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EDITED BY

Yuqing Dong,
The University of Tennessee, United States

REVIEWED BY

Zia Ullah,
Huazhong University of Science and
Technology, China
Kaiqi Sun,
Shandong University, China

*CORRESPONDENCE

Ghulam Hafeez,
✉ ghulamhafeez393@gmail.com

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Smart home load scheduling system with solar photovoltaic generation and demand response in the smart grid

Lyu-Guang Hua¹, S. Haseeb Ali Shah², Baheej Alghamdi^{3,4},
Ghulam Hafeez^{2*}, Safer Ullah⁵, Sadia Murawwat⁶, Sajjad Ali⁷
and Muhammad Iftikhar Khan⁸

¹Power China Hua Dong Engineering Corporation Limited, Hangzhou, China, ²Department of Electrical Engineering, University of Engineering and Technology, Mardan, Pakistan, ³Smart Grids Research Group, Center of Research Excellence in Renewable Energy and Power Systems, King Abdulaziz University, Jeddah, Saudi Arabia, ⁴Department of Electrical and Computer Engineering, Faculty of Engineering, King Abdulaziz University, Jeddah, Saudi Arabia, ⁵Department of Electrical Engineering, Quaid-e-Azam College of Engineering and Technology, Sahiwal, Pakistan, ⁶Department of Electrical Engineering, Lahore College for Women University, Lahore, Pakistan, ⁷Department of Telecommunication Engineering, University of Engineering and Technology, Mardan, Pakistan, ⁸Department of Electrical Engineering, University of Engineering and Technology, Peshawar, Pakistan

This study introduces a smart home load scheduling system that aims to address concerns related to energy conservation and environmental preservation. A comprehensive demand response (DR) model is proposed, which includes an energy consumption scheduler (ECS) designed to optimize the operation of smart appliances. The ECS utilizes various optimization algorithms, including particle swarm optimization (PSO), genetic optimization algorithm (GOA), wind-driven optimization (WDO), and the hybrid genetic wind-driven optimization (HGWDO) algorithm. These algorithms work together to schedule smart home appliance operations effectively under real-time price-based demand response (RTPDR). The efficient integration of renewable energy into smart grids (SGs) is challenging due to its time-varying and intermittent nature. To address this, batteries were used in this study to mitigate the fluctuations in renewable generation. The simulation results validate the effectiveness of our proposed approach in optimally addressing the smart home load scheduling problem with photovoltaic generation and DR. The system achieves the minimization of utility bills, pollutant emissions, and the peak-to-average demand ratio (PADR) compared to existing models. Through this study, we provide a practical and effective solution to enhance the efficiency of smart home energy management, contributing to sustainable practices and reducing environmental impact.

KEYWORDS

smart grid, demand response, home energy management, load scheduling, heuristic algorithms, renewable generation, solar, battery

1 Introduction

A reliable power system operation depends on the optimal scheduling of power usage (Wang et al., 2021a; Liu et al., 2023a). However, devising a framework for optimal power usage scheduling that bolsters reliability presents formidable challenges. These challenges are particularly pronounced as power demand surges due to population growth and elevated living standards. Presently, over 50% of the global population lives in urban zones, a marked increase from 30% in 1950, and this percentage is projected to reach 66% by 2050 (Amato et al., 2017). Additionally, electricity demand in power zones is anticipated to increase by 40% by 2025, with the domestic and commercial sectors experiencing a 25% increase from current levels, as projected by the Energy Information Administration (EIA) (Energy Information Administration, 2019). The EIA forecasts a 50% increase in power consumption between 2018 and 2050 (Energy Information Administration, 2019).

The widespread reliance on fossil fuels for electricity production is a main contributor to environmental pollution and proves unsustainable due to the dwindling reserves of conventional resources. Consequently, transitioning from conventional to modern renewable energy (RE) enhances reliability and environmental sustainability (Liu et al., 2023b; Yao et al., 2023). Nevertheless, conventional power systems are ill-equipped to meet the burgeoning energy demands and are ill-suited for integrating RE. Moreover, they fail to address challenges such as bidirectional power, bidirectional communication flow, hybrid power generation, and simultaneous information and power transfer systems (Yang et al., 2023a). To address these challenges, researchers actively explored innovative grid solutions, such as smart grids (SGs) (The Smart Grids, 2022). SGs encompass various advanced features such as demand response (DR), advanced metering infrastructure (AMI), sophisticated communication infrastructure (Palahalli et al., 2019), net metering, energy management (Ahmed et al., 2022), and flexible load (Shaker et al., 2023). This modern system also has technical aspects such as an energy-efficient framework for the internet of things (Jiang et al., 2022), a voltage and frequency stabilization control strategy (Zhang et al., 2023), monitoring house vacancy dynamics (Liu et al., 2023c), fast and accurate calculation methods (Li et al., 2022a; Song et al., 2022a), optimal planning (Ullah et al., 2021), and energy management. These advancements and modern technical aspects represent a pivotal step toward achieving a more reliable and sustainable power system in the face of evolving energy demands and environmental concerns. To bridge the energy supply–demand mismatch and address environmental concerns, the DR is used by utility companies. The DR aims to balance the fluctuating energy demands of users with the available utility generation capacity, thus avoiding extensive investments in additional energy generation infrastructure (Alzahrani et al., 2023a). The DR incorporates pricing mechanisms and incentive initiatives to optimize consumption patterns and reshape user demand. One such pricing mechanism is the time-of-use (ToU) structure. This involves three types of hours throughout the day, stimulating users to transition from peak hours to non-peak hours. Another approach is critical peak pricing (CPP), which assigns higher prices during peak hours. Real-time pricing (RTP) employs an hourly fluctuating mechanism (Silva et al., 2023a). To incentivize consumers to participate in load scheduling via DR,

utility companies offer incentives to manage the gap between energy demand and supply effectively. In addition, authors reshaped energy usage and use wide-area phasor measurements to ensure robust control and identify sources (Wang et al., 2021b; Yang et al., 2023b). Residential load scheduling has garnered considerable attention, yet a lack of knowledge is a significant challenge that residential users often face while adopting DR for load scheduling. To tackle this challenge, an energy consumption scheduler (ECS) was introduced using optimization techniques. The ECS was designed to encourage users to respond efficiently to price incentives offered by utility companies. It operates by receiving pricing incentive offers from power suppliers and orchestrating interruptible appliances (IAs) and non-interruptible appliances (non-IAs). Inês et al. (2020); Lu et al. (2020); and Ghayour and Taghi (2022) focused on scheduling residential loads using various optimization techniques to minimize electricity bills. Additionally, consumers were observed to integrate solar systems with batteries to generate energy for energy balancing effectively (Rehman et al., 2023a; Alzahrani et al., 2023b). However, it is worth noting that although these strategies aim to reduce electricity bills, they may inadvertently lead to peaks in demand. Li et al. (2022b) and Chen et al. (2023) developed a model to solve the economic dispatch problem. A modified gravitational search and particle swarm optimization (PSO) algorithm was developed to solve the multi-objective load dispatch problem in microgrids incorporating electric vehicles (Zhang et al., 2022a). Several DR strategies for appliance power usage scheduling benefited consumers and utility providers (Bizzozero et al., 2016; Mohammad and Mishra, 2019; Sarker et al., 2021; Song et al., 2022b; Chreim et al., 2022; Alahyari and Jooshaki, 2023; Rehman et al., 2023b; Reiszadeh et al., 2023). Consumers have adopted strategies involving photovoltaic (PV) units, batteries, and controllable loads within their homes to decrease their electricity bills while optimizing their consumption. For instance, a strategy was developed for scheduling an energy hub with risk constraints, incorporating RE, DR, and electric vehicles (Liu et al., 2023d; Yang et al., 2024). Furthermore, a low-carbon, fixed-tour scheduling challenge with time windows in a time-dependent traffic scenario was addressed by Zhang et al. (2022b). Nevertheless, none of the existing literature has simultaneously addressed the issues of electricity bills, pollutant emissions, or the peak-to-average demand ratio (PADR). It is indispensable to highlight that residential energy management is vital to enhancing the stability of the electricity grid, as the deployment of DR practices driven by more energy-efficient utilization by consumers can lead to significant energy savings (Parvin et al., 2022). Investigating load scheduling in the context of utility and PV systems holds promise for achieving more optimal energy utilization in residential areas. Thus, meta-heuristic approaches have emerged to address problems accompanied by game-theoretic models. For example, the PSO algorithm discussed by Disanayaka and Hemapala (2023) was developed to cater to load scheduling problems for electricity bill payments and load peak curtailment. However, the resultant system is complex. Some authors have developed evolutionary algorithms to address power usage scheduling problems (Alonso et al., 2012; Nawaz et al., 2020a; Lotfi et al., 2020; El et al., 2022). A segmented probabilistic strategy using multi-measurement data was utilized for the harmonic estimation of residential distribution systems considering non-intrusive residential loads (Xie and Sun, 2022; Lin et al., 2023;

Wang et al., 2023). Authors used the genetic optimization algorithm (GOA) for energy cost and utility bill reduction by optimizing power usage scheduling for residential loads (Arabali et al., 2012). Using SG, this study adjusts generation and load, measures and monitors data, and transmits and distributes power for optimal energy management. Mandal and Mandal (2020) developed an enhanced differential evolutionary algorithm (EDEA) for DR between users and aggregators. Silva et al. (2023a); Rehman et al. (2023c); Liu et al. (2023e); and Makroum et al. (2023) developed heuristic algorithms for optimal load scheduling in SGs. For example, Ullah et al. (2020a) adapted the cuckoo search algorithm (CSA) to maintain a balanced load curve considering the users' preferences and constraints. The gray wolf accretive satisfaction algorithm was proposed for smart home appliance control and monitoring by Ayub et al. (2020). The aim was to reduce energy costs and increase savings. Likewise, in Ahmad et al. (2023), a heuristic algorithm-based ECS was developed to solve power scheduling problems considering RE and pricing DR. The aim was to minimize utility bill payments, operation delay time, and peak energy consumption. The gray wolf and crow search optimization (GWCSO) algorithm was developed by Waseem et al. (2020) to solve residential load scheduling problems for peak energy consumption and energy cost optimization. Zhao et al. (2013); Ma et al. (2016); and Jiang and Xiao (2019a) developed the GOA to solve power usage scheduling problems using the DR for peak energy demand alleviation, operation delay minimization, and utility bill curtailment for single and multiple consumers. Likewise, Ullah et al. (2020b) adopted the PSO algorithm to solve load scheduling problems using incentive DR and RE in SGs. An energy management framework was developed. The ECS was programmed based on the GOA, Bacterial foraging optimization algorithm (BFOA), PSO, and genetically enhanced PSO algorithms by Jasim et al. (2023); Youssef et al. (2023); and Samadi et al. (2022) for peak load demand and utility bill payment curtailment. An optimal power flow solution using heuristic and meta-heuristic algorithms was introduced by Shaheen et al. (2022a) and Shaheen et al. (2022b) to maximize savings.

These techniques cannot handle the complexity and large-scale nature of load scheduling problems in real-time. Meta-heuristic algorithms emerge as the most suitable candidates to address these challenges, offering the capacity to handle complex and large-scale problems while providing near-optimal solutions within reasonable timeframes. However, their effectiveness is contingent on parameter choices and the quality of initial solutions, making it challenging to guarantee the discovery of globally optimal solutions. Thus, a smart home load scheduling system with solar PV generation and DR was developed under the umbrella of SGs. The main technical contribution is listed as follows:

- Introduction of the hybrid genetic wind-driven optimization (HGWDO) algorithm: An HGWDO algorithm is introduced, combining the GOA and wind-driven optimization (WDO) algorithms for optimal smart home load scheduling under real-time pricing DR and renewable generation.
- Development of the smart home load scheduling system: A smart home load scheduling system is devised, using heuristic techniques for the ECS to address the home

energy management problem. The system incorporates a PV system, batteries, and smart appliances to optimize home load behavior and reduce utility bills, pollutant emissions, and PADR.

- Comparative analysis and validation: Extensive simulations are conducted to evaluate the HGWDO algorithm against the PSO, GOA, and WDO algorithms. The results demonstrate the superior performance of the proposed HGWDO approach in terms of utility bill payment, pollutant emissions, and PADR. This work is a continuation of the previous work (Hafeez et al., 2020), where the energy management problem was solved for Internet of Things-enabled smart homes under price-based DR using the wind-driven bacterial foraging algorithm (WBFA). Validation is supported by comparison with the BPSO, GOA, GWDO, and GBPSO algorithms.

This work is organized as follows: first, an introduction is presented; second, the problem statement and formulation are presented; third, the modeling and methodology of the developed framework are discussed; fourth, the simulation results and discussions are presented; and finally, the work is concluded, and future directions are unfolded.

2 Problem statement and formulation

Initially, the smart home load scheduling problem is presented and defined separately for each specific objective, such as minimizing utility bill payments, reducing pollutant emissions, and alleviating the PADR. Subsequently, the load problem is structured as an optimization challenge. A more detailed explanation is presented below.

2.1 Problem statement

Smart home load scheduling is a challenge due to the unpredictable and nonlinear behavior of end users. Thus, most researchers have focused on smart appliance operation scheduling for optimal home energy management. Numerous strategies have emerged in the literature, primarily focusing on pricing-based DR mechanisms to govern smart appliance scheduling. Jiang and Xiao (2019b) and Hafeez et al. (2020) devised a GOA for scheduling appliances to reduce utility expenses and address the PADR. However, this approach comes at the cost of compromising consumer convenience while striving to minimize utility expenses, because it exhibits certain inherent limitations and issues related to uncontrolled mutation, resulting in imbalanced loads (Nawaz et al., 2020b). Another strategy, based on the BPSO algorithm, was presented for scheduling smart appliances by Imran et al. (2020). Nevertheless, this approach further subdivided the scheduling time horizon into shorter intervals, adding complexity to the model and increasing computational overhead, which can be avoided. The HGWDO algorithm is introduced with a strategy for programming the ECS to address these challenges. The ECS, using the HGWDO algorithm, automatically responds to DR pricing signals for effective

smart appliance operation schedules and efficient energy utilization. The WDO and GOA algorithms were chosen for the development of the HGWDO algorithm due to their ease of implementation, adaptability to specific constraints, low computational complexity, rapid convergence, and minimal computational time. The HGWDO algorithm-based ECS addresses smart home energy management with real-time price-based demand response (RTPDR) by yielding optimal schedules for smart appliances. End users can then follow these schedules to maximize energy utilization, minimize utility bill payments, mitigate the PADR, and reduce pollutant emissions.

2.2 Problem formulation

Smart appliance operation scheduling was structured as an optimization problem for efficient home energy management. From an optimization standpoint, it is highly desirable for these appliances to efficiently harness available energy resources to achieve a triple objective: reduce pollutant emissions, mitigate the PADR, and minimize the utility bills paid to the utility company. The formulation of the load scheduling problem as an optimization problem is given below:

$$\min (C_T, \Upsilon, R_a^p), \quad (1)$$

subject to.

$$E_T \leq \text{Capacity}, \quad (2a)$$

$$E_T^{\text{sch}} = E_T^{\text{unsch}}, \quad (2b)$$

$$T_i^{\text{o,sch}} \neq T_i^{\text{o,unsch}}, \quad (2c)$$

$$T_a^{\text{lo,sch}} = T_a^{\text{lo,unsch}}. \quad (2d)$$

Eq. 2a introduces a constraint that enforces the capacity limit of the power grid, ensuring that it can actively participate in the power usage scheduling of smart appliances without (W/O) utility overloading. Meanwhile, Eq. 2b constraints ensure that the net power consumption remains unchanged W/O scheduling. Eq. 2c indicates the status of an activity, distinguishing between continued and completed actions. The constraint is essential for facilitating a fair comparison. Finally, Eq. 2d stipulates that the duration of the time interval must remain consistent before and after scheduling, promoting fairness in the comparison process. In the subsequent sections, we elaborate on each objective and provide their formal formulations, inspired by [Hafeez et al. \(2020\)](#).

2.2.1 Energy consumption

Energy consumption refers to the electricity consumed by smart appliances during the scheduling period. This study considers three types of smart appliances: power-flexible appliances (PFAs), denoted by A_a^P ; critical appliances, denoted by A_a^C ; and time-flexible appliances (TFAs), denoted by A_a^T . The TFA is further classified into two subtypes: interruptible time-flexible appliances (ITFAs) and non-ITFAs. The hourly electricity consumption of ITFAs is formulated as follows:

$$E_c^I(t) = P_r^I \times S_t. \quad (3)$$

In this context, $E_c^I(t)$ stands for the hourly electricity consumption, P_r^I represents the power rating, and S_t functions as the on/off status indicator of the appliance. The net energy consumed by ITFAs is computed below:

$$E_T^I = \sum_{t=1}^{24} \sum_{a=1}^N E_c^I(t) \quad \forall I \in A, \quad (4)$$

where N is the number of appliances and E_T^I is the net energy consumption of ITFAs.

The net energy consumed by the non-ITFA is computed below:

$$E_c^{NI}(t) = P_r^{NI} \times S_t, \quad (5)$$

where $E_c^{NI}(t)$ is the consumed energy at each hour, P_r^{NI} indicates the power rating, and S_t is the non-ITFA status indicator. Thus, the total energy used by the non-ITFA is computed below:

$$E_T^{NI} = \sum_{t=1}^{24} \sum_{a=1}^N E_c^{NI}(t) \quad \forall N \in A. \quad (6)$$

Thus, the net energy consumed per day by the TFA is computed below:

$$E_T^{ta} = E_T^I + E_T^{NI}. \quad (7)$$

Here, E_T^I and E_T^{NI} denote the daily electricity consumption of ITFAs and non-ITFAs, respectively, while E_T^{ta} represents the combined net electricity consumption of both ITFAs and non-ITFAs. The hourly and daily energy consumption of PFAs is expressed below:

$$E_c^p(t) = \begin{cases} P_r^{\text{min}p} \times S_t & \text{for on - peak hrs of } \gamma(t) \\ P_r^{\text{max}p} \times S_t & \text{for off - peak hrs of } \gamma(t); \end{cases} \quad \forall p \in A, \quad (8)$$

$$E_T^p = \sum_{t=1}^{24} \sum_{a=1}^N E_c^p(t). \quad (9)$$

2.2.2 Utility bill payments

The utility bill represents the charges users must pay to the utility company for their electrical energy usage over a specified period. This research established a formula for utility bill payments based on RTPDR received from the utility company. The 2009 FERC Report shows that users engaged in DR initiatives for load scheduling enjoyed a 65% benefit. The formula for calculating the electricity bill that users pay to their utility company for the electricity consumed is expressed as follows:

$$C_T^{RP} = \sum_{t=1}^{24} \left(\sum_{a=1}^N E_c^a(t) \times S_t \times \gamma(t) \right). \quad (10)$$

Eq. 10 represents the electricity charges that consumers need to pay for the electricity they use through an RTPDR. The variable C_T^{RP} signifies the total bill paid by users to operate all types of smart appliances, whereas $E_c^a(t)$ represents the electricity consumed by each appliance a during hour t .

2.2.3 PADR

Utility companies encourage users to shift their electricity consumption from peak to off-peak hours to reduce the strain on the power grid and mitigate peak demand. The PADR is a metric used to measure the peak and average power usage ratio. It holds significant

importance for utility companies and users for two primary reasons: (a) it helps distribute the load more evenly, reducing the necessity for peak power generation, and (b) it leads to lower utility bill payments for users. The PADR is obtained as follows:

$$R_a^p = 24 \times \left(\frac{\max(E_c^l(t), E_c^{NI}(t), E_c^p(t), E_c^c(t))}{E_T} \right), \quad (11)$$

where R_a^p signifies the PADR and E_T represents the overall energy consumption.

2.2.4 Pollutant emissions

Pollutant emissions occur when carbon is released into the atmosphere during the operation of household appliances. Pollutant emissions are calculated as follows, as presented by Imran et al. (2020):

$$\Upsilon = \frac{avgEP}{\varepsilon \times \zeta \times \mathcal{J}}. \quad (12)$$

Eq. 12 shows the carbon emissions measured in pounds. In this equation, $avgEP$ represents the average electricity price, ε represents the price per kWh, ζ indicates the emission factor, and \mathcal{J} denotes hour of the day.

3 Methodology

This section presents the methodology of the developed system model, which consists of the generation and demand sides, focusing on smart home load scheduling in SGs. The AMI is pivotal in enabling RTPDR for smart home load scheduling. The homes on the demand side are equipped with an ECS, a home gateway, appliances, smart meters (SMs), remote control capabilities, a monitoring display (MD), and a wireless home area network. These components optimize energy consumption and enhance control over household energy usage. Figure 1 shows the key components of the system and their interactions. The AMI is a vital component of the SG, serving as a central nervous system for efficient smart home load scheduling. The AMI functions as a two-way communication system that connects utilities and consumers. Its primary role is the collection and real-time delivery of power consumption records from SMs to utility companies. Additionally, the AMI transmits RTPDR from utilities to consumers through SMs and home gateways. The home gateway may exist as a separate device or be integrated into the SMs, serving as a graphical user interface (GUI) between the HAN and the wired network. The SM, which can be installed indoors or outdoors in homes, is located between the ECS and the AMI. Its core responsibilities include measuring, recording, and processing energy consumption data and delivering this information to the utility. Furthermore, the SMs send an RTPDR to the ECS to facilitate optimal smart home load scheduling.

This study focuses on a home equipped with various types of smart appliances, including those with power-flexible, critical, and time-flexible appliances. PFAs have flexible power ratings and adhere to predefined operating schedules. Meanwhile, TFAs have adaptable operating times but operate at fixed power levels. The TFA is further divided into two categories: ITFAs (dishwashers,

tumble dryers, washing machines, etc.) and non-ITFAs (heaters, vacuum cleaners, etc.). To address the challenge posed by the lack of user knowledge, which often hinders the implementation of DR programs, an ECS is used in homes. The ECS, based on HGWDO, responds to the RTPDR on time. The HGWDO-based ECS considers factors such as the power ratings of smart appliances, RTPDR, the duration of appliance operations, and energy availability from the power grid. It uses these inputs to schedule the operation hours of the smart appliances while adhering to the objective function and various constraints. The ECS within the home can communicate with appliances via various communication networks, such as Wi-Fi, Z-Wave, Zigbee, and HomePlug, to share operation schedules with these appliances. Energy management within the home is achieved through the scheduling of smart appliances, and it can be monitored either through an MD or remotely via Android phones. The workflow shown in Figure 1 outlines the entire process of this study. This model was developed with motivation from Hafeez et al. (2020).

The proposed model remotely controls and monitors the operation of smart appliances to efficiently manage energy through automated scheduling, eliminating the need for human intervention via DR programs. The key objectives of this home energy framework are outlined as follows:

- Utility bill payment minimization
- PADR alleviation
- Pollutant emission mitigation

These objectives are obtained by smart home load scheduling using an ECS based on HGWDO under RTPDR to utilize energy for energy management optimally.

3.1 Inputs

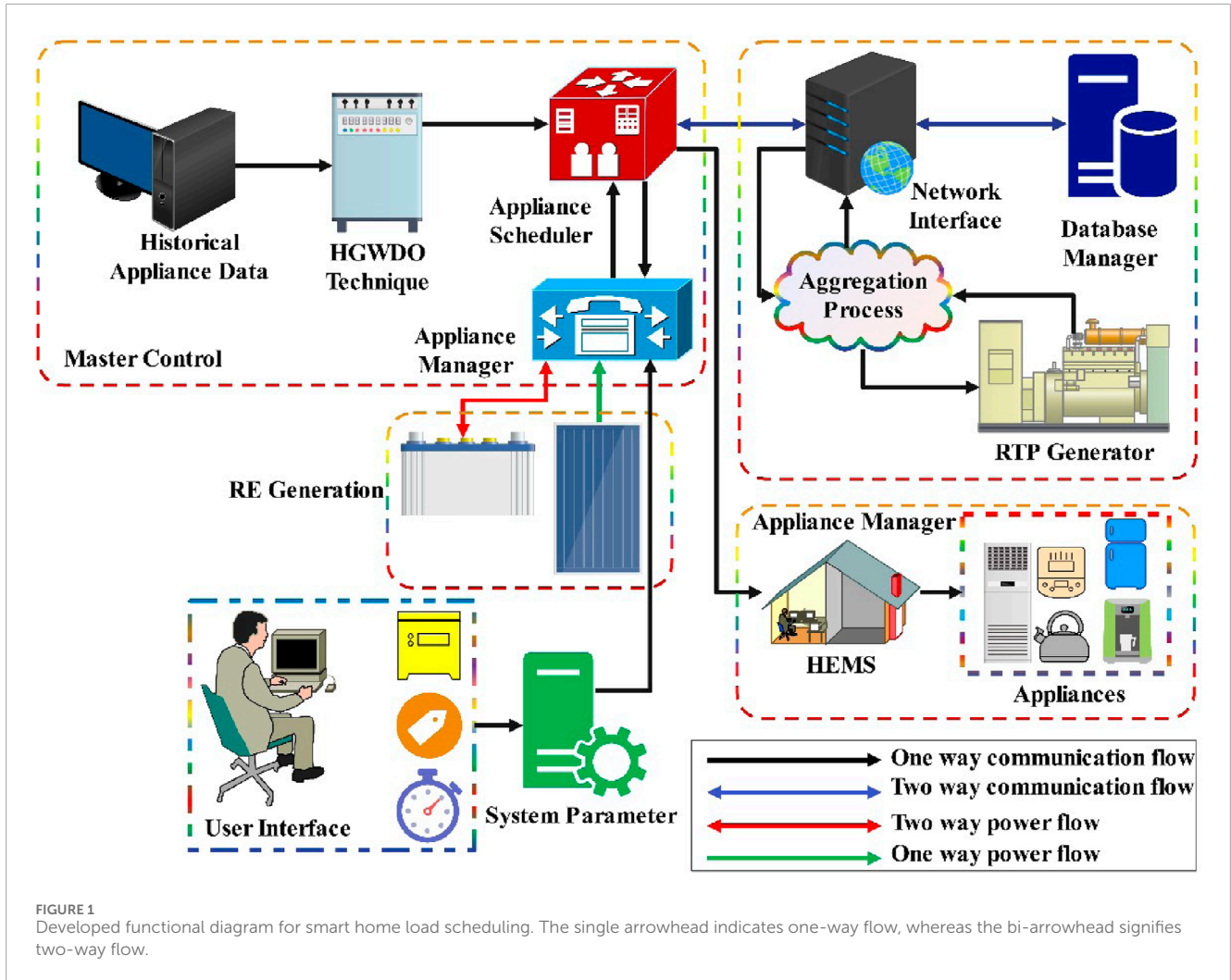
The developed system model receives input data, including the available energy from the power grid, solar PV, and battery, information about RTPDR, power ratings of appliances, duration of operation, and power usage patterns. A more comprehensive breakdown of these inputs is provided below.

3.1.1 Solar PV generation

RE includes wind, solar, fuel cell, biogas, and tidal energies. Among these REs, solar energy is plentiful, easily available, and free. Thus, this work considers solar energy as an RE. The aim is to use solar energy to reduce utility bill payments, peak energy consumption, etc. Solar energy is modeled and defined by Eq. 13 (Ahmad et al., 2023). The symbols used by Eq. 13 are defined as follows: E^{pv} is the generated output power, ∂^{pv} denotes the solar system efficiency, and A^{pv} shows the solar panel area. Likewise, $rad(t)$ and $T_p(t)$ denote the irradiation and temperature, respectively, and the temperature correction factor is constant and equal to 0.005.

$$P^{pv}(t) = \partial^{pv} \times A^{pv} \times rad(t) \times (1 - 0.005 \times (T_p(t) - 25)). \quad (13)$$

The Weibull probability function models solar radiation as in Eq. 14. The symbols used in Eq. 14 are defined as follows: θ_1 and θ_2



denote shape factors, $0 < rad(t) < \infty$, ω indicates the weight factor, and λ_1 and λ_2 represent scale factors.

$$F(rad(t)) = \omega \left(\frac{\theta_1}{\lambda_1} \right) \left(\frac{rad(t)}{\lambda_1} \right)^{(\theta_1-1)e^{-\left(\frac{rad}{\lambda_1}\right)^{\theta_1}}} + (1-\omega) \left(\frac{\theta_2}{\lambda_2} \right) \left(\frac{rad(t)}{\lambda_2} \right)^{(\theta_2-1)e^{-\left(\frac{rad}{\lambda_2}\right)^{\theta_2}}} \quad (14)$$

The ECS uses the maximum available solar energy during high-priced hours and charges batteries during low-priced hours to minimize utility bill payments.

3.1.2 Battery as energy storage

Batteries play a vital role in modern energy systems; they help balance the power grid, improve reliability and resilience, and enable RE integration. Power usage scheduling with batteries involves charging the batteries during periods of low demand, such as at night when many businesses are closed and electricity usage is lower. The stored energy can then be discharged during periods of high demand, such as during hot afternoons when many people run air conditioning units. By doing this, the batteries minimize the peak

electricity demand and alleviate the strain on the grid, leading to a more reliable and stable energy supply. Batteries are used to provide backup power during a power outage situation. For example, if a hospital has batteries installed, it can use the stored energy to power critical systems, such as life support equipment, during an outage until power is restored. In addition to load-scheduling and backup power, batteries can also help integrate RE, like solar power, into the power grid. The RE is variable and intermittent. Batteries can be used to store excess energy during periods of high production and then release it during periods of low production, providing a more stable and reliable energy source. Thus, batteries remarkably curtail pollutant emissions and notably alleviate utility bill payments. In addition, batteries exchange power with utility companies when the load demand is at its peak during the highest hours (Ahmad et al., 2023). The batteries are modeled and defined in Eq. 15. The symbols used are defined as follows: $BESS$, μ^{BESS} , η , EE^{Ch} , and EE^{Dch} represent the stored energy, efficiency, time duration, solar power supplied to batteries, and power released from batteries to load, respectively.

$$BESS(t) = BESS(t-1) + \eta \cdot \mu^{BESS} \cdot EE^{Ch}(t) - \frac{\eta \cdot EE^{Dch}(t)}{\mu^{BESS}} \forall t \quad (15)$$

Limits designed to resolve overcharging/deep discharging are presented as follows:

$$EE^{Ch}(t) \leq EE_{UB}^{Ch}, \quad (16)$$

$$EE(t)^{Dch} \leq EE_{LB}^{Dch}, \quad (17)$$

$$PS(t) \leq PS_{UB}^{Ch}. \quad (18)$$

3.1.3 Appliances

A smart home is outfitted with various types of smart appliances, including PFAs, denoted as A_a^P , TFAs, denoted as A_a^T , and critical appliances, denoted as A_a^C . These smart appliances are characterized by specific parameters encompassing well-defined operational time intervals, power ratings, priority levels, categories, statuses, and positions. The mathematical representation is as follows:

$$A = \{A_a^T, A_a^P, A_a^C\}. \quad (19)$$

The status indicator $S_t^a = \{1, 0\}$ and position indicator $X_t^a = (r_t^a, w_t^a)$ are assigned for every appliance, where r_t^a represents remaining hours and w_t^a represents waiting hours. The complete description of the appliance is presented as follows:

1. PFAs, referred to as A_a^P , exhibit adjustable power ratings. They operate at the minimum rated power level during high-priced hours and at the maximum rated power level during low-price hours, aiming to reduce utility bill payments, alleviate the PADR, and minimize pollutant emissions. These appliances are given a secondary priority. These are also known as power-regulating appliances. The formulation for the PFA in the current and subsequent hours is as follows:

$$X_t^N = (T_p^o, \beta - \alpha + T_p^o + 1), \quad (20)$$

$$X_{t+1}^P = \begin{cases} r_t^P, 0, P_r^{\min P} & \text{if } S_t = 1, r_t^P \geq 1 \\ r_t^P, 0, P_r^{\max P} & \text{if } S_t = 1, r_t^P \geq 1 \\ 0, 0 & \text{otherwise.} \end{cases} \quad (21)$$

In this context, X_t^P and X_{t+1}^P represent the present and subsequent status in the present and subsequent hours for PFAs, respectively. The parameter T_p^o represents the total operating time. α denotes the starting time of operation, β represents the ending time of operation, r_t^P indicates the remaining hours, and S_t serves as the status indicator for PFAs. These PFAs dynamically regulate their power output within the range of the minimum power rating, denoted as $P_r^{\min P}$, and the maximum power rating, denoted as $P_r^{\max P}$.

2. TFAs have flexible operating schedule functions at rated power levels. These appliances are denoted by A_a^T and can be further classified into two categories: non-ITFAs, labeled by A_T^{NI} , and ITFAs, denoted by A_T^I . These types of appliances are signed as the third and fourth priority, respectively. The mathematical characterization is outlined as follows:

$$A_a^T = \{A_T^I, A_T^{NI}\}. \quad (22)$$

- ITFAs, denoted as A_T^I , can adjust their operation times by advancing or delaying their schedules as required. The ITFA operation interruption/delay/advance during runtime before completing their assigned tasks significantly contributes to minimizing peak energy consumption. Additionally, these smart appliances can refrain from starting during high-priced hours. They can be either shut down or rescheduled to operate during low-priced hours to ensure utility bill payment reduction. These types of appliances are also referred to as deferrable appliances. The positioning of ITFAs for the current and subsequent hours is computed below:

$$X_t^I = (T_T^o, \beta - \alpha + T_T^o + 1), \quad (23)$$

$$X_{t+1}^I = \begin{cases} r_t^I, w_t^I - 1, P_r^I & \text{if } S_t = 0, w_t^I \geq 1 \\ r_t^I - 1, w_t^I, P_r^I & \text{if } S_t = 1, r_t^I \geq 1. \end{cases} \quad (24)$$

In this context, X_t^I represents the current status of the ITFAs, while X_{t+1}^I denotes their status in the next hour. The parameter T_T^o signifies the total hours of operation; α represents the start time of operation; β is the end time of operation; r_t^I represents the remaining hours; w_t^I indicates the waiting hours; P_r^I stands for the power rating; and S_t reflects the status indicator (on/off) of the ITFA.

- Non-ITFAs, designated as A_T^{NI} , can accommodate schedule delays but cannot tolerate interruptions during operation until the assigned task is completed. The positioning of the non-ITFA for the current and subsequent hours is defined as follows:

$$X_t^N = (T_N^o, \beta - \alpha + T_N^o + 1), \quad (25)$$

$$X_{t+1}^N = \begin{cases} r_t^N, w_t^N - 1, P_r^{NI} & \text{if } S_t = 0, w_t^N \geq 1 \\ r_t^N - 1, 0, P_r^{NI} & \text{if } S_t = 1, r_t^N \geq 1. \end{cases} \quad (26)$$

In this context, X_t^N represents the current status of the non-ITFAs, while X_{t+1}^N signifies their status in the next hour. The parameter T_N^o denotes the total hours of operation, α indicates the start time of operation, β represents the end time of operation, r_t^N indicates the remaining hours, w_t^N denotes the waiting hours, P_r^{NI} stands for the power rating, and S_t represents the status indicator (on/off).

3. Critical appliances, denoted as A_a^C , are smart devices operating at rated power levels and do not accept delay/interruption once their operation commences. They are given priority and follow a predefined schedule that does not disturb user convenience.

The input parameters for the smart appliances integrated into the home are briefly described and provided in [Table 1](#).

3.1.4 Price-based demand response

This study introduces the RTPDR, an input for the developed HGWDO-based smart home load scheduling system. The utility company provides the RTPDR to the HGWDO-based ECS, enabling smart appliance power usage scheduling to achieve objectives such as minimizing utility bill payments, reducing pollutant emissions, and mitigating the PADR. The RTPDR is adapted from the FERC (MISO, 2017). The RTPDR is structured with three pricing levels throughout the day, namely, high-, medium-, and low-price hours.

TABLE 1 Home appliance parameters, including factors such as their duration, category, operating time intervals, priority, and power rating.

Appliance	Power (kW)	Start time	End time
Washing machine	3.0	9:00	15:00
Tumble dryer	3.3	16:00	20:00
Dish washer	2.5	22:00	24:00
Vacuum cleaner	1.5	10:00	12:00
Water heater	1.8	5:00	8:00
Refrigerator	0.5–1.5	1:00	24:00
Air conditioner	0.8–1.8	1:00	24:00
Water dispenser	0.5–2.0	1:00	24:00
Microwave oven	1.2	14:00	16:00
	1.9	8:00	10:00
Electric kettle	1.9	16:00	18:00
	1.9	20:00	22:00
	1.2	7:00	9:00
Electric toaster	1.2	13:00	15:00
	1.2	20:00	22:00

The explanation is as follows: $\gamma(t)$ represents the electricity price at time step t , and γ_1 , γ_2 , and γ_3 denote the prices of the RTPDR during the off-, mid-, and on-peak periods, respectively. The RTPDR is defined for the entire day with an hourly resolution, meaning that the union of the time intervals T_1 , T_2 , and T_3 adds up to 24 h, satisfying the condition $\gamma_1 < \gamma_2 < \gamma_3$. To provide a breakdown, time intervals from 1 to 8 h and 22 to 24 h correspond to low-price hours, representing T_1 and γ_1 . Likewise, time intervals from 8 to 16 h and 21 to 22 h constitute average-price hours, corresponding to T_2 and γ_2 . Moreover, the time interval from 16 to 21 h falls within the high-price hours, indicating T_3 and γ_3 . Based on our proposed HGWDO algorithm, the ECS is designed to shift the load from peak to off-peak hours, aiming to curb utility bill payments, and pollutant emissions, and reduce the PADR.

4 Hybrid genetic wind-driven optimization algorithm

The HGWDO algorithm is our proposed hybrid algorithm that combines the complete WDO technique with the GOA algorithm mutation and crossover processes. This amalgamation was chosen because the GOA excels at PADR minimization, whereas the WDO algorithm proved to be efficient in utility bill payment and pollutant emission reduction. The strategy based on the HGWDO algorithm was designed to schedule appliance operations, aiming to satisfy the needs of both users and utility companies. The HGWDO algorithm

```

Input: RTPDR, Parameters initialization: cost, PADR, and carbon emission.
for hrs=1:T do
  For initial position
  for h=1:parcels do
    for i=1:n do
      if rand<0.5 then
        X=1
      else
        X=0
      end
    end
  end
  For velocity, first initial velocity computation
  for v=1:V do
    for i2=1:G do
      if timeslot=0 then
        H=0
      end
    end
  end
  Vbest1
  Pbest1
  begin
    Fitness evaluation Fitness function evaluation using first position and velocity of air parcels
    Velocity updating using corresponding Eq.
    Position updating using Eq.
    Vbest2
    Pbest2
    Fitness function evaluation using best position and velocity
    Crossover [Pbest1 and Pbest2]
    Return population after crossover operation=Cbest
    Mutate[Cbest], Return population after mutation operation = Gbest
  end
  Returned Gbest
  The return global best solution is the optimal smart load schedule.
  begin
    Objectives calculation
    for Calculate cost using returned global best solution do
      Calculate cost using Eq. (10) as
       $C_{RTP}^{HP} = \sum_{t=1}^{24} \left( \sum_{a=1}^A E_a^{HP}(t) \times S_a \times \gamma(t) \right)$ 
    end
    for Calculate PADR using returned global best solution do
      Calculate PADR using Eq. (11)
       $R_a^0 = 24 \times \left( \max \left( E_a^{HP}(t), E_a^{MP}(t), E_a^{LP}(t), E_a^{LP}(t) \right) \right)$ 
    end
    for Calculate pollution emission using returned global best solution do
      Calculate pollution emission using Eq. (12) as
       $T = \frac{C_{RTP}^{HP}}{k \times \gamma \times S}$ 
    end
  end
  for Solve the load scheduling problem do
    Solve problem modeled using Eq. (1) subjected to constraints from (2a)–(2d)
  end
end
end

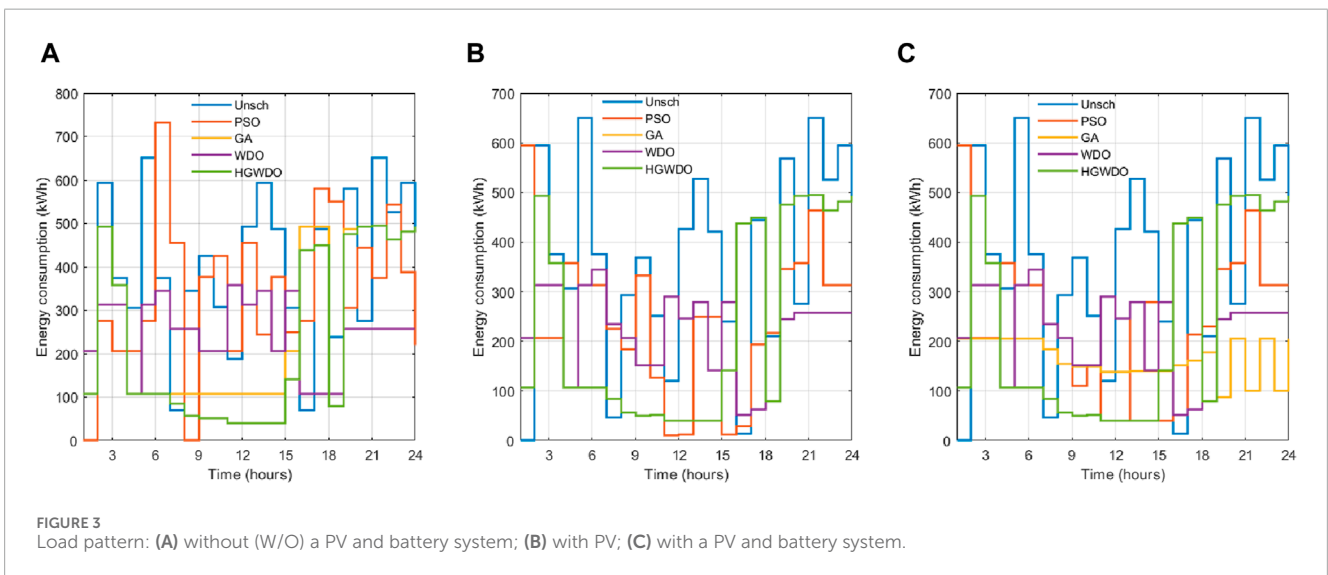
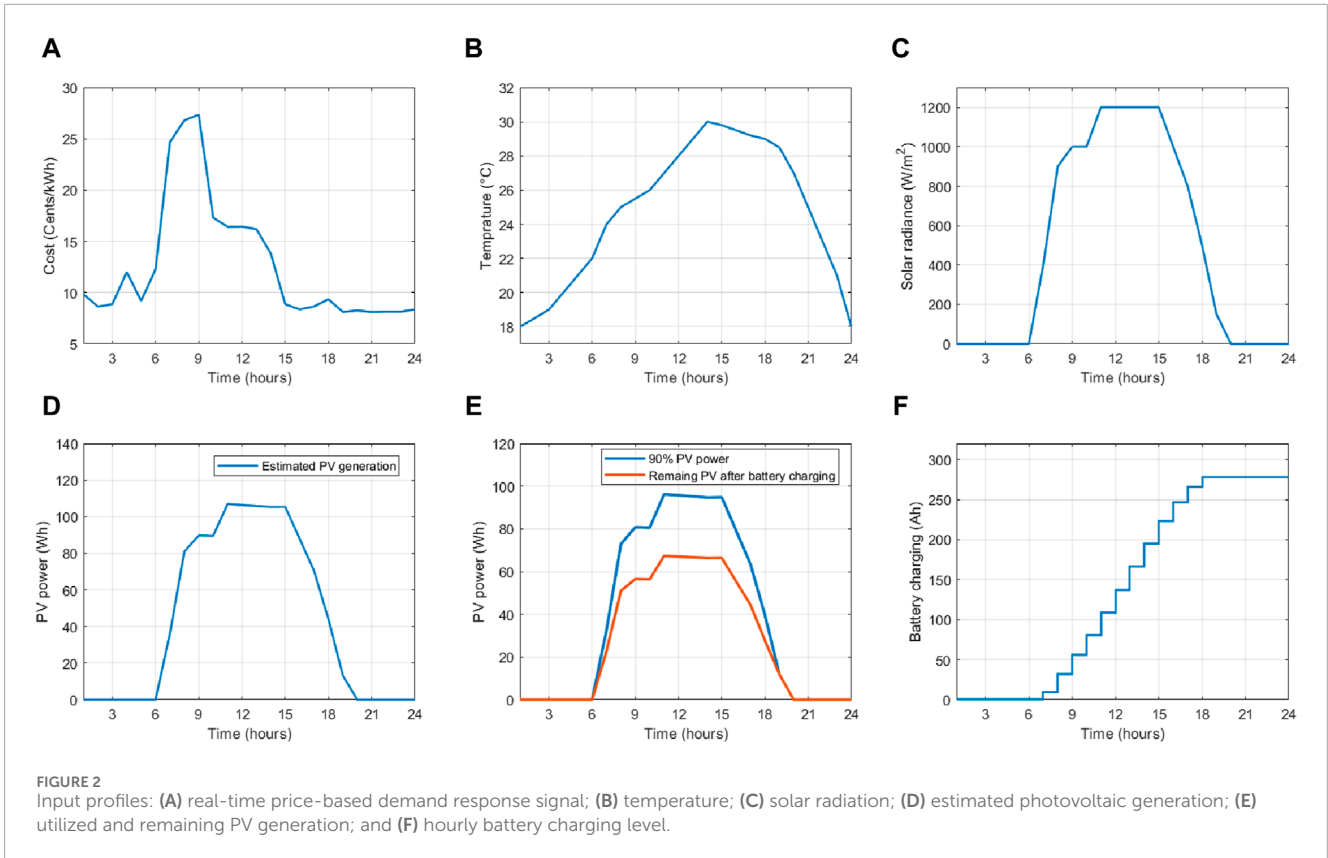
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Algorithm 1. HGWDO algorithm for smart home load scheduling in the smart grid.

comprises two steps: (a) the entire operational process of the WDO technique and (b) the mutation and crossover phases of the GOA algorithm (Hafeez et al., 2020). The optimal result obtained from the WDO technique was subjected to mutation and crossover phases of the GOA algorithm to derive the optimal operation schedule for appliances. Smart appliances then use this optimal schedule to minimize utility bill payments, pollutant emissions, and PADR. The HGWDO algorithm was configured with a population size of 10 individuals, a variable n set to 9, running for 100 iterations. Additionally, the algorithm used a parameter RT with a value of 3, g set to 0.2, α set to 0.4, and considered dimensions within the range of -5 – 5 . The maximum and minimum velocities (v_{max} and v_{min}) were set to 0.3 and -0.3 , respectively. The crossover probability (P_c) was set to 0.9, and the mutation probability (P_m) was set to 0.1. The complete implementation of the HGWDO algorithm to solve the smart home load scheduling problem is presented in Algorithm 1.

4.1 Output

The HGWDO-based ECS relies on various parameters of smart home appliances, such as their operating schedule, power consumption, priority, and current status. It also considers the RTPDR and the available energy from the power grid, PV, and battery. Using these inputs, it aims to efficiently manage the power consumption of homes by creating optimal operation schedules for appliances. The output of the developed system model is the optimal operation schedule of appliances aiming to achieve the desired objectives: utility bill payment, pollutant emission, and PADR

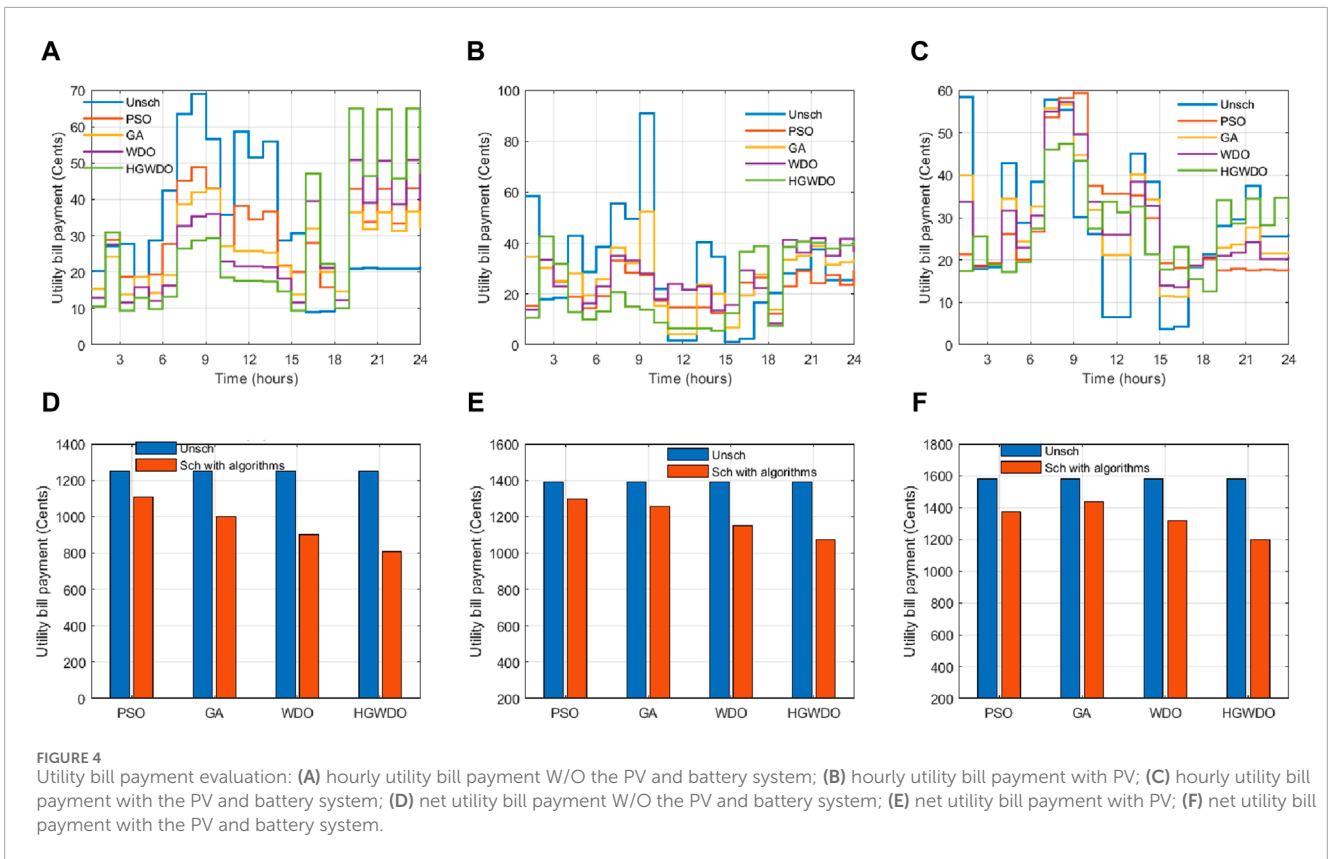


minimization. The smart appliances use the schedules generated by the HGWDO-based ECS to minimize utility bill payments, reduce pollutant emissions, and mitigate the PADR simultaneously.

5 Experimental results

The simulations for the developed model using the HGWDO algorithm were conducted using MATLAB R2017b, where the performance of the developed algorithm was compared to that of three benchmark algorithms: PSO, GOA, and WDO with respect

to energy consumption, utility bill payment, pollutant emissions, and PADR. We selected these algorithms as benchmarks due to their architectural similarities with the proposed algorithm. We carefully tuned the control parameters for the developed and benchmark algorithms to ensure a fair comparison. Experiments were conducted for three scenarios to evaluate the performance of our proposed and benchmark algorithms. In the first scenario, we considered a power grid as a source W/O the integration of PV and batteries. The second scenario involved a power grid with PV integration, and the third scenario included a grid with both PV and battery integration. The proposed HGWDO algorithm incorporates



the RTPDR, forecasted temperature, and solar irradiance, as shown in Figures 2A–C. The output power from solar energy systems depends on solar radiation (Figure 2C) and temperature (Figure 2B). We also considered the estimated PV generation, utilized PV generation, and remaining PV generation after battery charging, as depicted in Figures 2D, E, and the battery state of charge (Figure 2F).

A detailed discussion and performance evaluation of the developed HGWDO and other algorithms are presented in the following sections. The effectiveness assessment of the developed HGWDO technique was performed by comparing it with the PSO, GOA, and WDO algorithms in terms of energy consumption, utility bill payment, pollutant emissions, and PADR. By assessing the effectiveness of the HGWDO algorithm in optimizing these key metrics, we aimed to comprehensively understand its potential contributions to energy efficiency, cost reduction, environmental sustainability, and grid reliability. The comparative analysis sheds light on the suitability of the algorithm for addressing complex smart home load scheduling challenges and its potential to outperform established optimization techniques. A detailed analysis of each metric is presented in the following sections.

5.1 Energy consumption

The energy consumption profiles for scheduled operation using the PSO, GOA, WDO, and HGWDO algorithms, as well as unscheduled loads, were analyzed across three scenarios: W/O PV and battery system, with PV alone, and with PV and battery systems. Figure 3 represents these energy consumption patterns,

providing valuable insights into how the scheduling strategies of each algorithm impact energy usage under different configurations.

The load scheduling based on the PSO, GOA, WDO, and HGWDO algorithms, as well as the unscheduled load W/O PV and battery systems, is depicted in Figure 3A. For users W/O PV and battery systems, the unscheduled load exhibited consumption peaks of 800 Wh at 1, 2, 22, and 23 h, 700 Wh during 18–20 h, and 680 Wh during 7 and 8 h. On average, it consumed 300 Wh during the remaining hours.

The load scheduling based on the PSO for users exhibited peak energy consumption of 690 Wh at 2, 5, and 14 h, along with 510 Wh at 22–23 h. During the remaining hours, the load scheduling based on the PSO maintained a moderate energy consumption level. Notably, the peak energy consumption with the PSO was 13.75% lower than that in the unscheduled case. For users under the GOA-based load scheduling, peak energy consumption occurred at 510 Wh during 16–18 h and 495 Wh at 19 and 20 h, with moderate energy consumption in the remaining hours. This led to a significant curtailment of 36.25% in peak power consumption compared to W/O scheduling. In the created schedule, peak energy consumption reached 480 Wh during 21–24 h. Like the GOA, the WDO load scheduling exhibited moderate energy consumption during the remaining hours, with a 40% decrease in peak power consumption compared to the W/O scheduling case. The HGWDO-generated scheduling showed a peak power consumption of 500 Wh at 2, 3, and 19–24 h while maintaining moderate energy consumption in the remaining hours. Compared to the unscheduled scenario, HGWDO achieved a 37.75% reduction in peak power consumption. Similarly, the load scheduling results

TABLE 2 Evaluation with respect to utility bill payment, PADR, and carbon emission reduction.

Scenario	Algorithm	Utility bill payment reduction (%)	PADR reduction (%)	Carbon emission reduction (%)
1		-	-	-
	PSO	12.03	19.77	10.46
	GOA	10.75	11.46	17.15
	WDO	17.08	22.63	20.50
	HGWDO	24.05	31.23	23.84
2		-	-	-
	PSO	12.75	13.04	11.47
	GOA	14.09	16.72	14.75
	WDO	19.79	21.40	16.06
	HGWDO	29.53	31.43	18.46
3		-	-	-
	PSO	8.67	9.43	8.29
	GOA	17.35	16.98	10.59
	WDO	23.14	24.90	11.05
	HGWDO	32.64	30.18	13.08

based on the PSO, GOA, and WDO algorithms and the unscheduled scenario, both with PV and with PV and battery systems, are depicted in Figures 3B,C, respectively. Notably, the HGWDO algorithm outperformed the unscheduled scenario and the PSO, GOA, and WDO algorithms because it yielded the most optimal load schedule across all scenarios.

The load scheduling with PSO, GOA, WDO, and HGWDO algorithms with the PV and battery system is depicted in Figure 3. The developed HGWDO algorithm in the case of the PV and battery system was better than the other PSO, GOA, and WDO algorithms.

5.2 Utility bill payments

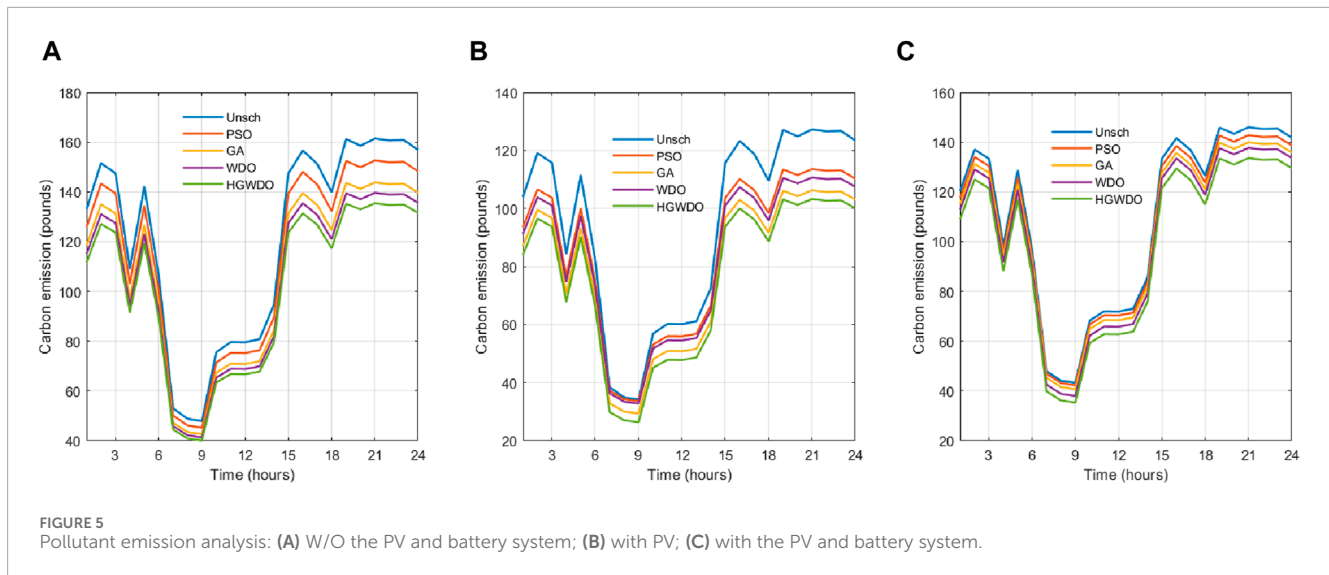
This section presents PSO, GOA, WDO, and HGWDO effectiveness assessments under different conditions: W/O PV and battery systems, with PV, and with PV and battery systems, emphasizing visualized in Figures 4A–F. The hourly evaluation with Figure 4B. The maximum utility bill of an unscheduled load is 91 cents at 10 h, the PSO is 37.87 cents at 8 h, the GOA is 52.5 cents at 10 h, the WDO is 42.32 cents at 22 h, and the HGWDO algorithm is 43.24 cents at 2 h. Similarly, in case 1, the utility bill payment W/O PV and battery systems are shown in Figure 4A. The maximum

utility bill payment of an unscheduled load is 69 cents at 8 h, the PSO is 49 cents at 8 h, the GOA is 42 cents at 10 h, the WDO is 51 cents at 20 h, and for the proposed HGWDO algorithm, it is 65.36 cents at 20 h. Likewise, the hourly utility bill payment assessment using PV and battery systems, with and W/O the scheduling-based proposed algorithm and existing algorithms, is depicted in Figure 4C. The maximum utility bill payment for the unscheduled load is 59.99 cents at 1 h, the PSO is 59.65 cents at 10 h, the GOA is 58.35 cents at 8 h, the WDO is 58.99 cents at 8 h, and the developed HGWDO algorithm is 47.87 cents at 8 h. The results conclude that HGWDO surpasses the performance of available techniques regarding hourly utility bill payments for all three scenarios.

The net utility bill payment evaluation of the proposed algorithm compared to the existing algorithms is listed in Table 2 and shown in Figures 4D–F. In 24 h, the net utility bill payment for the unscheduled load is 1,580 cents compared to those of the PSO, GOA, WDO, and HGWDO algorithms, which are 1,390, 1,410, 1,310, and 1,200 cents, respectively. Comparing all the benchmark heuristic algorithms with the HGWDO algorithm showed that the proposed algorithm has the minimum utility bill payment during the 24 h in scenario 1, presented in Figure 4D. Similarly, in scenario 2, in 24 h, the net utility bill payment for the unscheduled load is 1,490 cents compared to those of the PSO, GOA, WDO, and HGWDO algorithms, which are 1,300, 1,280, 1,195, and 1,050 cents, respectively, presented in Figure 4B. Likewise, in scenario 3, the net utility bill payment for the unscheduled load is 1,210 cents. On the other hand, the utility bill payments of the PSO, GOA, WDO, and HGWDO algorithms are 1,105, 1,000, 930, and 815 cents, respectively, depicted in Figure 4F. The graphical and numerical results validate that the net utility bill payment curtailment of the HGWDO algorithm is more significant than available techniques and W/O scheduling cases. Consequently, the developed HGWDO algorithm has the minimum utility bill payment on an hourly basis or aggregated level compared to the existing algorithms for all three scenarios.

5.3 Pollutant emissions

The evaluation of pollutant emissions from unscheduled and scheduled loads is depicted in Figures 5A–C and summarized in Table 2. Compared to the scenario W/O scheduling, the existing and proposed algorithms demonstrate reduced carbon emissions. However, it is noteworthy that the proposed algorithm consistently outperforms all benchmark algorithms regarding carbon emission reduction. For instance, in the scenario of W/O load scheduling (shown in Figure 5A), peak carbon emission occurs at 21 h, reaching 160 pounds. On the other hand, the PSO, GOA, WDO, and HGWDO algorithms exhibit maximum carbon emissions of 150 pounds, 142 pounds, 140 pounds, and 137 pounds, respectively, at 21 h. Consequently, all benchmark algorithms perform better than the unscheduled load scenario in reducing carbon emissions. Notably, the proposed algorithm achieves the lowest carbon emission at 21 h with only 137 pounds. Similarly, when considering the scenario with PV systems (shown in Figure 5B), the maximum carbon emission from the unscheduled load is 130 pounds at 21 h. On the other hand, PSO, GOA, WDO, and HGWDO produce maximum carbon emissions of 110 pounds, 105 pounds, 103



pounds, and 102 pounds, respectively, at 21 h. Remarkably, the proposed HGWDO algorithm emits only 101 pounds of carbon at 21 h, the lowest among all existing algorithms. Furthermore, it is worth noting that both the existing and proposed algorithms emit lower pollution than W/O scheduling. The peak pollutant emission is 145 pounds at 21 h for W/O scheduling in scenario 3 (presented in Figure 5C). In contrast, peak carbon emissions for PSO, GOA, WDO, and the proposed HGWDO algorithm are 142 pounds, 140 pounds, 137 pounds, and 130 pounds at 21 h, respectively. This analysis underscores the significant reduction in carbon emissions achieved by both the existing and proposed algorithms, particularly when compared to unscheduled load scenarios.

In scenario 1, when no power usage scheduling is applied, the total carbon emissions amount to 1,195 pounds. In contrast, benchmark algorithms such as PSO, GOA, WDO, and our proposed HGWDO algorithm emit 1,070, 990, 950, and 910 pounds of carbon, respectively. Comparatively, PSO reduced carbon emissions by 10.46%, GOA by 17.15%, WDO by 20.50%, and HGWDO by 23.84% compared to unscheduled carbon emissions. This demonstrates the effectiveness of our proposed algorithm in reducing carbon emissions both per hour and in total in scenario 1.

When considering the unscheduled load and PV generation scenario, the emissions stand at 915 pounds. The existing PSO, GOA, WDO, and our HGWDO algorithms emit 915, 810, 780, 768, and 746 pounds of carbon, respectively. In this context, PSO reduced carbon emissions by 11.47%, GOA by 14.75%, WDO by 16.06%, and HGWDO by 18.46%, marking the highest reduction among the algorithms. Therefore, the developed algorithm consistently outperformed the existing algorithms in pollutant emission reduction.

In scenario 3, the unscheduled load led to a total carbon emission of 1,085 pounds. The PSO, GOA, WDO, and HGWDO algorithms resulted in emissions of 995, 970, 965, and 943 pounds, respectively. Relative to the unscheduled carbon emissions, PSO reduced emissions by 8.29%, GOA reduced emissions by 10.59%, WDO by 11.05%, and HGWDO by 13.08%. Consequently, the HGWDO algorithm consistently produced lower carbon emissions than all benchmark algorithms.

5.4 Peak-to-average demand ratio

The assessment of the PADR is presented in Table 2 for three distinct scenarios. In scenario 1, the PADR values for the PSO, GOA, WDO, and developed HGWDO algorithms are 2.80, 3.09, 2.70, and 2.40, respectively. These algorithms collectively reduce the PADR by 19.77, 11.46, 22.63, and 31.23, respectively. The HGWDO algorithm successfully achieves load distribution during off-peak and mid-peak hours, meeting its objectives. In contrast, benchmark algorithms generate rebound peaks during power usage scheduling, posing threats to grid reliability. Consequently, the proposed HGWDO algorithm significantly mitigates the PADR compared to the existing algorithms. In scenario 2, the developed HGWDO algorithm and the PSO, GOA, and WDO algorithms reduce the PADR by 31.43, 13.04, 16.72, and 21.40, respectively. The proposed algorithm uniformly allocates the load during off-peak hours and optimizes grid capacity using a knapsack problem formulation, avoiding rebound peaks. Conversely, benchmark algorithms uniformly shift load, leading to rebound peaks that disrupt power grid reliability. These results demonstrate that HGWDO optimally shifts the load from high- to low-price hours, benefiting consumers and utility companies. The performance of the proposed algorithm shines when integrated with PV scheduling. Similarly, in scenario 3, PSO, GOA, WDO, and HGWDO algorithms curtail the PADR by 9.43, 16.98, 24.90, and 30.18, respectively. The HGWDO algorithm optimally distributes the load during off-peak hours and successfully meets its objectives. Some techniques create rebound peaks that jeopardize grid reliability. The evaluation of the PADR in the context of PV battery systems reveals that the developed HGWDO algorithm significantly reduces the PADR compared to the other techniques, benefiting utility providers and consumers.

6 Conclusion and future work

Optimal smart home load scheduling can be achieved through the DR program. However, a lack of knowledge can often hinder

the successful implementation of DR. The emergence of the ECS has helped overcome this challenge and led to the development of the HGWDO algorithm. The HGWDO algorithm-based ECS automatically responds to the RTPDR for optimal operation scheduling of smart appliances under PV, battery, and utility systems. The developed algorithm aims to address the smart home load scheduling problem for W/O PV and battery, with PV, and with PV and battery systems, aiming to simultaneously reduce utility bill payment, pollutant emission, and PADR. The results show that the developed HGWDO is more effective than other frameworks based on PSO, GOA, and WDO schemes. The future directions for this work are as follows:

- The Lyapunov technique will be used for real-time scheduling to address smart home load scheduling issues by responding to on-site events and requests.
- Dynamic power usage scheduling issues will be addressed by adapting multi-objective optimization algorithms.
- We will employ cloud computing for smart home load scheduling problems via the DR in SGs.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

L-GH: writing–review and editing, writing–original draft, validation, software, methodology, investigation, data curation, and conceptualization. SHAS: writing–review and editing, writing–original draft, validation, software, methodology, investigation, data curation, and conceptualization. BA: writing–original draft, data curation, methodology, formal analysis, validation, investigation, resources, and software.

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GH: writing–original draft, supervision, software, project administration, methodology, conceptualization, writing–review and editing, visualization, validation, resources, investigation, funding acquisition, formal analysis, and data curation. SU: writing–review and editing, visualization, validation, software, resources, funding acquisition, formal analysis, and data curation. SM: writing–review and editing, data curation, methodology, formal analysis, validation, investigation, resources, and visualization. SA: writing–review and editing, visualization, validation, software, resources, project administration, investigation, funding acquisition, formal analysis, and data curation. MIK: writing–review and editing, visualization, validation, resources, methodology, investigation, formal analysis, and data curation.

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