Integrated Optimization of Smart Home Appliances with Cost-effective Energy Management System

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***Abstract*—Smart grid enables consumers to control and schedule the consumption pattern of their appliances, minimize energy cost, peak-to-average ratio (PAR) and peak load demand. In this paper, a general architecture of home energy management system (HEMS) is developed in smart grid scenario with novel restricted and multi-restricted scheduling method for the residential customers. The optimization problem is developed under the time of use pricing (TOUP) scheme. To optimize the formulated problem, a powerful meta-heuristic algorithm called grey wolf optimizer (GWO) is utilized, which is compared with particle swarm optimization (PSO) algorithm to show its effectiveness. A rooftop photovoltaic (PV) system is integrated with the system to show the cost effectiveness of the appliances. For analysis, eight different cases are considered under various time scheduling algorithms.**

***Index Terms*—Demand side management, GWO, home energy management system, PSO, peak-to-average ratio.**

I. Introduction

EVER increasing electricity demand, rising energy generation cost and growing renewable energy generation posed the limit on the production of energy from the conventional energy sources [1]. All these challenges motivate the electric utilities to focus on demand side management (DSM) techniques. Electricity usage report in United States suggested that at least 30% of electric power is wasted from the 72% of the total power that is consumed by the residential and commercial users [2]. Further, European Union (EU) is also decided to enhance the renewable energy production up to 20% of the total electricity production till 2020. Along with that EU is also targeted to enhance the generation by improving the energy efficiency up to the level of 20% [3]. High quality and reliable power supply is available with the advancement of information and communication technology (ICT) in the field of energy sector. ICTs are the most important component in the smart grid, which transfer information between two nodes. This process is very much crucial to control and manage various smart grid components efficiently under variable demand situation. To reduce the cost of infrastructure, environmental impacts and increase the reliability of the system, distributed generations like solar and wind can be integrated with the smart grid [4]. This helps to manage the energy consumption of smart home appliances by energy management system (EMS), which is also the aspect of smart grid [5].

In DSM, various techniques and algorithms have been adopted to minimize the cost of electricity billing based on TOUP tariffs and incentives. Consumers can generate renewable energy to supply their appliances and if there is any excess production, they will sell it to the utility grid based on the grid codes and TOUP, which varies through the day [6]. A novel approach of power hubs is presented in [7] for demand side management in smart homes. These power hubs control the loads individually. Shah *et al*. [8] proposed an energy management system for smart building, integrated with energy storage system by using multi-agent system (MAS). This research ignored the PAR that controls the horizontal load distribution within a day. Mahmood *et al*. [9] utilized BPSO based realistic scheduling mechanism (RSM) to schedule the home appliances and minimize user frustration and maximize utilization of appliance under the given constraints. Huang *et al*. [10] proposed a hybrid PSO-DE algorithm in order to manage appropriate allocation of energy resources to the end users.

In [11], a cooperative PSO has been used to optimize the energy consumption of both time-shiftable and power-shiftable home appliances. Yang *et al*. [12] developed a new interactive teaching–learning optimization (ITLO) method for voltage source converter based high voltage direct current (VSC-HVDC) systems with the offshore wind farm integration. Kazemi *et al*. [13] developed the EMS to manage energy usage of appliances, by GWO, which is followed by genetic algorithm (GA), but the system is not integrated with ESS and energy-shiftable scheduling. Yang *et al*. [14] proposed a new grouped GWO (GGWO) technique for getting the optimum value of interactive proportional-integral controllers' parameters of doubly-fed induction generator based wind turbines. An efficient HEMS has been introduced by Zhao *et al*. [3] to minimize electricity cost and PAR. In this research GA is used to solve the formulated minimization problem and the inclining block rate (IBR) model is adopted to restrict over energy consumption of home appliances. Rahim

Manuscript received February 15, 2019; revised April 1, 2019; accepted May 17, 2019. Date of publication June 30, 2019; date of current version May 20, 2019.

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DOI: 10.17775/CSEEJPES.2019.00340

et al. [15] introduced the HEMS, which is formulated via multiple knapsacks and ant colony optimization (ACO).

However, due to the unpredictable nature of human behavior and variable performance of most of the home appliances with non-linear and complex energy consumption pattern, the majority of the techniques listed cannot tackle HEMS problem efficiently. To accomplish energy cost minimization, PAR reduction and peak load minimization sometimes these techniques ignored the comfort level of the users. In addition to that, when the number of appliances increased to a certain extent, the stated algorithms converged slowly. Therefore, in this work the following methods are taken:

1) GWO is implemented to minimize the energy billing and PAR, without highly affecting the comfort level of the user.

2) An optimal control model is developed for smart building appliances to schedule the load. Most of the literatures simplified these models as linear models. This work has extended these models as binary non-linear optimization problem.

3) Different constrained problems are solved simultaneously. The peak demand, PAR and cost of electricity consumption has been monitored without highly affecting the comfort level of the users by scheduling of the appliances to convenient times within a day.

4) Two novel techniques called 'restricted' and 'multi-restricted' time range scheduling are proposed for scheduling the appliances in an efficient way.

II. Load Categorization and Electricity Tariff

In EMS of residential building, scheduling of different loads can be achieved by specifying the type of loads to be scheduled and characteristics of the given loads. These characteristics include the operation duration and average energy utilization of each appliance. Generally, home appliances are classified into three major groups, i.e. base line (non-shiftable), uninterruptable and interruptable flexible loads [3].

A. Home Appliances Used

In this paper, for the analysis of the proposed problem a mid-size home is considered and the load profiles of each home appliance are discussed in Table I. A 5 kW roof top solar PV on-grid system has integrated into this work. For that purpose the PV generation profile of Hawassa city is presented in Fig. 1. Each of the appliances has a definite interval of time for the completion of the operation and thus has a definite power usage vector that has to be developed either from the specification of the given appliance or can be determined experimentally at equal duration of operation time. It is assumed that all the appliances are working with their maximum power rating specified in their Specification Manuel.

TABLE I
Appliances Used in This Study

List of appliances	Power rating (kW)
Washing machine with dryer	3
Electric oven (morning hours)	2.15
Electric oven (evening hours)	2.15
Refrigerator	0.225
Electric iron	1.5
Water heater	1.5
Table fan	0.025
Coffee grinder	0.1

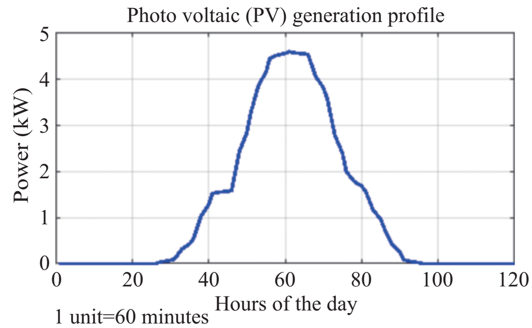

Fig. 1. PV generation profile of Hawassa city.

B. Electricity Tariff Model

The effectiveness of the proposed system, while solving the fitness function, is explained by taking Hawassa city, Ethiopia as a case study and implementing the TOUP model.

In order to promote the production of electricity by the users, the electric utility gives incentives for the customers those are generating power from the renewable energy sources. Beyond satisfying their energy demand, when they have surplus production, they tend to sell that surplus energy to the utility grid and benefit from the net metering.

In actual situation, to attract the users and produce energy from renewable sources, the feed in tariff should be higher than the grid tariff. But, in this study, to show the effectiveness of the proposed system model, the grid tariff (TOUP) and feed in tariff have taken the same value. In addition, to let the users shift their energy consumption from peak hour to off-peak hours, the electricity cost in off-peak duration must be lowered than that in the off peak hours. This can reduce the higher energy demand and following stress and instability problems in the utility grid.

The cost of the electricity in Ethiopia for residential consumers for the first 50 kWh is 0.2730 Birr/kWh. By assuming the electricity cost during peak duration is 50% higher than that of off-peak duration then, the TOUP model designed in this work is shown in Table II.

TABLE II
The Proposed TOUP Model

Hours	Price (TOUP) in Birr/kWh
10:00 PM–7:00 AM	0.2730
7:12 AM–9:48 PM	0.4095

III. Problem Development

Initially, 24 hours of the day are split into time slots. Each hour is split into 5 time slots, i.e. each time slot is of 12-minutes, and the total time slots available in a day are 120. These time slots are represented by $s \in S \triangleq \{1, 2 \ldots 120\}$. The time slot is made sufficiently small to conveniently perform the problem by GWO. Therefore, 12 minutes is the shortest operation time of any appliance. The integer multiples of the 12-minute time intervals is fixed to the length of operation time interval (LOT) of each schedulable appliance. The unit of LOT in this study is assumed to be the number of time slots. It represents very small errors of few seconds, which can be ignored. The power consumption scheduling vector $\boldsymbol{P}_a$ is given by:

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

where, P_a^s represents the power consumption of a^{th} appliance for s^{th} time slot in kWh. The power consumption value per hour is assumed to be fixed for all appliances based on their specifications. For appliance a, the energy consumption per hour is denoted by:

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

where, X_a represents the power consumption value per hour, during the time slot. Equation (2) represents the power rating of shiftable appliances per slot. In this case, the number of slots per hour is 5. For all schedulable appliances, the power consumption scheduling matrix $\boldsymbol{P}$ is defined as:

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

The scheduling vector is given by adding the "Power Matrix" column wise as shown below:

$$\boldsymbol{P}_{\text{sch}} = \{\boldsymbol{P}_{\text{sch}} | P_{\text{sch}}^s = \sum P_{ak}^s, \forall s \in \boldsymbol{S}\} \tag{4}$$

where $\boldsymbol{P}_{\text{sch}}$ is a vector representing the total power requirement of shiftable appliances in each time slot s.

A. The ON and OFF Decision Variable

The decision variable Y_{ak}^s determines the 'on' and 'off' status of the schedulable appliances.

The first objective of the HEMS is to reduce the billing cost by minimizing the PAR of the load. The minimum electricity cost is determined based on the TOUP within 24 hours of the day. Let C^s be the electricity price, based on the TOUP in the time slot s. The fitness function, f_{cost} becomes as follows.

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

where P_{ak}^s is the load demand in each appliance a in phase k at time slot s. Y_{ak}^s represents the 'on' and 'off' binary decision variable. The binary decision variable $Y_{ak}^s \in \{0, 1\}$ decided the 'on' and 'off' status of each appliances. t_a is a variable, which shows the optimal time for the operation of the appliance a. l_a is the LOT i.e. the power consumption of each appliance is valid within the proper scheduling, α_a and β_a be the start and end time slots of the operation of each appliance ($\beta_a > \alpha_a$).

With the incorporation of stand-alone roof-top solar PV, (5) becomes:

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

where, g^s is the feed-in tariff, ρ_{ij}^s represents the power produced by the roof top solar PV system in s^{th} time slot.

By replacing the variable $P_{ak}^s Y_{ak}^s$ with $P_{\text{sch},ak}^s$ and $\rho_{ak}^s Y_{ak}^s$ with $G_{\text{schm},ak}^s$, the objective function for reduction of consumers' electricity bill without including the solar PV system is presented by:

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

With the incorporation of the solar PV system, the objective function will be updated as:

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

The reduction of PAR is:

$$\min PAR = \frac{\text{Max}\left(\boldsymbol{P}_{\text{sch}}\right)}{\text{Avg}\left(\boldsymbol{P}_{\text{sch}}\right)} \tag{9}$$

A customer's dissatisfaction value can be minimized by scheduling. In order to model and quantify user dissatisfaction, a delay time rate function is introduced.

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

where, f_{sn} represents the discomfort related with the shiftable appliance. It is calculated by delay time rate (DTR) of shiftable appliances, as shown in (11) [16]:

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

where, α_a and β_a represents the start and end time ranges to finish the operation of the appliance. l_a is the length of operation duration, and t_a is the actual starting time. Additionally, a delay parameter $g > 1$ can also be inserted to associate f_{sn} as g^{DTR}. Thus, discomfort related with shiftable appliance is as follows:

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

B. Constraints

The following constraints are considered to solve the formulated objective functions.

1) Energy Constraints

The load phases of each appliance must fulfill their energy requirements. This constraint is explained as follows:

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

For appliance a, load phase k and time slot s, P_{ak}^s is the load, E_{ak} is the energy needed. The upper limits of the load for all appliances are restricted by the utility to certain predefined limit θ^s.

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

2) PV Generation Constraint

The power generated by the PV system is in between the minimum and maximum power produced by the PV panel capacity within a day.

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

where, $P_{g,\min}$ is the minimum power production and $P_{g,\max}$ is the maximum power production using the PV system within a day integrated to the grid system. When the power production from PV is minimum, i.e. $\rho < P_{g,\min}$, all the power demanded by the appliances will be fed from utility grid.

3) Power Balance Constraint

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

where, J is the number of controllable appliances, Q is the number of uncontrolled appliances and n is the total number of appliances.

4) Time Constraint

Each scheduled load appliance cannot be interrupted until it has finished its operation of load phases. It is also known that the next load phase cannot be started unless the previous load phases finished their operation.

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

When the value of binary decision variable Y_{ak}^{s} is binary 1, then the value of the auxiliary decision variable γ_{ak}^{s} is binary 0 and vice versa. Decision variable γ_{ak}^{s} indicates whether the previous task of operation has finished or not.

As previously assumed that all the appliances are operated at their specified ratings during operation periods, different constraints are required to satisfy the demand management, which are as follows:

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

The range of the operation start time is in between α_a and $\beta_a - l_a$.

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

The number of cycles for the appliances' operations is obtained as follows:

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

where, Θ is the number of cycles available for an appliance to operate, $S_{t,\text{st}}$ and $S_{t,\text{end}}$ are the starting and end times for the appliance's operation in the user defined range, and l_a is the LOT of an appliance. Table III presents the various parameters of schedulable load appliances.

IV. Novel Multi-restricted Time Range Scheduling

Multi-restricted time range scheduling is a type of scheduling in which one or more constrained, non-overlapping restricted operation cycles and home appliances are allowed to be scheduled within those operation time ranges. Without violating all energy and time constraints, the load scheduler has a freedom to search the best combination of operation cycles in which the appliance tends to operate. The fitness function would be calculated at minimum peak load while maintaining smooth horizontal load distribution within hours of the day as much as possible. Between these non-overlapping, restricted operation cycles, one cycle is selected at a time stochastically for each appliance within their length of operation duration and available operation cycles.

In multi-restricted time range scheduling, the length of operation duration and operation starting times are expressed as follows:

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

s.t.

$$\alpha_{a,1} \leq l_{a1} \leq \beta_{a,1} - \alpha_{a,1} \tag{22}$$

$$\alpha_{a,2} \leq l_{a2} \leq \beta_{a,2} - \alpha_{a,2} \tag{23}$$

The operation starting time is in the range of $t_{a,1}$ and $t_{a,2}$.

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

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

where, $l_{a,1}$, $l_{a,2}$ are the LOTs and $\alpha_{a,1}$, $\alpha_{a,2}$ are the starting time slots. $\beta_{a,1}$, $\beta_{a,2}$ are the end time slots and $t_{a,1}, t_{a,2}$ are the possible starting times between starting and end time of slot ranges.

V. Formulation of Grey Wolf Optimization Algorithm for Smart Home Appliances Scheduling

The GWO is a recent meta-heuristic technique, which mimics the leadership hierarchy and hunting mechanism of the grey wolves (canis lupus). To model the leadership hierarchy, four kinds of grey wolves are utilized. Those include the alpha, beta, delta and omega. The basis of GWO algorithm is the democratic behavior and the hunting mechanism of the grey wolves [17]. Both the male and female wolves are the

TABLE III
Parameters of Schedulable Load Appliances

Appliances	Power rating (kW)	Actual OTD (min)	Daily Energy consumption (kWh)	Energy consumption per slot (kWh)	Number of slots assigned
Washing machine with dryer	3	180	9	0.6	15
Electric oven-1 (morning hours)	2.15	45	1.72	0.43	4
Electric oven-2 (evening hours)	2.15	45	1.72	0.43	4
Refrigerator	0.225	1380	5.175	0.045	115
Electric iron	1.5	24	0.6	0.3	2
Water heater	1.5	60	1.5	0.3	5
Table fan	0.025	120	0.05	0.005	10
Coffee grinder	0.1	12	0.02	0.02	1

leaders in the pack and known as alpha (α). The second levels of the grey wolves (subordinate wolves) are known as beta (β). The tasks of the beta grey wolves are helping the alpha wolves in the decision making and other activities in the pack. The wolves at third level are known as delta (δ) those have to submit to alphas and betas, but control the lowest rank grey wolves i.e. omega (ω) in the hierarchy. These omega (ω) wolves act as scapegoat in the pack. Fig. 2 shows the flow chart of GWO for proposed smart home appliances scheduling problem.

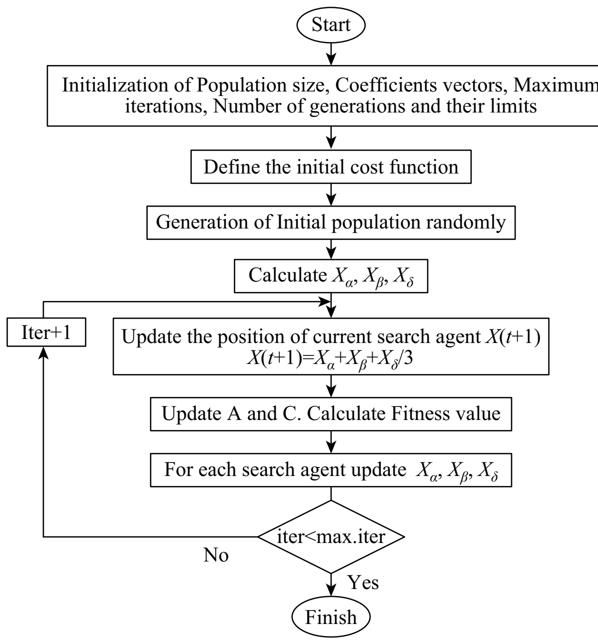

Fig. 2. GWO flow chart.

VI. Result and Discussion

The proposed smart home appliances scheduling problem is solved in eight different scenarios by using GWO algorithm. Further, a comparison is presented with PSO [18] technique to show the effectiveness of the GWO algorithm. The different scenarios for shiftable load appliances are introduced in the following subsections.

The maximum load constraint, control the peak load demand in home and it is less than or equal to 5.5 kW in the above cases.

A. Shiftable Load Appliances Scheduled with Fixed Time Range

In this scheduling, the operation time range for each appliance is adjusted by the user on the assigned time slots. There is one or more than one operation cycle available for each schedulable appliance in a day. Users always have to schedule and adjust the parameters of the appliances manually, followed by the utility electricity pricing (TOUP) signal. In Table IV parameters of residential load appliances for fixed time range scheduling are provided.

Figure 3 shows the residential daily load demands under fixed time scheduling with TOUP. It also shows the maximum load demand within 24 hours in a day. Fig. 4 shows the residential daily load demands in the fixed time range without scheduling. The maximum peak load in a day is found at time slot 38 up to 39, i.e. 7:24 AM to 7:36 AM, which is not preferable in terms of cost minimization. For example, rather than using electric iron during this period of time, the user can shift it to 12:00 AM to 12:48 AM, which is the off-peak duration. But it might not be good in terms of maximizing the comfort of the user who is not interested in using it early in the morning. Most of the time, slots from 1 up to 15, which are off-peak hours during night, are occupied.

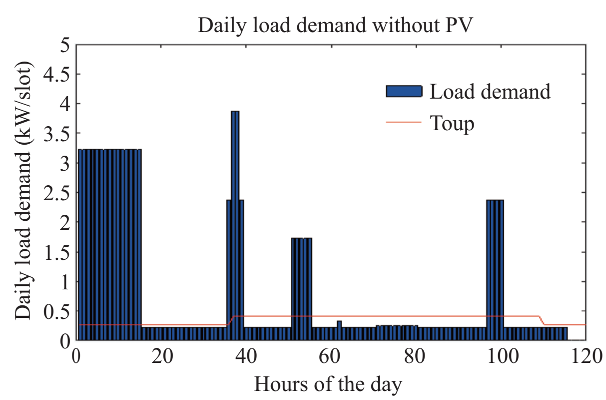

Fig. 3. Residential daily load demand pattern in fixed time scheduling (1unit = 12 minutes).

To measure the PAR during the day, the mean value of the scheduled load demand is calculated. For minimizing the peak load demand, the appliances scheduled should be distributed to all the time slots within a day, without disturbing the comfort level of the resident. To simulate the peak load, the fitness function in (9) is optimized within 24 hours of the day

TABLE IV
Parameters of Schedulable Appliances for Fixed Time Scheduling

Appliances	Power rating (kW)	Energy consumption per slot (kWh)	Number of slots assigned	Start time (hour)	End time (hour)	OTI (time slot)
Washing machine with dryer	3	15	15	12:00 AM	2:48 AM	1–15
Electric oven-1	2.15	4	4	7:00 AM	7:45 AM	36–39
Electric oven-2	2.15	4	4	7:15 PM	8:00 PM	97–100
Refrigerator	0.225	115	115	12:00 AM	10:48 PM	1–115
Electric iron	1.5	2	2	7:15 AM	7:30 AM	37–38
Water heater	1.5	5	5	10:00 AM	11:00 AM	51–55
Table fan	0.025	10	10	2:00 PM	3:00 PM	71–80
Coffee grinder	0.1	1	1	12:15 PM	12:20 PM	62

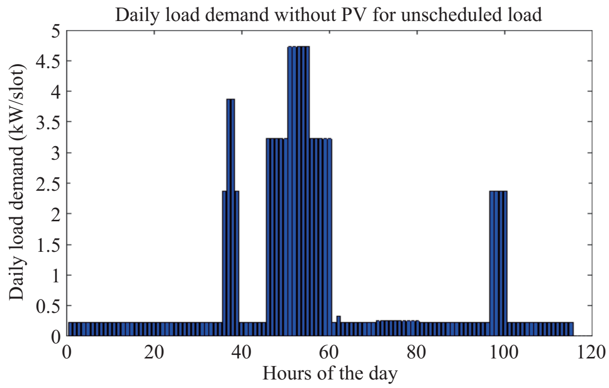

Fig. 4. Residential daily load in fixed time range without scheduling.

irrespective of the TOUP. The PAR calculated during 24 hours' time horizons is 4.7005.

The fitness value in (7) is calculated while minimizing PAR within a day. The total cost of electricity in fixed time range scheduling with the mean value of 4.7005 is 6.5568 Birr/day. The total energy consumption per day is 19.785 kWh. As seen from Table IV, the washing machine is scheduled to operate between 12:00 AM and 2:48 AM during night time. If the operation time of washing machine is shifted to day time during peak hours, for example from 9:00 AM to11:48 AM, then the cost of electricity will rise to 7.7853 Birr/day and the PAR will be 5.7316. The maximum peak load is 4.725 kW, which is between time slots 51 to 55 (i.e. 10:00 AM–10:48 AM).

B. Load Appliances Scheduling with Restricted Time Range

In this scheduling, the starting and end time slot ranges for the appliances' operation that the user wants the appliance to operate in between, are specified. Between these time ranges, the position of the appliance to operate is determined by the load scheduler stochastically.

Then, the proposed algorithm selects the best combination of operation with minimum PAR and electricity cost. In this scheduling, the appliances are scheduled in the allowed operation cycle ranges, which minimizes the allocation of appliances to the inconvenient time slots. Table V presents the operation start and end time for the restricted time scheduling.

From Fig. 5, the peak load demand per slot of appliances is below 5.5 kW, which satisfies the power demand constraint. The peak load during the day from time slot 3–15, i.e. 12:24 AM–2:48 AM, is 3.225 kW by GWO; and from time slot 35–36, i.e. 6:48 AM–7:00 AM, is 3.875 kW by PSO schedulers.

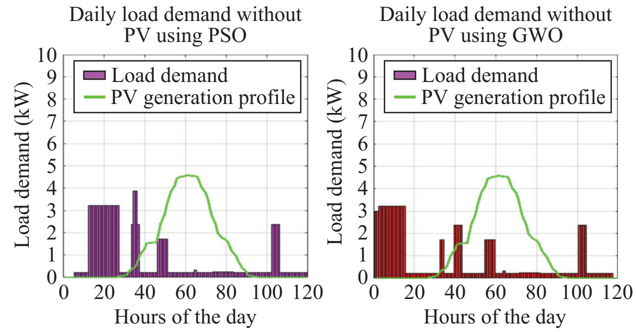

Fig. 5. The daily load pattern under restricted time scheduling and PV generation profile.

The PAR obtained with restricted time scheduling using GWO is 3.9121 and using PSO is 4.7005. The cost of electricity is 6.2988 Birr/day by GWO and 6.4394 Birr/day by PSO scheduler. In restricted time range scheduling, using GWO scheduler, the electric energy cost and PAR are 3.9% and 16.8%, lower than that of fixed time scheduling, respectively.

The daily peak power demand from grid without PV integration within a day using GWO is 3.225 kW for time slot 13 to 27, i.e. 2:24 AM to 5:12 AM. The net daily peak power demand from grid without PV integration within a day using PSO is 5.375 kW for time slot of 44 to 47, i.e. 8:36 AM to 9:12 AM. Due to low pricing time during off-peak hours, time slots from 31 to 50 are occupied in case of PSO load scheduler. With GWO scheduler, low peak load has been achieved compared to PSO scheduler.

From Fig. 6, the PAR without PV using GWO is 3.9121 while using PSO is 6.5201. The minimum cost without PV using GWO is 6.2988 Birr/day, while using PSO is 6.3397 Birr/day. Table VI presents the operation start and end time for multi-restricted time scheduling.

C. Load Appliances Scheduled with Variable Time Scheduling

In this scheduling, the possible operation starting time slot is 1 and end time slot is 120. But the length of operation time duration is greater than or equal to the starting time

TABLE V
OPERATION START AND END TIME FOR RESTRICTED TIME SCHEDULING

Group of Appliance	Appliances	Power rating (kW)	Possible operation start and end time range (hour)	Number of slots assigned	OTI
Non-interruptible Flexible load appliance	Washing machine with dryer	3	12:00 AM–5:48 AM	15	1–30
	Electric oven-1	2.150	6:24 AM−8:36 AM	4	33–44
	Electric oven-2	2.150	6:12 PM−9:00 PM	4	92–106
	Refrigerator	0.225	12:00 AM−10:48 PM	115	1–115
Interruptible flexible load appliances	Electric iron	1.5	6:24 AM−8:12 AM	2	33–42
	Water heater	1.5	9:00 AM−10:48 AM	5	46–55
	Table fan	0.025	12:48 PM−3:48 PM	10	65–80
	Coffee grinder	0.1	11:36 AM−1:24 PM	1	59–68

TABLE VI
OPERATION START AND END TIME FOR MULTI-RESTRICTED SCHEDULING

Schedulable Appliances	Power rating (kW)	Possible Operation Start and end time range (hour)	Number of slots assigned per operation cycle	OTI
Washing machine with dryer	3	12:00 AM–3:12 AM or 3:36 AM–6:36 AM	15	1–17 or 19–34
Electric oven-1	2.15	6:00 AM–6:48AM or 8:00 AM–9:36 AM	4	31–35 or 41–49
Electric oven-2	2.15	5:00 PM–6:12 PM or 7:12 PM–8:00 PM	4	86–92 or 97–101
Refrigerator	0.225	12:12 AM–11:48 PM	115	1–115
Electric iron	1.5	6:00 AM–7:00 AM or 7:36 AM–8:24 AM	2	31–36 or 39–43
Water heater	1.5	8:00 AM–9:24 AM or 9:48 AM–11:48 AM	5	41–48 or 50–60
Table fan	0.025	12:00 PM–1:48 PM or 2:12 PM–4:00 PM	10	61–70 or 72–81
Coffee grinder	0.1	12:00 PM–1:48 PM	1	46–54 or 61–70

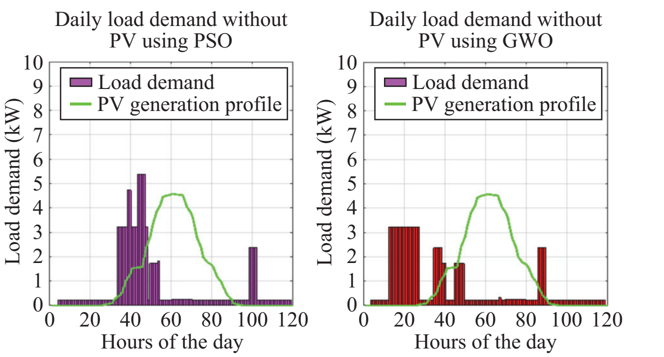

Fig. 6. The daily load demand pattern under multi-restricted time scheduling and showing PV generation profile.

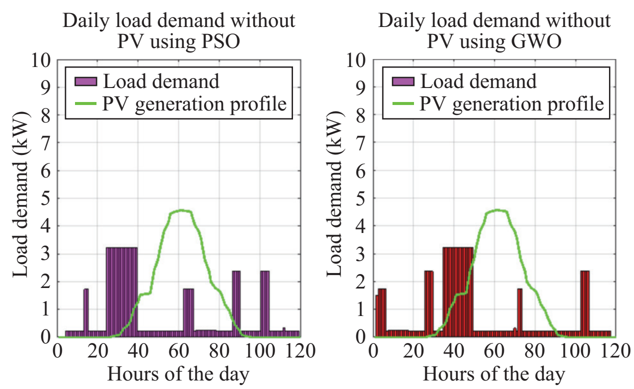

Fig. 7. Residential daily load pattern demands under variable time range.

slot and less than or equal to the end time slot minus the starting time slot. The starting operation time slots are within their available operation cycle range for an appliance, which has to be scheduled. Table VII shows parameters used for the simulation of schedulable load appliances under variable time range scheduling.

The daily load pattern under variable time scheduling scheme is shown in Fig. 7.

At maximum iteration, which is 500, the load demand pattern during the day is shown in Fig. 7. The peak load demand with GWO scheduler is 3.225 kW, which is from time slot 35 to 49 (i.e. from 6:48 AM to 9:36 AM).

Even if most of the time slots within a day are occupied, few of the loads are occupied between those time ranges, which increases the peak demand. Using PSO, the calculated peak load demand within a day is 3.25 kW, which is from the time slots 25–39 (i.e. 4:48 AM–7:36 AM). The drawback of this type of scheduling mechanism is that it assigns some of the appliances to inconvenient time slots to operate. The main concern in this scheduling is the minimization of peak load while maintaining the load distribution within a day as smooth as possible. The PAR obtained on variable time scheduling at maximum iteration using GWO and PSO are 3.9121 and 3.9424, respectively. The cost of electricity calculated by using GWO and PSO are 5.8497 and 6.0906 Birr/day, respectively.

TABLE VII
PARAMETERS OF SCHEDULABLE APPLIANCES

Appliances	Daily Energy consumption (kWh)	Energy consumption per slot (kWh)	Number of slots assigned	OTI (Slot No.)	Number of available operation cycles
Washing machine with dryer	9	0.6	15	1–120	106
Electric oven-1	1.72	0.43	4	1–120	117
Electric oven-2	1.72	0.43	4	1–120	117
Refrigerator	5.175	0.045	115	1–120	6
Electric iron	0.6	0.3	2	1–120	119
Water heater	1.5	0.3	5	1–120	116
Table fan	0.05	0.005	10	1–120	111
Coffee grinder	0.02	0.02	1	1–120	120

The peak load in restricted, multi-restricted and variable time range scheduling with the absence of PV generation is similar, which is 3.225 kW within a day using GWO load scheduler, but 16.8% lower than fixed time range scheduling.

D. Fixed Time Range Scheduling Integrated with PV

In addition to the electric energy from utility grid, a 5 kW roof-top solar PV system is installed and used during day time. The energy generated from the PV panels is supplied via an inverter, which is integrated with home area network (HAN). The priority to supply appliances is given primarily to PV panels under all scheduling scenarios. If the power generated from the PV panels is not sufficient to supply the load of appliances, the energy demand is fed from the utility grid. If the energy generated from PV panels has surplus energy, then it can be exported to the national grid. To optimize the objective function, the same procedure is used as in case 1 and parameters in Table IV are used with the integration of the PV system. The simulation result is shown in Fig. 8.

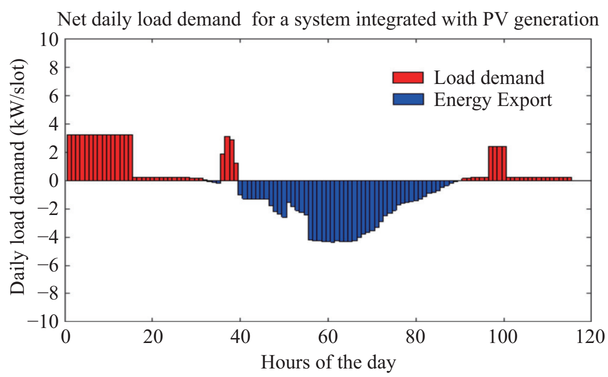

Fig. 8. The net daily load profile pattern integrated with PV energy under fixed time scheduling (1 unit = 12 minutes).

As seen from Fig. 9, the net peak load demand during the day is 3.225 kW, while the net peak PV generation after satisfying the load demand is −4.3566 kW per slot in 24 hours time horizon. PAR is 3.9121. The total energy demand per day of appliance is 19.785 kWh. The energy amount of 8.69852 kWh can be sold to utility grid based on TOUP tariff. The net energy imported from utility grid in kWh is 0. For example, if the shifting of the position of washing machine in day time during peak hours from 9:00 AM to 11:48 AM is done then the cost of electricity is rise to −3.82 Birr/day, which is 149% higher than the unscheduled load without PV. The PAR is 3.7523, which is 34% lower than the unscheduled load without integrating with PV energy production.

Daily demand pattern for un-scheduled load is shown in Fig. 9. Energy cost, peak load and PAR are lower in home

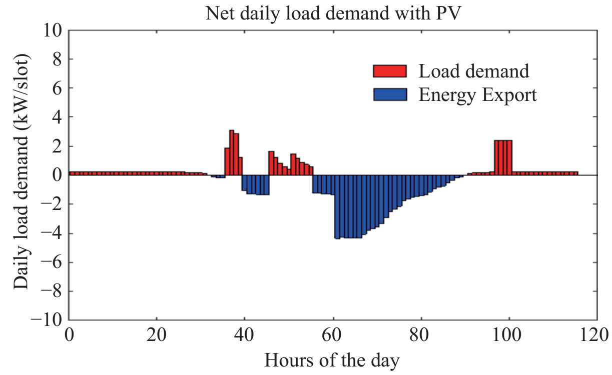

Fig. 9. The daily load profile pattern of unscheduled load appliances integrated with PV energy (1 unit = 12 minutes).

appliances, scheduled by using fixed time scheduling method than that of unscheduled load appliances for both the system integrated and not integrated with PV systems.

For a system not integrated with PV, both the peak load and PAR in fixed time range scheduling are 17.99% lower than the unscheduled load. The energy cost in a system not integrated with PV generation using fixed time range scheduling is 15.78% lower than the energy cost of unscheduled load. Similarly, for a system integrated with PV, by using fixed time range scheduling, the peak load and PAR are higher than unscheduled load. Most of the load demands in unscheduled load profile are compensated with PV than that of fixed time range scheduling.

Rather than compensating the load demand fully, most of the PV generation in fixed time scheduling is exported to utility grid. The cost of energy that utility should pay the users in a system integrated with PV using fixed time range scheduling is 2.35% higher than the energy cost in unscheduled load. A comparative analysis is presented in Table VIII.

E. Restricted Time Scheduling Integrated with PV

In restricted time range scheduling, the same parameters used in case 2 and Table V is used with the integration of 5 kW PV generation. Fig. 10 shows the net daily load demand pattern. The upper portion, which is greater than zero, shows the import from the utility grid. The lower portion, which is negative, shows the export to utility grid.

In a system, integrated with PV, energy cost in restricted time range scheduling is 4.86% and PAR is 1% lower than fixed time range scheduling, respectively by GWO scheduler.

The net daily peak power demand from utility grid with PV integration using GWO is 3.1909 kW and by PSO scheduler is 3.225 kW within a day. The minimum PAR with PV using

TABLE VIII
DETAIL SUMMERY AND RESULT COMPARISON BETWEEN FIXED TIME RANGE SCHEDULING AND A SYSTEM WITHOUT SCHEDULING

Type of scheduling mechanism	Working Mechanism	Peak load	PAR	Energy cost (Birr/day)	
				Utility paid for the user	User paid to the grid
Unscheduled	System without integration of PV	4.725	5.7316	0	7.7853
	System integrated with PV	3.0933	3.7523	3.82	0
Fixed time scheduling	System without integration of PV	3.875	4.7005	0	6.5568
	System integrated with PV	3.225	3.9121	3.9121	0

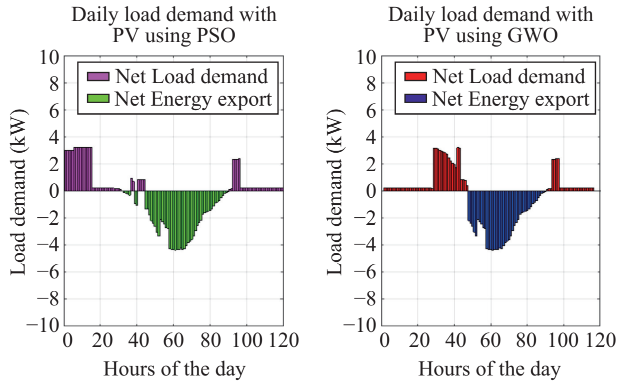

Fig. 10. The net daily load demand pattern integrated with PV generation for minimization of electricity cost under restricted time range scheduling.

GWO is 3.8707 while with PSO is 3.9121. The total energy demand per day of the appliances is 19.785 kWh. Net Energy imported from the utility grid is 0 while net energy exported to the utility grid is 8.6985 kWh. The minimum energy cost with PV using GWO is −5.3065 Birr/day while using PSO is −5.2478 Birr/day based on TOUP.

F. Multi-restricted Time Range Scheduling Integrated with PV

All the data used in case 3 and Table VI is used to optimize PAR, energy cost and peak load in multi restricted time range scheduling. The net daily load demand pattern for a system integrated with PV generation is shown in Fig. 11. The net daily peak power demand from grid with PV integration using GWO is 2.8543 kW while using PSO is 3.225 kW. The minimum PAR with PV integration using GWO is 3.4624, while with PSO is 3.8707. The minimum cost with PV integration using GWO is −5.3065 Birr/day while using PSO is −5.2246 Birr/day.

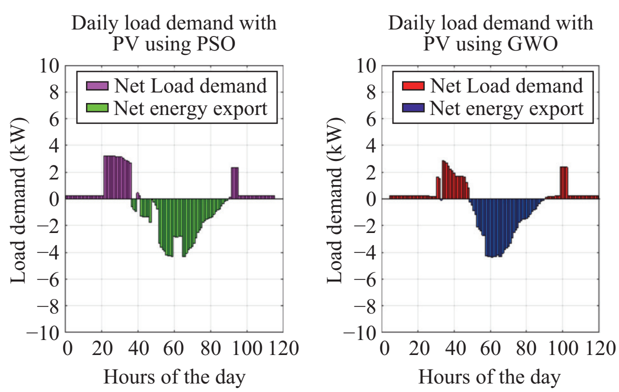

Fig. 11. The net daily load demand pattern integrated with PV generation for minimization of electricity cost under multi-restricted time range scheduling.

G. Variable Time Scheduling Integrated with PV

Since the scheduled load profile for the each appliance is selected stochastically up to the maximum iteration point, the shape of the load profile can be slightly changed during iteration.

For the system, which is not integrated with PV generation, energy cost in variable time range scheduling using GWO load scheduler is 7.13% lower than the restricted time range scheduling. Compared to fixed time range scheduling, the energy cost and PAR in variable time range scheduling are 24.86% and 16.77% lower, respectively. For a system, which is not integrated with PV energy generation, the peak load in variable time range scheduling and restricted time range scheduling are similar, which is 3.225 kW within a day. But, it is 20.16% lower than the fixed time range load scheduling. Fig. 12 presents the daily net load pattern of scheduled load appliances integrated with PV energy under variable time scheduling.

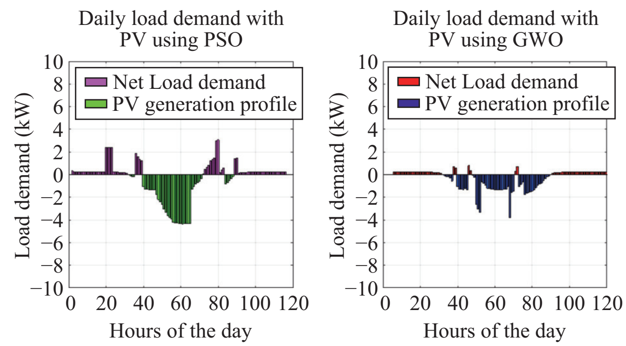

Fig. 12. The daily net load profile pattern of scheduled load appliances integrated with PV energy under variable time scheduling.

The net daily peak Power demand from grid with PV integration using GWO is 0.79773 kW while using PSO is 3.875 kW. The minimum PAR with PV integration using GWO is 1.0026 while using PSO is 2.881. The minimum total energy demand per day of appliances is 19.785 kWh. The net energy imported from utility grid is 0. The minimum cost with PV generation using GWO is −5.7555 Birr/day while using PSO is −5.5139 Birr/day based on TOUP.

VII. CONCLUSION

In this work, a smart home appliance scheduling problem is formulated and optimized using novel restricted and multi-restricted time range scheduling techniques, while satisfying all time and energy constraints. The first objective deals with the minimization of monthly electricity cost. The second and third objectives deal with the minimization of the PAR and maximum peak load demand, respectively. Since the problem is non-convex type in nature, two powerful binary type meta-heuristic optimization algorithms, i.e. GWO and PSO are utilized in order to effectively solve the problem. The system is integrated with a 5 kW roof-top PV panel with eight shiftable load appliances. To solve the problem, eight case studies are considered with and without PV integration and detailed comparative analysis is presented. Results show the effectiveness of the GWO technique over PSO in minimizing the cost of electricity, PAR and maximum peak load demand. PV integrated system enables users to export surplus energy to utility grid and benefit from the feed-in tariff. The futuristic enhancement of the current work may be to solve the problem with modified GWO algorithms such as GGWO or other recent meta-heuristic techniques such as ITLO under multi-objective optimization framework for further optimizing the solution.

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