Wind Driven Optimization With Smart Home Battery for Power Scheduling Problem in Smart Home

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***Abstract*—The power scheduling problem in smart home (PSPSH) refers to schedule smart appliances at suitable times in accordance with pricing system(s). Smart appliances can be rearranged and scheduled by moving their operation times from one period to another. Such a process aims to decrease the electricity bill and the power demand at peak periods and improve user satisfaction. Different optimization approaches were proposed to address PSPSH, where metaheuristics are the most common methods. In this paper, wind-driven optimization (WDO) is adapted to handle PSPSH and optimize its objectives. Smart home battery (SHB) is modelled and used to improve the schedules by storing power at off-peak periods and using the stored power at peak periods. In the simulation results, the proposed approach proves its efficiency in reducing electricity bills and improving user satisfaction. In addition, WDO is compared with bacterial foraging optimization algorithm (BFOA) to evaluate and investigate its performance. WDO outperforms BFOA in optimizing PSPSH objectives.**

***Index Terms*—Optimization, Power Scheduling Problem in Smart Home, Wind Driven Optimization, Smart Home Battery.**

I. Introduction

Power consumption is growing over time as a result of population increase and the appearance of new technologies such as smart home appliances that require more power to operate [1]. Consequently, the power system's stability of the old power grids became not guaranteed to meet such an enormous increment in power demand. Furthermore, owing to the rudimentary nature of the old power grids' construction, they are unable to install additional power generators to fulfil power needs [2][3] [4].

An alternative system is developed based on modern and smart technologies to handle the old grids' issues. The new system called the smart grid (SG). The transmission system is the major mechanism utilized in SGs, providing two-way contact between users and power supply companies (PSCs) to improve delivery and power systems. Such improvement enables PSCs to deliver extra power to consumers and satisfy their power requirements [5][6].

SGs enable consumers to manage their power usage by utilizing demand response (DR) schemes. DR offers many tools that encourage users to alter and balance the power consumption of appliances to keep the power system stable [7]. DR is divided into two types: incentive-based programs and dynamic pricing schemes [5]. Dynamic pricing schemes offer varying power costs over time, with high rates during peak hours and low rates during off-peak periods. These schemes encourage consumers to manage their appliances to run during off-peak hours [5][8].

The problem of rearranging and scheduling smart appliance operating time at appropriate intervals based on a dynamic pricing scheme is known as the power scheduling problem in smart home (PSPSH). PSPSH was modelled to lower the

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electricity bill (EB), balancing power consumption by lowering the peak-to-average ratio (PAR) and highering user comfort [3][4][5].

PSPSH has been handled in various research utilizing different optimization techniques. The metaheuristics are the most common in solving PSPSH because of their capability to effectively explore spacious and ragged search spaces [5]. Furthermore, the metaheuristics demonstrated their efficiency in various fields, such as authentication [9][10][11][12][13][14][15][16], text feature selection and clustering [17][18][19][20][21][22], gene selection [23] [24].

In this study, wind-driven optimization (WDO) is adapted for PSPSH and optimize its objectives due to its robust performance to penetrate search spaces with a high balance between local and global search capabilities. Furthermore, a smart home battery (SHB) is designed to improve schedules by banking power during low price times and releasing the stored power during high pricing times. In the evaluation processes, a dataset contains 36 appliances is used [4][6]. The adapted algorithm's performance is investigated and compared with another algorithm, called bacterial foraging optimization algorithm (BFOA)

The paper structure is prepared as follows. The essential research that proposed to address PSPSH are given in Section II. The formulation of PSPSH and the SHB are discussed in Section III. Section IV illustrates the WDO and the adaptation steps for PSPSH. In Section V, the results of the introduced method are illustrated, and Section VI summarizes the paper.

II. Related Work

Different optimization approaches, including exacts and metaheuristics, were adapted to handle PSPSH. In tackling PSPSH, metaheuristics are more common than exacts. This section discusses some of the research that used metaheuristics for PSPSH.

PSPSH was modelled as a multi-objective problem by the authors of [25]. PSPSH's multi-objective function was designed to optimize EB and user discomfort simultaneously. The ant colony optimization (ACO), binary particle-swarm algorithm (BPSO), and genetic algorithm (GA) were adapted to find the optimal schedule for 13 household appliances in a single day. GA exceeded ACO and BPSO in meeting PSPSH objectives.

PSPSH was modelled as a multi-objective problem to optimize both EB and user comfort level at the same time [26]. To balance electricity demand and ensure system stability, two dynamic pricing schemes were integrated. GA was modified to handle PSPSH utilizing 16 appliance operations over 90 days. The findings demonstrate the effectiveness of the suggested technique in lowering EB and increasing user comfort.

In [7], GA and biogeography-based optimization (BBO) were adapted to handle PSPSH. To schedule 12 appliances in one day, a dynamic pricing scheme, called time-of-use pricing, was applied. The simulation results demonstrated BBO's excellent performance, outperforming GA in the search for an optimal schedule.

The flower pollination algorithm (FPA) and GA were adapted to handle PSPSH in [27]. Sixteen appliances were utilized to assess the algorithms in lowering EB and PAR and increasing user satisfaction in line with a dynamic pricing scheme known as real-time price optimization (RTP). In simulated findings, FPA outperformed GA in terms of lowering EB and PAR, whereas GA outperformed FPA in terms of enhancing comfort level.

In [28], the authors used BAT and harmony search algorithm to produce a nearly optimum schedule for eleven appliances. In simulation findings, CPP was employed as the pricing scheme. The HSA had a better schedule than BAT and obtained more valuable results in balancing power used over time.

In [6], the PSO was adapted to find the best schedule for 36 appliance operations utilizing smart batteries. In simulation findings, the real-time price was utilized as a dynamic pricing scheme to calculate the EB. PSO's performance is evaluated in simulation results by comparing it with that of the GA. PSO had a better schedule than GA without and with the smart home battery.

III. Problem Formulation

PSPSH refers to schedule and manages appliances' operations at a particular period using dynamic pricing program(s). The main purposes of handling PSPSH are lowering PAR, EB, and user discomfort.

Two types of appliances can be in a smart home, including schedulable appliances and non-schedulable appliances. The schedulable appliances refer to the appliances that operated automatically and can be scheduled, such as washing machines, whereas the non-schedulable appliances operate manually, such as TV and PC charger. In this study, the schedulable appliances are considered in the scheduling processes with considering the non-schedulable appliances.

PSPSH objectives are presented and mathematically stated in this section. Furthermore, an SHB is specified to increase the quality of the schedule(s) and get a more acceptable schedule. The RTP is utilized as a dynamic pricing program and is combined with the inclining block rate (IBR) due to the IBR's efficiency in balancing power demand and lowering the PAR value [29][8].

A. Objectives Formulation

Because of the EB relevance in persuading users to reschedule their appliance operations, minimizing EB is a key goal of PSPSH. Eq. 1 expresses EB formulation.

$$EB = \sum_{i=1}^{S} \sum_{j=1}^{T} P_i^j \times pc^j \tag{1}$$

where S is the number of the utilized smart appliances, T is the number of slots, and P_i^j is the power required by appliance i at slot j. pc^j is price at slot j. In this study, the RTP is coupled with the IBR; thus, pc^j has two prices according to the power consumed as follows [8]:

$$pc^j = \begin{cases} a^j & \text{if } 0 \leq P^j \leq C \\ b^j & \text{if } P^j > C \end{cases} \tag{2}$$

$$b^j = \lambda \times a^j \tag{3}$$

where P^j is the power consumed by all appliances at slot j, C denotes the power threshold, a^j is normal price at slot j, b^j denotes high price at slot j, and λ is a positive number.

PAR refers to the ratio between average and highest power consumed, which is formulated as follows [8]:

$$PAR = \frac{P_{max}}{P_{avg}} \tag{4}$$

where P_{max} and P_{avg} are the maximum and average power consumed.

In this research, the UC level is calculated based on two comfort factors, including waiting time rate (WTR) and capacity power limit rate (CPR). WTR refers to the waiting time for the appliances to be scheduled, and CPR is the availability of the non-schedulable appliances to be operated within C. WTR and CPR can be formulated as follow [8]:

$$WTR_i = \frac{st_i - OTPs_i}{OTPe_i - OTPs_i - l_i}, \quad \forall i \in \boldsymbol{S} \tag{5}$$

where WTR_i is waiting time rate for appliance i, st_i is the appliance i starting time, l_i is cycle length of appliance i, and $OTPs_i$ and $OTPe_i$ are starting and finishing allowable time for appliance i to be scheduled, respectively.

$$CPR^j = \frac{\sum_{k=1}^{q} ONA_k^j}{q}, \tag{6}$$

where ONA denotes the number of non-schedulable appliances whose operation power exceeds C and q is the number of all non-schedulable appliances.

Average WTR and CPR are calculated as follow:

$$WTR_{avg} = \frac{\sum_{i=1}^{m} (st_i - OTPs_i)}{\sum_{i=1}^{m} (OTPe_i - OTPs_i - l_i)}, \tag{7}$$

$$CPR_{avg} = \frac{\sum_{j=1}^{n} \sum_{k=1}^{q} ONA_k^j}{q \times n}, \tag{8}$$

WTR_{avg} and CPR_{avg} value ranges are between 0 and 1. Accordingly, the UC percentage can be computed as follows:

$$UC_p = (1 - (\frac{WTR_{avg} + CPR_{avg}}{2})) \times 100\%, \tag{9}$$

B. Smart Home Battery (SHB)

The SHB is a type of storage battery system charged and discharged several times under certain conditions. SHB includes a built-in battery management system, which allows it to be more versatile in controlling charging and discharging activities [30].

SHB is a critical system in enhancing grid stability at peak intervals and balancing power production and consumption [30]. Furthermore, SHB can profit users by optimizing their consumption and giving a backup power source for use at unexpected breakdown periods [31][6][30].

In this study, SHB is designed to efficiently improve the quality of the solution(s) and optimize the PSPSH objectives. The SHB is able to minimize power consumption during peak periods efficiently because it is designed to store power at off-peak periods and release the stored power at peak periods.

The proposed SHB model considers the charging operations as SAs that can be scheduled using the adapted algorithm, whilst the discharging operations considered as an extra power source. The SHB is turned off in free operations. The SHB is developed to charge at any time, taking into account the amount of power that can be discharged. Furthermore, the SHB can be discharged at any time, taking into account the charging operations and the amount of power charged. The SHB is supposed to be entirely discharged by the end of the day.

As mentioned earlier, the SHB can be charged at any time using the adapted algorithm with considering the battery parameters, where the charging amount at any time must not exceed the allowable charging limit and the total power amount in the battery must not exceed its capacity. SHB's discharging operations is regarded as an extra source. In other words, the adapted algorithm will not consider the discharging operations during its searching operation. The discharging operations are managed by the roulette wheel method to choose the suitable time to operate.

The possible time slots for SHB to be charged and discharged is calculated as follows:

$$X_{SHB} = \begin{cases} 1 & \text{if} \quad PCH_j \leq CH \quad \text{and} \quad \sum PCH < CAP \\ 2 & \text{if} \quad P^j > 0 \quad \text{and} \quad \sum PCH \geq 0 \quad \text{and} \quad PDH_j \leq DH \\ 0 & \text{if} \quad \text{Otherwise} \end{cases} \tag{10}$$

where X_{SHB} is the status of the SHB operation, PCH_j and PDH_j are the power charged and discharged from SHB at time j, respectively, CH and DH are the allowable charging and discharging limits, respectively, CAP is the SHB capacity, and PCH denotes the power stored in the SHB.

IV. Wind Driven Optimization for PSPSH

WDO is a well-known swarm-based optimization method. The WDO method is intended to deal with continuous optimization problems. Due to the discrete character of the PSPSH solutions, WDO is adjusted into a discrete version.

The PSPSH solutions contain a vector of beginning times for each operation of the appliances. WDO's workflow consists primarily of six phases, which are illustrated in Algorithm 1. The first phase indicates the WDO, PSPSH, and SHB parameters initialization. The second phase is to initialize the PSPSH population matrix. The PSPSH population matrix is a two-dimensional matrix of size S $\times$ N, where S represents the total number of appliance operations and N represents the total number of solutions. Phase 3 is carried out to demonstrate the SHB improvement. Phase 3 involves calculating the amount of power utilized by the appliances and the charging operations. The fitness values of the solutions are determined in the fourth phase, with the best fitness value assigned to $GlobalBest$ parameter. Phase 5 involves updating the velocity and location of each air particle in the search space to update the PSPSH solutions (see Eqs. 11 and 12). In phase 6, The SHB will be discharged. The lase phase is to check the stop criteria.

$$velocity_{New} = (1-\alpha) \times velocity_{Old} - (g \times Position) + |1 - \frac{1}{N_c}| \times ((GlobalBest - Position) \times RT) + (c \times velocity_{Old}) \tag{11}$$

$$Position = round(Position + velocity) \tag{12}$$

where $velocity_{New}$ is the new air particle velocity, $velocity_{Old}$ is the current velocity, $Position$ is the air particle position in the search space, N_c is the air particle position in the population, α, RT, and c are coefficient parameters.

Algorithm 1 WDO with SHB Pseudo code

Phase 1: Initialize PSPSH, WDO, and SHB parameters
Phase 2: Initialize a PSPSH population
Phase 3:
while $(t < I)$ **do**
  for solution (N) **do**
    Compute the power consumed by SAs and SHB charging operations
  end for
  Phase 4:
  for solution (N) **do**
    Compute the fitness value
    Assign fittest value to $GlobalBest$
  end for
  Phase 5:
  for solution (N) **do**
    for appliance (S) **do**
      Update the solutions using Eqs.(11, 12)
    end for
  end for
  Phase 6: Discharge the SHB
  Phase 7: $t = t + 1$
  Is I reached?
end while
Return $GlobalBest$;

V. Experiments and Results

In this section, the experiments' findings and their explanation and illustration are provided. This section begins with a representation of the dataset utilized to test the proposed method. The impacts of SHB on the scheduling process and how to improve it are also discussed. Furthermore, the performance of the adapted WDO is compared to that of BFOA.

A. Experimental design

The time horizon is divided into 1440 slots, where each time slot is equaling 1 minute. RTP is used as the dynamic pricing scheme adopted from Commonwealth Edison Company [32] on June 1st, 2016.

As stated earlier, RTP is coupled with IBR to distribute power utilized and preserve power system stability. The IBR has two parameters, C and $lambda$ (see Eq.2). These parameters are assigned by 0.0333 per slot and 1.543 for [4][6], respectively.

In general, appliances can be used several times throughout a time horizon. Therefore, the evaluation results include 36 operations from nine appliances. Table I shows the primary parameters of these operations.

The same characteristics of Tesla Powerwall 2 are used for the proposed SHB [33], where CAP is 13.5 kWh, CH is 5 kW, DH is 5kW, and the SHB efficiency (μ) is 90%.

For the WDO parameters, the algorithm runs 20 times with 200 iterations in each run. Table II shows the WDO parameter setting.

Table II: Parameters used in WDO algorithm

Parameter	Value
N	20
I	200
RT	3
g	0.2
α	0.4
c	0.4

B. The Enhancement of SHB

In this part, the WDO is used to assess and evaluate SHB efficiency in achieving PSPSH objectives. The outcomes without and with the SHB are examined to see if SHB can improve the schedule's quality.

Table III presents EB, PAR, WTR, CPR, and UC obtained by WDO with and without using the SHB in the scheduling process. Notable that considering the SHB can enhance the results in terms of EB, WTR, CPR, and UC better than without the SHB, where EB, WTR, and CPR reduced to (41.8029) and (43.1565), (0.0122) and (0.0328), and (0.3122) and (0.3146), with and without the SHB, respectively. The UC level is improved with and without the SHB to 83.78% and 82.63%, respectively. However, the PAR value obtained by the approach without the SHB is better than that with the SHB due to the behavior of the proposed SHB to consume more power during the low pricing periods to get power with low tariff.

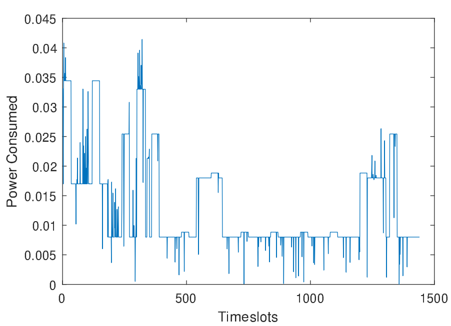
Table I: Appliances' Parameters utilized in the experiments

NO.	Appliance	l	OTPs - OTPe	Power(kW)	NO.	Appliance	l	OTPs - OTPe	Power(kW)
1	Dishwasher	105	540 - 780	0.6	19	Dehumidifier	30	1 - 120	0.05
2	Dishwasher	105	840 - 1080	0.6	20	Dehumidifier	30	120 - 240	0.05
3	Dishwasher	105	1200 - 1440	0.6	21	Dehumidifier	30	240 - 360	0.05
4	Air Conditioner	30	1 - 120	1	22	Dehumidifier	30	360 - 480	0.05
5	Air Conditioner	30	120 - 240	1	23	Dehumidifier	30	480 - 600	0.05
6	Air Conditioner	30	240 - 360	1	24	Dehumidifier	30	600 - 720	0.05
7	Air Conditioner	30	360 - 480	1	25	Dehumidifier	30	720 - 840	0.05
8	Air Conditioner	30	480 - 600	1	26	Dehumidifier	30	840 - 960	0.05
9	Air Conditioner	30	600 - 720	1	27	Dehumidifier	30	960 - 1080	0.05
10	Air Conditioner	30	720 - 840	1	28	Dehumidifier	30	1080 - 1200	0.05
11	Air Conditioner	30	840 - 960	1	29	Dehumidifier	30	1200 - 1320	0.05
12	Air Conditioner	30	960 - 1080	1	30	Dehumidifier	30	1320 - 1440	0.05
13	Air Conditioner	30	1080 - 1200	1	31	Electric Water Heater	35	300 - 420	1.5
14	Air Conditioner	30	1200 - 1320	1	32	Electric Water Heater	35	1100 - 1440	1.5
15	Air Conditioner	30	1320 - 1440	1	33	Coffee Maker	10	300 - 450	0.8
16	Washing Machine	55	60 - 300	0.38	34	Coffee Maker	10	1020 - 1140	0.8
17	Clothes Dryer	60	300 - 480	0.8	35	Robotic Pool Filter	180	1 - 540	0.54
18	Refrigerator	1440	1 - 1440	0.5	36	Robotic Pool Filter	180	900 - 1440	0.54

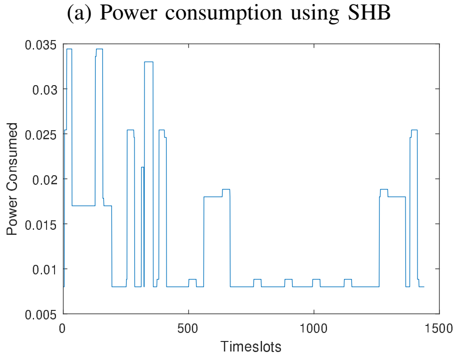
Figure 1 shows the power consumed with and without the SHB throughout the time horizon.

Table III: Result with and without SHB

With SHB				
EB	PAR	WTR	CPR	UC
41.8029	3.4508	**0.0122**	**0.3122**	**83.78**
Without SHB				
EB	PAR	WTR	CPR	
43.1565	**2.6394**	0.0328	0.3146	82.63



(a) Power consumption using SHB



(b) Power consumption without using SHB

Figure 1: Power consumption curve for the two approaches

Table IV: Comparison between WDO and BFOA using the SHB

	EB	PAR	WTR	CPR	UC
WDO	**41.80**	3.45	**0.012**	**0.312**	**83.7**
BFOA	42.39	**2.94**	0.084	0.328	79.4

C. *Comparison Study Between WDO and BFOA*

This section compares the adapted WDO with the BFOA. This comparative study is presented to demonstrate the results of WDO vs BFOA and to assess its performance.

Table IV compares the results of WDO and BFOA without and with SHB. The table demonstrates WDO's robust performance in terms of lowering EB, CPR, and WTR, and enhancing UC. Nevertheless, BFOA outperforms WDO in decreasing PAR value.

VI. Conclusion and Future Work

Scheduling the home appliances has high efficiency in maintaining power systems and lowering EB for users; thus, PSPSH is the key challenge facing power provider companies. PSPSH can be handled by changing the operating time of appliances from one period to the next based on a tariff scheme. The major goals of resolving PSPSH are to reduce EB and PAR while increasing user satisfaction.

WDO is adjusted in this paper to handle PSPSH using an RTP program. The RTP is used in combination with the IBR to balance power consumption over time efficiently. SHB is created and utilized as an extra source to try to improve the quality of the solution.

SHB demonstrates its efficacy in improving the solutions in optimizing EB, WTR, CPR, and UC better than without SHB. Furthermore, WDO is compared to BFOA in order to assess the results achieved. According to the comparison, WDO got a superior schedule in optimizing EB, WTR, CPR, and UC, whereas BFOA performed better in reducing PAR.

Different datasets can be included in the scheduling process in the future to assess WDO and SHB efficiently. Furthermore, renewable energy sources can be incorporated with the proposed SHB to enhance schedule quality.

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