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ORIGINAL RESEARCH

Optimizing energy consumption in smart homes: Load scheduling approaches

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Abstract

Rising fuel prices, global warming, and environmental damage are leading to increased demand for rooftop solar energy systems connected to the power grid. The development of smart grids, modern metering systems, and energy management could promote energy conservation in households. In this study, two different meta-heuristic optimization techniques were employed to schedule the shiftable load in suitable hours for decreasing electricity costs and minimizing peak to average ratio in a smart home while maintaining optimum user comfort. For power generation and storing energy, a grid-connected residential load with rooftop solar panels, a battery, and an inverter is considered. First, the problem is theoretically described using a load model and an objective function, with the primary goal of reducing power costs by moving the time of usage for certain home appliances. Simulations validate the proposed strategies, which effectively reduce power costs by 4.5% by shifting the time of use, with both optimization algorithms showing similar output. The residential electricity cost before optimization was 507.12 BDT/day, which decreased to 484.33 BDT/day after optimization without compromising load turn-off.

1 | INTRODUCTION

Recently, there has been a considerable increase in the world's energy use. Nowadays, fossil fuels account for the vast majority of energy production, which increases carbon emissions. To meet the growing demand for electricity while reducing carbon emissions, researchers have investigated alternative methods of generating energy known as renewable energy sources (RES). Also, the penetration of RES has greatly raised the complexity of the electricity system. Deploying RESs on a large scale to the existing conventional power grid could potentially intensify the vulnerability of an already heavily burdened power system [1]. The integration of cutting-edge information and communication technologies (ICTs) with the traditional power grid, or the conversion of the present electric power system to the "smart grid," is one of the greatest solutions to this problem [2]. These technologies allow the smart grid to effectively combine the RESs and DG in addition to making use of the stability and dependability of the electricity supply.

The growing population continuously uses more electric appliances, which raises the power demand. Because conventional means of power generation are expensive and have large carbon emissions, RESs offer scientists a profitable solution to the world's growing electricity need. Thus, it's essential to use RESs to produce more electricity locally. Also, in order to develop alternative power-generating strategies, we must maximize the currently available power sources. Researchers are aiming to increase the efficiency of the power sector's use of renewable energy generation for this purpose [3]. A microgrid is a component of a smart grid, which is a straightforward traditional electric system with ICT integration. The idea behind a microgrid is that more energy will be produced locally and that power may be used in an efficient and dependable manner. The electricity of a microgrid will meet the energy needs while also significantly lowering the cost and peak-to-average ratio (PAR). In order to successfully control demand on smart grids, the smart home energy management system (SHEMS) is a crucial residential system [4, 5]. In smart homes, it employs the human-machine interface to monitor and organize different home appliances in real-time based on the user's preferences in order to save power costs and increase energy consumption efficiency [6, 7]. There are more and more dispersed renewable energy sources, including wind turbines, solar panels, plug-in electric vehicles etc., as a result of rising worries about the security of the world's energy supply and environmental pollution would gradually increase penetration and be gird-integrated into the active distribution networks [8, 9]. Building renewable and stored energy sources placed at residential premises can be used in smart HEMS to increase the in-home efficiency of energy conversion and consumption [10].

Several research studies have been carried out to balance energy consumption by using load-shifting schemes to minimize the electricity cost and peak-to-average ratio to construct an efficient SHEM system. According to one study, combining RESs into the residential sector delivers the most cost-efficient alternatives [11–13], a transferable energy management system by incorporating the deep reinforcement learning method and dueling network architecture for hybrid electric vehicles [14]. This hybridization of RESs and utilization of distributed energy resources (DERs) increases energy flexibility, reliability, and sustainability while removing redundancies. The SHEM approach considers the peak power limitation DR plan for a smart household, which includes both smart appliances and EV charging [15, 16]. In ref. [17], the author discussed an effective energy management model for a grid-connected solar power and battery hybrid system. Their approach minimizes the cost of electricity while taking into account limitations on power balance, solar output, and battery capacity. In order to dispatch the power flow in real-time based on unknown distributions, they employed the open and closed loop approach. These two techniques produced significant cost savings and effective control. Additionally, the writers did not take UC into account. In ref. [17], the author looked into a power scheduling challenge using RESs and energy storage. They classified the appliances into five categories and offered an alternative approach and method for this model based on mixed integer programming (MIP). MIP complicated the situation and could not manage multiple gadgets. They also disregarded the UC. Another study used MILP to develop a framework for HEMS modeling and techno-economical sizing. They contrasted the DR actions for the daily energy consumption demand profile of household electronics to the usual daily power demand curve. They concentrated on distributed generation (DG) and Battery bank storage (BBS) cost reduction, load variation, and a dispersed generating profile for various times of the year. They also explored alternative sensitivity analyses for the presented model, taking into account the influence of differences in economic input for a long-term study. Reducing the electricity bill and peak-to-average ratio are the common objectives of various demand response (DR) and demand-side management strategies in the smart grid. Energy consumption is balanced via load-shifting plans employed by the research community to create an efficient SHEM system [18], Integer linear programming [19], dynamic programming, and multi-parametric programming [20] etc. Nevertheless, the energy consumption patterns of these algorithms are erratic, and they are unable to manage a wide variety of household equipment. Here a strategic approach is shown in this study which utilizes the combination of the solution in order to reduce the electricity bill and peak

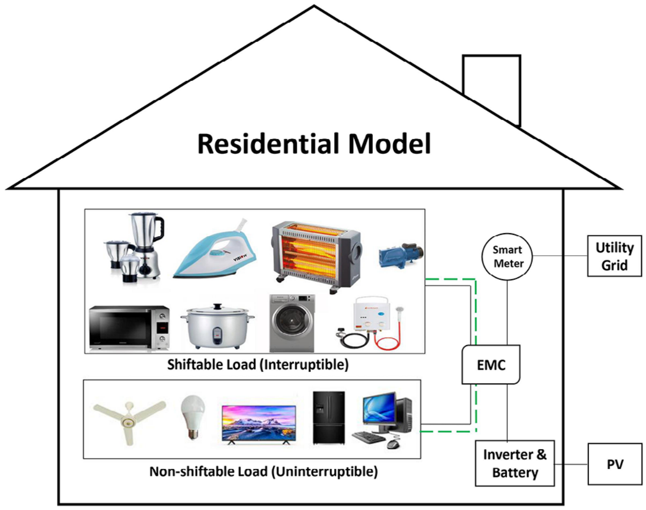


FIGURE 1 Proposed model.

to average usage of load demand. The majority of residential energy use in a typical smart home is typically accounted for by thermostatically controlled appliances, such as the heating, ventilation, and air conditioning system, electric water heater, and refrigerator. The usage of SHEMS has become more appealing to both power utilities and customers as a result of the issue with the energy crisis and rising load demand. Consequently, with the customers' approval, the SHEMS may play a significant role in ensuring the best coordination and scheduling of various smart appliances and the construction of renewable energy sources. By smartly shifting the load demand to the consumer end, the excess need for generation in the peak hour can be reduced. The key contributions of this study are as follows:

- Design a SHEMS consisting of solar panels as a renewable energy generator, Battery as energy storage, shiftable load demand, and non-shiftable load demand connected with the utility grid connection.
- Develop an optimization objective function for reducing the electricity bill by shifting the time of use (TOU) of the load demand.
- Employ two meta-heuristic approaches - particle swarm optimization (PSO) and real-coded genetic algorithm (RCGA), that can minimize the electricity bill, reduce the peak energy consumption by dispatching the load, and compare the outcome of both approaches.

2 | DEVELOPING MODEL

In this section, the methodology required for problem formulation is discussed. Figure 1 shows the proposed model, which is formulated using the mathematical approach to estimate the renewable generation and different types of load consumption appliances. The optimization technique is used to minimize electricity costs by finding the optimal TOU.

2.1 | Solar panel modeling

The proposed smart home includes a rooftop solar system since sunlight is more readily available and less expensive than other RESs such as wind turbines, biomass generators, bio-gas plants, tidal energy harvesters, and geothermal energy harvesters. A mathematical model is used to replicate how solar energy will be generated from solar irradiation and contribute to a home load consumption model as a renewable generation source. Solar photovoltaic (PV) cells are fundamentally p-n junction semiconductors whose photo-generated current is directly proportional to the amount of solar radiation [21]. An hourly generation from a rooftop solar panel can be calculated from the input solar radiation it receives which can be obtained using the Equation (1) [22].

$$G_{\text{solar}}(t) = V_{\text{solar,oc}} \times I_{\text{solar,max}}(t) \tag{1}$$

Here, $G_{\text{solar}}(t)$ is the hourly energy generation, t is the hourly vector, $V_{\text{solar,oc}}$ is the open circuit bus voltage of the inverter which is attached to the solar panel and $I_{\text{solar, max}}(t)$ is the hourly current generated by solar panel respect to the solar radiation.

The Equation (2) is used to estimate the current generated by the solar panels [23].

$$I_{\text{solar, max}}(t) = N_p.I_{\text{photo}}(t) - N_p.I_{\text{sat}}(t) \times \left[\exp\left(e\left(\frac{V}{A.k.N_s.T_c.}\right) - 1\right)\right] \tag{2}$$

Here, (I_{photo}) is the photo-generated current and (I_{sat}) is the saturation current which is calculated using Equation (4), and Equation (5) respectively [22, 24].

$$I_{\text{photo}}(t) = [I_{\text{sc}} + \sigma.(T_c - T_{\text{ref}}(t))] \times \text{DNI}(t) \tag{4}$$

$$I_{\text{sat}}(t) = I_{\text{rs}} \times \left(\frac{T_c}{T_{\text{ref}}(t)}\right)^3 \times \exp\left[\frac{e.E_{\text{bg}}\left(\frac{1}{T_{\text{ref}}(t)} - 1\right)}{k.A}\right] \tag{5}$$

Here, $\text{DNI}(t)$ is the hourly solar radiation, $E_{\text{bg}} = 1.11eV$, is the semiconductor's band-gap energy, $e = 1.6 \times 10^{-19}$ C is charge of one electron, and $k = 1.38065 \times 10^{-23} J.K^{-1}$ is the Boltzmann's constant. $T_{\text{ref}} = T(t) + 273.15$ K is the reference temperature of ambient temperature $T(t)$ in kelvin scale. All the other parameter values related to the selected solar panel Sunpower SPR-A450-COM (450W) are given in Table 1.

TABLE 1 Specification of solar panel [25].

Name	Symbol	Value
Rated capacity (STC)	$PV_{\text{rate,stc}}$	450 W
Rated capacity (PTC)	PV_{rate}	418.3 W
PV efficiency	η_{cell}	22.16%
Voltage (maximum point)	V_{mpp}	44 V
Current (maximum point)	I_{mpp}	10.2 A
Bus voltage (open-circuit)	V_{oc}	51.9 V
Max current (short-circuit)	I_{sc}	11 A
Wind speed	V	3.1 m/s
Reference temperature	T_{ref}	25°C
Normal operating cell temperature	T_{NOTC}	45°C
Temperature coefficient	σ	0.0035 A/K
Cell factor (ideal)	A	1.31
Number of series cells in a module	N_S	128
Number of parallel cells in a module	N_p	1
Number of series modules in a panel	Nm_S	10
Number of parallel modules in a panel	Nm_p	2

2.2 | Battery modeling

Energy generated by the solar panel is reserved in the battery pack through the inverter model when renewable generation is available. In the time of no renewable generation, the battery pack discharges the energy to the peak load demand. The instantaneous SOC of the battery (B_{SOC}) can be determined using the Equation (6) [13, 26].

$$\frac{B_{\text{SOC}}(t)}{B_{\text{SOC}}(t-1)} = \int_t^{t-1} \frac{G_{\text{solar}}(t).\eta_{\text{inverter}}}{V_{\text{solar, oc}}} dt \tag{6}$$

Here, $B_{\text{SOC}}(t)$ is the instantaneous SOC of the battery, $G_{\text{solar}}(t)$ is the hourly energy generated by the solar panel, maximum amount stored energy in the battery is estimated using $B_{\text{SOC}}^{\text{max}} = B_{\text{cap}} \times B_{\text{vol}}$, where $B_{\text{cap}} = 100$ Ah is the maximum amount of charge possible to store in the battery and $B_{\text{vol}} = 12$ V is the terminal voltage of the battery, $\eta_{\text{inverter}} = 90\%$ is the inverter's efficiency and t is denoted as the hourly vector.

2.3 | Residential load modelling

The load consumption model consists of two types of load, 1. Shiftable load and 2. Non-shiftable load. Shiftable appliances are interruptible loads whose time of use (TOU) can be shiftable when the electricity cost is loaded. or simpler terms, the load can be shifted in peak-load demand.

2.3.1 | Shiftable load

The hourly energy usage for the residences is taken into account while creating the electrical load model. The 24-h time is denoted as T, where, $T = [1, 2, 3, \dots .24]$ is assumed to be 24 h.

$$\text{CSL} = \{\alpha_1, \alpha_2, \dots, \alpha_n\} \tag{7}$$

Each interruptable load of home appliances is represented by α_i and consumes an amount of energy ($E^S_{t,\alpha_i \in \text{CSL}}$) where the

TABLE 2 Shiftable electrical load.

			Summer load			Winter load		
Electrical load	**Quantity**	**Power**	**Usage (h/day)**	**Wh/day**	**TOU (t)**	**Usage (h/day)**	**Wh/day**	**TOU (t)**
Blender	1	750	1	750	10:00AM - 11:00PM	1	750	10:00AM - 11:00PM
Iron	1	750	1	750	12:00PM - 1:00PM	1	750	12:00PM - 1:00PM
Heater	1	1000	11	11,000	7:00PM - 6:00AM	11	5500	7:00PM - 6:00AM
Microwave oven	1	1000	3	3000	7:00AM - 8:00AM; 5:00PM - 7:00PM	3	3000	7:00AM - 8:00AM; 5:00PM - 7:00PM
Rice cooker	1	750	3	2250	12:00PM - 1:00PM; 8:00PM - 11:00PM	2	1500	12:00PM - 1:00PM; 8:00PM - 9:00PM
Washing machine	1	1000	4	4000	9:00AM - 1:00PM	2	2000	9:00AM - 11:00PM
Water heater	1	1300	3	3900	7:00AM - 8:00AM; 12:00PM - 1:00PM; 9:00PM - 11:00PM	4	7800	7:00AM - 8:00AM; 12:00PM - 1:00PM; 8:00PM - 10:00PM
Water pump	1	750	3	2250	12:00PM - 1:00PM; 8:00PM - 10:00PM	2	2250	12:00PM - 1:00PM; 8:00PM - 9:00PM
Total			**29.4 kWh/day**			**24.3kWh/day**		

usage time $t \in T$ is given on Table 2. The daily energy consumption by shiftable load can be calculated using the Equation (8).

$$L_{\alpha}^{\mathrm{SL}} = \sum_{t=1}^{24}\left(\sum_{\alpha_i}^{\mathrm{CSL}} E_{t,\alpha\in\mathrm{CSL}}^{\mathrm{SL}}\right) = \left\{E_{t1,\alpha_1\in\mathrm{CSL}}^{\mathrm{SL}} + E_{t2,\alpha_2\in\mathrm{CSL}}^{\mathrm{SL}} + \cdots + E_{t24,\alpha_n\in\mathrm{CSL}}^{\mathrm{SL}}\right\} \quad (8)$$

Here, "t" is the usage time of each appliance and the start point of time of use is the decision variable which is later determined by the PSO algorithm.

2.3.2 | Non-shiftable load

ToU of non-shiftable Load remains uninterruptible regardless of the time. ToU and the usage time (t) both are fixed in this load model.

$$\mathrm{CNL} = \{\beta_1, \beta_2, \ldots, \beta_n\} \quad (9)$$

Each uninterruptible load of home appliances is represented by β_i and consumes an amount of energy ($E_{\tau,\beta_i\in\mathrm{CNL}}^{\mathrm{NL}}$) where the usage time $\tau \in T$ is fixed given on Table 2. The daily energy consumption by non-shiftable load can be calculated using the Equation (10).

$$L_{\beta}^{\mathrm{NL}} = \sum_{\tau=1}^{24}\left(\sum_{\beta_i}^{\mathrm{CNL}} E_{\tau,\beta\in\mathrm{CNL}}^{\mathrm{NL}}\right) = \left\{E_{\tau1,\beta_1\in\mathrm{CNL}}^{\mathrm{NL}} + E_{\tau2,\beta_2\in\mathrm{CNL}}^{\mathrm{NL}} + \cdots + E_{\tau24,\beta_n\in\mathrm{CNL}}^{\mathrm{NL}}\right\} \quad (10)$$

Here, "τ" is the usage time of each appliance fixed and defined with their respective power rating in Table 3.

The daily energy consumption by both shiftable and non-shiftable load by all load appliances can be calculated using the Equation (11).

$$L_{\mathrm{total}} = L_{\alpha}^{\mathrm{SL}} + L_{\beta}^{\mathrm{NL}} = \sum_{t=1}^{24}\left(\sum_{\alpha_1}^{\alpha_n} E_{t_i,\alpha_i\in\mathrm{CSL}} + \sum_{\beta_1}^{\alpha_n} E_{\tau,\beta_i\in\mathrm{CNL}}\right) \quad (11)$$

Here, t is the TOU for shiftable loads and also the decision variable. But τ is the TOU for uninterruptible loads which are not the decision variable which means loads are bound to run on the given moment without interruption.

2.4 | Energy pricing modeling

A real-time energy pricing model is employed to determine the electricity pricing of the day. The working hours can be classified as 1. Peak load demand hour, and 2. Off-peak hour. Energy pricing for shiftable loads is estimated using the Equation (12). Where E_{rtp} is the real-time pricing that defines the price in peak hour and off-peak hour.

$$\mathrm{Price}^{\mathrm{SL}} = \sum_{t=1}^{24}\left(\sum_{\alpha=1}^{\alpha_n}\left(L_{\alpha\in\mathrm{CSL}}^{\mathrm{SL}} \times \delta_{\alpha\in\mathrm{CSL}}\right) \times E_{\mathrm{rtp}}(t)\right) \quad (12)$$

$$\delta_{\alpha,\mathrm{SL}}(t) = \begin{cases} 1 & \text{if } \mathrm{CSL}_{\alpha} \text{ is ON} \\ 0 & \text{if } \mathrm{CSL}_{\alpha} \text{ is OFF} \end{cases} \quad (13)$$

TABLE 3 Non-shiftable electrical load.

			Summer load			Winter load		
Electrical load	**Quantity**	**Power**	**Usage h/day**	**Wh/day**	**TOU (τ)**	**Usage h/day**	**Wh/day**	**TOU (τ)**
Light	3	60	8	1440	5:00PM - 12:000AM	7	1260	5:00PM - 11:000AM
Celing fan	1	200	21	12,600	5:00PM - 10:00AM; 12:00AM - 2:00PM			
Refrigerator	1	1000	24	8400	12:00AM - 11:00PM	24	8400	12:00AM - 11:00PM
Television	1	1000	8	8000	3:00PM - 5:00PM; 8:00PM - 12:00AM	7	7000	3:00PM - 5:00PM; 8:00PM - 11:00AM
Computer	1	750	8	6000	3:00PM - 5:00PM; 8:00PM - 12:00AM	7	5250	3:00PM - 5:00PM; 8:00PM - 11:00AM
Total			**36.44kWh/day**			**21.91kWh/day**		

Energy pricing for uninterruptible loads is estimated using the Equation (14).

$$\text{Price}^{\text{NL}} = \sum_{t=1}^{24} \left(\sum_{\beta=1}^{\beta_n} \left(L^{\text{NL}}_{\beta\in\text{CNL}} \times \delta_{\beta\in\text{CNL}} \right) \times E_{\text{rtp}}(t) \right) \quad (14)$$

$$\delta_{\beta,\text{NL}}(t) = \begin{cases} 1 & \text{if } \text{CNL}_\beta \text{ is ON} \\ 0 & \text{if } \text{CNL}_\beta \text{ is OFF} \end{cases} \quad (15)$$

The total electricity price for the day is calculated by adding Price^{SL} and Price^{NL}.

3 | OPTIMIZATION APPROACH

3.1 | Objective function

The primary goal of this study is to reduce electricity costs for optimum user comfort through efficient management of smart appliances. A single smart home is assumed with PV and battery installed that can provide energy in the time of peak hours and deficit energy can be consumed from the existing grid. The energy management controller (EMC) makes a decision based on a predetermined objective function to let any smart appliance perform its action in a specific time slot shown in the Equation (16).

$$\min\left(\left(L_{\text{total}}(t) - G_{\text{solar}}(t) - B_{\text{soc}}(t)\right) \times E_{\text{rtp}}(t)\right) \quad (16)$$

3.2 | Constraints

It is an important factor for optimization problems to maintain all the conditions given before finding the minimum cost for the system as is shown in conditions (17). It is implemented such that only if all the given conditions are satisfied is the optimization algorithm allowed to take the sets of solutions that offer minimum cost for the system.

TABLE 4 Optimization parameter.

Parameter	Values
Population size	20
Maximum iteration	500
TOU dimension	8
Epochs number	3
Upper-limit	24
Lower-limit	1

$$\begin{aligned} &E^{\text{nim}}(t) \le E_{\text{ug}}(t) + G_{\text{solar}} + B_{\text{soc}}(t), \quad \forall\ 1 \le t \le 24 \\ &E^{\text{nim}}(t) = L^{\text{NL}}_{\text{req}} + L^{\text{SL}}_{\text{req}} \\ &t_0 \le t_{\text{sch}} \le t_{\max} \\ &B^{\min}_{\text{soc}} \le B_{\text{soc}}(t) \le B^{\max}_{\text{soc}} \end{aligned} \quad (17)$$

Here, t is the particular time slot, $E^{\text{nim}}(t)$ is the hourly energy consumption by load demand, and $E_{\text{ug}}(t)$ is the hourly energy that can be taken from the electrical grid. $t_0 \le t_{\text{sch}} \le t_{\max}$ are the lower bound and upper bound of the scheduling perspective boundaries, respectively. T_{sch} is the scheduling time of shiftable load appliances. $B^{\min}_{\text{soc}}$ is the lowest level SOC of the battery and $B^{\max}_{\text{soc}}$ is the highest level SOC of the battery.

3.3 | Decision variables

The Optimization parameter is listed in Table 4 and is used to check the constraints and determine the decision variable. Here, the dimensions of the populations and the number of solutions required to search within the specified limitations are provided. Each set of populations in the initial iteration of the PSO optimization contains the amount of time that is required to be moved. Population size determines how many sets of solutions to use, and the TOU dimension determines how many loads need to be relocated to obtain the lowest possible peak-to-average and electricity cost ratios. The number of hours that

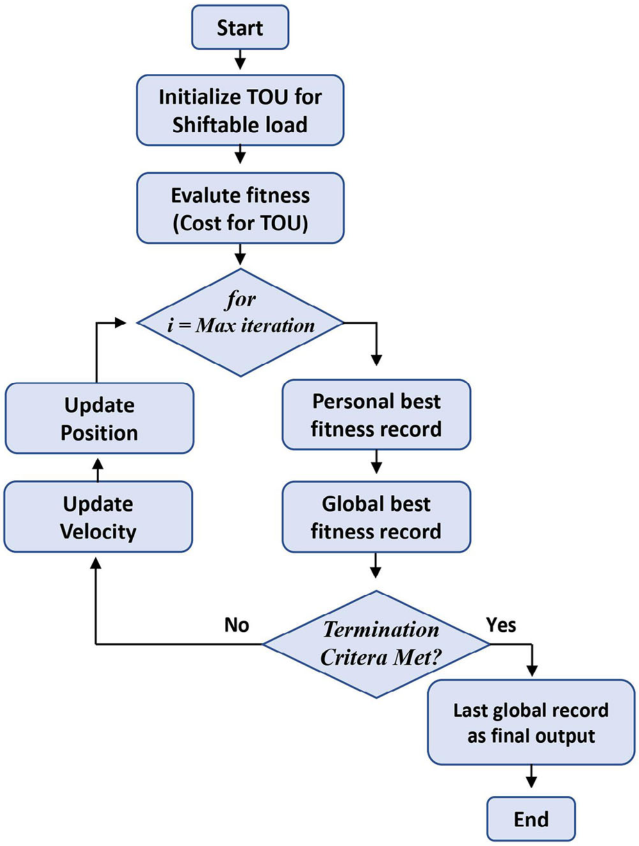


FIGURE 2 PSO flowchart.

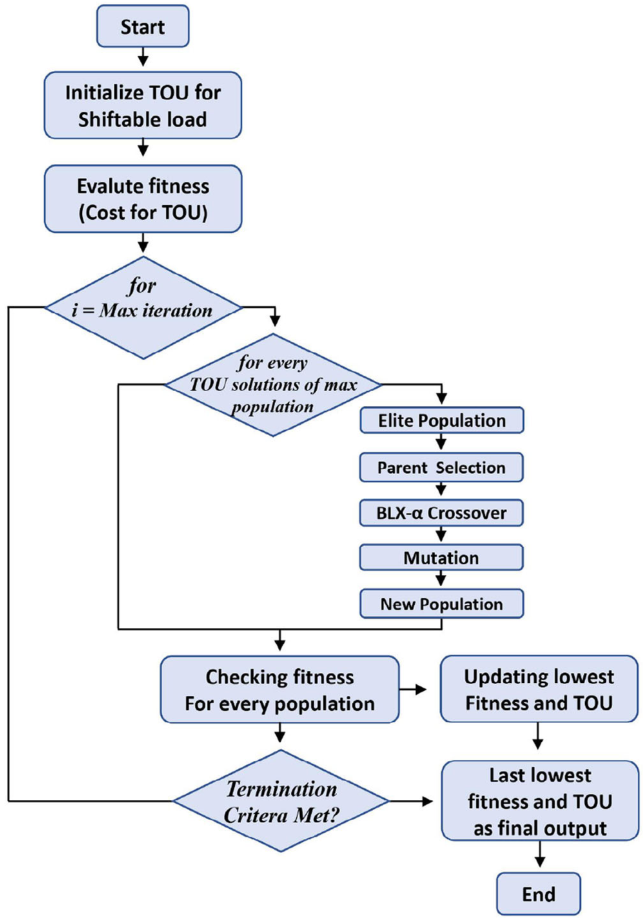


FIGURE 3 RCGA flowchart.

should be moved for specific loads is determined by the higher and lower limits. For the initial iteration of the optimization strategy, each of these variables is initially created. Beginning with the second iteration, the PSO and RCGA each use a different methodology, as seen in Figures 2 and 3. The final definition of Epochs number is the total number of times optimization progress has been made. The goal is to guarantee that three successive solutions get the best result.

TABLE 5 PSO and RCGA parameters [29, 30].

PSO		RCGA	
Parameters	Values	Parameters	Values
Velocity limit	$-5 < V < 5$	Elite population	2
Weight limit	$0.2 < W < 0.9$	Crossover probability	70%
Acceleration coeff.	2	Mutation probability	2%

3.4 | PSO modeling

PSO is a population-based optimization algorithm that is inspired by the social behaviour of bird flocking, where individuals coordinate their movements based on their own experiences and the experiences of their neighbours [27]. Here, PSO is employed to determine the best possible TOU for interruptible loads.

3.4.1 | Algorithm flowchart

The flowchart for the PSO is shown in Figure 2, where a population set of potential solutions, particles, flows around the search space in pursuit of the best solution. In this case, this is the TOU for the shiftable loads. Each TOU is a potential solution with its own position and velocity. A TOU's position correlates to a potential solution to the problem, and its velocity determines the amount and direction of its travel in the search space. TOU's mobility is controlled by their individual best-known position, Personal best for minimum electricity cost as well as the best-known position (lowest electricity cost) of the total iteration. Based on these two positions, each set of TOU adjusts its velocity and updates its own position. The personal best indicates the particle's best solution thus far, while the global best is the best solution found by any particle in the entire population.

In PSO, the velocity update equation includes three factors: the particle's current velocity, which represents the particle's personal best, and the social component represents the particle's global best as defined in Table 5. Particles traverse the search space while exploiting favourable places based on their previous experiences and population knowledge by altering these characteristics. PSO repeats maximum iteration as defined by the constraints, allowing particles to fine-tune their locations and velocities. As the population's best-known positions improve, particles tend to converge toward the ideal solution over time. If the termination criteria are met, then PSO breaks from the iteration loop and gives the output TOU as the solution which causes the lowest possible electricity value as the optimal value. For that particular TOU lowest electricity cost can be achieved.

3.5 | RCGA modeling

The RCGA is a subtype of the standard genetic algorithm (GA) using a real-valued representation instead of a binary one [28]. While the traditional GA uses a string of binary digits to express optimization problems, the RCGA uses real-valued vectors of TOU for the shiftable loads between $1 < t < 24$.

3.5.1 | Algorithm flowchart

The algorithmic flowchart for the RCGA optimization technique is shown in Figure 3. The core elements of a real-coded genetic algorithm are still essentially the same as those of a conventional GA, but they have been modified to properly handle real numbers. RCGA algorithm starts with the initialization of TOU at random, using a real-valued vector for each set. Based on the objective function, calculate the fitness of each set of the TOU. The objective of the function is the minimum electricity cost shown in Equation (16). Depending on their fitness, the elite population of TOU is chosen from members of the current population to make up the following generation. Better candidates have a larger probability of being chosen like the traditional GA. This step is also known as parent selection. To produce a fresh generation, perform crossovers amongst the selected parents. BLX-α crossover is applied in this case. Mutation operation is done on probability as defined in Table 5.

The purpose of mutation is to increase genetic diversity in a TOU by introducing random variations in a set TOU. For the subsequent generation, replace the present number with that of the child and parents together which creates a new population. This process of elitism, parent selection, crossover, mutation, and forming a new population set continues till the termination criteria are met. If the termination criteria are met, then RCGA breaks from the iteration loop and gives the output TOU as the solution which causes the lowest possible electricity value as the optimal value. For that particular TOU lowest electricity cost can be achieved.

In Table 5, the hyper-parameter for both PSO and RCGA is provided. PSO evaluates each set of populations from the initial population of 30 using their cost function. Following that, the weight function and velocity function are applied to the current population set. In the PSO, the weight limit specifies how long a particle must remain in a place before updating its average weight, while the velocity limit specifies how quickly a particle (in this example, the created population) should move.

TABLE 6 Analysis condition [32].

Usage hour		Tariff rate (E_{rtp})
Peak hour	11:00 AM to 5:00 PM	BDT 10.5
Off-peak hour	6:00 PM to 10:00 AM	BDT 7.56

Similar to this, under the RCGA technique, the two best populations are filtered out of the first population which resulted in the lowest and second-lowest power cost for their respective TOUs by defining 2 on the elite population. The RCGA is a natural selection procedure. The elite two population produces new two offspring. A 70% crossover between two elite parents guarantees that the new offspring from the BLX-alpha crossover maintains 70% of the variable from its elite parents 1 and 30% from its elite parents 2. The likelihood of mutation determines whether any components of a given population are altered arbitrarily. The units for this variable are specified in this manner.

4 | ANALYSIS CONDITIONS

The hourly solar radiation and temperature data for 24 h are shown in Figure 4. The residential load model is tested with location-specific meteorological data. National Renewable Energy Laboratory (NREL) data inspection tool is used for solar data [31]. A battery capacity of 1200Wh (12V and 100ah) is considered while developing the battery model with an initial SOC of 60% is considered while estimating the battery energy. In Table 6, the tariff rate considered for the optimization operation is given.

5 | RESULTS AND ANALYSIS

The hourly solar panel generation and the energy status stored in the battery model are shown in Figure 5. Peak solar generation is recorded at around 600 W. The excess energy from the solar panel after satisfying the load model is stored in the battery till it reaches the maximum capacity during the availability of solar generation.

The battery model is used when renewable generation is unavailable at the end of the peak hour (17:00 PM). Energy usage from the battery is seen two times, one is to charging the battery, and the other is when discharging the battery. The total load demand is shown in Figure 6 with its respective shiftable and non-shiftable parts for the designed residential load model. Energy consumption from the electric grid is observed to peak at 7.35 kWh at that time.

The home appliances are broken down into both shiftable load and non-shiftable for the summer seasons as shown in Figures 6(c) and 6(b), respectively.

The TOU of shiftable loads is evenly distributed throughout the day. The primary objective is to shift the TOU for these loads so that it does not collide with the peak hour, as

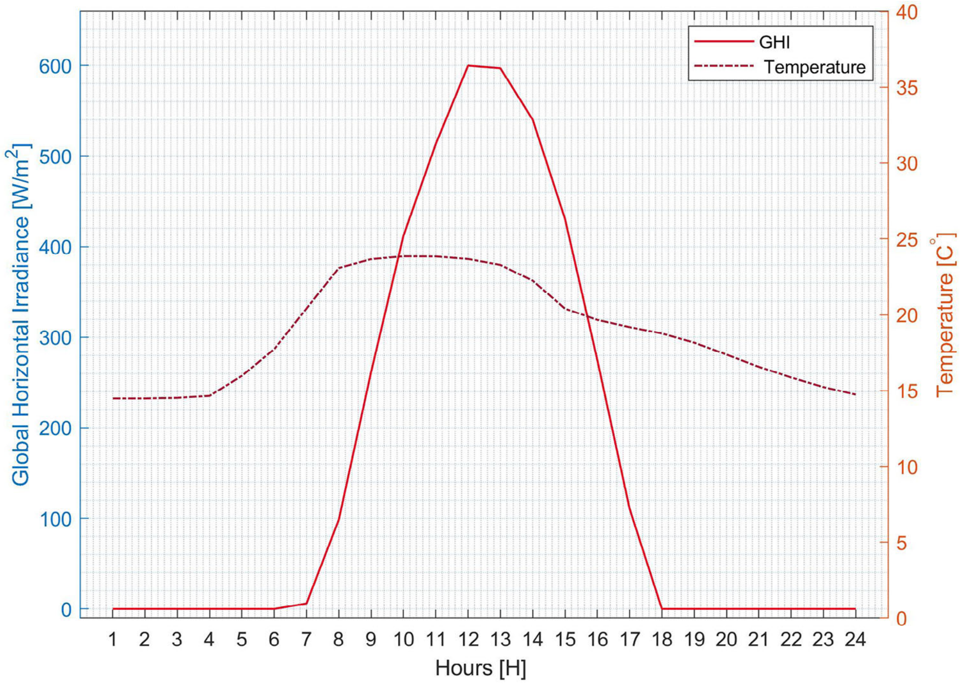


FIGURE 4 Hourly solar resources.

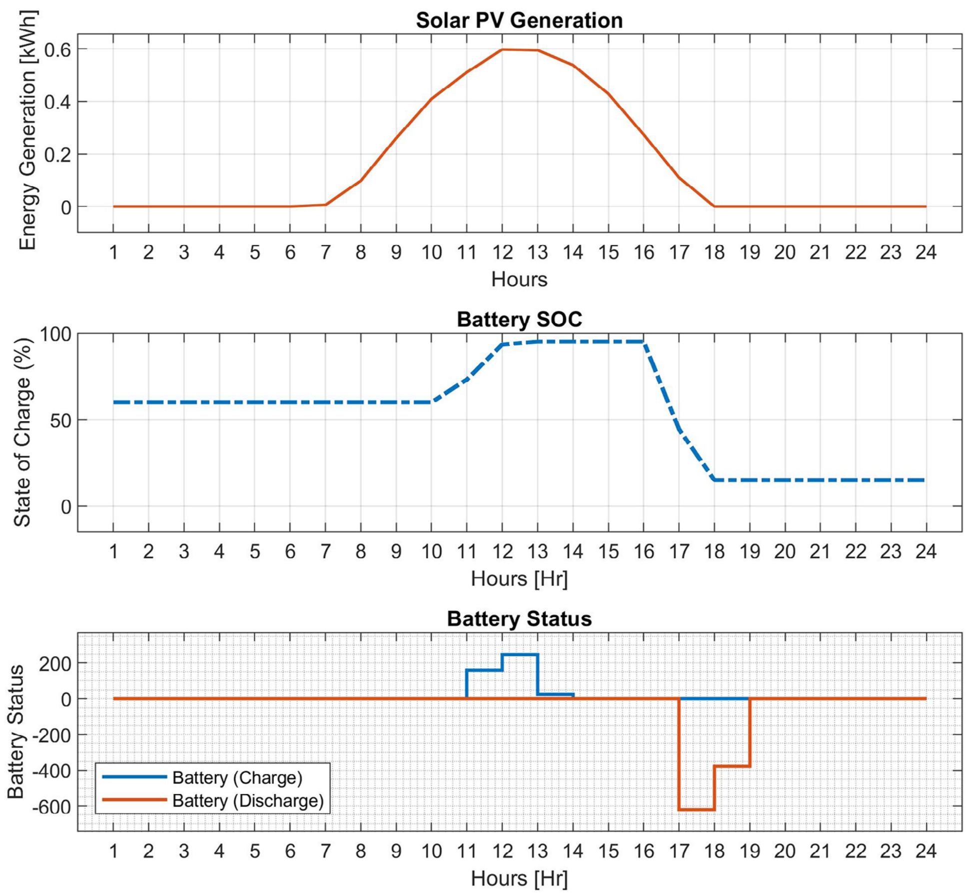
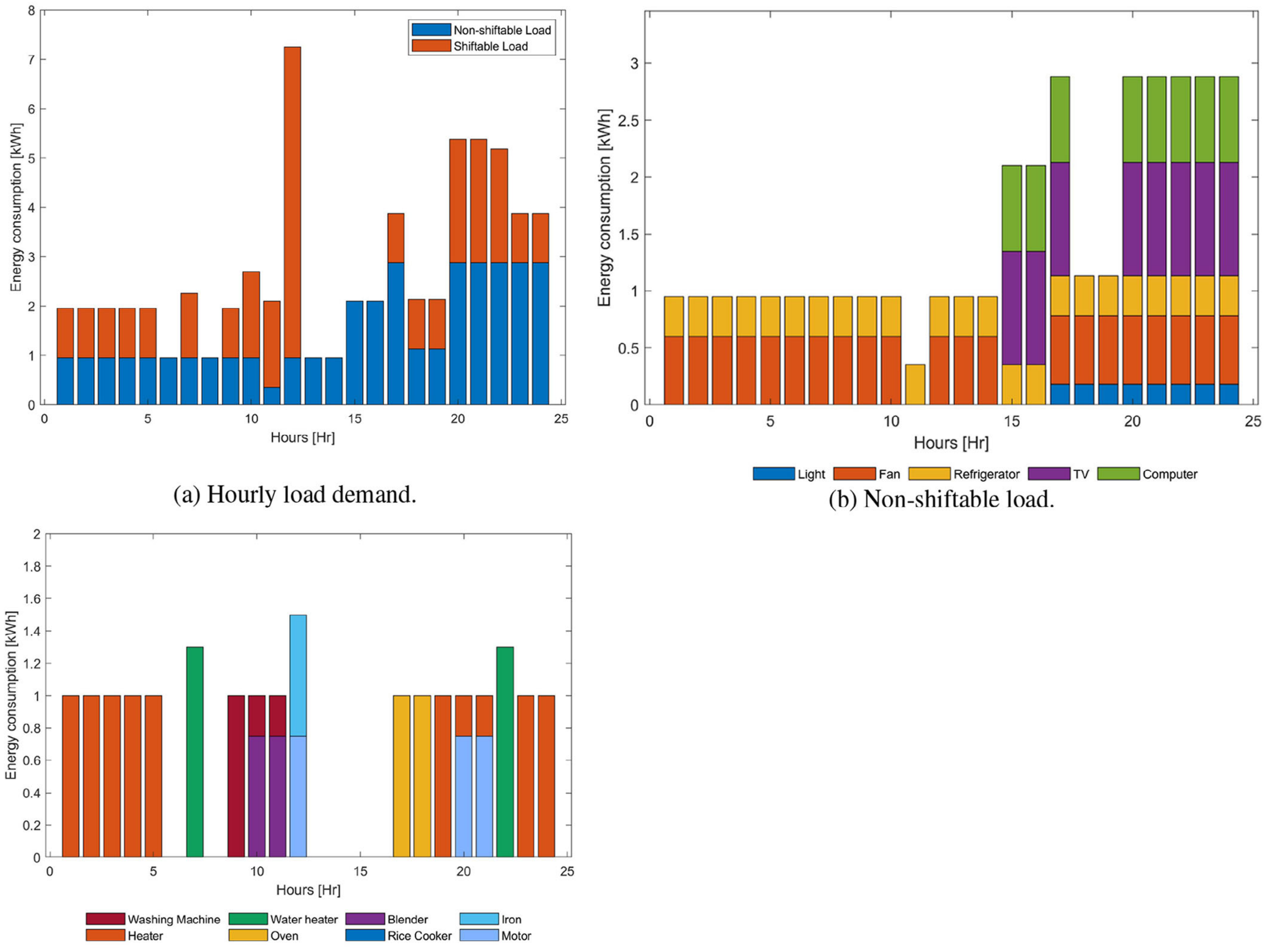


FIGURE 5 Solar generation and battery status.



(a) Hourly load demand.

(b) Non-shiftable load.

(c) Shiftable load.

FIGURE 6 Total load demand (before optimization).

energy consumption of peak hour is cost high compared to off-peak hours. After running the two optimization methods on this shiftable load model two optimal TOUs are found. Both results show the lowest electricity cost for the day. The convergence curve for PSO and RCGA is plotted in Figure 7 depicting how each iteration affects the objective values.

The convergence curve often begins with an initially somewhat high goal value and progressively drops during the course of the process. The convergence curve should ideally exhibit a decreasing trend because the method tries to minimize the objective function. Both PSO and RCGA repeat maximum iteration as defined by the constraints, allowing each set of TOU solutions to be checked by the objective function. The convergence happens only when the PSO is able to find a lower than the previous objective value. The algorithm breaks from the iteration loop when termination criteria are met and gives the output TOU as the solution which causes the lowest possible electricity value as the optimal value. The lowest possible electricity cost is achieved for that particular TOU from both optimization approaches. Both optimization approaches end up finding the lowest possible electricity cost which is around 484.33 BDT/day as shown in Figure 7. However, based on the convergence curve, PSO predicts the optimal TOU for the least amount of power expenditure faster than RCGA. The load curve obtained by adjusting the TOU of interruptible load for both techniques is shown in Figure 8.

On the newly produced load curves generated by PSO and RCGA by shifting the TOU for shiftable load, it is clear that PSO's peak point is greater than RCGA's, which is near 8.7 kWh. Both algorithms produced the lowest possible electricity bill 484.335 BDT/day as the objective function is the same, peak load demand is near 8.7 kWh at 20 of the x-axis (8:00 PM) for PSO which is higher than before the optimization peak demand of 7.5 kWh at 12 of the x-axis (12:00 PM) as shown in Figure 6(a). The load curve generated by the RCGA model looks more symmetrical peak point not exceeding the before the optimization peak demand point. The peak demand for the RCGA is recorded near 6.3 kWh, which is a more

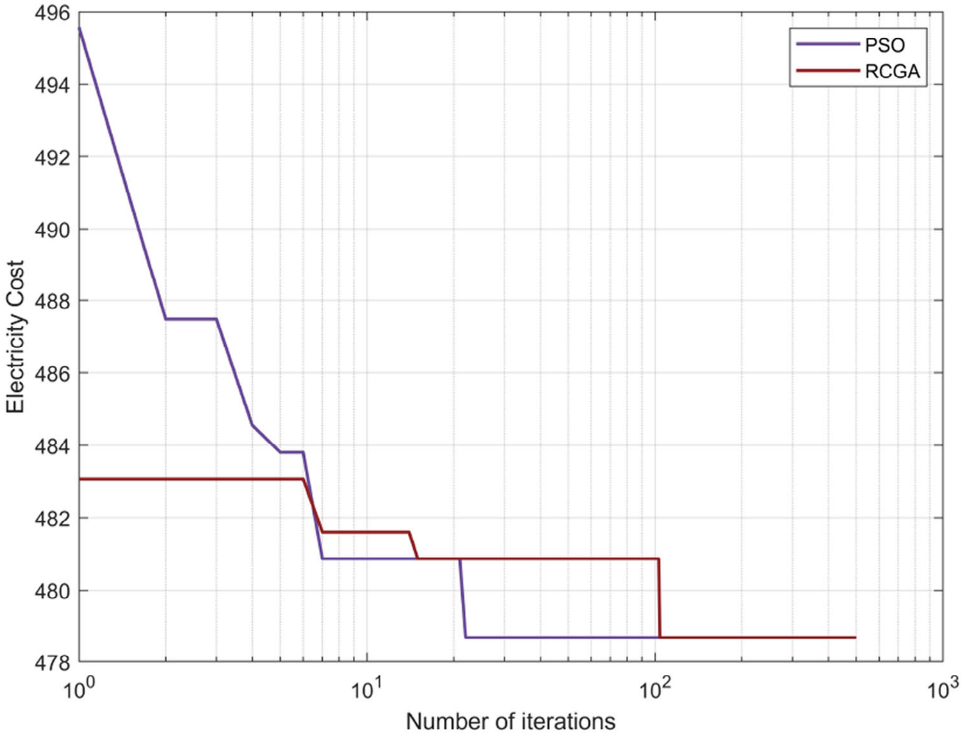


FIGURE 7 Comparison of convergence curve.

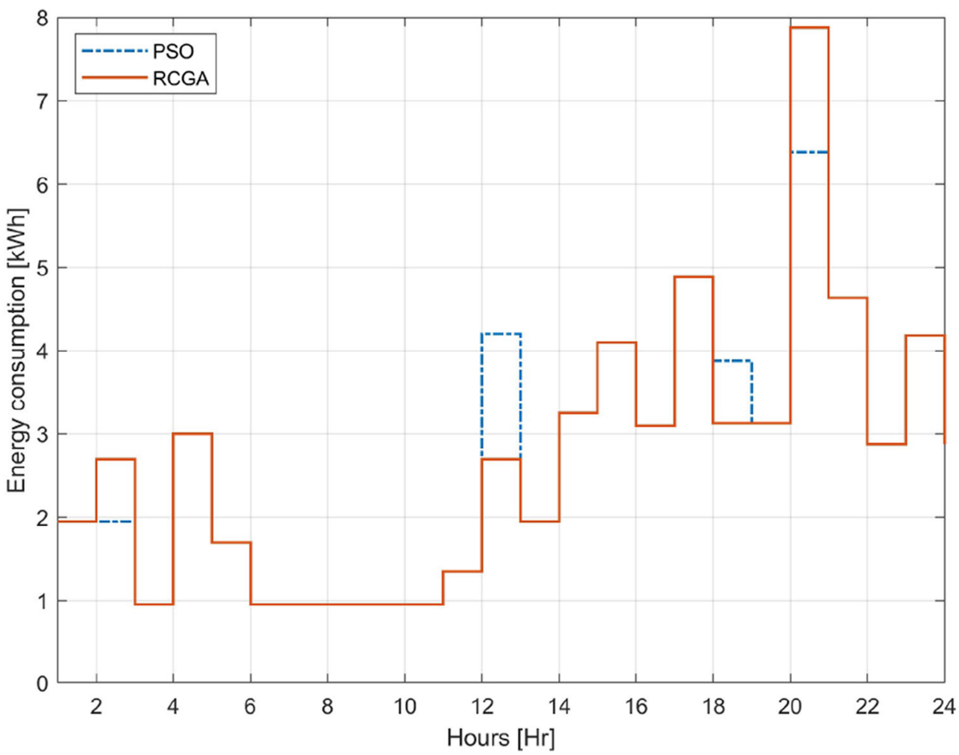
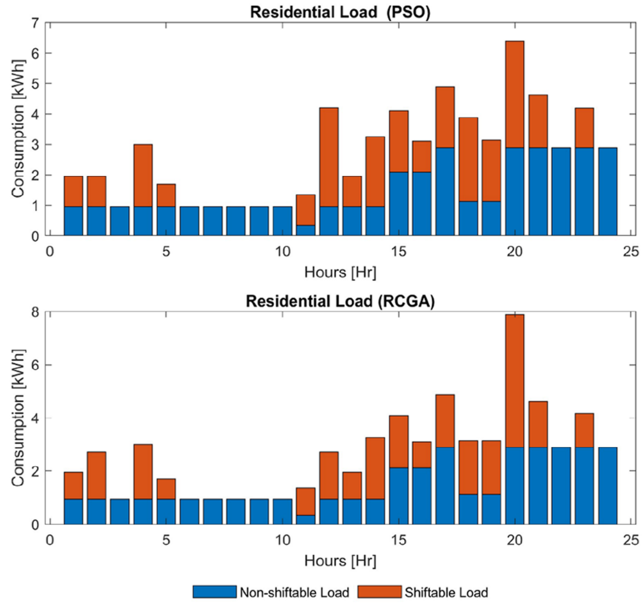
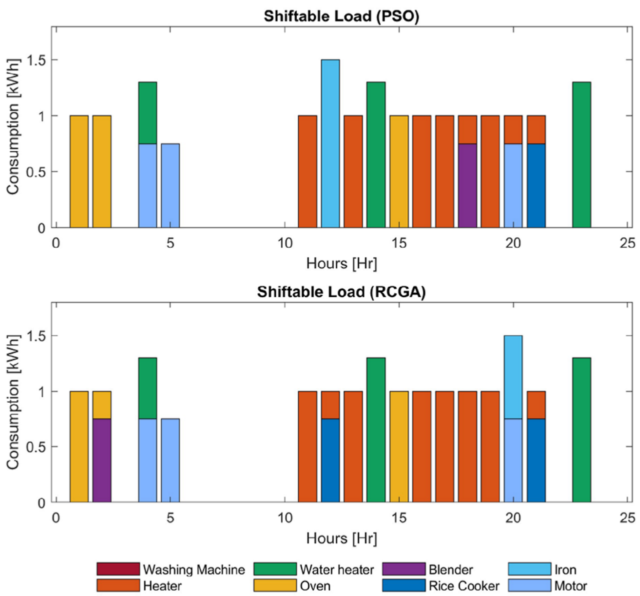


FIGURE 8 Load curve comparison (PSO vs RCGA).



(a) Residential load comparison (PSO vs RCGA).



(b) Shiftable load comparison (PSO vs RCGA)

FIGURE 9 Load TOU comparison.

symmetrical, and well-distributed load throughout the 24-h window. The overall performance of RCGA-generated TOU for shiftable loads is better than PSO-generated TOU for shiftable loads. Figure 9(a) shows the newly suggested TOU by the PSO and RCGA for both shiftable load and non-shiftable load for home appliances and their load demand. By shifting their electricity usage to off-peak hours, consumers can take advantage of the lower rates and potentially save on their electricity bills. Customers can take advantage of the cheaper rates and perhaps reduce their power costs by moving their consumption to off-peak hours.

To take advantage of TOU pricing, several utility providers also provide smart metering equipment, which enables customers to monitor their power usage in real-time and alter their consumption as necessary. Table 7, shows the detailed TOU for both PSO and RCGA optimization techniques for both the summer and winter seasons. After optimization, it can be seen that the majority of shiftable loads are transferred to alternative TOUs to avoid peak hours. The TOU is unchanged for non-shiftable loads because they are considered uninterruptible loads regardless of whether it is a peak hour or not. It is clear from this that the majority of the load density has been moved from peak to off-peak hours. When working with considerably more load that needs to be transferred for the residential load model's load balancing function, this could be quite helpful. The bulk of the load is moved to off-peak times when the tariff rate seems to be cheaper than during peak times. The estimated cost of electricity before the optimization is 507.12 BDT/day. After executing both TOU of shiftable load optimizations, 484.335 BDT/day in the summer season and 297.89 BDT/day in the winter season, respectively, are determined to be the lowest cost for electricity, representing a 4.5 percent price reduction for residential power bills.

6 | CONCLUSIONS

The study proposes an optimization strategy for a smart home's peak-to-average ratio reduction and cost reduction, focusing on shiftable and non-shiftable loads. while maximizing comfort for users. The model minimizes electricity costs by adjusting usage times using a meta-heuristic approach. A load model is developed consisting of two types of loads, one is shiftable load where the time of use can be shifted as per user needs to minimize the overload consumption on peak hours, and the second is the non-shiftable load, which must run throughout the day. The behaviour of energy consumption can be explained by setting certain arbitrary criteria. This study revealed the impact of SHEMS integration as well as the impact of temperature and wind speed on the power produced by solar panels. By implementing the two different optimization techniques, different TOUs for shiftable loads were tested and minimal electricity cost was achieved for the residential load. Both of the algorithms produced the lowest possible electricity bill 484.335 BDT/day in the summer season and 297.89 BDT/day in the winter season, but the load curve generated by the RCGA model looks more symmetrical peak point does not exceed the before the optimization peak demand point. After the optimization operation, the proposed model can minimize a 4.5% price on the household power bill.

Future studies should be focused on the same appliance types comprised of a hybrid renewable energy generating system consisting of PV, diesel generators, battery banks, and wind turbines. The two states of peak and off-peak hour are considered while optimizing the TOU, most of the developed country has a tariff rate that is changeable in real-time. This should also be considered while formulating the model. Several evolutionary algorithms may outperform the used

TABLE 7 Time of use comparison.

	Summer load		Winter load	
Electrical load	**TOU (PSO)**	**TOU (RCGA)**	**TOU (PSO)**	**TOU (RCGA)**
Blender	6:00PM - 7:00PM	7:00PM - 8:00PM	5:00PM - 6:00PM	6:00PM - 7:00PM
Iron	1:00PM - 2:00PM	1:00PM - 2:00PM	7:00PM - 8:00PM	7:00PM - 8:00PM
Heater	11:00AM - 9:00PM	11:00AM - 9:00PM	10:00AM - 8:00PM	11:00AM - 9:00PM
Microwave oven	1:00PM - 3:00PM;	1:00PM - 2:00PM;	12:00AM - 1:00AM	9:00AM - 11:00AM
	8:00PM - 9:00PM	7:00PM - 8:00PM	4:00PM - 5:00AM	3:00PM - 4:00AM
Rice cooker	12:00AM - 1:00PM;	12:00AM - 1:00PM;	11:00PM - 12:00PM;	12:00PM - 1:00PM;
	8:00PM - 10:00PM	8:00PM - 10:00PM	7:00PM - 8:00PM	7:00PM - 8:00PM
Washing machine	5:00PM - 9:00PM	5:00PM - 9:00PM	4:00PM - 6:00PM	5:00PM - 7:00PM
Water heater	6:00AM - 7:00AM;	5:00AM - 6:00AM;	3:00AM - 4:00AM;	4:00AM - 5:00AM;
	3:00PM - 4:00PM;	2:00PM - 3:00PM;	11:00AM - 1:00PM;	12:00PM - 2:00PM;
	8:00PM - 10:00PM	11:00PM - 12:00AM	9:00PM - 10:00AM	11:00PM - 12:00AM
Water pump	1:00PM - 2:00PM;	12:00PM - 1:00PM;	11:00PM - 12:00PM;	12:00PM - 1:00PM;
	9:00PM - 11:00PM	8:00PM - 10:00PM	7:00PM - 8:00PM	7:00PM - 8:00PM
Electricity cost	**BDT 484.34**		**BDT 297.89**	

algorithm. Exploring such matters should be carried out as future work.

AUTHOR CONTRIBUTIONS

Arafat Ibne Ikram: Conceptualization; data curation; formal analysis; methodology; project administration; resources; software; validation; visualization; writing—original draft; writing—review and editing. **Aasim Ullah**: Conceptualization; project administration; supervision; validation; writing—review and editing. **Durjoy Datta**: Conceptualization; data curation. **Ashraful Islam**: Formal analysis; methodology. **Tanvir Ahmed**: Methodology; writing—original draft.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

1. Guo, Y., Pan, M., Fang, Y.: Optimal power management of residential customers in the smart grid. IEEE Trans. Parallel Distrib. Syst. 23(9), 1593–1606 (2012). https://doi.org/10.1109/TPDS.2012.25
2. Agnetis, A., De-Pascale, G., Detti, P., Vicino, A.: Load scheduling for household energy consumption optimization. IEEE Trans. Smart Grid 4(4), 2364–2373 (2013). https://doi.org/10.1109/TSG.2013.2254506
3. Molderink, A., Bakker, V., Bosman, M.G., Hurink, J.L., Smit, G.J.: Management and control of domestic smart grid technology. IEEE Trans. Smart Grid 1(2), 109–119 (2010). https://doi.org/10.1109/TSG.2010.2055904
4. Iqbal, Z., Javaid, N., Iqbal, S., Aslam, S., Khan, Z.A., Abdul, W., et al.: A domestic microgrid with optimized home energy management system. Energies 11(4), 1002 (2018). https://doi.org/10.3390/en11041002
5. Brooks, A., Lu, E., Reicher, D., Spirakis, C., Weihl, B.: Demand dispatch. IEEE Power Energy Mag. 8(3), 20–29 (2010). https://doi.org/10.1109/MPE.2010.936349
6. Farhangi, H.: The path of the smart grid. IEEE Power Energy Mag. 8(1), 18–28 (2009). https://doi.org/10.1109/MPE.2009.934876
7. Li, F., Qiao, W., Sun, H., Wan, H., Wang, J., Xia, Y., et al.: Smart transmission grid: vision and framework. IEEE Trans. Smart Grid 1(2), 168–177 (2010). https://doi.org/10.1109/TSG.2010.2053726
8. Erol-Kantarci, M., Mouftah, H.T.: Wireless multimedia sensor and actor networks for the next generation power grid. Ad Hoc Networks 9(4), 542–551 (2011). https://doi.org/10.1016/j.adhoc.2010.08.005
9. Al-Ali, A., El-Hag, A., Bahadiri, M., Harbaji, M., El-Haj, Y.A.: Smart home renewable energy management system. Energy Proc. 12, 120–126 (2011). https://doi.org/10.1016/j.egypro.2011.10.017
10. Li, C., Shi, H., Cao, Y., Wang, J., Kuang, Y., Tan, Y., et al.: Comprehensive review of renewable energy curtailment and avoidance: a specific example in China. Renewable Sustainable Energy Rev. 41, 1067–1079 (2015). https://doi.org/10.1016/j.rser.2014.09.009
11. Zafar, M.A.B., Islam, M.R., Islam, M.S.U., Shafiullah, M., Ikram, A.I.: Economic analysis and optimal design of micro-grid using PSO algorithm. In: 2022 12th International Conference on Electrical and Computer Engineering (ICECE), pp. 421–442. IEEE, Piscataway, NJ (2022)
12. Sajjad-Ul-Islam, M., Arafat-Bin-Zafar, M., Ibne-Ikram, A., Saimur-Rahaman-Sachha, M., Ullah, S., Ahamed, R.: Optimal cost and component configuration analysis of micro-grid using SSO algorithm. In: 2023 1st International Conference on Innovations in High Speed Communication and Signal Processing (IHCSP), pp. 306–311. IEEE, Piscataway, NJ (2023)
13. Islam, M.S.U., Zafar, M.A.B., Ikram, A.I., Chowdhury, T.A., Sachha, M.S.R., Hossain, S.: Optimal cost and component configuration analysis of micro-grid using GWO algorithm. In: 2023 International Conference on Electrical, Computer and Communication Engineering (ECCE), pp. 1–6. IEEE, Piscataway, NJ (2023)
14. Xu, J., Li, Z., Du, G., Liu, Q., Gao, L., Zhao, Y.: A transferable energy management strategy for hybrid electric vehicles via dueling deep

deterministic policy gradient. Green Energy Intell. Transp. 1(2), 100018 (2022). https://doi.org/10.1016/j.geits.2022.100018
15. Kuzlu, M., Pipattanasomporn, M., Rahman, S.: Hardware demonstration of a home energy management system for demand response applications. IEEE Trans. Smart Grid 3(4), 1704–1711 (2012). https://doi.org/10.1109/TSG.2012.2216295
16. Pipattanasomporn, M., Kuzlu, M., Rahman, S.: An algorithm for intelligent home energy management and demand response analysis. IEEE Trans. Smart Grid 3(4), 2166–2173 (2012). https://doi.org/10.1109/TSG.2012.2201182
17. Wu, Z., Tazvinga, H., Xia, X.: Demand side management of photovoltaic-battery hybrid system. Appl. Energy 148, 294–304 (2015). https://doi.org/10.1016/j.apenergy.2015.03.109
18. Tsui, K.M., Chan, S.C.: Demand response optimization for smart home scheduling under real-time pricing. IEEE Trans. Smart Grid 3(4), 1812–1821 (2012). https://doi.org/10.1109/TSG.2012.2218835
19. Hubert, T., Grijalva, S.: Realizing smart grid benefits requires energy optimization algorithms at residential level. In: Innovative Smart Grid Technologies 2011, pp. 1–8. IEEE, Piscataway, NJ (2011)
20. Oberdieck, R., Pistikopoulos, E.N.: Multi-objective optimization with convex quadratic cost functions: a multi-parametric programming approach. Comput. Chem. Eng. 85, 36–39 (2016). https://doi.org/10.1016/j.compchemeng.2015.10.011
21. Ranabhat, K., Patrikeev, L., Antal'evna-Revina, A., Andrianov, K., Lapshinsky, V., Sofronova, E.: An introduction to solar cell technology. J. Appl. Eng. Sci. 14(4), 481–491 (2016). https://doi.org/10.5937/jaes14-10879
22. Phang, J., Chan, D., Phillips, J.: Accurate analytical method for the extraction of solar cell model parameters. Electron. Lett. 20(10), 406–408 (1984). https://doi.org/10.1049/el:19840281
23. Ikram, A.I., Islam, M.S.U., Bin-Zafar, M.A., Rocky, M.K., Imtiaz, Rahman, A.: Techno-economic optimization of grid-integrated hybrid storage system using GA. In: 2023 1st International Conference on Innovations in High Speed Communication and Signal Processing (IHCSP), pp. 300–305. IEEE, Piscataway, NJ (2023)
24. Patel, J., Sharma, G.: Modeling and simulation of solar photovoltaic module using Matlab/Simulink. Int. J. Res. Eng. Technol. 2(3), 225–228 (2013). https://doi.org/10.1051/matecconf/20141103018
25. SolarDesignTool. Specification of sunpower spr-a450-com (450W) solar panel. http://www.solardesigntool.com/components/module-panel-solar/Sunpower/6573/SPR-A450-COM/specification-data-sheet.html (2024). Accessed 27 Jan 2024
26. Javidsharifi, M., Pourroshanfekr, H., Kerekes, T., Sera, D., Spataru, S., Guerrero, J.M.: Optimum sizing of photovoltaic and energy storage systems for powering green base stations in cellular networks. Energies 14(7), 1895 (2021). https://doi.org/10.3390/en14071895
27. Kennedy, J., Eberhart, R.: Particle swarm optimization. In: Proceedings of ICNN'95-International Conference on Neural Networks, vol. 4, pp. 1942–1948. IEEE, Piscataway, NJ (1995). doi: https://doi.org/10.1109/ICNN.1995.488968
28. Deep, K., Singh, K.P., Kansal, M.L., Mohan, C.: A real coded genetic algorithm for solving integer and mixed integer optimization problems. Appl. Math. Comput. 212(2), 505–518 (2009). https://doi.org/10.1016/j.amc.2009.02.044
29. Chen, P.Y., Chen, R.B., Wong, W.K.: Particle swarm optimization for searching efficient experimental designs: a review. Wiley Interdiscip. Rev.: Comput. Stat. 14(5), e1578 (2022). https://doi.org/10.1002/wics.1578
30. Song, H., Wang, J., Song, L., Zhang, H., Bei, J., Ni, J., et al.: Improvement and application of hybrid real-coded genetic algorithm. Appl. Intell. 52(15), 17410–17448 (2022). https://doi.org/10.1007/s10489-021-03048-0
31. NREL's Data Inspection Tool | HOMER 2023, Accessed 28 Jul 2023
32. Ashuganj Power Station Company Limited. http://www.apscl.gov.bd/ (2023). Accessed 28 Jan 2023

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