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IoT-based Optimal Energy Management in Smart Homes using Harmony Search Optimization Technique

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Abstract

The Internet of things (IoT) has a variety of application domains including smart homes. A smart home is an automated intelligent home where IoT technologies are used to remotely control home appliances, manage home energy, enhance home security, and increase the comfort of home residents. On the other hand, renewable energy resources are highly speared to cover huge electricity demand. To save more energy and maximize energy efficiency, smart homes are engaged with energy management systems. Energy management and optimization solutions can help in decreasing the overall cost of energy while optimizing all operational performance.

This paper presents an IoT-based optimal energy management approach depending on the Harmony Search optimization technique to save energy usage in smart homes. PV and wind renewable energy systems are used to feed the home with electricity. These on-site energy sources help smart homes to decrease their dependence on power from the electricity grid. Energy storage systems are used to maintain energy system reliability due to the inherent randomness and intermittence of solar radiation and wind speed. The proposed algorithm depends on-demand response to the price variations in the electric energy over time and applies the Time-of-Use pricing principle for controlling household appliances. IoT technology is applied to exchange data between household appliances and the control center, in addition, to communicating both energy management systems and security systems with the control center. In this paper, the IoT system is based on ZigBee wireless technology which is described as the lowest power consumed wireless technology. The algorithm is applied to a proposed building consisting of five floors, each floor contains two apartments with a total area of 200 meters for one apartment. The obtained results prove the efficacy of the proposed Harmony Search-based optimization method in saving energy and reducing electricity bills in smart homes while satisfying the required constraints. Additionally, the performance of the proposed algorithm is validated against four AI algorithms including Genetic Algorithm, Artificial Immune System, Ant Lion Optimization, and Bat Algorithm. In addition to its simplicity in programming and formulation, the conducted comparison demonstrates a similarity in the results with an advantage in the proposed algorithm in improving both the electricity cost-saving and elapsed runtime

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Introduction

Smart Home expression was firstly used in 1984 by the American Association of House-builders.[1] In the past few years, there is increasing attention to Smart Home technology. Nowadays, smart homes provide so many supported services and remote-monitoring systems for their users.[2] In order to enable automation and remote control of the domestic environment, many technologies are included in smart homes such as monitors, sensors, interfaces, devices, and appliances networked together.[3] The primary objective of a smart home is to offer a convenient, comfortable, safe, and environment-friendly living system and provide efficient, easy service and management.[4] Smart homes appliances and devices include lighting devices, boilers, and fridges, washing machines, air conditioning, etc. Software and hardware systems are used to provide control functionality of smart home appliances and devices. All these devices should be wirelessly networked using appropriate communication protocols.[5]

A smart home represents one of the significant applications of the Internet of Things (IoT). In this home, all types of things interact with each other via the internet which helps to automate the home by making it smarter and strongly interconnected. IoT refers simply to a smart connection between the physical and digital worlds.[6]. The IoT expression was firstly reported by Ashton et al. in 1999.[7] According to .[8] several researchers have defined IoT in different forms. In brief, IoT is an “interconnection of sensing and actuating devices providing the ability to share information across platforms through a unified framework, developing a common operating picture for enabling innovative applications. This is achieved by seamless ubiquitous sensing, data analytics, and information”. Currently, there are many applications of this technology including the energy industry, health, and transportation,[6] self-driving vehicles, smart cities, and microgrids for distributed energy resources systems.[9-10]

The IoT concept, along with smart measuring devices can help increase the awareness of energy in smart homes. Currently, there is a growing effort in academic and practical research to incorporate the IoT paradigm in smart home solutions.[11-14]. The operation of the IoT-smart home system is illustrated in Fig.1.[15]

This paper presents an IoT-based optimal energy management approach to be applied in smart homes using the harmony search optimization technique. The main contributions of this paper are:

1. Proposing an optimal energy management system for smart homes based on the Time-of-Use (ToU) pricing principle and load appliances control.
2. Developing a complete mathematical model involving connected load, energy consumption, photovoltaic (PV) and wind systems, battery storage, energy pricing, demand response, and comfort models
3. Developing a Harmony search optimization algorithm to optimize the energy usage of household appliances in smart homes.
4. Applying IoT technology to exchange data between household appliances and the control center and to communicate between energy management systems and the control center.
5. Comparing the results of the proposed algorithm against four AI algorithms including Genetic Algorithm, Artificial Immune System, Ant Lion Optimization, and Bat Algorithm.

The rest of this paper is organized as follows. A literature review of the related work is introduced

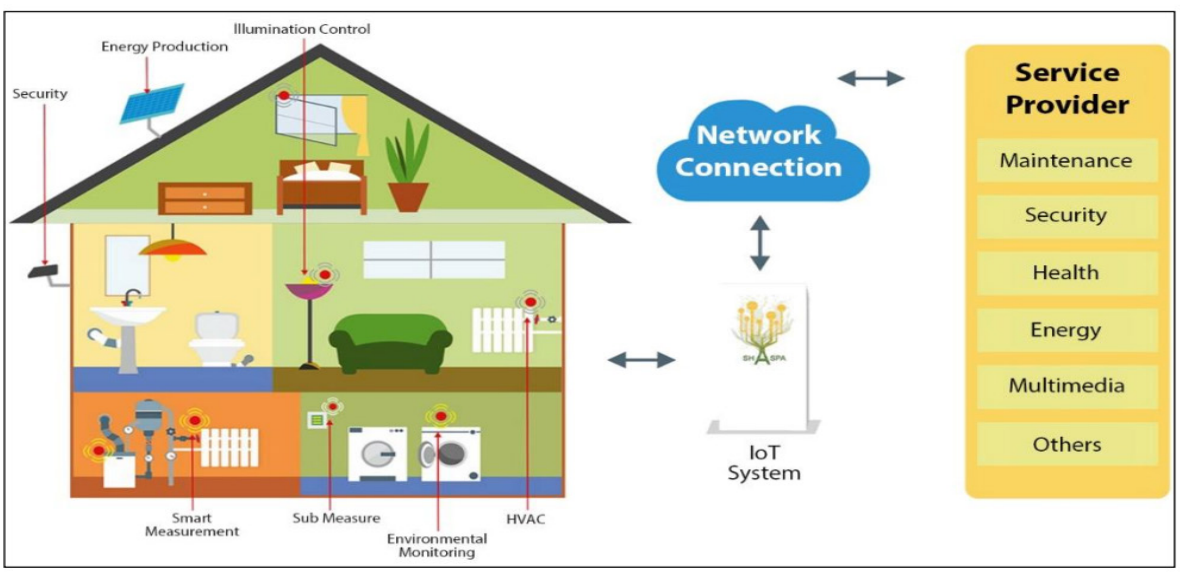

Fig. 1: Operation of IoT-smart home system[15]

in section 2. The IoT-based smart home architecture is described in section 3. The problem statement and proposed methodology are presented in sections 4 and 5 while the related mathematical model is derived in section 6. The proposed optimization model and Harmony Search-Based Algorithm are explained in section 7. Section 8 discusses the simulation results and section 9 introduces a verification of the proposed algorithm. The paper is finally concluded in section 10.

Literature review

Many researches have been done on the optimum energy usage and management in Smart Homes from different viewpoints. To optimally utilize renewable energy, smart homes require an efficient energy management system. Energy management is a link connecting both the utility grid and the power-consuming devices in the smart home. It provides profits and advantages for both of them. In other words, energy management is a group of technologies that apply both monitoring and controlling of the energy consumed or produced at the consumer level to achieve power balancing in energy systems.[16] Energy management controls the connection between the demand load and energy sources. This is accomplished by combining IoT and information technology to move toward cyber-physical energy systems. Paudyal and Ni[17] presented an energy optimization method based on shifting electric appliances and inventively compensating consumers for scheduling smart home appliances. The home appliances were fed only by the grid and the benefits of applying renewable energy were not investigated in that paper. Ref.[18] investigated energy management systems in smart homes and introduced a model to switch between different energy sources depending according to the load value. But the paper applied a constant electricity price regardless of its consumption time which might affect the cost of energy savings. A. Dibavar et. al.[19] proposed a smart home's optimal energy management in day-ahead and real-time energy markets under energy prices' uncertainties. The approach was applied to control the energy consumed in a smart home connected to both PV and battery storage systems. Ref.[20] presented an optimization approach for managing a smart home's energy. The proposed management system controlled renewable energy resources, energy storage devices, and smart domestic appliances. A methodology for managing energy in a smart home was presented in.[21] The approach aimed to find the best way to provide the appliances with their requirements under different constraints while considering the time of use pricing. A mixed-integer nonlinear programming problem was used to solve the problem in inadequate solving time. However, in papers[19]-[21] a constant electricity price was taken regardless of its time of use and both demand response and comfortable of the consumers were not considered which might affect both consumers' comfort and energy cost.

Artificial intelligence-based techniques were used in many researches to optimize the energy consumed in smart homes. In[22] fuzzy logic and heuristic optimization techniques were used for minimizing the cost and reducing the consumption of energy. Fuzzy logic was used to control the interruptible household appliances. Moreover, the heuristic op1timization algorithms, BAT inspired and flower pollination was applied for scheduling shiftable appliances. Although the authors classified the appliances according to their energy consumption pattern and applied an AI optimization technique for scheduling shiftable appliances, they didn't consider the changes in electricity prices. In addition, they didn't investigate the impact of applying renewable energy sources to share the feeding of the home with electricity. In [23] a proposed differential evolution algorithm was utilized for employing demand response between utility and consumers. While a combined genetic and cross-entropy algorithm was proposed in[24] to solve a traditional mixed-integer linear programming paradigm to minimize the total energy cost in a smart home. A proposed metaheuristic approach incorporating a combined differential evolution and harmony search algorithms for managing energy in a smart home was presented in[25] The method was applied to optimize energy consumption and minimize the cost of energy consumption under some defined constrained.

Although the abovementioned papers [23]-[25] have applied different AI algorithms for implementing demand response between the grid and consumer and investigated the impacts of applying renewable energy sources to feed a part of the smart home load, but they have used a fixed energy price all over the day and didn't explore the impact of changes of the price with the time of use.

Applying IoT for energy management in smart homes was the subject of interest in many research papers. IoT is technology applied to allow electric appliances and other household electronic devices to exchange data via the internet network.[26]

An optimal method for home energy management systems based on IoT was presented in.[27] The paper applied a multi-objective optimization technique based on ZigBee wireless technology for home energy management. The home was supplied by the electric grid in addition to different renewable energy sources and batteries. An improved butterfly optimization algorithm was used to increase the efficiency of the system in terms of both energy consumptions cost and user comfort. Different electricity prices were used including peak, flat, and valley prices according to time of use. However, the results were compared with the normal consumption system but not validated with any other optimization technique. Jaihar et al.[28] presented a methodology to control home appliances in order to enhance energy efficiency in a smart home. They applied machine-learning algorithms to combine and explore the user's requirements and the surrounding conditions to estimate actions and minimize user interaction. The machine learning model was used to detect the ON or OFF switching of the home appliances in the most efficient energy-saving way. The paper didn't investigate the impact of renewable energy on the control system and the price of consumed energy. Also, the paper utilized a fixed price for the electrical energy supplied by the grid instead of using Time of use pricing methods. Majeed et al.[29] presented a proposed approach based on support vector machine for intelligent decision-making and blockchain technology for IoT devices security. The remote control of the household devices was done by an Android application and a linear kernel for decision-making was utilized to detect the statuses of the home devices appliances. In that paper, consumers' comfort was not considered, and no investigation of the renewable energy impacts on energy savings. Y. Y. Chen et al.[30] presented a methodology for residential demand-side management in Nigeria by applying Fog-Cloud analytics to monitor nonintrusive appliance load in a smart home. The embedded IoT controllers connected IoT end devices, such as meters and sensors, and serve as a gateway in a smart building for residential demand-side management. The paper didn't apply the ToU pricing principle and consumer comfort was not considered. Finally, the benefits of energy management were explored in[31] where the electricity cost was investigated for IoT-enabled smart homes supplied by PV and energy storage systems combined with the electricity grid. In that study, the energy management problem was executed by considering both PV uncertainties and end-users comfort constraints.

This paper aims to develop an energy management program to optimize the energy consumption in "IoT-based smart homes. The paper applied Harmony Search (HS) optimization algorithm which is a new and efficient optimization technique for energy management systems in IoT-based smart homes. The proposed optimal energy management system depends on demand response to the price changes in the electricity over time and applies the ToU pricing principle to control the time of use of household appliances. The ToU pricing principle helps in decreasing the energy cost while optimizing other operational performance. Most of the surveyed papers have applied fixed prices. Real-time data are implemented to help improve energy consumption. Another important contribution of this paper lies in feeding the smart home with different energy sources including PV, wind, and battery storage in addition to the electricity grid which helps in reducing both the energy cost and the CO2 emission of the energy consumed.

IoT-based Smart Home Architecture

The smart home is a building that uses the IoT, computer technology, control technology, and communication technology to interconnect different services via a network to meet all the needs for the automation of the home and provide more convenient control and management of energy usage. Smart home buildings provide a healthier, more productive, and more comfortable space for the people residing in them with advanced climate and lighting controls. They also improve indoor air quality and lighting considerably. Basic smart home automation is performed using different types of sensors including light, temperature, humidity, and gas sensors. These sensors can automatically control the household appliances without any human intervention by exchanging Data in the form of signals with a control center.

Recently, new communication technologies with a long-range communication opportunity over unlicensed bands have been proposed and most of them are appropriate for smart home automation. These technologies include narrowband IoT (NB-IoT), Long Term Evolution (LTE), and Long Term Evolution Advanced (LTE-A), as well as ZigBee and Bluetooth low energy (BLE) technologies. Among wireless technologies, ZigBee is the lowest energy consumed one. Hence it is adopted for the smart home in this study as it can help in saving energy usage of the home. The ZigBee wireless network has many advantages compared to other wireless networks (WiFi and Bluetooth) including low-cost, low power consumption, and low data rates. So it is suitable for smart home applications. It can be used to collect energy information and provide intelligent and efficient management of household appliances in real-time.[32-34] A ZigBee home network is illustrated in Figure 2.

The overall architecture of the sustainable energy-smart home system can be represented in Fig. 3. In this architecture, a centralized smart

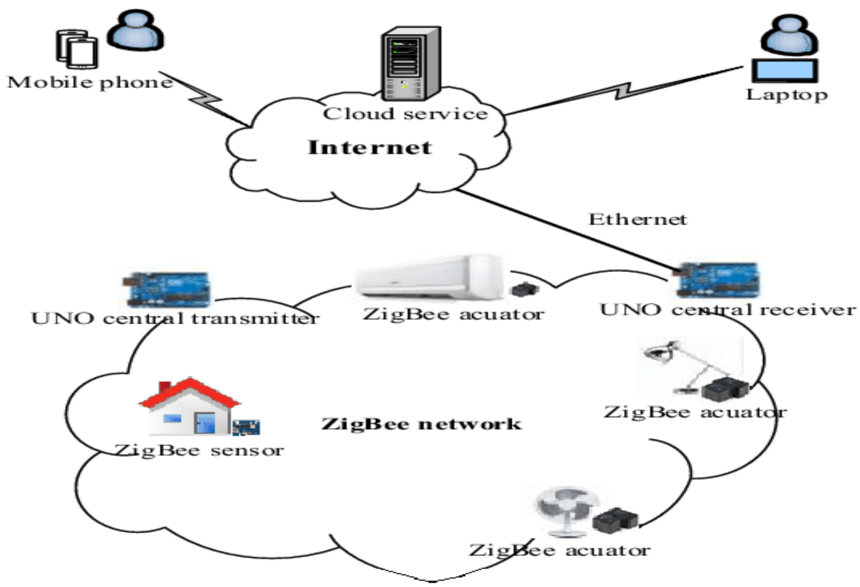

Fig. 2: ZigBee home network

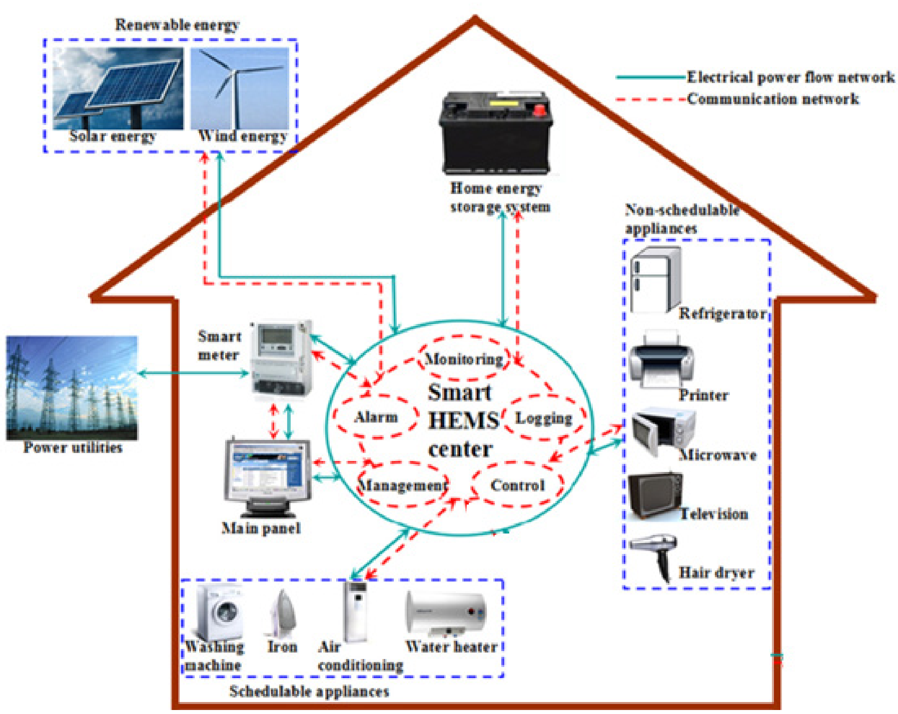

Fig. 3: Architecture of the sustainable energy-smart home system

controller is constructed to provide the homeowner with the specified control functionalities via different monitoring modules.[24]

The main panel of the smart home collects the real-time data of the electricity consumed by each appliance in the home and then it implements optimal demand dispatch for schedulable appliances. Smart meters are used as a cooperative communication interface between the electric grid and the smart home in real-life deployment. In this way, the smart meter receives a demand response signal from the electric grid as an input to the home, and then the control center implements the optimization of home appliance scheduling.

On the other hand, the utilization of renewable energy in smart homes is an interesting option to save energy supplied by the electric grid and hence save money and reduce electricity bills with the possibility of profiting from selling surplus energy to the electric grid. In this study both the PV and wind, renewable energy systems combined with battery storage are used to feed the home with electricity. These local energy sources can be fully incorporated into the interactive generation management and operations of the home. However, it is preferable to incorporate energy storage devices with renewable energy resources to maintain the energy system's reliability.[24]

Moreover, IoT technology is used to interconnect all appliances in the smart home with the smart home energy management system (HEMS) center. The main IoT platform composed of different layers is applied for accumulating data in addition to monitoring and managing energy usage. In this platform, all energy sources and household appliances are connected and incorporated. The layers included in the main platform are shown in Fig.4. Each layer is responsible for one of the basic functions of the system. So, there is one layer responsible for energy resources, another layer for household appliances, the third one is responsible for communication network, the fourth for energy management, the fifth for the smart home controller, and finally, the sixth layer is responsible for IoT service.

The energy supply layer incorporates all the available energy resources feeding the home and determines the energy sharing between these resources to feed the load demands. The household appliances monitor and control the status of all the home appliances. The protocol that regulates the interconnection between the connected home

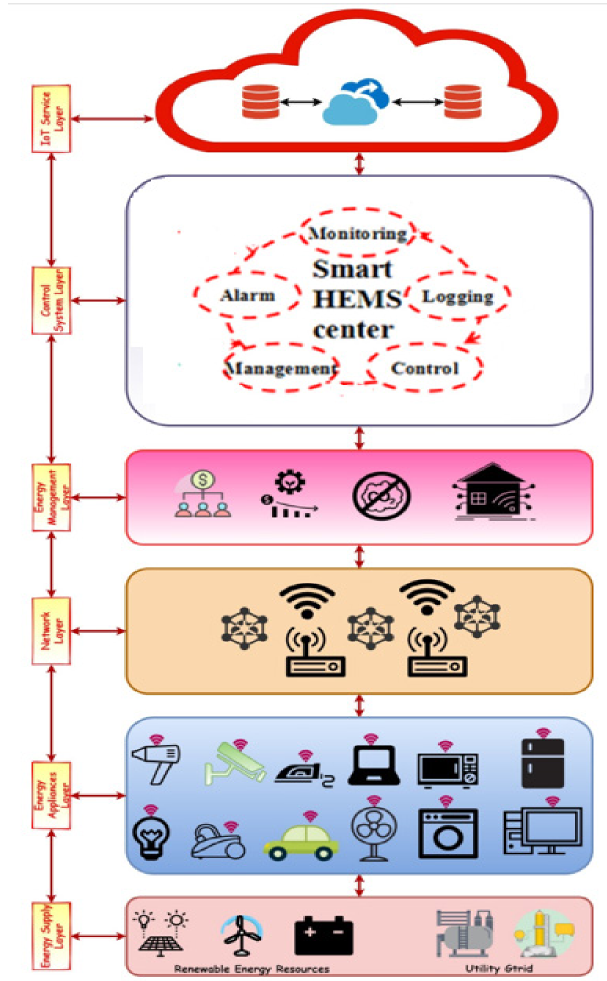

Fig. 4: IoT layers for the proposed method

appliances and the Internet is involved in the communication network layer. To reduce the energy cost, the operation of the home's load depending on the ToU pricing principle is implemented via the energy management layer. The smart home controller layer regulates the smart home monitoring and alarm taking into account any variations in loads. Finally, the data collected from both energy sources and household appliances are stored in a storage memory included in the IoT service layer. Furthermore, the collected data is analyzed in this layer in order to get optimal use of it.

Problem Statement

Nowadays, the quantity of energy consumed in residential buildings by electrical appliances such as washing machines, refrigerators, freezers, vacuum cleaners, dishwashers, air conditioning, fan, iron, heater, etc., is very high. With the growth of the global energy crisis and the increasing trend towards energy conservation to achieve energy sustainability, it is important to develop a new program for energy management in residential homes and cities. So, improving the energy performance of residential facilities has become essential support of energy policies [35]. The key objective is to reduce the energy consumption in residential buildings to minimize the buildings' footprint on the surrounding environment.

This paper proposes a new algorithm for optimum energy usage in smart homes. The primary target of the optimization technique is to minimize the overall cost of energy consumed while meeting the load requirements and the prescribed constraints. Optimizing energy management in smart homes requires efficient scheduling of home devices to optimize energy usage. Different optimization techniques can be used to achieve that task. With the rapid increase in computer hardware that generally improves the speed and capacity of computers, artificial intelligence optimization techniques become an efficient tool for solving many complex problems. The HS algorithm is applied to solve the optimization problem in this paper. HS algorithm is simple, flexible, and easy to implement. Such a simple algorithm can be very flexible in solving complex problems as the optimization problem applied in this study

Proposed Method

As aforementioned, the key objective of this paper is to develop a HS algorithm for optimum energy usage in IoT-based smart homes. It is required to minimize the overall cost of the consumed energy while meeting the load requirements and the prescribed technical and environmental constraints. To achieve this objective, the following sub-objectives must be implemented:

- To investigate and understand the structure of smart homes and the main types and functionality of sensors and networks used within them.
- To identify the values and time of the load demand and electricity sources
- To explore and study different issues related to IoT and its applications in smart home
- To derive a mathematical model that represents the required objective function and constraints.
- To apply an appropriate optimization method to solve the research problem.

The methodology used to achieve these objectives can be summarized in the following steps:

- Collect the necessary information, such as the energy consumption time and values, the smart home location, and the wireless communication protocols.
- Select a suitable structure for the smart home and define the required appliance and lighting in it
- Identify the required sensors, monitor devices, and interfaces required to enable automation and remote control of the home.
- Identify the required communication wireless sensor networks that are used for employing IoT
- Using an optimization algorithm to access the best optimal point to reduce energy in a smart home while satisfying the required load demand.

Mathematical Model

It is well known that the energy consumed by electrical appliances in residential premises is very high, which requires the consumption of large quantities of fossil fuels. Reducing the total energy consumed by residential buildings and utilizing renewable energy sources will help in reducing the consumption of fossil fuels and thus reducing the emission of carbon dioxide, which negatively affects the environment. To model the energy usage in smart homes, different systems have to be modeled first. The mathematical model involves modeling of connected load and energy consumption, modeling of both renewable energy and battery storage, and modeling of demand response as illustrated in Fig. 5.

Electricity grid model

It is well known that the electricity price is high during the peak demand hours. For this case, the smart home's load is supplied mainly from RES and ESS integrated with the electric grid. On the contrary, during off-peak hours and whenever there the electricity price is low, the demand is privately supplied from the grid. A contract is required between the owner of the smart home and the utilities to regulate the process of energy exchange. The share of renewable energy in supplying different smart homes will decrease the dependency on traditional generating units and hence reduce the CO2 emissions cost. Besides, the contract allows the electric grid to buy energy from smart homeowners which will improve its reliability. Considering the price signal, the cost of energy supplied by the grid ($) is given as [36];

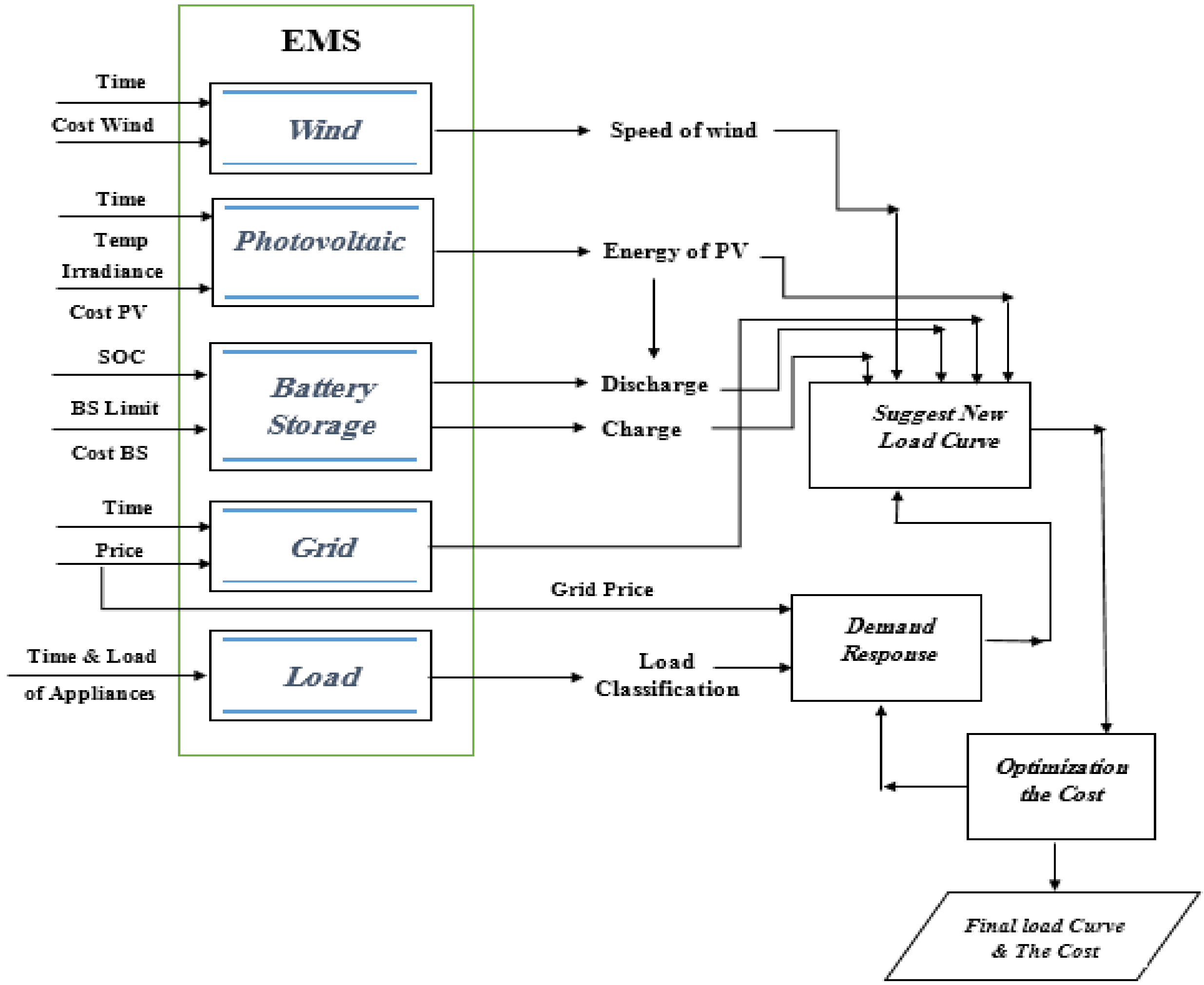

Fig. 5: Mathematical Model Description

$$C_g = \sum_{t=1}^{T} [E_{gc}(t) - E_{gs}(t)]\, \lambda(t) \qquad (1)$$

where E_{gc} (t) is the total paid energy from the grid (kWh) throughout time t (hours), is the surplus smart home-generated electricity which will be sold to the grid throughout time t in kWh, and is the ToU energy price signal in $/kWh at time t.

The cost of emissions ($) of the traditional generators can be represented as follows [36];

$$C_{emg} = \sum_{t=1}^{T} \left[\alpha \left(P_{gc}(t)\right)^2 + \beta\, P_{gc}(t) + \gamma\right] \qquad (2)$$

where α.β.and γ are coefficients that represent the traditional thermal generators.

Modelling of Photovoltaic System

The PV power of the installed rooftop modules can be represented as [37];

$$P_{pv}(t) = \eta_{pv}\, A_{pv}\, I_r(t)[1 - C_f(T_a(t) - T_{Amb})] \qquad (3)$$

$$P_{pv\,min} \le P_{pv} \le P_{pv\,max} \qquad (4)$$

where η_{pv} is the percentage efficiency of the inverter, is the area of the PV cells in m[2], I_r $(t)_{pv}$ is the solar radiation in kW/m[2] at a certain time t, ▫_f, is the temperature factor, T_{Amb} and T_a are the temperatures of ambient room and outdoor (°C) respectively.

To model the hourly distribution of the PV output power and to evaluate its probability, a probability density function must be used. In this study, the Weibull probability density function (WPDF) is used. The WPDF of the power produced by PV is expressed

$$f\left(P_{pv}(t)\right) = \frac{k}{c}\left(\frac{I_r(t)}{c}\right)^{k-1} e^{-\left(\frac{I_r(t)}{c}\right)^k} \qquad (5)$$

Where k and c are the shape and scale parameters of the WPDF and they are gotten using the following two formulas.

$$k = \left(\frac{\sigma}{\bar{x}}\right)^{-1.086} \qquad c = \frac{\bar{x}}{\Gamma\left(1+\frac{1}{k}\right)} \tag{6}$$

where $\bar{X}$ and σ are the athematic mean and the standard deviation of the data, and is the gamma function.

The PV levelized energy and operating costs (C_s and C_{pv}) can be formulated as follows [37];

$$C_s = \frac{C_{s\,inv} + \sum_{i=1}^{n} C_{s\,om}(1+D_r)^{-i}}{\sum_{i=1}^{n} E_{pv\,an}(1-\sigma_s)^{i-1}(1+D_r)^{-i}} \tag{7}$$

$$C_{pv} = \sum_{t=1}^{T} C_s\, P_{pv}(t)\, f\left(P_{pv}(t)\right) \tag{8}$$

Where

C_s Levelized PV energy cost, \$/kWh,

C_{pv} PV operating costs, \$/kWh,

$C_{(s\,inv)}$ PV investment cost, \$,

C_(s om) operating and maintenance cost, \$/year

$E_{(pv\,an)}$ the annual energy produced by the PV system, kWh,

D the discount rate,

n the life period of the PV system in years, and

σ^s the degradation in the produced PV energy after the first year.

Modelling of Wind Power system

In this study, a domestic wind turbine is utilized, the power produced from the turbine can be obtained using the following equations [39];

$$P_w(t) = \frac{\rho}{2}\, c_p(\lambda)\, A_r \left(V_w(t)\right)^3 \tag{9}$$

$$P_{w\,min} \le P_w \le P_{w\,max} \tag{10}$$

where c_p (λ) is the pitch-controlled performance coefficient curve for the turbine, the rotor swept the area in m², and V_w (t) is the wind speed at a certain time (m/s).

Again a probability density function must be used to model the hourly distribution of the wind output power and to evaluate its probability. The WPDF used in this study can be expressed as follows [40];

$$f\left(P_w(t)\right) = \frac{k}{c}\left(\frac{V_m(t)}{c}\right)^{\kappa-1} e^{-\left(\frac{V_m(t)}{c}\right)^{\kappa}} \tag{11}$$

where the shape and scale parameters are given in (6). Therefore, the Levelized wind energy costs and wind operating cost can be respectively modeled as follows [41];

$$C_w = \frac{C_{w\,inv} + \sum_{i=1}^{n} C_{w\,om}(1+D_r)^{-i}}{\sum_{i=1}^{n} E_{w\,an}(1-\sigma_w)^{i-1}(1+D_r)^{-i}} \tag{12}$$

So, the total wind energy cost can be calculated as;

$$C_{tw} = \sum_{t=1}^{T} C_w\, P_w(t)\; f\left(P_w(t)\right) \tag{13}$$

where C_(w inv) is the investment cost (\$), $C_{(w\,om)}$ is the operating and maintenance cost, E(w an) is the annual output energy (kWh), σ_w is the degradation in the produced wind energy after the first year, and C_{tw} is the total wind energy cost (\$).

Energy Storage System model

In this study, a battery energy storage system is utilized to supply the load periods and lessen the variations produced by RESs. The Li-ion batteries are used in this study because of their high energy density. The decisions of charging and discharging the batteries are done according to the price signal gotten from the grid. Whenever the price is larger than a prespecified value, the batteries discharge, and vice versa. Additionally, the batteries are used to store the surplus generated powers of the PV and wind when the storage level is lesser than the upper charge level. So, the stored energy in the batteries can be represented as follows [42].

$$E_s(t) = E_s(t-1) + T_s\, \eta_C\, P_{ch}(t) - \frac{T_s\; P_{dch}(t)}{\eta_D} \tag{14}$$

where E^s (t) is the energy stored in the batteries (kWh) at time t, Ts is the duration time in hours, $\eta_C.\eta_D$ are the percentage efficiencies of batteries charging and discharging processes, and P^{ch} (t).P_{dch} (t) are the charging and discharging power at time (kW).

To avoid battery overcharging and deep discharging, maximum and minimum charging borders must be considered as operational constraints. These constraints can be given as:

$$P_{ch}^{min} \le P_{ch}(t) \le P_{ch}^{max} \tag{15}$$

$$P_{dch}^{min} \le P_{dch}(t) \le P_{dch}^{max} \tag{16}$$

$$E_s^{min} \le E_s(t)$$

where P_{ch}^{max} and P_{dch}^{max} are the maximum charging and discharging power (kW), and are the maximum and minimum energy stored (kWh).

The Levelized operational and degradation cost of the batteries can be presented as follows [37];

$$C_b = \frac{1}{2}\frac{[C_{b\,inv} + \sum_{i=1}^{n} C_{b\,om}(1+D_r)^{-i}](1+D_r)^n - SV}{(1+D_r)^n X_{Tf} X_{Tc} X_{Dc} Y_{Rc} E_{Rb}} \quad (18)$$

where $C_{(b\,inv)}$ is the batteries investment cost ($), $C_{(b\,om)}$ is the batteries operating and maintenance costs ($), SV is the batteries salvage value at the end of its life period, X_{Tf} is a temperature-dependent power fading factor, is the capacity fading factor, X_{Dc} is the depth of discharge (DoD), Y_{Rc} is the batteries rated life cycle, and E_{Rb} is the rated capacity of the batteries. Consequently, the total cost of the batteries is formulated as:

$$C_{bop} = \sum_{t=1}^{T} C_b \left(\eta_C\, P_{ch}(t) + \frac{P_{dch}(t)}{\eta_D}\right) \quad (19)$$

Energy consumption model

Smart home load appliances can be categorized into three types including shiftable, non-shiftable, and fixed appliances. In shiftable appliances, the consumers when required can change their operation to low-price times, in addition, their operation can be interrupted after starting. This type includes vacuum cleaners, water pumps, water heaters, fans…etc, and can be represented by $S = \{a_1.a_2.□.a_s\}$. Non-shiftable appliances can't be stopped during their operation until it is completed. This type includes washing machines, cloth-dryers, dishwashers…etc, and can be represented by $U = \{b_1.b_2.□.b_u\}$.

The appliances operating time cannot be modified for the fixed appliances which contain air conditioners, refrigerators, ovens, ... etc, and can be represented by $F = \{c_1.c_2.□.c_f\}$. The daily consumed energy of these three types over an identified time horizon, are given in the following equations [43-45]:

$$E_a(t) = \sum_{s=1}^{S} E_s^a(t)\, X_s^a(t) \quad (20)$$

$$E_b(t) = \sum_{u=1}^{U} E_u^b(t)\, X_u^b(t) \quad (21)$$

$$E_c(t) = \sum_{f=1}^{F} E_f^c(t)\, X_f^c(t) \quad (22)$$

where $E_s^a(t).\ E_b(t)$ and $E_f^c(t)$ are the energy consumption (kWh) by the three appliances types during time t, and $X_s^a(t)$, $X_u^b(t)$, and $X_f^c(t)$ are the ON/OFF states of them. The total daily consumed energy can be expressed as:

$$E_{total} = \sum_{t=1}^{24} (E_a(t) + E_b(t) + E_c(t)) \quad (23)$$

Energy pricing model

To determine the total electricity bill (i.e. total energy price), the energy consumed by the smart home is multiplied by the pricing signal.

In the literature, many electrical tariffs were used to reduce the energy pricing over a day [37]. In this study, the ToU pricing pattern is used since it offers some motivations to consumers to reduce their consumption during peak periods. This pricing pattern is a static pricing scheme because it divides the daytime into three blocks; off-peak, mid-peak, and peak. The cost of the daily consumed energy can be represented as:

$$C_T = \sum_{t=1}^{24} [E_a(t) + E_b(t) + E_c(t)]\, \lambda(t) \quad (24)$$

Demand response model

Demand response indicates " the variation in electricity consumption by the consumers from their normal patterns according to price changes in the electricity over time" [38]. The utility grid defines a tariff-based incentive by passing on short-term rises in the electricity price. If the consumers give access to the grid operators to control shiftable load entities, the operators can adjust these loads to off-peak times, the periods of lower generation by the grid, and the grid outage periods, while satisfying system constraints. In this case, consumers provide the utility with information about the capacity and shiftable periods of their deferrable loads. The specified loads are allowed to be shifted forward, backward, or both. Figure 6 illustrates the demand response shift mechanism [46].

The consecutive or non-consecutive shift instants are allowed. In all cases, they must stay between starting and final times (t_S, and t_F). Furthermore, the size of the set of shiftable time must be fewer than the overall simulation time, as expressed in (25) [47].

$|T_{sh}| \le t_F - t_S$

Similarly, in the proposed smart homes, the consumers can utilize their demand response model themselves by applying the proposed software model for energy saving in their homes. Equation (26) gives a proposed demand response model [48]

In this equation, islanding responsive factors are assumed to motivate consumers to shift load from

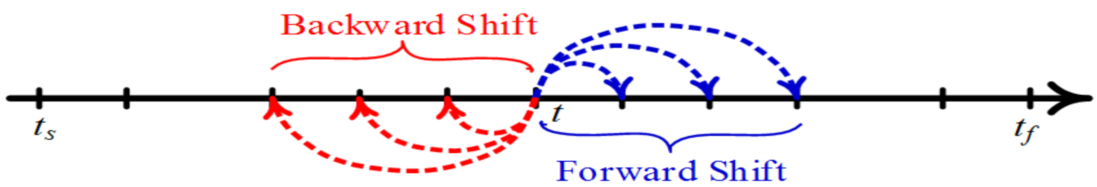

Fig. 6: Demand response shift mechanism

scheduled islanding times (they are times during scheduled maintenance of the electrical grid) to normal operation periods.

$$\pi_t^{dr} = \begin{cases} (\delta_1 + \rho_1 z_t) & \pi_t^{g^+} & t \in \mathcal{T}_1 \\ (\delta_2 + \rho_2 z_t) & \pi_t^{g^+} & t \in \mathcal{T}_2 \\ (\delta_3 + \rho_3 z_t) & \pi_t^{g^+} & t \in \mathcal{T}_3 \end{cases} \quad (26)$$

Where

π_t^{dr} demand response incentive price at time t,

$\pi_t^{g^+}$ buying electricity prices at time t.

z_t islanding status at time t, z_t =1 for islanding status and z_t = 0 otherwise

$\delta_1,\delta_2,\delta_3$ set of off-peak, mid-peak, and on-peak periods.

$\mathcal{T}_1, \mathcal{T}_2, \mathcal{T}_3$ set of off-peak, mid-peak, and on-peak energy prices.

ρ_1,ρ_2,ρ_3 scheduled islanding sensitive scaling factors for demand response incentives.

In case that intensive price is used the ToU energy price signal is replaced by demand response incentive price

Demand response constraint

The demand response in this study is an incentive-based demand response depending on price elastic coefficients. It is an interesting way to motivate consumers to modify their consumption shapes throughout normal operation.

The demand response model offers the consumers to share in supplying the load during both normal and scheduled islanding times. In this model, incentives are provided to motivate consumers to shift the load to normal operating periods in order to reduce the load lost during the scheduled maintenance period. The incentive-based demand response constraints are provided in [48]:

$$0 \le \delta_1 . \delta_2 . \delta_3 < 1 \quad (27)$$

$$0 \le \rho_1 . \rho_2 . \rho_3 < 1 \quad (28)$$

$$\mathcal{T}_1 \cup \mathcal{T}_2 \cup \mathcal{T}_3 = \mathcal{T} \quad (29)$$

Where δ_1, δ_2, δ_3 scaling factors for incentive demand response, ρ_1, ρ_2, ρ_3 are are islanding scaling factors for incentive demand response, and , , represent the energy prices through off-peak, mid-peak, and on-peak times respectively.

Comfort Model

To achieve energy savings, different appliances are managed by the building energy management systems including ventilation, heating, lighting, and air conditions. Anyway, it is necessary to take into account the internal conditions to ensure the comfort of the occupant. An arbitrary index of the suitability of environmental conditions for physical activity is called global comfort index, . This index computes the average of the thermal, , and visual factor, , During the period of occupancy for each area, . Accordingly, the global comfort index can be defined as [49]:

$$G_{i.z} = \frac{1}{\tau \kappa_{i.z}^{Oc}} \sum_{t \in \tau_{i.z}^{k}} \left(\omega^T G_{i.z.t}^T\right) + \left(\omega^I G_{i.z.t}^I\right) \qquad \forall i.z.t$$

Where w^I and w^T, are the weight factors of thermal and visual comfort respectively.

In case $G_{i,z}$ = 1, then the comfortable points identified are exactly achieved. On the other hand, factors and are quantifying the deviation from the comfortable predetermined values, as shown in (31) and (32) [43].

$$G_{i.z.t}^T = 1 - \left(\Delta_{i.z.t}^T / \mu o_{i.z}^T\right)^2 \qquad \forall i.z.t$$

$$G_{i.z.t}^I = 1 - \left(\Delta_{i.z.t}^I / \mu o_{i.z}^I\right)^2 \qquad \forall i.z.t$$

Where are the temperature comfortable set point, are deviations from comfortable set points. These two deviations are based on the deviation between the present set points and the predetermined comfortable conditions and are considered only when the zone is occupied, as defined in (33) and (34)

$$\Delta^{T}_{i.z.t} = T_{i.z.t} - \mu o^{T}_{i.z} \qquad \forall i.z.t$$
$$\Delta^{I}_{i.z.t} = I_{i.z.t} - \mu o^{I}_{i.z} \qquad \forall i.z.t$$

Where $T_{i,z,t}$ is the temperature set point in the zone, $I_{i,z,t}$ is the illuminance set point in the zone.

Comfort constraints *[49]*

$$G_{i.z} \geq M_i \qquad \forall i.z \qquad \textbf{(35)}$$
$$0 \leq G_{i.z} \leq 1 \qquad \forall i.z \qquad \textbf{(36)}$$
$$\mu o^{T}_{i.z\,min} \leq T_{i.z.t} \leq \mu o^{T}_{i.z\,max} \qquad \forall i.z.t \qquad \textbf{(37)}$$
$$\mu o^{I}_{i.z\,min} \leq I_{i.z.t} \leq \mu o^{I}_{i.z\,max} \qquad \forall i.z.t \qquad \textbf{(38)}$$
$$\mu o^{I}_{i.z\,min} \leq I_{i.z.t} + I^{N}_{i.z.t} \leq \mu o^{I}_{i.z\,max} \qquad \forall i.z.t \qquad \textbf{(39)}$$

Where

G M_i minimum permissible comfort index,
$\mu o^{T}_{i.z}$ global comfort index,
temperature comfortable set point,
$T_{i.z.t}$ temperature set point in the zone,
$\mu o^{I}_{i.z}$ illuminance comfortable set point,
$I_{i.z.t}$ illuminance set point in the zone, and
$I^{N}_{i.z.t}$ external or natural component of each zone's lighting level.

Optimal Design Methodology

The objective function of this study is to minimize the overall cost of electricity consumed to achieve maximum user comfort and other technical and operational constraints. Smart homes are equipped with smart meters that transmit the consumer's demand and preferences to the electricity grid. Accordingly, the electricity grid sends demand response signals which contain the required load information.

Objective function and constraints

The optimization is applied to minimize the total operating cost of the system as expressed in (40). This optimization cot function consists of the following costs; PV cost (8), wind system cost (13), batteries cost (19), the daily consumed energy cost (1), and the gird emissions cost (2).

Minimize¤ $C_{\_total}$

$$= C_{pv} + C_{tw} + C_{bop} + C_{g} + C_{emg} \qquad (40)$$

Subject to PV system (4), wind energy system (10), batteries (14–17), DR (25), and comfort constraint (35-39)

Harmony Search-Based Algorithm

In the literature, many optimization techniques were applied to solve numerous optimization problems in different fields. For a long time, traditional techniques were used to solve optimization problems. These techniques include Linear programming, Non-linear programming, Derivative-Free, Global, and Discrete Optimization methods. Many weaknesses of these traditional techniques led to creat other types of techniques built emulating artificial or natural phenomena, including heuristic optimization techniques such as Simulated annealing, Tabu search, Evolutionary algorithms, ...etc. A new heuristic algorithm called Harmony Search (HS) will be applied in this study. HS is a method firstly proposed by Geem [50], that simulates the basic principles of improvisation by musicians to reach harmony [50]. It is similar to a music improvisation procedure. Musicians use the process of improvisation to reach the perfect state of harmony that is achieved during the improvisation of music in the case of jazz. The algorithm has many advantages including its simplicity, easy implementation, and efficient search. It is robust and requires fewer mathematical equations. It has been successfully used in different areas in recent years [51]. HS algorithm is represented mainly by different parameters including [52]: harmony memory (HM), the size of the harmony memory (HMS), and the maximum number of iterations (NI). A flowchart that summarizes the HS algorithm steps is shown in Fig. 7. [53]

The probability of decision variables stored in harmony memory is called Harmony memory consideration rate (HMCR) whereas the probability of randomly modifying selected values from harmony memory is called Pitch adjusting rate (PAR). Finally, the range at which the selected parameters in HM are modified is called generation bandwidth (bw).

One of the following rules must be followed by the HS algorithm [54]:

- picking the value of the decision variable from the harmony memory,
- picking any value close to HS memory,
- picking any random value from the predetermined limits.

Based on the HMCR, the decision variables can be chosen: either from the harmony memory or randomly depending on the predetermined bounds of the variables. If the decision variable is chosen from the harmony memory, it can be chosen from the ith dimensions of the memory elements or it is mutated using the pitch adjusting rate.

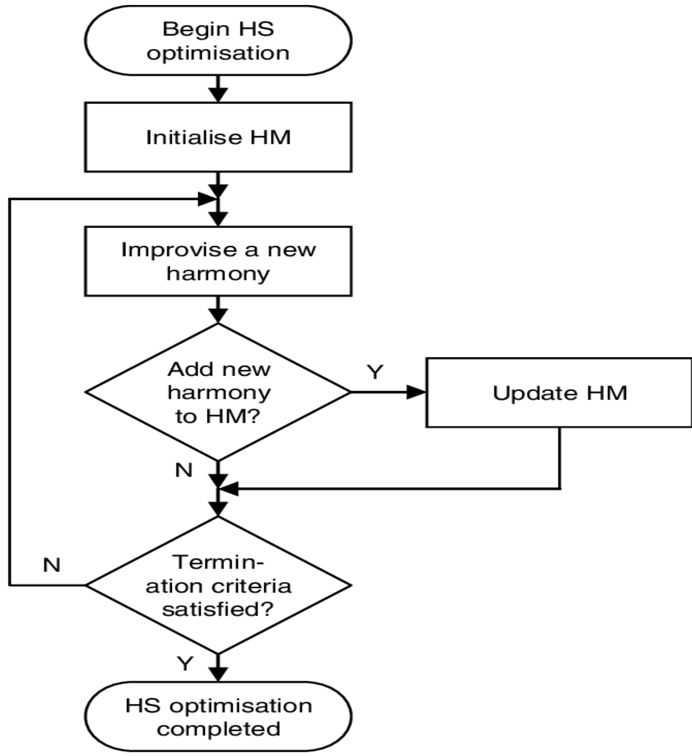

Fig. 7 A flowchart summarized the HS algorithm steps

The flowchart of applying the HS optimization algorithm for smart home energy management is shown in Fig.8. The basic pseudocode of the HS algorithm applied in this paper is expressed as shown in Algorithm 1.

Results and Discussion

The proposed algorithm has been represented in MATLAB/Simulink environment, verified via a hypothetical IoT-based smart building. The smart home system consists of PV, wind, and batteries integrated with the electric grid and supplying the electrical load of the building.

Input data

The hypothetical IoT-based smart building is composed of five floors, each floor containing two apartments with a total area of 200 meters for one apartment. Each apartment contains three groups of appliances such as a refrigerator, washing machine, air conditioner, microwave, etc. The expected power rating of each appliance type and its time of use per day is given in Table 1. The daily load curves for the proposed load types are illustrated in Fig. 9. The figure represents

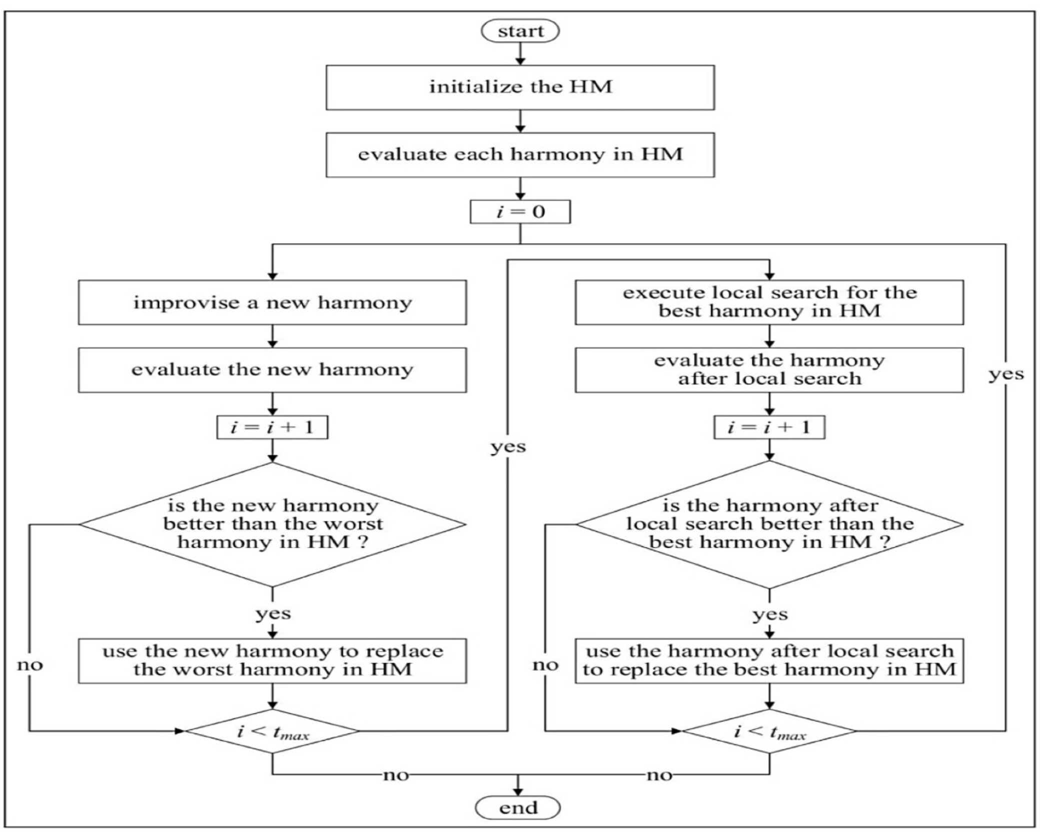

Fig. 8: A flowchart of applying the harmony search-based algorithm [55]

Table 1: Categories and parameters of home devices

Load Type	Device	Power Rating (KW)	Daily Used (Hours)
Fixed	Lights	0.8	8
	Electric Refrigerator	0.25	24
	Security Camera	0.1	24
	Laptop	0.2	5
	HVAC	3	5
	Steam Iron	1.2	3
	Television	0.2	3
Uninterruptible	Electric Mixer	0.75	2
	Electric grill	2	2
	Microwave	1.2	2
	Washing Machines	3	4
	Dish Washer	2.5	4
	Cloth Dryer	3.4	2
Shiftable	Electric Geyser	3.5	3
	Electric Boiler (kettle)	1.9	3
	Vacuum Cleaners	1.6	3
	Water Heater	2.5	3

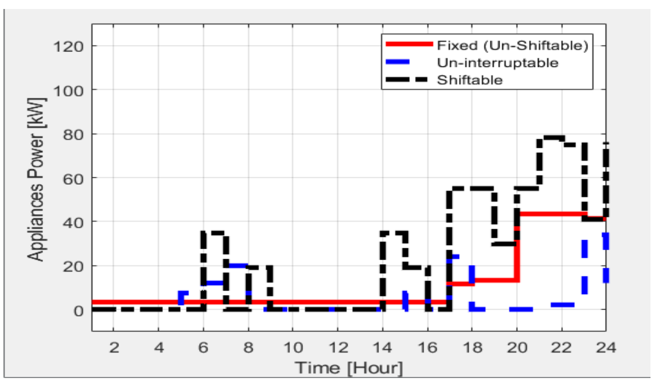

Fig. 9: Daily load for each load type.

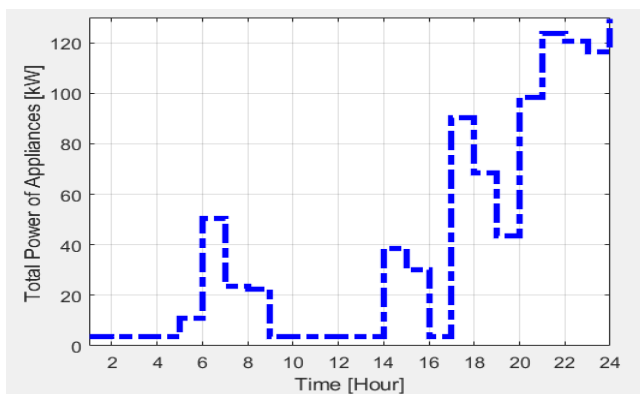

Fig. 10: Total daily load curve before applying the proposed method.

the daily load of all consumers with the three groups of household devices and their time of operation.

Figure 10 gives the total daily load curve before applying the proposed method by summing the three load types at each time slot. The figure explains the customers' daily load including the three proposed types of appliances, and their time of operation. This curve is gotten from the daily energy consumed using IoT and the smart home storage data which are previously collected from the habits and lifestyles of the home residents. The smart home load curve varies depending on the year's seasons and whether it is a normal day or holiday.

The hourly price of the electricity consumed from the grid is illustrated in Fig 11. The simulation has been accomplished and verified for 24 hours. Whereas, the daily solar radiation and wind speed collected from Mansoura city, Egypt are depicted in Figs. 12. and 13.[46]

Figure 14. defines the processes of battery charging and discharging depending on the hourly electricity prices. Whenever the hourly price of electricity is lower than 25 cents, the consumers' load is mainly supplied by the utility because its electricity price is

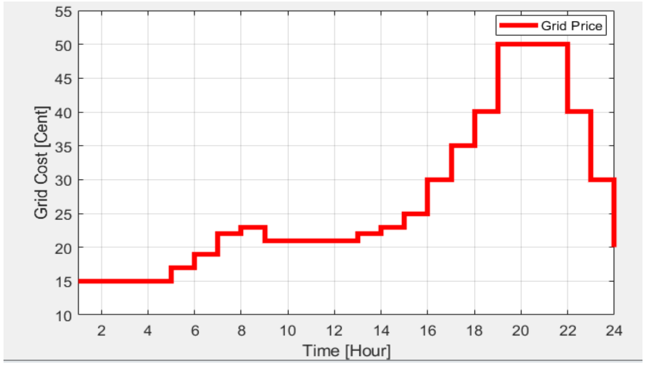

Fig. 11: Hourly grid price

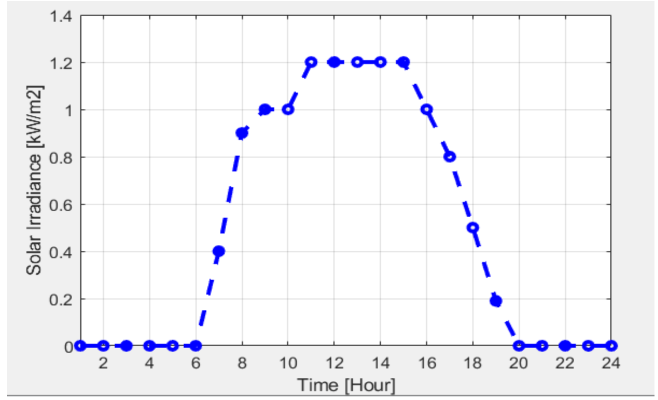

Fig. 12: Daily forecasted solar radiation for Mansoura city [37]

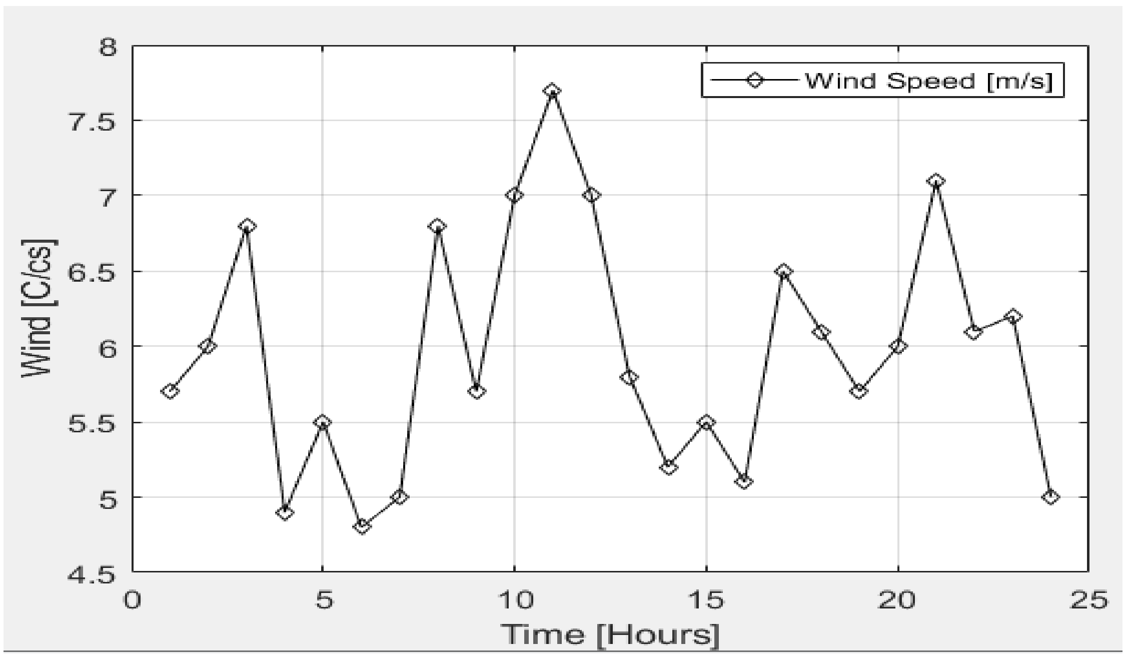

Fig. 13: Daily forecasted wind speed

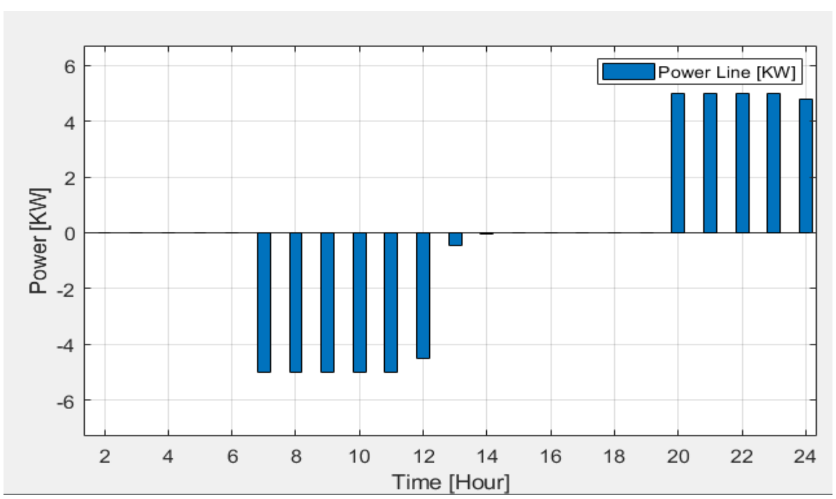

Fig. 14: Daily battery storage power according to the electricity price

low. Conversely, in case the hourly electricity price is more than 25 cents, the consumers are provided with the electricity from PV and/or battery storage systems. Figures 14 and 15 illustrate daily battery storage power and energy according to the price of electricity.

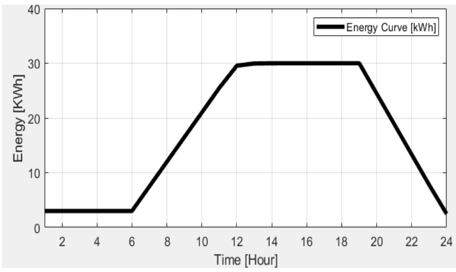

Fig. 15: Daily battery storage energy based on the electricity price

Simulation Results

By implementing the proposed algorithm, the daily PV output and generated wind are shown in Figs. 16. and 17. The operation time for both the uninterruptible and shiftable loads are moved to the low price hours as explained in Fig. 18, whereas the total modified daily load curve is shown in Fig. 19.After applying the

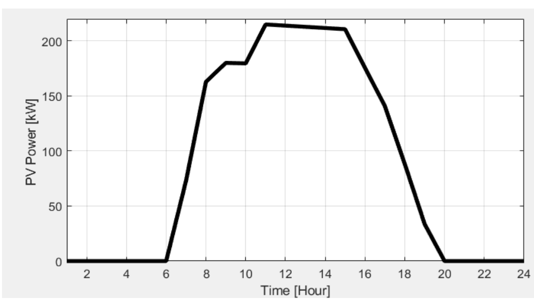

Fig. 16:: Daily generated PV output power for Mansoura city

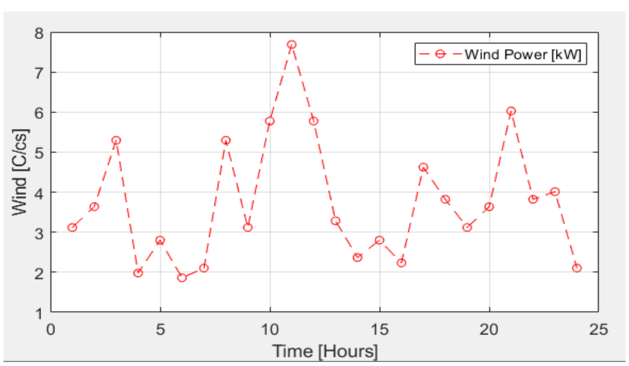

Fig. 17: The generated wind power

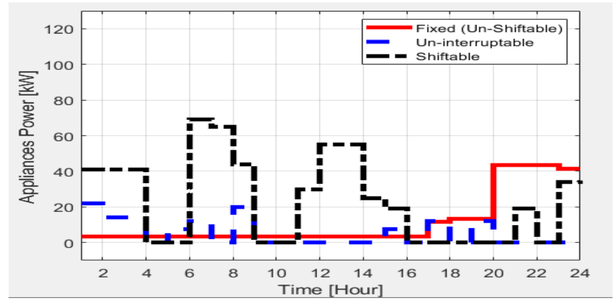

Fig. 18: Daily load for each load type after applying demand response

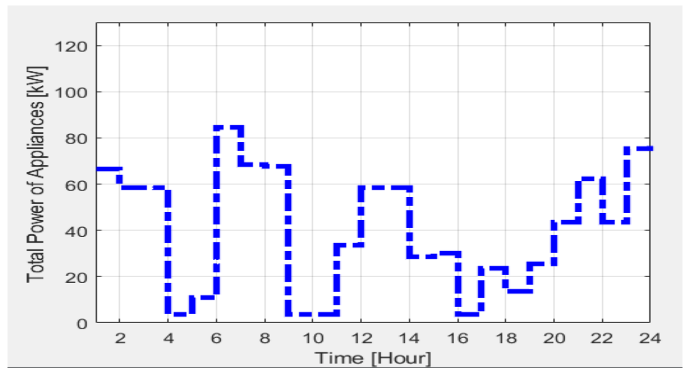

Fig. 19: Total modified daily load curve after implementing the proposed algorithm.

proposed method to the modified load curve in Fig. 19, the cost of energy supplied by the electric grid is reduced in two ways. First, the PV, battery storage, and wind turbine supplied a part of the load. Second, a part of the load curve is shifted towards low price hours. Hence a comparison between the energy supplied by the electric grid before and after applying the proposed preprogram is depicted in Fig. 20

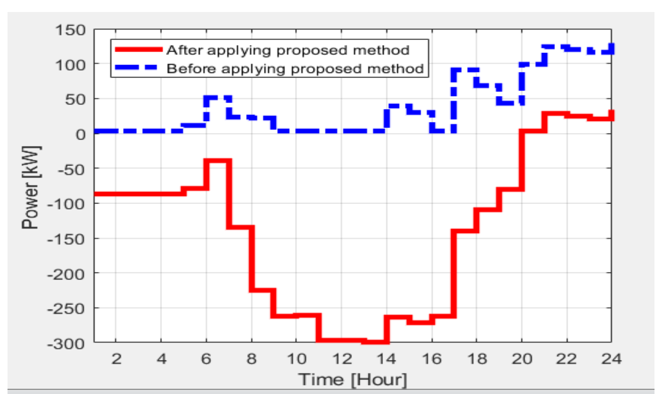

Fig. 20: Energy consumed by the electric grid before and after applying the proposed algorithm.

A comparison between the energy supplied by the electric grid before and after applying the GA is depicted in Fig. 21

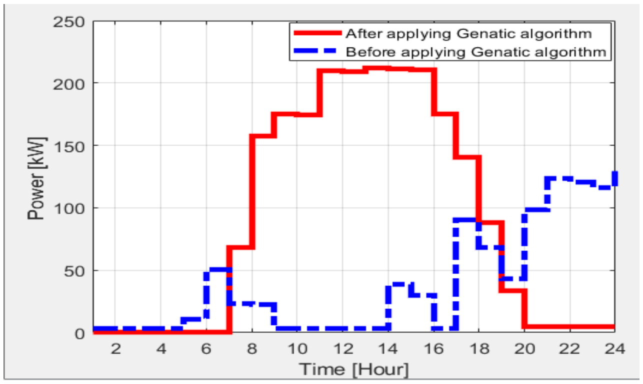

Fig 21: Energy consumed by the electric grid before and after applying the GA

The total daily electricity cost before applying the proposed energy management algorithm is 2910 cents (i.e. 87300 cents per month). After connecting the PV, battery storage, and wind turbine, and with applying the proposed method the total electricity cost per day is lowered to 2232 cents (i.e. 66960 cents per month) with a percentage decrease of 23.9%. The results show that the suggested method reduces the electricity bill, reduces the CO2 emission, by utilizing a PV system, and saves electric energy supplied by the electric grid while satisfying the required constraints.

The applicability and effectiveness of the proposed algorithm are verified by comparing its calculation results with other similar algorithms. Hence, in addition to GA, three other AI algorithms are implemented to compute the total electricity cost for the same test system and under the same assumptions. These algorithms include Artificial Immune System (AIS), Ant Lion Optimization (ALO), and Bat Algorithm (BA).

The AIS is an intelligent algorithm derived from the principles inspired by the principles and processes of the human immune system. ALO is a new swarm-based metaheuristic algorithm that mimics the hunting mechanism of antlions in nature. Whereas BA is a Swarm based metaheuristic algorithm inspired by the foraging behavior of micro-bats, it is mimicking the natural pulse loudness and emission rate of real bats. In addition to its simplicity in programming and formulation, the comparison between the five algorithms shows a similarity in the results with an advantage in the proposed algorithm in improving both the electricity cost-saving and elapsed runtime as explained in Table 2.

Conclusion

This paper presented a harmony search optimization algorithm that can be applied for energy management usage in IoT-based smart homes. The proposed algorithm aimed to decrease the overall cost of energy while optimizing all operational performance. The proposed algorithm depended on demand response to the price changes in the electricity over time and applied the ToU pricing principle to control the time of use of household appliances. The proposed smart home was fed by different energy sources used to supply the home with electricity including PV, wind, and battery storage in addition to the electricity grid. IoT system based on ZigBee was used to communicate different appliances in the home. The proposed algorithm has been implemented using Matlab and applied to a proposed house consisting of five floors, each floor contains two apartments with a total area of 200 meters for one apartment. (The results show that the total electricity cost per day is decreased from 2910 to 2232 cents per day after applying the harmony search algorithm)

The results proved the efficacy of the proposed Harmony Search-based optimization method in saving energy and reducing electricity bills in smart homes while satisfying the required constraints. Additionally, the performance of the proposed algorithm was validated against four AI algorithms. The proposed algorithm resulted in a total electricity cost per day of

Table 2: Comparison between the proposed HS algorithm and different AI algorithms

Optimization method	*Total electricity cost*	*% Improvement*	*Elapsed runtime*	*% Reduction*
AIS	2564.13 cents	11.88%	18.96 sec	---
ALO	2521.25 cents	13.35%	10.65 sec	43.82%
BA	2485.15 cents	14.59%	9.23 sec	51.31%
GA	2322.5 cents	20.18%	16.31 sec	13.97%
HS	2232 cents	23.29%	8.26 sec	56.43%

2232 cents compared to 2322.5, 2485.15, 2521.25, and 2564.13 cents for GA, BA, ALO, and AIS respectively. Elapsed runtime of the proposed algorithm was 8.26 seconds compared to 16.31, 9.23, 10.65, and 18.96 seconds for GA, BA, ALO, and AIS respectively. The comparison revealed the applicability and effectiveness of the harmony search-based algorithm.

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