Arabian Journal for Science and Engineering (2024) 49:12655–12678
https://doi.org/10.1007/s13369-024-08755-7

RESEARCH ARTICLE-COMPUTER ENGINEERING AND COMPUTER SCIENCE

A Hybrid Marine Predators Algorithm with Particle Swarm Optimization Using Renewable Energy Sources for Energy Scheduling Problem-Based IoT

Sharif Naser Makhadmeh[1,2] · Mohammed Azmi Al-Betar[2] · Ammar Kamal Abasi[3] · Anessa Al-Redhaei[2] · Osama Ahmad Alomari[4] · Shaimaa Kouka[2]

Received: 22 February 2023 / Accepted: 11 January 2024 / Published online: 26 February 2024
© King Fahd University of Petroleum & Minerals 2024

Abstract

The energy scheduling problem (ESP) is a complex NP-hard optimization scheduling problem of finding the best schedule for the energy consumed through a time horizon by smart appliances according to several constraints and dynamic pricing scheme(s). The primary goal of addressing ESP is to optimize electricity bills for users, the highest energy consumption through a time horizon, and the comfort level of users. Several communication and controlling techniques were utilized to interconnect and centralize the smart appliances to be scheduled, where the Internet of Things (IoT) technique is the most helpful. Several studies have proposed different optimization methods to address the ESP optimally. Unfortunately, due to the low performance of the utilized methods and the high number of the problem's constraints, the best schedules were not achieved in many cases. In this paper, a new improved optimization method on the basis of a hybridization approach between two well-established optimization methods, called the marine predators algorithm and particle swarm optimization, is proposed to handle ESP optimally. The proposed method is mainly established and utilized to enhance the schedules with the worse fitness values to improve them to be more acceptable. Furthermore, to avoid the high complexity of the ESP constraints, Renewable Energy Sources (RESs) based on real-world dataset is utilized along the proposed method. Also, the IoT technique is utilized to establish the connection and build the scheduling system. Finally, to optimize the ESP objectives simultaneously, ESP is formulated as a multi-objective problem. In the evaluation stage, the proposed hybrid method with RESs is tested among four different comparison studies and phases, including the adapted methods with and without RESs, hybrid methods with and without RESs, and based state-of-the-arts. The proposed hybrid method with RESs proves its efficiency and high performance in all comparison phases, where it achieved the best results among all compared methods.

Keywords Energy scheduling problem · Marine predators algorithm · Particle swarm optimization · Renewable energy sources · Multi-objective approach

✉ Sharif Naser Makhadmeh
sharif.makhadmeh@uop.edu.jo

Mohammed Azmi Al-Betar
m.albetar@ajman.ac.ae

Ammar Kamal Abasi
ammar.abasi@mbzuai.ac.ae

Anessa Al-Redhaei
202211654@ajmanuni.ac.ae

Osama Ahmad Alomari
osama.alomari@adu.ac.ae

Shaimaa Kouka
s.kouka@ajman.ac.ae

1 Department of Data Science and Artificial Intelligence, University of Petra, Amman 11196, Jordan

2 Artificial Intelligence Research Center (AIRC), College of Engineering and Information Technology, Ajman University, University Street, Ajman 00000, United Arab Emirates

3 Machine Learning Department, Mohamed Bin Zayed University of Artificial Intelligence (MBZUAI), Abu Dhabi, United Arab Emirates

4 Department of Computer Science and Information Technology, College of Engineering, Abu Dhabi University, Abu Dhabi, United Arab Emirates

1 Introduction

Over the last decades, the emergence of Smart Grid (SG) technology has become very attractive to improve the energy systems in the energy suppliers and to increase the comfortable usage of smart appliances for the users. In reality, SG success totally depends on the advanced technology used in the current communication systems. The bi-directional model used in the current communication systems all the energy suppliers to supply the required energy flow to the user and receive proper feedback [1–4]. Therefore, the bi-directional features embed in the communication system enrich quicker interconnection between users and their home appliances.

The Internet of Things (IoT) technology is an advance and powerful technology that can be utilized to control the interaction between users and their home appliances via the internet using wireless network technology [5–7]. The IoT technology can fulfil the user need and control the energy systems much better. However, energy suppliers can get stuck in serious issues with regard to huge energy consumption during the peak period. Therefore, the user needs cannot be covered in a proper way. The unfit solution usually suggested is to build more power generators to cover the user's needs which will raise the cost of energy production and price [1, 4].

In order to address the peak period shortcomings, the price model of the energy suppliers is shifted from fixed to dynamic. In the dynamic price model, the price of the energy is changeable from time to time, where the user has to pay a higher price in the peak period and a lower price in the off-peak period [3]. Therefore, the users will operate their shiftable appliances during the off-peak period to reduce their Electrical Bill (EB) cost. The energy usage will span the whole day hours; thus, the load balancing will be stabilized [8–11]. The most common schemes for the dynamic price model are Critical Period Price, Time-of-Use (ToU) Price, Inclining Block Rate (IBR), and Real-Time Price (RTP) [4, 12, 13].

To control energy consumption, home appliances should be run during the off-peak period rather than the peak period. To schedule these home appliances and reduce the EB, an Energy Scheduling Problem (ESP) is defined where it is the process of scheduling the shiftable home appliances in the off-peak period to reduce the EB with respect to several constraints, such as increasing the users' comfort and achieve the Peak-to-Average Ratio (PAR) where energy system is preserved by distributing the energy through the time horizon [4].

The ESP is formulated in the context of a constrained optimization problem where the basic objective is to find the optimal home appliances schedule with minimum EB with respect to achieving maximum User Comfort (UC) and PAR. It has been formulated as a multi-objective scheduling problem to achieve all objectives using a weighted sum mechanism [14–17]. The most suitable approach to finding the optimal schedule for the ESP is the metaheuristic algorithm. The metaheuristic algorithms are a general optimization framework that is able to find the optimal solution by iteratively exploring different regions of the problem search space and exploiting the problem accumulative knowledge through intelligent operators controlled by a set of parameters. They are not problem-dependent, and they can be adapted for any optimization problem. Also, they are derivative-free, parameter-less, simple-in-use, sound and complete. Normally, they are designed to tackle optimization problems with continuous and flat search space. However, some search spaces, such as the ESP one, are rugged and constrained and cannot be easily explored and exploited using the basic operations of any metaheuristic algorithm. Therefore, these metaheuristic algorithms must be modified or hybridized to be familiar with the ESP search space. Therefore, several modified versions of metaheuristic algorithms are utilised to tackle ESP, such as hybrid white shark equilibrium optimizer [18], modified differential evolution algorithm [19], hybrid multi-verse optimizer with grey wolf optimizer [18], hybrid differential evolution and harmony search algorithm [20], modified coronavirus herd immunity optimizer [21], multi-objective hybrid grey wolf optimizer [10, 17], non-dominated sorting genetic algorithm [22], and many others [4]. In addition, several studies have utilized additional sources to have more avoidance to the high complexity of the ESP constraints and find better candidate solutions and schedules for the ESP. Renewable Energy Sources (RESs) are the most sufficient and able to improve the schedules significantly. The most prevalent RESs are geothermal energy, hydro energy, wind energy, biomass energy, tidal energy, and solar energy, where the latter is the most popular.

Although several research works have been adopted to tackle ESP, there is no single research work has been able to achieve the optimal solution for all ESP cases. This is also emphasized in the No Free Lunch theorem of optimization, where there is no single superior metaheuristic algorithm that can excel others for all optimization problems or for the same optimization problem with different cases. Therefore, the door is still open to investigate other means of hybrid metaheuristic algorithms to yield better scheduling solutions for ESP.

Recently, a novel nature-inspired metaheuristic optimization has been proposed called the Marine Predators Algorithm (MPA). It is inspired by the hunting strategies used by marine predators to locate their prey using the Levy strategy and Brownian movements [23]. Due to its impressive characteristics and its manoeuvre behaviour in exploring and exploiting the problem search space, MPA has been intensively used to tackle a wide range of optimization problems, such as feature selection [24], photovoltaic models parameters [25, 26], engineering problems [27], computed tomography image segmentation [28], and many others. In spite of this success, different modified and hybridized versions of MPA have been proposed to cope with problem search space structure and complexity.

In this paper, the MPA is empowered by the particle swarm optimization (PSO) components to be more suitable to the ruggedness and complexity of multi-objective ESP. The main goal of the proposed improvement is to boost the searching abilities of the MPA and enhance the bad schedules for the ESP. The primary contributions of this research are summarized as follows:

1. The MPA is adapted to address the ESP and optimize its objectives.
2. A new hybrid optimization method, called MPAP, based on the MPA and PSO searching components, is proposed to boost the searching capabilities of the MPA. The proposed MPAP is mainly established and utilized to enhance the schedules with the worse fitness values to improve them to be more acceptable. Furthermore, avoid local optimum stagnation and find the global optimum by enhancing the best exploration and exploitation balance.
3. Renewable energy sources based on real-world dataset is utilized and used to avoid the high complexity of the ESP constraints. The RESs are utilized along the proposed MPAP method to achieve more feasible candidate solutions and find better schedules. The MPAP with the RESs is called RMPAP.
4. The IoT technique is utilized to establish the connection and build the scheduling system to improve the exchanging data between the scheduling system components.

In the evaluation stage, four well-known optimization algorithms are adapted along the MPA. These algorithms are Differential Evolution (DE), Grey Wolf Optimizer (GWO), Multiverse Optimizer (MVO), and Wind-Driven Optimizer (WDO). The results obtained by these algorithms are evaluated on the basis of four different comparison studies and phases. The first comparison study is conducted to show the impact of using the RESs of the results obtained by the adapted algorithm. The second comparison is designed to prove the enhancement of the proposed hybrid approach and its positive impact on the results. The third comparison presents the best hybrid method among all adapted. The last comparison is conducted to compare the proposed hybrid method with four state-of-the-art methods.

The organization of this paper is managed as follows: The background of using the IOT technology in the smart home, as well as the definition and formulation of ESP, are discussed in Sect. 3. The proposed method, which includes the foundation of the two algorithms MPA and PSO, and how the two algorithms are hybridized to solve ESP is thoroughly described in Sect. 4. The experimental results and discussion to evaluate the performance of the proposed hybrid method are also analysed in Sect. 5. Finally, the paper is concluded where the main findings are provided as well as the possible directions for future expansion are given in Sect. 6.

2 Related Works

Research into tackling ESP commenced a decade ago. ESP has been approached through diverse scheduling techniques, with metaheuristic optimization techniques emerging as the most prevalent. The core of ESP involves framing it as an optimization problem, wherein the optimal scheduling of appliance usage times in a smart home is determined while taking into account EB, PAR, and UC levels. Various metaheuristics, encompassing both pure and hybrid approaches, have been modified to handle ESP effectively.

The first impacted research addressed the ESP was published in 2013 [16]. In this work, the authors merged two distinct electricity pricing schemes (RTP and IBR). This amalgamation was suggested to equilibrate the power consumption patterns of users across a specific time horizon. The ESP was modelled as a multi-objective optimization problem, aiming to enhance EB and UC levels. The genetic algorithm (GA) was employed to address the ESP effectively and yielded the most promising outcomes. The findings highlighted the strong performance of the GA in optimizing both EB and PAR compared to the unscheduled solutions. Nonetheless, there was an observed trade-off between reducing EB and enhancing UC.

The authors of [29] proposed a new hybrid method on the basis of White Shark Optimizer (WSO) and Equilibrium Optimizer (EO). The new method is called White Shark Equilibrium Optimizer (WSEO). The introduced approach is executed using a residential IoT system to enhance the effective management of appliances. Furthermore, the ESP is expressed mathematically as a multi-objective problem, considering three key objectives: EB, PAR, and UC. In the assessment phase, a new case study related to the United Arab Emirates (UAE) is put forth, encompassing a comprehensive collection of appliances commonly found in the UAE. The evaluation process is structured into three primary phases: original evaluation, original evaluation employing a hybrid approach, and evaluation involving the hybrid approach. It was observed that the proposed WSEO algorithm outperformed all other methods under comparison in optimizing the ESP.

In the study conducted by Rahim et al. (2016) [30], GA, PSO, and Ant Colony Optimization (ACO) were all employed to tackle the ESP. The ESP was modelled as a multi-objective optimization problem to optimize both EB and UC. A new RES modelling was proposed by the authors to enhance the scheduling and find better outcomes. The simulation experiments utilized TOU pricing to compute the electricity consumption cost of household appliances. The outcomes derived from the GA demonstrated its efficacy in addressing the ESP, surpassing the performance of both PSO and ACO in meeting ESP objectives. The results highlighted an inverse correlation between the reduction of EB and the enhancement of UC. Notably, GA achieved the most favourable compromise between these factors in comparison to the other optimization algorithms.

In work presented by Javaid et al. (2017) [31], a novel approach was taken by hybridizing GA with the WDO, resulting in a new algorithm termed the hybrid Genetic Wind-Driven (GWD). This amalgamated algorithm was designed to address the ESP. The RTP scheme was utilized to compute the EB of 12 appliances. In the simulation results, two types of datasets were employed, encompassing single and multiple smart homes. For single smart homes, the performance of the proposed GWD was compared with WDO and GA. The GWD showed superior performance in reducing both EB and PAR when compared to GA and WDO. Nevertheless, all three algorithms achieved the same level of enhancement in UC. In the context of multiple homes, the authors assessed the effectiveness of various algorithms-Binary Particle Swarm Optimization (BPSO), GA, Bacterial Foraging Optimization Algorithm (BFOA), and WDO-across 50 homes. The results indicated that GA exhibited remarkable performance in reducing EB, yielding the most favourable EB value. On the other hand, BFOA demonstrated the best performance in terms of PAR compared to the other algorithms, while BPSO achieved the highest level of improvement in UC.

Another hybridization, called MVOG, was proposed by [18] by combining the components of MVO and GWO to address ESP efficiently. The main objective of MVOG is to enhance the performance of the MVO by updating the least promising solutions and enhancing scheduling outcomes through the utilization of the GWO. Data exchange among the components within the smart home system is orchestrated through IoT technologies, thereby enhancing data communication. The empirical evaluation involves subjecting the MVOG to examination through seven distinct consumption scenarios. The hybridization technique proposed is extended to include four additional optimization methods, thereby assessing its efficacy across diverse approaches. The performance assessment of the proposed algorithm is executed through three distinct comparative analyses: against original methods, hybrid methods, and hybrid methods. Notably, the MVOG demonstrates remarkable efficacy in addressing the ESP when compared with other algorithms.

3 Background

3.1 Smart Home-Based IoT

Formerly, smart homes were defined as the utilization of Information and Communication Technology (ICT) devices for home control purposes, such as appliance control and automation that can be utilized to control temperature, windows, light, etc. Contemporary smart homes feature integration between IoT technologies and artificial intelligence, such as Siri, google assistant and analysing and adapting to the consumer's usage pattern for power and resource-saving.

The main benefit of IoT smart homes is the ability to optimize and automate the usage of smart appliances. The daily usage of home appliances, gadgets, and sensors is vital information depicting the consumption pattern over a continuous period of time. The consumption trends that are captured and identified using complex artificial intelligence algorithms are employed for various purposes, such as increasing security, reducing power consumption, and home automation. Examples of the IoT devices used for home automation are portable gadgets, mounted gadgets and applications available on smartphones, laptops, and desktops.

IoT provides the connectivity/link between physical home appliances where sensors report data over time to the cloud computing system. The information sharing and exchanging data is implemented via a unified framework for providing a common operation for the given appliances, applying data analytics [6, 7, 32].

The infrastructure of the IoT components is designed to enhance communication, timeliness, and productivity of everyday services and activities in many aspects, such as healthcare services, education, transportation, security, and many other services, that raise the quality of residents' life [33, 34].

The latest generations of smart home appliances, such the smart thermostats Nest or Ecobee, have built-in IoT support, where the data is constantly captured from its sensors and automatically adapts and controls the devices according to the sensed environment to satisfy the designed purpose. The aim in the smart thermostat example is scheduling predefined settings and/or maintaining the desired temperature throughout the day, which is constantly measured using the sensors and adjusted when needed remotely, therefore, saving energy, time, and resources effortlessly. In terms of resource consumption, IoT devices typically require a minimal supply of power and memory for exchanging and transmitting data via IoT gateways and protocols [35]. Figure 1 depicts a generic IoT architecture.

Smart homes are designed to raise the quality of life for humans enabling humans to invest their time in meaningful takes, automating time-consuming and routine tasks. Fig-

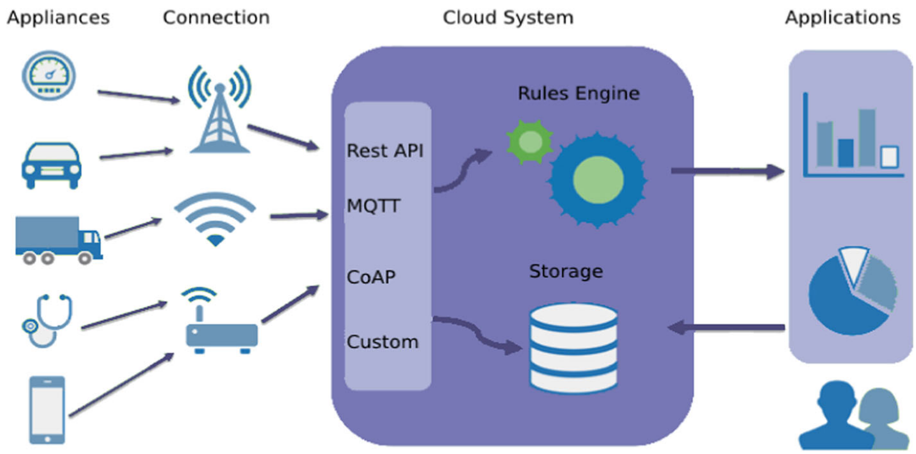


Fig. 1 The generic IoT architecture

ure 2 shows some of the main smart home IoT components [5, 7].

Smart home-based IoT components are presented in Fig. 2. The Energy Management Controller (EMC) is the most vital element as it is responsible for components' interconnection and coordination. Smart devices, such as smartphones, laptops, desktop computers, and smart gadgets, are integrated with the IoT system allowing consumers to control and interact with the system via applications remotely.

Smart IoT components are capable of wireless communication with other devices, such as a smart meter, which is responsible for supervising the consumed power by all devices and accordingly giving its informative feedback to the residential power and electricity supplier in an effort to match the customers' (users') supply demands. Advanced metering technology is emerging where bi-directional communication between the power supplier and customer is supported such that electricity can be exported and/or received. Furthermore, these advanced metering technologies introduce higher accuracy, control and better distribution of the power system based on demands.

Another example is the smart plug that connects smart home appliances to a WiFi network, thus enabling communication between the devices. Some of the most famous communication devices are IEEE 802.16 based WiMAX, IEEE 802.11 based wireless LAN, and IEEE 802.15.4 based ZigBee [36]. The system is closely monitored and controlled via a web application or mobile application while additional smart devices such as renewable energy sources and storage systems are easily added to the system

3.2 ESP Foundation

The ESP, as discussed previously, is a problem of finding the best schedule for the energy consumed through a time horizon by home smart appliances to minimize EBs, PAR, and discomfort levels for users. Addressing ESP is done according to several hard and soft constraints and dynamic pricing scheme(s). The smart appliances could be Schedulable Appliances (SAs) that are operated automatically without user intervention and Non-Schedulable Appliances (NSAs) that are fully controllable by users. The hard constraints that must be satisfied include the length of the Operation Cycle (OC) and Operation Time Period (OT) for SAs.

Massive research were introduced and proposed to address the ESP using different datasets and optimization methods. The utilized methods include original and improved/enhanced methods [4].

The genetic algorithm was extensively utilized and improved in these studies, where it was hybridized with the moth-flame optimizer to solve the ESP and mainly optimized the UC level [37]. Several comparisons were conducted in this study to evaluate the proposed method's performance. the obtained results proved the robust performance of the proposed method compared to all compared methods. Another hybrid method based on the genetic algorithm and the wind-driven was proposed in [31] to optimally handle the ESP and find a solution with the best EB and UC. In the experimental evaluation, the proposed method was tested and compared with other well-known methods. The proposed hybrid method achieved the best results where it outperformed all compared methods.

Also, the grey wolf optimizer was adapted and improved in several studies, where its searching capabilities were combined with the min-conflict algorithm to enhance its local search and avoid any stagnation [17]. The obtained results by the proposed method proved its high performance in addressing the ESP and optimizing its objectives compared to the other methods. The grey wolf optimizer was also improved in [38] to address the same drawback in the algorithm and find better candidate solutions for the ESP with better values for the objectives. In the testing phase, the proposed method showed significant results, where it almost obtained the best results among all compared methods.

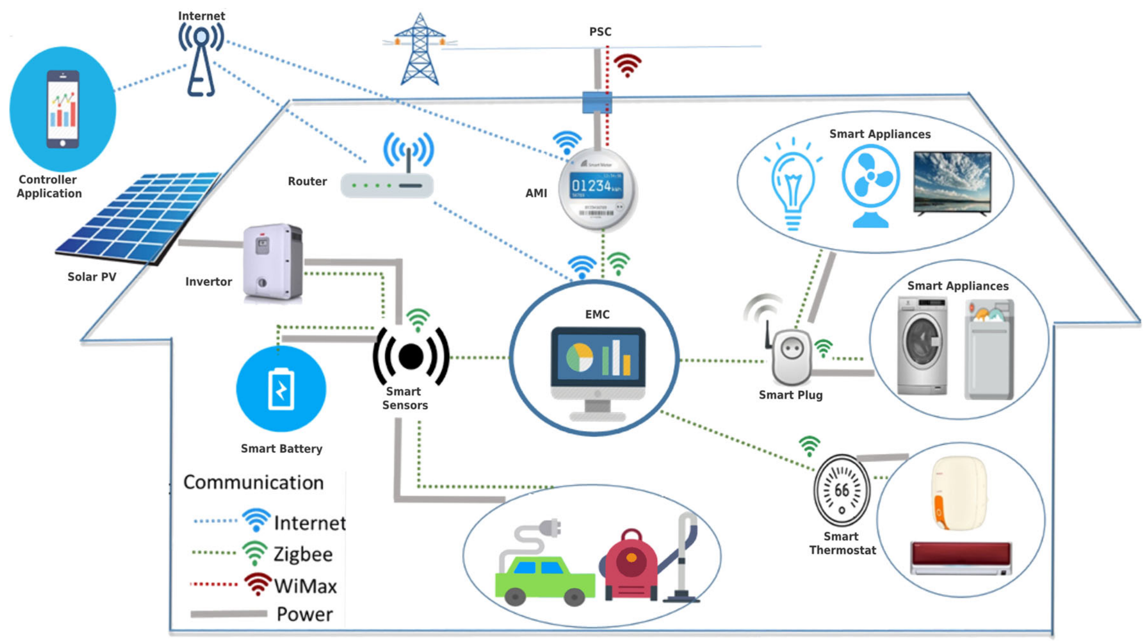


Fig. 2 Smart home-based IoT components

The bacterial foraging optimizer was improved in several studies, where it was hybridized with the flower pollination optimizer in [39] and with the harmony search algorithm in [40] to improve its searching and optimization capabilities and find a better schedule for the ESP. Both hybrid methods presented good and robust optimization implementation compared to all compared methods in the testing and evaluation stage.

A review study was conducted to present the most significant method utilized and proposed to address the ESP [4]. The analysis study presented in this review research showed and proved the significance of the optimization methods in addressing the ESP and optimizing its objectives, including EB, PAR, and UC, particularly the hybridized optimization methods.

3.3 ESP Formulation

Conventionally, smart home appliances can be classified with respect to their operation mechanism and utilization [13, 41]. This study divides the appliances with respect to their operation into two classes, including SAs and NSAs, as mentioned previously. Accordingly, in SAs, a set of time parameters need to be defined, such as OC and OT. The mathematical formulation of energy consumed along with the time parameters are described as follows:

- **Schedulable Appliances** The SAs can be mathematically expressed by utilizing a vector of appliances SP as follows [17, 21]:

$$\mathrm{SP} = [\mathrm{sp}_1, \mathrm{sp}_2, \ldots, \mathrm{sp}_d], \tag{1}$$

where sp_i refers to the appliance i in SP, while d refers to the number of the appliances. The time interval of running the appliances symbolizes using (T). T is sliced into multiple slots as follows:

$$T = [t^1, t^2, \ldots, t^f], \tag{2}$$

where t^i indicates the time i in the time horizon, and f stands for the number of major slots in the time horizon. The mathematical formulation with respect to the capacity of the energy entailed by each SA at any slot can be modelled as follows [8, 18]:

$$\boldsymbol{EC} = \begin{bmatrix} \mathrm{ec}_1^1 & \mathrm{ec}_2^1 & \cdots & \mathrm{ec}_d^1 \\ \mathrm{ec}_1^2 & \mathrm{ec}_2^2 & \cdots & \mathrm{ec}_d^2 \\ \vdots & \vdots & \cdots & \vdots \\ \mathrm{ec}_1^f & \mathrm{ec}_2^f & \cdots & \mathrm{ec}_d^f \end{bmatrix}, \tag{3}$$

ec_i^j symbolizes the energy required by sp_i at t^j. As mentioned previously, the OT and OC are time parameters of SA that need to be set by the user. The OT contains its starting (OT_s) and ending (OT_e) period. Mathematically, this can be modelled as follows [17, 29]:

$$\mathrm{OT}_s = [\mathrm{OT}_{s1}, \mathrm{OT}_{s2}, \ldots, \mathrm{OT}_{sd}], \tag{4}$$

$$\mathrm{OT}_e = [\mathrm{OT}_{e1}, \mathrm{OT}_{e2}, \ldots, \mathrm{OT}_{ed}], \tag{5}$$

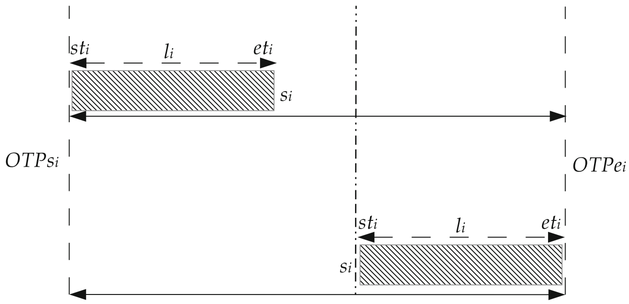


Fig. 3 Illustration of Time parameters of SAs

The OT_{si} and OT_{ei} symbolize the starting and ending allowable period for running the appliance sp_i, respectively. The second time parameter OC for all appliances is expressed as follows [4, 8, 17]:

$$\mathrm{OC} = [\mathrm{oc}_1, \mathrm{oc}_2, \ldots, \mathrm{oc}_d], \tag{6}$$

where oc_i refers to the OC of sp_i. The following vectors are used to represent the operations schedule of the appliances, including appliances' starting (St) and ending (Et) operation:

$$\mathrm{SO} = [\mathrm{so}_1, \mathrm{so}_2, \ldots, \mathrm{so}_d], \tag{7}$$

$$\mathrm{EO} = [\mathrm{eo}_1, \mathrm{eo}_2, \ldots, \mathrm{eo}_d], \tag{8}$$

The start and end operations of sp_i are expressed as so_i and eo_i respectively. The SAs time parameters are depicted in Fig. 3.

- **Non-shiftable Appliances** In NSAs, the time settings are not required since this type of appliance is operated manually. For instance, users are not concerned with determining the OT and OC for TV [10, 17]. The NSAs are represented mathematically by using the NSP vector as follows:

$$\mathrm{NSP} = [\mathrm{nsp}_1, \mathrm{nsp}_2, \ldots, \mathrm{nsp}_k], \tag{9}$$

where ns_q denotes NSA q in NSP, and k symbolizes the total number of NSAs. The energy entailed for NSAs to complete their operation cycle can be modelled as follows:

$$\mathrm{NEC} = [\mathrm{nec}_1, \mathrm{nec}_2, \ldots, \mathrm{nec}_k], \tag{10}$$

Note the energy required by nsp_q is expressed as ens_q.

3.3.1 Electricity Bill

The users gain leverage from such systems in reducing the EB by rescheduling the time settings of running home appliances. Mathematically, EB can be modelled as follows [14, 42]:

$$\mathrm{EB} = \sum_{j=1}^{f} \sum_{i=1}^{d} \mathrm{ec}_i^j \times \mathrm{pc}^j, \tag{11}$$

where pc^j is the electricity price derived from the dynamic pricing scheme for the time slot j. The RTP dynamic pricing scheme is adopted in this study because the cost is updated with respect to the generation cost. This scheme is in line with IBR suggested by [13, 43] to adequately balance and flatten the energy demand. Two costs are calculated in IBR during T with respect to the electricity consumption in the j interval, which is formulated as follows:

$$\mathrm{pc}^j = \begin{cases} l^j & \text{if } 0 \leq \mathrm{ec}^j \leq \mathrm{TH} \\ h^j & \text{if } \mathrm{ec}^j > \mathrm{TH} \end{cases}, \tag{12}$$

$$h^j = \lambda \times l^j, \tag{13}$$

Here l^j stands for the normal cost, whereas h^j stands for the high cost. Furthermore, TH is the limited amount of energy consumed within a time slot, and λ is a non-negative number that symbolizes the percentage between the two electricity prices.

3.3.2 Peak-to-Average Ratio

The PAR is calculated based on the percentage between the highest and the average consumption in T. The decrease in the PAR tends to boost the performance of the SGs energy system. This is because PAR tries to reduce energy consumption and contribute to the balance of the electricity demand during peak hours. Mathematically, PAR is modelled as follows [10, 17, 42]:

$$\mathrm{PAR} = \frac{\mathrm{EC}_{\max}}{\mathrm{EC}_{\mathrm{Avg}}}, \tag{14}$$

where

$$\mathrm{EC}_{\mathrm{Avg}} = \frac{\sum_{j=1}^{f} \mathrm{EC}^j}{f}, \tag{15}$$

Note that $\mathrm{EC}_{\max}$ stands for the maximum power demand at T, and $\mathrm{EC}_{\mathrm{avg}}$ stands for the average power demand at T.

3.3.3 User Comfort

In this study, the Capacity Energy Limit (CEL) and Waiting Time Limit (WTL) are used as two parameters in evaluating the level of UC. The WTL can improve UC by reducing the waiting time of running SAs, while CEL is responsible to run a larger number of NSAs but with the constraint of not exceeding TH [8, 17].

For SA i, the WTL can be estimated utilizing equation Eq. 16.

$$\mathrm{WTL}_i = \frac{\mathrm{so}_i - \mathrm{OTs}_i}{\mathrm{OTe}_i - \mathrm{OTs}_i - \mathrm{oc}_i}, \quad \forall i \in \boldsymbol{SP}, \tag{16}$$

For a smart home, the average WTL over all SAs can be estimated as follows:

$$\mathrm{WTL}_{\mathrm{avg}} = \frac{\sum_{i=1}^{d} (\mathrm{so}_i - \mathrm{OTs}_i)}{\sum_{i=1}^{d} (\mathrm{OTe}_i - \mathrm{OTs}_i - \mathrm{co}_i)}, \tag{17}$$

The CEL at interval j can be estimated as follows:

$$\mathrm{CEL}^j = \frac{\sum_{q=1}^{k} \mathrm{ONA}_q^j}{k}, \tag{18}$$

where $\sum_{q=1}^{k} \mathrm{ONA}_q^j$ stands for the number of $NSAs$ demanded extra energy than existing energy at time interval j.

$$\mathrm{ONA}_q^j = \begin{cases} 0 & \text{if } \mathrm{NEC}_q < \mathrm{AP}^j \\ 1 & \text{otherwise}, \end{cases}, \tag{19}$$

$$\mathrm{AP}^j = \mathrm{TH} - \mathrm{EC}^j, \tag{20}$$

where AP^j refers to the amount of energy that entails running the NSAs at time interval j.

The average value of CEL over all time intervals is estimated utilizing Eq. 21.

$$\mathrm{CEL}_{\mathrm{avg}} = \frac{\sum_{j=1}^{f} \sum_{k=1}^{d} \mathrm{ONA}_q^j}{k \times f}, \tag{21}$$

The values of $\mathrm{WTL}_{\mathrm{avg}}$ and $\mathrm{CEL}_{\mathrm{avg}}$ are constrained to fall between in the [0,1] interval and the level of UC increases when their values are approaching zero. The UC level percentage is estimated using the following formula:

$$\mathrm{UC}_p = \left(1 - \left(\frac{\mathrm{WTL}_{\mathrm{avg}} + \mathrm{CEL}_{\mathrm{avg}}}{2}\right)\right) \times 100\%, \tag{22}$$

3.4 Multi-objective Function

This study models the ESP as a multi-objective optimization problem in which the EB, PAR, WTL, and CEL must be optimized simultaneously. To tackle such a multi-objective problem, the weighted sum method, which is the non-Pareto scalar technique, is used because it is very simple, easy to implement, and commonly utilized in the ESP literature [4]. Because the multi-objective optimization problem used in this study embeds more than three objectives, the Pareto optimality concept is not considered [44–46]. Accordingly, the ESP can be represented as a multi-objective optimization problem using Eqs. 11, 14, 17, and 21, as follows:

$$\begin{aligned} \min F(X) = w_1 \times \frac{\mathrm{EB}}{\mathrm{EB} + A} + w_2 \times \frac{PAR}{PAR + B}, \\ + w_3 \times \mathrm{WTL}_{\mathrm{avg}} + w_4 \times \mathrm{CEL}_{\mathrm{avg}} \end{aligned} \tag{23}$$

Note that A and B are two non-negative numbers, and w_1, w_2, w_3, and w_4 are a set of weighting parameters that assess the importance of each objective function.

4 The Proposed Method

In this section, the proposed hybrid approach is presented and illustrated. The section starts with the MPA inspiration and mathematical procedures description. Subsequently, the PSO illustration is presented. After that, the proposed MPAP hybrid method optimization and adaptation steps for ESP are deeply described.

4.1 Marine Predators Algorithm (MPA)

The MPA is a metaheuristic that draws its inspiration from nature and imitates the Levy strategy and Brownian motions utilized by marine predators to find their prey [23]. The implemented approach is mostly centred on the concentration of prey. If there is a low concentration of prey, the Levy technique is used; if there is a high concentration of prey, the marine predators use the Brownian movement. The velocity ratio v from the prey to the predators represents the trade-off between the two techniques as follows:

1. **High velocity (when $v > 10$)**: the predator moves at a considerably faster rate than the prey. The optimal action to take for predators in this case is to maintain their position and not move, regardless of whether the prey is moving in Levy motion or Brownian motion.
2. **Unit velocity (when $v = 1$)**: both the prey and the predators are travelling at the same speed. In this case, if the prey is travelling in Levy motion, the predator's best action to take is to use Brownian motion.
3. **Low velocity (when $v < 0.1$)**: the prey moves at a significantly faster rate than the predator. The optimum tactic for predators in this situation, regardless of the prey's movement (Levy or Brownian), is to use the Levy motion.

Hence, the optimization process of the MPA is divided based on the above three conditions. Figure 4 visualizes each phase of the MPA. The optimization processes of the MPA and its phases are discussed below.

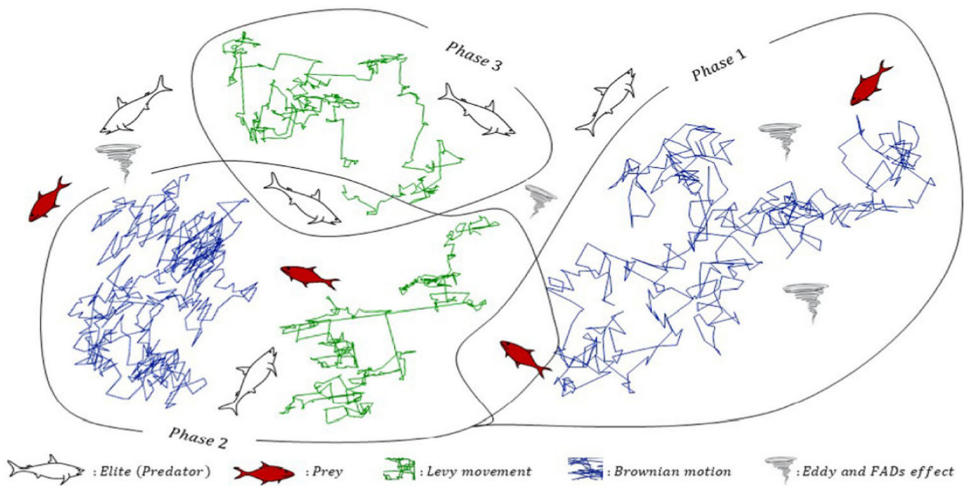


Fig. 4 Marine Predators Algorithm's stages [23]

4.1.1 Initialization

The initialization stage starts by initializing a group of prey in the search space using Eq. 24 which represents the lower and the upper bounds by $X_{\min}$ and $X_{\max}$, respectively, and uses a random number ranging between 0 and 1 denoted by rand.

$$X = X_{\min} + \mathrm{rand}(X_{\max} - X_{\min}) \tag{24}$$

After initializing the prey, the fitness of each predator is determined and the top predator (X^I) is the one with the highest fitness value. According to the evolutionary law, X^I is the best forager, which is used to construct the $Elite$ matrix with ($n \times d$) dimension, where n is the individuals' number in the population and d is the dimensions' number as shown in Eq. 25.

$$\mathrm{Elite} = \begin{bmatrix} X^I_{1,1} & \ldots & X^I_{1,d} \\ \vdots & \ddots & \vdots \\ X^I_{n,1} & \ldots & X^I_{n,d} \end{bmatrix} \tag{25}$$

In order to update the positions of the predators, a second matrix called Prey that has the same dimension as the Elite matrix is also created, as shown in Eq. 26.

$$\mathrm{Prey} = \begin{bmatrix} X_{1,1} & X_{1,2} & \ldots & X_{1,d} \\ \vdots & \vdots & \vdots & \vdots \\ X_{n,1} & X_{n,2} & \ldots & X_{n,d} \end{bmatrix} \tag{26}$$

4.1.2 High-Velocity Ratio Stage

As mentioned before, in this stage, the speed of the predator is higher than the prey and the best practice for the predators is to stay motionless. In this stage, the exploration phase is taken place. The exploration phase is keep conducting while $iter < \frac{1}{3} \times max\_iter$ and it is mathematically modelled using Eqs. 27 and 28:

$$\overrightarrow{stepsize_i} = \overrightarrow{R}_B \otimes \left(\overrightarrow{Elite_i} - \overrightarrow{R}_B \otimes \overrightarrow{Prey_i}\right) i = 1, \ldots, n \tag{27}$$

$$\overrightarrow{Prey_i} = \overrightarrow{Prey_i} + P.\overrightarrow{R} \otimes \overrightarrow{stepsize_i} \tag{28}$$

In Eq. 27, the Brownian motion is represented by $\overrightarrow{R_B}$ which is a vector of random numbers built using the normal distribution. According to the authors of the original paper, P is a constant set to 0.5 in Eq. 28, and R is a uniform random vector with a range of 0 to 1. In both equations, $\otimes$ is the entry-wise multiplication operation.

4.1.3 Unit Velocity Ratio Stage

This stage is executed when both the prey and predators have identical movement speeds. It takes place in the middle part of the optimization process, as the exploitation stage gradually replaces the exploration stage, where the following condition $\frac{1}{3} \times max_{iter} < iter < \frac{2}{3} \times max_{iter}$ is satisfied. Eqs. 29 and 30 express the mathematical models of the first half of the population which uses the Levy movement.

$$\overrightarrow{stepsize_i} = \overrightarrow{R}_L \otimes \left(\overrightarrow{Elite_i} - \overrightarrow{R}_L \otimes \overrightarrow{Prey_i}\right) i = 1, \ldots, \frac{n}{2} \tag{29}$$

$$\overrightarrow{Prey_i} = \overrightarrow{Prey_i} + P.\overrightarrow{R} \otimes \overrightarrow{stepsize_i} \tag{30}$$

Whereas the second half of the population that uses the Brownian movements is expressed mathematically by Eqs. 31 and 32:

$$\overrightarrow{stepsize_i} = \overrightarrow{R}_B \otimes \left(\overrightarrow{R}_B \otimes \overrightarrow{Elite_i}\right.$$

$$-\overrightarrow{Prey_i}\Big)\, i = \frac{n}{2}, \ldots, n \tag{31}$$

$$\overrightarrow{Prey_i} = \overrightarrow{Elite_i} + P.CF \otimes \overrightarrow{stepsize_i} \tag{32}$$

where the Levy and Brownian motions are donated by $\overrightarrow{R_L}$ and $\overrightarrow{R_B}$ vectors, respectively, and CF (an adaptive parameter) in Eq. 32 used to manage the step size. It can be formulated by Eq. 33:

$$CF = \left(1 - \frac{iter}{max_{iter}}\right)^{\frac{2(iter)}{max_{iter}}} \tag{33}$$

4.1.4 Low-Velocity Ratio Stage

In this stage, the speed of the prey is much higher than the predator and the best strategy for predators is utilizing the Levy motion in their hunting process. The low-velocity stage simulates the exploitation phase. It occurs in a late stage of the optimization process when $iter > \frac{2}{3} \times max_{iter}$ and it can be expressed mathematically using the following equations (Eqs. 34 and 35):

$$\overrightarrow{stepsize_i} = \overrightarrow{R}_L \otimes \Big(\overrightarrow{R}_L \otimes \overrightarrow{Elite_i} - \overrightarrow{Prey_i}\Big)\, i = 1, \ldots, n \tag{34}$$

$$\overrightarrow{Prey_i} = \overrightarrow{Elite_i} + P.CF \otimes \overrightarrow{stepsize_i} \tag{35}$$

According to some studies [47], environmental factors like Eddy formulation and Fish Aggregating Devices (FADs) have an impact on the behaviour of the prey. The FADs process has an impact on the predators' seeking time because it results in them spending 80% of their time searching locally and 20% in pursuit of prey elsewhere. FADs is calculated using Eq. 36.

$$\overrightarrow{Prey_i} = \begin{cases} \overrightarrow{Prey_i} + CF\big[\overrightarrow{X}_{min} + \overrightarrow{R} \otimes (\overrightarrow{X}_{max} - \overrightarrow{X}_{min})\big] \otimes \overrightarrow{U} & \text{if } r \leq FADs \\ \overrightarrow{Prey_i} + [FADs(1-r) + r]\Big(\overrightarrow{Prey_{r1}} - \overrightarrow{Prey_{r2}}\Big) & \text{if } r > FADs \end{cases} \tag{36}$$

In the notation of Eq. 36, $\overrightarrow{U}$ is a binary vector that contains arrays of one and zero. It is constructed by generating a random vector ranging between 0 and 1 for each array in $\overrightarrow{U}$, if the generated number is < 0.2 then the array turns into zero otherwise; it turns into one. Additionally, r is a uniform random number created between 0 and 1, and FADs = 0.2 indicates the probability of FADs' effect on the searching process, and Random indexes of the $prey$ matrix are represented by the subscripts r_1 and r_2 and the dimensions of the lower bound and the upper bound are stored in $\overrightarrow{X}_{\min}$ and $\overrightarrow{X}_{\max}$, respectively.

By preserving the former position of the prey and updating the current solutions, the MPA simulates the remarkable memory behaviour of marine predators. The fitness values of each current solution and its prior one are compared. If the old solution's fitness value is higher than the current one, the swapping is taken place. Algorithm 1 presents the MPA steps indicated above.

Algorithm 1 Marine Predators Algorithm

```
Initialization Stage
    Initialize the algorithm's parameters P = 0.5
    Initialize position of the solution populations (Prey) i = 1, 2, ..., n
while iter ≤ max_iter do
    Compute the fitness
    Build the Elitematrix
    Accomplish memory saving
Stage 1: High-Velocity Ratio
    if iter < (1/3) max_iter then
        Update Prey_i using Eq. 28
Stage 2: Unit-Velocity Ratio
    else if (1/3) max_iter < iter < (2/3) max_iter then
        if i < (1/2) n then
            Update Prey_i using Eq. 30
        else
            Update Update Prey_i using Eq. 32
        end if
Stage 3: Low-Velocity Ratio
    else if iter > (2/3) max_iter then
        Update Update Prey_i using Eq. 35
    end if
    Accomplish memory saving
    Update Elite
    Using Eq. 36 to apply FADs effect for each Prey_i
    iter = iter + 1
end while
```

4.2 Particle Swarm Optimization

PSO is a computational method used to find the optimal solution to a problem [48]. It is based on the behaviour of social animals, such as birds and bees, and utilizes a group of "particles" to search for the best solution. Each particle represents a potential solution, and the algorithm uses the particles to explore the solution space and find the optimal solution [43].

In PSO, each particle adjusts its position in the solution space based on its own experience and the experiences of other particles. Each particle is influenced by two forces: its personal best position, which is the best solution it has found so far, and the global best position, which is the best solution found by any particle in the group. The particles adjust their positions by moving towards their personal and global best positions.

This method is often used to solve optimization problems, such as finding the minimum or maximum of a function. It is simple to implement and requires a few parameters to be adjusted. PSO has been applied to a wide range of problems, including function optimization, feature selection, and clustering [49].

At each iteration, t, the position and velocity of each particle in the PSO algorithm are represented by the vectors $X(iter)$ and $V(iter)$, respectively. The movement of each particle is governed by specific equations that determine how the particle updates its position and velocity based on its current position, velocity, and the positions and velocities of other particles in the swarm.

$$V(iter+1) = w * V(iter) + c1 * rand() * (pbest - X(iter)) + c2 * rand() * (gbest - X(iter)) \quad (37)$$

$$X(iter+1) = X(iter) + V(iter+1) \quad (38)$$

where w is the inertia weight, which controls the influence of the previous velocity on the current velocity. $c1$ and $c2$ are constants that control the influence of the pbest and gbest positions, respectively. pbest is the personal best position of the particle (i.e., the best solution the particle has found so far), and gbest is the global best position (i.e., the best solution found by any particle in the group). The function rand() produces a random number within the interval [0, 1], where the numbers 0 and 1 are excluded. This means that the function can generate any number in the range $0 < x < 1$.

The particles continue to move through the solution space and update their positions and velocities until the algorithm reaches a stopping condition, such as a maximum number of iterations or a satisfactory level of fitness.

Some of the common applications of PSO include:

- Function optimization: PSO can be used to find the minimum or maximum of a function by adjusting the position of the particles in the solution space.
- Feature selection: PSO can be used to select the most relevant features from a large set of features for a machine learning model.
- Clustering: PSO can be used to group data points into clusters based on their similarity.
- Machine learning: PSO can be used to optimize the hyperparameters of a machine learning model, such as the learning rate or the regularization coefficient.
- Control systems: PSO can be used to design controllers for dynamic systems.
- Scheduling: PSO can be used to schedule tasks in a way that minimizes makespan or maximizes the utilization of resources.
- Network design: PSO can be used to design networks, such as communication or transportation networks, in a way that minimizes costs or maximizes efficiency.

Here is a pseudocode of the PSO algorithm:

Algorithm 2 Particle Swarm Optimization (PSO) algorithm

1: Initialize the positions and velocities of the particles in the population randomly.
2: Evaluate the fitness of each particle.
3: **while** $iter \leq max_{iter}$ **do**
- Update the velocity of each particle using the equation: $V(iter+1) = w * V(iter) + c1 * rand() * (pbest - X(iter)) + c2 * rand() * (gbest - X(iter))$
- Update the position of each particle using the equation: $X(iter+1) = X(iter) + V(iter+1)$
- Evaluate the fitness of each particle.
- Update the best position of each particle and the global best position.

4: **end while**
5: Return the global best position as the solution.

4.3 MPSO for ESP

In this part, the adaptation of the proposed MPAP method to handle the ESP is defined and described in detail. The PSO is used as a component in the MPA to improve the MPA searching capabilities and solutions by enhancing the solutions with the worse fitness values. Due to the robust and high-optimization implementation of the PSO, it is utilized in this research to lead such enhancement. In addition, it has high exploitation and exploration balance, making it the best candidate for finding the optimal or near-optimal schedule. Briefly, once the MPA finishes its optimization processes, the worse solutions in the population will be filtered out into a new population and sent to the PSO to improve them. This optimization behaviour is deeply discussed below and presented in Fig. 5.

Phase 1: ESP and MPAP parameters initialization In this phase, the parameters of the ESP and the proposed MPAP are initialized in this phase. The ESP parameters include **SP**, **NSP**, **T**, **OC**, **OTs**, **OTe**, **EC**, **NEC**, **pc**, whereas the MPAP parameters are β, P, $FADs$, $wMax$, $wMin$, $c1$, and $c2$. The population size (N), iterations (Max_{Itr}), upper bound (ub), and lower bound (lb) are initialized for both algorithms.

Step 2: MPAP population initialization The population of the MPAP is created and initialized randomly in this phase. To initialize the population, the SAs number (d) and their starting operation time so are taken into account, as presented in Eq. 39

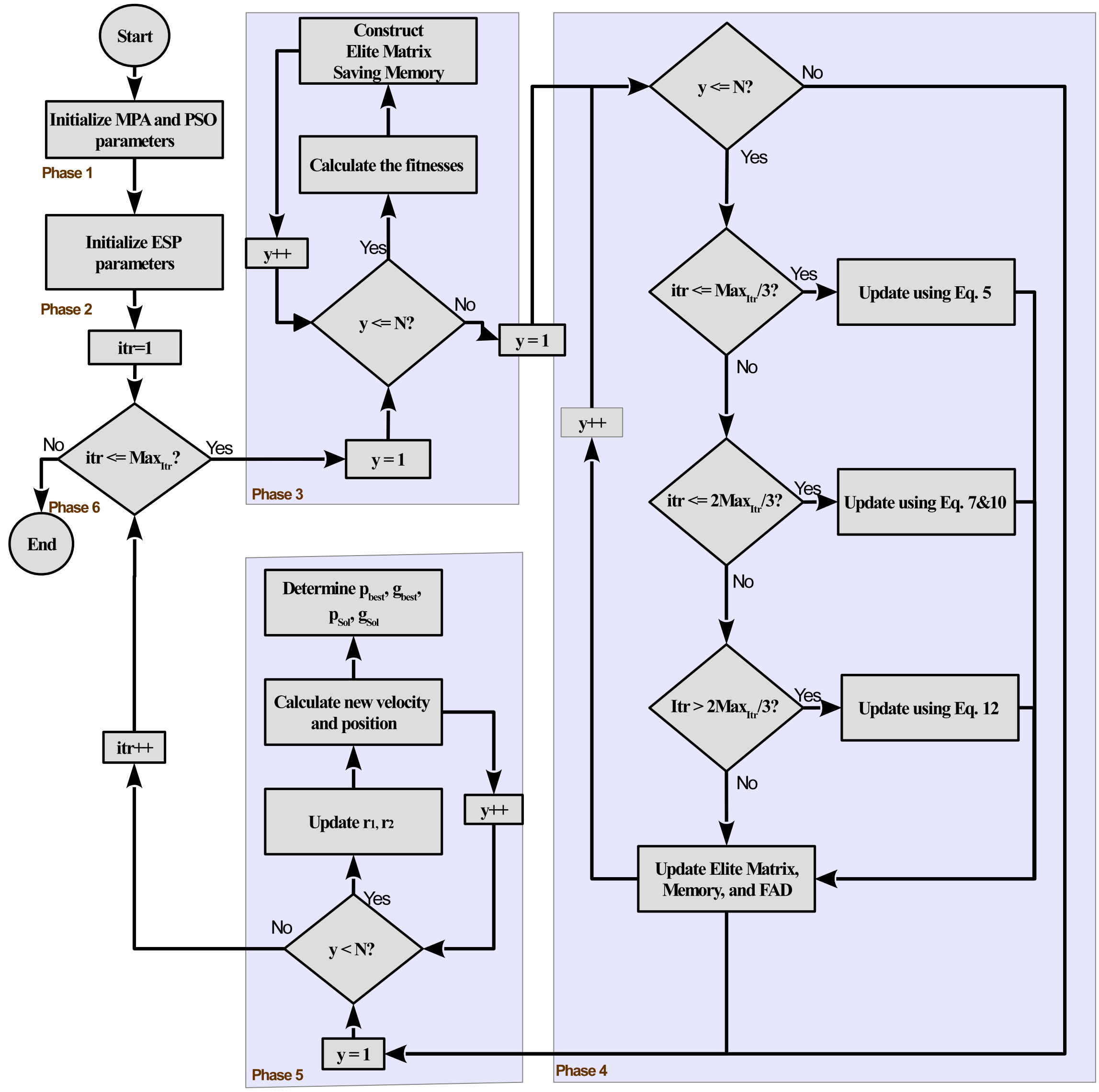


Fig. 5 The MPAP Adaptation Phases for ESP

$$\textit{MPAP Population} = \begin{bmatrix} so_1^1 & so_2^1 & \cdots & so_d^1 \\ so_1^2 & so_2^2 & \cdots & so_d^2 \\ \vdots & \vdots & \cdots & \vdots \\ so_1^N & so_2^N & \cdots & so_d^N \end{bmatrix}, \tag{39}$$

Phase 3: Solutions Evaluation In this phase, the objective function (Eq. 23) is used to evaluate the generated solutions in the population. Subsequently, the Elite matrix in MPA will be generated, and the solution with the best fitness value will be assigned to the top predator solution X^I. Furthermore, the saving memory will be created.

Phase 4: MPA operation The search agents of the MPA will start their operations for searching and updating their positions in attempting to find better schedules for the ESP in this phase. Equations 28, 30, 32, and 35 will be used to in the updating processes for the search agents. Thereafter, The effect of FADs will be involved and updated using Eq. 36. Subsequently, a new solution will be generated and evaluated using Eq. 23. Accordingly, the memory and Elite matrix will be modified.

Phase 5: PSO operation The PSO will start its optimization operation in this phase. Initially, all solutions in the population will be sorted ascending on the basis of their fitness values. The PSO will consider the first half of the new sorted solution as an input to its population. After that, the best global solution will be assigned to $gbest$ and the best personal to $pbest$. Subsequently, the PSO will start updating the solutions and its best solutions ($gbest$

Table 1 SAs time parameters

NO.	Appliances	LOC	OTPs–OTPe	NO.	Appliances	LOC	OTPs–OTPe
1	DW	105	540–780	19	DH	30	1–120
2	DW	105	840–1080	20	DH	30	120–240
3	DW	105	1200–1440	21	DH	30	240–360
4	Aircon	30	1–120	22	DH	30	360–480
5	Aircon	30	120–240	23	DH	30	480–600
6	Aircon	30	240–360	24	DH	30	600–720
7	Aircon	30	360–480	25	DH	30	720–840
8	Aircon	30	480–600	26	DH	30	840–960
9	Aircon	30	600–720	27	DH	30	960–1080
10	Aircon	30	720–840	28	DH	30	1080–1200
11	Aircon	30	840–960	29	DH	30	1200–1320
12	Aircon	30	960–1080	30	DH	30	1320–1440
13	Aircon	30	1080–1200	31	Electric Water Heater	35	300–420
14	Aircon	30	1200–1320	32	Electric Water Heater	35	1100–1440
15	Aircon	30	1320–1440	33	Coffee Maker	10	300–450
16	Washing Machine	55	60–300	34	Coffee Maker	10	1020–1140
17	Clothes Dryer	60	300–480	35	Robotic Pool Filter	180	1–540
18	Refrigerator	1440	1–1440	36	Robotic Pool Filter	180	900–1440

and *pbest*). In the end, the PSO will send its solutions to the MPA and add the best of them to the population.

Phase 6: Check the stop criterion In this phase, the third, fourth, and fifth phases will be reprised until reaching the stop state.

5 Experiment Results

5.1 Dataset Design

In this section, the experimental procedures and proposed dataset used to examine and test the proposed methods is presented. Seven different scenarios are evaluated using the average of thirty separate runs each to ensure a fair and thorough evaluation of all scenarios [17, 50]. The proposed dataset includes 36 SAs and 14 NSAs, which are listed in Tables 1 and 2, respectively [18, 21].

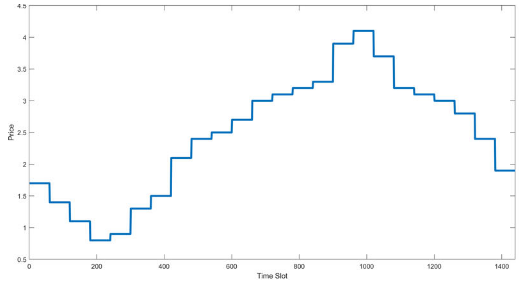
In this study, we utilized a demand pricing system that combines RTP and IBR to flatten the energy consumption curve as much as possible. The RTP was selected for its ability to provide prices based on users' actual consumption, and the IBR was used because it helps to reduce peak consumption at certain times [4, 16]. The RTP used in this evaluation was adopted from the Commonwealth Edison Company (Hourly Pricing, n.d.). Figure 6 illustrates the RTP for seven scenarios. In the IBR, the parameter λ was set to 1.543 according to Eq. 13 [16, 17]. The time horizon, T, was divided into 1440 minutes, with each minute representing a time slot. The values of the proposed MPAP parameters and the weight of each objective in Eq. 23 are listed in Table 3.

Table 2 NSAs characteristics

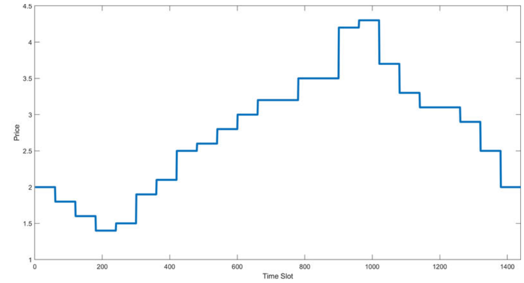
No.	Appliances	Power (kW)
1	Cleaner [16]	1.5
2	TV [51]	0.3
3	Hair Dryer [51]	1.2
4	Hand Drill [51]	0.6
5	Water Pump [51]	2.5
6	Blender [51]	0.3
7	Microwave [30]	1.18
8	Electric Vehicle [52]	9
10	Computer Charger [51]	1.5
11	Toaster [51]	1
12	Iron [30]	1.5
13	Table Fan [51]	0.8
14	Attic Fan [51]	0.3
15	Light [30]	0.6

5.2 Experimental Evaluation

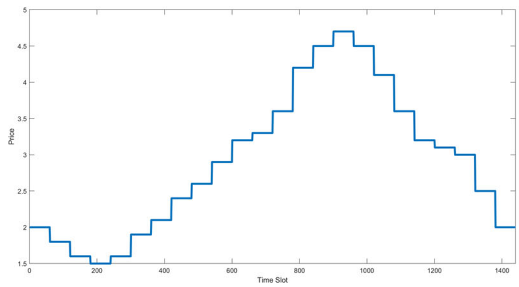
This section presents the impact of utilizing RESs on the results of the adapted methods, including DE, GWO, MPA, MVO, and WDO, where the adapted methods are compared with its method-based RES (RES with DE (RDE), RES with



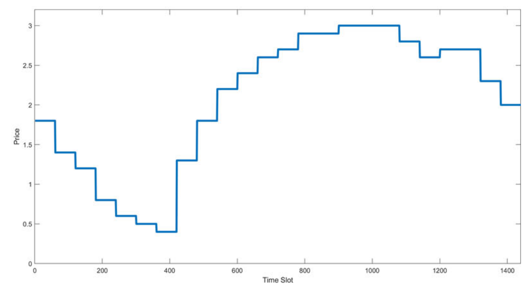
(a) Price curve for scenario#1



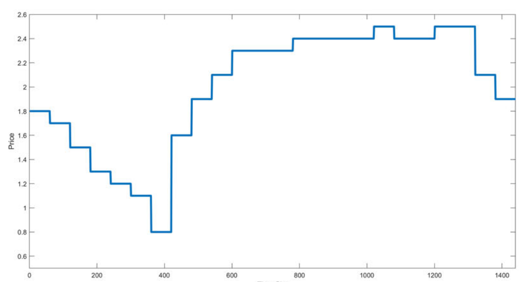
(b) Price curve for scenario#2



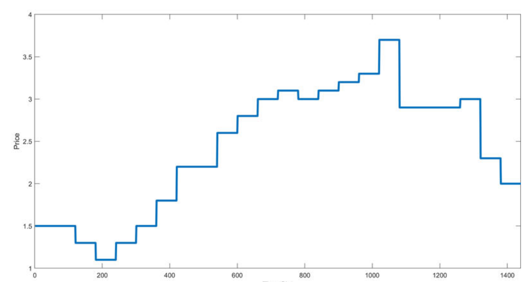
(c) Price curve for scenario#3



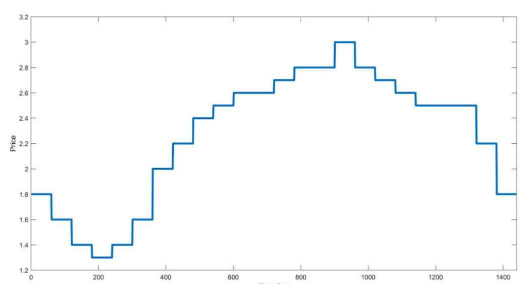
(d) Price curve for scenario#4



(e) Price curve for scenario#5



(f) Price curve for scenario#6



(g) Price curve for scenario#7

Fig. 6 The price curve for seven scenarios

Table 3 Parameters of MPA and PSO algorithms

Parameter	Value
$thres$	0.5
$beta$	1.5
P	0.5
$FADs$	0.2
$wMax$	1
$wMin$	0.4
$c1$	2
$c2$	2
w_1	0.4
w_2, w_3, w_4	0.2
Max Iteration ($Iter$)	1000
Population Size (N)	40

GWO (RGWO), RES with MPA (RMPA), RES with MVO (RMVO), and RES with WDO (RWDO)). Furthermore, the new hybrid methods with RESs are presented, tested, evaluated, and compared with their original versions to present the high performance of the proposed hybrid approach in enhancing the outcomes. The new hybrid methods with RESs are called RDEP, RGWOP, RMPAP, RMVOP, and RWDOP, respectively. Also, to show the performance of the best hybrid method with RESs, the results obtained by these five methods are compared. Finally, statistical analysis on the basis of the results obtained by the best hybrid method with RESs is presented to show the significant results.

5.2.1 RES Impact on the Original Methods

The enhancement of the RESs on the results of the original methods is evaluated in this section, where the obtained results by method-based RES are compared with those of the original methods.

Table 4 presents the EBs achieved by all original and RES methods. It is clearly noticed that the RESs have a very high impact on the values of the EBs for all proposed methods and utilized scenarios, where the proposed RDE, RGWO, RMPA, RMVO, and RWDO obtained much better EBs than the original methods in all scenarios, where the bold results indicate the best. Furthermore, the methods-based RES outperformed all original methods in obtaining the best average EB among all scenarios.

In terms of PAR reduction, the PAR values obtained by all original and RES methods are presented in Table 5. It is notable from the table that the impact of RES on optimizing PAR is terrible, where the original methods achieved the best PAR values in all scenarios compared to the RES methods. These results are not due to an increment in the highest energy consumption, but it is because of the RESs impact in reducing the average energy consumed throughout a day (see Eq. 14). In other words, when the average energy consumed is reduced by the RESs without decreasing the highest energy consumption, the PAR value will be increased. Figure 7 describes the energy consumption differences between the two approaches.

Tables 6 and 7 show the two UC parameters, including WTL and CEL, respectively, obtained by the RES and original methods. As presented in the tables, most of the original methods performed better in optimizing the WTL, where using the RES makes more available time slots with low prices to operate the appliances even if not at the beginning of the operation period. On the other hand, the RES methods outperformed the original ones in optimizing CEL in all scenarios. These results are due to the RES enhancements in giving more flexibility and energy to operate NSA.

To show the impact of the RES on enhancing the UC in general, a comparison based on the UC results is conducted and presented in Table 8. The Presented results proved the high performance of the RES in enhancing the UC level, where the RES methods outperformed all original methods and achieved better UC outcomes. In addition, the RES methods obtained better average improvements.

To show the overall enhancement for the results obtained by the original and RES methods, the fitness values (FF) for all methods and all scenarios are presented in Table 9. The table compares FF achieved by each method and its RES version for all scenarios. The presented results proved the high performance of the proposed RES approach in improving the overall results, where it obtained the best results among all scenarios and average reduction.

5.2.2 Proposed Hybrid Approach Impact on RES Methods

In this section, the hybrid methods with RES (i.e., RDEP, RGWOP, RMPAP, RMVOP, and RWDOP) are tested, evaluated, and compared with the RES methods to show the enhancement of utilizing the proposed hybrid approach on the results and schedules. Table 10 shows the EBs obtained by the proposed methods with RES and RES methods for each scenario. It can be noticed that some hybrid approaches with RES obtained better results in some scenarios and worse results in others, where RDEP, RGWOP, RMPAP, RMVOP, and RWDOP achieved better EBs in 3, 4, 7, 5, and 4 scenarios, respectively, as highlighted in bold. For the average reduction, only RMPAP and RMVOP got the best results.

Similarly, in optimizing PAR values, the proposed hybrid methods with RES obtained better results in some scenarios, where RDEP, RGWOP, RMPAP, RMVOP, and RWDOP got better PAR in 3, 5, 1, 4, and 5 scenarios, respectively. In terms of average PAR reduction, three hybrid methods with RES achieved the best results.

The same behaviour is noticed in optimizing WTL and CEL in Tables 12 and 13, where RDEP and RWDOP got the

Table 4 Comparison between method-based RES and original method in terms of EB

Scenario	DE	RDE	GWO	RGWO	MPA	RMPA	MVO	RMVO	WDO	RWDO
S1	43.81	**11.11**	43.50	**13.24**	32.04	**12.04**	43.03	**10.05**	43.16	**10.73**
S2	64.96	**12.31**	64.56	**7.59**	45.71	**7.27**	64.07	**11.61**	65.06	**12.98**
S3	67.44	**22.73**	66.11	**26.23**	68.32	**24.57**	65.88	**21.79**	66.15	**23.19**
S4	64.26	**9.53**	62.59	**10.75**	63.13	**8.67**	61.48	**7.37**	64.65	**9.26**
S5	47.57	**12.36**	46.29	**12.94**	46.94	**11.32**	46.03	**10.63**	46.29	**12.45**
S6	52.78	**8.65**	52.30	**8.85**	52.76	**8.68**	52.21	**8.33**	52.67	**8.74**
S7	63.35	**14.77**	62.64	**15.52**	63.71	**14.12**	62.62	**13.18**	64.41	**16.95**
AVG	57.74	**13.06**	56.86	**13.59**	53.23	**12.38**	56.47	**11.85**	57.48	**13.47**

Table 5 Comparison between method-based RES and original method in terms of PAR

Scenario	DE	RDE	GWO	RGWO	MPA	RMPA	MVO	RMVO	WDO	RWDO
S1	**2.604**	6.373	**2.600**	6.245	**2.602**	6.309	**2.582**	6.463	**2.639**	6.328
S2	**2.445**	7.348	**2.445**	7.322	**2.445**	7.457	**2.429**	7.646	**2.870**	7.757
S3	**2.231**	4.598	**2.227**	4.515	**2.229**	4.735	**2.222**	4.721	**2.315**	4.502
S4	**2.110**	5.685	**2.228**	5.682	**2.242**	5.753	**2.182**	6.516	**2.525**	8.091
S5	**2.231**	6.163	**2.231**	6.021	**2.225**	6.354	**2.231**	6.785	**2.231**	5.847
S6	**2.523**	7.975	**2.523**	7.851	**2.523**	7.949	**2.516**	8.310	**2.575**	7.857
S7	**2.007**	5.801	**2.042**	5.946	**2.151**	6.007	**2.232**	6.269	**2.594**	7.179
AVG	**2.307**	6.278	**2.328**	6.226	**2.345**	6.366	**2.342**	6.673	**2.536**	6.794

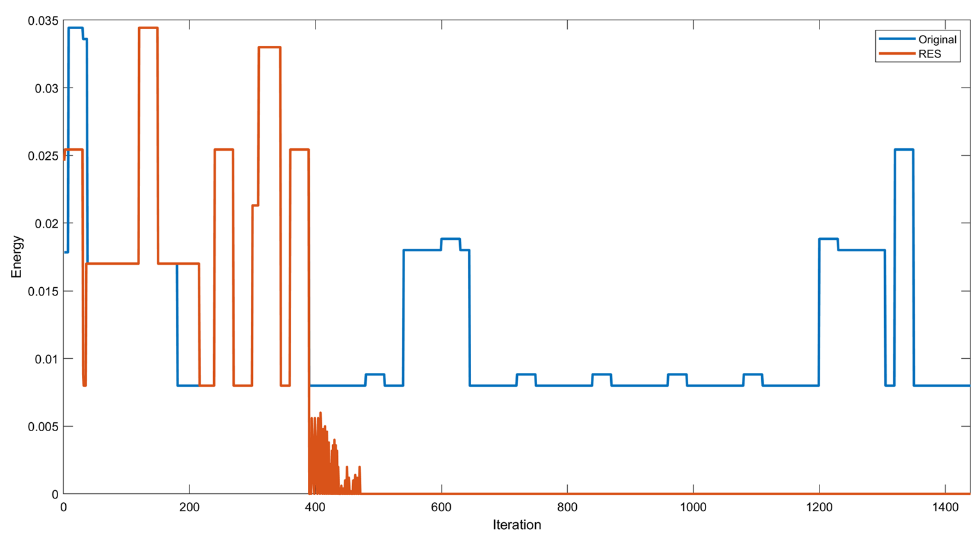


Fig. 7 Energy consumption differences between the original and RES approaches

Table 6 Comparison between method-based RES and original method in terms of WTL

Scenario	DE	RDE	GWO	RGWO	MPA	RMPA	MVO	RMVO	WDO	RWDO
S1	**0.0151**	0.1692	0.0302	**0.0043**	**0.0136**	0.0341	**0.0881**	0.1203	**0.0329**	0.0387
S2	**0.0046**	0.1901	**0.0242**	0.0307	**0.0171**	0.0419	**0.0590**	0.1253	**0.0146**	0.0670
S3	**0.0281**	0.1387	0.0379	**0.0106**	**0.0132**	0.0263	**0.0801**	0.1026	0.0392	**0.0180**
S4	**0.0293**	0.1369	0.0580	**0.0268**	**0.0300**	0.0686	**0.1366**	0.1961	**0.0185**	0.0468
S5	**0.0281**	0.1457	0.0397	**0.0110**	**0.0171**	0.0407	**0.0861**	0.1312	0.0424	**0.0241**
S6	**0.0136**	0.1450	0.0269	**0.0073**	**0.0102**	0.0213	**0.0757**	0.1040	**0.0216**	0.0387
S7	**0.0260**	0.1426	0.0587	**0.0339**	**0.0262**	0.0647	**0.1162**	0.1886	**0.0115**	0.0276
AVG	**0.0207**	0.1526	0.0394	**0.0178**	**0.0182**	0.0425	**0.0917**	0.1383	**0.0258**	0.0373

Table 7 Comparison between method-based RES and original method in terms of CEL

Scenario	DE	RDE	GWO	RGWO	MPA	RMPA	MVO	RMVO	WDO	RWDO
S1	0.3122	**0.2013**	0.3148	**0.2021**	0.3133	**0.2033**	0.3185	**0.1988**	0.3147	**0.2057**
S2	0.3449	**0.1490**	0.3455	**0.1536**	0.3472	**0.1531**	0.3463	**0.1463**	0.3432	**0.1591**
S3	0.3812	**0.2251**	0.3815	**0.2267**	0.3788	**0.2212**	0.3851	**0.2239**	0.3800	**0.2351**
S4	0.5044	**0.2208**	0.5034	**0.2137**	0.4994	**0.2192**	0.5132	**0.2026**	0.4943	**0.2153**
S5	0.3812	**0.1963**	0.3822	**0.2020**	0.3796	**0.1960**	0.3862	**0.1847**	0.3804	**0.2059**
S6	0.3482	**0.1612**	0.3505	**0.1649**	0.3482	**0.1636**	0.3509	**0.1567**	0.3494	**0.1662**
S7	0.4629	**0.2150**	0.4688	**0.2067**	0.4605	**0.2064**	0.4665	**0.1998**	0.4498	**0.2197**
AVG	0.3907	**0.1955**	0.3924	**0.1957**	0.3896	**0.1947**	0.3952	**0.1875**	0.3874	**0.2010**

Table 8 Comparison between method-based RES and original method in terms of UC

Scenario	DE	RDE	GWO	RGWO	MPA	RMPA	MVO	RMVO	WDO	RWDO
S1	**83.64**	81.48	82.75	**89.68**	83.66	**88.13**	79.67	**84.04**	82.62	**87.78**
S2	82.52	**83.04**	81.51	**90.79**	81.79	**90.25**	79.74	**86.42**	82.11	**88.69**
S3	79.54	**81.81**	79.03	**88.13**	80.40	**87.62**	76.74	**83.68**	79.04	**87.35**
S4	73.31	**82.12**	71.93	**87.97**	73.53	**85.61**	67.51	**80.06**	74.36	**86.90**
S5	79.54	**82.90**	78.91	**89.35**	80.17	**88.17**	76.39	**84.21**	78.86	**88.50**
S6	81.91	**84.69**	81.13	**91.39**	82.08	**90.76**	78.67	**86.97**	81.45	**89.75**
S7	75.55	**82.12**	73.62	**87.97**	75.67	**86.45**	70.86	**80.58**	76.93	**87.63**
AVG	79.43	**82.59**	78.41	**89.33**	79.61	**88.14**	75.65	**83.71**	79.34	**88.09**

Table 9 Comparison between method-based RES and original method in terms of FF

Scenario	DE	RDE	GWO	RGWO	MPA	RMPA	MVO	RMVO	WDO	RWDO
S1	**0.3484**	0.3543	0.3531	**0.3290**	0.3511	**0.3257**	0.3610	**0.3402**	0.3532	**0.3284**
S2	0.3569	**0.3393**	0.3594	**0.2950**	0.3550	**0.2983**	0.3683	**0.3180**	0.3674	**0.3228**
S3	0.3651	**0.3549**	0.3630	**0.3306**	0.3613	**0.3329**	0.3703	**0.3388**	0.3623	**0.3290**
S4	0.3899	**0.3466**	0.3952	**0.3426**	0.3924	**0.3264**	0.4086	**0.3497**	0.3940	**0.3537**
S5	0.3621	**0.3530**	0.3650	**0.3265**	0.3600	**0.3196**	0.3752	**0.3447**	0.3632	**0.3341**
S6	0.3648	**0.3527**	0.3659	**0.3310**	0.3642	**0.3296**	0.3736	**0.3332**	0.3654	**0.3252**
S7	0.3812	**0.3490**	0.3804	**0.3363**	0.3832	**0.3279**	0.3992	**0.3418**	0.3856	**0.3455**
AVG	0.3669	**0.3500**	0.3688	**0.3273**	0.3668	**0.3229**	0.3795	**0.3380**	0.3702	**0.3341**

Table 10 Comparison between hybrid method with RES and RES methods in terms of EB

Scenario	RDE	RDEP	RGWO	RGWOP	RMPA	RMPAP	RMVO	RMVOP	RWDO	RWDOP
S1	**11.11**	12.57	**13.24**	**13.24**	12.04	**11.64**	10.05	**10.01**	10.73	**10.70**
S2	12.31	**12.14**	7.59	**7.56**	7.27	**7.17**	11.61	**11.44**	**12.98**	13.17
S3	**22.73**	22.95	**26.23**	**26.23**	24.57	**24.09**	21.79	**21.74**	**23.19**	**23.19**
S4	**9.53**	9.59	10.75	**10.72**	8.67	**7.87**	**7.37**	**7.37**	**9.26**	9.61
S5	12.36	**12.08**	**12.94**	12.99	11.32	**11.15**	**10.63**	10.78	12.45	**12.39**
S6	**8.65**	9.97	**8.85**	8.86	8.68	**8.61**	**8.33**	8.37	**8.74**	8.78
S7	14.77	**14.64**	**15.52**	15.59	14.12	**13.50**	13.18	**13.08**	16.95	**16.88**
AVG	**13.06**	13.42	**13.59**	13.60	12.38	**12.00**	11.85	**11.83**	**13.47**	13.53

Table 11 Comparison between hybrid method with RES and RES methods in terms of PAR

Scenario	RDE	RDEP	RGWO	RGWOP	RMPA	RMPAP	RMVO	RMVOP	RWDO	RWDOP
S1	6.373	**6.323**	**6.245**	**6.245**	**6.309**	6.358	6.463	**6.406**	6.328	**6.249**
S2	**7.348**	7.504	**7.322**	7.358	**7.457**	7.519	**7.646**	7.731	7.757	**7.710**
S3	4.598	**4.568**	**4.515**	**4.515**	**4.735**	4.736	**4.721**	4.723	**4.502**	**4.502**
S4	**5.685**	5.767	5.682	**5.678**	**5.753**	6.037	**6.516**	6.710	8.091	**7.728**
S5	**6.163**	6.169	**6.021**	6.031	6.354	**6.329**	6.785	**6.659**	**5.847**	5.862
S6	7.975	**7.451**	7.851	**7.848**	**7.949**	8.011	8.310	**8.174**	7.857	**7.838**
S7	**5.801**	5.864	5.946	**5.920**	**6.007**	6.087	6.269	**6.249**	**7.179**	7.180
AVG	6.278	**6.235**	**6.226**	6.228	**6.366**	6.440	6.673	**6.664**	6.794	**6.724**

Table 12 Comparison between hybrid method with RES and RES methods in terms of WTL

Scenario	RDE	RDEP	RGWO	RGWOP	RMPA	RMPAP	RMVO	RMVOP	RWDO	RWDOP
S1	0.1692	**0.0964**	**0.0043**	**0.0043**	**0.0341**	0.0448	**0.1203**	0.1227	**0.0387**	0.0394
S2	**0.1901**	0.2073	**0.0307**	0.0330	**0.0419**	0.0488	**0.1253**	0.1334	0.0670	**0.0617**
S3	0.1387	**0.1375**	0.0106	**0.0102**	**0.0263**	0.0303	0.1026	**0.0946**	**0.0180**	**0.0180**
S4	0.1369	**0.1368**	**0.0268**	0.0306	**0.0686**	0.0972	0.1961	**0.1868**	0.0468	**0.0340**
S5	**0.1457**	0.1458	0.0110	**0.0087**	**0.0407**	0.0415	0.1312	**0.1234**	**0.0241**	0.0255
S6	0.1450	**0.0738**	**0.0073**	**0.0073**	**0.0213**	0.0287	0.1040	**0.0977**	0.0387	**0.0349**
S7	**0.1426**	0.1453	0.0339	**0.0320**	**0.0647**	0.0787	0.1886	**0.1752**	**0.0276**	0.0297
AVG	0.1526	**0.1347**	**0.0178**	0.0180	**0.0425**	0.0529	0.1383	**0.1334**	0.0373	**0.0348**

Table 13 Comparison between hybrid method with RES and RES methods in terms of CEL

Scenario	RDE	RDEP	RGWO	RGWOP	RMPA	RMPAP	RMVO	RMVOP	RWDO	RWDOP
S1	**0.2013**	0.2156	**0.2021**	**0.2021**	0.2033	**0.2020**	**0.1988**	0.2014	**0.2057**	0.2064
S2	0.1490	**0.1473**	0.1536	**0.1525**	0.1531	**0.1518**	0.1463	**0.1448**	**0.1591**	0.1592
S3	**0.2251**	0.2256	0.2267	**0.2265**	**0.2212**	0.2233	0.2239	**0.2236**	**0.2351**	**0.2351**
S4	0.2208	**0.2202**	**0.2137**	0.2148	0.2192	**0.2082**	**0.2026**	0.2062	**0.2153**	0.2189
S5	**0.1963**	0.1985	0.2020	**0.2018**	**0.1960**	0.1973	**0.1847**	0.1868	**0.2059**	**0.2059**
S6	**0.1612**	0.1688	**0.1649**	**0.1649**	0.1636	**0.1622**	**0.1567**	0.1581	0.1662	**0.1661**
S7	0.2150	**0.2139**	**0.2067**	0.2080	0.2064	**0.2033**	0.1998	**0.1977**	**0.2197**	0.2198
AVG	**0.1955**	0.1986	**0.1957**	0.1958	0.1947	**0.1926**	**0.1875**	0.1884	**0.2010**	0.2016

Table 14 Comparison between hybrid method with RES and RES methods in terms of FF

Scenario	RDE	RDEP	RGWO	RGWOP	RMPA	RMPAP	RMVO	RMVOP	RWDO	RWDOP
S1	0.3543	**0.3500**	0.3290	**0.3267**	**0.3257**	0.3258	**0.3402**	0.3410	**0.3284**	0.3319
S2	**0.3393**	0.3409	**0.2950**	0.2980	**0.2983**	0.2993	**0.3180**	0.3270	0.3228	**0.3208**
S3	**0.3549**	0.3553	**0.3306**	0.3319	0.3329	**0.3306**	**0.3388**	0.3403	**0.3290**	0.3296
S4	**0.3466**	0.3506	0.3426	**0.3394**	0.3264	**0.3184**	**0.3497**	0.3531	**0.3537**	0.3586
S5	0.3530	**0.3467**	**0.3265**	0.3288	0.3196	**0.3162**	0.3447	**0.3422**	0.3341	**0.3335**
S6	0.3527	**0.3495**	0.3310	**0.3253**	**0.3296**	0.3302	0.3332	**0.3327**	0.3252	**0.3239**
S7	0.3490	**0.3468**	0.3363	**0.3311**	0.3279	**0.3265**	0.3418	**0.3394**	**0.3455**	0.3476
AVG	0.3500	**0.3486**	0.3273	**0.3259**	0.3229	**0.3210**	**0.3380**	0.3394	**0.3341**	0.3351

best WTL IN 4 scenarios and RGWOP and RMVOP in 5 scenarios. RMPAP achieved the worse WTL in all scenarios. In terms of CEL, RDEP, RMVOP, and RWDOP achieved better results in 3 scenarios, whereas RGWOP and RMPAP in 5 scenarios.

As presented and noticed in previous tables, the results obtained by the proposed hybrid methods with RES and the RES methods are fluctuated, where the hybrid methods with RES got better results in some scenarios and objectives and RES methods performed better in others. Therefore, the FF parameter is included in this comparison to show the overall reduction and present the best approach to optimizing all objectives simultaneously. FF results obtained by the two approaches are presented in Table 14. The table shows that RDEP, RGWOP, and RMPAP outperformed the methods with RES in optimizing all objectives in most scenarios and the average reduction. However, RMVO and RWDO achieved better outcomes than RMVOP and RWDOP with only minor improvements up to 0.001.

5.2.3 Comparison Based on the Hybrid Methods

This section conducts a comparison between the proposed hybrid methods with RES (i.e., RDEP, RGWOP, RMPAP, RMVOP, RWDOP), to present the best-utilized hybrid method among all methods. The comparison is conducted based on the ESP objectives.

Table 15 shows the achieved EBs by the proposed hybrid methods, where the bold results indicate the best. The RMVOP method got the best EB compared to all methods in 6 scenarios and average reduction, whereas the RMPAP achieved the best EB in the second scenario. However, in terms of PAR reduction, the results are not stable for one method, as presented in Table 16, where RGWOP obtained the best outcomes in three scenarios and the average reduction, and RDEP and RWDOP performed better in two scenarios. Accordingly, no method achieved significant PAR reduction among all methods.

For the UC parameters, the RGWOP indicates the best performance in optimizing WTL for all seven scenarios, as shown in Table 17. In addition, it reached the best average WTL reduction. In terms of CEL optimization, RMVOP outperformed all methods in six scenarios, whereas RMPAP got the best outcomes in the third scenario, as presented in Table 18. According to these results, the best average CEL reduction for all scenarios is obtained by RMVOP.

The UC improvements by all hybrid methods are presented and compared in Table 19. The results verified the robust optimization performance of RGWOP in improving the UC, where it outperformed all compared methods and obtained the best average UC for all scenarios.

As mentioned previously, when the obtained results by the compared methods are fluctuated, FF should be presented

Table 15 Comparison between hybrid method with RES in terms of EB

Scenario	RDEP	RGWOP	RMPAP	RMVOP	RWDOP
S1	12.57	13.24	11.64	**10.01**	10.70
S2	12.14	7.56	**7.17**	11.44	13.17
S3	22.95	26.23	24.09	**21.74**	23.19
S4	9.59	10.72	7.87	**7.37**	9.61
S5	12.08	12.99	11.15	**10.78**	12.39
S6	9.97	8.86	8.61	**8.37**	8.78
S7	14.64	15.59	13.50	**13.08**	16.88
AVG	13.42	13.60	12.00	**11.83**	13.53

Table 16 Comparison between hybrid method with RES in terms of PAR

Scenario	RDEP	RGWOP	RMPAP	RMVOP	RWDOP
S1	6.323	**6.245**	6.358	6.406	6.249
S2	7.504	**7.358**	7.519	7.731	7.710
S3	4.568	4.515	4.736	4.723	**4.502**
S4	5.767	**5.678**	6.037	6.710	7.728
S5	6.169	6.031	6.329	6.659	**5.862**
S6	**7.451**	7.848	8.011	8.174	7.838
S7	**5.864**	5.920	6.087	6.249	7.180
AVG	6.235	**6.228**	6.440	6.664	6.724

Table 17 Comparison between hybrid method with RES in terms of WTL

Scenario	RDEP	RGWOP	RMPAP	RMVOP	RWDOP
S1	0.0964	**0.0043**	0.0448	0.1227	0.0394
S2	0.2073	**0.0330**	0.0488	0.1334	0.0617
S3	0.1375	**0.0102**	0.0303	0.0946	0.0180
S4	0.1368	**0.0306**	0.0972	0.1868	0.0340
S5	0.1458	**0.0087**	0.0415	0.1234	0.0255
S6	0.0738	**0.0073**	0.0287	0.0977	0.0349
S7	0.1453	**0.0320**	0.0787	0.1752	0.0297
AVG	0.1347	**0.0180**	0.0529	0.1334	0.0348

Table 18 Comparison between hybrid method with RES in terms of CPL

Scenario	RDEP	RGWOP	RMPAP	RMVOP	RWDOP
S1	0.2156	0.2021	0.2020	**0.2014**	0.2064
S2	0.1473	0.1525	0.1518	**0.1448**	0.1592
S3	0.2256	0.2265	**0.2233**	0.2236	0.2351
S4	0.2202	0.2148	0.2082	**0.2062**	0.2189
S5	0.1985	0.2018	0.1973	**0.1868**	0.2059
S6	0.1688	0.1649	0.1622	**0.1581**	0.1661
S7	0.2139	0.2080	0.2033	**0.1977**	0.2198
AVG	0.1986	0.1958	0.1926	**0.1884**	0.2016

Table 19 Comparison between hybrid method with RES in terms of UC

Scenario	RDEP	RGWOP	RMPAP	RMVOP	RWDOP
S1	84.4006	**89.6804**	87.6612	83.7914	87.7136
S2	82.2689	**90.7268**	89.9700	86.0912	88.9543
S3	81.8480	**88.1662**	87.3164	84.0916	87.3443
S4	82.1498	**87.7344**	84.7286	80.3491	87.3548
S5	82.7854	**89.4736**	88.0595	84.4898	88.4273
S6	87.8702	**91.3905**	90.4548	87.2117	89.9486
S7	82.0430	**88.0033**	85.9001	81.3550	87.5263
AVG	83.3380	**89.3107**	87.7272	83.9114	88.1813

Table 20 Comparison between hybrid method with RES in terms of FF

Scenario	RDEP	RGWOP	RMPAP	RMVOP	RWDOP
S1	0.3500	0.3267	**0.3258**	0.3410	0.3319
S2	0.3409	**0.2980**	0.2993	0.3270	0.3208
S3	0.3553	0.3319	0.3306	0.3403	**0.3296**
S4	0.3506	0.3394	**0.3184**	0.3531	0.3586
S5	0.3467	0.3288	**0.3162**	0.3422	0.3335
S6	0.3495	0.3253	0.3302	0.3327	**0.3239**
S7	0.3468	0.3311	**0.3265**	0.3394	0.3476
AVG	0.3486	0.3259	**0.3210**	0.3394	0.3351

and compared to show the best method in reaching the best overall reduction for all objectives. The achieved FF results by all hybrid methods are shown in Table 20. The presented results clearly show the high performance of the RMPAP in optimizing all objectives in most scenarios and the best average reduction. Even the RMPAP did not show the best results in optimizing the objectives individually; it obtained the best overall reduction. This is due to its searching behaviour to reach the optimal schedule considering all objectives and constraints simultaneously.

In order to show the optimization behaviour of all methods graphically during the optimization processes, the convergence behaviour toward the optimal schedule is shown in Fig. 8. The figure presents the high and robust performance of RMPAP in approaching its optimal schedule among other methods, where it reached the finest FF in four scenarios. Furthermore, it emphasizes the capabilities of exploration and exploitation by approaching a high balance between them and moving smoothly toward its optimal schedule with no stagnation in local optima, particulate in the last third of its optimization processes.

Table 21 Comparison between hybrid method with RES and state-of-the-art in terms of EB

Scenario	HGPO	GWD	HGWDE	RMPAP
S1	13.17	14.04	13.00	**11.64**
S2	14.01	14.02	12.34	**7.17**
S3	22.10	22.39	**21.93**	24.09
S4	7.26	8.65	**6.46**	7.87
S5	11.11	12.04	**10.66**	11.15
S6	8.03	8.87	**6.56**	8.61
S7	13.54	14.14	**12.08**	13.50
AVG	12.74	13.45	**11.86**	12.00

Table 22 Comparison between hybrid method with RES and state-of-the-art in terms of PAR

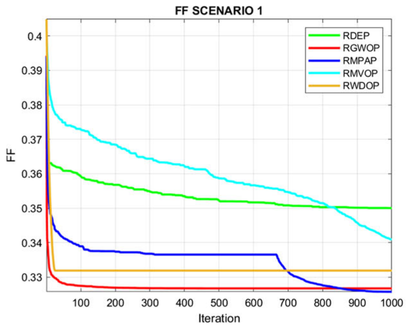
Scenario	HGPO	GWD	HGWDE	RMPAP
S1	6.311	6.342	6.342	**6.309**
S2	7.509	**7.424**	**7.424**	7.457
S3	4.707	**4.600**	**4.600**	4.735
S4	6.526	6.744	6.358	**5.753**
S5	6.474	**6.235**	**6.235**	6.354
S6	7.950	7.980	7.980	**7.949**
S7	6.112	6.658	6.042	**6.007**
AVG	6.513	6.569	6.426	**6.366**

5.2.4 Comparison Between Hybrid Methods and State-of-the-Art Methods

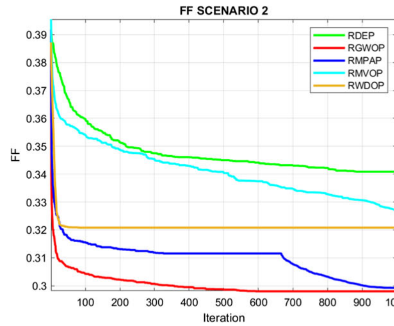
In this section, another comparison based on the results obtained by the proposed RMPAP and three state-of-the-art hybrid methods is presented. This comparison is conducted on the basis of all ESP objectives using the presented datasets in Sect. 5.1. The three state-of-the-art hybrid methods are HGWDE [53], GWD [31], HGPO [54]. The RMPAP is considered in this section because it outperformed all other methods in previous sections in terms of overall optimization.

Table 21 presents the EBs obtained by the compared methods. The table shows that the HGWDE method performed better than the proposed RMPAP and other compared methods in optimizing EBs for five scenarios and average reduction, as highlighted in bold. In terms of PAR reduction, the proposed method outperformed all other methods, where it got better PAR values for four scenarios and average optimization for all scenarios, as shown in Table 22.

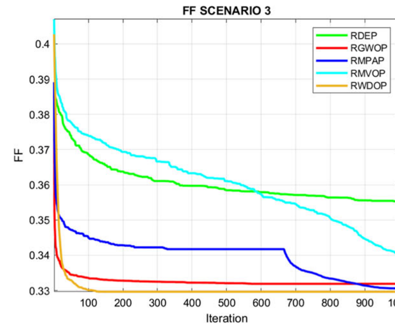
Tables 23 and 24 prove the high performance of the proposed RMPAP in achieving the best WTL and CEL, where it achieved the best outcomes among the compared methods. In addition, it reached the best average reduction. Furthermore, the RMPAP presents a high performance in improving the



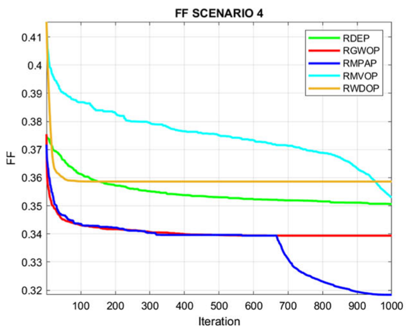
(a) Convergence of scenario#1



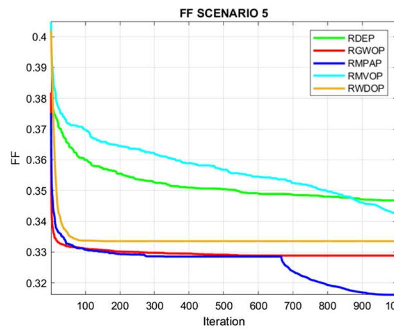
(b) Convergence of scenario#2



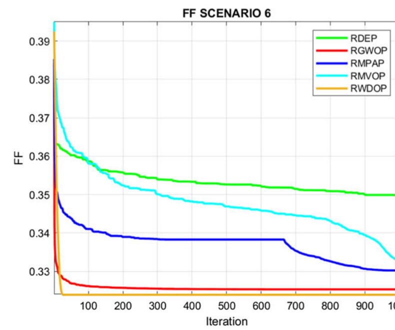
(c) Convergence of scenario#3



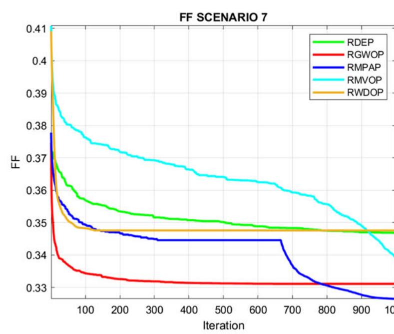
(d) Convergence of scenario#4



(e) Convergence of scenario#5



(f) Convergence of scenario#6



(g) Convergence of scenario#7

Fig. 8 Convergence behaviour of hybrid method for all scenarios

UC level, as shown in Table 25. However, the GWD methods obtained the best UC in only one scenario.

5.2.5 Discussion

In this paper, a new hybrid approach on the basis of PSO is proposed and combined with RESs to achieve the best and optimal schedule for the ESP and optimize its objectives. The same hybrid approach is employed for five optimization algorithms. These algorithms are DE, GWO, MPA, MVO, and WDO. The hybrid methods are abbreviated as EDEP, RGWOP, RMPAP, RMVOP, and RWDOP.

Table 23 Comparison between hybrid method with RES and state-of-the-art in terms of WTL

Scenario	HGPO	GWD	HGWDE	RMPAP
S1	0.0757	0.0753	0.1310	**0.0341**
S2	0.1007	0.0926	0.1908	**0.0419**
S3	0.0528	0.0867	0.1001	**0.0263**
S4	0.0802	**0.0483**	0.1835	0.0686
S5	0.0663	0.0864	0.1213	**0.0407**
S6	0.0696	0.0492	0.1308	**0.0213**
S7	0.0852	**0.0583**	0.1843	0.0647
AVG	0.0758	0.0710	0.1488	**0.0425**

Table 24 Comparison between hybrid method with RES and state-of-the-art in terms of CEL

Scenario	HGPO	GWD	HGWDE	RMPAP
S1	0.2124	**0.2030**	0.2111	0.2033
S2	0.1589	**0.1527**	0.1647	0.1531
S3	0.2414	0.2241	0.2350	**0.2212**
S4	0.2096	**0.2014**	0.2415	0.2192
S5	0.2094	0.2139	0.2083	**0.1960**
S6	0.1752	0.1822	0.1782	**0.1636**
S7	0.2290	0.2164	0.2374	**0.2064**
AVG	0.2051	0.1991	0.2109	**0.1947**

Table 25 Comparison between hybrid method with RES and state-of-the-art in terms of UC

Scenario	HGPO	GWD	HGWDE	RMPAP
S1	85.5984	86.0863	82.8953	**88.13**
S2	87.0213	87.7314	82.2236	**90.25**
S3	85.2899	84.4625	83.2423	**87.62**
S4	85.5118	**87.5170**	78.7508	85.61
S5	86.2151	84.9836	83.5227	**88.17**
S6	87.7631	88.4269	84.5520	**90.76**
S7	84.2901	86.2658	78.9175	**86.45**
AVG	85.9557	86.4962	82.0149	**88.14**

In the evaluation stage, the impact of utilizing RESs on the results of the adapted algorithms are analysed by comparing its results with that obtained by the method-based RESs. The obtained results proved the high performance of the RESs in enhancing the results and schedules. Furthermore, the proposed hybrid approach is studied by comparing its outcomes with the original methods-based RESs. The proposed method showed more efficient performance, where it obtained the best results in most of the scenarios and objectives. In addition, another comparison is conducted between the hybrid methods to show the best method for optimizing the ESP objectives. The obtained results by the compared methods are fluctuated, where some methods achieved the best results in some scenarios and objectives and the worse in others. This fluctuation is due to the multi-objective behaviour that focuses on optimizing the objective function rather than one objective. Accordingly, the proposed RMPAP did not achieve the best results in optimizing the objectives, but it reached the best for all of them together when they combined in the objective function.

In addition, the proposed RMPAP (the best hybrid method) results are compared with four state-of-the-art hybrid methods to show its performance among other methods. The RMPAP outperformed all compared methods in most objectives.

Accordingly, the proposed system (based on the results) is able to provide several benefits to the current energy management systems and users, including optimising electricity bills and comfort levels for the users and reducing the amount of energy consumed by the energy supplier companies; thus, reduce the amount of energy generation and its cost.

6 Conclusion and Future Work

The ESP, as discussed previously, is a problem of finding the best schedule for the energy consumed through a time horizon by home smart appliances to minimize EBs, PAR, and discomfort levels for users. Addressing ESP is done according to several hard and soft constraints and dynamic pricing scheme(s). The components of ESP are centralized and controlled by IoT. A new hybrid optimization method, called MPAP, based on the MPA and PSO searching components, is proposed to boost the searching capabilities of the MPA. The proposed MPAP is mainly established and utilized to enhance the schedules with the worse fitness values to improve them to be more acceptable. In addition, RESs based on a real-world dataset is utilized and used to avoid the high complexity of the ESP constraints. The RESs are utilized along the proposed MPAP method to achieve more feasible candidate solutions and find better schedules.

In the evaluation stage, four well-known optimization algorithms are adapted along the MPA: DE, GWO, MVO, and WDO). The results obtained by these algorithms are evaluated on the basis of four different comparison studies and phases. The first comparison study is conducted to show the impact of using RESs on the results obtained by the adapted algorithm. The second comparison is designed to prove the enhancement of the proposed hybrid approach and its positive impact on the results. The third comparison presents the best hybrid method among all adapted. The last comparison is conducted to compare the proposed hybrid method with four state-of-the-art methods. The presented results proved the high impact of the RESs and enhancement of the hybrid approach on the results compared with the original and the state-of-the-art methods.

In future directions, the hybrid approach based on the MPA and PSO can be enhanced by adjusting its optimization behaviour for better local and global optimization and improving the balance between them by employing a new adaptive parameter. In addition, using adjustable weights for the multiobjective function to find fitter schedules.

Acknowledgements The authors acknowledge financial support from Ajman University, Ajman, UAE

Data Availability The code and data for producing the presented results will be made available by request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

1. Yan, Y.; Qian, Y.; Sharif, H.; Tipper, D.: A survey on smart grid communication infrastructures: motivations, requirements and challenges. IEEE Commun. Surv. Tutor. **15**(1), 5–20 (2013)
2. Paul, S.; Rabbani, M.S.; Kundu, R.K.; Zaman, S.M.R.: A review of smart technology (smart grid) and its features. In: Non Conventional Energy (ICONCE), 2014 1st International Conference On, pp. 200–203 (2014). IEEE
3. Vardakas, J.S.; Zorba, N.; Verikoukis, C.V.: A survey on demand response programs in smart grids: pricing methods and optimization algorithms. IEEE Commun. Surv. Tutor. **17**(1), 152–178 (2015)
4. Makhadmeh, S.N.; Khader, A.T.; Al-Betar, M.A.; Naim, S.; Abasi, A.K.; Alyasseri, Z.A.A.: Optimization methods for power scheduling problems in smart home: survey. Renew. Sustain. Energy Rev. **115**, 109362 (2019)
5. Sharda, S.; Singh, M.; Sharma, K.: Demand side management through load shifting in IOT based hems: overview, challenges and opportunities. Sustain. Cities Soc. **65**, 102517 (2020)
6. Adriano, D.B.; Budi, W.A.C.; et al.: Iot-based integrated home security and monitoring system. In: Journal of Physics: Conference Series, vol. 1140, p. 012006 (2018). IOP Publishing
7. Wang, X.; Mao, X.; Khodaei, H.: A multi-objective home energy management system based on internet of things and optimization algorithms. J. Build. Eng. **33**, 101603 (2021)
8. Makhadmeh, S.N.; Khader, A.T.; Al-Betar, M.A.; Naim, S.: Multi-objective power scheduling problem in smart homes using grey wolf optimiser. J. Amb. Intel. Human. Comput. **10**, 1–25 (2018)
9. Iftikhar, H.; Asif, S.; Maroof, R.; Ambreen, K.; Khan, H.N.; Javaid, N.: Biogeography based optimization for home energy management in smart grid. In: International Conference on Network-Based Information Systems, pp. 177–190 (2017). Springer
10. Makhadmeh, S.N.; Al-Betar, M.A.; Alyasseri, Z.A.A.; Abasi, A.K.; Khader, A.T.; Damaševičius, R.; Mohammed, M.A.; Abdulkareem, K.H.: Smart home battery for the multi-objective power scheduling problem in a smart home using grey wolf optimizer. Electronics **10**(4), 447 (2021)
11. Colak, I.; Kabalci, E.; Fulli, G.; Lazarou, S.: A survey on the contributions of power electronics to smart grid systems. Renew. Sustain. Energy Rev. **47**, 562–579 (2015)
12. Khan, A.R.; Mahmood, A.; Safdar, A.; Khan, Z.A.; Khan, N.A.: Load forecasting, dynamic pricing and dsm in smart grid: A review. Renew. Sustain. Energy Rev. **54**, 1311–1322 (2016)
13. Makhadmeh, S.N.; Khader, A.T.; Al-Betar, M.A.; Naim, S.: An optimal power scheduling for smart home appliances with smart battery using grey wolf optimizer. In: 2018 8th IEEE International Conference on Control System, Computing and Engineering (ICCSCE), pp. 76–81 (2018). IEEE
14. Makhadmeh, S.N.; Al-Betar, M.A.; Abasi, A.K.; Awadallah, M.A.; Alyasseri, Z.A.A.; Alomari, O.A.; Doush, I.A.: Wind driven optimization with smart home battery for power scheduling problem in smart home. In: 2021 Palestinian International Conference on Information and Communication Technology (PICICT), pp. 1–6 (2021). IEEE
15. Nadeem, Z.; Javaid, N.; Malik, A.; Iqbal, S.: Scheduling appliances with ga, tlbo, fa, osr and their hybrids using chance constrained optimization for smart homes. Energies **11**(4), 888 (2018)
16. Zhao, Z.; Lee, W.C.; Shin, Y.; Song, K.-B.: An optimal power scheduling method for demand response in home energy management system. IEEE Trans. Smart Grid **4**(3), 1391–1400 (2013)
17. Makhadmeh, S.N.; Khader, A.T.; Al-Betar, M.A.; Naim, S.; Abasi, A.K.; Alyasseri, Z.A.A.: A novel hybrid grey wolf optimizer with min-conflict algorithm for power scheduling problem in a smart home. Swarm Evol. Comput. **60**, 100793 (2021)
18. Makhadmeh, S.N.; Abasi, A.K.; Al-Betar, M.A.: Hybrid multi-verse optimizer with grey wolf optimizer for power scheduling problem in smart home using iot. J. Supercomput. **78**(9), 11794–11829 (2022)
19. Essiet, I.O.; Sun, Y.; Wang, Z.: Optimized energy consumption model for smart home using improved differential evolution algorithm. Energy **172**, 354–365 (2019)
20. Khan, Z.A.; Zafar, A.; Javaid, S.; Aslam, S.; Rahim, M.H.; Javaid, N.: Hybrid meta-heuristic optimization based home energy management system in smart grid. J. Amb. Intell. Human. Comput. **10**(12), 4837–4853 (2019)
21. Makhadmeh, S.N.; Al-Betar, M.A.; Awadallah, M.A.; Abasi, A.K.; Alyasseri, Z.A.A.; Doush, I.A.; Alomari, O.A.; Damaševičius, R.; Zajančkauskas, A.; Mohammed, M.A.: A modified coronavirus herd immunity optimizer for the power scheduling problem. Mathematics **10**(3), 315 (2022)
22. Chang, C.-Y.; Tsai, P.-F.: Multiobjective decision-making model for power scheduling problem in smart homes. Sustainability **14**(19), 11867 (2022)
23. Faramarzi, A.; Heidarinejad, M.; Mirjalili, S.; Gandomi, A.H.: Marine predators algorithm: a nature-inspired metaheuristic. Expert Syst. Appl. **152**, 113377 (2020)
24. Abd Elminaam, D.S.; Nabil, A.; Ibraheem, S.A.; Houssein, E.H.: An efficient marine predators algorithm for feature selection. IEEE Access **9**, 60136–60153 (2021)
25. Abdel-Basset, M.; El-Shahat, D.; Chakrabortty, R.K.; Ryan, M.: Parameter estimation of photovoltaic models using an improved marine predators algorithm. Energy Convers. Manag. **227**, 113491 (2021)
26. Abd Elaziz, M.; Thanikanti, S.B.; Ibrahim, I.A.; Lu, S.; Nastasi, B.; Alotaibi, M.A.; Hossain, M.A.; Yousri, D.: Enhanced marine predators algorithm for identifying static and dynamic photovoltaic models parameters. Energy Convers. Manag. **236**, 113971 (2021)
27. Fan, Q.; Huang, H.; Chen, Q.; Yao, L.; Yang, K.; Huang, D.: A modified self-adaptive marine predators algorithm: framework and engineering applications. Eng. Comput. **38**(4), 3269–3294 (2022)
28. Abd Elaziz, M.; Ewees, A.A.; Yousri, D.; Alwerfali, H.S.N.; Awad, Q.A.; Lu, S.; Al-Qaness, M.A.: An improved marine predators algorithm with fuzzy entropy for multi-level thresholding: real world example of covid-19 ct image segmentation. IEEE Access **8**, 125306–125330 (2020)
29. Makhadmeh, S.N.; Al-Betar, M.A.; Assaleh, K.; Kassaymeh, S.: A hybrid white shark equilibrium optimizer for power scheduling problem based iot. IEEE Access (2022)
30. Rahim, S.; Javaid, N.; Ahmad, A.; Khan, S.A.; Khan, Z.A.; Alrajeh, N.; Qasim, U.: Exploiting heuristic algorithms to efficiently utilize energy management controllers with renewable energy sources. Energy Build. **129**, 452–470 (2016)
31. Javaid, N.; Javaid, S.; Abdul, W.; Ahmed, I.; Almogren, A.; Alamri, A.; Niaz, I.: A hybrid genetic wind driven heuristic optimization algorithm for demand side management in smart grid. Energies **10**(3), 319 (2017)
32. Shi, W.; Cao, J.; Zhang, Q.; Li, Y.; Xu, L.: Edge computing: vision and challenges. IEEE Internet Things J. **3**(5), 637–646 (2016)
33. Al-Odat, Z.A.; Srinivasan, S.K.; Al-qtiemat, E.; Dubasi, M.A.L.; Shuja, S.: Iot-based secure embedded scheme for insulin pump

data acquisition and monitoring. arXiv preprint arXiv:1812.02357 (2018)

34. Arasteh, H.; Hosseinnezhad, V.; Loia, V.; Tommasetti, A.; Troisi, O.; Shafie-khah, M.; Siano, P.: Iot-based smart cities: A survey. In: 2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC), pp. 1–6 (2016). IEEE
35. Khan, M.A.; Salah, K.: Iot security: review, blockchain solutions, and open challenges. Futur. Gener. Comput. Syst. **82**, 395–411 (2018)
36. Usman, A.; Shami, S.H.: Evolution of communication technologies for smart grid applications. Renew. Sustain. Energy Rev. **19**, 191–199 (2013)
37. Ullah, I.; Hussain, S.: Time-constrained nature-inspired optimization algorithms for an efficient energy management system in smart homes and buildings. Appl. Sci. **9**(4), 792 (2019)
38. Makhadmeh, S.N.; Abasi, A.K.; Al-Betar, M.A.; Awadallah, M.A.; Doush, I.A.; Alyasseri, Z.A.A.; Alomari, O.A.: A novel link-based multi-objective grey wolf optimizer for appliances energy scheduling problem. Clust. Comput. **25**(6), 4355–4382 (2022)
39. Awais, M.; Javaid, N.; Aurangzeb, K.; Haider, S.; Khan, Z.; Mahmood, D.: Towards effective and efficient energy management of single home and a smart community exploiting heuristic optimization algorithms with critical peak and real-time pricing tariffs in smart grids. Energies **11**(11), 3125 (2018)
40. Rahim, M.H.; Khalid, A.; Javaid, N.; Alhussein, M.; Aurangzeb, K.; Khan, Z.A.: Energy efficient smart buildings using coordination among appliances generating large data. IEEE Access **6**, 34670–34690 (2018)
41. Rasheed, M.; Javaid, N.; Ahmad, A.; Khan, Z.; Qasim, U.; Alrajeh, N.: An efficient power scheduling scheme for residential load management in smart homes. Appl. Sci. **5**(4), 1134–1163 (2015)
42. Makhadmeh, S.N.; Khader, A.T.; Al-Betar, M.A.; Naim, S.; Alyasseri, Z.A.A.; Abasi, A.K.: A min-conflict algorithm for power scheduling problem in a smart home using battery. In: Proceedings of the 11th National Technical Seminar on Unmanned System Technology 2019, pp. 489–501 (2021). Springer
43. Makhadmeh, S.N.; Khader, A.T.; Al-Betar, M.A.; Naim, S.; Alyasseri, Z.A.A.; Abasi, A.K.: Particle swarm optimization algorithm for power scheduling problem using smart battery. In: 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT), pp. 672–677 (2019). IEEE
44. Farina, M.; Amato, P.: Fuzzy optimality and evolutionary multiobjective optimization. In: International Conference on Evolutionary Multi-Criterion Optimization, pp. 58–72 (2003). Springer
45. Farina, M.; Amato, P.: A fuzzy definition of "optimality" for many-criteria optimization problems. IEEE Trans. Syst. Man Cybern. Part A Syst. Humans **34**(3), 315–326 (2004)
46. López Jaimes, A.; Coello Coello, C.A.: Some techniques to deal with many-objective problems. In: Proceedings of the 11th Annual Conference Companion on Genetic and Evolutionary Computation Conference: Late Breaking Papers, pp. 2693–2696 (2009)
47. Filmalter, J.; Dagorn, L.; Cowley, P.; Taquet, M.: First descriptions of the behavior of silky sharks, carcharhinus falciformis, around drifting fish aggregating devices in the indian ocean. Bull. Mar. Sci. **87**, 325–337 (2011). https://doi.org/10.5343/bms.2010.1057
48. Kennedy, J.; Eberhart, R.: Particle swarm optimization. In: Proceedings of ICNN'95-international Conference on Neural Networks, vol. 4, pp. 1942–1948 (1995). IEEE
49. Abasi, A.K.; Khader, A.T.; Al-Betar, M.A.; Alyasseri, Z.A.A.; Makhadmeh, S.N.; Al-laham, M.; Naim, S.: A hybrid salp swarm algorithm with $beta$-hill climbing algorithm for text documents clustering. Evolutionary Data Clustering: Algorithms and Applications, 129–161 (2021)
50. Alomari, O.A.; Khader, A.T.; Al-Betar, M.A.; Abualigah, L.M.: Gene selection for cancer classification by combining minimum redundancy maximum relevancy and bat-inspired algorithm. Int. J. Data Min. Bioinform. **19**(1), 32–51 (2017)
51. Sales, G.: Wattage Calculator — centralmainediesel.com. http://www.centralmainediesel.com/wattage-calculator.asp (2017)
52. Ogwumike, C.; Short, M.; Abugchem, F.: Heuristic optimization of consumer electricity costs using a generic cost model. Energies **9**(1), 6 (2015)
53. Naz, M.; Iqbal, Z.; Javaid, N.; Khan, Z.A.; Abdul, W.; Almogren, A.; Alamri, A.: Efficient power scheduling in smart homes using hybrid grey wolf differential evolution optimization technique with real time and critical peak pricing schemes. Energies **11**(2), 384 (2018)
54. Ahmad, A.; Khan, A.; Javaid, N.; Hussain, H.M.; Abdul, W.; Almogren, A.; Alamri, A.; Azim Niaz, I.: An optimized home energy management system with integrated renewable energy and storage resources. Energies **10**(4), 549 (2017)

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.