Science and Technology for Energy Transition **79**, 61 (2024)

https://doi.org/10.2516/stet/2024057

Available online at:
stet-review.org

Decarbonizing Energy Systems: Smart Grid and Renewable Technologies
Fang Rui-ming and Qiangqiang Liao (Guest Editors)

REGULAR ARTICLE OPEN ACCESS

Modeling techno-economic multi-objectives of smart homes considering energy optimization and demand management

Mohammad Ahmar Khan[1], A. K. Kareem[2], Shavan Askar[3], Dilsora Abduvalieva[4], Roopashree R.[5], K. D. V Prasad[6], Aanchal Sharma[7], Abhishek Sharma[8], Nouby M. Ghazaly[9], and M. Mohmmedi[10,*]

[1] Department of MIS, Dhofar University, Salalah, Oman
[2] Biomedical Engineering Department, College of Engineering and Technologies, Al-Mustaqbal University, Hillah 51001, Babil, Iraq
[3] Erbil Polytechnic University, Erbil Technical Engineering College, Information System Engineering Department, Erbil, Iraq
[4] Department of Mathematics and Information Technologies, Tashkent State Pedagogical University, Bunyodkor Avenue, 27, Tashkent 100070, Uzbekistan
[5] Department of Chemistry and Biochemistry, School of Sciences, JAIN (Deemed to be University), Bangalore, Karnataka, India
[6] Symbiosis Institute of Business Management (SIBM), Symbiosis International (Deemed University) (SIU), Kothur Mandal, Mamidipally, Mahabubnagar, Hyderabad, Telangana, India
[7] Chandigarh Pharmacy College, Chandigarh Group of Colleges, Jhanjeri, Mohali 140307, Punjab, India
[8] Department of Medicine, National Institute of Medical Sciences, NIMS University Rajasthan, Jaipur, India
[9] Technical College, Imam Ja'afar Al-Sadiq University, Baghdad, Iraq
[9] Mechanical Engineering, Faculty of Engineering, South Valley University, Egypt
[10] Department of Electrical Engineering, Islamic Azad University, Branch of Central Tehran, Tehran, Iran

Received: 30 April 2024 / Accepted: 18 July 2024

Abstract. The research suggests an approach that prioritizes customer needs and aims to reduce energy expenses while safeguarding customer privacy. Furthermore, it is recommended that smart homes incorporate a home energy management system to optimize appliance energy consumption. Conversely, the introduction of demand-side management addresses the energy management challenges faced by smart households. The main goal of this approach is to decrease energy usage and electricity costs for customers. Moreover, it enhances user satisfaction while waiting at common intervals. The primary emphasis of this study is on a smart residence furnished with energy management technology and smart home gadgets capable of supplying electricity to the grid. These objectives are considered distinct aspects in the multi-objective optimization issue stemming from this approach. The study utilizes the grasshopper optimization algorithm (GOA) to optimize battery and home appliance scheduling in smart homes with flexible devices. The goal is to reduce the overall cost of microgrid systems through demand-side management implementation. This comparison highlights the superiority of the proposed method in optimizing energy consumption and reducing carbon emissions in a variety of scenarios. By achieving lower energy costs and carbon emissions while maintaining a comfortable indoor environment, the proposed method proves to be a highly effective and sustainable solution for energy management in buildings. These simulation results provide strong evidence of the method's potential to significantly impact energy efficiency and environmental sustainability in real-world applications. Furthermore, the consistent minimization of the discomfort index showcases the method's ability to prioritize occupant comfort while still achieving significant energy savings and emissions reductions. Overall, the comparison with other algorithms solidifies the effectiveness and practicality of the proposed method in addressing the complex challenges of energy management and sustainability in smart homes.

Keywords: Customer-focused, Demand-side management, Smart home, Multi-objective optimization problem, Energy cost.

* Corresponding author: mahmud.en.ac@gmail.com

1 Introduction

1.1 Motivations and aims

The adoption of alternative energy sources has risen due to increasing worries about the amount, quality, cleanliness, and reliability of electrical power [1]. It is expected that distributed generation (DG) technologies will play a more significant role in the energy sector in the coming years [2]. The grid must be linked with unconventional energy sources to harness electricity from them. Conversely, an extensive amount of distributed generation poses numerous challenges that could potentially impact the power grid's ability to operate securely and effectively [3, 4]. Microgrids, smaller versions of traditional grids, are implemented to help address some of these challenges [5, 6]. Distributed generation sources are interconnected within microgrids and linked to the low-voltage grid [7, 8]. These systems, which consist of unconventional and renewable energy sources like solar panels and generators, offer cost-effective and environmentally friendly solutions that have overcome previous limitations related to expenses and emissions [9–13]. It can be difficult to manage renewable energy sources like solar and wind power because of their unpredictable and fluctuating nature [14, 15]. Operators need to closely monitor and make adjustments to ensure these sources can meet power demand, even if they may not always perform as expected [16]. To secure a dependable and consistent electricity supply, grid managers need to uphold an energy reserve [17, 18]. This reserve can be established by either increasing the electricity sourced from the main grid or by enhancing the utilization of distributed energy storage devices, such as batteries. However, the substantial installation expenses of these reserve units might outweigh the financial advantages of renewable energy [19, 20].

1.2 Related researches

Energy management is crucial for the development of smart grids. Recently, there has been a significant increase in research initiatives focusing on this area. The concept of demand-side management (DSM) was initially introduced by researchers in [21] to ensure the efficient functioning of residential and rural microgrid systems. Furthermore, the researchers investigated the application of firefly hybridization combined with particle swarm optimization in their research on DSM [22]. In [23], a community microgrid scheduling system was introduced by the authors to operate in real time. In the event of a power outage, developers showcased a novel method for scheduling DGs to provide power to loads within a microgrid (MG) [24]. To tackle DSM concerns, innovators proposed a logical energy consumption distribution strategy within the grid [25]. A new optimized energy management system solution was presented by the authors, which included multi-MG systems in reference [26]. A new method was presented in reference [27] to enhance power generation for photovoltaic systems. Moreover, a demand management program based on an optimization algorithm was proposed for residential loads in reference [28]. Reference [29] discusses a control technique for inverters operating in parallel for eco-friendly purposes. Additionally, reference [30] highlights the availability of demand response for renewable-based MGs in power networks. In [31], a new algorithm was presented to address the issue of minimizing load change in demand management for smart devices. The smooth load transfer capability can help decrease consumer frustration. Meanwhile, the authors of [32] suggested a novel approach to tackle day-ahead scheduling obstacles by utilizing the Internet of Things. Additionally, [33] recommended employing a cloud-based multi-agent framework to promote the integration of smart grid technology in residential sections. They are concentrating on minimizing peak load and energy expenses in smart homes by employing microgrids and intelligent home agents. In contrast, a multi-objective scheduling strategy using arithmetic optimization techniques was presented for energy management in [34]. Furthermore, the authors in [35] designed a power generation model for constructing islanded microgrids with multiple systems. A study in [36] examined modeling energy consumption by implementing efficient demand management strategies. The researchers in [37] analyzed factors such as energy consumption patterns and technical indices to determine the most effective load management technique.

1.3 Contributions and research gaps

The description provided indicates that extensive research has been carried out to minimize the peak-to-average ratio (PAR) of the load curve, lower energy expenses, and enhance customer savings and utility benefits. Regrettably, current methods do not prioritize user satisfaction when implementing time of use (TOU), particularly for low-income individuals in economically challenged countries. Additionally, when it comes to an incline block tariff, it is crucial to accurately determine the block size to ensure financial advantages for both utility companies and customers. Some articles fail to utilize metaheuristic techniques like the grasshopper optimization algorithm (GOA) to cut costs in various systems. The researchers have yet to release a two-stage model utilized for the optimization of energy storage systems layered size planning and energy scheduling in grid-connected. This study aims to tackle these obstacles through the contributions outlined below:

1. The discussed publications serve as valuable sources for pertinent research that tackles scheduling challenges to some extent. Each method comes with its own set of characteristics and limitations that enhance its effectiveness. For instance, issues involving stochastic and nonlinear effects, demands for scheduling during odd hours, and the risk of high dimensionality cannot be resolved through mathematical approaches. Even in cases where mathematical calculations yield accurate outcomes, they are inherently complex and time-intensive.
2. Heuristic algorithms often face premature convergence, resulting in a decrease in population diversity, parameter adjustment, and termination criteria. Previous initiatives did not address the reduction of user discomfort along with energy costs. To overcome

these challenges, a new model is required. A ToU system is implemented in which evolutionary algorithms are used to optimize the power rate and block size, thereby benefiting both residential consumers and the utility company financially. The recommended algorithm ensures that customers with low incomes will not have to worry about making any payments. The proposed approach's results are compared to those of existing methods, along with anticipated cost savings on electricity expenses for various consumer groups.

3. The authors of the study have introduced a novel two-stage stochastic model for nested capacity planning and energy scheduling co-optimization of energy storage systems in grid-connected mode. This model is specifically based on the two-stage algorithm. It is the first research of its kind to focus on energy optimization utilizing the advanced meta-heuristic algorithm two-stage algorithm, which aims to reduce the cost of purchasing storage capacity. Through the application of a two-stage algorithm, the study successfully identified the most efficient energy storage system design from a selection of more than forty cutting-edge evolutionary algorithms. The decision to use a two-stage algorithm was based on its proven statistical superiority in MG capacity planning applications.

2 System modeling

Every household needs to install a small-scale photovoltaic energy storage system due to the rapid growth of distributed energy. The system structure diagram for a residential house, depicted in Figure 1, is designed around a smart home energy management system (SHEMS). Each load under management is linked to a smart socket, enabling direct control by the SHEMS. This article focuses on optimizing controllable loads and scheduling energy storage devices to minimize carbon emissions and household power costs. Additionally, the model accounts for electricity exchange between homes and the grid, detailing decision variables, objectives, constraints, and how the energy storage system handles limitations.

2.1 Mathematical modeling

The six distinct characteristic categories of the residential house model have been chosen as the determining factors to optimize electricity consumption as follows:

$$C = \left[I_{i,t}^{\text{Gridbuy}}, I_{i,t}^{\text{Gridsell}}, I_{i,l,t}^{\text{Cut}}, P_{i,t}^{\text{Gridbuy}}, P_{i,t}^{\text{Gridsell}}, P_{i,t}^{\text{ESS}}\right] \quad (1)$$

where
t = Time;
i = Number of home.
$I_{i,t}^{\text{Gridsell}}$ = Binary variable of power purchasing.
$I_{i,t}^{\text{Gridbuy}}$ = Binary variable of power selling.
$I_{i,l,t}^{\text{Cut}}$ = Controllable load's.
$P_{i,t}^{\text{Gridsell}}$ = Power purchasing.
$P_{i,t}^{\text{Gridbuy}}$ = Power selling.
$P_{i,t}^{\text{ESS}}$ = Power of energy storage system.

2.2 Objective functions modeling

The optimization goals include electricity cost, demand reduction value, and carbon emissions, considering the residents' electrical usage, demand involvement, and environmental factors to maximize the economic and social advantages of consumption.

2.2.1 Power generation cost

The electricity cost objective function encompasses the expenses associated with obtaining power for the household, as well as the operational costs of storage units and photovoltaic units.

$$E\_\text{Cost} = \sum_{i=1}^{I}\sum_{t=1}^{T}\Big(I_{i,t}^{\text{Gridbuy}} \times P_{i,t}^{\text{Gridbuy}} \times \pi_t^{\text{Gridbuy}} - I_{i,t}^{\text{Gridsell}} \times P_{i,t}^{\text{Gridsell}} \times \pi_t^{\text{Gridsell}}\Big) + M\_\text{Cost} \quad (2)$$

In a day with T total hours, the electricity cost is denoted as $E_$Cost. The total number of residential microgrids is represented by I, where π_t^{Gridsell} and π_t^{Gridbuy} are the prices of power bought and sold. The operating expenses of photovoltaic and energy storage devices are expressed in terms of $M_$Cost, calculated as follows:

$$M\_\text{Cost} = \sum_{i=1}^{I}\sum_{t=1}^{T}\left(P_{i,t}^{\text{PV}} \times \pi^{\text{pv}} + \left|P_{i,t}^{\text{ESS}}\right| \times \pi^{\text{ESS}}\right) \quad (3)$$

where $P_{i,t}^{\text{PV}}$, π^{ESS}, π^{pv}, and $P_{i,t}^{\text{ESS}}$ are photovoltaic power, storage cost, photovoltaic cost, and storage power, respectively.

2.2.2 DSM modeling

The demand curtailment value, defined as a measure of resident participation in the demand program, is utilized by reducing loads.

$$DR = \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{l=1}^{L}\left(P_{i,l,t}^{\text{Cut}} \times I_{i,l,t}^{\text{Cut}} \times \rho_t^{\text{Cut}}\right) \quad (4)$$

In this instance, DR represents the demand curtailment value, $P_{i,l,t}^{\text{Cut}}$ signifies the demand curtailment rate, and L denotes the total number of controlled loads. The power of the load at time t equals the reduced power of the lth controlled load. The weight factor, ρ_t^{Cut}, is set up to decrease partial loads.

2.2.3 Emission modeling

It is crucial to prioritize the adoption of low-carbon electricity among residents as carbon dioxide emissions greatly contribute to the greenhouse effect. The emission function is as follows:

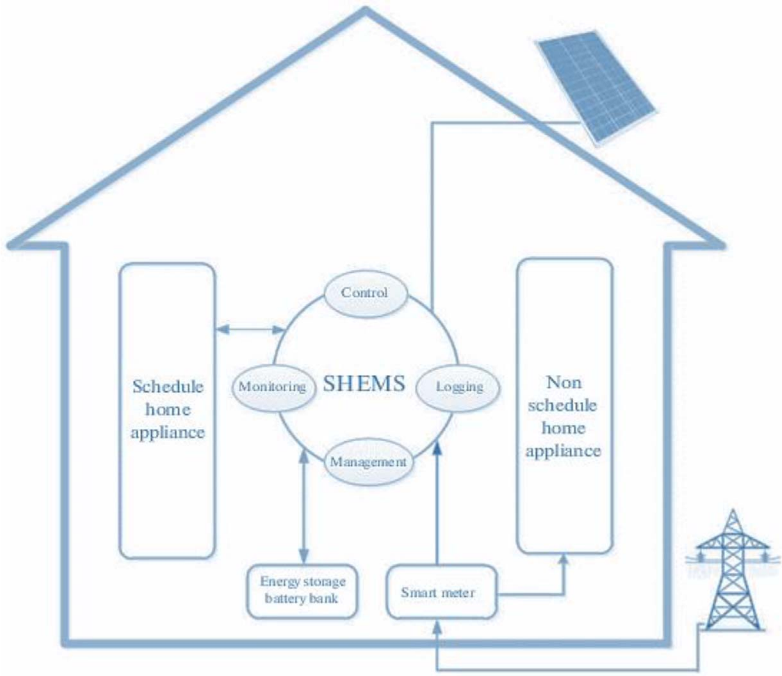

Fig. 1. SHEMS model.

$$\text{Emission} = \lambda \times \sum_{i=1}^{I}\sum_{t=1}^{T}\left(I_{i,t}^{\text{Gridbuy}} \times P_{i,t}^{\text{Gridbuy}}\right) \tag{5}$$

where λ is the emission factor of the grid.

2.3 Constraints' modeling

The schedule optimization model must adhere to the following constraints to ensure consistent communication between households and the grid:

2.3.1 Power balance modeling

The balance between the demand and generation sides is modeled as follows:

$$P_{i,t}^{\text{Gridbuy}} + P_{i,t}^{\text{PV}} + P_{i,t}^{\text{dch}} = P_{i,t}^{\text{Load}} + P_{i,t}^{\text{ch}} + P_{i,t}^{\text{Gridsell}}. \tag{6}$$

2.3.2 Constraints of energy storage device

The charging and discharging powers of the energy storage device are denoted as by $P_{i,t}^{\text{ch}}$ and $P_{i,t}^{\text{dch}}$, respectively. $P_{i,t}^{\text{Load}}$ indicates the electricity demand at time t.

$$P_{i,t}^{\text{ch}} = P_{i,t}^{\text{ESS}}, \ \& \ P_{i,t}^{\text{ESS}} > 0 \tag{7}$$

$$P_{i,t}^{\text{dch}} = P_{i,t}^{\text{ESS}}, \ \& \ P_{i,t}^{\text{ESS}} < 0. \tag{8}$$

2.3.3 Inequality constraints

The inequality constraints like controlled loads, power of grid, and power transaction among grid and MGs are modeled by (9)–(12), respectively.

$$0 \le I_{i,l,t}^{\text{Cut}} \le 1 \tag{9}$$

$$0 \le I_{i,t}^{\text{Gridbuy}} + I_{i,t}^{\text{Gridsell}} \le 1 \tag{10}$$

$$0 \le P_{i,t}^{\text{Gridbuy}} \le P_{i,t}^{\text{Gridbuy.max}} \tag{11}$$

$$0 \le P_{i,t}^{\text{Gridsell}} \le P_{i,t}^{\text{Gridsell.max}}. \tag{12}$$

2.4 Appliances' modeling

Residential homes are equipped with various loads. Users can categorize air conditioners, water heaters, and dishwashers based on their lifestyle preferences. Appliances in the hybrid category have a programmable work cycle, while non-interruptible appliances must be used immediately. This article discusses the operational constraints and mathematical modeling of key household appliances, determining the required runtime for each appliance [38–40].

$$O_i(t) = \begin{cases} 1 & \text{if } t \in \tau_i, \forall, \ i \in A \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

3 Optimization algorithm

Grasshopper swarms in natural environments can be simulated using the GOA. Below is a mathematical representation of the behavior exhibited by these swarms [41–43]:

$$P_i = SO_i + GRE_i + W_i \tag{14}$$

where P_i represents the grasshoppers' position, So_i represents their social interaction force, GRE_i represents their gravitational force, and W_i represents their wind advection. It is essential for all metaheuristic algorithms to have a random distribution of search agents across the search space. The GOA random nature is demonstrated by modifying equation (14) in the following manner:

$$P_i = r_1 SO_i + r_2 GRE_i + r_3 W_i. \tag{15}$$

The random integers r_1, r_2, and r_3 within the range [0, 1] are denoted. The GOA recognized social connection as the primary search determinant.

$$SO_i = \sum_{\substack{j=1;\\ j\neq i}}^{N} s\left(d_{ij}\right)\hat{d}_{ij} \tag{16}$$

where
N = Grasshoppers number.
d_{ij} = Euclidean distance among Grasshoppers.
Also

$$d_{ij} = \left|P_j - P_i\right|. \tag{17}$$

Furthermore, the procedure described here can be utilized to acquire $\hat{d}_{ij}$, which denotes a solitary vector from the ith to the jth grasshoppers.

$$\hat{d}_{ij} = \frac{\left(P_j - P_i\right)}{\left|P_j - P_i\right|}. \tag{18}$$

Below, you can observe that "s" denotes a function that describes the intensity of social forces.

$$s = f\exp\left(-\frac{r}{l}\right) - \exp(-r). \tag{19}$$

The symbols l and f represent the length scales of attraction and lustfulness. Grasshoppers utilize two distinct types of forces, namely attraction and repulsion, in their social interactions. The GRE_i (gravity force) of the ith grasshopper is defined as:

$$GRE\_i = -g\hat{e}_g. \tag{20}$$

The gravitational constant, denoted as $(\hat{e}_g)$, indicates the center of the earth, along with the unity vector pointing in the direction of g. The wind advection of the ith grasshoppers, W_i, can be calculated in the following manner:

$$W_i = u\hat{e}_w. \tag{21}$$

The drift constant (u) and unity vector $(\hat{e}_w)$ represent the wind direction and direction, respectively. Adjusting the values of the components mentioned earlier in equation (14) can be expressed in the following manner:

$$P_i = \sum_{\substack{j=1\\ j\neq i}}^{N} s\left(\left|P_j - P_i\right|\right)\frac{\left(P_j - P_i\right)}{\left|P_j - P_i\right|} - g\hat{e}_g + u\hat{e}_w. \tag{22}$$

It is important to note that due to the grasshopper swarm not converging to a single site, equation (21) cannot directly address the optimization problem. To tackle the challenges posed by the equation, a modified form of equation (23) is being considered.

$$P_i^{\mathrm{d}} = c\left(\sum_{\substack{j=1\\ j\neq i}}^{N} c\frac{ub_{\mathrm{d}} - lb_{\mathrm{d}}}{2} s\left(\left|P_j^{\mathrm{d}} - P_i^{\mathrm{d}}\right|\right)\frac{\left(P_j - P_i\right)}{\left|P_j - P_i\right|}\right) + \hat{T}_d \tag{23}$$

where
c = Swarm closer to target.
T_{d} = Dimension goal.
ub_{d} = Upper bounds inside the dth dimension.
lb_{d} = Lower bounds inside the dth dimension.

The reduction coefficient, which is the initial adjusting parameter of the GOA algorithm, should be decreased in line with the number of iterations. The update is carried out using the formula below.

$$c = c_{\max} - t\frac{c_{\max} - c_{\min}}{t_{\max}}. \tag{24}$$

In this study, the variables $c_{\max}$ and $c_{\min}$ represent the maximum and minimum coefficient values of c. The symbols t and $t_{\max}$ stand for the current and maximum iterations, respectively. Algorithm 1 displays the pseudocode for GOA [41–43].

5 Optimal sizing of storage system capacity

Calculating the economic value of an energy storage system investment involves creating an objective function that incorporates the concepts of net present cost (NPC) and net present value (NPV). The NPC, which is associated with each newly installed component like the inverter and battery, can be obtained as [44]:

$$\mathrm{NPC} = \mathrm{N_c} \times \left(\mathrm{CC} + \mathrm{RC} \times \mathrm{SPPW} + \frac{\mathrm{O\&M}}{\mathrm{CRF(ir, PL)}} - \mathrm{SV}\right) \tag{27}$$

$$\mathrm{SPPW} = \sum_{i=1}^{N} \frac{1}{(1+\mathrm{ir})^{\mathrm{CL}\times i}} \tag{28}$$

$$N = \begin{cases} \left\lfloor \frac{\mathrm{PL}}{\mathrm{CL}} \right\rfloor - 1 & \textit{if}\ \mathrm{PLmodCL} = 0 \\ \left\lfloor \frac{\mathrm{PL}}{\mathrm{CL}} \right\rfloor & \textit{if}\ \text{otherwise} \end{cases} \tag{29}$$

$$\mathrm{CRF(ir, PL)} = \frac{\mathrm{ir}(1+\mathrm{ir})^{\mathrm{PL}}}{(1+\mathrm{ir})^{\mathrm{PL}} - 1} \tag{30}$$

Algorithm 1. GOA pseudocode.

Start: input, Grasshopper Optimization Algorithm parameters
Initialize: the swarm of grasshoppers randomly
Initialize: C_{min}, C_{max}, and maximum number of ittrations t_{max}
Evaluate: the fitness of each grasshopper $f(P_i)$
$T =$ the best solution
while $(t < t_{max})$ Do
update: C
for $i = 1,2 \ldots, n$ Do
for $j = 1:1:N$ Do
Normalize: the distance among grasshoppers
update the present position of the grasshopper
fetch the present grasshopper if it drives out the limits
end for
update T if the present solution is better than the previuse optimum solution
$t \leftarrow t + 1$
end while
output: return $T =$ optimum soluion
end

$$\mathrm{SV} = \mathrm{RC} \times \frac{\mathrm{CL} - \left(\mathrm{PL} - \mathrm{CL} \times \left\lfloor \frac{\mathrm{PL}}{\mathrm{CL}} \right\rfloor\right)}{\mathrm{CL}} \tag{31}$$

where
Nc = Ideal capacity.
CC = Capital cost.
RC = Replacement cost.
O&M = Operation and maintenance cost.
CRF = Recovery factor.
SPPW = Single-payment present-worth factor.
PL = Project lifespan.
CL = Component lifetime.
ir = interest rate.

The lifespan of the storage components can be readily transformed into calendar life by utilizing the subsequent equation:

$$R_\mathrm{S} = \frac{N_\mathrm{S} \times Q_\mathrm{life}}{Q_\mathrm{thr}} \tag{32}$$

where
N_s = Capacity of energy storage system.
Q_thr = Annual Stored energy.
Q_life = Lifetime of storage system.

Furthermore, the total power exchanged with the grid over the project's lifetime can be used to calculate the NPV by utilizing the formula provided.

$$\mathrm{NPV}_\mathrm{exch} = \sum_{i=1}^{\mathrm{PL}} \frac{C^i_\mathrm{exch}}{(1+\mathrm{ir})^i} \tag{33}$$

where C^i_exch is as follows:

$$C_\mathrm{exch} = \sum_{t=1}^{T} P_\mathrm{im}(t) \cdot \pi(t) - P_\mathrm{ex}(t) \cdot FiT. \tag{34}$$

Consequently, the objective function for the storage sizing problem is defined as:

$$\min \mathrm{TNPC} = \mathrm{NPC_B} + \mathrm{NPC_I} + \mathrm{NPV_{exch}} \tag{35}$$

where $\mathrm{NPV_{exch}}$ is NPV of power exchanges, and $\mathrm{NPC_B}$, $\mathrm{NPC_{SC}}$, and $\mathrm{NPC_I}$ stand for battery based on $\mathrm{NPV_{exch}}$ for inverter, respectively.

6 Two-stage optimization modeling

The diagram in Figure 2 illustrates the two-stage solution approach developed for the hybrid storage capacity optimization model using meta-heuristics. The problem is split into two parts, as depicted in Figure 2: the nested optimal energy scheduling problem and the outer loop storage sizing problem. The hybrid storage capacity optimization model's two-stage solution approach using meta-heuristics is a sophisticated method that allows for the efficient and effective optimization of storage capacity in a hybrid energy system. By breaking down the problem into two stages, the model can tackle the complex issues of energy scheduling and storage sizing separately, allowing for a more focused and targeted approach to finding the optimal solution. In the first stage, the nested optimal energy scheduling problem is addressed. This involves determining the best energy scheduling options for the system based on various decision variables. The outer loop then uses this information to make choices for the inner loop, which generates wait-and-see options for further evaluation. The second stage focuses on the outer loop storage sizing problem. This stage determines the optimal storage sizes for the system based on the choices made in the first stage. By iteratively solving the optimal scheduling problem every 24 h during the baseline year, the model can continuously evaluate the design fitness and make adjustments as needed. The MATLAB two-stage operational planning model takes this approach a step further by formulating the long-term investment planning problem as a linear programming problem. This allows for the creation of an investment portfolio that includes optimal storage sizes and dispatch schedules at each iteration, ensuring that the system is constantly optimized for maximum efficiency and effectiveness.

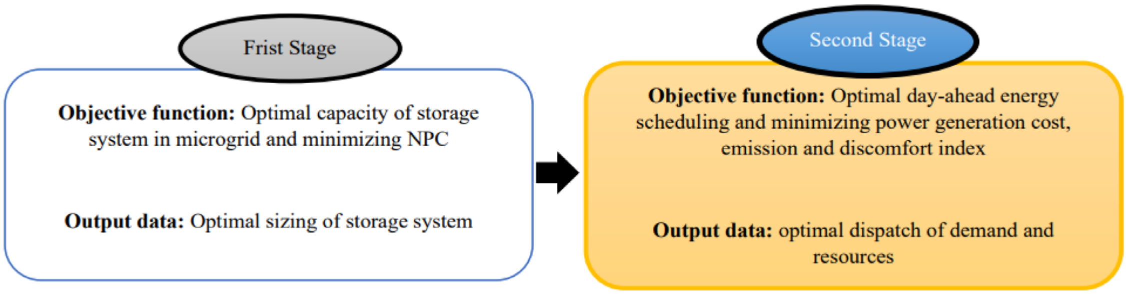

Fig. 2. Framework of optimization approach.

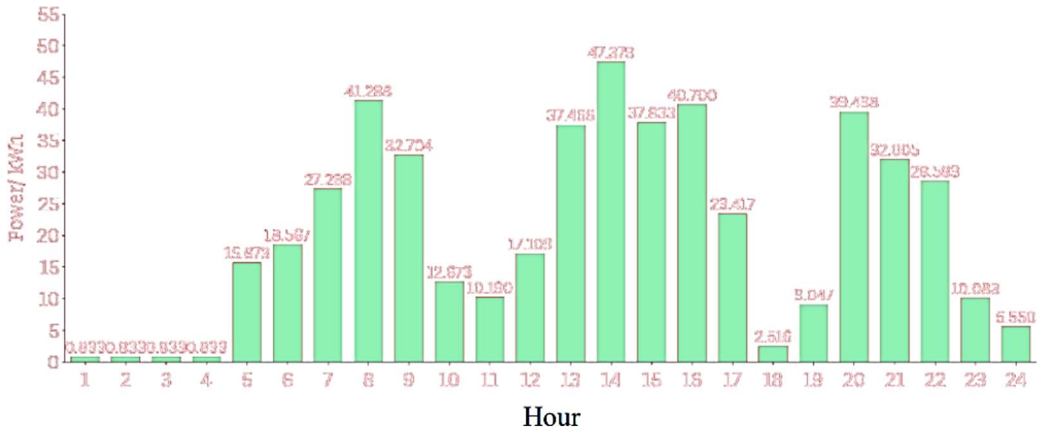

Fig. 3. Energy optimization without demand management.

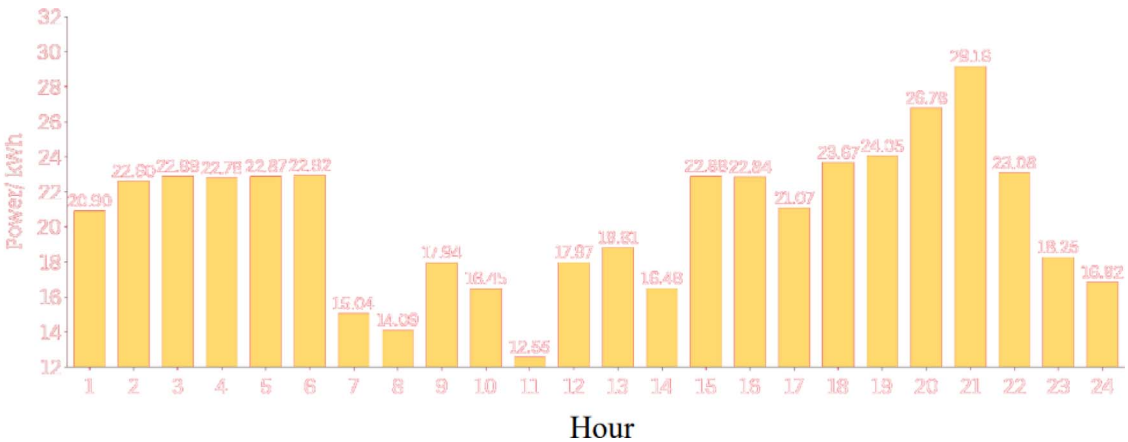

Fig. 4. Energy optimization with demand management and GOA.

7 Numerical results

The results of the recommended SHEMS simulation are presented in this part. The primary goals of this software include decreasing PAR, cutting down on electricity costs, and enhancing User Comfort by reducing wait times. According to this study, a 24-hour schedule is believed to achieve a satisfactory balance among these objectives. The data of simulation for SHEMS and resources are extracted from references [45–48]. A comparison is made between the results of the artificial rabbits optimization algorithm (AROA) and the GOA algorithms to validate the system's precision. Figure 3 demonstrates the success of the suggested modeling without demand-side management in households. Figure 4 showcases the efficiency of the proposed home demand-side control using the GOA technique. Figure 5 displays the effectiveness of the proposed home demand-side regulation through the AROA method. The cost of the recommended home demand-side management without the corrective action is displayed in

Fig. 5. Energy optimization with demand management and AROA.

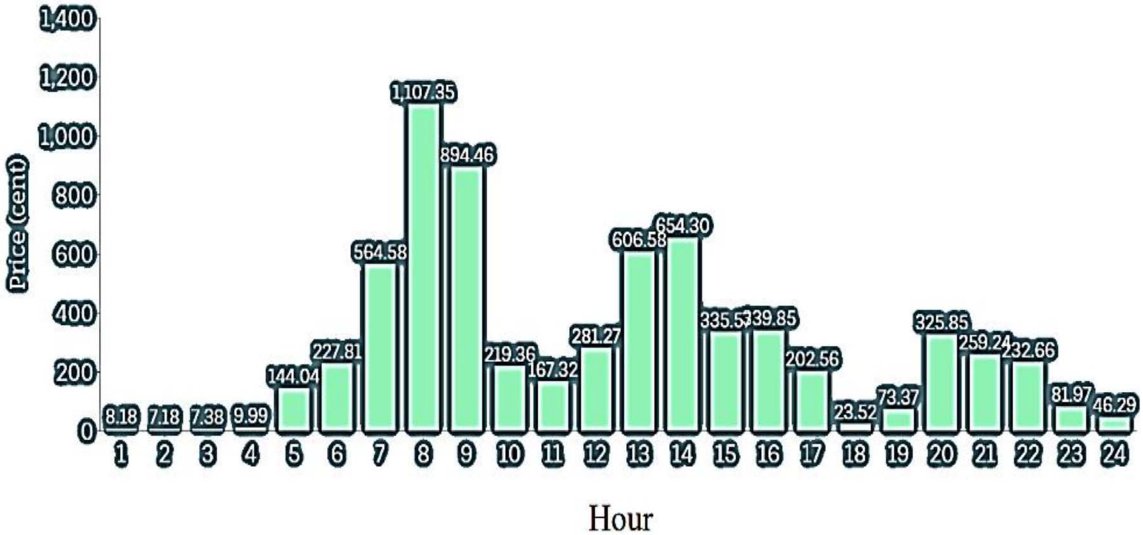

Fig. 6. Cost of system without demand management.

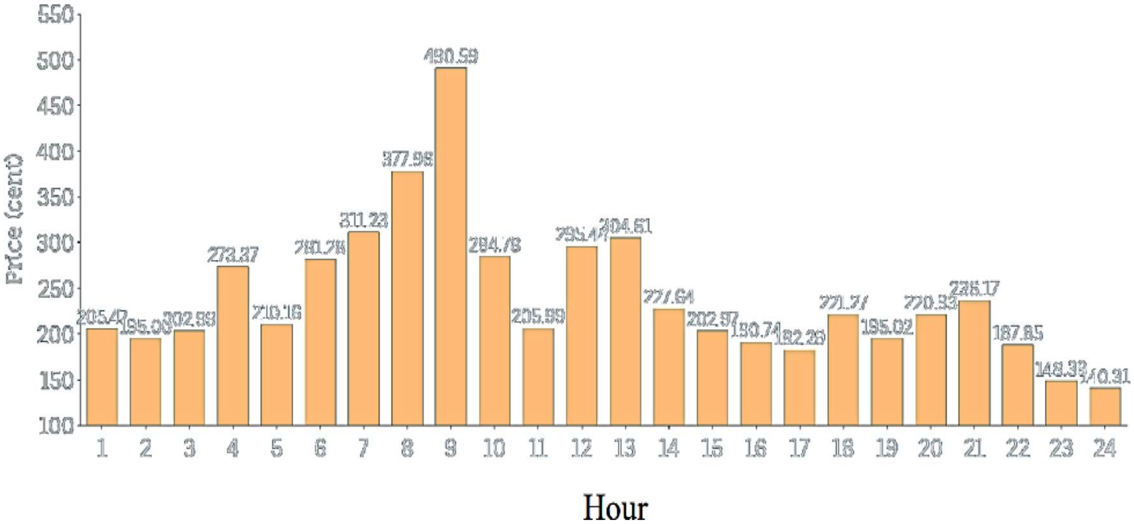

Fig. 7. Cost of system with demand management and GOA.

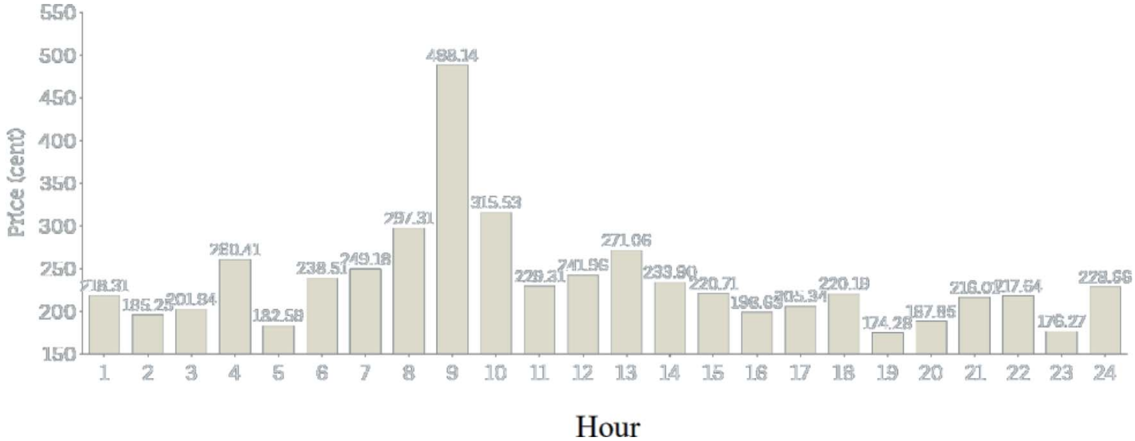

Fig. 8. Cost of system with demand management and AROA.

Table 1. Electrical consumption and cost of MG without demand management.

Hours	Electricity consumption (kWh)	Cost of purchase (cent)
1	0.8325	8.183475
2	0.8325	7.184475
3	0.8325	7.384275
4	0.8325	9.99
5	15.6732	144.036708
6	18.5666	227.812182
7	27.2875	564.578375
8	41.2883	1107.352206
9	32.7043	894.462605
10	12.6725	219.360975
11	10.1898	167.316516
12	17.1088	281.268672
13	37.4662	606.577778
14	47.3785	654.297085
15	37.8325	335.574275
16	40.7	339.845
17	23.4173	202.559645
18	2.516	23.5246
19	9.0465	73.367115
20	39.4975	325.854375
21	32.005	259.2405
22	28.5825	232.66155
23	10.0825	81.970725
24	5.55	46.287

Table 2. Electrical consumption and cost of MG with demand management by AROA.

Hours	Electricity consumption (kWh)	Cost of purchase (cent)	Improving%
1	20.90278	205.4743274	17%
2	22.5959	195.002617	18%
3	22.8845	202.985515	19%
4	22.7809	273.3708	20%
5	22.86822	210.1589418	16.6%
6	22.92446	281.2831242	16%
7	15.04272	311.2338768	17.5%
8	14.09256	377.9624592	17.4%
9	17.9376	490.59336	18%
10	16.45168	284.7785808	19%
11	12.54522	205.9925124	20%
12	17.9709	295.441596	21%
13	18.8145	304.606755	20.9%
14	16.4835	227.637135	17%
15	22.88228	202.9658236	16%
16	22.84306	190.739551	18%
17	21.07372	182.287678	16%
18	23.6652	221.26962	15%
19	24.0463	195.015493	16%
20	26.77986	220.933845	16.7%
21	29.15674	236.169594	15.9%
22	23.0769	187.845966	17.1%
23	18.2521	148.389573	16.8%
24	16.8239	140.311326	17.2%

Figure 6. The cost of implementing the proposed GOA demand-side control strategy at home is shown in Figure 7. Meanwhile, the expense of the suggested home demand-side management system utilizing the AROA method is presented in Figure 8. Optimal systems with random patterns exhibit a higher maximum periodic energy consumption compared to the recommended technique. The findings also indicate that, in all simulated scenarios, the top systems attempt to schedule loads outside of peak hours to minimize the user's expenses during peak hours. Figures 6 and 7, demonstrate the total daily electricity costs for planned patterns using electrical price signals as the electricity rates,

Table 3. Electrical consumption and cost of MG with demand management by GOA.

Hours	Electricity consumption (kWh)	Cost of purchase (cent)	Improving%
1	22.20814	218.3060162	19%
2	22.62476	195.2516788	19%
3	22.7661	201.935307	20%
4	21.7005	260.406	18%
5	19.86826	182.5893094	17%
6	19.43832	238.5081864	21%
7	12.0435	249.180015	18%
8	11.0852	297.305064	17%
9	17.84806	488.144441	22%
10	18.22842	315.5339502	23%
11	13.96528	229.3098976	22.3%
12	14.71786	241.9616184	23.9%
13	16.7425	271.061075	21.2%
14	16.93712	233.9016272	18%
15	24.8825	220.707775	19%
16	23.78804	198.630134	21%
17	23.73846	205.337679	21.5%
18	23.54976	220.190256	23%
19	21.4896	174.280656	23.9%
20	22.7698	187.85085	24%
21	26.66738	216.005778	23.2%
22	26.73694	217.6386916	21%
23	21.682	176.27466	18%
24	27.417	228.65778	17%

amounting to 6820.690 cents. Overall, the cost of implementing the proposed demand-side control strategies at home is significant, but the potential savings in daily electricity expenses are substantial. The AROA method shows a 17.75% reduction in costs, while the GOA strategy results in a 20.31% decrease in daily electricity expenses. These findings highlight the potential for significant cost savings through the implementation of demand-side management systems and the importance of considering different strategies to optimize energy consumption and reduce expenses. Additionally, the comparison of optimal systems with random patterns emphasizes the effectiveness of the recommended techniques in scheduling loads outside of peak hours to minimize costs for the user. These results provide valuable insights for homeowners and policymakers looking to implement demand-side control strategies to manage electricity expenses. Thus, based on a proposed method optimum scheduling scheme, the simulations show that SHEMS finds the best trade-off between the target functions and performs well in doing so. Without considering demand management, the expense is 6820.6 (cents). However, after applying the AROA, the cost is found to be 5792.45, and after applying the GOA, it is 5668.9. When comparing the suggested approach to the traditional way, the GOA saved 20.31% daily and the AROA saved 17.75% daily. Table 1 shows the electricity consumption and cost of purchase/hour of MG without demand management. Table 2 shows the electricity consumption and cost of purchasing of microgrid using AROA, Table 3 shows the electricity consumption and cost of purchasing of microgrid using GOA. In Table 4, value of emission, PAR, and discomfort index by proposed algorithms considering demand management is listed.

Table 4. Values of emission, PAR, and discomfort index by proposed algorithms.

Indices	Modes of system operation		
	Without demand management	With demand management by AROA	With demand management by GOA
Emission (g)	865.3	823.4	805.3
PAR (%)	1.86	1.56	1.23
Discomfort (%)	31.3	29.6	27.6

8 Conclusion and future aspects

The research paper presented an approach to energy management in smart homes, with a focus on customer satisfaction and cost reduction. The study advocates for the integration of a home energy management system to effectively manage energy consumption and electricity expenses for users. By implementing demand-side management, the research aims to optimize energy usage and improve user satisfaction through the use of smart devices and energy management technology. The study utilizes the GOA to enhance battery and appliance scheduling flexibility, ultimately reducing microgrid system costs. The comparison of the proposed method with other algorithms demonstrates its effectiveness in optimizing energy consumption and reducing carbon emissions across various scenarios. The simulation results highlight the potential of the proposed method to significantly enhance energy efficiency and environmental sustainability in practical applications, while also minimizing discomfort for occupants and achieving substantial energy savings and emissions reductions. Overall, the study offers a sustainable solution for energy management in buildings and validates the efficiency and feasibility of the proposed method in addressing energy management challenges considering minimizing emission, cost, discomfort index, and PAR values.

This paper can be expanded into more topics such as optimal energy flow in commercial and industrial sections with new optimization approaches and objective functions.

References

1 Hemmati M., Messadi T., Gu H., Seddelmeyer J., Hemmati M. (2024) Comparison of embodied carbon footprint of a mass timber building structure with a steel equivalent, *Buildings* **14**, 5, 1276. https://doi.org/10.3390/buildings14051276.

2 Serajian S., Shamsabadi A.A., Gnani Peer Mohamed S.I., Nejati S., Bavarian M. (2024) MXenes in solid-state batteries: current status and outlook, *J. Power Sources* **610**, 234721. https://doi.org/10.1016/j.jpowsour.2024.234721.

3 Ghorbani M., Wang H., Roberts N. (2024) Analytical and numerical modeling of phase change material and hybrid PCM-heat sinks for high-power wireless EV charging, *Int. Commun. Heat Mass Transfer* **154**, 107460. https://doi.org/10.1016/j.icheatmasstransfer.2024.107460.

4 Ghorbani M., Wang H., Roberts N. (2023) Numerical study of thermal management systems using phase change materials integrated with heat sink for wireless super-fast charging stations of EVs in constant heat flux condition, in: *ASME 2023 Heat Transfer Summer Conference*, Washington, DC, USA, July 10–12, vol. **87165**, ASME, p. V001T10A005. https://doi.org/10.1115/HT2023-107128.

5 Mohaghegh S., Kondo S., Yemiscioglu G., Muhtaroglu A. (Dec. 2022) A novel multiplier hardware organization for finite fields defined by all-one polynomials, *IEEE Trans. Circuits Syst. Express Briefs* **69**, 12, 5084–5088. https://doi.org/10.1109/TCSII.2022.3188567.

6 Kiani S., Salmanpour A., Hamzeh M., Kebriaei H. (2024) Learning robust model predictive control for voltage control of islanded microgrid, *IEEE Trans. Autom. Sci. Eng.* https://doi.org/10.1109/TASE.2024.3388018.

7 Seifi N., Al-Mamun A. (2024) Optimizing memory access efficiency in CUDA Kernel via data layout technique, *J. Comput. Commun.* **12**, 124–139. https://doi.org/10.4236/jcc.2024.125009.

8 Shokouhi S., Mu B., Thein M.W. (2023) September). Optimized path planning and control for autonomous surface vehicles using B-splines and nonlinear model predictive control, in: OCEANS 2023 – MTS/IEEE US Gulf Coast, Biloxi, MS, USA, 25–28 September, IEEE, pp. 1–9. https://doi.org/10.23919/OCEANS52994.2023.10337066.

9 Atashpanjeh H., Behfar A., Haverkamp C., Verdoes M.M., Al-Ameen M.N. (2022) Intermediate help with using digital devices and online accounts: understanding the needs, expectations, and vulnerabilities of young adults, in: *International Conference on Human-Computer Interaction*, Springer International Publishing, Cham, pp. 3–5. https://doi.org/10.1007/978-3-031-05563-8_1.

10 Nguyen V.D., Mirza S., Zakeri A., Gupta A., Khaldi K., Aloui R., Mantini P., Shah S.K., Merchant F., Merchant F. (2024) Tackling domain shifts in person re-identification: a survey and analysis, in: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 4149–4159.

11 Hajrasouliha A., Ghahfarokhi B.S. (2021) Dynamic geo-based resource selection in LTE-V2V communications using vehicle trajectory prediction, *Comput. Commun.* **177**, 239–254.

12 Monfaredi P., Emami S.M.M., Moghadam A.S. (2022) Seismic behavior of hollow-core infilled steel frames: an experimental and numerical study, *J. Construct. Steel Res.* **192**, 107244.

13 Monfaredi P., Nazarpour M., Moghadam A.S. (2021) Influence of hollow-core wall panels on the cyclic behavior of different types of steel framing systems, *PCI J.* **66**, 5, 39–53.

14 Nazarpour M., Monfaredi P., Moghadam A.S. (2019) Experimental evaluation of hollow-core wall orientation in steel moment frame, *PCI J.* **64**, 92–103.

15 Mozafarjazi M., Rabiee R. (2024) Experimental and numerical study on the load-bearing capacity, ductility and energy absorption of RC shear walls with opening containing zeolite and silica fume, *Eng. Solid Mech.* **12**, 3, 237–246.

16 Keivanimehr M., Chamorro H.R., Zareian-Jahromi M., Segundo-Sevilla F.R., Guerrero J.M., Konstantinou C. (2021) Load shedding frequency management of microgrids using hierarchical fuzzy control, in: *2021 World Automation Congress (WAC)*, Taipei, Taiwan, 01–05 August, IEEE, pp. 216–221.

17 Jahromi M.H.M., Tafti H.D., Hosseini S.M., Jalali A., Keivanimehr M. (2020) Maximum power point tracking of a network-connected photovoltaic system based on gravity search algorithm and fuzzy logic controller, *J. Solar Energy Res. Updates* **7**, 52–63.

18 Rostam-Alilou A.A., Zhang C., Salboukh F., Gunes O. (2022) Potential use of bayesian networks for estimating relationship among rotational dynamics of floating offshore wind turbine tower in extreme environmental conditions, *Ocean Eng.* **244**, 110230.

19 Rouhi K., Motlagh M.S., Dalir F., Perez J., Golzary A. (2024) Towards sustainable electricity generation: Evaluating carbon footprint in waste-to-energy plants for environmental mitigation in Iran, *Energy Rep.* **11**, 2623–2632.

20 Rouhi K., Shafiepour Motlagh M., Dalir F. (2023) Developing a carbon footprint model and environmental impact analysis of municipal solid waste transportation: a case study of Tehran, Iran, *J. Air Waste Manag. Assoc.* **73**, 12, 890–901.

21 Jasim A.M., Jasim B.H., Neagu B.-C., Alhasnawi B.N. (2023) Coordination control of a hybrid AC/DC smart microgrid with online fault detection, diagnostics, and localization using artificial neural networks, *Electronics* **12**, 1, 187. https://doi.org/10.3390/electronics12010187.

22 Alhasnawi B.N., Jasim B.H., Sedhom B.E. (2021) Distributed secondary consensus fault tolerant control method for voltage and frequency restoration and power sharing control in multi-agent microgrid, *Int. J. Electr. Power Energy Syst.* **133**, 107251.

23 Alhasnawi B.N., Jasim B.H., Issa W., Esteban M.D. (2020) A novel cooperative controller for inverters of smart hybrid AC/DC microgrids, *Appl. Sci.* **10**, 17, 6120. https://doi.org/10.3390/app10176120.

24 Li Q., Cui Z., Cai Y., Su Y., Wang B. (2023) Renewable-based microgrids' energy management using smart deep learning techniques: Realistic digital twin case, *Solar Energy* **250**, 128–138. https://doi.org/10.1016/j.solener.2022.12.030.

25 Tostado-Véliz M., Arévalo P., Kamel S., Zawbaa H.M., Jurado F. (2022) Home energy management system considering effective demand response strategies and uncertainties, *Energy Rep.* **8**, 5256–5271. https://doi.org/10.1016/j.egyr.2022.04.006.

26 Alhasnawi B., Jasim B., Rahman Z.-A., Guerrero J., Esteban M. (2021) A novel internet of energy based optimal multi-agent control scheme for microgrid including renewable energy resources, *Int. J. Environ. Res. Public Health* **18**, 8146. https://doi.org/10.3390/ijerph18158146.

27 Alhasnawi B.N., Jasim B.H. (2020) Internet of Things (IoT) for smart grids: a comprehensive review, *J. Xi'an Univ. Archit.* **63**, 1006–7930.

28 Rahman Z.-A.S.A., Jasim B.H., Al-Yasir Y.I.A., Hu Y.-F., Abd-Alhameed R.A., Alhasnawi B.N. (2021) A new fractional-order chaotic system with its analysis, synchronization, and circuit realization for secure communication applications, *Mathematics* **9**, 20, 2593. https://doi.org/10.3390/math9202593.

29 Zhang W., Qiao H., Xu X., Chen J., Xiao J., Zhang K., Long Y., Zuo Y. (2022) Energy management in microgrid based on deep reinforcement learning with expert knowledge, in: *Proceedings of SPIE 12492, International Workshop on Automation, Control, and Communication Engineering (IWACCE 2022)*, Wuhan, China, 9 December, p. 124920Z. https://doi.org/10.1117/12.2662727.

30 Alhasnawi B.N., Jasim B.H., Mansoor R., Alhasnawi A.N., Rahman Z.-A.S.A., Haes Alhelou H., Guerrero J.M., Dakhil A.M., Siano P. (2022) A new Internet of Things based optimization scheme of residential demand side management system, *IET Re-new. Power Gener.* **16**, 1992–2006. https://doi.org/10.1049/rpg2.12466.

31 Rahman Z.-A.S.A., Jasim B.H., Al-Yasir Y.I.A., Abd-Alhameed R.A., Alhasnawi B.N. (2021) A new no equilibrium fractional order chaotic system, dynamical investigation, synchronization, and its digital implementation, *Inventions* **6**, 3, 49. https://doi.org/10.3390/inventions6030049.

32 Alhasnawi B.N., Jasim B.H., Sedhom B.E., Hossain E., Guerrero J.M. (2021) A new decentralized control strategy of microgrids in the internet of energy paradigm, *Energies* **14**, 2183. https://doi.org/10.3390/en14082183.

33 Vardakas J.S., Zorba N., Verikoukis C.V. (2016) Power demand control scenarios for smart grid applications with finite number of appliances, *Appl. Energy* **162**, 83–98. https://doi.org/10.1016/j.apenergy.2015.10.008.

34 Li C., Yu X., Yu W., Chen G., Wang J. (2017) Efficient computation for sparse load shifting in demand side management, *IEEE Trans. Smart Grid* **8**, 250–261.

35 Alhasnawi B.N., Jasim B.H., Siano P., Alhelou H.H., Al-Hinai A. (2022) A novel solution for day-ahead scheduling problems using the IoT-based bald eagle search optimization algorithm, *Inventions* **7**, 3, 48. https://doi.org/10.3390/inventions7030048.

36 Vagdoda J., Makwana D., Adhikaree A., Faika T., Kim T. (2018) A cloud-based multiagent system platform for residential microgrids towards smart grid community, in: *IEEE Power & Energy Society General Meeting (PESGM)*, Portland, OR, USA, 24 December.

37 Bahmanyar D., Razmjooy N., Mirjalili S. (2022) Multi-objective scheduling of IoT-enabled smart homes for energy management based on Arithmetic Optimization Algorithm: A Node-RED and NodeMCU module-based technique, *Knowledge-Based Syst.* **247**, 108762. https://doi.org/10.1016/j.knosys.2022.108762.

38 Wang Y., Nguyen T.-L., Xu Y., Tran Q.-T., Caire R. (2020) Peer-to-peer control for networked microgrids: multi-layer and multi-agent architecture design, *IEEE Trans. Smart Grid.* https://doi.org/10.1109/TSG.2020.3006883.

39 Wang K., Li H., Maharjan S., Zhang Y., Guo S. (2018) Green energy scheduling for demand side management in the smart grid, *IEEE Trans. Green Commun. Netw.* **2**, 2, 596–611.

40 Golmohamadi H., Keypour R., Bak-Jensen B., Pillai J.R. (2019) A multi-agent based optimization of residential and industrial demand response aggregators, *Int. J. Electr. Power Energy Syst.* **107**, 472–485.

41 Saremi S., Mirjalili S., Lewis A. (2017) Grasshopper optimisation algorithm: theory and application, *Adv. Eng. Software* **105**, 30–47.

42 Aljarah M., Faris I., Hammouri H., Ala'M A.Z., Mirjalili S. (2019) Binary grasshopper optimisation algorithm approaches for feature selection problems, *Expert Syst. Appl.* **117**, 267–286.

43 Qin P., Hu H., Yang Z. (2021) The improved grasshopper optimization algorithm and its applications, *Sci. Rep.* **11**, 1, 23733.

44 Luna A.C., Diaz N.L., Graells M., Vasquez J.C., Guerrero J.M. (2017) Mixed-integer-linear-programming-based energy management system for hybrid PV-wind-battery microgrids: modeling, design, and experimental verification, *IEEE Trans. Power Electron.* **32**, 4, 2769–2783. https://doi.org/10.1109/TPEL.2016.2581021.

45 Chamandoust H., Hashemi A., Derakhshan G., Abdi B. (2017) Optimal hybrid system design based on renewable energy resources, In: *2017 Smart Grid Conference (SGC)*, Tehran, Iran, 20–21 December, IEEE, pp. 1–5.

46 Chamandoust H., Bahramara S., Derakhshan G. (2020) Multi-objective operation of smart stand-alone microgrid with the optimal performance of customers to improve economic and technical indices, *J. Energy Stor.* **31**, 101738.

47 Dashtaki A.A., Khaki M., Zand M., Nasab M.A., Sanjeevikumar P., Samavat T., Nasab M.A., Khan B. (2022) A day ahead electrical appliance planning of residential units in a smart home network using ITS-BF algorithm, *Int. Trans. Electr. Energy Syst.* **2022**, 2549887. https://doi.org/10.1155/2022/2549887.

48 Song Z., Guan X., Cheng M. (2022) Multi-objective optimization strategy for home energy management system including PV and battery energy storage, *Energy Rep.* **8**, 5396–5411. https://doi.org/10.1016/j.egyr.2022.04.023.