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Optimization of Demand-Response-Based Intelligent Home Energy Management System with Binary Backtracking Search Algorithm

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Abstract: In many nations, limited power from providers and an increase in demand for electricity have created new opportunities that can be used by home energy management systems (HEMSs) systems to enforce proper use of energy. This paper presents a virtual intelligent home with demand response (DR) model home appliances that have an inverter air conditioner, water pump, washing machine, and inverter refrigerator. A binary backtracking search algorithm (BBSA) is proposed to introduce the optimal schedule controller. With the proposed BBSA schedule controller, the highest energy consumption during DR can be reduced by 33.84% during the weekends and by 30.4% daily during the weekdays. The results indicate the effectiveness of the proposed HEMS. Additionally, the model can control the appliances and maintain total residential energy consumption below the defined demand limit.

Keywords: home energy management system (HEMS); demand response; binary backtracking search algorithm (BBSA)

1. Introduction

As the world progresses, the proportion of electrical energy used by residential customers is increasing dramatically, mainly in developing countries [1]. The main global problems include rising electricity prices and power demand, climate change, global warming, restrictions in traditional electricity generation, and their accompanying environmental concerns. These problems have resulted in economic and severe political crises around the world [2]. Home energy management systems (HEMSs) are becoming increasingly important due to the above concerns as they help to reduce demand for energy, especially through peak load periods. HEMSs must not only be taken as a way to reduce greenhouse gas emissions, but also to allow the electricity of a house to be automatically managed [3]. HEMSs can assist with the reduction of the overall consumption of energy by scheduling domestic home appliances without causing discomfort to customers [4].

Demand response (DR) plays an important role in decreasing energy use at peak hours and can help increase efficiency and reliability in operation [2,5–7]. DR is a program that encourages homeowners to decrease their energy consumption during periods of high-power demand. Therefore, DR can be described as changes in the use of electricity by demand-side sources from their normal types of response consumption, and changes in electricity costs or incentives to reduce electricity consumption during periods with high wholesale prices [8–10]. To efficiently schedule home devices, many heuristic optimization techniques have been exploited to automatically create an optimal schedule of household appliances for adjusting power usage during high demand periods [11–15]. Optimization is a method of finding the best solutions to problems after selecting the objective function that is subjected to constraints.

The objective function is often formulated according to specific applications and can take the form of minimal cost, minimal error, or optimal management [16]. Optimization has been successfully applied to several areas; reference [17] proposed a new gravitational search algorithm optimization technique for generating optimal path planning for a robot traveling in unknown environments. Precup et al. [18] implemented the grey wolf optimizer to tune the proportional-integral-fuzzy controller parameters for a class of nonlinear servo systems. Goli et al. [19] applied an accelerated cuckoo optimization algorithm for the vehicle routing problem under competitive conditions with the objective of increasing customer satisfaction and reducing cost. Zeng et al. [20] applied an adaptive population extremal optimization-based PID neural network for complex control systems. Several optimization methods have been used to assist end-users to create optimal devices scheduling of energy use based on pricing schemes, different feed-in tariffs, and comfort settings. Optimal energy management consumption scheduling depending on linear programming was implemented to reduce the waiting time for any home appliance that works with a real-time pricing tariff and to reduce the electricity bill [21]. An optimal method based on game theory was applied to reduce the cost of electricity and determine the optimal schedule for a district subscriber [22]. In Fan et al. [23], the Lyapunov optimization technique was implemented to decrease the predictable long-term electricity costs for the energy consumption of home devices, involving renewable energy, uncontrollable loads, and controllable loads. Particle swarm optimization (PSO) was implemented [24] to schedule energy resources, as well as DR and distributed generation resources scheduling, minimizing the operation costs.

Previous studies indicated that using a wholly automated DR is critical to improving HEMSs. The optimization approach was introduced [25] to minimize the tariff to provide the consumer with the efficient operation of home appliances at variable prices mainly based on DR signals. Setlhaolo et al. [16] developed mixed nonlinear integer technology for scheduling household electrical appliances with installed battery storage. Anvari et al. [26] used mixed integer non-linear programming for best scheduling of home devices, accounting for comfortable lifestyles and energy saving. Optimal scheduling of home devices using the game concept was developed using battery storage and an electric vehicle to minimize electricity consumption at home [27]. Wang, et al. [28], used the PSO algorithm to improve desirable points through the devices work time. Parameters such as user preferences, appliance priority, and weather conditions were considered. Pedrasa et al. [29] used the PSO technique for scheduling interruptible appliances and controllable residential energy resources. The objective function was to achieve maximize net gain of customers and decrease energy consumption and cost. The scheduling results displayed showed that PSO is an efficient optimization technique for scheduling interruptible housing loads by creating schedules without impacting customer comfort. A genetic algorithm with data acquisition and supervisory control was applied to schedule home appliance with optimized power usage in the local sector to decrease electricity bill [30]. The methodology consists of changeable loads and renewable energy like wind turbines, photovoltaics, and fuel cells. A comparison was conducted under different situations between mixed- integer nonlinear and GA, and the results showed that GA schedule controller is better than the mixed-integer technique for decreasing power.

Previous studies illustrated that a heuristic scheduling system is the basis of achieving the best solutions. Ogwumike et al. [31] introduced an optimization model and efficient heuristic approach to control and schedule residential smart home devices and power storage systems to achieve active energy management. Intelligent bee colony optimization technique for HEMS was implemented [32] to schedule home devices based on user comfort and priority. In [33], the wind-driven optimization technique for scheduling home devices was applied by reducing maximizing comfort level and electricity cost. The simulation displayed that the wind-driven optimization technique produced a best PSO in terms of minimized energy consumption, of 8.4%, due to optimal scheduling of home loads. The PSO technicality was implemented for optimal scheduling of home appliances. to decrease cost via categorizing devices based on DR program and priority [34]. However, experiential results displayed that the heuristic scheduling optimization based on PSO is comparatively ineffective in terms of computing time, making it inconvenient for use in a real-time schedule. Haider et al. [35] implemented dynamic home load scheduling to improve the scheduling of household devices, which permits customers to decrease peak loads and minimize electricity bills.

From these studies, both heuristic and mathematical optimization can be applied to resolve scheduling matters. The mathematical optimization technique's capability provides exact solutions but are generally time-consuming for resolving complex optimization matters. To control the drawbacks of the mathematical optimization technique, heuristic optimization is now widely applied. However, the extensively applied heuristic optimization techniques, such as PSO, have some constraints: high computational complexity, slow convergence, they can easily become trapped in local minima solutions [36], and difficulty choosing optimal control parameters, leading to wrong solutions. Derrac et al. [37] provided more statistical tests to compare different algorithms. Ahmed et al. [38] described a new binary backtracking search algorithm (BBSA) "as a suitable controller for HEM systems". The proposed BBSA minimizes electricity costs and energy consumptions during peak hours on weekdays and weekends. To check the accuracy of the HEMS controller, the binary PSO and BBSA were compared; the results showed that the BBSA schedule controller is better than PSO. Sisodiya et al. [8] applied a novel HEMS with DR incorporating energy storage systems for electricity bill and power reduction in a home using a PSO algorithm. The result showed that the scheduling of loads with a PSO algorithm was better than without in terms of minimized energy consumption, which was reduced by 14.58%. Smart meters work together with real-time and device scheduling via HEMS. Therefore, the above works motivated us to use a comparatively novel optimization technique like the BBSA to develop a method for virtual HEMS schedule control with robust exploration capabilities and fast convergence solution that searches for the best use of populations and works in the domain to obtain the use.

Previous studies on scheduling household appliances concentrated only on minimizing electric bills and saving energy; they were constrained to using outdated home appliances. Unfortunately, there has not been enough research since HEMSs were introduced that incorporate the use of effective heuristic optimization techniques, customer comfort, and DR to manage power consumption in home appliances.

Many studies on air conditioner response to demand mainly focused on air conditioners that have constant speed [39]. However, in recent years, users have switched to using inverter air conditioners because of their comfort and energy-saving advantages.

The inverter system provides a desired constant power to the utility [40]. The inverter transforms incoming AC to DC before generating the needed frequency current (high or low frequency) through modulation in an electrical circuit inverter. The inverter motor or variable-speed motor can minimize operation costs, unlike constant motor speed. Countries such as China have witnessed a significant increase in the installation of air conditioners following the formulated national energy-savings and emission reduction policies [41]. Hence it is essential to study the role IAC plays in meeting demand needs.

The main contributions of this study can be summarized as follows:

- The development and creation of an intelligent HEM system with DR-enabled considering the cost of electricity, home occupancy, and achieving the best energy savings, costs, and the optimal schedule for home appliances.
- Considering user comfort as the main energy management process priority to promote the integration of the program into the consumer's everyday routine without impacting their lifestyle.
- Inverter appliances are used for the first time because most studies focused on older appliances as the use of inverter appliances is more suitable and better than traditional devices in loads management in terms of energy and cost savings.

2. Novel Home Energy Management System Software Implementation

The system, which consists of the proposed BBSA algorithms and includes the HEMS graphical user interface (GUI) and DR-enabled models, was developed in C#.

As shown in Figure 1, the novel HEMS is advanced as part of the proposed HEM program. It is an easy-to-use program that analyzes the two algorithms by entering information and variables of household appliances in the main interface. The variables include the temperature for the inverter air conditioner and refrigerator, the duration and number of operation cycles for the washing machine, and information about the size of the tank for the water pump, adding constants and variables to the values of equations for all devices, and adding information about the daily temperature. The average temperature of one day in the summer was adopted, as shown in Figure 2, as a case study.

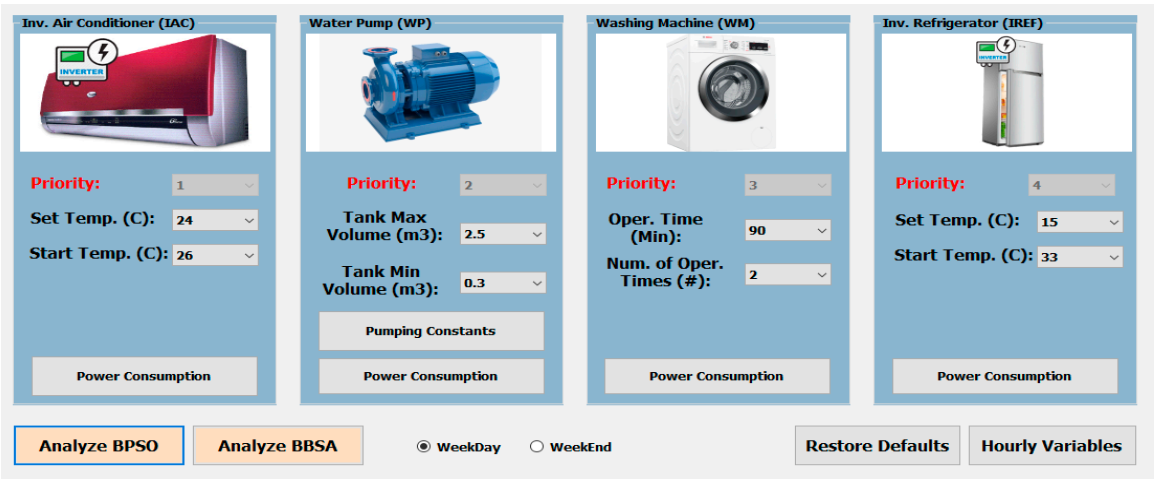

Figure 1. The developed home energy management system (HEMS) dashboard.

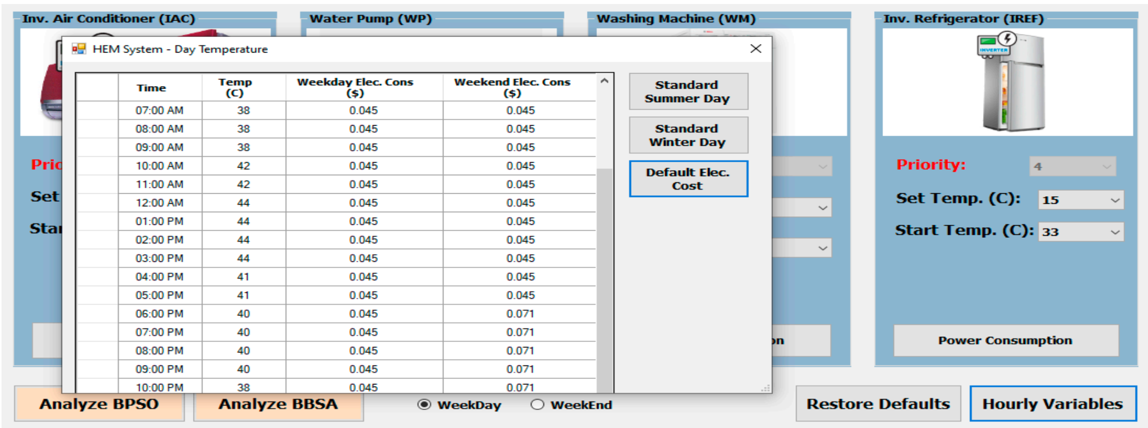

Figure 2. Pricing and temperature in the HEMS.

The program functions as a dashboard for users to control their device conditions, household power consumption, water level, room temperatures, demand limit, consumption of the device, demand cost, total cost, and related comfort settings preferences. The dashboard can be used for changing the priority settings and preferences. Every displayed parameter on the dashboard is updated at specific intervals to provide the most accurate up-to-date information.

3. Home Energy Management System Strategy by Electrical Device Type

A mathematical home appliance model is needed to conduct a residential DR. In addition, it is essential for determining the features and operating conditions of household appliances to achieve optimum scheduling for the residential DR application.

We investigated the power load scheduling of four electrical appliances using the utility under DR to decrease residential electricity costs. The model includes the following appliances:

3.1. Inverter Air Conditioner (IAC)

The inverter air conditioner's compressor speed changes depending on the changing frequency of power supply through a frequency convertor to control compressor power. Therefore, inverter air conditioners (IACs) can provide excellent user comfort, low power loss, and seamless temperature control. The inverter's active power consumption during the temperature maintenance stage is close to 30% that of a fixed speed air conditioner.

Depending on the room temperature, the IAC is controlled by the HEMS. The IAC is operated by the HEMS when the room temperature is more than 26 °C. The IAC stops working when the room temperature is below than 20 °C. The HEMS automatically controls the peak hours if the room temperature is between 20 and 26 °C. The IAC is maintained in accordance with the comfort preferences of the customer:

$$N_{IAC,k} = \left\{ \begin{array}{ccc} 0 & T_{IAC,k} < & 20\ ^{\circ}\mathrm{C} \\ 1 & T_{IAC,k} > & 26\ ^{\circ}\mathrm{C} \\ N_{IAC,\ k-1} & 20\ ^{\circ}\mathrm{C}\ \leq \Delta\, T_{IAC} \leq & 26\ ^{\circ}\mathrm{C} \end{array} \right\}, \tag{1}$$

where $N_{IAC,k}$ denotes to the condition of the appliance at time k (0 = switched off and 1 = switched on) [42] and $T_{IAC,k}$ denotes to the room temperature at time interval k.

The power consumption of IAC in watts is related to the operating frequency of the appliance and can be written as: [14]

$$W\_(IAC,k) = \left(k\_p + f_{C,\ k} + M\_p\right) * N_{IAC,k} \tag{2}$$

where k_p and M_p are the constant coefficients of the IAC. fc is the total frequency, it can be regulated in a range, as seen below.

$$f\_c\_min \leq fc \leq f\_c\_max \tag{3}$$

Figure 3 shows the IAC power consumption parameters that were used to develop the proposed HEMS. We applied the proposed optimization technique and used the IAC in an experimental case study to improve load management.

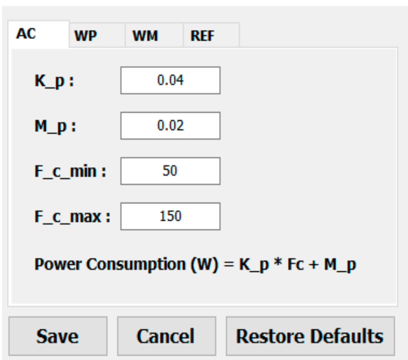

Figure 3. IAC power consumption parameters.

3.2. Water Pump (WP)

Residents are often faced with the challenge of inadequate water supply and availability. As a result, they use of roof-top tanks to store water, which needs to be driven from the basement to the tanks with the aid of a water pump. A systematic method of solving the problem of water insufficiency is by setting up an automatic water pump. Because of their home energy management system, smart water pumps are completely self-operational. Since water pumps are known to consume large amounts of energy, we decided to find a solution to this problem. Before switching itself on, the water pump first checks if the water level in the basement tank is adequate, then it checks the rate of energy consumption at that particular time. If the water level in the basement tank is low but the energy consumption rate is high, the pump will not turn on. After checking the state of the energy consumption rate, the water pump will turn on if the water level falls below 20% and will turn off if the water level is more than 80%. Sometimes, when the water level is below 20%, the pump will turn on if the energy consumption rate is low.

The power consumption of wp in watts ($W\_(wp, k)$) and can be determined by [43],

$$u\_(wp,\ (k+1)) = u\_(wp, (k)) + \left(\frac{\xi * W\_(wp, k)}{L}\right) - Dm\_k \tag{4}$$

where ξ is the motor efficiency, Dm_k is the water demand (m3/(hr)), $u\_(wp)$ is the tank diameter (m3), W_wp, k is the energy consumption in watt, and L is the head of water level (m). Figure 4 illustrates the WP power consumption parameters.

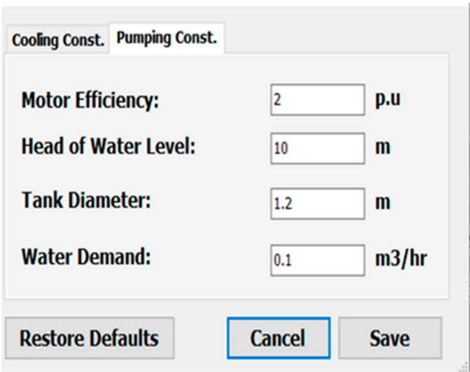

Figure 4. WP power consumption parameters.

3.3. Washing Machine (WM)

In the residential sector washing machine (WM) electricity consumption accounts for around 7.2% of total energy consumption [44]. A WM can turn on/off and need a minimum period of 90 min to complete its work. When the total time arrives at the desired time, the WM turns off the motor. WM condition (N_{wP}) is

$$N_{\text{wm,k}} = \left\{ \begin{array}{ccc} 0 & k_{\text{wm,k}} > & 90 \text{ min} \\ 1 & k_{\text{wm,k}} < & 90 \text{ min} \\ N_{\text{wm, k}-1} & 90\text{min} \le k_{\text{wm,k}} \le 90 \text{ min} \end{array} \right\}, \tag{5}$$

where $N_{\text{wm,k}}$ is the condition of the appliance at time k (0 = switched off and 1 = switched on) and $k_{\text{wm,k}}$ is the time period k.

$W\_(WM, k\ )$ is the power consumption of the WM in watt and can be determined by a set time period [43],

$$W\_(WM, k) = W\_(WM) * N_{\text{wm,k}}, \tag{6}$$

where $W\_(WM, k)$ is the amount of watt-rated WM power.

3.4. Inverter Refrigerator (IREF)

The inverter refrigerator (IREF) contains a compressor. The compressor component typically has power consumption within a range of several hundred watts. The *IREF* works all the time and consumes energy according to the internal *IREF* temperature: if the temperature is high, it consumes more energy, and if the temperature is low, it consumes less energy. As soon as the internal temperature reaches to the upper limit, the compressor switches on, which causes the temperature to decrease.

The *IREF* is operated by the HEMS when the internal *IREF* temperature is more than 8 °C. Lastly, the *IREF* stops working when the internal *IREF* temperature is below 4 °C. The HEMS automatically controls the peak hours if the internal *IREF* temperature is between 4 and 8 °C. The *IREF* is maintained in accordance with the comfort preferences of the customer:

$$N_{IREF,k} = \left\{ \begin{array}{cc} 0 & T_{IREF,k} < \quad 4\,^{\circ}\mathrm{C} \\ 1 & T_{IREFk} > \quad 8\,^{\circ}\mathrm{C} \\ N_{IREF,\,k-1} & 4 \leq \Delta T_{IREF,k} \leq 8\,^{\circ}\mathrm{C} \\ \end{array} \right\}, \tag{7}$$

where $T_{IREF,k}$ denotes to the internal *IREF* temperature at time period k and $\Delta T_{IREF,k}$ is the internal *IREF* temperature comfort level.

The power consumption of IREF in watts ($W\_(IREF, k)$) is related to the operating frequency of the compressor and is seen as [45]

$$W\_(IREF, k) = (K\_f + f\_c\ (k) + M\_f) * N_{IREF,k} \tag{8}$$

where K_f and M_f are constant coefficients of the *IREF*. The *IREF* power consumption parameters are illustrated in Figure 5. The IREF's novel feature is the easy regulation of the internal temperature, which improves food storage and regulates power consumption. This task was applied in this study.

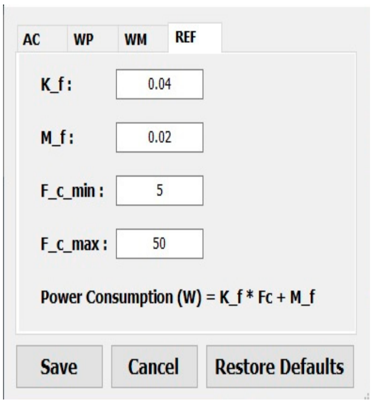

Figure 5. IREF power consumption parameters.

4. Proposed HEMS

Several challenges must be faced in finding the best schedule for home appliances and the proper changes in consumer rules using basic rules to minimize electrical power usage in DR events. Thus, advanced optimization techniques should provide optimum schedules for home appliances. As shown in Figure 6, the DR signal is sent from the utility to the smart meter and, finally, to the HEMS, which shows duration and load amount. The HEMS controller sends DR signals to every home appliance.

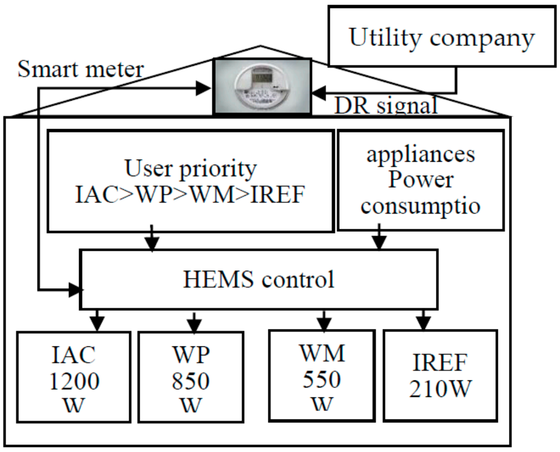

Figure 6. HEMS architecture.

Table 1 indicates that the first target is IAC, where the room temperature should be maintained within the 20–26 °C range. The second target is WP, with the level of water tank maintained within the appropriate 20–80% range. In the case of a washing machine, a homeowner may specify full time, maximum OFF heating coils, and minimum ON heating coils time (90 min) to complete its work. For the IREF, it operates at 24 h.

Table 1. Load priority and preference settings.

Appliance	Priority	Comfortable Level
Inverter AC (IAC)	1	Room temperature 20–26 °C
Water pump (WP)	2	Water level 20–80%
Washing machine (WM)	3	Different intervals
IREF	4	24 h

Before implementing the HEM algorithm, homeowners first need to set their load priority and comfort preferences, as shown in Table 1. The HEMS algorithm determines the status of each appliance according to the parameters of customer preference and a requested demand limit. Parameters of consumer choice vary with different types of appliances. Figure 7 shows the proposed HEMS algorithm with schedule controller conditions for electrical loads.

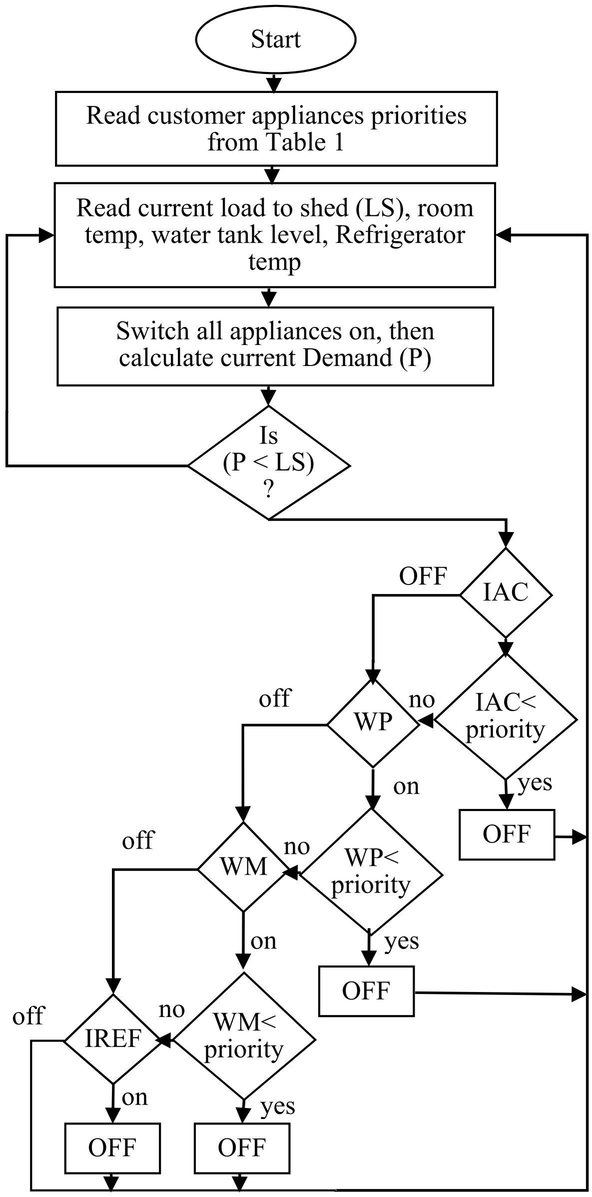

Figure 7. HEMS Flowchart.

5. Objective Function and Constraint

The energy consumption is used as the objective function to enhance the HEMS efficiency by reducing the 24-hour energy consumption, which contributes to a reduction in the electricity bill. The objective function this problem is as follows.

$$objective function = \sum_{i=0}^{m} Wt * k, \tag{9}$$

where k is the time in hour and Wt is the total power consumption in Watts. And the constraints of this problem can be written as follows.

$$0 < W\_(IAC, k) < W_{IAC,max} \tag{10}$$

$$20\ ^{\circ}\mathrm{C} \leq \Delta\, T_{IAC} \leq 26\ ^{\circ}\mathrm{C} \tag{11}$$

$$0 \; < \; W\_(wp,k) \; < \; W_{wp,max} \tag{12}$$

$$u_{\; wp,\; min} \; < \; u\_(wp,(k) \; < \; u_{\; wp,\; max} \tag{13}$$

$$0 \; < \; W\_(wm,k) \; < \; W_{wm,max} \tag{14}$$

$$90\text{min} \; \leq k_{\text{wm},k} \leq 90 \text{ min} \tag{15}$$

$$0 \; < \; W\_(IREF,k) \; \; < \; W_{IREF,max} \tag{16}$$

$$4 \; \leq \Delta \text{T}_{IREF,k} \; \leq 8\,^{\circ}\text{C} \tag{17}$$

6. Binary Back Tracking Search Algorithm (BBSA) Optimization

The binary backtracking search algorithm (BBSA) is an efficient optimization algorithm proposed by CIVICIOGLU that solves optimization problems. It is an evolutionary algorithm that focuses on serving the population as an energy consumption minimizer. However, there is already a new BBSA that is being studied [46]. The algorithm has a basic structure and only calculates one control parameter while updating equations. Mutation and crossover occur. BBSA leads the search for the best use of populations and it works in the domain to obtain the use, having very robust exploration capabilities [47]. It was used in many studies and is commonly used to solve optimization problems. It consists of the following processes:

Initialization: In BSA's initialization process, the search-space randomly generates the individuals in populations. BSA initializes the population q_{ij}:

$$q_{ij} = rand * \left(up_j - \; low_j\right) + \; low_j, \tag{18}$$

where $i \; = \; 1, \; 2,3, \; 4\ldots\ldots, \; M$; $j = 1,2,3, \; 4,\ldots D$; M and D are the size of the population and the problem dimension of the data set, respectively; rand is a random number; and the target person in the initial population is upj and $lowj$.

Selection: The first selection specifies the $old\; q_{ij}$ historical population, which is used to measure the direction of search. $old\; q_{ij}$ is calculated by Equation (19) before iteration and will be redefined and modified in Equation (20) and with a random variable in Equation (21) at the beginning of each iteration procedure.

$$old\; q_{ij} = rand * \left(up_j - \; low_j\right) + \; low_j \tag{19}$$

$$If\; a < b\; then\; old\; q_{ij} = q_{ij} \tag{20}$$

$$old\; q_{ij} = \; permuting\; old\left(q_{ij}\right) \tag{21}$$

Mutation: The mechanism of mutation by BBSA generates the trail population via Equation (22), where the F value controls the amplitude of the search-direction ($oldq_{ij} - \; q_{ij}$).

$$Mutant = \; q_{ij} \; + \; F * \left(old\; q_{ij} - q_{ij}\right) \tag{22}$$

The conditions for the schedule controller are implemented by following the BBSA flowchart shown in Figure 8 and the priority of load given in Table 1. The algorithm and its binary version have considerable potential to find near-optimal high-dimensional scheduling control and non-continuous optimization problems.

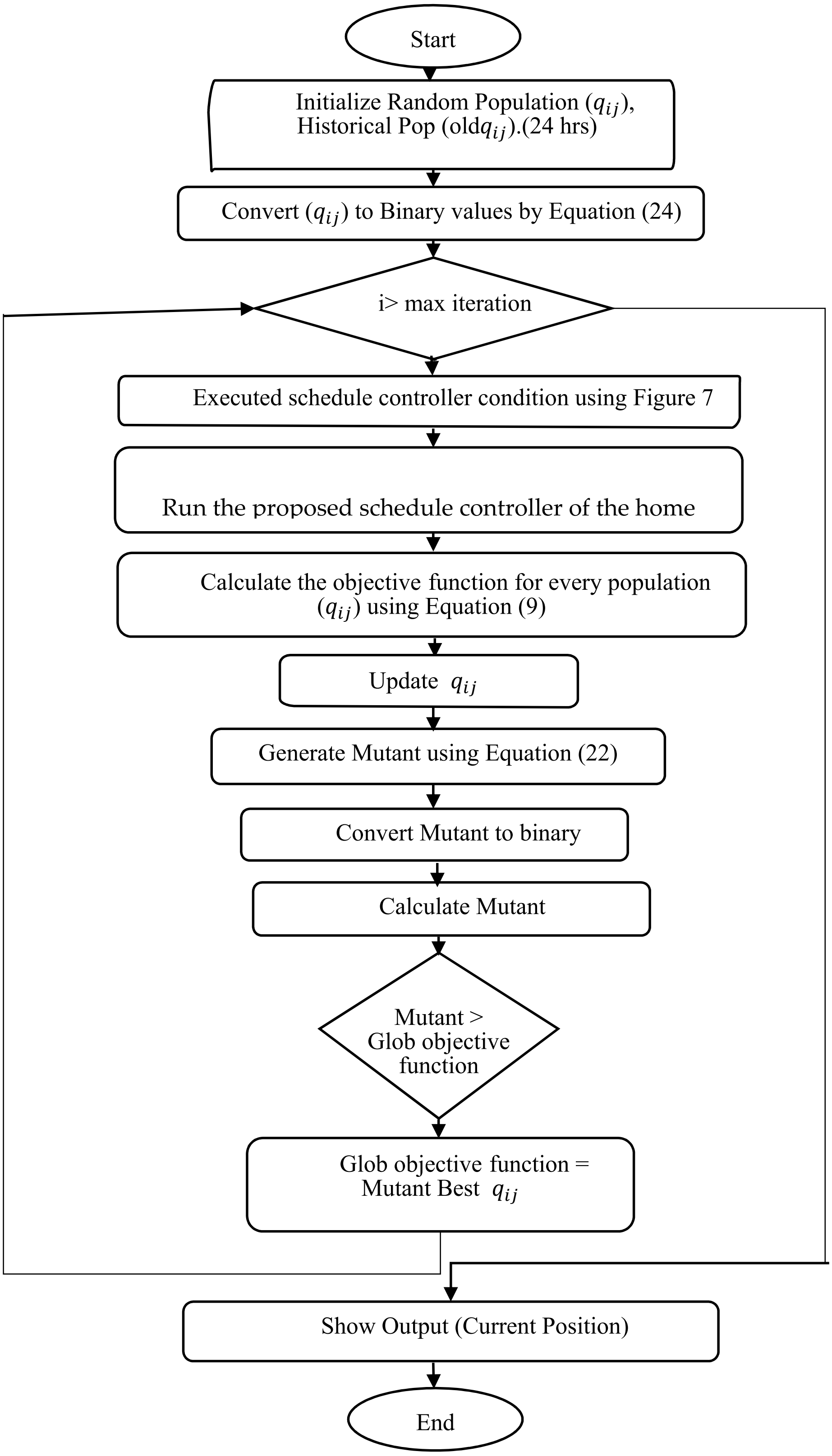

Figure 8. BBSA algorithm flowchart.

After the schedule controller requirements are enforced, the proposed home appliances schedule controller based on BBSA is implemented for each population (q_{ij}). Afterward, the objective function is calculated for each population.

MAYTHAM [38] implemented a BBSA algorithm to solve the optimization of discrete parameters. In BBSA, the population individuals are represented as a binary vector, and by the sigmoid function g_i , the population value is converted to 0 or 1.

$$g_i = \frac{1}{1 + e^{w}}, \tag{23}$$

PB is the value of the population. The value of the binary population is updated as:

$$PB = \begin{bmatrix} 0, & g_i < 0 \\ 1, & g_i > 1 \end{bmatrix} \tag{24}$$

7. Results

In this study, we considered weekends and weekdays as the two cases for the DR scenario. The DR event runs at around 9:30 a.m._12:30 p.m., 4:30 p.m._6:30 p.m., and 9:30 p.m._11:30 p.m. on weekends, while it starts on a weekday from 4:30 p.m. until around 11:30 p.m. The BBSA and schedule controller implementation was aimed at minimizing the energy consumption, which was the predefined objective function. We assumed that the value of the electrical demand limit was 1250 W, and this value should be greater than the overall energy consumption. The values of the overall power consumption were found to be 189,22.71 W on weekends and 18,191.57 W during the weekdays.

To verify the accuracy of the HEM system controller, we compared the BBSA and binary PSO for weekdays. To determine the best energy savings as well as achieve the optimal schedule for the home appliances under consideration, the BBSA was used as a schedule controller for the HEMS. For proper comparison, the maximum iteration and population size for BBSA schedule algorithm controllers were fixed at 30 and 900, respectively.

7.1. Optimal Weekend Controller Schedule

The BBSA schedule was implemented to minimize the energy consumption, which was the predefined objective function. After applying the BBSA schedule controllers, the power consumption of each device and the overall power consumption, and the daily cost are shown in Figures 9 and 10, respectively. For the weekend case, a demand limit of 1250 W was imposed on the DR signal, and there were three various time intervals consisting of 9:30 a.m._12:30 p.m., 4:30 p.m._6:30 p.m., and 9:30 p.m._11:30 p.m.

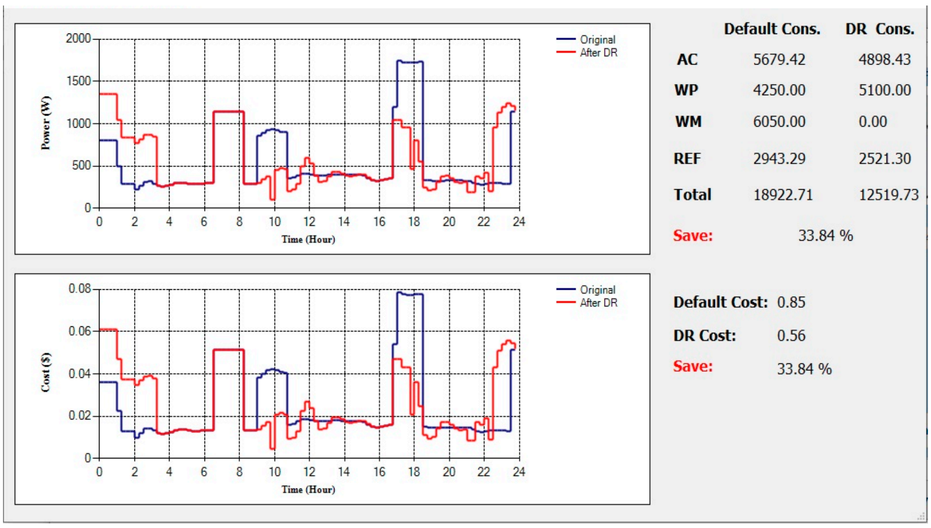

Figure 9. Total power consumption at weekend before and after implementing the BBSA schedule controller.

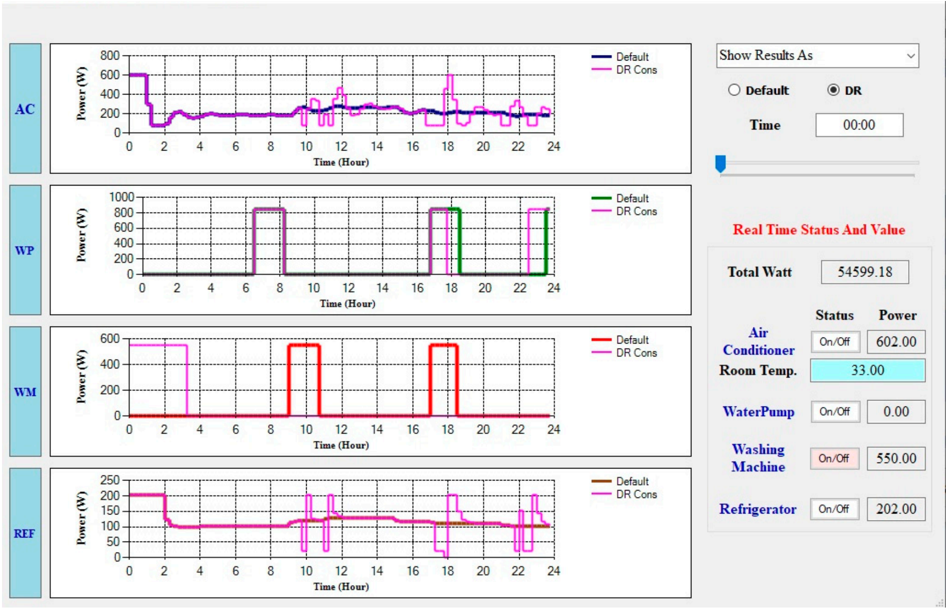

Figure 10. Power consumption data with BBSA schedule.

The total power consumptions of IAC, WP, WM, and IREF were found to be 5679, 4250, 6050, and 2943, respectively, and the total power consumption was 18,922.7 W without BBSA, which is above the demand limit. In contrast, with BBSA, the power consumptions were 4898, 5100, 0, and 2521 W for IAC, WP, WM, and IREF, respectively, and the total power consumption was 12,519.7 W during a DR event (33.84%). Figure 9 shows that the overall energy consumed and cost were reduced during the DR periods, where the 1250 W demand limit is greater than the overall power consumption value.

When the overall energy consumption exceeds the demand limit, as seen in Figure 9, the lower-priority device is turned off and scheduled to an off-peak hour by the BBSA schedule controller which tries to maintain the overall energy consumption under the demand limit.

From Figure 10, the BBSA schedule controllers in the HEMS switched the four household appliances OFF or ON, which included the IAC, WP, WM, and IREF according to the customer lifestyle, priority of appliances, and the DR condition, ensuring that the appliances operate within the demand limit value. Since the IAC has higher priority than the WP, the WP is placed on hold as soon as the IAC begins to keep the total household consumption below the 1250 W demand limit.

7.2. Optimal Weekday Controller Schedule

To verify the accuracy of the algorithms and the performance appliances, the BBSA and binary PSO were compared. The weekday data for power consumption and cost were collected over a period of 24 h. Without using the schedule controller, the overall power consumption and the cost for every home device (which included IAC, WP, WM, and IREF) were also collected from the HEMS, as presented in Figures 11 and 12 for BBSA and binary PSO respectively. From 4:30 to 11:30 p.m., a 1250 W demand limit was imposed on the DR event during a weekday.

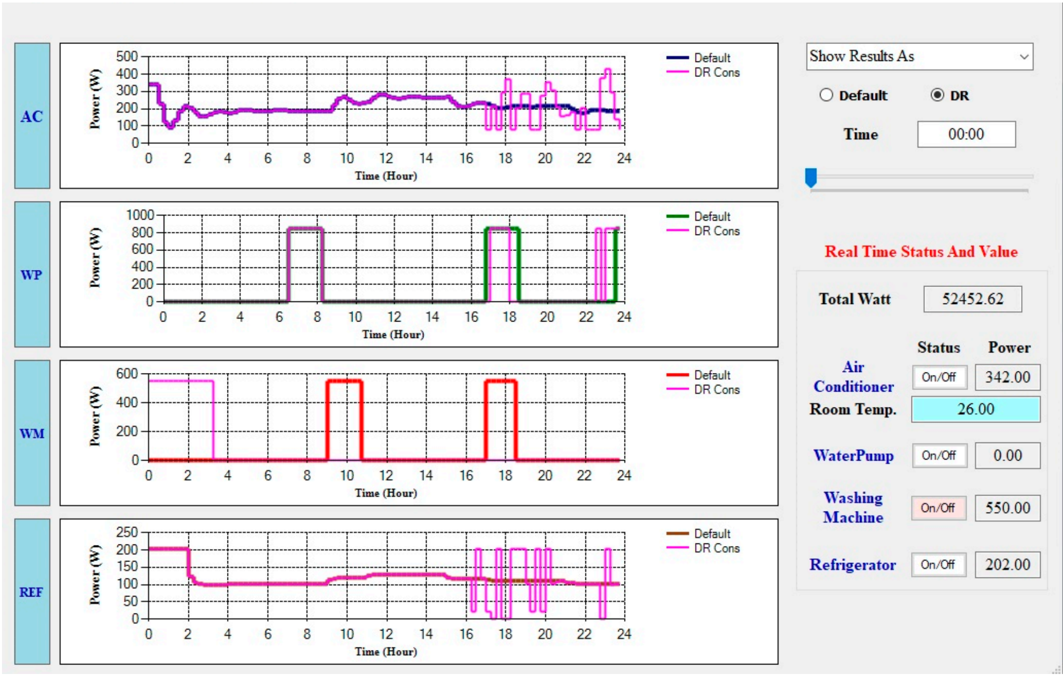

Figure 11. Power consumption data with BBSA schedule.

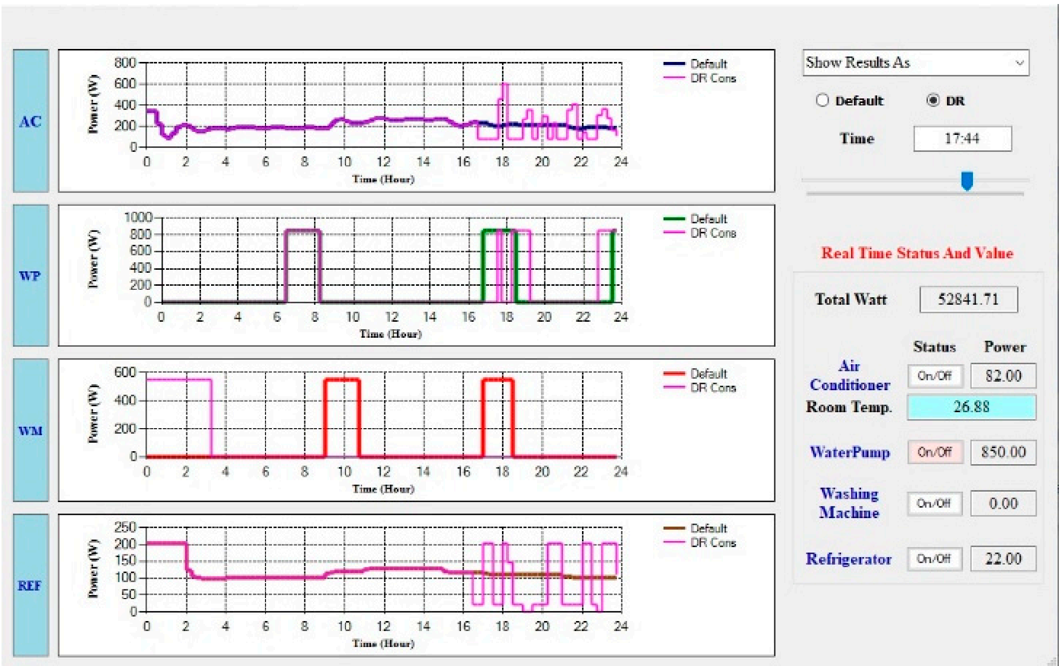

Figure 12. Power consumption data with binary PSO schedule.

The total power consumptions of IAC, WP, WM, and IREF were 5866, 5950, 3300, and 3074, respectively, and the total power consumption was 18,191.57 W without BBSA. With BBSA, the power consumptions were 5531, 4250, 0, and 2879 W for IAC, WP, WM, and IREF, respectively, and the total power consumption was 12,661.5 W during a DR event (30.40%) every day, as shown in Figure 13. The total power consumption with binary PSO was 12.8 W during a DR event (29.24%) every day, as shown in Figure 14. When the overall energy consumption exceeds the demand limit, as shown in Figure 13, the lower priority device is turned off and scheduled to an off-peak hour by the BBSA schedule controller, which tries to keep the overall energy consumption under the demand limit.

The BBSA schedule controller enhances energy savings by 5.5 kWh (30.4%) every day. Conversely, the PSO algorithm controller reduces energy consumption by 5.3 kWh or (29.24%) every day. The results showed that the BBSA schedule controller is better than the binary PSO. The results illustrate the capability of the proposed HEMS algorithm to maintain total energy consumption below the demand limit by reducing the peak load and scheduling the home appliances during the week without denying homeowners the comfort of using their appliances.

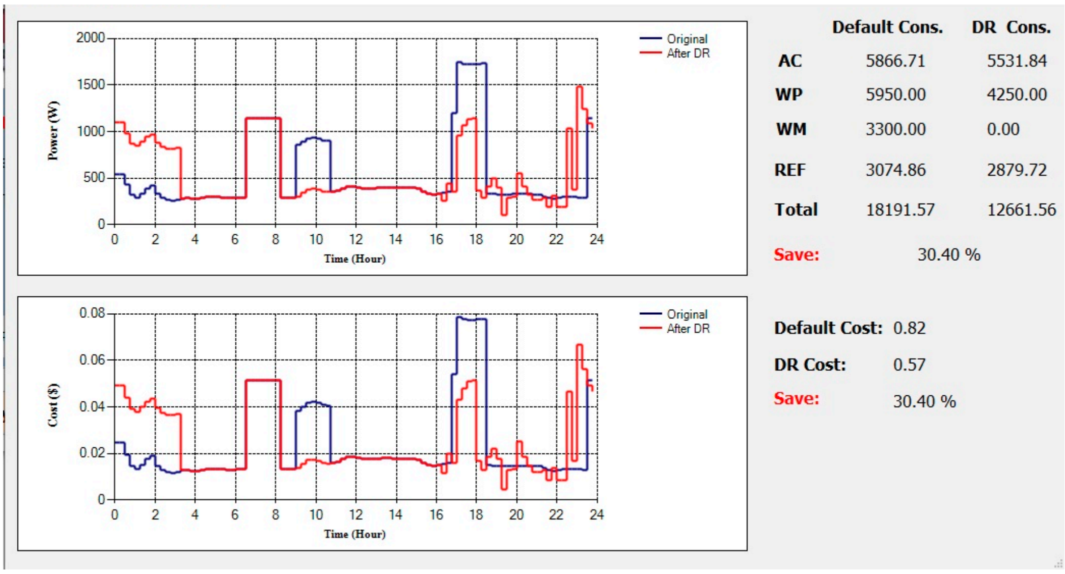

Figure 13. Total power consumption during the weekdays before and after implementing the BBSA schedule controller.

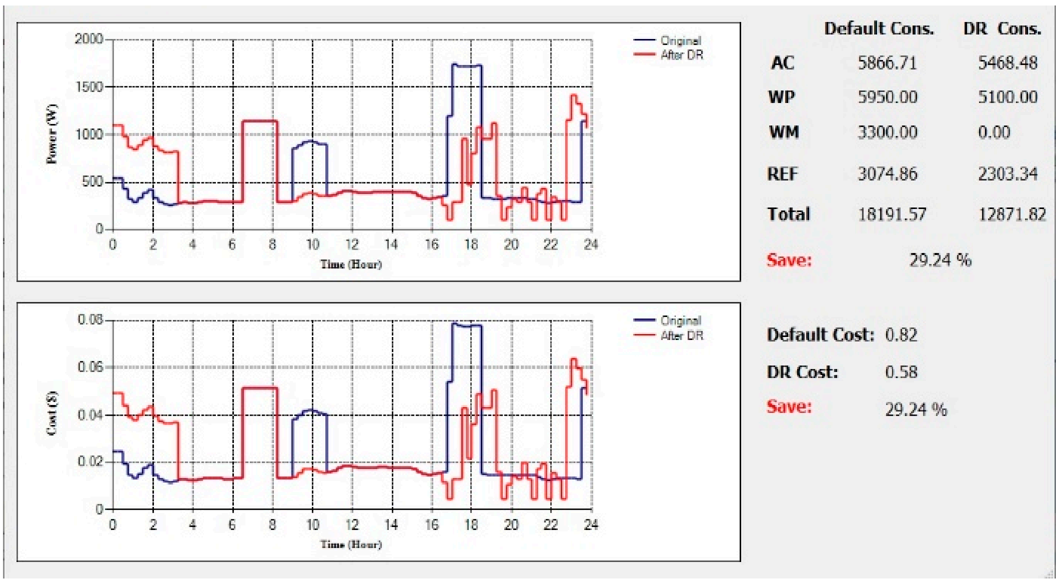

Figure 14. Total power consumption during weekdays before and after implementing the binary PSO schedule controller.

8. Conclusions

In this study, we aimed to determine the household electric power consumption and cost based on the BBSA. With the proposed BBSA schedule controller, the highest energy consumption during DR can be reduced by 30.4%, or 5.5 kWh, daily during the weekdays and by 33.84%, or 6.4 kWh, daily during the weekend. This intelligent HEMS can accurately determine scheduling and can shift domestic load operation during peak-hour energy consumption by seamlessly scheduling electrical appliances at specified intervals without making users uncomfortable. The BBSA results were compared with the PSO schedule controller and the results showed that the BBSA schedule controller is better than the PSO. The results revealed that the BBSA schedule controller performs better in minimizing the energy consumed by household devices during both weekends and weekdays. The results indicated that the proposed HEMS is effective. In addition, the model can control the appliances and keep total consumption of residential energy below the given demand limit.

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References

1. Lin, G.; Yang, Y.; Pan, F.; Zhang, S.; Wang, F.; Fan, S. An optimal energy-saving strategy for home energy management systems with bounded customer rationality. *Future Internet* **2019**, *11*, 88. [CrossRef]
2. Shareef, H.; Ahmed, M.S.; Mohamed, A.; Al Hassan, E. Review on home energy management system considering demand responses, smart technologies, and intelligent controllers. *IEEE Access* **2018**, *6*, 24498–24509. [CrossRef]
3. Beaudin, M.; Zareipour, H. Home energy management systems: A review of modelling and complexity. In *Energy Solutions to Combat Global Warming*; Springer: New York, NY, USA, 2017; pp. 753–793.
4. Ahmed, M.; Mohamed, A.; Homod, R.; Shareef, H. Hybrid LSA-ANN based home energy management scheduling controller for residential demand response strategy. *Energies* **2016**, *9*, 716. [CrossRef]
5. Leitão, J.; Gil, P.; Ribeiro, B.; Cardoso, A. A survey on home energy management. *IEEE Access* **2020**, *8*, 5699–5722. [CrossRef]
6. Shakeri, M.; Shayestegan, M.; Abunima, H.; Reza, S.S.; Akhtaruzzaman, M.; Alamoud, A.; Sopian, K.; Amin, N. An intelligent system architecture in home energy management systems (HEMS) for efficient demand response in smart grid. *Energy Build.* **2017**, *138*, 154–164. [CrossRef]
7. Ghadimi, N.; Nojavan, S.; Abedinia, O.; Dehkordi, A.B. Deterministic-based energy management of DC microgrids. In *Risk-Based Energy Management*; Academic Press: Cambridge, MA, USA, 2020; pp. 11–30.
8. Sisodiya, S.; Kumbhar, G.; Alam, M. A home energy management incorporating energy storage systems with utility under demand response using PSO. In Proceedings of the 2018 IEEMA Engineer Infinite Conference (eTechNxT), New Delhi, India, 13–14 March 2018; pp. 1–6.
9. Jordehi, A.R. Optimisation of demand response in electric power systems, a review. *Renew. Sustain. Energy Rev.* **2019**, *103*, 308–319. [CrossRef]
10. Ko, W.; Vettikalladi, H.; Song, S.-H.; Choi, H.-J. Implementation of a demand-side management solution for South Korea's demand response program. *Appl. Sci.* **2020**, *10*, 1751. [CrossRef]
11. Gupta, A.; Singh, B.P.; Kumar, R. Optimal provision for enhanced consumer satisfaction and energy savings by an intelligent household energy management system. In Proceedings of the 2016 IEEE 6th International Conference on Power Systems (ICPS), New Delhi, India, 4–6 March 2016; pp. 1–6.
12. Perez, K.X.; Baldea, M.; Edgar, T.F. Integrated HVAC management and optimal scheduling of smart appliances for community peak load reduction. *Energy Build.* **2016**, *123*, 34–40. [CrossRef]

13. Silva, B.N.; Han, K. Mutation operator integrated ant colony optimization based domestic appliance scheduling for lucrative demand side management. *Future Gener. Comput. Syst.* **2019**, *100*, 557–568. [CrossRef]
14. Jamil, A.; Alghamdi, T.A.; Khan, Z.A.; Javaid, S.; Haseeb, A.; Wadud, Z.; Javaid, N. an innovative home energy management model with coordination among appliances using game theory. *Sustainability* **2019**, *11*, 6287. [CrossRef]
15. Thaeer Hammid, A.; Awad, O.I.; Sulaiman, M.H.; Gunasekaran, S.S.; Mostafa, S.A.; Manoj Kumar, N.; Khalaf, B.A.; Al-Jawhar, Y.A.; Abdulhasan, R.A. A review of optimization algorithms in solving hydro generation scheduling problems. *Energies* **2020**, *13*, 2787. [CrossRef]
16. Setlhaolo, D.; Xia, X. Optimal scheduling of household appliances with a battery storage system and coordination. *Energy Build.* **2015**, *94*, 61–70. [CrossRef]
17. Purcaru, C.; Precup, R.-E.; Iercan, D.; Fedorovici, L.-O.; David, R.-C.; Dragan, F. Optimal robot path planning using gravitational search algorithm. *Int. J. Artif. Intell.* **2013**, *10*, 1–20.
18. Precup, R.-E.; David, R.-C.; Petriu, E.M.; Szedlak-Stinean, A.-I.; Bojan-Dragos, C.-A. Grey wolf optimizer-based approach to the tuning of pi-fuzzy controllers with a reduced process parametric sensitivity. *IFAC-PapersOnLine* **2016**, *49*, 55–60. [CrossRef]
19. Goli, A.; Aazami, A.; Jabbarzadeh, A. Accelerated cuckoo optimization algorithm for capacitated vehicle routing problem in competitive conditions. *Int. J. Artif. Intell.* **2018**, *16*, 88–112.
20. Zeng, G.-Q.; Xie, X.-Q.; Chen, M.-R.; Weng, J. Adaptive population extremal optimization-based PID neural network for multivariable nonlinear control systems. *Swarm Evol. Comput.* **2019**, *44*, 320–334. [CrossRef]
21. Nunna, H.V.K.; Aziz, N.A.B.; Srinivasan, D. A smart energy management framework for distribution systems with perceptive residential consumers. In Proceedings of the 2018 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), Kota Kinabalu, Malaysia, 7–10 October 2018; pp. 434–438.
22. Carli, R.; Dotoli, M.; Palmisano, V. A distributed control approach based on game theory for the optimal energy scheduling of a residential microgrid with shared generation and storage. In Proceedings of the 2019 IEEE 15th International Conference on Automation Science and Engineering (CASE), Vancouver, BC, Canada, 22–26 August 2019; pp. 960–965.
23. Fan, W.; Liu, N.; Zhang, J. An event-triggered online energy management algorithm of smart home: Lyapunov optimization approach. *Energies* **2016**, *9*, 381. [CrossRef]
24. Faria, P.; Soares, J.; Vale, Z.; Morais, H.; Sousa, T. Modified particle swarm optimization applied to integrated demand response and DG resources scheduling. *IEEE Trans. Smart Grid* **2013**, *4*, 606–616. [CrossRef]
25. Tsui, K.M.; Chan, S.-C. Demand response optimization for smart home scheduling under real-time pricing. *IEEE Trans. Smart Grid* **2012**, *3*, 1812–1821. [CrossRef]
26. Anvari-Moghaddam, A.; Monsef, H.; Rahimi-Kian, A. Optimal smart home energy management considering energy saving and a comfortable lifestyle. *IEEE Trans. Smart Grid* **2014**, *6*, 324–332. [CrossRef]
27. Mirabbasi, D.; Beydaghi, S. Optimal scheduling of smart home appliances considering PHEV and energy storage system. In Proceedings of the 2015 4th International Conference on Electric Power and Energy Conversion Systems (EPECS), Sharjah, UAE, 24–26 November 2015; pp. 1–6.
28. Wang, Z.; Yang, R.; Wang, L. Multi-agent control system with intelligent optimization for smart and energy-efficient buildings. In Proceedings of the IECON 2010-36th Annual Conference on IEEE Industrial Electronics Society, Glendale, AZ, USA, 7–10 November 2010; pp. 1144–1149.
29. Pedrasa, M.; Spooner, E.; MacGill, I. Robust scheduling of residential distributed energy resources using a novel energy service decision-support tool. In Proceedings of the ISGT, Anaheim, CA, USA, 17–19 January 2011; pp. 1–8.
30. Fernandes, F.; Sousa, T.; Silva, M.; Morais, H.; Vale, Z.; Faria, P. Genetic algorithm methodology applied to intelligent house control. In Proceedings of the 2011 IEEE Symposium on Computational Intelligence Applications In Smart Grid (CIASG), Paris, France, 11–15 April 2011; pp. 1–8.
31. Ogwumike, C.; Short, M.; Denai, M. Near-optimal scheduling of residential smart home appliances using heuristic approach. In Proceedings of the 2015 IEEE International Conference on Industrial Technology (ICIT), Seville, Spain, 17–19 March 2015; pp. 3128–3133.
32. Zhang, Y.; Zeng, P.; Zang, C. Optimization algorithm for home energy management system based on artificial bee colony in smart grid. In Proceedings of the 2015 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER), Shenyang, China, 8–12 June 2015; pp. 734–740.

33. Rasheed, M.B.; Javaid, N.; Ahmad, A.; Khan, Z.A.; Qasim, U.; Alrajeh, N. An efficient power scheduling scheme for residential load management in smart homes. *Appl. Sci.* **2015**, *5*, 1134–1163. [CrossRef]
34. Mahmood, D.; Javaid, N.; Alrajeh, N.; Khan, Z.A.; Qasim, U.; Ahmed, I.; Ilahi, M. Realistic scheduling mechanism for smart homes. *Energies* **2016**, *9*, 202. [CrossRef]
35. Haider, H.T.; See, O.H.; Elmenreich, W. Dynamic residential load scheduling based on adaptive consumption level pricing scheme. *Electr. Power Syst. Res.* **2016**, *133*, 27–35. [CrossRef]
36. Lu, K.; Zhou, W.; Zeng, G.; Zheng, Y. Constrained population extremal optimization-based robust load frequency control of multi-area interconnected power system. *Int. J. Electr. Power Energy Syst.* **2019**, *105*, 249–271. [CrossRef]
37. Derrac, J.; García, S.; Molina, D.; Herrera, F. A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. *Swarm Evol. Comput.* **2011**, *1*, 3–18. [CrossRef]
38. Ahmed, M.S.; Mohamed, A.; Khatib, T.; Shareef, H.; Homod, R.Z.; Ali, J.A. Real time optimal schedule controller for home energy management system using new binary backtracking search algorithm. *Energy Build.* **2017**, *138*, 215–227. [CrossRef]
39. Che, Y.; Yang, J.; Zhao, Y.; Xue, S. Control strategy for inverter air conditioners under demand response. *Processes* **2019**, *7*, 407. [CrossRef]
40. Sun, L.; Jin, Y.; Pan, L.; Shen, J.; Lee, K.Y. Efficiency analysis and control of a grid-connected PEM fuel cell in distributed generation. *Energy Convers. Manag.* **2019**, *195*, 587–596. [CrossRef]
41. Chen, M.; Sun, X.; Huang, L. Extraction of high frequency operating parameters of a compressor motor for a variable frequency air conditioner. *J. Tsinghua Univ. (Sci. Technol.)* **2011**, *1*, 8.
42. Pipattanasomporn, M.; Kuzlu, M.; Rahman, S. An algorithm for intelligent home energy management and demand response analysis. *IEEE Trans. Smart Grid* **2012**, *3*, 2166–2173. [CrossRef]
43. Ahmed, M.S.; Mohamed, A.; Homod, R.Z.; Shareef, H. A home energy management algorithm in demand response events for household peak load reduction. *PrzeglAd Elektrotechniczny* **2017**, *93*, 2017. [CrossRef]
44. Bertoldi, P.; Hirl, B.; Labanca, N. *Energy Efficiency Status Report 2012–Electricity Consumption and Efficiency Trends in the EU-27*; European Commission Joint Research Centre Institute for Energy and Transport: Ispra, Italy, 2012.
45. Hui, H.; Ding, Y.; Lin, Z.; Siano, P.; Song, Y. Capacity allocation and optimal control of inverter air conditioners considering area control error in multi-area power systems. *IEEE Trans. Power Syst.* **2019**, *35*, 332–345. [CrossRef]
46. Chen, D.; Zou, F.; Lu, R.; Li, S. Backtracking search optimization algorithm based on knowledge learning. *Inf. Sci.* **2019**, *473*, 202–226. [CrossRef]
47. Lin, Q.; Gao, L.; Li, X.; Zhang, C. A hybrid backtracking search algorithm for permutation flow-shop scheduling problem. *Comput. Ind. Eng.* **2015**, *85*, 437–446. [CrossRef]