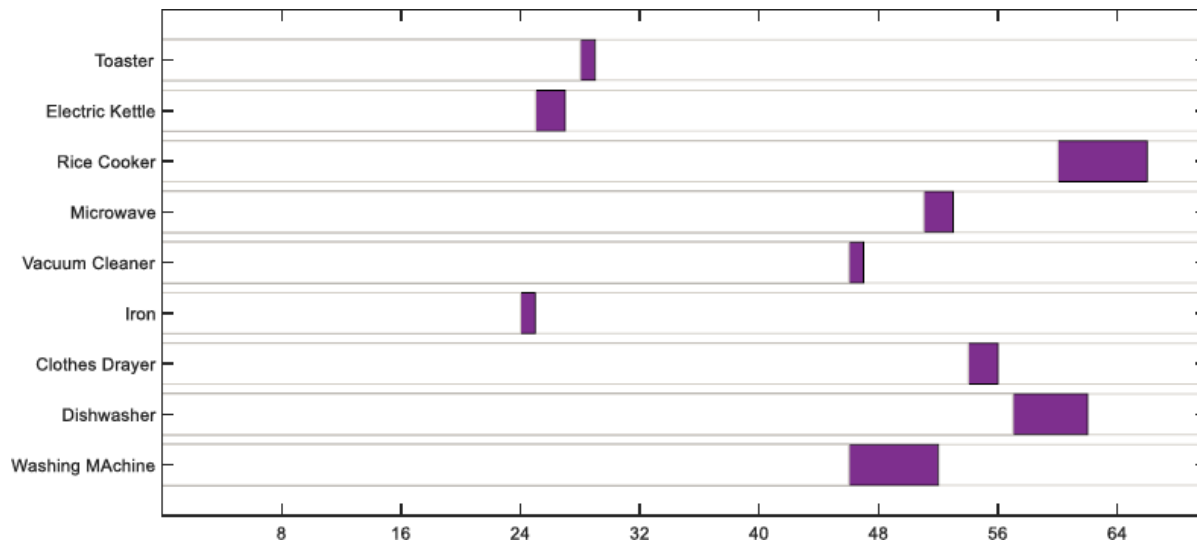


Fig. 4-7: The performance of devices in a stair-step manner.



The performance of the air conditioning system is illustrated in Fig. 4-8. The red bar graph represents room temperature throughout the day with the ventilation system's operation decisions which is made between the minimum and maximum temperature determined by the HEMS system. Considering the user-set temperature (25 degrees Celsius), occupants will experience nearly optimal satisfaction with the ambient temperature, as the room temperature fluctuates between 24 to 26 degrees Celsius throughout each quarter hour.

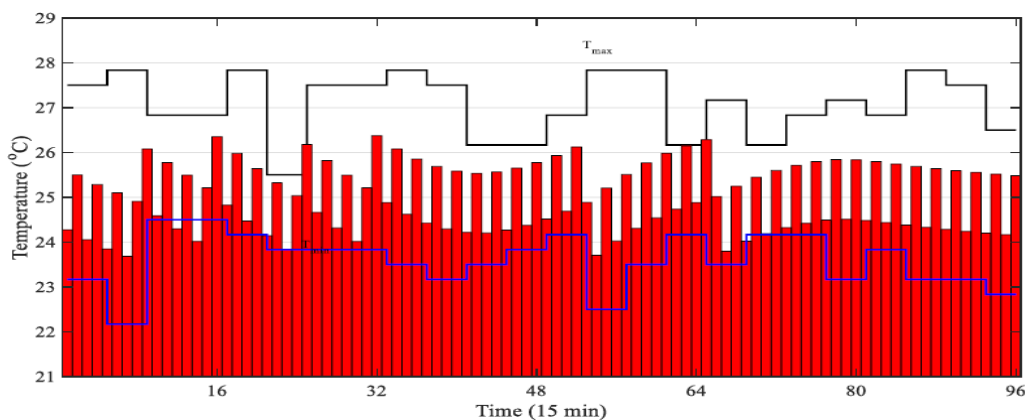


Fig. 4-8: The performance of the ventilation system.

The gray bar diagram in Fig. 4-9 also shows the predicted hot water temperature throughout the day. As observed, using the proposed method, the hot water temperature fluctuates almost across all time intervals between the user-defined temperature range (40 to 60 degrees Celsius).

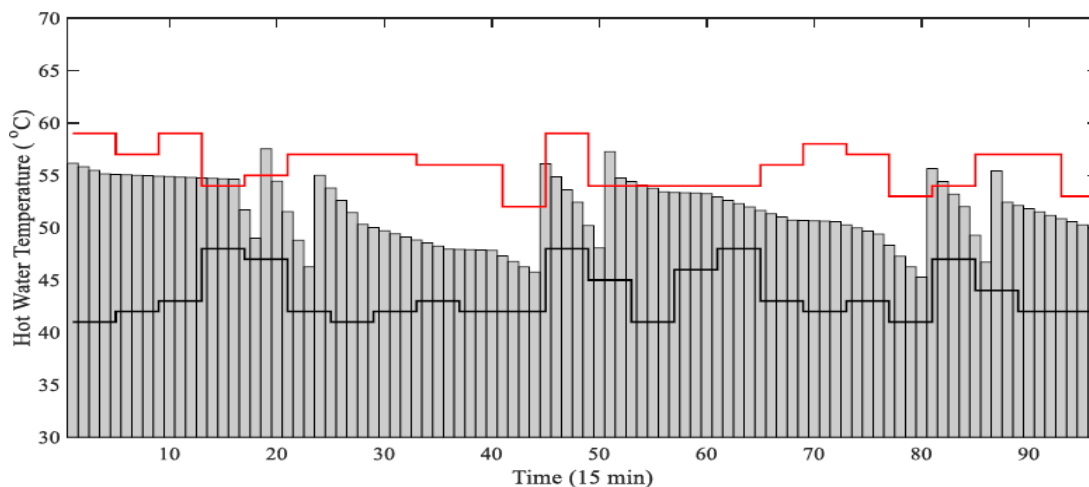


Fig. 4-9: The predicted hot water temperature throughout the day.



The operation times of the home heating system and water heater are also observed in 15-minute intervals in Fig. 4-10.

Due to the severe cold outside, it is anticipated that the heating system will be activated frequently over extended time intervals. If one-hour intervals are chosen, accurate predictions will not be feasible because hourly operation may significantly increase or decrease temperatures, affecting the heating system's performance and consequently reducing thermal comfort levels.

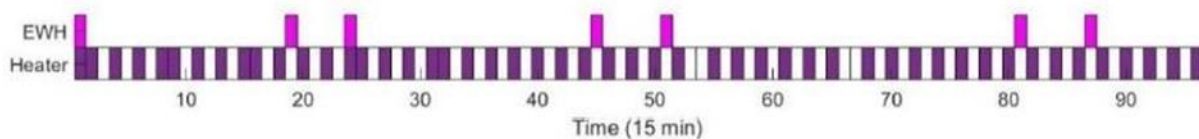


Fig. 4-10: Time intervals of home heating and water heating system operation

The power consumption of appliances along with the generated power from the photovoltaic generator is indicated in Fig. 4-11. The green bars indicate the net power received from the electrical grid. The red bars represent battery exchange power. Negative values indicate battery discharge; Positive values indicate battery charge. The photovoltaic power generation curve is also depicted similarly to Fig. 4-11.

Additionally, the average received power from the grid is plotted as a dashed line, resulting in a value of 3.0524 as obtained from Fig. 4-11. The 24-hour electricity cost, based on the PAR performance forecast and devices based on the real-time electricity price with the implementation of IBR (Incentive-Based Regulation), is \$4.5390.

The power consumption of appliances and the power generated by the photovoltaic generator panel are illustrated in Fig. 4-11.

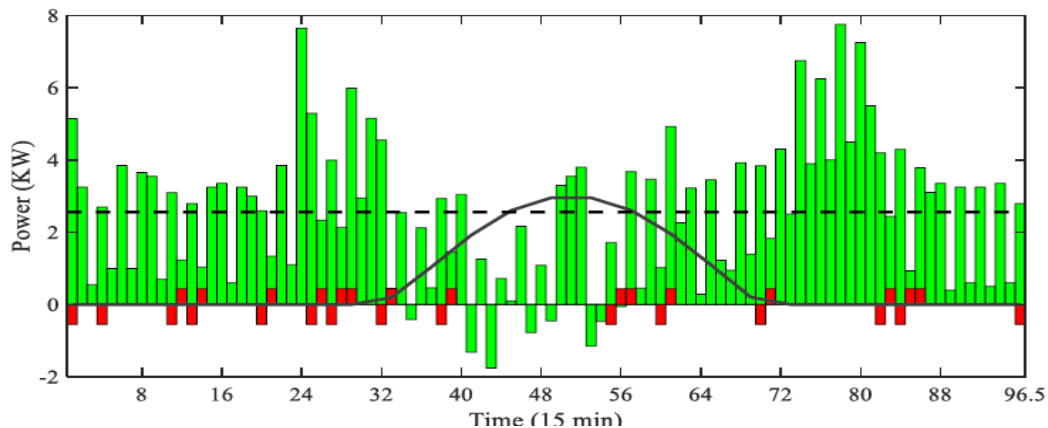


Fig. 4-11: The amount of power consumed by the devices and the production power of the photovoltaic generator

4-5- Simulation Part 2

In this section, the performance of the proposed method is also simulated in one-hour time intervals. An important point to note is that appliances such as washing machines, as indicated in Table 4-2, require a duration of 45 minutes, necessitating the consideration of two intervals for them (Table 4-1). Due to the hourly scheduling, room temperature is predicted hourly (Fig. 4-12), causing temperature to often drop below the minimum or exceed the maximum, leading the system to turn the HVAC system on or off in reality. This divergence from the predicted scenario will result in increased costs.

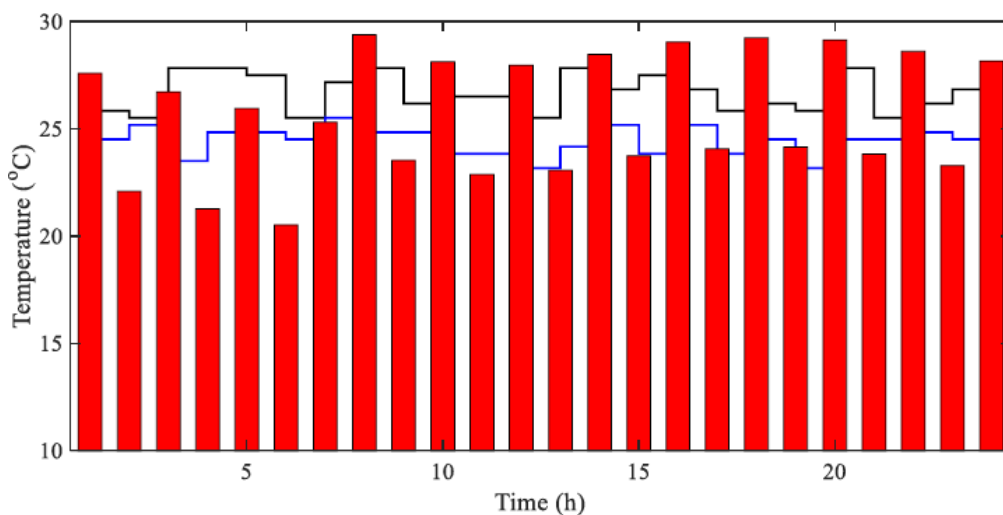


Fig. 4-12: Room Temperature Based on Hourly Scheduling (24-hour)



Additionally, the predicted power consumption of appliances along with the generated power from photovoltaic and battery power are also observable in Fig.4-13.

The green bars diagram represents the power consumption of appliances, while the red bars indicate the status of battery charge and discharge power. The average net power consumption is shown as a dashed line. Furthermore, the power generated from the photovoltaic panel is also specified.

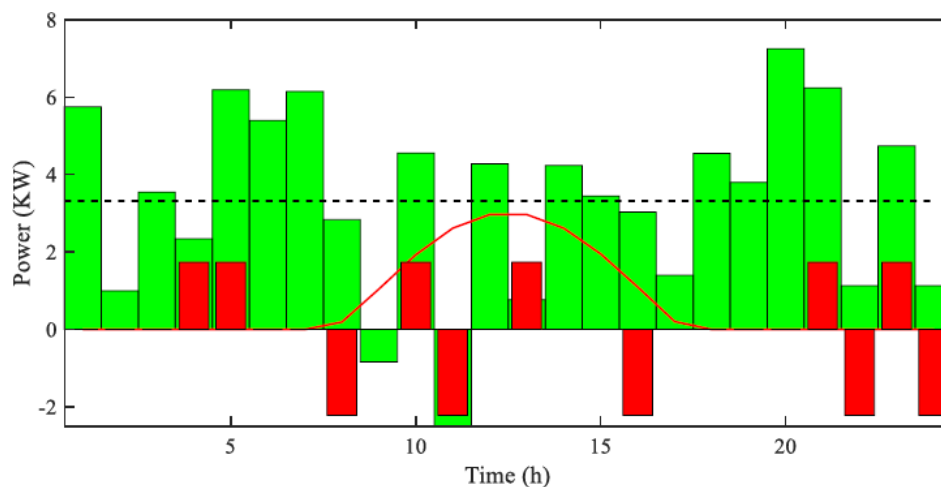


Fig. 4-13: The power consumption of appliances along with the power obtained from photovoltaics and battery power.

To make a proper comparison between the 96 (quarter-hour) and 24 (hourly) methods, it is necessary to input the actual kilowatt-hour durations of appliances in calculating the cost of the second method. For this purpose, the operational lifespan of the equipment is considered in Table 4-2., and we calculate the cost accordingly.

- ✓ Total cost in the 24-hour method: \$6.15
- ✓ Total cost in the 96-quarter-hour method: \$4.54

Therefore, it can be concluded that with the first method, in addition to increasing comfort and thermal welfare, the electricity cost is also lower due to accurate prediction of the system's condition.

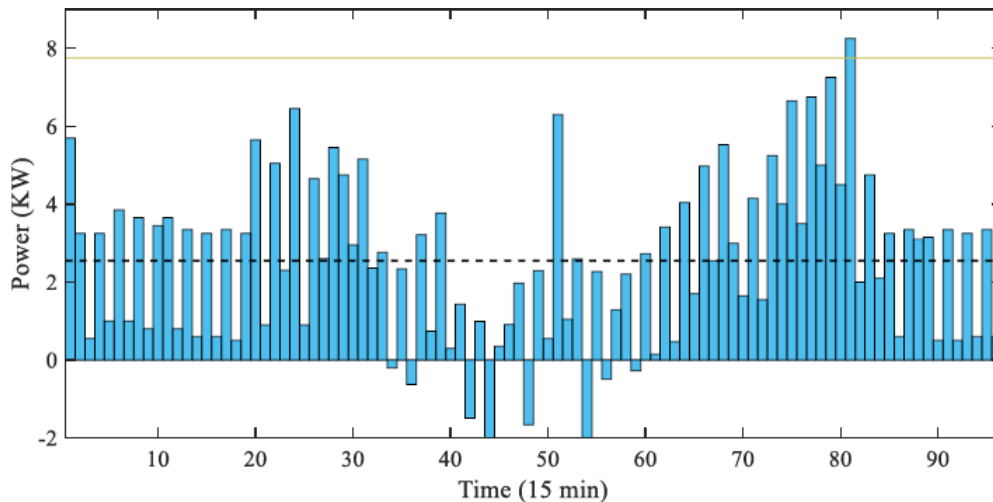
4-6- Simulation Part 3

In this section, we deactivate the Real-Time Pricing (RTP) simulation and solely consider the Instantaneous Block Rate (IBR) to optimizing. We perform optimization with RTP and IBR, combining again.

Fig. 4-14 demonstrates P_D related to the power of the consumer's demand from the network during the day and night along with the average load without considering the load. In this state, PAR value is 3.24, while PAR is 3.05 in the simulation part 1. In other words, considering the PAR simulation,



we observed that the peak power value decreased from 8.75 kilowatts to 8.25 kilowatts, but the electricity cost in the RTP and IBR combination is higher than in the RTP-only state, such that the electricity cost in the first state is approximately \$4.5, and in the IBR-excluded state, it is \$3.5.



Fi. 4 -14: Consumer demand power profile over the day without considering IBR

To validate the effectiveness of the proposed model, simulations were conducted using various scenarios based on real data, and the results obtained were compared.

5- Conclusion

In order to evaluate the effectiveness of the proposed method, a case study was examined, and the numerical results obtained were analyzed. The numerical results demonstrate the positive impact and cost-effectiveness of employing an energy management system. The aim of this paper was to present a mathematical model for operational planning of a smart home, including appliance scheduling considering allowable intervals and user priorities, enhancing thermal comfort levels, preventing peak consumption during off-peak hours, and utilizing solar cells and electrical energy storage. By conducting this paper, the following results are obtained: The obtained results indicate the significant impact of the energy management system on the costs of supplying energy needed for the home using the proposed method (15-minute intervals instead of hourly and IBR technology). Simulation results demonstrate that approximately 30% energy cost savings are achieved compared to hourly planning, and in addition, user comfort level and thermal comfort are also ensured. It is recommended that the following aspects be considered in future studies:

❖ Incorporating uncertainty in electricity prices.



solar unit production, and considering the role of electric vehicles in energy management problems.

❖ Considering equipment failure rates such as batteries, solar units, converters, and electrical loads.

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