Energy Reports 8 (2022) 5396–5411

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Research paper

Multi-objective optimization strategy for home energy management system including PV and battery energy storage

Ziye Song, Xin Guan *, Meng Cheng

School of Energy and Power Engineering, University of Shanghai for Science and Technology, Shanghai, 200093, China

A R T I C L E I N F O

Article history:
Received 1 December 2021
Received in revised form 27 February 2022
Accepted 7 April 2022
Available online 22 April 2022

Keywords:
Multi-objective home energy management
Optimal load scheduling
Real time tariff
Peak load reduction
Genetic algorithm

A B S T R A C T

As an important part of the smart grid, home energy management system (HEMS) is closely related to power usage, in which consumers are not only the users of the power grid, but also the suppliers of distributed power. In this paper, an intelligent HEMS with three adjustable strategies is proposed to maximize economic benefits and consumers' comfort. Besides, a novel objective function mainly focusing on satisfying users' needs is developed by innovating a tri-objective model concerning different weight coefficients which is integrated into a new algorithm to reach a balance among the running costs, peak–valley balance index and the satisfaction index. Moreover, this paper innovates historical weather data to predict the outcome of photovoltaic power. The benefits of HEMS with photovoltaic and battery energy storage system which is beneficial for peak load shaving and grid stability utilizing three different strategies are analyzed by two different scenarios. The simulation results demonstrate that the proposed model has highly cut the expenditure of electricity bill by 39.81% and maintain the balance of the power grid by reducing peak load by 50.37%, meanwhile, the index of users' comfort improves about 1.6 times.

1. Introduction

1.1. Motivation

In the past decades, worldwide energy consumption has risen sharply, which has brought about a variety of devastating problems like energy shortage and environmental pollution (Cao et al., 2016). Renewable energy which has less impact on the environment can be integrated into a smart grid to alleviate pollution and global warming problems. In addition, it has huge potential and relatively low operating and maintenance costs (Li et al., 2021). Renewable energy resources (RESs) are growing rapidly in the grid due to the decrease in conventional energy resources and the increase in power demand. It is worth noting that due to the direct dependence of the production of RESs on climatic conditions, there are many uncertainties in the operation of RESs. Therefore, microgrids with RESs and energy storage systems (ESSs) can be effectively integrated to store and manage the additional RESs production (Tan et al., 2021). Because RESs are non-dispatchable and exhibit poor load following especially in residential power consumptions, the successful implementation of HEMS can get through these restricts.

The HEMS is an interface to demand response (DR) programs used by end users, which helps end users in a time-varying energy price environment to solve a scheduling problem that considers the generation of renewable energy, the demand for each device in the household, battery storage capacity, and grid constraints. The goal of the scheduling problem is to achieve the minimum energy consumption cost in the face of uncertainty in supply and demand and electricity prices without reducing the comfort of end users. It is worth mentioning that in addition to the impact on the environment, power distribution system operators also pay special attention to the need to reduce operating costs and improve network reliability, so as to provide users with lower emission levels, optimal costs and sufficient reliability (He and Giesselmann, 2015). Therefore, the DR program is considered to be a new measure to help countries control electricity consumption, and is utilized to change the normal demand consumption by reducing or increasing the load according to the supplier's situation when there is a shortage or surplus of electricity. Needless to mention, DR programs cannot singly control the electricity consumption or influence the rate of participants to reduce the demand. In most of the cases, consumers do not like or cannot spend their time to calculate and analyze their power consumption and schedule the running time of their appliances in order to save their money (Faruqui and Sergici, 2010). DR programs have been used extensively in recent years for demand curve modification. Furthermore, by modifying the load peak and

* Corresponding author.
E-mail address: cindy_guan@usst.edu.cn (X. Guan).

https://doi.org/10.1016/j.egyr.2022.04.023
2352-4847/

Nomenclature

Full scripts

$X_{i,j}$	Operating status of appliance i at time instant j.
X_{day}^{total}	Total state matrix of the appliance.
t_i	Opening time of appliance i.
L_i	Permitted operating time of appliance i.
a_i, b_i	Upper and lower opening time limits for appliance i.
PV_j	Power of photovoltaic panels at time instant j.
S_{array}	Total area of photovoltaic panels.
η	Photoelectric conversion efficiency.
T_j	Average photovoltaic panels temperature at time instant j.
I_j	Total irradiance at time instant j.
SoC_j	Battery state of charge (SOC) level at time instant j.
$Charge_j$, $Discharge_j$	Battery charge and discharge rate at time instant j.
k_d	Battery self-discharging rate.
X_j	Battery state of charge at time instant j.
X_j^{total}	Matrix of battery state of charge at each time slot.
$\gamma_1,\gamma_2,\gamma_3$	The weight coefficient of the three optimization objectives.
P_{price}	Total real-time power price matrix.
K_j	Real-time power price at time instant j.
L_n	Power consumption matrix of the load.
$Load_j$	Total load demand of consumers at time instant j.
G_j	Actual obtained electricity from the grid at time instant j.
m_j'	Demand electricity obtained from the grid at time instant j.
N	The running costs of the day.
G_j'	Calculated buy or sell electricity at time instant j.
N'	Calculated running costs of the day.
Sa_i	The satisfaction index of users.
$t_{a,i}$	Actual opening period for appliance i.
Sat_{max}	The total maximum satisfaction index.
σ_m	The peak–valley balance index.
m_i	Obtained electricity from the grid at time instant i.
$m_{average}$	Average power purchase in a day.
$\mathrm{Tar}_{\max}$	Overall optimization objective.
$\sigma_{m,max}$	Maximum variance of real-time power purchase profile.

transferring a part of the load from the peak hours to the off-peak hours, DR programs reduce the demand during the peak hours, and subsequently increase system reliability and reduce the operation costs (Shakeri et al., 2017). Therefore, HEMS with smart controllers can independently respond to changing environments without human intervention. Generally speaking, by increasing the penetration of smart homes in the power distribution system and integrating renewable energy systems, energy storage systems, and scheduling systems, the stability of the grid is improved and operating costs and emissions are reduced to some extent, which is in line with sustainable city policies and improves the level of sustainable urban development (Al-Ghussain et al., 2020).

1.2. Literature review

The methods that seek to integrate smart home into DR programs on the purpose of peak demand reduction and system load curve modification become even more important. Therefore, in recent years, these programs have played an important role in energy management programs and numerous researches have been carried out on HEMS considering DR programs. In this regard, Ref. Zeng et al. (2018) innovatively proposes a low-carbon real-time electricity price (LCEP) mechanism, which effectively reflects the external characteristics of renewable energy, and an energy management optimization strategy based on mixed linear integer programming is proposed to intelligently control all flexible resources in the family. Making full use of the flexibility of demand side resources to integrate with the grid brings economic benefits on the user side owing to the overall lower power price. The results substantiate that the LCEP mechanism not only provides a good signal to alleviate RESs restrictions but also maximizes the profits of demand side with RESs grid integration. A type of residential complexes (RCs) integrates with distributed energy resources generation system and electric vehicles (EVs) is proposed in Ref. Barhagh et al. (2020). Operators of RC energy systems equipped with local generator sets can benefit from a DR program to reduce operating costs. The problem of optimal operation of a grid-connected EV energy system is examined in the presence of real-time pricing of a DR program. In this reference, a mixed-integer linear programming (MILP) model for optimal operation of energy systems integrated into RCs is presented. The simulation results indicate that the total expected cost of RCs is reduced by 37.31%. In Ref. Wang et al. (2021), a heuristic method has been exploited for load demand management based on the generated power and the appraised market-clearing price. The model takes the utilization of renewable energy resources and the fluctuation of the power grid into consideration and the results demonstrate that demand response has highly cut the expenditure of electricity bill and maintain the balance of the power grid. The power system load serving entities pay special attention to voltage stability improvement and valley fillings and peak shavings of load demand profile. A novel methodology in Ref. Gupta and Verma (2021) is proposed for residential consumers using Battery Energy Storage Systems (BESSs) as a key component for demand side management. The results show that centralized control of power dispatch from energy storage devices minimizes the use of node voltages and makes a great contribution to load curtailment optimization and social welfare maximization. A simulation model that reflects the flexibility requirements of power system and the assignment of Time-of-use (TOU) pricing to maximize the profits of power suppliers and the stability of the grid is described in Ref. Kumamoto et al. (2020). The results indicate that it is profitable to adopt TOU pricing for energy costs reduction by obtaining flexibility from users. In Ref. Teki et al. (2021), a solar photovoltaic system with battery storage is modeled, which is beneficial for peak load shaving and grid stability utilizing particular control and energy management. This energy management contributes to integrate solar photovoltaic power into the grid network and reduces peak loads about 47.14% and the peak efficiency of the system scales between 90% and 94%. A two-stage stochastic programming has been presented in Ref. Zeynali et al. (2020) targeting on reducing the electricity procurement cost of normal residential households.

In this study, a proper analytical battery degradation cost model according to cost function is proposed and future battery storage cost reductions on the HEMS is investigated which results in total economic benefits.

There are several recent research papers on the home energy management (HEM) strategies. A water filling energy distributive algorithm-based HEMS is proposed in Ref. Rajendhar and Jeyaraj (2020), in which minimization of total electrical energy costs are considered as the main objective and the index of comfort, the stress of the battery and the main grid are also included. The structural properties associated with the optimal control of a HEMS is developed in Ref. Langer and Volling (2020). In this model, a representative building with an air-sourced heat pump, a photovoltaic system, a battery storage system, and thermal storage systems is considered. Based on optimal control and considering seasonal effects, the target states of charge (SOC) of the storage systems can be derived and the solution time can be effectively reduced by utilizing the approach of rolling horizon. In Ref. Khemakhem et al. (2019), a double layer supervision strategy is proposed to flatten power load profile in a residential scenario with the method of implementing a demand response algorithm and Plug-in Electric Vehicle power management, which contributes to flatten the fluctuations in demand and achieve the near optimal power. An interactive building power demand management strategy based on genetic algorithm is adopted to facilitate the optimization of the grid in Ref. Xue et al. (2014). In this paper, building thermal masses are also integrated into the model of the building, which contributes to a significant relief of grid power fluctuations. An article Ref. Elma and Selamogullari (2015) mainly focused on reducing peak demand and residential appliances shifting is developed by innovating the method of voltage control which is integrated into a new HEM algorithm to increase the energy efficiency. A hybrid algorithm, Genetic Binary Particle Swarm Optimization (GBPSO), is innovatively proposed in Ref. Javaid et al. (2017), the results show that GBPSO based HEM controller has a good performance on cost reduction and Peak-to-Average Ratio curtailment. In Ref. Shakeri et al. (2018) a novel control algorithm for the HEMS considering battery storage system is demonstrated to apply in any conventional houses, which achieves up to 15% of electricity cost reduction and maximization of comfort index. In Ref. Shirazi and Jadid (2015) represents a technique which can conduct optimal scheduling of residential energy consumption automatically resulting from home automation system shortage and lack of response to time-varying pricing of users. The results demonstrate that the model proposed and an appropriate scheduling load consumption can reduce energy costs and ensure residents' comfort as much as possible. A heuristic Forward–Backward Algorithm (F-BA) in minimization of energy costs of thermal appliances considering comfort index is proposed in Ref. Golmohamadi et al. (2019). This paper also presents a Peak Flatten Scheme in response to peak demands that emerged in the power system and optimizes the power distribution on the bus by shifting the power load from the weak lines to alleviate congestion, which contributes to economic benefits and the stress of the power grid relief.

1.3. Contribution

Recently, in addition to economic goals, HEMS have pursued other goals such as reducing grid fluctuations, improving user satisfaction, reducing environmental impact, and so on. It should be noted that these goals affect and restraint each other. For example, When the HEMS is performing optimal scheduling, the HEMS model adopts different objectives according to the perspective of the decision maker. Minimization of the running costs is the most commonly used objective, mainly due to its family demands and ease of utilization. Maximizing the comfort or well-being of users, optimizing processing to reduce peak demand load profiles, and minimizing greenhouse gas emissions or maximizing the use of renewable energy are other main goals adopted. Therefore, in order to realize a compound HEMS scheduling model, comprehensively considering the aspects of technology, economy and environment objectives, a multi-objective optimization method should be utilized (Costanzo et al., 2012; Qayyum et al., 2015; Vilar and de Mattos Affonso, 2016).

The objective functions studied in the previously literatures are mainly concentrated on coping with one, such as cost reduction, environment protection, and user comfort improvement. This paper poses a compound integrated multi-objective optimization function to take weights and integrate them into one objective function. In addition, one of the main contributions of this paper is the integration of predicted real-time generated PV power for scheduling, while in the previous literatures, there is no photovoltaic power taken into account and lacking of utilizing photovoltaic prediction data for prescheduling. Though there are many works in the literature, most of the HEM works neither consider a photovoltaic integration nor include the storage of surplus energy. This paper proposes a combined strategy of battery energy storage integration to solve the problem that RESs are non-dispatchable and exhibit poor load following especially in residential power consumptions.

In this paper, three different strategies are presented considering HEM scheduling, photovoltaic integration, and battery energy storage integration. A mixed integer nonlinear programming model integrated into HEMS for optimal operation of energy systems is presented. Moreover, a real-time price-based DR program is used, and historical weather data is utilized as the input of weather prediction model to predict the outcome of photovoltaic power. Finally, the main contributions of this paper are as follows:

- Providing a tri-objective and three-in-one objective optimization framework for day-ahead energy management of household considering smart homes.
- Providing three different strategies considering scheduling of residential appliances, electricity dispatch based on PV integration, and energy storage integrated power dispatching.
- Providing photovoltaic prediction data with deep learning for the input of the optimization scheduling.
- Investigating the effect of different weights of objectives on the peak–valley balance index, the running costs and the satisfaction index.
- Investigating the effect of battery energy storage system on the operating time of residential appliances and peak–valley balance index.

2. Problem formulation

The problem of obtaining the optimal power matching and price revenue in HEMS which efficiently integrates power generation, energy storage option, and electrical energy consumption or load is addressed. The proposed HEMS manages the devices by regulating the loads that cannot be arbitrary interrupted, regarding the same kind of electrical appliances that operates at multiple periods as different loads, and converting thermostatically controlled loads (TCLs) into flexible loads (FLs) at the same time. The opening time range of loads is mainly determined by comfortable temperature range for users. Whereas, users can also set the opening time freely according to actual needs, which is more user-friendly.

The HEMS problem is, therefore, to find one or a set of the best (according to one or multiple objectives) strategies that decide on

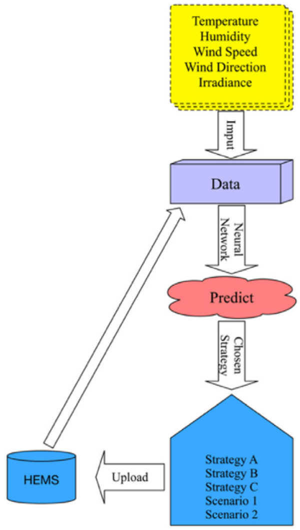

Fig. 1. The overall schematic for managing the electrical energy in a smart home.

how much energy to buy from or sell to the grid or how much energy to store in the battery (Zupančič et al., 2020).

The overall schematic that illustrates the problem of managing the electrical energy in a smart home is presented in Fig. 1. The historical weather data is first retrieved and used to predict the photovoltaic power generation data which is used as an input for the optimization procedure every half hour in the next day. The user or the HEMS operator then chooses a solution strategy (regarding the specific working period and rated power of the electrical appliances participating in the scheduling in the next day, and optimization objectives) that is preferred by the user, which is then uploaded to the HEMS central unit and utilized to manage the energy flows within the system. Finally, the corresponding algorithm is activated to obtain the specific schedule for electricity consumption in the next day and carried out. In this paper, 24 h are divided into 48 time slots in a day, namely, half an hour for each time slot. And the day begins at 24:00 lasting for 24 h, therefore, time slot at 0 corresponds to the time at 24:00, time slot at 24 corresponds to the time at 12:00, and so on. According to the RTP tariff, the electrical energy consumption charges for different time slots are given in Fig. 2.

2.1. Optimization runs

The optimization was performed using a workstation with an Apple Silicon M1 CPU @3.2 GHz with 16 GB of RAM. Python (Python) was used as the programming language and the Geatpy library (Geatpy) was used as the optimization framework. The data preprocessing was implemented using the NumPy (van der Walt et al., 2011) and Pandas (McKinney) libraries.

Due to the resource-intensive experiment, the parameter settings were chosen based on a smaller set of preliminary runs. As a result, the parameter settings for two scenarios and three strategy optimizations specified in Tables 1 and 5, respectively, were set. Each optimization was executed 40 times in order to obtain representative results.

2.2. Model

The home energy management system, an intelligent network control system based on the smart grid, comprises components that are energy generation equipment (distributed photovoltaic modules, wind generators), energy consumption (load), energy supply source (grid) and energy storage equipment (battery). The HEMS is responsible for managing the hardware and the energy flows between the home energy components. All the components involved in this paper are addressed as follows.

Table 1
Parameter settings for three strategies and two scenarios.

Parameter name	Parameter value
Number of parents	200
Number of offspring	200
Number of generations	300
Gene mutation probability	0.1
Crossover probability	0.9

Electrical load. Appliances are the main energy consumption in the HEMS, therefore, particular regulation is of great importance to home appliances. After the appliance is turned on, the operation cannot be interrupted until the operation is satisfied. All equipment will not be interrupted by process, therefore, under the premise that the required working time of the equipment is known, as long as the opening period is determined, the working status of the day will be determined. Mathematical formulation of the proposed model is shown as follows:

$$X_{i,j} = \begin{cases} 0, & j \notin [t_i, t_i + L_i] \\ 1, & j \in [t_i, t_i + L_i] \end{cases} \tag{1}$$

$$X_{day}^{total} = \begin{bmatrix} X_{1,1} & \cdots & \cdots & \cdots & X_{1,48} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ X_{i,1} & \cdots & X_{i,j} & \cdots & X_{i,48} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{n,1} & \cdots & \cdots & \cdots & X_{n,48} \end{bmatrix} \tag{2}$$

$$1 \le a_i \le b_i \le 48, t_i \in [a_i, b_i] \tag{3}$$

Here, Eqs. (1) and (2) define the operating status of a single device and the total state matrix of the devices in a day, where subscript i denotes the ith device and subscript j denotes the jth time interval. In this paper, 48 time slots are considered in a day which means HEM is implemented for every 30 min slot. Eqs. (3) ensures that the upper limit and lower limit of the ith device (a_i and b_i, respectively) are under the time slots limit. Where t_i denotes the opening time, and L_i denotes the operating time that permitted.

Photovoltaics. A regression model (Muzathik, 2014) is used to determine the energy generation for the given weather conditions and solar panels with fixed installation angle. Given the total area of the photovoltaic panels (S_{array}), the power output (PV_j), where subscript j denotes the jth time interval, can be approximated as follows:

$$PV_j = \eta S_{array} I_j \left(1 - 0.005 \left(T_j + 25\right)\right) \tag{4}$$

where η denotes photoelectric conversion efficiency of solar panels, I_j denotes the total irradiance, where subscript j denotes the jth time interval, T_j denotes the average photovoltaic panels temperature. Within the same day, the inclination and the physical properties of the panel will not change, so η and S_{array} can be regarded as a constant. Whereas, the correlation coefficient of T_j is far less than 1, and only I_j and T_j are the influence variable of PV_j. There is a strong linear relationship between PV_j and I_j.

Battery. The battery's state of charge at the end of the jth time interval (SoC_j) is calculated from the previous state of charge (SoC_{j-1}), the battery charge ($Charge_j$), the discharge ($Discharge_j$), and the self-discharging rate k_d:

$$SoC_j = k_d \cdot SoC_{j-1} + Charge_j - Discharge_j \tag{5}$$

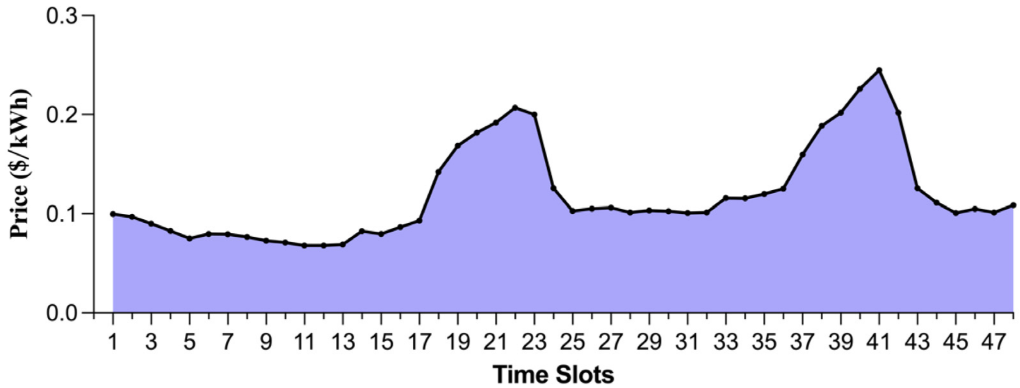

Fig. 2. Details of RTP tariff scheme for different time slots.

$$X_j = \begin{cases} 1, & Charging \\ 0, & Not\ working \\ -1, & Discharging \end{cases} \tag{6}$$

$$X_j^{total} = [X_1, X_2, \ldots, X_{48}] \tag{7}$$

Here, Eqs. (6) defines the battery states of charge and discharge. During each time interval, the battery has three different states and each state runs independently. Further, the energy can be transferred between the grid and the battery. Eqs. (7) indicates the charge and discharge states of the battery for 48 time slots.

The smart grid sends the price signal to the HEMS. P_{price} denotes the total real-time power price matrix in Eqs. (8), and real-time power price at time instant j is denoted with K_j. The power consumption matrix of the load is denoted with L_n in Eqs. (9). Consumers aggregate load demand at time instant j is denoted with $Load_j$ that is calculated from the multiply between L_n and X_{day}^{total} in Eqs. (10):

$$P_{price} = \left[K_0, \ldots, K_j, \ldots, K_{47}\right] \tag{8}$$

$$L_n = [P_1, \ldots, P_n] \tag{9}$$

$$Load_j = L_n \cdot X_{day}^{total} \tag{10}$$

The HEMS prioritizes the use of photovoltaic modules to supply the power to the customers when the strategy is deployed. The smart grid receives the electric energy from the grid when the photovoltaic power is insufficient to meet the needs of users. Conversely, the HEMS sells the remaining electric energy to the grid at the real-time power sale price(half of the real-time power purchase price) when there is a surplus of photovoltaic power. Eqs. (11) indicates the actual amount of electricity that needs to be obtained from the grid, where m_j' denotes the electric energy that needs to be obtained from the grid at time instant j, when $m_j' < 0$ indicates that the HEMS has surplus photovoltaic power sold to the grid during this period:

$$G_j = Load_j - PV_j = \left[m_1', \ldots, m_j', \ldots, m_{48}'\right] \tag{11}$$

2.3. Objectives

Usually, the electricity bill of the day is set to be the only optimization objective to seek the greatest economic benefits for users (Zhou et al., 2014; Missaoui et al., 2014). The future humanized home energy management system should also take the needs of users into account in all aspects. At the same time, the impact on the environment and the fluctuation to the grid have to be taken into consideration. Often-used objectives in HEMS include running costs, CO_2 emission, maximum peak load, aggregated energy consumption and battery life expectancy. The objectives considered in this paper are customer satisfaction, grid balance and the running costs.

The **running costs** (N) comprise the cost of buying and profit of selling the electric energy during each time interval. G_j' is obtained by multiplying the values less than 0 in G_j by 0.5 (surplus electric energy sells for half of the real-time power purchase price). The running costs of the day is calculated in Eqs. (12):

$$N = G_j' \times P_{price} \tag{12}$$

Introduce the upper limit of electricity consumption per unit time (limit), and penalize the strategies that do not meet the upper limit of electricity consumption. The actual running costs of the day (N') are defined in Eqs. (13):

Limit

$$N' = \begin{cases} N, & Electricity\ consumption\ at\ all\ times\ is\ less\ than \\ & or\ equal\ to\ limit \\ N+99, & Electricity\ consumption\ at\ a\ certain\ moment\ is \\ & greater\ thanlimit \end{cases} \tag{13}$$

The **satisfaction index** (Sat) refers to the impact on users caused by the change of residential load operating time before and after optimization. The more operating time changes, the lower comfort of residents. It comprises the allowable opening period of the device and the actual opening period of the device:

$$Sa_i = \begin{cases} \dfrac{b_i - t_{a,i}}{b_i - a_i}, & t_{a,i} \in [a_i, b_i] \\ 0, & else \end{cases} \tag{14}$$

where b_i and a_i denote the upper and lower limits of the opening period of the device respectively, and subscript i indicates ith device. $t_{a,i}$ denotes the actual opening period of the device. Eqs. (15) defines the total maximum satisfaction index model:

$$Sat_{max} = \sum_{i=1}^{n} Sa_i \tag{15}$$

Here, the device is turned on in the allowable opening period at the earliest time when $t_{a,i}$ equals a_i and the value of the satisfaction index is 1. In contrast, the value of the satisfaction index is 0 when the device is turned on outside the allowable opening period, to which the minimum value of the satisfaction index reaches.

The **peak–valley balance index** (σ_m) is used to measure the degree of grid fluctuation which is significant to shave the peak and fill the valley to the load of power purchasing profile in the contemporary urban power grid system. With the growing demand for electricity user side, power generators also increase in order to fully meet the electricity demand of the load side. If there is a mismatch between power supply and demand, it will cause huge power equipment investment and operational redundancy. The demand-side optimization algorithm balances the load profile, which can effectively reduce power fluctuations in the grid, realize the flexibility of electric load and improve the flexibility of energy regulation. The peak–valley balance index is defined in Eqs. (16):

$$\sigma_m = \frac{\Sigma_{i=1}^{48}(m_i - m_{average})^2}{48} \tag{16}$$

where σ_m denotes the variance of real-time power purchase profile, m_i denotes the amount of electricity that needs to be obtained from the grid, subscript i indicates *i*th time, and $m_{average}$ denotes average power purchase in 48 periods of the day. The lower σ_m indicates better peak–valley balance.

Further, when discussing the balance of the power profile of home energy management system with storage batteries, the reference should be the power purchase profile.

2.4. Multiple objective optimization model

Multiple objective optimization model is proposed to evaluate the performance of the strategies according to the specific objectives that mentioned above. In this model, all optimization objectives are normalized, the weight of which is determined by the weight coefficient. The objective function Tar $_{\max}$ is defined in Eqs. (17):

$$Tar_{\max} = \gamma_1 \frac{Sat}{Sat_{\max}} - \gamma_2 \frac{\sigma_{\mathrm{m}}}{\sigma_{m,\max}} - \gamma_3 \frac{N}{N_{\max}} \tag{17}$$

where Sat_{max} denotes the maximum value of satisfaction index which reaches to the peak when all flexible load devices are turned on at the time when users are most satisfied, $\sigma_{m,max}$ denotes maximum variance of real-time power purchase profile, N_{max} is the maximum value of the running costs. $\gamma_1, \gamma_2, \gamma_3$ denote the weight coefficient of the three optimization objectives respectively, the value of which is between 0 and 1, and the sum of them is 1. It can be set freely according to actual needs when conducting different optimization steps.

3. Strategies for home energy management system

With the rapid development of power grid technology, the concept of the Internet of Things (IoT) has been integrated into modern buildings to meet the electricity demand of residents in terms of comfort, safety, and efficiency (Amin and Wollenberg, 2005). The IoT promotes the deployment of smart sensors and other advanced metering devices, making it possible to remotely interact with electricity consumption information and to monitor and drive residential appliances. From the perspective of the demand side, HEMS conforms to the intelligent process of the power grid. It can interact with residential equipment and public utility equipment and adjust the equipment operation schedule to respond to external information. Meanwhile, HEMS has achieved the access to renewable energy power generation, allowing users to use photovoltaic power to meet their own daily electricity demands or sell electricity for profit. HEMS is mainly composed of smart meters, smart appliances, user interaction terminals, central control platforms, distributed photovoltaic modules and battery energy storage systems, and implements its functions through these equipment.

The system architecture of the proposed HEM model is depicted in Fig. 3. Smart meter is an advanced metering device, which is based on advanced communication, computer and measurement technology to collect, analyze and manage electrical energy information data. In addition to the functions of power consumption recording and power transmission, smart meters can be used to measure some physical quantities, such as temperature, humidity, and light intensity. At the same time, it also collects the specific energy consumption of each residential appliance. Taking the access of distributed photovoltaic modules into account, smart meters also have bidirectional multi-rate metering functions and user-side control functions. The central control platform is an intelligent computing framework built into the user interaction terminal, which aims to manage and optimize energy utilizing proposal. It also receives the information from the smart meters and adopts the scheduling mechanism which arranges the work sequence of the smart residential appliances participating in the scheduling through optimized algorithm calculations. The battery energy storage system (BESS) in the home energy management system can store photovoltaic power that cannot be consumed in real time, and improve the utilization of renewable energy; on the other hand, it can adjust the charging and discharging strategy to buy electricity during the low electricity demand period and use electricity during the peak period to alleviate the regional electricity load and make economic profits for users.

As a part of HEMS, smart residential appliances can be integrated with smart meters, and central control platform to complement smart residential functions. The residential appliances are classified into three groups based on their inherent operating characteristics. Those are rigid loads (RGLs), flexible loads (FLs) and temperature-controlled loads (TCLs). RGLs such as lights, and refrigerators, etc. have fixed time and power consumption patterns in conformity with consumers' needs. The scheduling of RGLs will bring a great negative impact on the user experience, whereas which have influence on the maximum limits for residential power and have to be counted in the real-time electricity consumption. So, the RGLs are considered in the optimal load scheduling. FLs such as dishwashers, washing machines, televisions etc. have continuous power consumption patterns but these can be shifted to preferable time slots. Once the flexible loads are turned on, they will maintain stable operation at the rated power and cannot be stopped until the required working time is reached. Therefore, FLs can be scheduled by controlling the opening time. TCLs such as air conditioners, electric water heaters, etc. have flexible power consumption patterns but these can be influenced by consumers' needs. According to residential consumers' daily requirements, they can fix their specific operating time periods regarding to suitable temperature ranges. Therefore, TCLs can be transformed into FLs to improve the satisfaction index at the sacrifice of increasing the running costs.

The proposed HEM model is validated in this section with three different strategies studies and two different scenarios for each strategy. In each strategy, the simulation results of HEM model are compared with normal model without optimization. In this paper, a multi-objective mixed integer nonlinear (MINLP) problem method is performed using Python with genetic algorithm to solve the proposed HEM model.

3.1. Optimization algorithm

In this paper, the genetic algorithm framework based on Python is selected for optimization calculation. Geatpy is a high-performance Python genetic algorithm library and open evolutionary algorithm framework. It provides library functions of many implemented genetic and evolutionary algorithm related

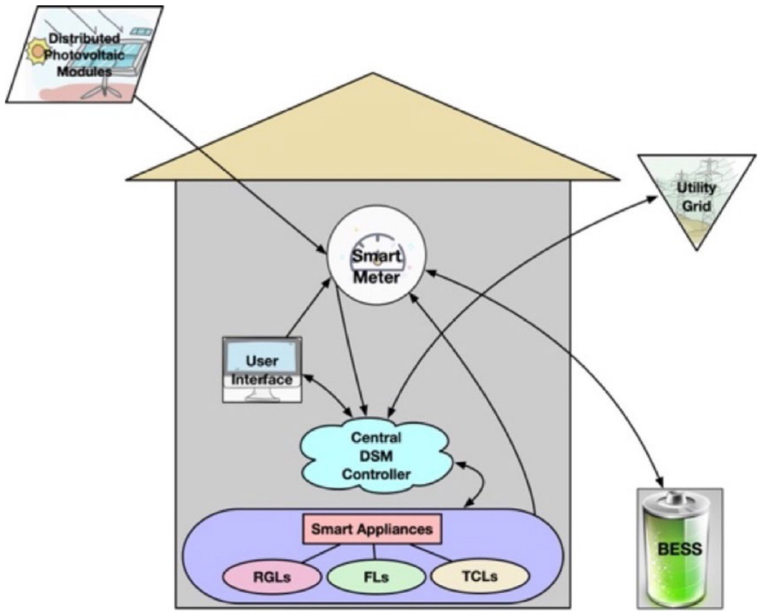

Fig. 3. The architecture of home energy management system.

Table 2
The implementation of the optimization algorithm for the optimization of the HEMS strategy.

```
Chromosome population K is generated according to the opening period of residential appliances
Generate a 16 * 48 matrix X to record the operation of residential appliances, which is initially a zero matrix
for i in K:                                                  # Select a chromosome
    for j in range(0,16):         # Start to consider the operation of the j-th residential appliances
        for k in range(0,period[j]):       # Mark the period when the j-th appliance is running
            x.itemset((j, i[j]+k),1)
        M = np.dot(power, x)      # The power consumption matrix M of each period is obtained
        M1 = M-PV                                            # Add photovoltaic output
        M2 = []
    for i in M1:
        if  i<0:
            M2.append（i/2）
        else:
            M2.append（i）
        N = np.dot(M2, price)                                #obtain the running costs N
    for i in M1:                  # Consider the upper limit of power consumption per unit period
        if  i>limit:              # Introducing penalty function
            N=N+99
```

operators, such as population initialization, selection, crossover, mutation, reinsertion, multi population migration, multi-objective optimization, etc. It also provides an open evolutionary algorithm framework to realize diversified evolutionary algorithms.

According to the above algorithm steps, the chromosome fitness function code is designed in Geatpy, as shown in Table 2. The lower the electricity costs, the higher the fitness:

According to the fitness function, input various parameters and variables, write the specific problem description script, import it into the main framework script of genetic algorithm, and select SOEA_ EGA_ Templet (single objective genetic algorithm template with elite individual reservation) is the evolutionary algorithm template used in this optimization work for simulation calculation.

3.2. Demand response (DR) strategy

Demand response strategy which is the fundamental structure is first integrated into the optimal strategy. Operating parameters of residential appliances in this strategy are tabulated in Table 3. Under the circumstance without optimal load scheduling, all electrical appliances start to operate in the earliest constrained time period, and the value of real-time power consumption is shown in Fig. 4. Most of the power consumption behavior of users is

Table 3
Operating parameters of residential appliances.

Serial number	Residential appliances	Opening period	Rated power/kW	Duration/h
1	Water Heater (WH)	17:00–22:00	3	2
2	Air Conditioner 1 (AC1)	19:00–21:00	1.5	3
3	Air Conditioner 2 (AC2)	11:00–12:00	2	2
4	Air Conditioner 3 (AC3)	17:00–21:00	2	3
5	Rice Cooker 1 (RC1)	11:00–11:30	1	0.5
6	Rice Cooker 2 (RC2)	17:00–17:30	1	0.5
7	Microwave Oven 1 (Oven1)	11:00–11:30	2	0.5
8	Microwave Oven 2 (Oven2)	17:00–17:30	2	0.5
9	Electric Vehicle (EV)	0:00–4:00	2.4	3.5
10	Sweeping Robot (SR)	8:00–23:00	0.7	0.5
11	Dishwasher 1 (DW1)	13:00–16:30	1	0.5
12	Dishwasher 2 (DW2)	19:00–23:00	1	0.5
13	Washing Machine (WM)	7:00–22:30	0.3	0.5
14	Illumination 1 (Light1)	6:00	0.03	2
15	Illumination 2 (Light2)	18:00	0.03	6
16	Refrigerator	0:00	0.6	24

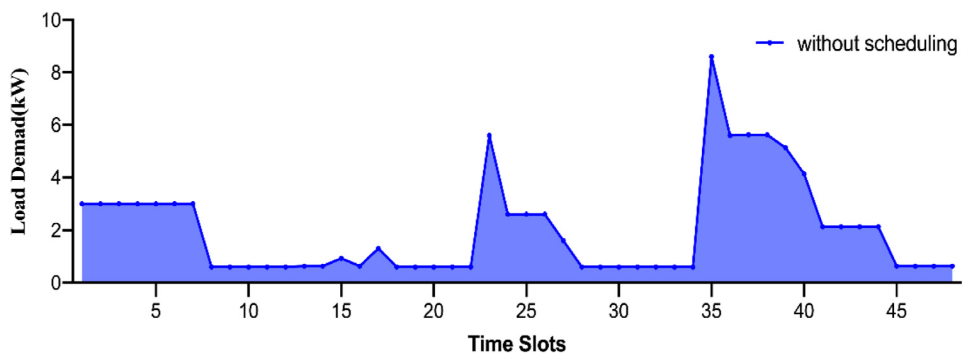

Fig. 4. Real-time power consumption of the day without scheduling.

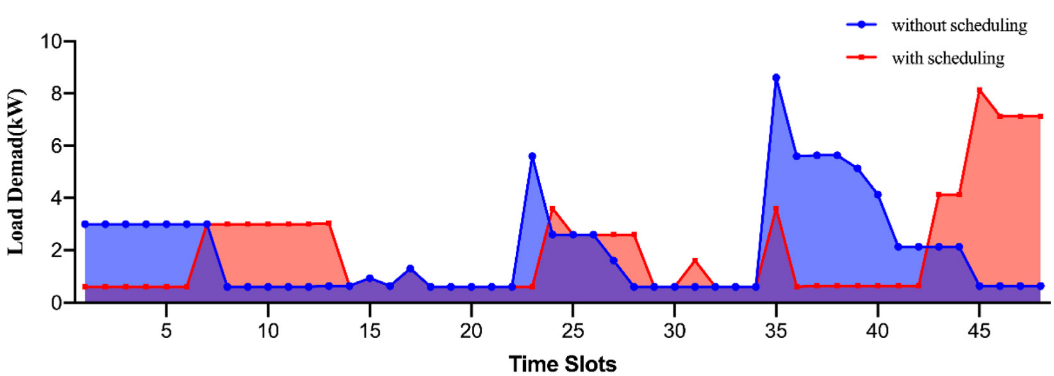

Fig. 5. Real-time consumption of the day with and without scheduling in strategy(A).

concentrated in the three time periods of 11:00–12:30, 17:00–21:30 and 0:00–3:00 in strategy (A), namely, power consumption at noon, daily power consumption in the evening and the charge of electric vehicles in the early morning. The running costs of strategy (A) are 6.44$ calculated.

The power consumption of each time slot with optimal load scheduling which compared with strategy (A) is given in Fig. 5. The optimal load scheduling of all residential appliances with strategy (A) are shown in Fig. 6. Compared with strategy (A), the charging time of electric vehicles in the early morning after scheduling is postponed to 3:00–6:00, and the power consumption during the noon period is postponed to the low electricity price period and the distribution is more even. The peak of power consumption at 11:00 in strategy (A) is shaved and most of the power consumption in the evening is switched to the time slots after 21:00 which is staggered with the evening electricity price peak.

3.3. Photovoltaic (PV) integrated strategy

It will have a great impact on power consumption during the day time after integrating photovoltaic modules. The daily power consumption profile and the usage of photovoltaic power without and with optimal load scheduling are depicted in Figs. 7 and 8 respectively. Fig. 7 shows that all photovoltaic power is used completely in real time during the period form 11:00 to 12:30, which alleviates the electricity load during the noon peak period to a certain extent, but the peak during the noon period still exists. From Fig. 8, it is clear that the power consumption profile during the noon period is smoother, and the peak of the power purchase profile during the noon period is also shaved compared with Fig. 7. The power consumption during the noon period is postponed as evenly as possible to the time period when there is a photovoltaic power surplus, and the photovoltaic utilization rate is also increased after scheduling.

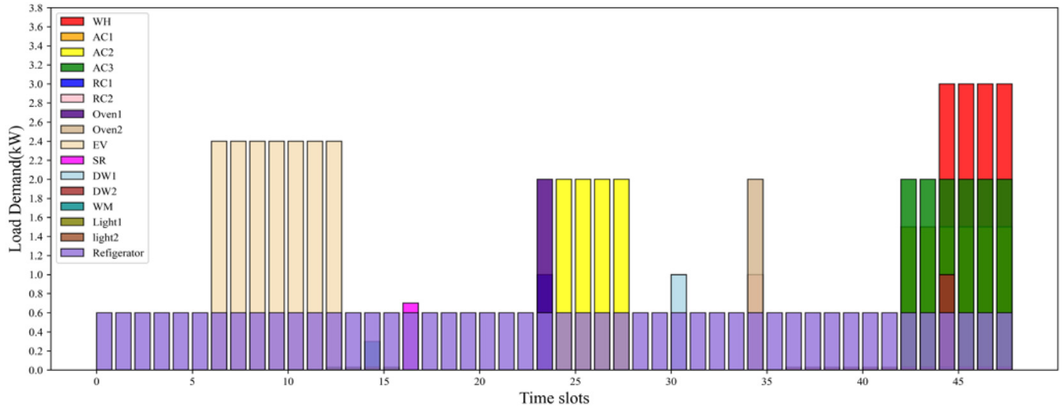

Fig. 6. The optimal load scheduling of all residential appliances in strategy(A).

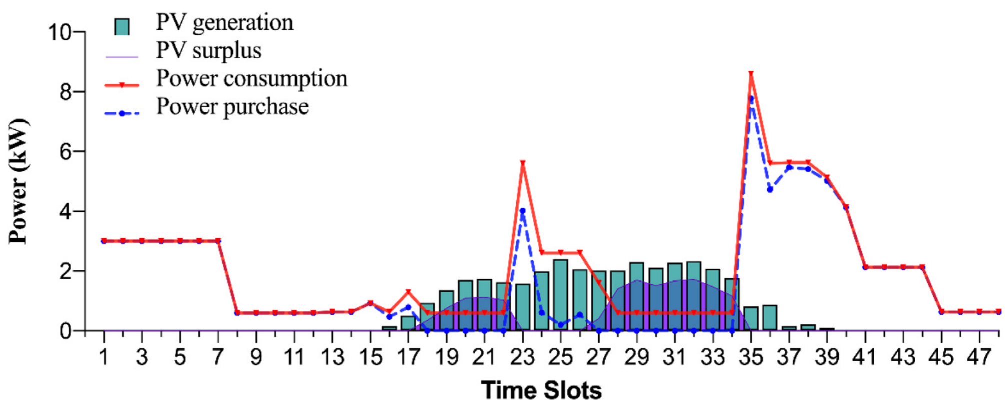

Fig. 7. The daily power consumption and the usage of photovoltaic power without scheduling in strategy(B).

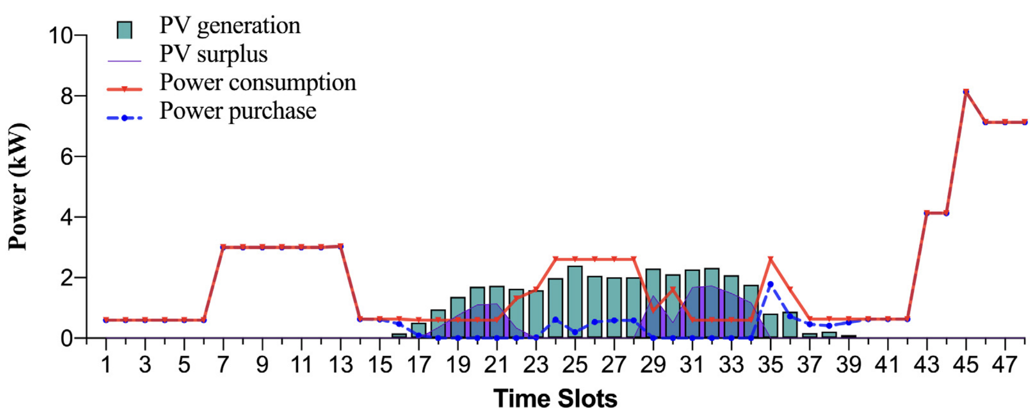

Fig. 8. The daily power consumption and the usage of photovoltaic power with scheduling in strategy(B).

When calculating the benefits of photovoltaics, the cost of photovoltaic power generation needs to be considered. The peak value of photovoltaic power generation in this paper is 2.3 kW. Taking into account the costs of solar panels, installation materials, supporting instruments, and maintenance fees, the cost of photovoltaic power generation is about 2$/W, namely, the total cost of the photovoltaic system is 4600$. The life of the photovoltaic system is about 20 years, and the calculation shows that the daily cost of the photovoltaic system is 0.63$.

The optimal load scheduling of all residential appliances in strategy (B) are shown in Fig. 9. The running costs and photovoltaic utilization rate in strategies above are tabulated in Table 4. Compared with two schemes in strategy A, the optimization algorithm proposed in this paper has an effective benefit on costs reduction, and the daily electricity expense decreases from 6.44$ to 5.06$ after optimization scheduling (a reduction of 21.43%). Compared with scheme 1 and scheme 3, although the installation cost of the household photovoltaic power generation system is high, it can be found that the user's daily power generation cost is reduced from 6.44$ to 5.308$ (a reduction of 17.57%). This shows that the introduction of photovoltaic power generation in the home energy management system will pay equipment costs, but will still bring obvious practical economic benefits. At the same time, it can be found in comparison with the top three schemes.

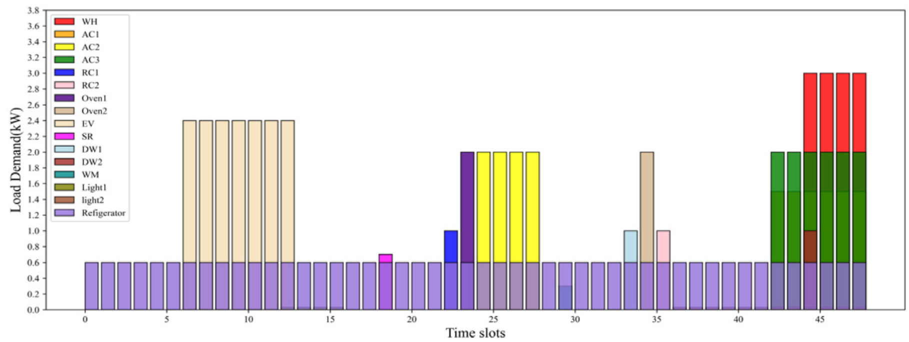

Fig. 9. The optimal load scheduling of all residential appliances in strategy(B).

Table 4
Simulation results of HEM optimization model for four different schemes in two strategies.

Strategy number	Scheme number	With or without photo-voltaics	With or without scheduling	The running costs ($/day)	Utilization rate of photovoltaics (%)
A	1	Without	Without	6.440	0
	2	Without	With	5.060	0
B	3	With	Without	5.308	56.03
	4	With	With	3.876	66.97

Table 5
The general battery storage system specifications.

S. no.	Parameter	Rating
1	Battery capacity	7.2 kWh
2	Charging efficiency	85%
3	Discharging efficiency	95%
4	SOC limit	5%–95%
5	Charging power limit	0 kW–3 kW
6	Discharging power limit	0 kW–3 kW

In scheme 4, when the photovoltaic system is integrated, the optimized scheduling algorithm will further reduce the power cost of users and maximize the saving of users, and the proportion of the running costs is reduced by 39.81% compared with scheme 1. It is clear that the optimization scheduling algorithm is used to optimize the opening time when integrating the photovoltaic system, which will reduce the running costs and maximize the savings for the users.

3.4. Battery energy storage (BES) integrated strategy

As is depicted in Fig. 8, the peak of power consumption is concentrated in the evening, and the peak of photovoltaic power generation is at noon, therefore, the peak of photovoltaic power can only meet the demands of peak power consumption at noon, it is hard to increase the overall photovoltaic utilization rate by the measure of scheduling. Considering the issues above comprehensively, this section integrates battery energy storage system into the HEMS based on the opening period obtained from the optimization results of the previous section in strategy (B), which stores the surplus power in time during the peak period of photovoltaic power generation at noon and uses it during the peak period at night to increase the utilization rate of photovoltaics. And the general battery storage system specifications are given in Table 5.

The lithium iron phosphate battery banks are usually preferred for the home energy storage system applications because of its high battery capacity, excellent performance, life cycle characteristics, easy availability, and environment friendly. In this study, the battery storage capacities of all residential households are assumed to be the same which is 7.2 kWh. And the charging efficiency and discharging efficiency are 85% and 95% respectively. The SOC limit of the battery will be constrained between 5% and 95% to ensure the battery safety. Also Charging power limit and discharging power limit are constrained under 3 kW both. In this way, it can not only ensure that the remaining photovoltaic power generation can be fully absorbed in real time, but also the battery has the ability to ensure all RGLs and some FLs of users in the emergency of external power failure. The battery cost is 500$, the battery life is 4500 cycles, and the daily cost of the battery is 0.1$.

The overall schematic that illustrates the specific implementation mode under the framework of genetic algorithm is presented in Fig. 10. The charge and discharge states of the battery for 48 time slots as the novel chromosomes is first retrieved and used as an input for the optimization procedure. The result of the optimization is the fitness. The battery energy storage strategy designed in this section is:

1. Generate the novel chromosomes to be the charge and discharge states vector of the battery for 48 time slots X_j^{total}.
2. Initialize the values of SOC and k, and read X_j according to the time sequence to confirm the strategy of charge and discharge state in this period.
3. If X_j is equal to 1, the strategy of discharge is adopted. In the case of photovoltaic surplus, the photovoltaic power supply is given priority to the equipment. If there is no photovoltaic surplus power, the battery will be considered to supply power to the equipment. The shortfall will be made up by the purchase of electricity from the grid.
4. If X_j is equal to 0, the battery does not work and the photovoltaic power supply is given priority to the equipment. The shortfall will be made up by the purchase of electricity from the grid.
5. Add penalty function to filter and eliminate unreasonable schemes.

Further, photovoltaic power has priority over the grid when considering the power supply to charge the battery. Additionally, when considering the power supply to the equipment, the priority of photovoltaic power is greater than that of the battery. And both of them have priority over the grid. Finally, benefiting from the strategy the photovoltaic power generated in real-time is consumed as much as possible at any period.

The daily power consumption profile and the usage of photovoltaic power of strategy with battery integration are depicted in Fig. 11. It is clear that the photovoltaic power that is not consumed in real-time is completely stored by the battery and realizes the full utilization of the power. Due to the abundant output of photovoltaics, except for 11:00, there is almost no

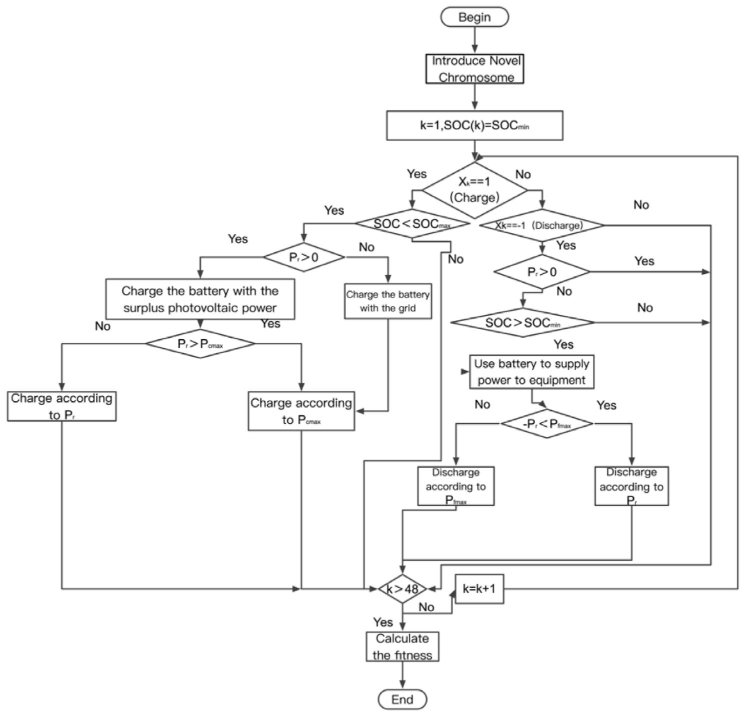

Fig. 10. The specific implementation mode under the framework of genetic algorithm.

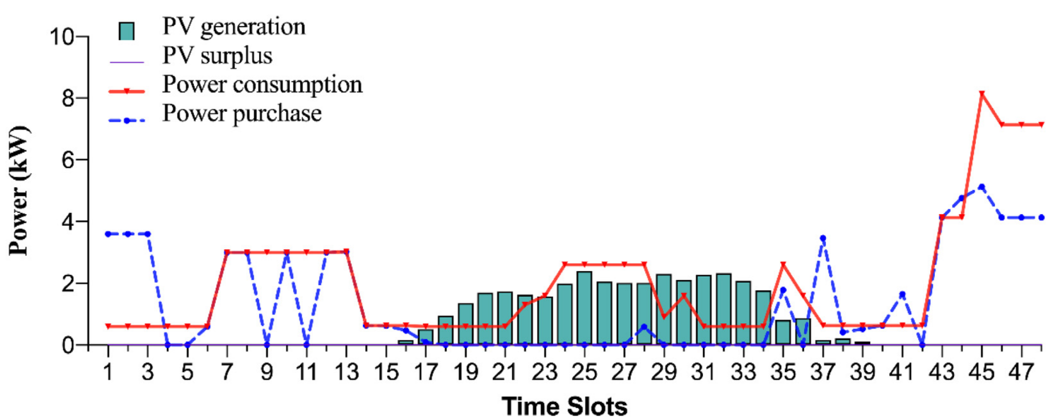

Fig. 11. The daily power consumption and the usage of photovoltaic power of strategy with battery integration.

electricity purchase from 8:00 to 16:00, which shows that photovoltaic power combined with battery supply fully meets the real-time power demand during the day. The strategy makes full utilization of low electricity price period at dawn for power purchase, electric vehicle charging, and battery use. The advantages of the battery have been fully demonstrated after 18:00 in the evening. The power purchase profile is lower than the power consumption profile for most of the time except 21:00, indicating that the proposed HEM model with battery energy storage systems enhances the energy management benefits. The battery SOC levels in strategy (C) are shown in Fig. 12.

4. Simulation results

Most of the previous studies on the optimization of the home energy management system, the daily electricity bill is set to a single objective optimization for users seeking to maximize economic benefits. Humanized home energy management system should also take the demands of users in all aspects into account in the future. First of all, the satisfaction index is considered, the HEMS chooses different opening time slots within the allowable operating period of the equipment will make a difference. In addition, the peak and valley balance of the power purchase profile is considered, with reference to the stability of the grid and power consumption safety, the fluctuation of the power purchase profile should be minimized. From the previous section, however, the introduction of suitable battery energy storage system can consume all the photovoltaics, so we will not discuss the photovoltaic utilization rate in this section.

The proposed HEM model is validated in this section with one case study and two different scenarios for this case. This case analyzes two mathematical models of optimization objectives, and a multi-objective optimization model that meets multiple needs.

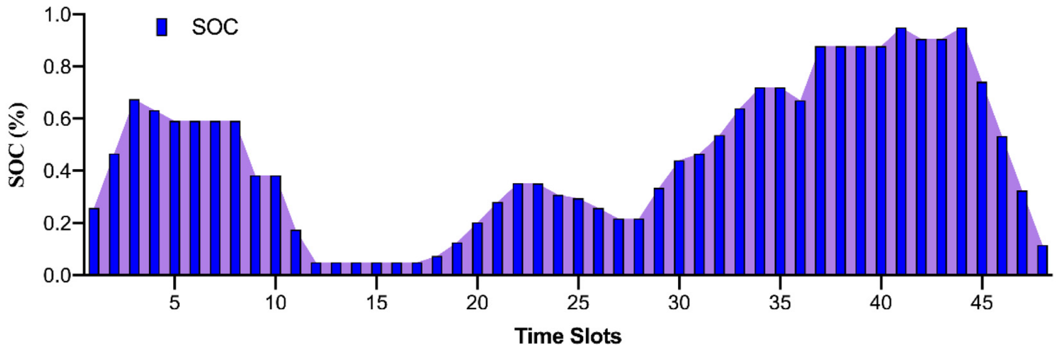

Fig. 12. The battery SOC levels in strategy(C).

4.1. Case study

The main aim of this case study is to analyze the peak load management and cost management for each scenario separately. The battery energy storage system is integrated in this case to obtain best multi-objective optimization results. Scenario 1 represents the balance of power consumption profile and power purchase profile under the circumstance of peak–valley balance index as the single optimization objective. Multi-objective optimization model according to the running costs, the satisfaction index and peak–valley balance index is considered in Scenario 2. Scenario 1 tries to minimize the power consumption profile and the power purchase profile by shifting FLs and TCLs from high load demand periods to low load demand periods. Consequently, the running costs of this scenario might increase. Scenario 2 is a compromised approach which covers three optimization objectives compared to Scenario 1.

4.2. Scenario 1

When scheduling the opening periods of all residential appliances in the first step, coefficients ($\gamma_1 = \gamma_3 = 0, \gamma_2 = 1$) in Eqs. (17) are assigned. The optimal load scheduling of all residential appliances with single optimization objective in Scenario 1 is shown in Fig. 13. The opening time periods of optimization with battery integrated in the second step are on the basis of optimal load scheduling in the first step. The daily power consumption profile and the usage of photovoltaic power with peak–valley balance objective in Scenario 1 are depicted in Fig. 14. It is clear that the multiple peaks of the power purchase profile have been reduced in the early morning. The battery SOC levels in Scenario 1 are depicted in Fig. 15. In Scenario 1, the battery has only two charge and discharge cycles, therefore, the power purchase profile in the evening is flatter, and there are no charge and discharge cycles in the early morning when the electric vehicle is being charged at a rated power. It is clear that the stationarity of power purchase profile has been improved in the early morning in Scenario 1. Scenario 1 in case study with single optimization objective according to peak–valley balance index deals with the optimization problem of the fluctuation of the grid, this approach may not meet the optimal aggregated objective function values. That is why authors have implemented the proposed HEM model in another scenario which is explained as follows.

4.3. Scenario 2

In this scenario, a multi-objective optimization model according to the running costs, the satisfaction index and the peak–valley balance index is considered. The satisfaction index can only be optimized when scheduling the opening periods, and the peak–valley balance index is better optimized when implementing the HEM strategy with battery energy storage system integrated. Therefore, the satisfaction index and the running costs are optimized merely when scheduling the opening periods at the first step, and the peak–valley balance index and the running costs are optimized merely when the BES strategy is integrated. When scheduling the opening periods of all residential appliances in the first step, coefficients ($\gamma_1 = 0.66, \gamma_2 = 0, \gamma_3 = 0.34$) in Eqs. (17) are assigned. The optimal load scheduling of all residential appliances with multiple optimization objectives in Scenario 2 are shown in Fig. 16. The daily power consumption profile and the usage of photovoltaic power without battery installation in the first step are depicted in Fig. 17. The opening time periods of optimization with battery integration in the second step is on the basis of optimal load scheduling in the first step. Coefficients ($\gamma_1 = 0, \gamma_2 = 0.66, \gamma_3 = 0.34$) are assigned with battery integration in the second step. The daily power consumption profile and the usage of photovoltaic power with multi-objective optimization and battery integration are presented in Fig. 18. The battery SOC levels of Scenario 2 are shown in Fig. 19. As is depicted in Fig. 18, compared with Strategy (C), the fluctuation of the power purchase profile is more moderate and the opening periods of residential appliances have been scheduled, which are more satisfactory.

4.4. Discussion

The main aim of this paper is to strike a balance among the objectives of the proposed HEM model simultaneously which is tabulated in Table 6. It seems that optimization with a single objective might cause losses to other objectives that have not been integrated. For example, when the peak–valley balance index is used as the single optimization objective, the running costs are 5.802$, which is two times more compared with it that is used as the optimization objective. Considering that there is a wide range of demands for power consumption strategies in practical applications, it is necessary to establish a multi-objective optimization model.

There is a certain inverse proportional relationship between the running costs and the variance of the power purchase profile. This is because when pursuing low running costs, power consumption will be concentrated in the low electricity price period, resulting in a sharp increase in power consumption during this period. The integration of battery energy storage and photovoltaic systems can alleviate the problem to a certain extent. The multi-objective model of scenario 2 emphasizes the peak–valley balance index, so the running costs are 78.5% of the maximum value, and the variance is only 40% of the maximum value. It proves that the model responds more sensitively to

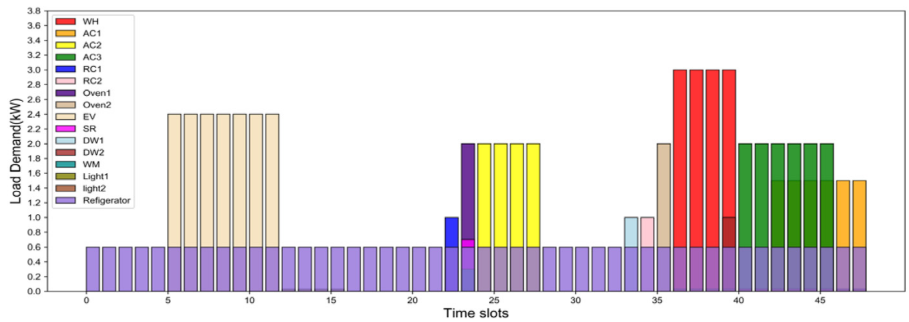

Fig. 13. The optimal load scheduling of all residential appliances with single optimization objective in Scenario 1.

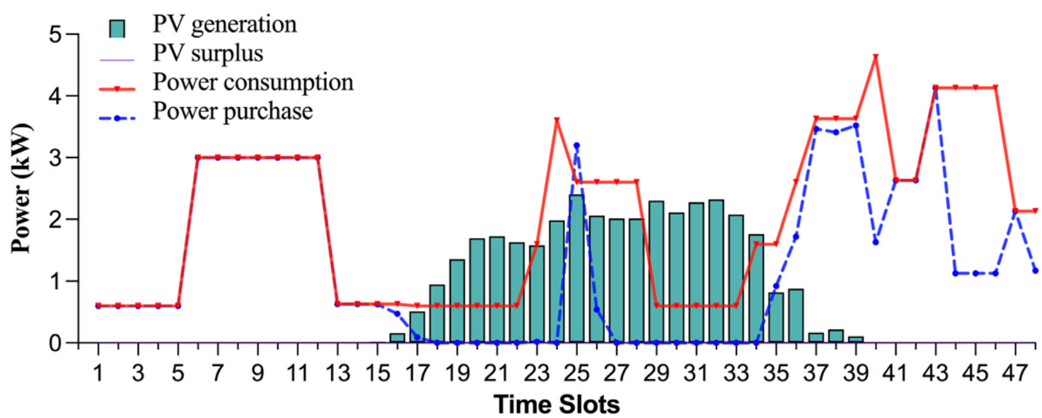

Fig. 14. The daily power consumption profile and the usage of photovoltaic power with peak–valley balance objective.

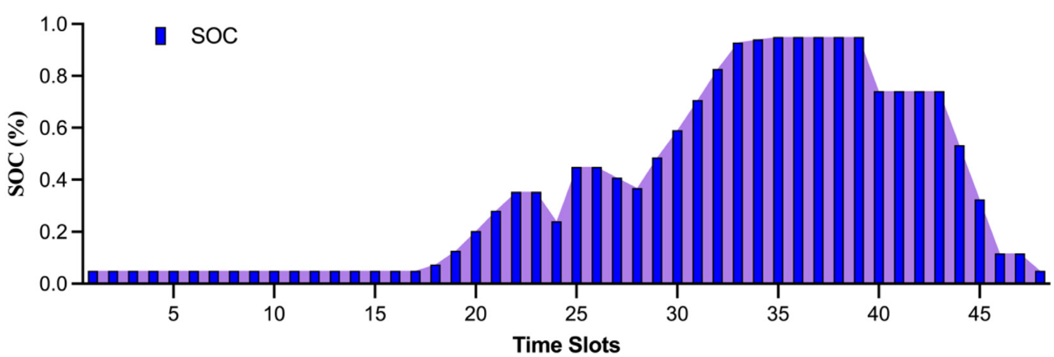

Fig. 15. The battery SOC levels in Scenario 1.

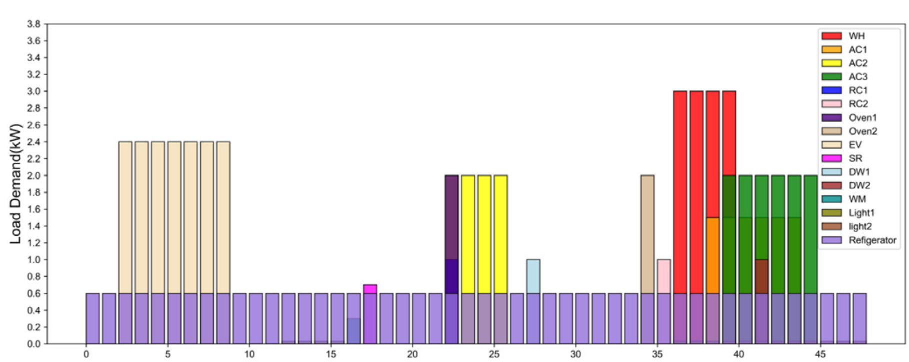

Fig. 16. The optimal load scheduling of all residential appliances with multiple optimization objectives in Scenario 2.

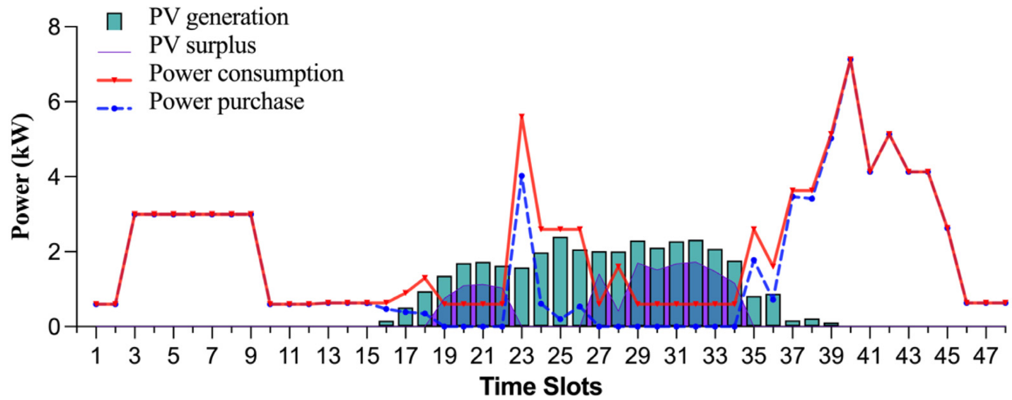

Fig. 17. The daily power consumption profile and the usage of photovoltaic power without battery integration in Scenario 2.

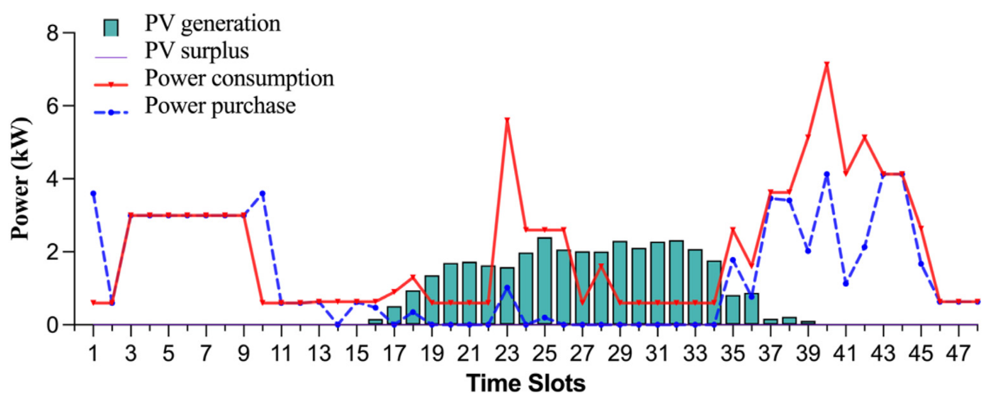

Fig. 18. The daily power consumption profile and the usage of photovoltaic power with multi-objective optimization and battery integration in Scenario 2.

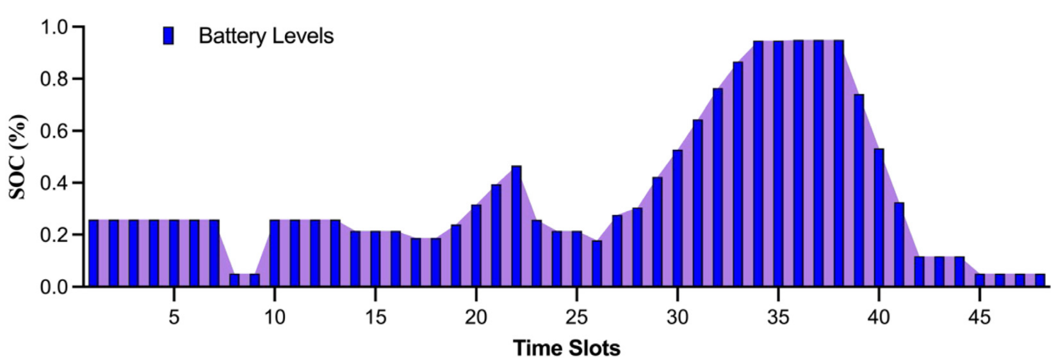

Fig. 19. The battery SOC levels in Scenario 2.

Table 6
Simulation results of HEM optimization mode for three different conditions.

Strategies	Optimization objectives	The peak–valley balance index	The running costs ($/day)	The satisfaction index
Strategy C	N	4.03	2.840	0.30
Scenario 1	σ_m	1.58	5.802	0.44
Scenario 2	σ_m, N, and Sat	2.00	5.054	0.79

changes in the peak–valley balance index and the weight coefficient of the running costs.

Most of the predecessors neglected the satisfaction index when they were optimizing. After single objective optimization of the running costs and peak–valley balance index respectively, the satisfaction index of which are less than 0.5 either. Therefore, when scheduling the opening periods of residential appliances, it is necessary to assign a larger weight for the satisfaction index. The results show that the optimization benefit is more obvious that the value of satisfaction index in Scenario 2 is increased by

163.33% on the basis of Strategy (C). From the overall analysis, the proposed HEM model in Scenario 2 is the most practical case compared to all other scenarios and strategies.

5. Conclusion

The multi-objective home energy management system with three different strategies according to HEM scheduling, photovoltaic integration, and battery energy storage integration is proposed in this paper for residential consumers. The HEM problem with a novel three-in-one objective function is modeled as a multi-objective non mixed integer linear problem, and genetic algorithm is used to solve the complex problem. In this paper, a real-time pricing tariff scheme is utilized to engage in the HEMS scheduling model and which prices are given in different time periods. The proposed problem is implemented to simulate two scenarios selected by users in a practical system.

With the method of genetic algorithm framework, the home energy management system with three different strategies integration is scheduled and calculated. Finally, photovoltaic equipment and optimization strategy have brought good economic benefits, compared with the initial scheme, the running cost of which is reduced by 39.81%. The battery integration strategy can recover the excess photovoltaic power in time, and can purchase power in the low-price period. And the benefits of the proposed model with the integration of battery energy storage system are greatly enhanced by the way of optimizing the charge and discharge sequence of the battery based on the optimization of equipment start-up time, which has decreased the cost of the electricity bill. The results show that the operation cost of the battery integration strategy is reduced by 26.73% based on the photovoltaic integration strategy. From the overall analysis, the proposed HEM model with multi-weight optimization objectives can take the case of three objectives into account at the same time, furthermore, it has obviously enhanced the flexibility of user selection compared with single objective optimization.

The future work to the current study can be done in the following areas:

(a) The current household energy management system still needs users to set their preferences and power demand in advance, and the interactions are cumbersome. With the development of science and technology, the intelligent interactive terminal of the future HEMS will automatically sense users' power consumption habits, and can flexibly respond to emergencies (power failure, sudden weather change, etc.), so that users can really feel convenient.

(b) In the future, the smart perception systems can adjust the weights by analyzing the behavior of the residents automatically with help of big data and artificial intelligence, and it can regulate a certain range of residents by establishing a virtual community.

(c) In order to simplify the research, this paper divides a day into 48 periods, and the start-up and operation of all equipment are in half an hour, which is ideal. The unit period of equipment operation can be further subdivided to improve the practical significance of the optimization strategy on the premise that computational capacity allows.

CRediT authorship contribution statement

Ziye Song: Conceptualization, Methodology, Writing – original draft, Data curation, Writing – review & editing, Software, Formal analysis. **Xin Guan:** Writing – review & editing, Investigation, Supervision. **Meng Cheng:** Software, Validation, Software, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Al-Ghussain, L., Samu, R., Taylan, O., 2020. Sizing renewable energy systems with energy storage systems in microgrids for maximum cost-efficient utilization of renewable energy resources. Sustainable Cities Soc. 55, 102059.

Amin, S.M., Wollenberg, B.F., 2005. Toward a smart grid: power delivery for the 21st century. IEEE Power Energy Mag. 3, 34–41.

Barhagh, S., Abapour, M., Mohammadi-Ivatloo, B., 2020. Optimal scheduling of electric vehicles and photovoltaic systems in residential complexes under real-time pricing mechanism. J. Clean. Prod. 246, 119041.

Cao, X., Dai, X., Liu, J., 2016. Building energy-consumption status worldwide and the state-of-the-art technologies for zero-energy buildings during the past decade. Energy Build. 128, 198–213.

Costanzo, G.T., Zhu, G., Anjos, M.F., 2012. A system architecture for autonomous demand side load management in smart buildings. IEEE Trans. Smart Grid 3, 2157–2165.

Elma, O., Selamogullari, U.S., 2015. A new home energy management algorithm with voltage control in a smart home environment. Energy 91, 720–731.

Faruqui, A., Sergici, S., 2010. Household response to dynamic pricing of electricity: a survey of 15 experiments. J. Regul. Econ. 38, 193–225.

2021. Geatpy. https://www.geatpy.com/. [Accessed Dec 2021].

Golmohamadi, H., Keypour, R., Bak-Jensen, B., 2019. Optimization of household energy consumption towards day-ahead retail electricity price in home energy management systems. Sustainable Cities Soc. 47, 101468.

Gupta, P., Verma, Y.P., 2021. Voltage profile improvement using demand side management in distribution networks under frequency linked pricing regime. Appl. Energy 295, 117053.

He, M., Giesselmann, M., 2015. Reliability-constrained self-organization and energy management towards a resilient microgrid cluster. In: 2015 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT). pp. 1–5.

Javaid, N., Naseem, M., Rasheed, M.B., 2017. A new heuristically optimized home energy management controller for smart grid. Sustainable Cities Soc. 34, 211–227.

Khemakhem, S., Rekik, M., Krichen, L., 2019. Double layer home energy supervision strategies based on demand response and plug-in electric vehicle control for flattening power load curves in a smart grid. Energy 167, 312–324.

Kumamoto, T., Aki, H., Ishida, M., 2020. Provision of grid flexibility by distributed energy resources in residential dwellings using time-of-use pricing. Sustain. Energy Grids Netw. 23, 100385.

Langer, L., Volling, T., 2020. An optimal home energy management system for modulating heat pumps and photovoltaic systems. Appl. Energy 278, 115661.

Li, C., Yao, Y., Zhao, R., Xie, K., 2021. Optimization model for time-varying settlement of renewable energy consumption considering accommodation difficulty and supply–demand interaction. Int. J. Electr. Power Energy Syst. 125, 106469.

McKinney, W., 2010. Data structures for statistical computing in Python. In: Proceedings of the 9th Python in Science Conference. pp. 51–56.

Missaoui, R., Joumaa, H., Ploix, S., 2014. Managing energy smart homes according to energy prices: analysis of a building energy management system. Energy Build. 71, 155–167.

Muzathik, A.M., 2014. Photovoltaic modules operating temperature estimation using a simple correlation. Int. J. Energy Eng. 4, 151.

2019. Python. https://www.python.org/. [Accessed May 2019].

Qayyum, F.A., Naeem, M., Khwaja, A.S., 2015. Appliance scheduling optimization in smart home networks. IEEE Access 3, 2176–2190.

Rajendhar, P., Jeyaraj, B.E., 2020. A water filling energy distributive algorithm based HEMS in coordination with PEV. Sustain. Energy Grids Netw. 22, 100360.

Shakeri, M., Shayestegan, M., Abunima, H., 2017. An intelligent system architecture in home energy management systems (HEMS) for efficient demand response in smart grid. Energy Build. 138, 154–164.

Shakeri, M., Shayestegan, M., Reza, S.M.S., 2018. Implementation of a novel home energy management system (HEMS) architecture with solar photovoltaic system as supplementary source. Renew. Energy 125, 108–120.

Shirazi, E., Jadid, S., 2015. Optimal residential appliance scheduling under dynamic pricing scheme via HEMDAS. Energy Build. 93, 40–49.

Tan, K.M., Babu, T.S., Ramachandaramurthy, V.K., Kasinathan, P., Solanki, S.G., Raveendran, S.K., 2021. Empowering smart grid: A comprehensive review of energy storage technology and application with renewable energy integration. J. Energy Storage 39, 102591.

Teki, V.K., Maharana, M.K., Panigrahi, C.K., 2021. Study on home energy management system with battery storage for peak load shaving. Mater. Today: Proc. 39, 1945–1949.

van der Walt, S., Colbert, S.C., Varoquaux, G., 2011. The NumPy array: a structure for efficient numerical computation. Comput. Sci. Eng. 13, 22.

Vilar, D.B., de Mattos Affonso, C., 2016. Residential energy management system with photovoltaic generation using simulated annealing. In: 2016 13th International Conference on the European Energy Market (EEM). pp. 1–6.

Wang, C., Zhang, Z., Abedinia, O., 2021. Modeling and analysis of a microgrid considering the uncertainty in renewable energy resources, energy storage systems and demand management in electrical retail market. J. Energy Storage 33, 102111.

Xue, X., Wang, S., Sun, Y., 2014. An interactive building power demand management strategy for facilitating smart grid optimization. Appl. Energy 116, 297–310.

Zeng, W., Von Appen, J., Selzam, P., 2018. Active residential load management based on dynamic real time electricity price of carbon emission. Energy Procedia 152, 1027–1032.

Zeynali, S., Rostami, N., Ahmadian, A., et al., 2020. Two-stage stochastic home energy management strategy considering electric vehicle and battery energy storage system: An ANN-based scenario generation methodology. Sustain. Energy Technol. Assess. 39, 100722.

Zhou, S., Wu, Z., Li, J., 2014. Real-time energy control approach for smart home energy management system. Electr. Power Compon. Syst. 42, 315–326.

Zupančič, J., Filipič, B., Gams, M., 2020. Genetic-programming-based multi-objective optimization of strategies for home energy-management systems. Energy 203, 117769.