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A Novel Time-of-Use Pricing Based Energy Management System for Smart Home Appliances: Cost-Effective Method

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Abstract: Smart grids (SG) allow users to plan and control device usage patterns optimally, thereby minimizing power costs, peak-to-average ratios (PAR), and peak load demands. The present study develops a typical framework of a home energy management system (HEMS) for SG scenarios using newly limited and multi-limited planning approaches for domestic users. Time-of-use pricing (TOUP) is used to develop, handle, and manage the optimization problem properly. As a capable method for optimizing the proposed problem, this paper uses a robust meta-heuristic algorithm named wind-driven optimization algorithm (WDOA) and compares it to the other optimization algorithms in order to demonstrate its efficiency. In addition, it integrates a rooftop photovoltaic (PV) system with the system in order to show that all devices are cost-effective if managed properly. Eight diverse case studies are analyzed using a variety of time planning algorithms. The simulation results advocate for the quality and high performance of the proposed model by minimizing the total cost and managing energy consumption economically.

Keywords: demand side management; peak-to-average ratio; wind-driven optimization algorithm; energy management system; smart home appliances

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1. Introduction

As the population increases, energy consumption increases. At present, power demand cannot be met by traditional power grids. Smart grids (SGs) are developed to meet these demands [1]. Energy-effective sources, smart controllers, smart meters (SM), renewable energy resources (RER), and smart devices are part of SGs [2]. Utilities and users are exchanging data through SM in SGs. As a result of the data, smart homes can be optimized for energy efficiency. Research has outlined some demand-side management (DSM) methods [3]. Through such methods, power usage patterns are optimized by shifting loads, filling valleys, clipping peaks, and so on. By implementing such methods, demand and supply can be balanced. In this way, such methods encourage the consumer for shifting its load from on-peak to off-peak periods [4]. DSM has two major tasks: demand response (DR) and load management (LM) [5].

Load management focuses on managing the user's load profile efficiently. As a result, the main grid will be less likely to suffer from problems and power outages will be avoided. Moreover, it helps reduce peak-to-average ratios (PARs), energy usage, and energy prices. Users perform DR to respond to dynamic pricing (DP) from utilities [6]. As power usage increases, grid stability will become increasingly hard to maintain. The supply and demand of electric power are out of balance as consumers' load demands increase. This ultimately causes load shedding and poses a threat to grid integrity across a wide region almost instantly. In this way, DR serves as a highly efficient method of educating power users and obtaining incentives in exchange for tolerating inconvenience.

There are two types of DR programs: incentive-driven DR program and cost-driven DR program. The demand–supply balance was more precise with such DP models compared to fixed-rate price methods. There are several types of DP tariffs, including time of use (TOU), real-time pricing (RTP), day-ahead pricing (DAP), critical peak pricing (CPP), and inclined block rate (IBR). Furthermore, RTP has been proven to be the best costing method for the electricity market [7]. SG's energy management targets include minimizing power costs, reducing PAR, increasing customer satisfaction, minimizing total energy usage, and integrating RES. The above targets were achieved using DSM methods recently. Refs. [8,9] applied non-integer linear programming (NILP), mixed-integer linear programming (MILP), mixed-integer non-linear programming (MINLP), and convex programming for minimizing the price and power usage. There is, though, a limitation to such methods in terms of handling many devices. The drawbacks of such techniques lead to the introduction of meta-heuristic optimization methods for SG energy management. Accordingly, refs. [10,11] applied a genetic algorithm (GA) to minimize energy costs. Refs. [12,13] applied ant colony optimization (ACO) and differential evolution (DE) for reducing energy costs and total energy usage.

Ref. [14] presented a DSM model that is suitable to be used in domestic areas. The goal was to minimize energy costs, PAR, and runtime while maximizing consumer satisfaction. The paper evaluated its goals with three optimization methods: binary particle swarm optimization (BPSO), ACO, and GA. Energy costs are calculated using combined TOU and IBR costing methods. The paper used Energy Management Center (EMC) for home energy management (HEM). The paper demonstrated that its suggested scheme reduces costs and PAR more effectively with GA than with BPSO and ACO. Ref. [15] applied a heuristic-driven evolutionary algorithm for solving optimization problems. The paper aimed to minimize energy costs and PAR. There are three kinds of consumers considered in this paper: domestic, commercial, and industrial. Using the suggested algorithm, many controllable appliances of different kinds can be controlled, and PAR and power costs are significantly reduced. According to ref. [16], GA can be used to minimize costs in SG. RES and energy storage systems such as batteries are discussed in the study. Batteries get charged using RES, and energy is used from the batteries in high energy demand or cost. Ref. [17] examined an advanced energy management system. The paper examined supply side management. The optimum set point is determined for various types of distributed power sources in the study. A modified bacterial foraging algorithm (MBFO) was applied to schedule the procedure. The suggested method reduced operating costs and net emissions, without taking DSM into account. Ref. [18] examined Hybrid DE using a harmony search (DE-HS) algorithm. The study examined a production planning approach for microgrids (MGs), including conventional generators, photovoltaic (PV), wind power, storage systems, and the electric vehicle (EV). The EVs serve as both the storage unit and the load demand. The planning problems are solved using the suggested hybrid DE-HS algorithm. The paper modeled wind and PV systems' uncertainties in order to ensure that MG was stable.

Almost all of the methods mentioned are unable to solve the HEMS problems effectively because of the unpredictability of individual behavior and the non-linear and complicated power usage profiles of many domestic devices. Often, methods for reducing power costs, PARs, and peak loads are used without considering consumers' satisfaction. Moreover, the proposed algorithms converge less quickly with an increase in the number of devices. Accordingly, the novel contributions of this paper are summarized as follows:

(1) This paper implements a wind-driven optimization algorithm (WDOA) for minimizing the power bills and PAR, with minimal impact on consumer satisfaction.

(2) This paper develops an optimum control scheme for smart home devices for scheduling the load.

(3) It is possible to solve several restricted problems at once. Scheduled devices are scheduled for optimal periods during the day in order to monitor peak demand, PAR, and energy costs while maintaining user satisfaction.

(4) This paper proposes two new planning methods named 'restricted' and 'multi-restricted' to schedule devices efficiently.

Throughout the study, the following sections are described: Section 2 discusses load classification and energy tariffs. The problem development has been discussed in Section 3. The new multi-restricted planning method is described in Section 4. Section 5 presents WDOA. Section 6 presents the outcomes and the discussion. Section 7 concludes the study.

2. Load Classification and Energy Tariffs

It is possible to schedule various loads in the EMS of domestic buildings based on the load kind and its features. Aspects such as the period of use and the average power usage of different appliances are included in the features. In general, domestic devices can be divided into three categories: baseline or non-shiftable (such as emergency loads hospitals or health clinics), uninterruptable load (lightning, automation, etc.), and interruptible flexible loads (washing machines, dishwashers, tumble dryers, etc.) [19].

2.1. Domestic Devices Applied

The present study analyzes the suggested problem using a medium-sized house, and Table 1 presents load profiles for all appliances. The study integrates a 5 kW rooftop solar PV on-grid system. As a result, Figure 1 shows the case study's PV production profile. There is a specific duration for appliances to complete the function, and therefore a specific energy consumption vector must be determined both based on the characteristics or through experimentation in equal periods during operation.

Table 1. The applied devices in the paper.

Appliances	Washing Machine with Dryer	Refrigerator	Electric Iron	Electric Oven (Morning Hours)	Electric Oven (Evening Hours)	Water Heater	Table Fan	Coffee Grinder
Power rating (kW)	0.225	1.5	2.15	2.15	1.5	0.025	0.1	

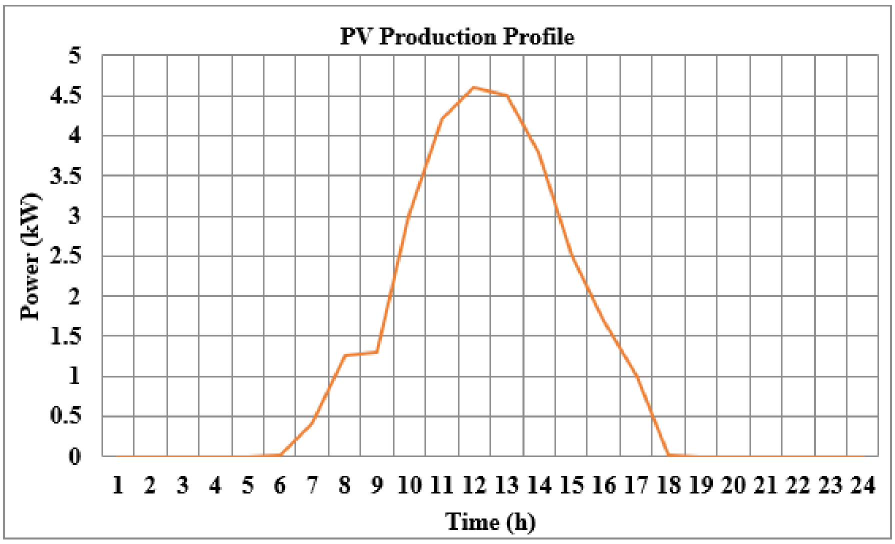


Figure 1. Case study's PV production profile.

2.2. Energy Tariff Scheme

As a result, feed-in tariffs need to be greater in comparison to grid tariffs in order to appeal to consumers and generate renewable energy in real situations. The grid tariff

(TOUP) and feed-in tariff (FIP) are set at equal levels for this paper as a demonstration of the scheme's efficiency. A lower energy price during off-peak periods will also allow consumers to move their power usage from peak to off-peak times.

On average, household users pay 0.00517 USD per kWh for the 1st 50 kWh of energy they consume. Using the assumption that peak energy costs are 50% greater compared to off-peak energy costs, Table 2 shows the proposed TOUP scheme [20].

Table 2. The proposed TOUP scheme.

Hours	22:00–7:00	7:12–21:48
Cost (TOUP) in USD/kWh	0.00517	0.00775

3. Problem Development

In the beginning, there are 24 time slots throughout the day. In a day, there are 120 time slots, every one of which lasts 12 min, and an hour has been divided into five time slots. $s \in S \triangleq \{1, 2, 120\}$ shows the time slots. By making the time slot short, WDOA can easily solve the problem. The minimum operating time of all appliances will be 12 min. A schedulable device's length of operation time interval (LOT) will be determined by integer multiples of the 12 min periods. Time slots are presumed to be the unit of LOT for the paper. This indicates minor errors within a short time that are not worth paying attention to. P_a shows the energy usage planning vector and would be:

$$P_a \triangleq \left[P^1, P^2, \ldots, P^{120}\right] \tag{1}$$

According to their characteristics, every appliance has constant energy usage hourly. The device a has the power usage hourly of:

$$P_a^s = \frac{X_a}{5} \tag{2}$$

A shiftable appliance's (SA's) energy rate is represented by Equation (2). This case has five slots for each hour. In the case of schedulable devices, the energy usage planning matrix P would be:

$$P = \begin{cases} P \Big| P_a^s = \frac{X_a}{5}, & \forall a \in A\ s \in [t_a, t_a + l_a] \\ P_a^s = 0 & \forall a \in A\ s \in S \backslash [t_a, t_a + l_a] \end{cases} \tag{3}$$

The planning vector can be obtained through the addition of the "Power Matrix" column-wise in the following way:

$$P_{sch} = \left\{P_{sch} \middle| P_{sch}^s = \sum P_{ak}^s, \forall s \in S\right\} \tag{4}$$

3.1. The off and on Decision Variable

The 'on' and 'off' modes of the schedulable devices are determined by the decision variable Y_{ak}^s.

A HEMS is designed to minimize the PAR of the load in order to decrease the bill. During the day, the TOUP determines the lowest energy price. C^s shows the energy cost, according to the TOUP at the time slot s. The fitness function, f_{cost}, would be:

$$F_{cost,1} = min \sum_{s=1}^{n} C^s \left(\sum_{a=1}^{m} \sum_{k=1}^{u} P_{ak}^s Y_{ak}^s \right) \quad s.t.\ \alpha_a \leq t_a \leq (\beta_a - l_a) \tag{5}$$

In which, P_{ak}^s shows the load demand in every device a in phase k for time slot s. Y_{ak}^s shows the 'on' and 'off' binary decision variable. The binary decision variable $Y_{ak}^s \in \{0, 1\}$ determined the 'on' and 'off' modes of all devices. t_a represents the optimum time for the function of the device a. l_a represents the LOT meaning the energy usage of all appliances follows the appropriate schedule, α_a and β_a are the beginning and ending time slots of the function of all appliances ($\beta_a > \alpha_a$).

When an independent roof-top solar PV is incorporated, Equation (5) is as follows:

$$F_{cost,2} = min \sum_{s=1}^{n} \sum_{a=1}^{m} \sum_{k=1}^{u} (C^s P_{ak}^s Y_{ak}^s - g^s \rho_{ak}^s Y_{ak}^s) \tag{6}$$

Through the replacement of the variable $P_{ak}^s Y_{ak}^s$ with $P_{sch,ak}^s$ and $\rho_{ak}^s Y_{ak}^s$ with $G_{schm,\,ak}^s$, the objective function for the decrease in users' power bills in the absence of the solar PV system would be:

$$min \sum_{s=1}^{120} (C^s P_{sch}^s) \quad s.t.\ \alpha_a \leq t_a \leq (\beta_a - l_a) \tag{7}$$

Incorporating the solar PV system will update the objective function in the following way:

$$min \sum_{s=1}^{120} (C^s P_{sch}^s - g^s G_{schm}^s) \quad s.t.\ \alpha_a \leq t_a \leq (\beta_a - l_a) \tag{8}$$

The decrease in PAR would be:

$$minPAR = \frac{Max(P_{sch})}{Avg(P_{sch})} \tag{9}$$

Planning helps minimize a user's discomfort level. Customer discomfort can be modeled and quantified using a delay time rate function.

$$min \sum a \in A f_{sn} \tag{10}$$

In which, f_{sn} shows the dissatisfaction associated with the SA. Equation (11) calculates it using the delay time rate (DTR) of SAs [20]:

$$\text{DTR} = \left(\frac{t_a - \alpha_a}{\beta_a - l_a - \alpha_a} \right) \forall a \in A \tag{11}$$

In addition, it is possible to insert a delay parameter $g > 1$ for associating f_{sn} as g^{DTR}. Therefore, dissatisfaction associated with SA would be:

$$f_{sn} = \sum_{a \in A} g^{\text{DTR}} \tag{12}$$

3.2. Limitations

Solving the formulated objective functions requires the consideration of the below limitations.

3.2.1. Power Limitations

Power demands must be met by the load phases of all appliances. The limitation can be described in the following way:

$$\frac{1}{5} \sum_{s=1}^{m} P_{ak}^s = E_{\text{ak}}\ \forall \{a, k\} \tag{13}$$

In the case of device a, load phase k, and time slot s, P_{ak}^s represents the load and E_{ak} shows the power required. For each appliance, the maximum load restrictions have been set with the utility to a specified predetermined bound θ^s.

$$\sum_{s=1}^{m} P_{ak}^{s} \leq \theta^{s} \tag{14}$$

3.2.2. Solar Unit Production Limitation

Daily, the PV system generates between minimal and maximal energy through the PV panels.

$$P_{g,min} \leq \rho \leq P_{g,max} \tag{15}$$

Whenever the energy generated by PV occurs at the lowest, meaning $\rho < P_{g,min}$, the utility is expected to provide the entire amount of energy needed for devices.

3.2.3. Power Balance Limitation

$$J + Q = n \tag{16}$$

In which, the number of controllable devices has been shown by J, the number of uncontrolled devices has been shown by Q, and n represents the entire number of devices.

3.2.4. Time Limitation

Scheduled load appliances (ScLAs) are not interruptible till all load phases have been completed. The following load phase cannot begin until the prior load phases have completed their operations.

$$Y_{ak}^{s} + \gamma_{ak}^{s} = 1 \tag{17}$$

In the case of a binary decision variable Y_{ak}^{s} which has a binary 1 value, consequently, the auxiliary decision variable γ_{ak}^{s} must have a binary 0 value and the opposite is true. The decision variable γ_{ak}^{s} determines whether or not the prior function was finished. Based on the assumption that devices operate at their predetermined rate in operational times, it is necessary to impose various restrictions on demand management in the following manner:

$$\beta_a - l_a \geq l_a \tag{18}$$

Typically, the operational starting time occurs between α_a and $\beta_a - l_a$.

$$t_a \in [\alpha_a , \beta_a - l_a] \tag{19}$$

For the devices' functions, the cycle count would be:

$$\Theta = S_{t,end} - S_{t,st} - l_a + 2 \tag{20}$$

In which, Θ represents the cycle count of a device in operation, $S_{t,st}$ represents the start time and $S_{t,end}$ shows the ending time for the device's function in the consumer certain range, and l_a represents the LOT for a device. The different parameters for ScLAs are shown in Table 3.

Table 3. Variables for ScLAs.

Devices	Coffee Grinder	Water Heater	Washing Machine with Dryer	Electric Iron	Table Fan	Electric Oven-(Morning Hours)	Electric Oven-2 (Morning Hours)	Refrigerator
Number of slots allocated	1	5	15	2	10	4	4	115
Power usage per day (kWh)	0.02	1.5	9	0.6	0.05	1.72	1.72	5.172
Real OTD (min)	12	60	180	24	120	45	45	1380
Power usage per day slot (kWh)	0.02	0.3	0.6	0.3	0.05	0.43	0.43	0.045
Power rate (kW)	0.1	1.5	3	1.5	0.025	2.15	2.15	0.225

4. New Multi-Restricted Time Range Planning

For multi-restricted time range planning, operational durations and start times would be described in the following manner:

$$l_a = \begin{cases} l_{a,1} \; if t_{a,1} \in [\alpha_{a,1} \, , \, \beta_{a,1} - l_{a,1}] \\ l_{a,2} \; if t_{a,2} \in [\alpha_{a,2} \, , \, \beta_{a,2} - l_{a,2}] \\ 0 \qquad\qquad\qquad\qquad , else \end{cases} \tag{21}$$

$$\alpha_{a,1} \leq l_{a,1} \leq \beta_{a,1} - \alpha_{a,1} \tag{22}$$

$$\alpha_{a,2} \leq l_{a,2} \leq \beta_{a,2} - \alpha_{a,2} \tag{23}$$

The operational start time would be between $t_{a,1}$ and $t_{a,2}$.

$$t_{a,1} \in [\alpha_{a,1} \, , \, \beta_{a,1} - l_{a,1}] \tag{24}$$

$$t_{a,2} \in [\alpha_{a,2} \, , \, \beta_{a,2} - l_{a,2}] \tag{25}$$

In which, $l_{a,1}$, $l_{a,2}$ represent the LOTs and $\alpha_{a,1}$, $\alpha_{a,2}$ represent the start time slots. $\beta_{a,1}$, $\beta_{a,2}$ represent the ending time slots and $t_{a,1}$, $t_{a,2}$ represent the probable start times in the range of the start and ending times of slot ranges.

5. Wind-Driven Optimization Algorithm

This study makes use of the WDOA as the optimizer due to its special characteristics including the high convergence rate, and the sub-division ability, which helps to solve the multi-modal problems, having powerful local operators and highly random searches. Due to these features, it becomes a very successful and optimal option for the proposed nonlinear optimization problem. WDO would be a meta-heuristic algorithm based on wind movement within the atmosphere. For WDO, a search space is filled with incredibly small air parcels, and four various forces are employed for equalizing pressure on air parcels. The four forces involve the Coriolis force, the pressure gradient force, the gravitational force, and the frictional force. The Coriolis force moves winds horizontally, in other words, rotates winds around the earth, while a pressure gradient force changes the wind's pressure as it moves. Wind pressure is balanced horizontally by equalizing Coriolis force and pressure gradient force. In addition, the gravitational force pushes winds vertically towards their center, causing the friction to decrease wind speed, slowing down the speed of the Coriolis force. The mathematical expressions for each force would be [21]:

$$C_F = -2\Omega \times \mu \tag{26}$$

$$P_{GF} = -\nabla P \delta V \tag{27}$$

$$F_g = \rho \delta V g \tag{28}$$

$$F_f = \rho \alpha \mu \tag{29}$$

Firstly, Equation (30) has been used to generate the random solution (v_i):

$$v_i = V_{max} \times 2 \times (rand(populationsize, n) - 0.5) \tag{30}$$

The fitness function evaluates all random solutions and reproduces reasonably acceptable solutions whilst neglecting undesirable solutions. During every stage, the air parcel's velocity and position are assessed, and the air parcel's velocity has been updated. The new velocity (V_{new}) of air parcels can be expressed by Equation (31):

$$V_{new} = (1-\alpha)V_{cur} - V_{cur} \times g(R \times T\left|\frac{1}{j} - 1\right|(x_{new} - x_{old})) + \frac{cV_{cur}}{P_{cur}} \tag{31}$$

$$V_{new} = V_{max}\ if\ V_{new} > V_{max} \tag{32}$$

$$V_{new} = V_{min}\ if\ V_{new} < V_{max} \tag{33}$$

$$x_{new} = x_{cur} + (V_{new} \times \Delta t) \tag{34}$$

Equation (34) is used to generate a new generation, and the procedure continues after an ending criterion has been achieved, meaning optimum planning of power usage and in of energy prices. Table 4 provides the optimum outcomes when taking into account the parameters [22].

Table 4. WDO parameters.

Parameters	**g**	**α**	**RT**	**Population Sizing**	**DimMax**
Amounts	0.2	0.4	3	30	5
Parameters	**DimMin**	V_{max}	V_{min}	**Maximum iteration**	
Amounts	−5	0.1	0.9	200	

6. Simulation Results and Discussions

This section assesses the performance of the proposed model on a standard test system. As the optimizer, WDOA is used to solve the suggested smart home device planning problem in eight various cases. For the case of efficacy, WDOA has then been compared with DE [23] method to demonstrate its efficiency. In the following subsections, shiftable load appliances (SLAs) will be presented and analyzed in various cases. It is worth noting that peak load demand in the residence is controlled by the maximal load limitation, which must be lower than or equal to 5.5 kW.

6.1. SAs Scheduled in a Constant Time Range

As part of the planning, the user adjusts the run time range for all appliances according to the allocated time slots. Daily, all schedulable appliances have at least one operational cycle. Schedules and adjustments to the appliance parameters must be done manually by the consumer. Then, the utility electricity pricing (TOUP) signal is sent. Table 5 provides the parameters of domestic load devices for constant time-range planning.

A typical home daily load demand is shown in Figure 2 for constant-time planning using TOUP. Moreover, it displays the highest load demand for each 24 h. A constant time range is shown in Figure 3 with no planning for the household's daily load. Time slot 38 to 39 has the highest peak load in a day, in other words, 7:24 AM to 7:36 AM, so it is not the best time to minimize costs. Daily PAR can be determined using the mean of planned load demand. It is important to distribute the appliances to each time slot throughout the day to minimize the peak load demands while maintaining user satisfaction [24,25]. Equation (9) optimizes the fitness function in 24 h for the purpose of simulating peak load, regardless of TOUP. On a 24 h time horizon, the PAR equals 4.7.

As a result of the minimization of PAR daily, the fitness value in Equation (7) can be found. Using a constant time-range planning using a mean value of 4.7, the overall energy price equals 0.12 USD/day. There is an overall power usage of 19.79 kWh per day. According to Table 5, the washing machine has been planned to run from 12:00 AM to 2:48 AM. A washing machine operated in the daylight at peak times, such as from 9:00 AM to 11:48 AM, is likely to increase the energy price to 7.79 and the PAR is likely to be 5.73. There is a maximal peak load of 4.73 kW for time slots 51 and 55 (that is 10:00 AM to 10:48 AM).

Table 5. Parameters of schedulable of devices for constant-time planning.

Devices	Coffee Grinder	Water Heater	Washing Machine with Dryer	Electric Iron	Table Fan	Electric Oven-1 (Morning Hours)	Electric Oven-2 (Morning Hours)	Refrigerator
Number of slots allocated	1	5	15	2	10	4	4	115
OTI (time slot)	62	51–55	1–15	37–38	71–80	36–39	97–100	1–115
Starting Time (h)	12-15 PM	10-00 AM	12-00 AM	7-15 AM	2-00 PM	7-00 AM	7-15 PM	12-00 AM
Ending Time (h)	12-20 PM	11-00 AM	2-48AM	7-30AM	3-00 PM	7-45AM	8-00 PM	10-48 PM
Power usage per day slot (kWh)	1	5	15	2	10	4	4	115
Power rate (kW)	0.1	1.5	3	1.5	0.025	2.15	2.15	0.225

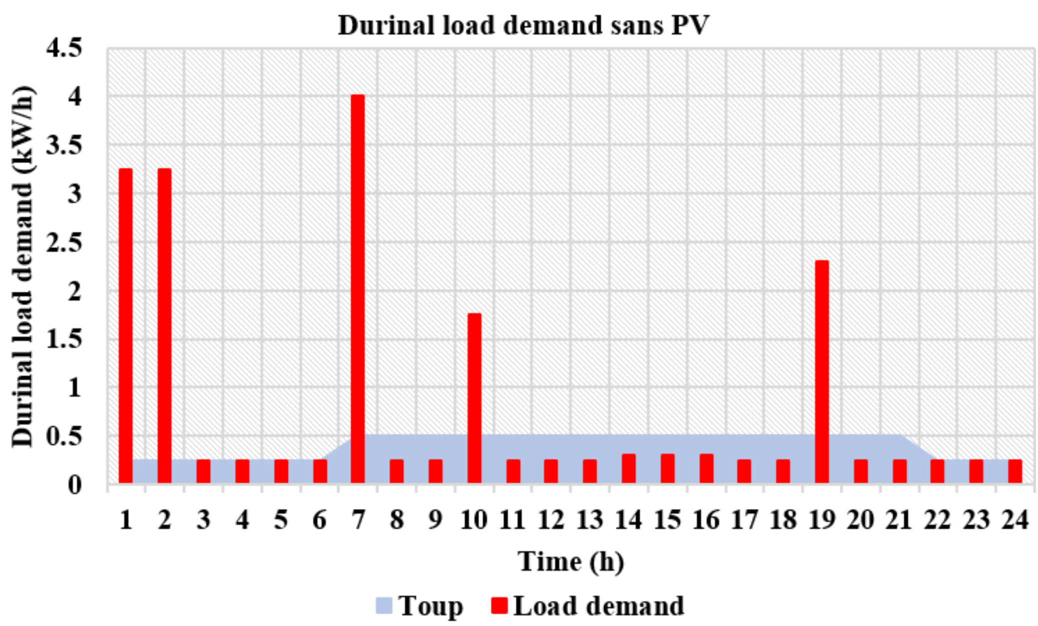


Figure 2. Domestic load demand pattern per day in constant-time planning.

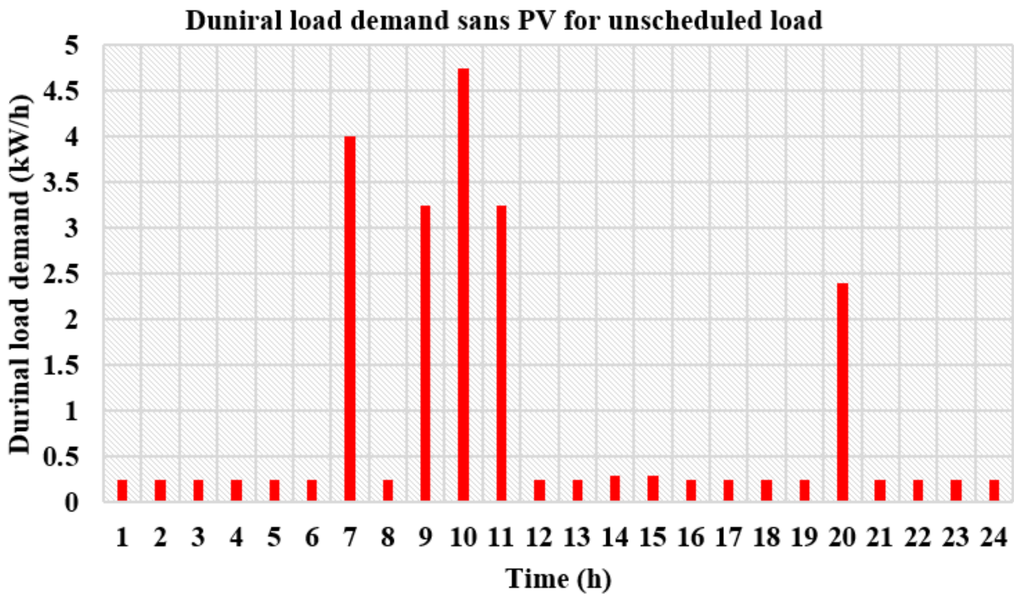


Figure 3. Domestic load per day in a constant time range in the absence of planning.

6.2. ScLAs (Scheduled Load Appliances) Using Restricted Time Range

The planning specifies the start and end time slots for the devices' function that users wish the devices to function during. The load scheduler randomly determines the appliance's location to function during the times. As a result, the suggested algorithm determines the optimal combinations that have the lowest PAR and energy costs. By planning devices into acceptable operational cycles, undesirable time slots are minimized. According to Figure 4, the power demand limitation is satisfied by devices requiring less than 5.5 kW per slot. WDOA forecasts peak load at 3.23 kW during time slots 3 to 15, which are 12:24 AM to 2:48 AM; and DE forecasts peak load at 3.88 kW during time slots 35 to 36, which are 6:48 AM to 7:00 AM. The operational starting and ending times for the restricted time planning are shown in Table 6.

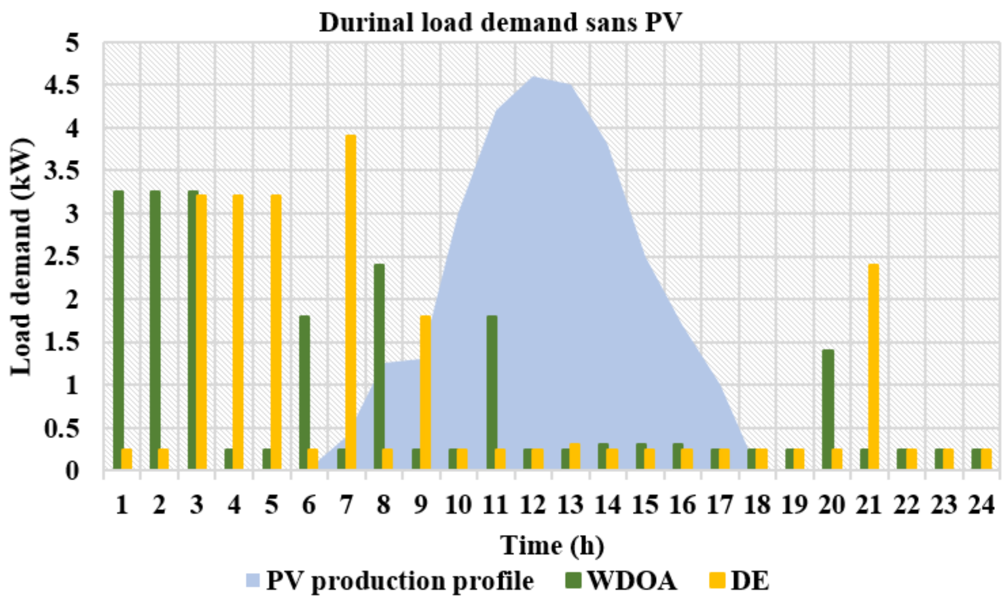


Figure 4. Load pattern per day within restricted time planning and PV production profile.

Table 6. Operational starting and ending times for restricted time planning.

Interruptible Flexible Load Devices				
Appliances	**Electric Iron**	**Coffee Grinder**	**Water Heater**	**Table Fan**
Number of slots allocated	2	1	5	10
OTI	33–42	59–68	46–55	65–80
Power rate (kW)	1.5	0.1	1.5	0.025
Feasible operational starting and ending time (h)	6:24–8:12	11:36–13:24	9:00–10:48	12:48–15:48
Non-interruptible flexible load devices				
Appliances	**Electric oven-1**	**Electric oven-2**	**Refrigerator**	**Washing machine with dryer**
Number of slots allocated	4	4	115	15
OTI	33–44	92–106	1–115	1–30
Power rate (kW)	2.15	2.15	0.225	3
Feasible operational starting and ending time (h)	6:24–8:36	18:12–21:00	12:00–22:48	00:00–5:48

A PAR of 3.91 can be achieved by WDOA and a PAR of 4.71 can be achieved by DE. WDOA has 0.119 USD/day for energy price, whereas DE has 0.121 USD/day. WDOA's scheduler reduces electricity costs and 3.9% and PAR by 16.8% when compared to constant-time planning. In the time slots 13 to 27, that is 2:24 AM to 5:12 AM, there is the peak power demand from the grid of 3.23 kW with no PV system. Figure 5 shows that there would be a PAR with no PV by WDOA of 3.91 and by DE of 6.52. WDOA's minimal price with no PV equals 0.119 USD/day, whereas DE's minimal price equals 0.120 USD/day. The operational starting and ending times for multi-restricted time planning are shown in Table 7.

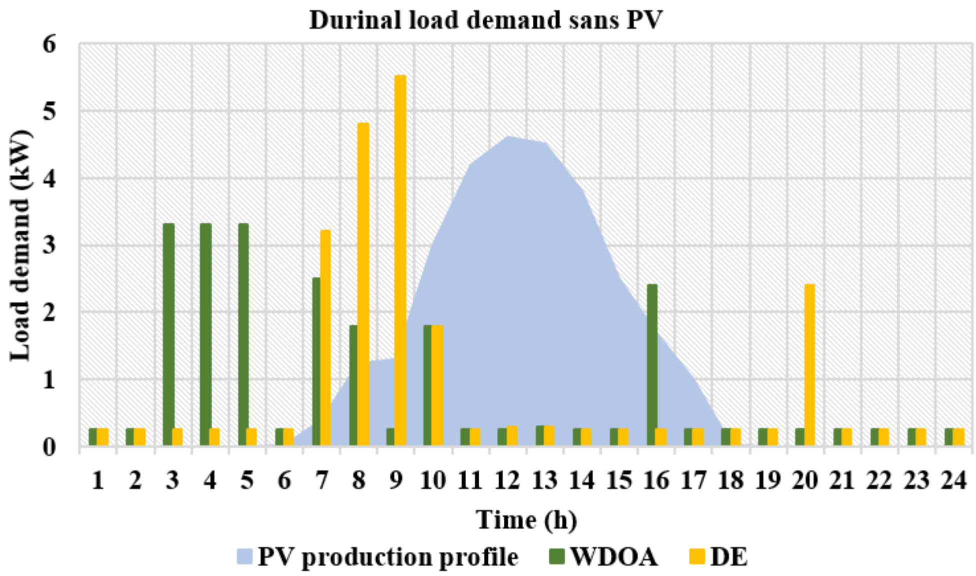


Figure 5. Load demand pattern per day with multi-restricted time planning and demonstrating PV production profile.

Table 7. Operational starting and ending times for multi-restricted planning.

Schedulable Devices	Washing Machine with Dryer	Water Heater	Table Fan	Electric Oven-1	Electric Oven-2	Refrigerator	Electric Iron
Number of slots allocated	15	5	10	4	4	115	2
OTI (time slot)	1–17 or 19–34	41–48 or 50–60	61–70 or 72–81	31–35 or 41–49	86–92 or 97–101	1–115	31–36 or 39–43
Power rate (kW)	3	1.5	0.025	2.15	2.15	0.225	1.5
Feasible operational starting and ending time (h)	00:00–3:12 or 3:36–6:36	8:00–9:24 or 9:48–11:48	12:00–13:48 or 14:12–16:00	6:00–6:48 or 8:00–9:36	17:00–18:12 or 19:12–20:00	12:12–23:48	6:00–7:00 or 7:36–8:24

6.3. ScLAs (Scheduled Load Appliances) Using Variable Time Planning

According to this planning, the probable operational start time slot equals 1, and the probable operational end time slot equals 120. Nonetheless, the operational period exceeds or equals the start time slot, but below or equal to the ending time slot minus the start time slot. A device that requires scheduling has a range of start operational times during its operating cycle. In Table 8, the parameters applied to simulate ScLAs with variable time range planning are shown. Figure 6 shows the load pattern per day with a variable time planning model. Figure 6 shows the load demand pattern daily for the highest iteration of 500. WDOA scheduler's peak load demand equals 3.23 kW during time slots 35 to 49 (that is between 6:48 AM and 9:36 AM).

Variable time scheduling using WDOA results in PAR of 3.91and DE results in PAR of 3.94. DE calculates the energy price at 0.115 USD/day, whereas WDOA calculates it at 0.11 USD/day. WDOA load scheduler shows a similar peak load in restricted, multi-restricted, and variable time range planning without PV production, which equals 3.23 kW daily, however, 16.8% below constant time-range planning.

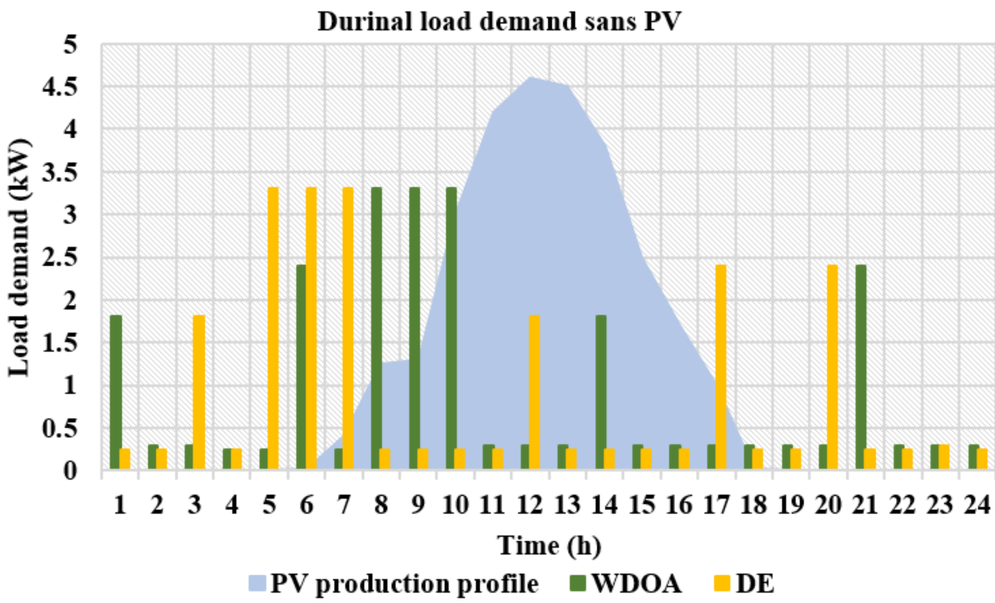


Figure 6. Domestic load pattern per day demands with variable time range.

Table 8. Parameters of schedulable devices.

Devices	Washing Machine with Dryer	Water Heater	Coffee Grinder	Table Fan	Electric Oven-1	Electric Oven-2	Refrigerator	Electric Iron
Number of slots allocated	15	5	1	10	4	4	115	2
OTI (time slot)	1–120	1–120	1–120	1–120	1–120	1–120	1–120	1–120
Power usage per day (kWh)	9	1.5	0.02	0.05	1.72	1.72	5.17	0.6
Number of exiting operational cycles	106	116	120	111	117	117	6	119
Power usage per slot (kWh)	0.6	0.3	0.02	0.005	0.43	0.43	0.045	0.3

6.4. Constant Time-Range Planning Combined with PV

PV panels are given priority over electronic devices in every planning scenario. When PV panels cannot generate enough power for supplying the devices' load, the power is supplied from the power grid. PV panels can export excess power to the main grid when they generate excess power. The process has been employed for optimizing the objective function similarly to scenario 1, and Table 5 parameters have been applied to integrate the PV system. Figure 7 shows the simulation outcomes. Figure 8 shows that there is a net peak load demand daily of 3.23 kW, but the net peak PV production following satisfaction of the demands equals −4.36 kW per slot. PAR equals 3.91. There is an overall energy demand of 19.79 kWh for devices daily. The TOUP tariff allows the sale of 8.7 kWh of energy to the power grid. In kWh, there is 0 net energy entering the utility. As a result, the PAR equals 3.75, 34% less compared to the unplanned load with no PV.

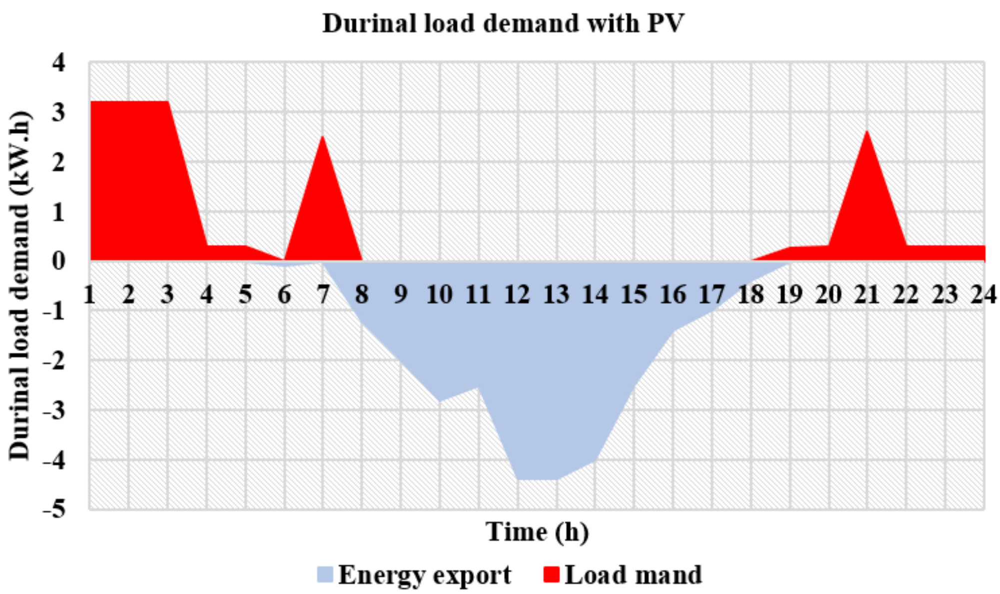


Figure 7. Net load profile pattern per day using PV energy with constant time planning.

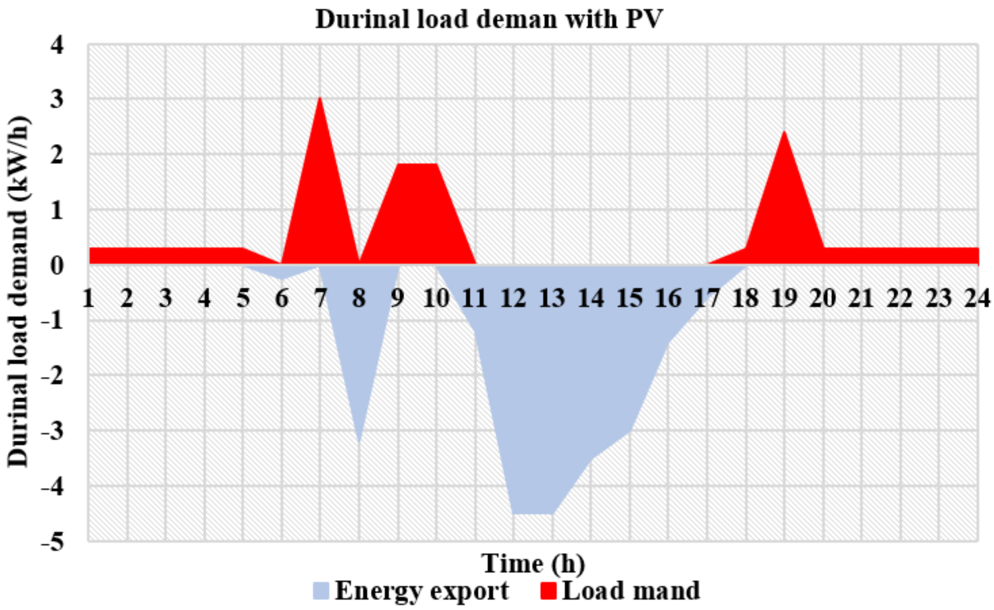


Figure 8. Load profile pattern per day of USLAs using PV.

Figure 8 shows the pattern of demand per day for unplanned loads. The power prices, peak loads, and PARs of domestic devices that are planned with a constant-time planning approach tend to be below those of unscheduled load appliances (USLAs) without PVs. The peak load and PAR for a system without PV equal 17.99% below the unplanned loads. The power price for a system without PV production with constant time range planning equals 15.78% less compared to the power price of the unplanned loads. When utilizing constant time-range planning, the peak load and PAR of a PV system exceed the unplanned loads. PV compensates for the majority of load demands in unplanned loads compared to constant time-range planning. Instead of satisfying the load demand completely, the majority of PV production for constant-time planning has been sent to the utilities. In a system integrating PV utilizing constant time-range planning, the utility must pay the consumers 2.35% more for power compared to unplanned loads. Table 9 presents a comparison.

Table 9. Details of comparing constant a system with time-range planning and a system with no planning.

Devices	**Unplanned**		**Fixed Time Planning**	
Operational layout	System using PV	System sans PV	System using PV	System sans PV
PAR	3.75	5.73	3.91	4.70
Peak load	3.09	4.73	3.23	3.88
Power price (USD/day) consumer paid for grid	0	0.148	0	0.124
Power price (USD/day) grid paid for consumer	0.072	0	0.74	0

6.5. Restricted Time Scheduling Integrated with PV

When integrating 5 kW PV power production into restricted time-range planning, the identical parameters are applied as in scenario 2 and Table 6. The net load demand pattern per day is shown in Figure 9. Utility imports are indicated by the upper portion that exceeds 0. Utility exports are shown in the lower portion that is below 0.

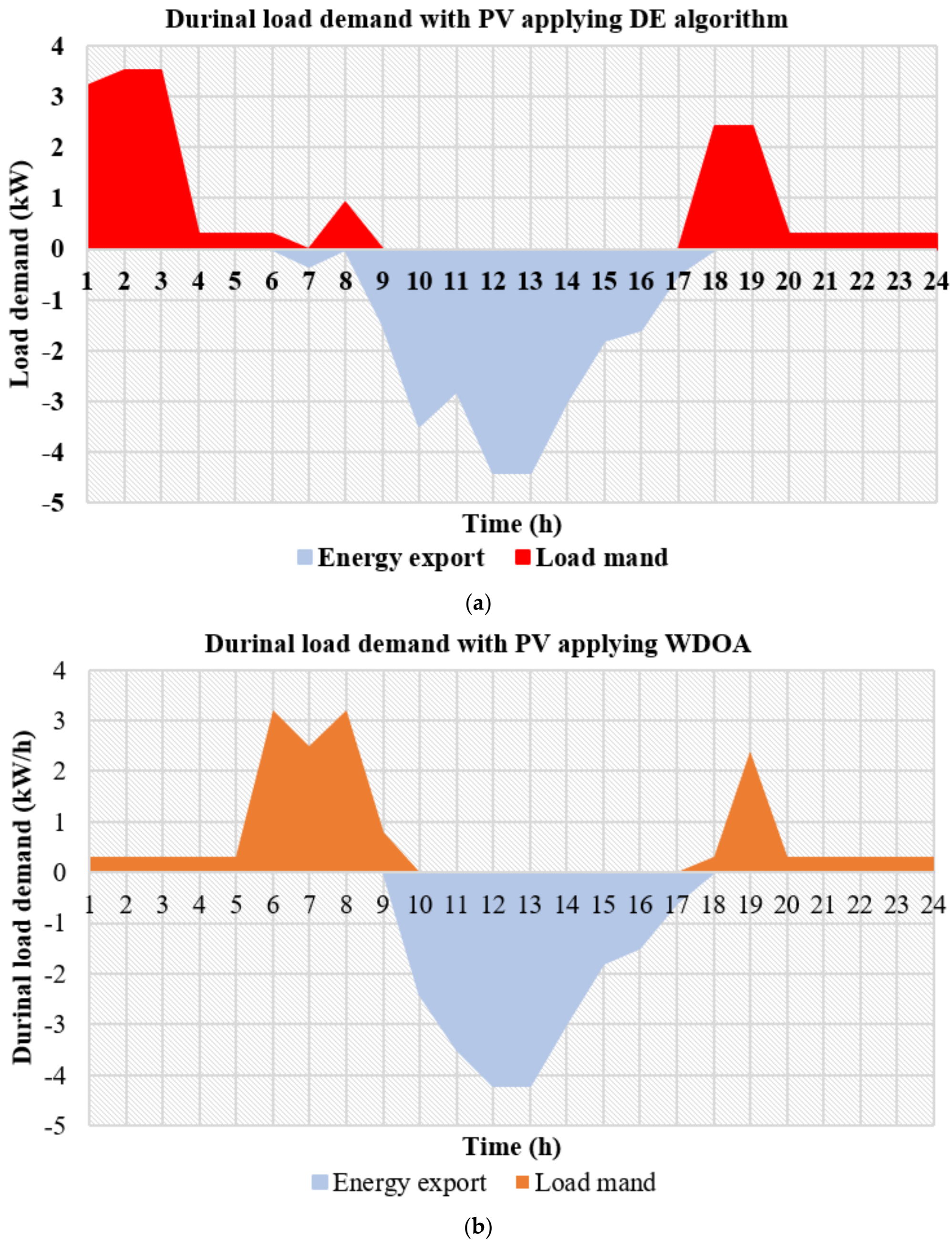
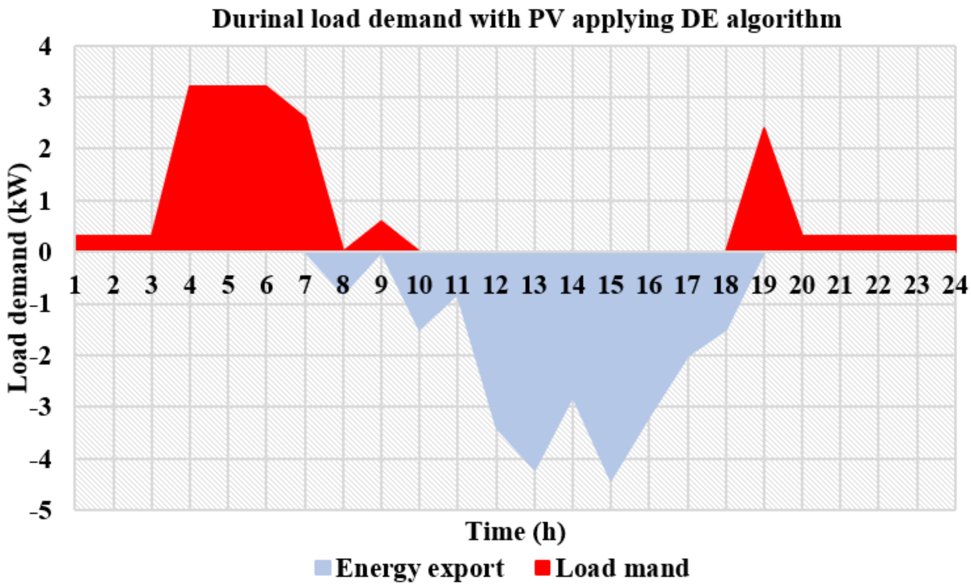


Figure 9. The net load demand pattern per day using PV production in order to minimize energy price with restricted time-range planning; (**a**) DE algorithm; (**b**) WDOA.

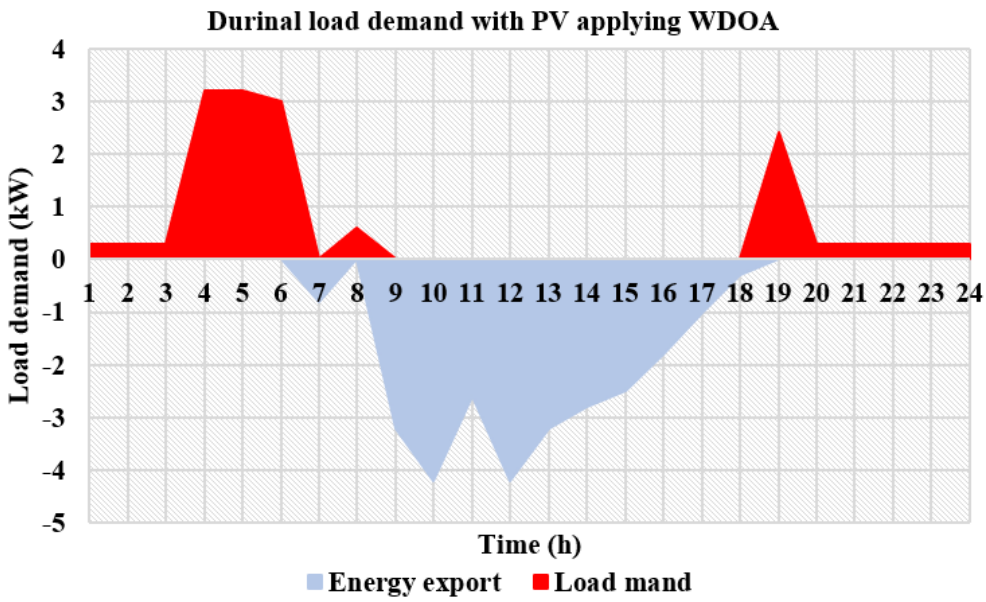
The WDOA scheduler calculates power price and PAR in a system using PV at 4.86% and 1% below constant time-range planning, respectively. In the case of PV production with WDOA, the net peak load demand per day from the utility equals 3.19 kW, and with the DE scheduler, it equals 3.23 kW. PV utilizing WDOA has a minimal PAR of 3.87, whereas PV utilizing DE has a minimal PAR of 3.91. There is an overall energy demand daily of 19.79 kWh for the devices. The grid's net power import equals zero, and the grid's net power export equals 8.7 kWh. PV utilizing the WDOA has a minimal power price of −0.1 USD/day, whereas PV utilizing the DE has a minimal power price of −0.099 USD/day.

6.6. Multi-Restricted Time Range Scheduling Integrated with PV

In multi-restricted time-range planning, the parameters in scenario 3 and Table 7 are utilized for optimizing PAR, power price, and peak load. Figure 10 shows the net load demand pattern per day for a PV production system. In WDOA, the net peak power demand per day from the grid using PV equals 2.85 kW; whereas, in DE, the net peak power demand per day equals 3.23 kW. PV system utilizing WDOA results in the lowest PAR of 3.46; whereas, the PV system utilizing DE results in the lowest PAR of 3.87. PV system utilizing WDOA has the lowest price of −0.01 USD/day; whereas, DE has the lowest price of −0.099 USD/day.



(**a**)



(**b**)

Figure 10. The net load demand pattern per day using PV generation in order to minimize energy price with multi-restricted time-range planning; (**a**) DE algorithm; (**b**) WDOA.

6.7. Variable Time Scheduling Integrated with PV

Because all appliances' load profiles are chosen randomly up to the highest iteration point, the load profile shape can vary slightly with each iteration. ScLAs using PV production with variable time planning are depicted in Figure 11. When PV is integrated into the grid utilizing WDOA, the net peak power demand per day equals 0.8 kW; whereas, when utilizing DE, the peak power demand equals 3.88 kW. WDOA has a minimal PAR of 1 with PV, whereas DE has a minimal PAR of 2.88. The minimal overall energy demand daily for devices equals 19.79 kWh. Utility grid energy imports are zero. According to TOUP, the minimal price of PV production with WDOA equals −0.11 USD/day, whereas with DE equals −0.104 USD/day.

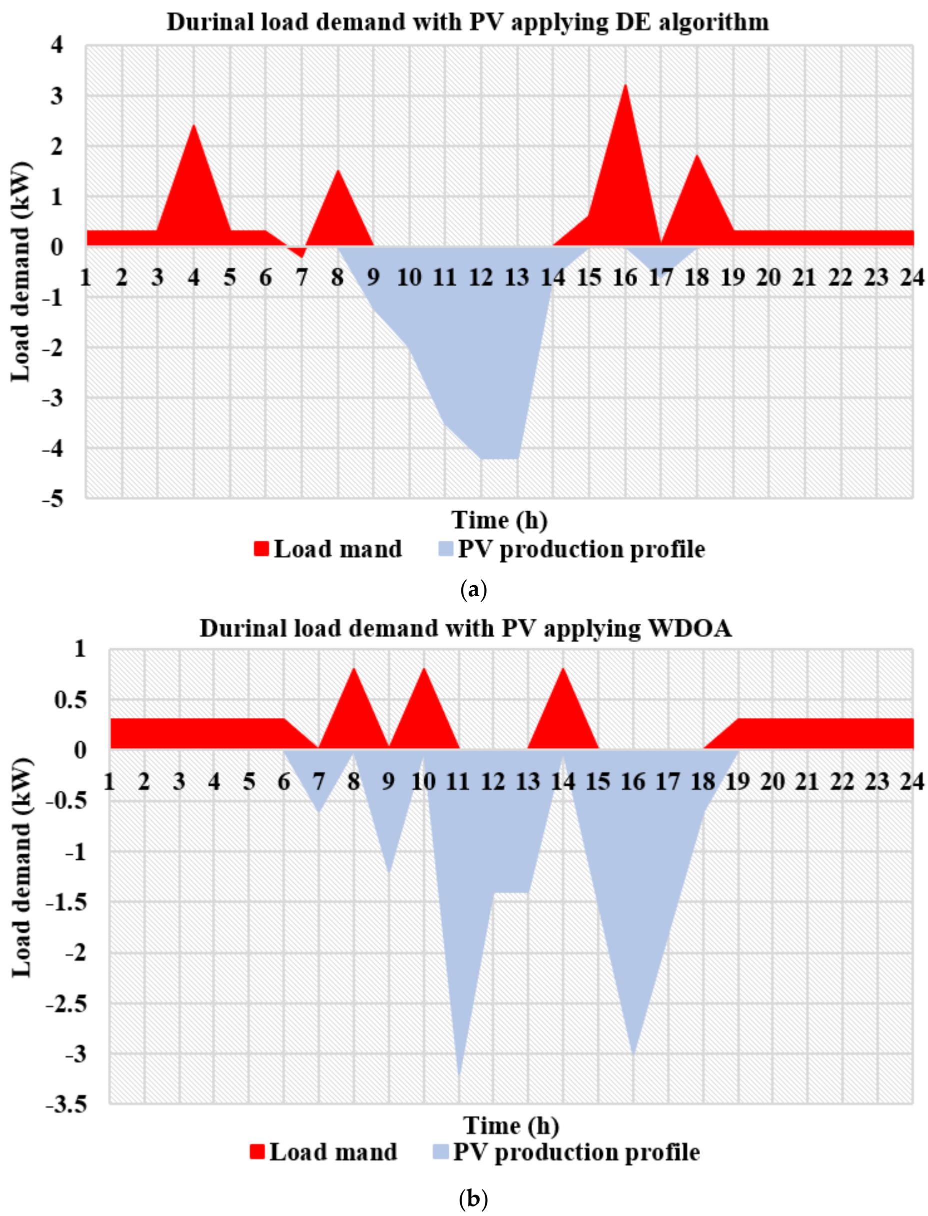


Figure 11. The net load profile pattern per day of ScLAs using PV power production with variable time planning; (**a**) DE algorithm; (**b**) WDOA.

7. Conclusions

The paper formulates and optimizes a smart house device planning problem with new restricted and multi-restricted time-range planning methods to satisfy both time and power requirements. Minimizing energy prices per month is the first goal. The second and third goals are to minimize peak-to-average ratios and maximize peak load demand. As the problem is non-convex, two efficient binary meta-heuristic optimization algorithms, a wind-driven optimization algorithm, and differential evolution have been used for solving it. There are eight shiftable appliances using a 5 kW roof-top PV panel. This problem is addressed by comparing eight scenarios including and excluding PV production. The outcomes show that the wind-driven optimization algorithm method minimizes energy costs, peak load demand, and peak-to-average ratios over differential evolution. With PV production, consumers can send excess power to the utility and take advantage of feed-in tariffs. It was seen that considering renewable sources of PV would result in a reinforced grid with a higher power supply in the unscheduled programs. According to the results, the power price for a system without PV production with constant time-range planning equals 15.78% less compared to the power price of the unplanned loads. Moreover, from the consumers' points of view, the utility must pay the consumers 2.35% more for power compared to unplanned loads in a system integrating PV utilizing constant time-range planning. The time-of-use pricing would result in less costs and more flexibility in the system that can finally add to the social welfare of societies. In the future, authors would assess the security of data transaction within the system from a cyber point of view.

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Nomenclature

C^s	Energy cost.
f_{cost}	Fitness function.
J	Number of controllable devices.
g^s	The feed-in tariff.
g	A constant value in the optimization algorithm.
l_a	The LOT meaning the energy usage of all appliances follows the appropriate schedule.
$l_{a,1}$, $l_{a,2}$	The LOTs.
P_a^s	Energy usage of a^{th} device at s^{th} time slot in kWh.
$P_{g,min}$	The minimal energy generation.
$P_{g,max}$	The maximal energy generation by applying the PV system daily in the grid.
P_{sch}	A vector that represents the overall energy demand of SAs for every time slot s.
P_{ak}^s	Load demand in every device a in phase k for time slot s.
Q and n	The number of uncontrolled devices.
t_a	The optimum time for the function of the device a.
$t_{a,1}$, $t_{a,2}$	The probable start times in the range of the start and ending times of slot ranges.
$S_{t,st}/S_{t,end}$	The start time and end time for the device's function in the consumer certain range.
X_a	Energy usage value hourly, at the time slot.
Y_{ak}^s	The 'on' and 'off' binary decision variable.
V_{max}	Maximum velocity of the particle in the algorithm.
α_a and β_a	The beginning and ending time slots of the function of all appliances ($\beta_a > \alpha_a$).
ρ_{ij}^s	The energy generated via the rooftop solar PV system in s^{th} time slot.

Θ	The cycle count of a device in operation.
$\alpha_{a,1}, \alpha_{a,2}$	The start time slots.
$\beta_{a,1}, \beta_{a,2}$	The ending time slots.

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