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RESEARCH ARTICLE

A Hybrid White Shark Equilibrium Optimizer for Power Scheduling Problem Based IoT

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ABSTRACT The power schedule problem (PSP) is the problem of managing, controlling, and scheduling power consumption of electrical appliances/devices to operate at the best periods according to several constraints and objectives. The PSP is a complex and high-constraint scheduling problem, making its search space extensive and rugged. The PSP components can be controlled and managed by utilizing a communication approach that interconnects the appliances and enhances exchanging data. Several communication approaches were used for the PSP, where the Internet of Things (IoT) is the best for data exchange. The PSP has been extensively handled using various optimization approaches, particularly metaheuristics, due to their capabilities to optimize different search space scales. Nevertheless, in some cases, these optimization algorithms suffer from low execution abilities, especially with huge search spaces like the PSP. In this study, a recent metaheuristic, called white shark optimizer (WSO), is adapted and enhanced to address the PSP efficiently. The proposed enhanced method is introduced to improve the WSO optimization performance and find better schedules for the PSP by hybridizing the WSO components with a well-known optimization algorithm called equilibrium optimizer. The proposed method is called the white shark equilibrium optimizer (WSEO). The proposed method is operated through a residential IoT system to manage home appliances efficiently. Moreover. the PSP is mathematically formulated as multi-objective PSP considering three main objectives, including electricity bills, power consumption balance, and users' comfortabilities. In the evaluation stage, a new case study in the United Arab Emirates (UAE) is proposed that contains most of the available appliances in the UAE. The evaluation is presented in three main phases, including original, original with a hybrid approach, and hybrid approach evaluations. The proposed WSEO outperformed all compared methods in optimizing the PSP.

INDEX TERMS White shark optimizer, equilibrium optimizer, white shark equilibrium optimizer, power schedule problem, IoT.

I. INTRODUCTION

Smart grid technology has significantly emerged in the last decade due to its efficiency in improving power systems for power suppliers and the comfortability for users by making all home appliances smarter. The major key to such enhancement is the technologies used in the communication system. The smart grid utilized a two-directional communication system between all grid components to send power flow and receive feedback [1], [2], [3], [4].

The two-directional communication system enhances the interaction between users and their home appliances and makes it faster. Several promising technologies can be utilized and applied to control such a system, where the Internet of Things (IoT) is the essential [5], [6], [7]. The IoT is a new and promising technology that stands for the interrelations between electrical devices through the internet. The main components of the IoT are wireless networks used

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for transmitting and collecting data and electrical devices or appliances [5], [7].

Although the smart grid and IoT can significantly enhance power systems and user satisfaction, scholars expect power suppliers and users to face an issue related to power consumption inflation in peak periods, which leads to a shortage in generating enough power for users. Accordingly, the power suppliers will oblige to operate additional power generators to address such an issue and generate enough power. Thus, operating new power generators increases the cost of the power production and the electricity bill (EB) for users [1], [4]. To address such an issue, power suppliers provide a solution to minimize the power consumption at peak periods by converting the fixed pricing scheme into a dynamic, where the power prices are high at peak periods and low during the off-peak periods. The dynamic pricing scheme incentivizes users to operate their appliances during off-peak periods and consume power at a lower cost [3]. Thus, the power will be distributed throughout the day, and the power system stability and reliability will be maintained [8], [9], [10], [11]. The most popular dynamic pricing schemes are time-of-use price, critical period price, real-time price, and inclining block rate [4], [12], [13].

Managing, controlling, and scheduling power consumption of home appliances to operate at off-peak periods is called the power scheduling problem (PSP). The PSP conduct several constraints that increase the complexity of finding the best schedule, including optimizing EB and comfortability for users and maintaining the power system by despreading power through the time horizon, called peak-to-average ratio (PAR) [4].

The PSP is mathematically formulated as an NP-hard optimization problem to find the best schedule considering all constraints/objectives, including EB, user comfort (UC), and PAR. The optimization problems can be formulated as single- or multi-objective problems based on the number of their objectives. The PSP is formulated as a single objective to optimizing EB and as multi-objective to address all objectives [14], [15], [16], [17].

Various optimization methods were proposed to handle the PSP and find the optimal power schedule. The metaheuristic (MH) algorithms are the most common ones. HM algorithms are general optimization frameworks that initiated with random solution(s). They are iteratively optimize the current solutions based on intelligent operators controlled by specific parameters to explore a vast search space region and making use of accumulative search until a "good enough" solution is obtained. Conventionally, The research community categorized the MH algorithms in accordance with the number of initial solutions into local search-based and population-based where the later is classified into evolutionary-based algorithms and swarm-based algorithms. The MH algorithms used for PSP problems include Genetic algorithm [18], [19], [20], Particle swarm optimization [21], [22], differential evolution [23], [24], grey wolf optimizer [25], and Artificial immune algorithms. [26].

Recently, a new swarm-based MH algorithm have been introduced called White Shark Optimizer (WSO) to emulate the hunting behaviour of white shark [27]. It is very impressive MH algorithms with several common advantages such as it is derivative-free, parameter-less, simple and adaptable, admissible and monotone, sound and complete. Therefore, it has been used to tackle power flow solution of power systems with renewable energy sources [28]. However, WSO like other MH algorithm have some drawbacks such as slow convergence and unbalanced diversity. Since the PSP is NP-hard due to its vast, rugged, and deep search space, the basic version of WSO should be modified or hybridized to cope with the PSP search space complexity. Indeed, a large number of hybrid MH algorithms have been introduced for PSP as reported in [4].

In this paper, a hybrid version of WSO is proposed to address the PSP efficiently. The hybrid WSO abbreviated as WSEO is introduced on the basis of the components of a robust optimizer called Equilibrium Optimizer (EO). According to the authors knowledge, this hybrid scheme is the first trial to add components from EO within the iterative improvement loop of WSO. The primary aim of proposing the WSEO is to enhance the WSO searching capabilities and emphasize exploration and exploitation and achieved the best balance between them. The main contributions of this paper are as follows:

- The PSP is reformulated and modelled as an optimization problem considering all its objectives, including EB, PAR, and UC. Two parameters are modelled that affect the UC level to obtain more accurate comfort results. These parameters are appliances waiting time and capacity power limit. The PSP is formulated as a multi-objective optimization problem to find the best schedules that optimize all objectives simultaneously. The scalarization method is utilized for the objective function due to its efficiency in dealing with more than three objectives.
- The WSO is adapted and utilized to address the PSP and optimize all its objectives efficiently.
- The WSEO is proposed by hybridizing and combining the searching components of the WSO and EO to enhance the performance of the WSO search agents in finding the best schedules by emphasizing the exploration and exploitation capabilities and obtain the optimal balance between them to avoid stagnation in local optima. The EO is utilized to modify and enhance the worst solutions in the WSO population.
- The IoT technologies are used to design the system to enhance the data exchanging between its components and improve controlling and monitoring the appliances operations.

In the experimental results, a new case study in the United Arab Emirates is proposed to test and evaluate the WSEO. In the case study, a new dataset is constructed and created on the basis of the available smart appliances in UAE homes. The dataset contains seven scenarios with up to 123 appliances. In terms of comparison, firstly, the performance of the WSO is compared with four well-known optimization algorithms: Differential Evolution (DE), Dwarf Mongoose Optimization Algorithm (DMOA), Grey Wolf Optimizer (GWO), and Salp Swarm Algorithm (SSA). Secondly, the proposed hybrid approach is applied to these algorithms and compared with the original methods to show and investigate the enhancement of the hybrid approach. The new hybrid methods are DEEO, DMEO, GWEO, and SSEO. Finally, the proposed WSEO is compared with the DEEO, DMEO, GWEO, and SSEO to find the best hybrid method for addressing the PSP.

The structure of this study is organized as follows. Section II presents the the IoT technologies that can be used to promote the communication system in the homes. The PSP background, related works, and formulation as singe and multi-objective are presented in Section III. The adaptation of the WSO and the proposed WSEO illustration are shown in Section IV. The obtained results by the proposed method and the comparison study are presented in Section V. Section VI concludes the paper.

II. SMART HOME BASED IoT

Surprisingly, the initial generation of smart homes focused on automation and remote control rather than intelligence. A smart home was formerly defined as a futuristic setting where users could control their blinds with their smartphone or teach their thermostat to remember their preferred temperature. Now, this term will imply a lot more.

A smart home nowadays meets, if not surpasses, the consumer's expectations. Sensors, gadgets, appliances, and the entire areas in their home capture data on how they use them on a continuous basis. They use complex algorithms to learn about the behaviours and identify consumption trends. This information may then be used to tailor users' experience down to the last detail. Figure 1 shows some devises can be used for smart home manage and automation. This automation can be done using The IoT.

FIGURE 1. Smart home controllers.

IoT is a connectivity of physical appliances or/and devices equipped with sensors that share information and exchange data via the internet utilizing cloud computing. Through a unified framework, the appliances have the ability to exchange and share data utilizing software [6], [7]. IoT components and infrastructure are built on the basis of smart environments and technologies that allow high-quality and fast connections among appliances in order to enhance the efficiency of real-life services and activities, like healthcare, education, transportation, safety, and others services that improve the comfort of residents [29], [30].

Consider the newest thermostats, such as Nest or Ecobee. Smart home gadgets of the latest generation, which are based on the IoT, use their sensor data to automatically modify users' routines' regimes. They constantly monitor your location and adjust the warmth as needed. The most enjoyable portion is that you don't need to make any action at all. Smart thermostats employ algorithms to customize your home's heat to user requirements and thus save you money on power costs. For power savings, IoT devices are typically supplied with minimal memory, low power, and restricted processing units. Through gateways, the IoT devices may be interconnected internationally utilizing controller apps [31]. Figure 2 depicts an IoT architecture in general.

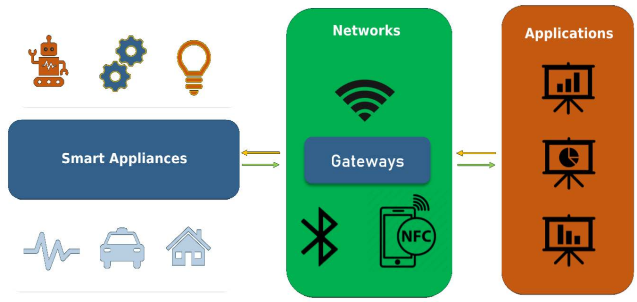


FIGURE 2. IoT architecture.

In urban areas, the IoT is utilized to improve user comfort and quality of life, and it is linked to smart homes to enable users to inspect and operate their home equipment easily. The smart plugs, energy management controller, controller application, smart appliances, communication technologies, and advanced metering infrastructure are the six core components of the smart home-based IoT, as seen in Figure 3 [5], [7]. The controller of energy management is regarded as the smart home's heart since it is in charge of interconnecting all smart home components and coordinating all components. Smart devices used to be combined with the technology of IoT to allow users to remotely engage with smart apps via smartphones or tablets.

Smart devices may wirelessly share data with the smart meter, which is in charge of monitoring the power utilized by all devices and allowing feedback to the company of power supply and users in order to enhance power consumption and generation. Advanced metering technology is at the forefront of smart home networking, allowing power suppliers and their customers to communicate bi-directionally to transfer and receive electricity. Furthermore, modern metering technology may increase the accuracy, control, and distribution of the power system. The smart plug transforms ordinary household devices into smart home appliances by connecting

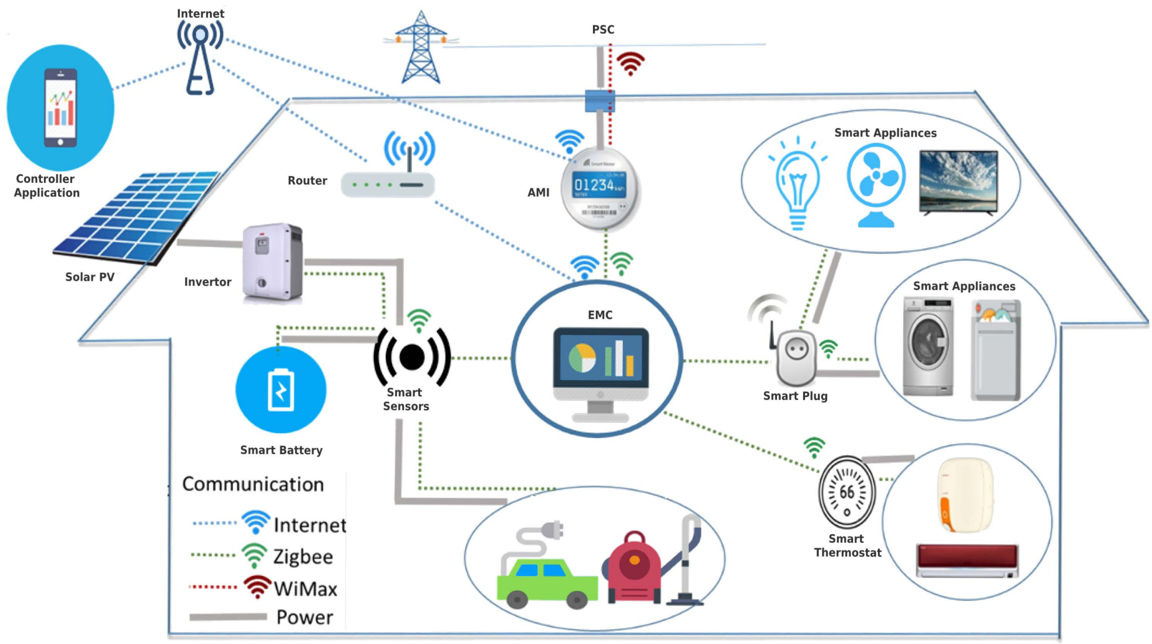


FIGURE 3. Smart home based IoT components.

them to a wifi network, allowing them to communicate and share information between devices. Wireless methods of communication utilised to communicate diverse smart home devices include IEEE 802.16 based WiMAX, IEEE 802.11 based wireless LAN, and IEEE 802.15.4 based ZigBee [32]. Customers can communicate with the appliance via the controlling software. Additional smart devices, like controller sensors, thermostats, renewable energy sources, and storage systems have the ability to be added to the system.

III. PSP FOUNDATION

The primary components of PSP and its modelling are presented in this section. Section III-A defines the PSP and discusses the most famous state-of-the-arts. Section III-B models the PSP as single and multi-objective optimization problems.

A. BACKGROUND

As illustrated earlier, PSP refers to scheduling the appliances' operation time in a time horizon defined ahead of time on the basis of a dynamic pricing scheme and several hard and soft constraints. The main purpose of addressing the PSP is to optimize EBs, PAR, and UC. The appliances can be categorized into shiftable appliances (SAs) and non-shiftable appliances (NSAs). The SAs are controllable appliances that operate automatically; however, NSAs are operated manually. Thus, users can determine the operation time period (OT) and length of operation cycle (OC) for the SAs, whereas it seems unusable to define these parameters for NSAs that operate manually.

Several studies were presented to address the PSP efficiently and optimally. A review analysis and study was proposed in [4] that presents the essential research that were proposed to address the PSP utilizing optimization methods. The authors describe all aspects of the PSP, including background, formulation, and datasets used by the state-of-the-art. The study shows and presents the main advantages of utilizing metaheuristics as optimization methods to address PSP. A provided analysis proved the high efficiency of the metaheuristics in handling the PSP.

The genetic algorithm was hybridized with the wind-driven optimizer to propose a new hybrid method that can optimize all PSP objectives efficiently. The obtained results by the proposed method were compared with other well-established methods. The proposed method proved the high performance on the suggested hybridization, where it achieved the best results compared to all methods.

The genetic algorithm was also hybridized with the moth-flame optimization algorithm for the same purpose [33]. Appliances time constraints were utilized with the proposed method to enhance its performance in optimizing the UC level. The results obtained by the proposed method was compared with five well-known optimization algorithms. The outcomes proved the high performance of the proposed method, where it demonstrated all compared methods in optimizing the objectives.

The bacterial foraging optimization algorithm was hybridized with the flower pollination algorithm in [34] to address the PSP using 14 home appliances. The primary purpose of proposing such a method was to enhance the bacterial foraging optimization algorithm searching capabilities and optimize more solutions. The achieved results by the proposed method presented its significance, where it obtained the best results among all compared methods.

The bacterial foraging optimization algorithm was also hybridized with the harmony search algorithm to provide better schedules for the PSP in [35]. The authors tested the proposed method using 11 home appliances. The experimental results showed that the proposed method exhibited better schedules in most of the scenarios.

A new hybrid metaheuristic version was proposed in [17] to enhance GWO optimization behaviour and emphasize its exploitation capabilities utilizing the min-conflict algorithm. The experimental results proved the proposed hybrid method's performance in addressing the PSP, where it achieved the best results among all compared methods.

Notably, the aforementioned studies showed the robust performance of the hybridized optimization methods in handling the PSP compared with the pure versions of the optimization methods. The hybridized optimization methods demonstrated the pure methods in most testing scenarios. Thus, such methods are the most appropriate for finding the most satisfactory schedules for PSP.

B. PSP FORMULATION

The appliances in any smart home can be categorized into SAs and NSAs, as mentioned in Section III-A. The SAs are controllable appliances that operate automatically, whereas the NSAs are operated manually. Thus, users can determine the OT and OC for the SAs, whereas it seems unusable to define these parameters for NSAs that operate manually. The mathematical modelling for all SAs and NSAs parameters is illustrated below.

- **Shiftable Appliances**
  The parameters of the SAs are formulated and described in this section. All SAs are presented as a vector S as follows [4], [8], [17]:

$$S = [s_1, s_2, \dots, s_m], \tag{1}$$

s_i represents the appliance i, and m represents the total appliances. All SAs should be operated at a time horizon (TH). TH is presented in as slots in a horizon as follow:

$$TH = [th^1, th^2, \dots, th^n], \tag{2}$$

t^j represents a slot j in TH, and n is the total number of times slots in TH.
The power required by each SA at any slot can be demonstrates in the following formulation:

$$PR = \begin{bmatrix} pr_1^1 & pr_2^1 & \cdots & pr_m^1 \\ pr_1^2 & pr_2^2 & \cdots & pr_m^2 \\ \vdots & \vdots & \cdots & \vdots \\ pr_1^n & pr_2^n & \cdots & pr_m^n \end{bmatrix}, \tag{3}$$

where pr_i^j is the required power by s_i at th^j.
As mentioned early, the parameters of the SAs, including OT and OC, should be predefined by users. The OT presents the starting OT_s and ending OT_e of the operation periods. OT_s and OT_e are formulated as follow:

$$OT_s = [OT_{s1}, OT_{s2}, \dots, OT_{sm}], \tag{4}$$

$$OT_e = [OT_{e1}, OT_{e2}, \dots, OT_{em}], \tag{5}$$

where OT_{si} and OT_{ei} are the starting and ending operation period of s_i, respectively.
The OC parameter is mathematically described as follows:

$$OC = [oc_1, oc_2, \dots, oc_m], \tag{6}$$

oc_i is the OC of s_i. The starting SO and ending EO the operations of SAs are modelled as follows:

$$SO = [so_1, so_2, \dots, so_m], \tag{7}$$
$$EO = [eo_1, eo_2, \dots, eo_m], \tag{8}$$

st_i and et_i are the starting and ending operations of s_i, respectively.
Figure 4 presents all parameters of the SAs.

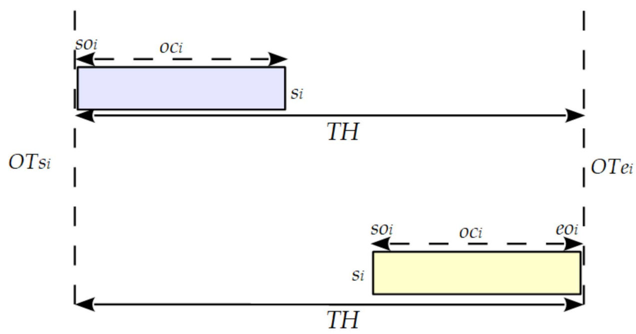


FIGURE 4. Parameters of the SAs.

- **Non-shiftable Appliances**
  The users are not able to predefined the parameters of the NSAs, where these appliances are operated manually.
  The NSAs are illustrated and formulated as a vector NS as follows:

$$NS = [ns_1, ns_2, \dots, ns_q], \tag{9}$$

ns_k represents the NSA k, and q is the total NSAs. The power required by the NSAs to complete the operation cycle is modelled as follows:

$$PRN = [prn_1, prn_2, \dots, prn_q], \tag{10}$$

the power required by ns_k is represented as prn_k.

1) ELECTRICITY BILL

Most of the users implement the optimization systems to minimize the EB by rescheduling the appliances in the home. The EB is formulated as follows:

$$EB = \sum_{j=1}^{n} \sum_{i=1}^{m} pr_i^j \times ep^j, \tag{11}$$

ep^j denotes the electricity prices during the slot j. In this study, the real-time price is adopted and combined with the inclining block rate to increase the usage flexibility and balance the power demand, as suggested by [8], [13], [21].

The inclining block rate uses two prices through TH as follows:

$$ep^j = \begin{cases} l^j & \text{if } 0 \le ep^j \le C \\ h^j & \text{if } ep^j > C \end{cases}, \tag{12}$$

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

where l^j is the normal prices and h^j is the highest. C denotes the threshold of power consumed during the TH, and λ represents a non-negative value which is the ratio between l^j and h^j.

2) PEAK-TO-AVERAGE RATIO

The ratio between the average and highest power consumed during TH is represented as PAR. The power systems' performance can be enhanced by minimizing the value of PAR. The PAR is modeled as follows:

$$PAR = \frac{PR_{max}}{PR_{Avg}}, \tag{14}$$

where

$$PR_{Avg} = \frac{\sum_{j=1}^{n} pr^j}{n}, \tag{15}$$

where PR_{max} is the maximum power demand during TH, and PR_{avg} represents the average power demand during TH.

3) USER COMFORT

The UC level is enhanced in this research by utilizing two parameters. These parameters are appliances waiting time (AWT) and capacity power limit (CPL). The AWT can enhance the UC level by minimizing the delay time to operate SAs, and CPL enhance it by operating NSAs without surpassing C.

The AWT is computed using the following model:

$$AWT_i = \frac{so_i - OTs_i}{OTe_i - OTs_i - oc_i}, \quad \forall i \in S, \tag{16}$$

The CPL at time slot j is calculated as follows:

$$CPL^j = \frac{\sum_{k=1}^{q} NAP_k^j}{q}, \tag{17}$$

where $\sum_{k=1}^{q} NAP_k^j$ is the total $NSAs$ that required additional power to the available at time slot j.

$$NAP_k^j = \begin{cases} 0 & \text{if } PRN_k < AE^j \\ 1 & otherwise, \end{cases}, \tag{18}$$

$$AE^j = C - PR^j, \tag{19}$$

AE^j is the power amount that available to operate the NSAs during time slot j.

The UC level is calculated as follows:

$$UC = (1 - (\frac{AWT + CPL}{2})) \times 100\%, \tag{20}$$

C. MULTI-OBJECTIVE FUNCTION

In this study, the PSP is formulated as a multi-objective optimization problem to optimize EB, PAR, AWT, and CPL. Several multi-objective methods were utilized, including Pareto and non-Pareto. The Pareto methods proved their efficiency for the multi-objective optimization problem with two and three objectives, whereas these methods can't be utilized for optimization problems with more than three objectives like the PSP [36], [37], [38]. Accordingly, one of the non-Pareto methods called the weighted sum method is used to aggregate all objectives and consider them as a single objective. The weighted sum method is utilized due to its flexibility, simplicity, and widely utilized for the PSP in the literature [39], [40], [41]. The multi-objective formulation of the PSP is formulated as follows:

$$\min F(X) = w_1 \times \frac{EB}{EB + A} + w_2 \times \frac{PAR}{PAR + B} + w_3 \times AWT + w_4 \times CPL, \tag{21}$$

where w_1, w_2, w_3, and w_4 are four weight parameters measures the significance of each objective. A and B are two non-negative values.

IV. THE PROPOSED METHOD

A. WHITE SHARK OPTIMIZER (WSO)

A detailed description and illustration of the WSO are presented in this section. This section shows the inspiration of the white shark in nature and its behaviour. Subsequently, the main optimization processes and steps of the WSO are discussed.

1) INSPIRATION

The WSO is a meta-heuristic population-based algorithm inspired by the behaviour of the great white shark and was recently proposed in [27]. Great white sharks have fully adapted predators and impressive hunters, with powerful muscles, good eyesight, and a fine sense of smell. Its prey includes many marine and non-marine organisms, such as crustaceans, invertebrates, mammals, amphibians, and sea birds. They usually hunt prey by ambush, in which a shark seeks to catch a target off guard and attacks with a big and lethal bite. The far more fascinating aspects of great sharks' collective behaviour are their unique abilities to catch prey via swimming, as well as their unusual senses of smelling prey scents and hearing.

2) PREY TRACKING

Like every other organism in nature, sharks roam the ocean in search of prey and adjust their location accordingly. They use practically every tool at their disposal to keep track, chase, and locate their victims in this regard. They have a variety of senses that are integrated and complementary, as shown in Figure 5.

To begin with, sharks have a surprisingly good hearing ability, which they utilize to explore a broad area while hunting for prey. Second, they have a keen sense of smell

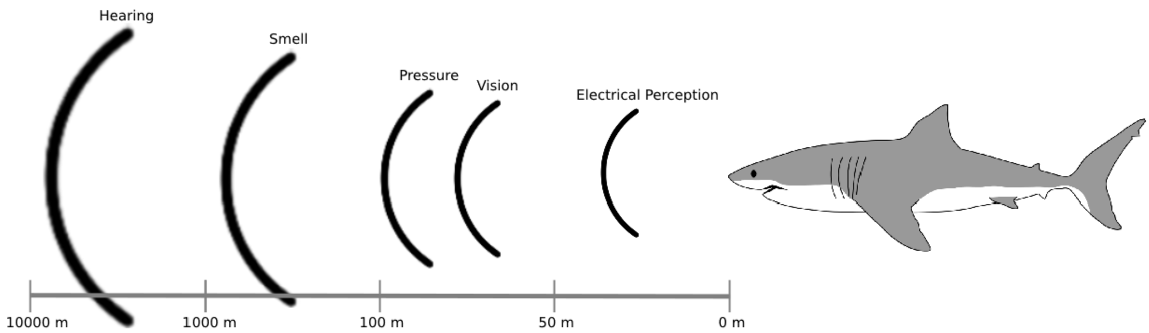


FIGURE 5. White shark's senses: smell, sight and hearing.

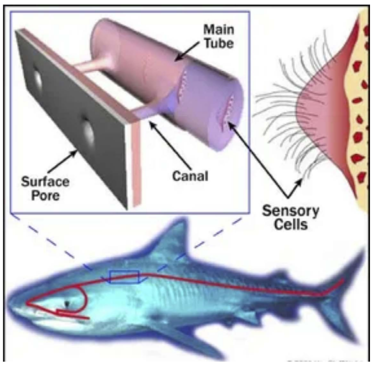


FIGURE 6. A great white shark with a hearing line sensor shown on its torso.

that allows them to detect the fragrance of prey. These characteristics enable sharks to explore the entire search space and exploit every potential area of the search zone for prey.

3) EXPLORATION (SEARCH FOR PREY)

While searching for prey, great sharks use an unusual sense of hearing to explore the field of search space. They can hear from the whole length of their bodies, which is depicted in Figure 6 as two lines on either side of their bodies [42].

Changes in water pressure can be detected by these two lines, suggesting prey movements. White sharks will be enticed to approach a turbulent prey by fluctuations in water pressure released by the prey. Also, it has organs which can detect the minute electromagnetic fields created by prey movement. The shark can then precisely detect the position of prey and its size based on waves frequency drifting to them during the prey's mobility and its turbulence. Whenever the shark comes dangerously near to its prey that it can sense electromagnetic fields, it will advance toward the prey in an undulating fashion

Following is the mathematical expression that can be used to describe the undulating speed of sharks:

$$v = x \times f \tag{22}$$

where v is the wavy motion's speed, x is the wavelength, which defines the distance a shark must travel in an wavy mobility to complete one revolution, and f is the undulating motion's wave frequency, which is calculated on the basis of revolutions (i.e., cycles) that completed per second by the shark, where Hertz (Hz) is the cycle per second.

4) EXPLOITATION (SEARCH FOR PREY)

Sharks use their smell extraordinary sense to exploit every available area in search space for prey. A shark's sense of smell kicks in whenever it gets close to the prey. Once great sharks arrive near their prey, their smell sense can increase exponentially until they properly locate the prey's location. The following kinematic expression with continuous acceleration can be utilized to update the location of sharks as they approach prey:

$$x = x_i + v_i \times \Delta pt + \frac{1}{2}a(\Delta pt)^2 \tag{23}$$

where shark's new position is indicated by the letter x, the primitive position is denoted by x_i, the time interval among the starting and current positions is represented by Δpt, and the constant acceleration factor is denoted by a.

In several situations, prey such as seals leaves their smells upon leaving their location, so sharks locate no prey when they are in close proximity to the aroma. In this situation, sharks must use their active senses of smell, hearing, and sight to search in adjacent regions and explore other spots in the search space at random.

5) OPTIMIZER MECHANISM

To locate prey positions, sharks adopt three different behaviours: (i) the motion towards prey is dependent on the waves' hesitation caused by the mobility of prey; the shark navigates to prey by using its related senses of hearing and scent in a wavy manner, (ii) the haphazard hunt for prey in the ocean's depths, while sharks do this by moving towards prey and staying near to the optimal prey, and (iii) the activity of a shark when looking for prey in the area. In this case, the shark mimics the behaviour of a school of fish by moving towards the best shark that is extremely close to the best prey. Based on these behaviours, all sharks' locations will be updated with the best ideal solutions in case the prey is not identified in a timely manner. Such behaviours are modelled mathematically as follows:

1) **Initialization of WSO**
When starting the optimization process to address a problem, WSO produces a set of random initial solutions because it is a population-based method. The following 2d matrix presents a population of N sharks (i.e., population size) in search space with d-dimensional (i.e., problem dimension), where each shark's position represents a potential solution to a problem:

$$\begin{bmatrix} \omega_1^1 & \omega_2^1 & \omega_3^1 & \cdots & \omega_d^1 \\ \omega_1^2 & \omega_2^2 & \omega_3^2 & \cdots & \omega_d^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \omega_1^N & \omega_2^N & \omega_3^N & \cdots & \omega_d^N \end{bmatrix}$$

where all sharks in the search area are represented by the letter ω, the decision variables number for a particular problem is denoted by d, and the i^{th} white shark's location in the d^{th} dimension is indicated by ω_d^i.
A uniform random initialization is used to establish the initial population, as follows:

$$\omega_j^i = l_j + r \times (u_j - l_j) \quad (24)$$

where ω_j^i is the i^{th} white shark's starting vector in the j^{th} dimension, the upper and lower boundaries in the j^{th} dimension are represented by u_j and l_j, respectively, and r is a random number generated between 0 and 1.

2) **Movement Speed Towards Prey**
When a shark detects a prey's position depending on the pause in the waves it hears as the prey travels, it moves in a wavy motion that can be characterized as indicated in Eq. 25.

$$v_{k+1}^i = \mu[v_k^i + p_1(\omega_{gbest_k} - \omega_k^i) \times c_1 + p_2(\omega_{best}^{v^i k} - \omega_k^i) \times c_2] \quad (25)$$

where the updated speed vector of the i^{th} shark in the $(k+1)^{th}$ step is denoted by v_{k+1}^i, v_k^i specifies the present velocity vector of the i^{th} shark, ω_{gbest_k} denotes the global best position vector achieved by any shark so far, ω_k^i is the i^{th} shark's present location vector in the k^{th} step, $\omega_{best}^{v^i k}$ is the swarm's i^{th} best known location vector, v^i is the i^{th} index vector of sharks attaining the best position specified as in Eq.26, two uniformly generated random numbers between 0 and 1 are c_1 and c_2, the forces of the sharks that influence the impact of ω_{gbest_k} and $\omega_{best}^{v^i}$ on ω_k^i are represented by p_1 and p_2, that are calculated using Eqs.27 and 28, and μ is the constriction factor proposed by WSO to evaluate the behavior of convergence of sharks, and it is calculated by Eq.29.

$$v = \lfloor n \times rand(1, n) \rfloor + 1 \quad (26)$$

in which, rand(1, n) is a vector of randomly generated numbers with a uniform distribution between 0 and 1.

$$p_1 = p_{max} + (p_{max} - p_{min}) \times e^{-(\frac{4k}{k})^2} \quad (27)$$

$$p_2 = p_{min} + (p_{max} - p_{min}) \times e^{-(\frac{4k}{k})^2} \quad (28)$$

in which, the present and max number of repetitions are denoted by k and K, respectively, and the starting b and subordinate speeds to accomplish good mobility for sharks are p_{min} and p_{max}. After a thorough examination, the values of p_{min} and p_{max} were discovered to be 0.5 and 1.5, respectively.

$$\mu = \frac{2}{|2 - \tau - \sqrt{\tau^2 - 4\tau}|} \quad (29)$$

where τ stands for the acceleration coefficient, that equal 4.125, and this number was discovered after much research.

3) **Movement Towards Optimal Prey**
The aroma of the prey is often left in that place, whereas the shark can still smell it. In this scenario, the shark moves to random sites in pursuit of prey, similar to how a school of fish searches for food. The location update mechanism described in Eq.30 was utilized to characterize the behaviour of sharks as they approached prey in this scenario.

$$\omega_{k+1}^i = \begin{cases} \omega_k^i . \neg \bigoplus \omega_0 + u.a + l.b & rand < m_v \\ \omega_k^i + v_k^i / f & rand \geq m_v \end{cases} \quad (30)$$

where the updated location vector of the i^{th} shark in the $(k+1)^{th}$ iteration step is denoted by ω_{k+1}^i, a negation operator donated by $\neg$, Eqs.31 and 32 define a and b as one-dimensional binary vectors, respectively, the upper and lower boundaries of the search space are denoted by u and l, respectively, ω_0 is a logical vector that is defined as seen in Eq.33, f represents the frequency of a shark's undulating movement, as given in Eq. 34, random number in the range of [0,1] is denoted as $rand$, and m_v symbolizes the motion force that grows with the number of rounds as the white shark reaches the prey, that is given as Eq 35.

$$a = sgn(\omega_k^i - u) > 0 \quad (31)$$

$$b = sgn(\omega_k^i - l) < 0 \quad (32)$$

$$\omega_0 = \bigoplus(a, b) \quad (33)$$

$$f = f_{min} + \frac{f_{max} - f_{min}}{f_{max} + f_{min}} \quad (34)$$

$$m_v = \frac{1}{(a_0 + e^{(K/2 - k)/a_1})} \quad (35)$$

4) **Movement Towards the Best White Shark**
Sharks can keep their location in front of the optimal one, which is near to the prey. Eq.36 shows how this phenomenon is expressed.

$$\omega'^{i}_{k+1} = \omega_{gbest_k} + r_1 \times \vec{D}_\omega \times sgn(r_2 - 0.5) \quad r_3 < s_s \tag{36}$$

where ω'^{i}_{k+1} represents the updated location of the i^{th} shark in relation to the location of prey, $sgn(r_2 - 0.5)$ returns either -1 or 1 to control the search direction, the coefficients r_1, r_2, and r_3 are all random numbers in the range between 0 and 1, $\vec{D}_\omega$ is the spacing among the prey and the shark, as described in Eq. 37, s_s is a coefficient proposed to expressing the strength of sharks' senses of sight and smell once they pursue other sharks near to best prey, as presented in Eq.38.

$$\vec{D}_\omega = |rand \times (\omega_{gbest_k} - \omega^i_k)| \tag{37}$$

$$s_s = |1 - e^{(-a_2 \times k/K)}| \tag{38}$$

5) **Fish School Behavior**
To mathematically mimic the behaviour of the school of white sharks, the 1^{st} two best solutions were kept, and the locations of other white sharks could be refreshed in accordance with these optimal positions. The following equation was introduced to determine shark fish school behaviour:

$$\omega^i_{k+1} = \frac{\omega^i_k + \omega'^{i}_{k+1}}{2 \times rand} \tag{39}$$

Sharks have the ability to update their location according to the best shark that got the best location, which is extremely close to the prey, as seen in Eq.38. Sharks' final location can be someplace in the search space which is extremely near to the best prey. The collective behaviour of WSO is identified by fish school behaviour and the sharks' movement into the best shark, which expands the possibility for improved exploration and exploitation features.

B. EQUILIBRIUM OPTIMIZER (EO)

EO is a physical law-based metaheuristic algorithm recently proposed in [43]. The mechanism of EO is presented in this section.

EO uses the dynamic mass balancing technique that is based on the volume control. A mathematical formula is utilized to express mass balance in specifying the concentration of nonreactive elements in a dynamic control volume environment. This formula is represented as a function with multiple processes under various source and sink conditions. For establishing the dynamic environment of the control volume, the mass balance formula is used to apply physical mass conservation anatomical concepts to the conservation of mass entering, exiting, and so on. As illustrated in Eq.40, a first-order differential formula can be used to represent a general mass balance formula. It explains the quantity of mass entering the system plus the amount created within minus the amount that departs the system as a function of time.

$$V\frac{dC}{dt} = QC_{eq} - QC + G \tag{40}$$

where, $V\frac{dC}{dt}$ denotes mass change rate in the volume of control, C is the concentration of control volume (V), Q characterize the volumetric flow rate (in and out of volume of control), QC_{eq} stands for concentration in the equilibrium state, and G denotes the rate of mass creation within the volume of control. $V\frac{dC}{dt}$ reaches zero to attain steady state equilibrium.

After rearranging Eq.40 as a function of time and integration, the resultant formula to find the concentration in the control volume (C) is as follows:

$$C = C_{eq} + (C_0 - C_{eq}) \times F + \frac{G}{\lambda \times V} \times (1 - F) \tag{41}$$

where F in Eq.41 can be calculated as:

$$F = exp[-\lambda \times (t - t_0)] \tag{42}$$

t_0 and C_0 in the preceding formulas denote the initial start time and concentration, respectively, which are dependent on the integration interval. The formula in Eq.41 is used to compute the average turnover rate using a simple linear regression with a known generation rate and other parameters or to compute the concentration of control volume with a known turnover rate.

EO's main framework is made out of a number of formulas. The word particle refers to a proposed solution, and concentration is similar to particle position. Three terms available in Eq.41:

- C_{eq} stands for concentration of equilibrium, and it refers to one of the most effective options chosen at random from the pool of equilibrium.
- $(C_0 - C_{eq})$ stands for the difference in variance among particle C_0 and the equilibrium state C_{eq}. It is in charge of searching the region for macro-searches.
- $\frac{G}{\lambda \times V}$ demonstrates a high generation rate in order to hit notable exploitation, which also helps with exploration whereas staying away from local minima.

On the basis of these concepts, the general conceptual description of EO can be summarized as follows:

1) RANDOM POPULATION INITIALIZATION

Within a particular search zone, the random population (initial concentration) is initialized by employing a uniform distribution depending on particle number and dimension.

$$C^{initial}_i = C_{min} + rand_i(C_{max} - C_{min}), i = 1, 2, \ldots, n \tag{43}$$

where $C^{initial}_i$ stands for the initial concentration vector of the i^{th} particle, C_{max} and C_{min} denote upper and lower bound, respectively, $rand_i$ stands for uniform random numbers produced in the range [0,1], and n denotes population size.

2) EQUILIBRIUM POOL VECTOR

A pool of four promising candidates, including another particle with a concentration equivalent to the arithmetic mean of such four particles, must be discovered to establish the equilibrium state (global optima). As indicated in Eq.44, the pool vector is formed by these particles.

$$\overrightarrow{C}_{eq.pool} = \{\overrightarrow{C}_{eq(1)}, \overrightarrow{C}_{eq(2)}, \overrightarrow{C}_{eq(3)}, \overrightarrow{C}_{eq(4)}, \overrightarrow{C}_{eq(ave)}\} \tag{44}$$

Over the process of evolution, the first particle adjusts its concentration depending on $\overrightarrow{C}_{eq(1)}$ in the first generation; however, in the second generation, the improvement can occur on $\overrightarrow{C}_{eq(ave)}$. Following that, every particle with all possible candidates is modified until the evolution process is complete.

3) BALANCE BETWEEN EXPLORATION AND EXPLOITATION

The exponential component F in Eq.42 helps EO achieve a appropriate balance among exploitation and exploration. To manage the turnover rate in real control volume, λ have to be a random number between [0, 1].

$$\overrightarrow{F} = e^{-\overrightarrow{\lambda}(Itr - Itr_0)} \tag{45}$$

where Itr is supplied as a function of iteration number and can be expressed as:

$$Itr = (1 - \frac{Itr}{Max\_itr}) \times (a_2 \times \frac{Itr}{Max\_itr}) \tag{46}$$

where Max_itr denotes the maximum iteration and a_2 used to manage the EO ability of exploitation.

The following statement is also used to assure convergence while improving the algorithm's global and local search capabilities:

$$\overrightarrow{Itr_0} = \frac{1}{\overrightarrow{\lambda}} \times In(-a_1 \times sign(\overrightarrow{r} - 0.5) \times [1 - e^{-\overrightarrow{\lambda} Itr}]) + Itr \tag{47}$$

where a_1 and a_2 are utilized to adjust the EO algorithm's global and local search capabilities. The portion $sign(\overrightarrow{r} - 0.5)$ is in charge of the exploration and exploitation strategy. The values of a_1 and a_2 in EO are set to 2 and 1, respectively.

The expressions will be altered as follows by replace Eq.47 in Eq.45:

$$\overrightarrow{F} = a_1 \times sign(\overrightarrow{r} - 0.5) \times [e^{-\overrightarrow{\lambda} Itr} - 1] \tag{48}$$

4) GENERATION RATE

The EO algorithm's generation rate (G) is used to enhance exploitation, which can be used as a function of time [43]. The G of a multifunctional model's first order exponential decay process can be defined as:

$$\overrightarrow{G} = \overrightarrow{G_0} \times e^{-\overrightarrow{k}(Itr - Itr_0)} \tag{49}$$

where the initial value is donated by G_0 and the decay parameter is donated by k.

At last, assuming $k = \lambda$, the following is the expression for the generation rate:

$$\overrightarrow{G} = \overrightarrow{G_0} \times e^{-\overrightarrow{\lambda}(Itr - Itr_0)} = \overrightarrow{G_0} \times \overrightarrow{F_0} \tag{50}$$

G_0 is computed as follows in Eq.50:

$$\overrightarrow{G_0} = G\overrightarrow{C}P \times (\overrightarrow{C}_{eq} - \overrightarrow{\lambda} \times \overrightarrow{C}) \tag{51}$$

$$G\overrightarrow{C}P = \begin{cases} 0.5 \times r_1, & r_2 \geq 0 \\ 0, & r_2 < 0 \end{cases} \tag{52}$$

where r1 and r2 parameters are random in the [0,1] range and GCP is used to regulate the rate of generation.

Based on all of the preceding formulas, the final concentration updating formula is defined as follows:

$$\overrightarrow{C} = \overrightarrow{C}_{eq} + (\overrightarrow{C} - \overrightarrow{C}_{eq}) \times \overrightarrow{F} + \frac{\overrightarrow{G}}{\overrightarrow{\lambda} V} \times (1 - \overrightarrow{F}) \tag{53}$$

There are 3-terms in the updating formula, as follow:

- The equilibrium concentration is available at the first one.
- The global search is available at the second term.
- The third one is in charge of doing local searches to get more precise solutions.

C. WHITE SHARK-EQUILIBRIUM OPTIMIZER (WSEO)

This section presents the illustration of creating and adapting the proposed WSEO method to address the PSP. In the proposed WSEO, the EO is utilized to enhance the WSO searching capabilities and improve the worst solutions in its population. The EO is utilized due to its high performance in searching deeply in the rugged search spaces with maintaining the balance between the global and local searches. The WSO adopts the EO to enhance the bad solutions by sorting the population and considering the second half as its population. The EO will enhance the bad half of the population and send it back to the WSO to reevaluate the population and select the best solutions. The adaptation steps of the proposed WSEO for the PSP are presented in Figure 7 and discussed below.

Step 1: Initialization of the PSP, WSO, and EO parameters:
This step is to initialize the PSP, WSO, and EO parameters. For the PSP, the parameters that must be initialized are S, NS, TH, OC, OTs, OTe, ERN, PR, ep. eight and two parameter should be defined for the WSO and EO, respectively. For the WSO, the parameters are v, u, l, τ, f_{min}, f_{min}, p_{min}, and p_{max}. For EO, the parameters are GP and V.

Step 2: Initialization of the population:
The proposed WSEO population is generated in this step. Like other swarm-based optimizers, the population is produced randomly, considering the number of SAs (m) and their starting time st. Eq. 54

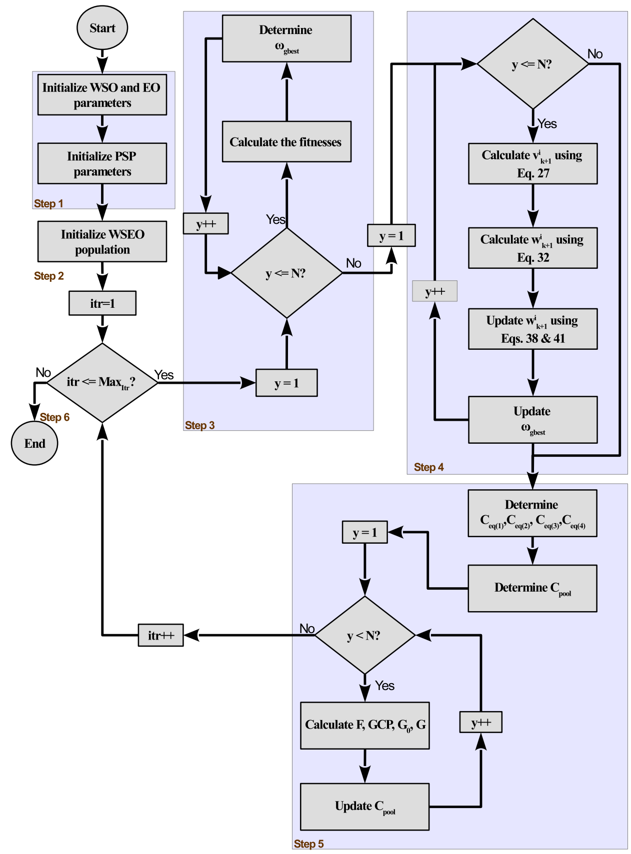


FIGURE 7. The adaptation steps of WSEO for PSP.

shows the WSEO population.

$$Population = \begin{bmatrix} st_1^1 & st_2^1 & \cdots & st_m^1 \\ st_1^2 & st_2^2 & \cdots & st_m^2 \\ \vdots & \vdots & \cdots & \vdots \\ st_1^N & st_2^N & \cdots & st_m^N \end{bmatrix}, \tag{54}$$

Step 3: Calculation of the fitness values:

The fitness value of the solutions in the WSEO population is calculated and evaluated using Eq.21 in this step. Subsequently, the WSO will assign the best solution with the fittest values to the ω_{gbest}

Step 4: Operation of the WSO:

This step operates the search agents of the WSO to update the solutions in the population and find better schedules for the PSP. Once calculating the fitness values for all solutions in the population and assign the best solution to the ω_{gbest}, the WSO operations will update and generate new solutions according to the ω_{gbest} as shown in Section IV-A. The new solutions will replace the worst solutions if they have a better fitness value.

After that, the solutions in the population are ranked based on their fitness values, where the best solutions are ranked highly, and the bad solutions are ranked lowly.

Step 5: Operation of the EO:

After ranking the solutions, as shown in step 4, the EO will take the solutions with the low ranks in the WSO population for further enhancements. The low-ranked solutions will be used as the main population for the EO. The EO will assign the best four solutions to $\overrightarrow{C}_{eq(1)}$, $\overrightarrow{C}_{eq(2)}$, $\overrightarrow{C}_{eq(3)}$, and $\overrightarrow{C}_{eq(4)}$ to generate $\overrightarrow{C}_{eq.pool}$ using Eq. 44. Accordingly, the EO will update its population to enhance their fitness values and find better schedules. Subsequently, the EO will return the new solutions to the WSO population.

Step 6: Check the stop criterion:

Steps 3, 4, and 5 are repeated until reach the stop criterion.

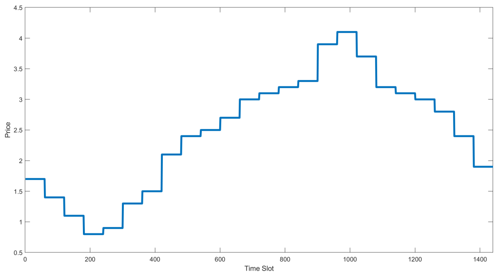
V. EXPERIMENT RESULTS

The proposed WSEO is tested experimentally to evaluate its performance in addressing the PSP and achieving the best schedules. In this experiment, the consumption profiles in UAE are used as a case study to investigate the proposed method's performance. A new dataset is constructed based on the users' consumption and available home appliances in UAE. The obtained results by WSEO are compared with types of optimization methods to presents its significant enhancement on the results.

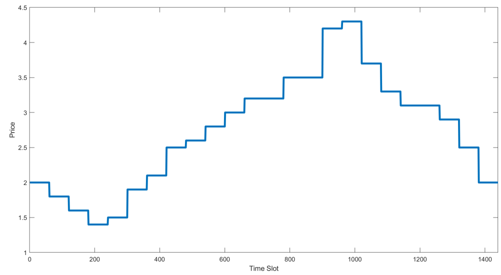
A. DATASET AND EXPERIMENTAL DESIGN

Designing the experimental procedures and the proposed dataset are presented in this section. The proposed methods are examined and tested using seven different scenarios. Each scenario is evaluated using thirty separate runs to have an adequate and fair evaluation among all scenarios [17]. The proposed dataset contains 123 SAs and 26 NSAs. Tables 1 and 2 present all used SAs and NSAs in this experiment. These can be considered as the experimental scenarios that will be used in the evaluation stage. In Table 1, the 'Scenario' column explains the number of scenarios that contain an appliance. For example, scenarios number 1, 2, 3, 4, 6, and 7 contain the first appliance (Water Heater), and scenarios 1, 2, 3, 4, 5, 6, and 7 contain the last appliance (Room AC).

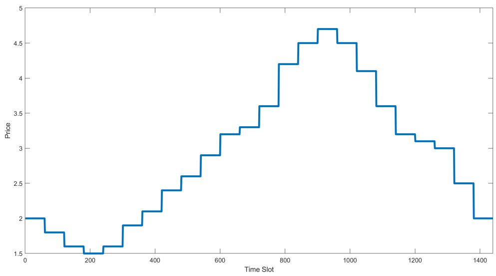
The dynamic pricing scheme utilized in this evaluation is a combination of the real-time price and inclining block rate to flatten the consumption curve as much as can. The real-time price is used due to its flexibility, where its prices are provided based on the users' real consumption, and the inclining block rate is utilized due to its impact on reducing the outstanding consumption at specific periods [4], [16]. The real-time price is adopted from the Commonwealth Edison Company's [44], which is presented in Figure 8 for seven scenarios. For the inclining block rate, according to Eq.13, the *lambda* value is set to $1,543$ [16], [17]. The time horizon T is divided into 1440 minuets, where each minuet represent a time slot.



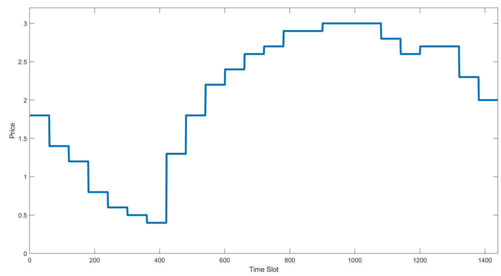
(a) price curve for S#1



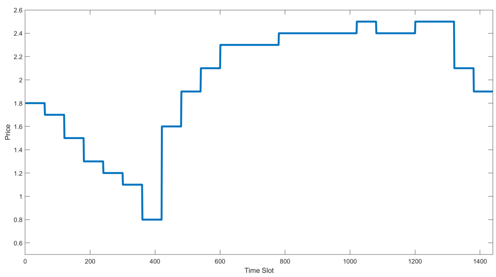
(b) price curve for S#2



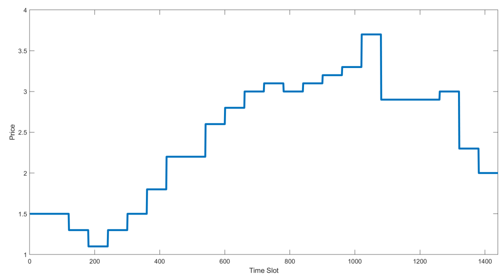
(c) price curve for S#3



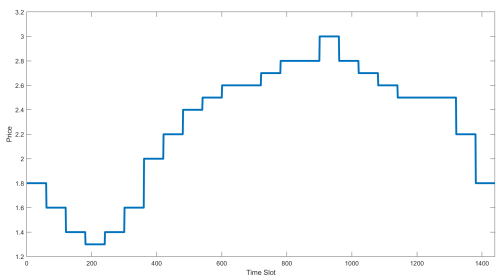
(d) price curve for S#4



(e) price curve for S#5



(f) price curve for S#6



(g) price curve for S#7

FIGURE 8. **The price curve for seven scenarios.**

The values of proposed WSEO parameters in addition to the weight of each objective in Eq. 21 are presented in Table 3.

B. EXPERIMENTAL EVALUATION

This section contains three main comparisons to investigate the proposed WSEO comprehensively. In these comparisons, the original version of WSO is compared with the DE, DMOA, SSA, and GWO to present its performance without any enhancement. Subsequently, the proposed hybridization is utilized for all methods, including DEEO, DMEO, SSEO, and GWEO, and compared with the original methods to show the impact of the proposed hybridization approach in improving the methods and their results. To investigate the performance of the proposed hybridization approach for all methods, the results obtained by proposed WSEO are compared with that of DEEO, DMEO, SSEO, and GWEO.

TABLE 1. SAs used in the evaluation stage.

NO.	Appliances	LOC	OTPs	OTPe	power	Scenario	NO.	Appliances	LOC	OTPs	OTPe	power	Scenario
1	Water Heater	35	300	420	1.5	1,2,3,4,6,7	63	Water Cooler	15	360	420	1	1,2,3,4,5,6,7
2	Water Heater	35	1100	1440	1.5	2,3,5,7	64	Water Cooler	15	420	480	1	1,2,3,4,5,6,7
3	Dish Washer	105	540	780	0.6	1,2,3,4,5,6,7	65	Water Cooler	15	480	540	1	1,2,3,4,5,6,7
4	Dish Washer	105	840	1080	0.6	2,3,4,6,7	66	Water Cooler	15	540	600	1	1,2,3,4,5,6,7
5	Dish Washer	105	1200	1440	0.6	1,3,4,5,7	67	Water Cooler	15	600	660	1	1,2,3,4,5,6,7
6	Refrigerator	1440	1	1440	0.5	1,2,3,4,5,6,7	68	Water Cooler	15	660	720	1	1,2,3,4,5,6,7
7	Clothes Washer	55	60	300	0.38	3,5,7	69	Water Cooler	15	720	780	1	1,2,3,4,5,6,7
8	Clothes Dryer	60	300	480	0.8	3,5,7	70	Water Cooler	15	780	840	1	1,2,3,4,5,6,7
9	Coffee Maker	10	300	450	0.8	1,2,4,5,6,7	71	Water Cooler	15	840	900	1	1,2,3,4,5,6,7
10	Coffee Maker	10	1020	1140	0.8	2,3,4,6,7	72	Water Cooler	15	900	960	1	1,2,3,4,5,6,7
11	DeHumidifier	30	1	60	0.05	1,2,3,4,5,6,7	73	Water Cooler	15	960	1020	1	1,2,3,4,5,6,7
12	DeHumidifier	30	60	120	0.05	1,2,3,4,5,6,7	74	Water Cooler	15	1020	1080	1	1,2,3,4,5,6,7
13	DeHumidifier	30	120	180	0.05	1,2,3,4,5,6,7	75	Water Cooler	15	1080	1140	1	1,2,3,4,5,6,7
14	DeHumidifier	30	180	240	0.05	1,2,3,4,5,6,7	76	Water Cooler	15	1140	1200	1	1,2,3,4,5,6,7
15	DeHumidifier	30	240	300	0.05	1,2,3,4,5,6,7	77	Water Cooler	15	1200	1260	1	1,2,3,4,5,6,7
16	DeHumidifier	30	300	360	0.05	1,2,3,4,5,6,7	78	Water Cooler	15	1260	1320	1	1,2,3,4,5,6,7
17	DeHumidifier	30	360	420	0.05	1,2,3,4,5,6,7	79	Water Cooler	15	1320	1380	1	1,2,3,4,5,6,7
18	DeHumidifier	30	420	480	0.05	1,6,7	80	Water Cooler	15	1380	1440	1	1,2,3,4,5,6,7
19	DeHumidifier	30	480	540	0.05	1,6,7	81	Water Purifier	15	300	360	0.06	1,2,3,4,5,6,7
20	DeHumidifier	30	540	600	0.05	1,6,7	82	Water Purifier	15	360	420	0.06	1,2,3,4,5,6,7
21	DeHumidifier	30	600	660	0.05	1,6,7	83	Water Purifier	15	420	480	0.06	1,2,3,4,5,6,7
22	DeHumidifier	30	660	720	0.05	1,6,7	84	Water Purifier	15	480	540	0.06	1,2,3,4,5,6,7
23	DeHumidifier	30	720	780	0.05	1,6,7	85	Water Purifier	15	540	600	0.06	1,2,3,4,5,6,7
24	DeHumidifier	30	780	840	0.05	1,5,6,7	86	Water Purifier	15	600	660	0.06	1,2,3,4,5,6,7
25	DeHumidifier	30	840	900	0.05	1,3,5,6,7	87	Water Purifier	15	660	720	0.06	1,2,3,4,5,6,7
26	DeHumidifier	30	900	960	0.05	1,3,5,6,7	88	Water Purifier	15	720	780	0.06	1,2,3,4,5,6,7
27	DeHumidifier	30	960	1020	0.05	1,2,3,4,5,6,7	89	Water Purifier	15	780	840	0.06	1,2,3,4,5,6,7
28	DeHumidifier	30	1020	1080	0.05	1,2,3,4,5,7	90	Water Purifier	15	840	900	0.06	1,2,3,4,5,6,7
29	DeHumidifier	30	1080	1140	0.05	1,2,3,4,5,7	91	Water Purifier	15	900	960	0.06	1,2,3,4,5,6,7
30	DeHumidifier	30	1140	1200	0.05	1,2,3,4,5,7	92	Water Purifier	15	960	1020	0.06	1,2,3,4,5,6,7
31	DeHumidifier	30	1200	1260	0.05	1,2,3,4,5,7	93	Water Purifier	15	1020	1080	0.06	1,2,3,4,5,6,7
32	DeHumidifier	30	1260	1320	0.05	1,2,3,4,5,7	94	Water Purifier	15	1080	1140	0.06	1,2,3,4,5,6,7
33	DeHumidifier	30	1320	1380	0.05	1,2,3,4,5,7	95	Water Purifier	15	1140	1200	0.06	1,2,3,4,5,6,7
34	DeHumidifier	30	1380	1440	0.05	1,2,3,4,5,7	96	Water Purifier	15	1200	1260	0.06	1,2,3,4,5,6,7
35	Freezer	1440	1	1440	0.6	1,2,3,4,5,6,7	97	Water Purifier	15	1260	1320	0.06	1,2,3,4,5,6,7
36	Air Purifier	30	1	60	0.05	1,2,3,4,5,6,7	98	Water Purifier	15	1320	1380	0.06	1,2,3,4,5,6,7
37	Air Purifier	30	60	120	0.05	1,2,3,4,5,6,7	99	Water Purifier	15	1380	1440	0.06	1,2,3,4,5,6,7
38	Air Purifier	30	120	180	0.05	1,2,3,4,5,6,7	100	Room AC	30	1	60	1	1,2,3,4,5,6,7
39	Air Purifier	30	180	240	0.05	1,2,3,4,5,6,7	101	Room AC	30	60	120	1	1,2,3,4,5,6,7
40	Air Purifier	30	240	300	0.05	1,2,3,4,5,6,7	102	Room AC	30	120	180	1	1,2,3,4,5,6,7
41	Air Purifier	30	300	360	0.05	1,2,3,4,5,6,7	103	Room AC	30	180	240	1	1,2,3,4,5,6,7
42	Air Purifier	30	360	420	0.05	1,2,3,4,5,6,7	104	Room AC	30	240	300	1	1,2,3,4,5,6,7
43	Air Purifier	30	420	480	0.05	6,7	105	Room AC	30	300	360	1	1,2,3,4,5,6,7
44	Air Purifier	30	480	540	0.05	6,7	106	Room AC	30	360	420	1	1,2,3,4,5,6,7
45	Air Purifier	30	540	600	0.05	6,7	107	Room AC	30	420	480	1	1,2,3,4,5,6,7
46	Air Purifier	30	600	660	0.05	6,7	108	Room AC	30	480	540	1	1,2,3,4,5,6,7
47	Air Purifier	30	660	720	0.05	6,7	109	Room AC	30	540	600	1	1,2,3,4,5,6,7
48	Air Purifier	30	720	780	0.05	6,7	110	Room AC	30	600	660	1	1,2,3,4,5,6,7
49	Air Purifier	30	780	840	0.05	5,6,7	111	Room AC	30	660	720	1	1,2,3,4,5,6,7
50	Air Purifier	30	840	900	0.05	3,5,6,7	112	Room AC	30	720	780	1	1,2,3,4,5,6,7
51	Air Purifier	30	900	960	0.05	3,5,7	113	Room AC	30	780	840	1	1,2,3,4,5,6,7
52	Air Purifier	30	960	1020	0.05	3,4,5,7	114	Room AC	30	840	900	1	1,2,3,4,5,6,7
53	Air Purifier	30	1020	1080	0.05	1,2,3,4,5,7	115	Room AC	30	900	960	1	1,2,3,4,5,6,7
54	Air Purifier	30	1080	1140	0.05	1,2,3,4,5,7	116	Room AC	30	960	1020	1	1,2,3,4,5,6,7
55	Air Purifier	30	1140	1200	0.05	1,2,3,4,5,7	117	Room AC	30	1020	1080	1	1,2,3,4,5,6,7
56	Air Purifier	30	1200	1260	0.05	1,2,3,4,5,7	118	Room AC	30	1080	1140	1	1,2,3,4,5,6,7
57	Air Purifier	30	1260	1320	0.05	1,2,3,4,5,7	119	Room AC	30	1140	1200	1	1,2,3,4,5,6,7
58	Air Purifier	30	1320	1380	0.05	1,2,3,4,5,7	120	Room AC	30	1200	1260	1	1,2,3,4,5,6,7
59	Air Purifier	30	1380	1440	0.05	1,2,3,4,5,7	121	Room AC	30	1260	1320	1	1,2,3,4,5,6,7
60	Robotic Pool Filter	180	1	540	0.54	3,5,7	122	Room AC	30	1320	1380	1	1,2,3,4,5,6,7
61	Robotic Pool Filter	180	900	1440	0.54	1,4,7	123	Room AC	30	1380	1440	1	1,2,3,4,5,6,7
62	Water Cooler	15	300	360	1	1,2,3,4,5,6,7							

TABLE 2. NSAs used in the evaluation stage.

NO.	Appliances	power
1	Lighting	0.6
2	Attic Fan	0.3
3	Table Fan	0.5
4	Iron	1.5
5	Toaster	1
6	Computer Charger	1.5
7	Vacuum Cleaner	1.5
8	TV	0.3
9	Hair Dryer	1.2
10	Hand Drill	0.6
11	Water Pump	2.5
12	Blender	0.3
13	Electric Stove	1.5
14	Microwave	1.18
15	Rice Cooker	0.5
16	Electric Kettle	1.5
17	Electric Vehicle	1
18	Food Processor	0.45
19	Instant Pot	1
20	Slow Cooker	1.2
21	Stand Mixer	1.1
22	Waffle Iron	0.7
23	Bread Machine	1.2
24	Deep Fryer	1.8
25	Sewing Machine	0.01
26	Food Dehydrator	4.4

1) COMPARISON BASED THE ORIGINAL METHODS

In this section, the original DE, DMOA, GWO, SSA, and WSO are compared to show the best original optimization method in addressing the PSP and optimize its objectives, including EB, PAR, AWT, CPL, and UC.

TABLE 3. Parameters of WSO and EO algorithms.

Parameter	Value
Population Size (N)	40
Max Iteration (I)	500
u	$OTPe - LOC$
l	$OTPs$
f_{max} & f_{min}	0.75 & 0.07
p_{max} & p_{min}	1.5 & 0.5
τ	4.11
GB	0.5
V	1
w_1	0.4
w_2, w_3, w_4	0.2

The EBs obtained by these methods are presented and compared in Table 4. In addition, the average EB reduction is presented in the table to show the best method for reducing the overall EBs. Note that the EBs achieved by SSA are the minimum for all scenarios compared with the other methods. In addition, the SSA obtained the best average EB reduction, where it reduced the EBs by up to 5.7%, 3.6%, 6.4%, and 5.7% compared to DE, DMOA, GWO, and WSO, respectively.

Furthermore, the SSA achieved the best PAR reduction among all compared methods for almost all scenarios and

TABLE 4. Comparison between the original methods in terms of EB.

S#	DE	DMOA	GWO	SSA	WOS
S#1	186.7013	183.9933	186.3214	**182.9417**	186.2564
S#2	163.002	157.6297	162.91	**150.9627**	162.9829
S#3	186.9801	178.0941	185.796	**172.3181**	185.5184
S#4	129.9951	124.8881	129.4037	**119.9059**	129.2415
S#5	117.4161	113.0481	117.2714	**109.5016**	117.1113
S#6	90.57785	93.30303	94.18147	**88.92552**	92.09618
S#7	103.4956	103.8463	106.6849	**98.1965**	104.9312
AVG	139.7383	136.4004	140.367	**131.8217**	139.734

TABLE 5. Comparison between the original methods in terms of PAR.

S#	DE	DMOA	GWO	SSA	WOS
S#1	**1.752344**	2.409371	1.812272	1.845504	1.775498
S#2	2.018357	2.705188	2.018357	**1.954358**	1.965356
S#3	**1.870788**	2.477312	2.050713	1.978436	1.893509
S#4	2.069565	2.674761	2.224711	**1.96007**	2.136284
S#5	2.00528	2.366447	**1.911153**	1.935508	1.998697
S#6	2.218101	3.297638	2.337568	**2.11412**	2.249074
S#7	2.320454	3.316818	2.405779	**2.113269**	2.345276
AVG	2.036413	2.749648	2.10865	**1.985895**	2.051956

TABLE 6. Comparison between the original methods in terms of AWT.

S#	DE	DMOA	GWO	SSA	WOS
S#1	0.009729	0.096802	0.041765	0.236154	**4.92E-03**
S#2	0.004281	0.101451	0.048244	0.235466	**0.003868**
S#3	0.009374	0.108337	0.055445	0.237402	**0.005491**
S#4	0.00678	0.097928	0.047608	0.232015	**0.004188**
S#5	**0.002284**	0.098107	0.04719	0.218092	0.004656
S#6	0.022994	0.094213	0.062635	0.251828	**0.007527**
S#7	0.021616	0.124357	0.057612	0.263566	**1.32E-02**
AVG	0.011008	0.103028	0.0515	0.239218	**0.006266**

TABLE 7. Comparison between the original methods in terms of CPL.

S#	DE	DMOA	GWO	SSA	WOS
S#1	**0.598745**	0.627224	0.614615	0.638926	0.599363
S#2	**0.481784**	0.485751	0.484393	0.502368	0.482069
S#3	0.54773	0.553519	0.54812	0.566138	**0.544263**
S#4	0.503267	0.509598	0.503567	0.531129	**0.498933**
S#5	**0.484589**	0.496676	0.486391	0.505983	0.489797
S#6	0.363257	0.343892	0.357252	**0.328385**	0.360929
S#7	0.417842	**0.39786**	0.414859	0.399667	0.415151
AVG	0.485316	0.487788	0.487028	0.496085	**0.484358**

average reduction. The SSA obtained the best results in optimizing PAR in 4 scenarios, where as DE achieved the best in two scenarios and GWO in only one scenario. Table 5 presents the achieved PAR results.

In terms of AWT and CPL optimization, WSO shows a significant minimization, where it achieved the best AWT and CPL values in six and two scenarios, respectively. Furthermore, the WSO obtained the best overall reduction for both AWT and CPL, as shown in Tables 6 and 7. Accordingly, due to the AWT and CPL affect to the UC level, the WSO outperformed all compared methods in enhancing the UC level, as presented in Table 8, where it obtained the best results in six scenarios and the overall improvement by up to 0.28%, 5.03%, 2.39%, and 12.23% for DE, DMOA, GWO, and SSA, respectively.

Note that the WSO achieved the best AWT, CPL, and UC, and the second best PAR values in almost all scenarios, whereas the SSA achieved the best results in reducing the EB and PAR values. The presented results proved the high

TABLE 8. Comparison between the original methods in terms of UC.

S#	DE	DMOA	GWO	SSA	WOS
S#1	69.57634	63.79868	67.181	56.24599	**69.78602**
S#2	75.69676	70.6399	73.36815	63.1083	**75.70313**
S#3	72.14483	66.90724	69.82178	59.82301	**72.51229**
S#4	74.49764	69.6237	72.44126	61.8428	**74.84391**
S#5	**75.65639**	70.26088	73.32098	63.79625	75.27737
S#6	80.68747	78.09472	79.00562	70.98935	**81.57719**
S#7	78.02713	73.88917	76.37646	66.83835	**78.58183**
AVG	75.18379	70.45918	73.07361	63.23487	**75.46882**

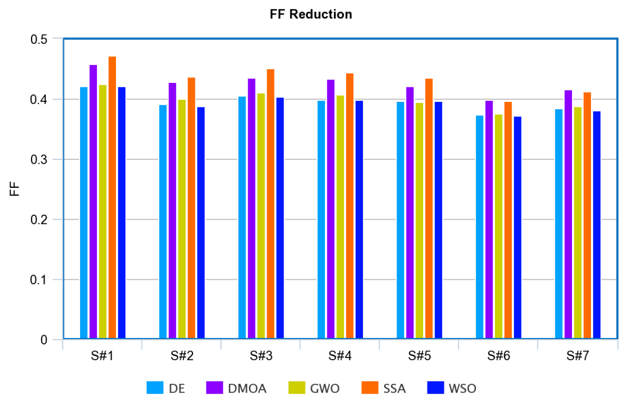


FIGURE 9. FF reduction for original methods.

performance of the WSO in addressing PSP and optimizing most of the objectives. To investigate the original method optimization performance in reducing the overall objective function (FF) (Eq. 21) for the PSP, Figure 9 presents the FF comparison between the compared original methods.

2) COMPARISON WITH THE ORIGINAL METHODS

In this section, the original DE, DMOA, GWO, SSA, and WSO are compared with the hybridized versions, including DEEO, DMEO, GWEO, SSEO, and WSEO, to show the performance and significance of the proposed hybrid approach in addressing the PSP and enhancing the results.

The obtained EB, PAR, AWT, CPL, and UC results by DE and DEEO are presented in Table 9. The presented results proved the high performance of the proposed hybridization, where the DEEO outperformed the original DE in optimizing PAR, AWT, CPL, and UC. Furthermore, it obtained better results for two scenarios in terms of EB reduction. Similarly, the GWEO performed better in optimizing the same objectives compared GWO. However, the GWO obtained better results in only optimizing the EB than the GWEO, as shown in Table 10.

The DMEO shows low capabilities in optimizing the objectives compared to the DMOA, where the DMOA outperformed the proposed DMEO in optimizing PAR and AWT. The original DMOA shows better investigation and results in reducing the overall values of EBs and CPL. Furthermore, it presents a good performance in enhancing the UC level. Although the DMOA obtains better results in EB, CPL, and UC, the proposed DMEO performed better in

TABLE 9. Comparison between the DE and DEEO in terms of all objectives.

	EB		PAR		AWT		CPL		UC	
S#	DE	DEEO	DE	DEEO	DE	DEEO	DE	DEEO	DE	DEEO
S#1	**186.7013**	186.7253	1.752344	**1.746896**	0.009729	**0.009276**	**0.598745**	**0.598745**	69.57634	**69.59897**
S#2	**163.002**	163.0807	2.018357	**2.008419**	0.004281	**0.003567**	**0.481784**	0.482033	75.69676	**75.71997**
S#3	**186.9801**	187.052	**1.870788**	**1.870788**	**0.009374**	0.009773	0.54773	**0.547516**	**72.14483**	72.13557
S#4	**129.9951**	130.0447	**2.069565**	2.059989	0.00678	**0.006554**	**0.503267**	0.503285	74.49764	**74.50805**
S#5	**117.4161**	**117.4161**	**2.00528**	**2.00528**	**0.002284**	**0.002284**	**0.484589**	**0.484589**	**75.65639**	**75.65639**
S#6	90.57785	**90.51618**	2.218101	**2.204827**	0.022994	**0.022534**	**0.363257**	0.363542	80.68747	**80.69622**
S#7	**103.4956**	103.6935	2.320454	**2.27973**	0.021616	**0.017077**	0.417842	**0.416448**	78.02713	**78.32378**
AVG	**139.7383**	139.7898	2.036413	**2.025133**	0.011008	**0.010152**	0.485316	**0.485165**	75.18379	**75.23413**

TABLE 10. Comparison between the GWO and GWEO in terms of all objectives.

	EB		PAR		AWT		CPL		UC	
S#	GWO	GWEO	GWO	GWEO	GWO	GWEO	GWO	GWEO	GWO	GWEO
S#1	**186.3214**	186.415	1.812272	**1.806824**	**0.041765**	0.042112	0.614615	**0.613967**	67.181	**67.19606**
S#2	**162.91**	162.9345	**2.018357**	**2.018357**	**0.048244**	0.05197	**0.484393**	0.485383	**73.36815**	73.13236
S#3	**185.796**	186.0742	2.050713	**2.041808**	0.055445	**0.045792**	**0.54812**	0.548661	69.82178	**70.27736**
S#4	129.4037	**129.3719**	2.224711	**2.206834**	0.047608	**0.037951**	0.503567	**0.502009**	72.44126	**73.00202**
S#5	117.2714	**117.2035**	1.911153	**1.906546**	0.04719	**0.033738**	0.486391	**0.485377**	73.32098	**74.0442**
S#6	**94.18147**	94.44758	2.337568	**2.326063**	0.062635	**0.056488**	0.357252	**0.357224**	79.00562	**79.3144**
S#7	**106.6849**	106.9298	2.405779	**2.363504**	**0.057612**	0.058825	**0.414859**	0.415173	**76.37646**	76.30012
AVG	**140.367**	140.4824	2.10865	**2.095705**	0.0515	**0.046697**	0.487028	**0.486828**	73.07361	**73.32379**

TABLE 11. Comparison between the DMOA and DMEO in terms of all objectives.

	EB		PAR		AWT		CPL		UC	
S#	DMOA	MDEO	DMOA	MDEO	DMOA	MDEO	DMOA	MDEO	DMOA	MDEO
S#1	**183.9933**	184.2877	2.409371	**2.1093**	**0.096802**	0.100226	**0.627224**	0.630674	**63.79868**	63.4549
S#2	**157.6297**	158.0312	2.705188	**2.186901**	0.101451	**0.097883**	**0.485751**	0.48964	**70.6399**	70.62381
S#3	**178.0941**	180.263	2.477312	**2.117708**	0.108337	**0.092169**	0.553519	**0.552374**	66.90724	**67.77289**
S#4	**124.8881**	125.0243	2.674761	**2.285939**	0.097928	**0.092866**	**0.509598**	0.509825	69.6237	**69.86541**
S#5	113.0481	**112.8372**	2.366447	**2.042667**	**0.098107**	0.105134	**0.496676**	0.498568	**70.26088**	69.81486
S#6	93.30303	**92.72405**	3.297638	**2.441459**	**0.094213**	1.06E-01	**0.343892**	0.346186	**78.09472**	77.38604
S#7	103.8463	**103.8177**	3.316818	**2.462326**	0.124357	**0.122413**	**0.39786**	0.404037	**73.88917**	73.67751
AVG	**136.4004**	136.7121	2.749648	**2.2351**	0.103028	**0.102397**	**0.487788**	0.490186	**70.45918**	70.3707

optimizing these objectives in some scenarios, as shown in Table 11.

The SSA performs better in optimizing the EBs and PARs than the SSEO, where the SSA obtained better results by up to 1% and 1.4% for EB and PAR, respectively. However, the proposed SSEO shows a better performance than SSA in reducing AWT and CPL, and improving UC level, as presented in Table 12. Note that the SSA achieved better EB and PAR than SSEO in low percentage.

The proposed WSEO, in Table 13, also proved the high performance of the proposed hybrid approach in enhancing the quality of the solutions, where the proposed WSEO achieved better results than WSO in optimizing PAR, AWT, CPL, and UC, and better EB in the second and sixth scenarios. However, the WSO obtained a better EB average reduction for the seven scenarios than the WSEO.

Note that the the WSO achieved the best AWT, CPL, and UC, and the second best PAR values in almost all scenarios, whereas the SSA achieved the best results in reducing the EB and PAR values. The presented results proved the high performance of the WSO in addressing PSP and optimizing most of the objectives.

As presented in Tables 9, 11, 10, 12, and 13, the proposed hybrid approach proves its high performance and capability to enhance the original methods searchability and achievements, where the proposed methods outperformed all original methods in optimizing most of the PSP objectives. To presents the high achievements of the proposed hybrid approach graphically, a comparison between the original and hybrid methods contains the overall reduction of the FF is presented in Figure 10.

3) COMPARISON BASED THE HYBRID METHODS

In this section, the proposed methods, including DEEO, DMEO, GWEO, SSEO, and WSEO, are compared in terms of all PSP objectives to investigate the performance of the best-proposed hybrid method.

Table 14 presents the EBs obtained by the proposed hybrid methods. As the original SSA showed a high performance in optimizing EB, it also shows the best performance when hybridizing it with the EO, where it obtains the best EB results among all other methods for all scenarios. In addition, the proposed SSEO yields good performance in optimizing PAR values by achieving the best results in two scenarios and average PAR reduction, as shown in Table 15. Note that either the DEEO obtained the best PAR in three scenarios, its average reduction is not the best due to its low performance in the other scenarios.

By contrast, the SSEO shows the worst performance in most scenarios in optimizing AWT and CPL. The proposed WSEO presents an outstanding performance in minimizing AWT values, as shown in Table 16, where it achieved the best reduction by up to 39%, 93%, 87%, and 96% compared to DEEO, DMEO, GWEO, and SSEO, respectively. Furthermore, the WSEO performs better than the compared methods in two scenarios and an overall reduction of the CPL, as presented in Table 17. However,

TABLE 12. Comparison between the SSA and SSEO in terms of all objectives.

	EB		PAR		AWT		CPL		UC	
S#	SSA	SSEO	SSA	SSEO	SSA	SSEO	SSA	SSEO	SSA	SSEO
S#1	**182.9417**	183.7268	**1.845504**	1.848991	0.236154	**0.156471**	0.638926	**0.624881**	56.24599	**60.93244**
S#2	**150.9627**	153.7173	**1.954358**	2.06215	0.235466	**0.169243**	0.502368	**0.496241**	63.1083	**66.7258**
S#3	**172.3181**	175.8481	**1.978436**	2.037449	0.237402	**0.160976**	0.566138	**0.558682**	59.82301	**64.01709**
S#4	**119.9059**	122.1334	1.96007	**1.941554**	0.232015	**0.155134**	0.531129	**0.523725**	61.8428	**66.05706**
S#5	109.5016	**109.4127**	1.935508	**1.91971**	0.218092	**0.161562**	**0.505983**	0.506129	63.79625	**66.61547**
S#6	88.92552	**88.88319**	**2.11412**	2.1535	0.251828	**0.191584**	**0.328385**	0.329736	70.98935	**73.93396**
S#7	**98.1965**	98.4042	**2.113269**	2.14802	0.263566	**0.217189**	**0.399667**	0.401204	66.83835	**69.08036**
AVG	**131.8217**	133.1608	**1.985895**	2.015911	0.239218	**0.173165**	0.496085	**0.491514**	63.23487	**66.76602**

TABLE 13. Comparison between the WSO and WSEO in terms of all objectives.

	EB		PAR		AWT		CPL		UC	
S#	WSO	WSEO	WSO	WSEO	WSO	WSEO	WSO	WSEO	WSO	WSEO
S#1	**186.2564**	186.5623	1.775498	**1.765964**	4.92E-03	**0.004872**	**0.599363**	0.599681	**69.78602**	69.77235
S#2	162.9829	**162.834**	**1.965356**	1.970325	**0.003868**	0.003932	**0.482069**	0.482101	**75.70313**	75.69835
S#3	**185.5184**	185.5695	**1.893509**	1.900571	**0.005491**	0.005997	0.544263	**0.543812**	**72.51229**	72.50956
S#4	**129.2415**	129.4868	2.136284	**2.121919**	0.004188	**0.003586**	0.498933	**0.497751**	74.84391	**74.93316**
S#5	**117.1113**	117.2098	**1.998697**	**1.998697**	0.004656	**0.003698**	0.489797	**0.489532**	75.27737	**75.33852**
S#6	92.09618	**91.69527**	2.249074	**2.244649**	**0.007527**	0.007941	0.360929	**0.360458**	81.57719	**81.58009**
S#7	**104.9312**	105.013	2.345276	**2.307655**	1.32E-02	**0.01319**	0.415151	**0.413399**	78.58183	**78.67056**
AVG	**139.734**	139.7672	2.051956	**2.044254**	0.006266	**0.006173**	0.484358	**0.483819**	75.46882	**75.50037**

TABLE 14. Comparison between the hybrid methods in terms of EB.

S#	DEEO	DMEO	GWEO	SSEO	WSEO
S#1	186.7253	184.2877	186.415	**183.7268**	186.5623
S#2	163.0807	158.0312	162.9345	**153.7173**	162.834
S#3	187.052	180.263	186.0742	**175.8481**	185.5695
S#4	130.0447	125.0243	129.3719	**122.1334**	129.4868
S#5	117.4161	112.8372	117.2035	**109.4127**	117.2098
S#6	90.51618	92.72405	94.44758	**88.88319**	91.69527
S#7	103.6935	103.8177	106.9298	**98.4042**	105.013
AVG	139.7898	136.7121	140.4824	**133.1608**	139.7672

TABLE 15. Comparison between the hybrid methods in terms of PAR.

S#	DEEO	DMEO	GWEO	SSEO	WSEO
S#1	**1.746896**	2.109350	1.806824	1.848991	1.765964
S#2	2.008419	2.186901	2.018357	2.06215	**1.970325**
S#3	**1.870788**	2.117708	2.041808	2.037449	1.900571
S#4	2.059989	2.285939	2.206834	**1.941554**	2.121919
S#5	2.00528	2.042667	**1.906546**	1.91971	1.998697
S#6	**2.204827**	2.441459	2.326063	2.1535	2.244649
S#7	2.27973	2.462326	2.363504	**2.14802**	2.307655
AVG	2.025133	2.235193	2.095705	**2.015911**	2.044254

TABLE 16. Comparison between the hybrid methods in terms of AWT.

S#	DEEO	DMEO	GWEO	SSEO	WSEO
S#1	0.009276	0.100226	0.042112	0.156471	**0.004872**
S#2	**0.003567**	0.097883	0.05197	0.169243	0.003932
S#3	0.009773	0.092169	0.045792	0.160976	**0.005997**
S#4	0.006554	0.092866	0.037951	0.155134	**0.003586**
S#5	**0.002284**	0.105134	0.033738	0.161562	0.003698
S#6	0.022534	0.106093	0.056488	0.191584	**0.007941**
S#7	0.017077	0.122413	0.058825	0.217189	**0.01319**
AVG	0.010152	0.10239	0.046697	0.173165	**0.006173**

DEEO obtains better CPL in three scenarios and SSEO in only two.

Due to the high performance of the WSEO in optimizing AWT and CPL, it yields and exhibits the best results in improving the UC level. The proposed WSEO enhance the UC by up to 0.3%, 5.2%, 2.2%, and 9% compared to DEEO, DMEO, GWEO, and SSEO, respectively.

To investigate the best method's performance in optimizing the whole solution considering all objectives among all other methods, the convergence behaviour of all methods,

TABLE 17. Comparison between the hybrid methods in terms of CPL.

S#	DEEO	DMEO	GWEO	SSEO	WSEO
S#1	**0.598745**	0.630674	0.613967	0.624881	0.599681
S#2	**0.482033**	0.48964	0.485383	0.496241	0.482101
S#3	0.547516	0.552374	0.548661	0.558682	**0.543812**
S#4	0.503285	0.509825	0.502009	0.523725	**0.497751**
S#5	**0.484589**	0.498568	0.485377	0.506129	0.489532
S#6	0.363542	0.346186	0.357224	**0.329736**	0.360458
S#7	0.416448	0.404037	0.415173	**0.401204**	0.413399
AVG	0.485165	0.490186	0.486828	0.491514	**0.483819**

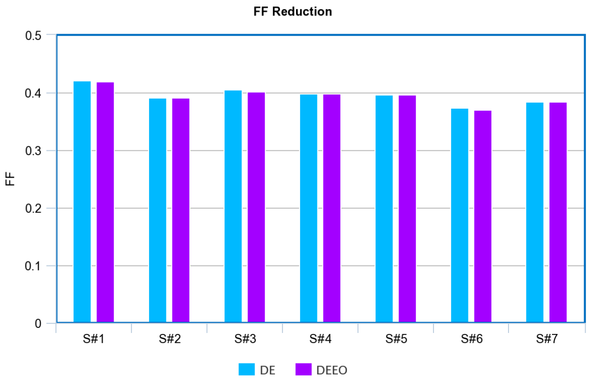
TABLE 18. Comparison between the hybrid methods in terms of UC.

S#	DEEO	DMEO	GWEO	SSEO	WSEO
S#1	69.59897	63.45493	67.19606	60.93244	**69.77235**
S#2	**75.71997**	70.62381	73.13236	66.7258	75.69835
S#3	72.13557	67.77289	70.27736	64.01709	**72.50956**
S#4	74.50805	69.86541	73.00202	66.05706	**74.93316**
S#5	**75.65639**	69.81486	74.0442	66.61547	75.33852
S#6	80.69622	77.38604	79.3144	73.93396	**81.58009**
S#7	78.32378	73.67751	76.30012	69.08036	**78.67056**
AVG	75.23413	70.37077	73.32379	66.76602	**75.50037**

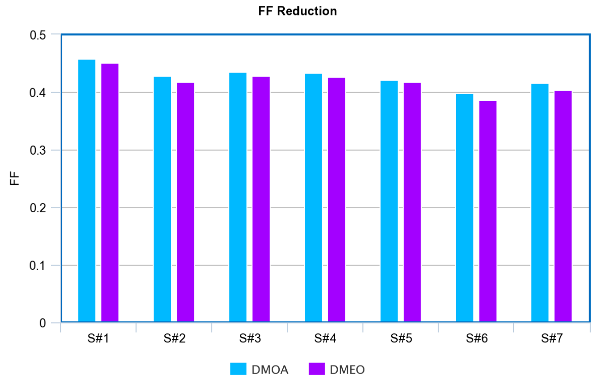
including DEEO, DMEO, GWEO, SSEO, and WSEO, for the seven scenarios is studied, analyzed, and presented in Figure 11. The figure shows the high performance of the WSEO in reaching its optimal solution compared to the other methods, where it achieved the best FF among all methods in six scenarios. In addition, the WSEO shows a high balance between exploration and exploitation calabilitites during its optimization processes, where it is moves smoothly into its optimal solution without stagation in local optima except the last few iterations due to the best solution achievment.

4) DISCUSSION

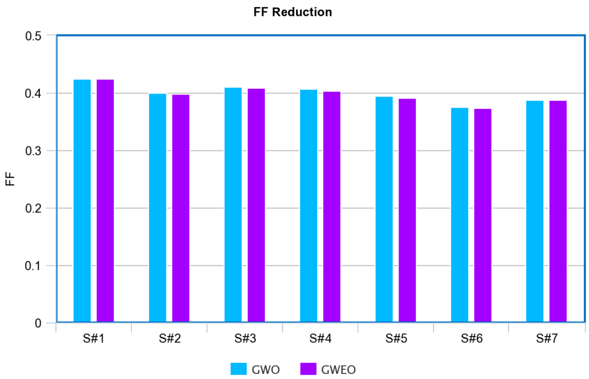
In this paper, a new hybrid method based on the EO is proposed to efficiently address the PSP and optimize its objectives, including EB, PAR, AWT, CPL, and UC. The proposed hybrid approach is utilized for five well-known metaheuristic optimization methods: DE, DMOA, GWO, SSA, and WSO. The proposed hybrid methods are DEEO, DMEO, GWEO, SSEO, and WSEO.



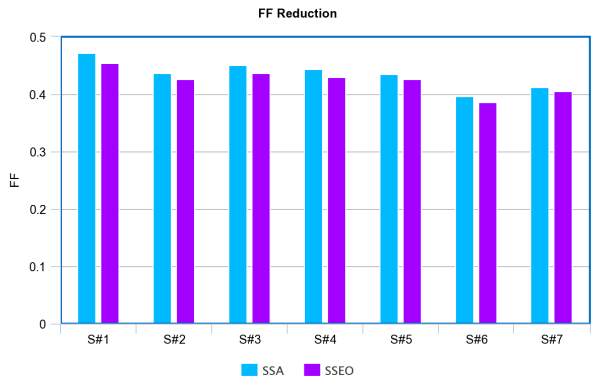
(a) FF reduction of DE and DEEO



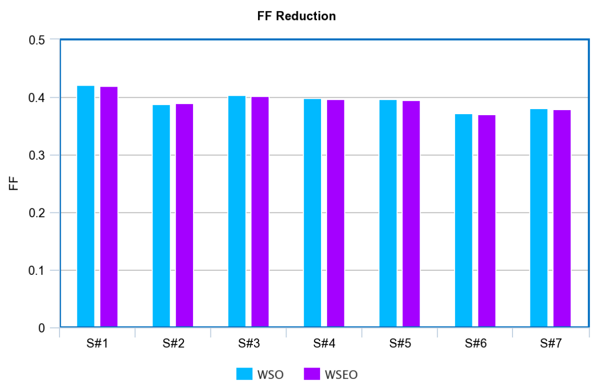
(b) FF reduction of DMOA and DMEO



(c) FF reduction of GWO and GWEO



(d) FF reduction of SSA and SSEO



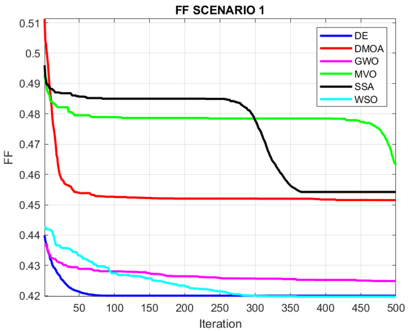
(e) FF reduction of WSO and WSEO

FIGURE 10. **FF comparison between original and hybrid methods.**

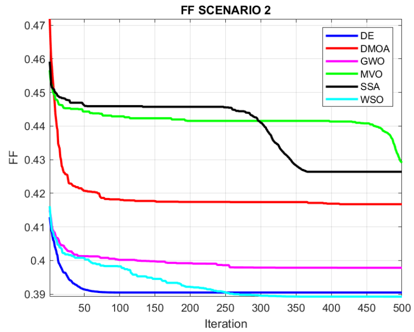
Firstly, the original methods are compared in terms of all objectives and FF to show the best adapted original method for PSP. The results proved the high performance of the WSO compared with the other methods in addressing the PSP due to the WSO searching mechanism that has a high exploration and exploitation balance to reach its optimal solution without stagnation in local optima.

Secondly, the original methods are compared with their hybrid versions to investigate the performance of the proposed hybrid approach in enhancing the original versions' performance and solutions quality. The obtained results that are presented in Tables 9, 10, 11, 12, and 13, proved the significant performance of the hybrid approach in improving the results, where the proposed hybrid methods achieved better results than the original versions in optimizing most of the objectives and FF.

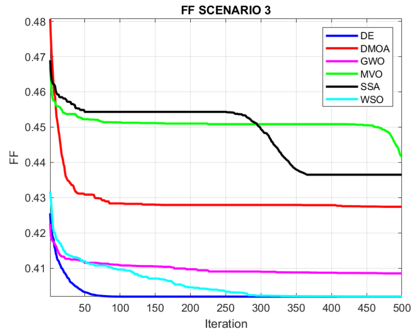
Thirdly, the proposed hybrid methods are compared to show the best hybrid method for optimizing the PSP and its objectives. Due to the high searching balance and capabilities of the proposed WSEO, it obtained the best results compared with the SEEO, DMEO, GWEO, and SSEO.



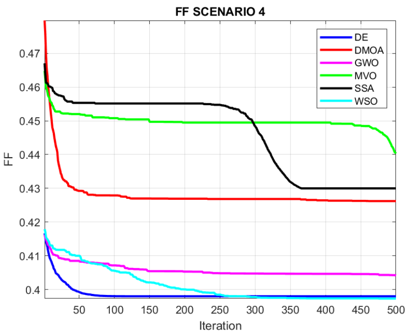
(a) The convergence behaviour for S#1



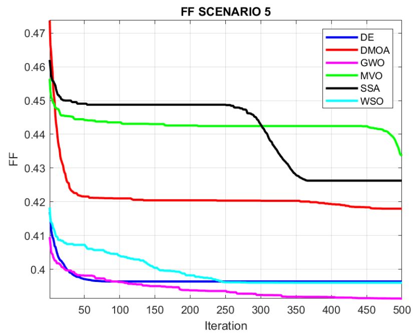
(b) The convergence behaviour for S#2



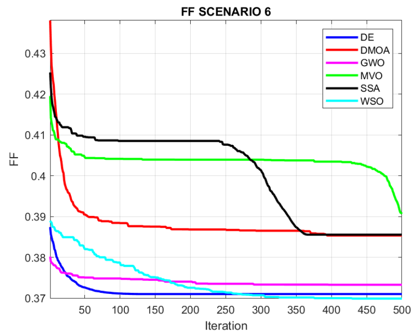
(c) The convergence behaviour for S#3



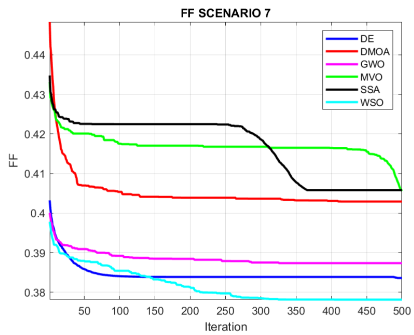
(d) The convergence behaviour for S#4



(e) The convergence behaviour for S#5



(f) The convergence behaviour for S#6



(g) The convergence behaviour for S#7

FIGURE 11. Convergence behavior of hybrid method for all scenarios.

VI. CONCLUSION AND FUTURE WORK

The PSP is the problem of managing, controlling, and scheduling power consumption of appliances to operate at the best periods according to three main objectives: EBs, PAR, AWT, and CPL. The PSP is modelled as a multi-objective PSP to consider all its objectives. The PSP components can be controlled using several communication approaches, where the IoT is the best for data exchange. A new hybrid approach called WSEO is proposed to efficiently address the PSP and find the optimal schedule. The primary purposes of proposing the WSEO are to enhance the WSO optimization performance utilizing the components of the EO and enhance the PSP solutions' quality.

In the experimental results, a new case study in the UAE is proposed to test and evaluate the WSEO. In the case study, a new dataset is constructed and created on the basis of the available smart appliances in UAE homes. The dataset contains seven scenarios with up to 123 appliances. In terms of comparison, firstly, the performance of the WSO is compared with four well-known optimization algorithms: DE, DMOA, GWO, and SSA. The WSO performed better than the compared algorithms in most of the objectives and scenarios. Secondly, the proposed hybrid approach is applied to these algorithms and compared with the original methods to show and investigate the enhancement of the hybrid approach. The hybrid approach proved its high capabilities in enhancing the original algorithms' performance. Finally, the proposed WSEO is compared with the DEEO, DMEO, GWEO, and SSEO to find the best hybrid method for addressing the PSP. The proposed WSEO outperformed all compared hybrid methods in achieving the best schedules for the PSP.

In future studies, several directions can be considered to enhance the obtained results. These directions can be summarized as follows:

Expand Scenarios: In this study, seven scenarios are constructed to evaluate the proposed methods on the basis of the available smart appliances in UAE homes. The number of scenarios can be increased to 30 scenarios to cover one month of power consumption instead of one week.

Addition Power Sources: New additional renewable energy sources can be integrated into the considered smart home to reduce and optimize the amount of power consumed. In addition, a new storage system can be utilized to store power at low prices periods and discharge the stored power at high pricing periods.

Method enhancement: The proposed WSEO method can be improved by modifying its behaviour to enhance local and global search balance by utilizing a new parameter.

Weights Parameters: The weights used in the objectives function can be tuned and dynamically changed to find their best values.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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