Investigation on Optimization Algorithms for Smart Home Energy Management with Different Electricity Pricing

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Abstract—**The focus of this paper is on energy consumption optimization in smart homes (with/without RES) and increasing the user comfort level. The paper presents a functional and adaptable home energy management system with RES and an energy storage device for designing and implementing Demand Response (DR) programs. The four meta-heuristic techniques: Genetic Algorithm (GA), Wind-Driven Optimization (WDO), Grey Wolf Optimization (GWO) and Salp Swarm Optimization (SSA), are used to optimize the energy consumption cost for a home energy environment. In the process of identifying and proposing a dedicated home energy optimization algorithm, this paper investigated four optimization algorithms with four different pricing schemes: Time of Use (TOU) pricing, Real-Time Pricing (RTP), Critical Peak Pricing (CPP), and Day-Ahead Pricing (DAP) schemes. The results obtained using these pricing schemes are validated and compared in a common smart home environment. Further, the results show that by integrating Renewable Energy Sources (RES) and a battery reduces the electricity bill by 10.89% (without RES) and 38.88% (with RES), as well as the peak-to-average ratio (PAR) by 59.97% (without RES) and 64.98% (with RES) when compared to the energy consumption cost obtained without-scheduling technique. Moreover, without RES, the SSA algorithm based home energy management system outperforms the other algorithms particularly with the TOU pricing scheme.**

Index Terms—**Home energy management, renewable energy sources, salp swarm optimization, peak-average ratio, time of use price, real-time price, critical peak price, Day-ahead price**

I. Introduction

Smart homes are an integral part of the electric power system that has become an essential component of a smart grid due to its considerable environmental and economic benefits. Also, the smart grid encourages the usage of renewable energy like wind and solar, which further helps to reduce peak demand issues and power prices [1]. In addition, the smart home plays a significant role in reducing the additional investments in power generation, transmission and distribution to satisfy future electricity demand. Nowadays, the utility control center gradually facing stress as the energy demand for residential buildings consistently increases [2]. The primary energy consumers in a country are residential buildings, which consume almost 30% to 40% of the total energy generation [3]. It reflects more on the consumers electricity bill; it indicates the necessity to reduce consumers energy usage costs. Since most electricity prices are not stable all the time, it ultimately depends on the amount and period of power generation, time of use, and climatic conditions. If the load demand is higher at a specific time interval, then the duration is considered a peak and the cost of power usage is fixed high. The off-peak period is considered with the lowest price, as the demand request of consumers during the specific time interval is less. The mid-period has moderate demand, so the energy usage cost is normal [4]-[7]. It is to be noted that, normally, if the load demand exceeds the threshold power limit for a day, the critical peak price is employed in conjunction with the existing pricing strategies. Particularly during the peak period, the CPP cost is very high, and the utility control center effectively uses this price to regulate the energy consumption in residential buildings [8], [9]. Various other pricing schemes also exist in the literatures and they are classified based on the following categories [10].

- Consumer incentive for overall energy savings
- Consumer incentive for peak demand savings
- Financial risk to utility
- Financial risk to consumer
- Consumers financial benefit
- Pricing profile

Fig. 1 depicts the different electricity costs accessible on the energy market, which fluctuate by day and season. These prices always fluctuate based on energy consumption, especially in the late afternoon when demand is typically high, referred to as the peak period. Most pricing schemes include both peak and off-peak periods. Some pricing schemes include a third price, the "mid-peak price," between peak and off-peak hours.

The demand-side management (DSM) is intended to profit the consumers more by reducing their electricity bills by controlling and managing their load demand. At the same time, the DSM also takes care of the utility

Manuscript received April 28, 2022; revised June 15, 2022; accepted July 8, 2022.

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doi: 10.18178/ijeetc.11.6.435-449

control center benefits by reducing the burden during the peak period by ensuring reliable service to the consumers. In order to balance the consumers' load demand and energy supply, the Demand Response (DR) program is implemented by the utility control center. Thus, Fig. 2 portrays the categorization of DR based on price and incentives.

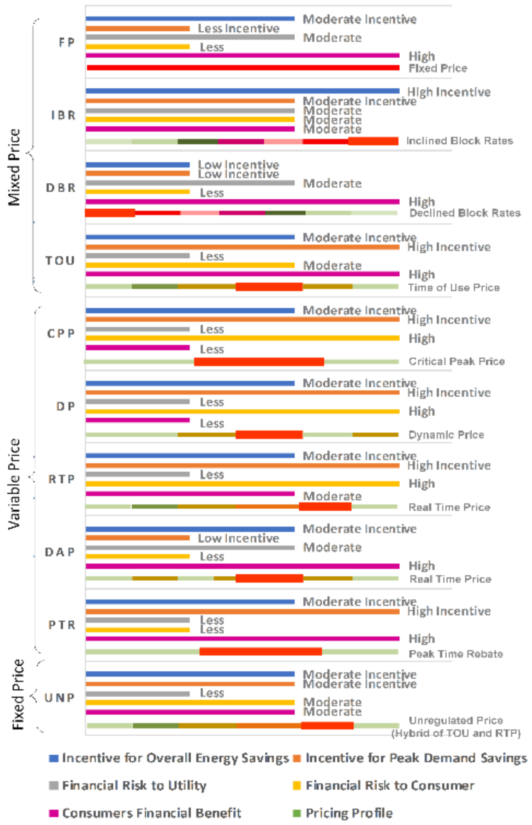


Fig. 1. Characteristics of electricity pricing.

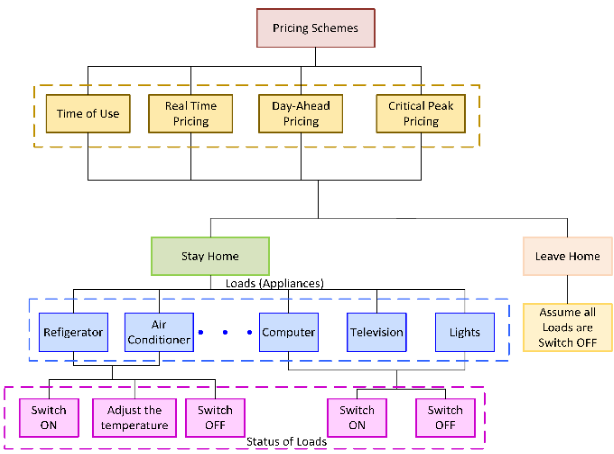


Fig. 2. Classification of DR programs and pricing schemes (considered)

The demand response programs with many pricing schemes are mainly for the monetary benefit of consumers. Also, it is observed from literatures that the real-time price (RTP), time of use (TOU), critical peak price (CPP) and day-ahead price (DAP) have played a vital role in the monetary benefit of residential building consumers. As aforementioned, the RTP (dynamic) pricing scheme fluctuates continuously for each time slot and entirely depends on load demand. Time-of-use pricing is based on fixed electricity prices with respect to time intervals. It is structured according to peak and off-peak periods and based on how the consumer utilizes the electricity. The day-ahead price is also a fixed price assigned to each time slot by the utility control center based on the previous day load demand profile of the consumers.

The objective of this paper is to identify a novel optimization algorithm for reducing the energy consumption cost with an electricity pricing scheme by scheduling operations (with and without RES). Therefore, for the first time, the four different pricing (TOU, RTP, CPP and DAP) schemes are implemented along with SSA, GA, WDO, GWO optimization algorithms and without scheduling technique.

A. *Highlights of This Paper*

The following features are the main contributions of this paper and it is as follows.

1. The metaheuristic salp-swarm optimization algorithm (SSA) technique is utilized for appliance scheduling and results are compared with genetic algorithm (GA), wind-driven optimization (WDO), grey wolf optimization (GWO), and without-scheduling techniques.
2. Environmental factors -RES (solar and wind) with battery is considered.
3. Reduction in energy consumption costs, peak-average ratio (PAR) and increase in the level of user comfort are the objectives of this paper.

This paper considers multiple constraints on consumers so as to keep the user's comfort level maximum.

This paper is organized as follows. A review of related research works on various optimization methods and pricing systems is provided in Section II. Section III discusses the problem formulation with various constraints. The four bio/nature-inspired meta-heuristic optimization algorithms are portrayed in Section IV. Section V illustrates the simulation results and the SSA algorithm robustness is described in Section VI and concluded in Section VII.

II. Related Works

In the past decades, several DSM techniques have been proposed to minimize energy consumption costs and peak average ratio (PAR). This section summarizes the optimization techniques employed to schedule the home appliances with an electricity pricing strategy for the above-discussed objective.

Since the home energy management system has enough potential to reduce electricity consumption costs with efficient usage of electricity. So, need proper monitoring and control of each appliance are required to optimize the energy consumption. The work [11] focuses on minimizing electricity usage costs with a graph search-based algorithm named the DijCostMin algorithm under multiple constraints. This optimization technique is implemented with the time of use (TOU) price, to shift the set of home (schedulable and non-schedulable) appliances from the peak to off-peak period based on the information accumulated at the smart meter that is connected to the house so that the peak load demand is reduced. Mostly, all the techniques involve shifting the loads to the off-peak period, which again creates the peak demand problem.

With the same objective but in different home environmental conditions, a hybrid grey wolf-differential optimization algorithm was developed with Real-Time Price (RTP) and Critical Peak Pricing (CPP) strategies [12]. Their proposed optimization process is carried out with 17 different power ratings of home appliances by placing them in three groups: schedulable, non-schedulable and controllable appliances. It is worth noting that the non-schedulable appliances have to be kept in ON condition for the entire day, which has fixed energy usage. In such cases, these hybrid optimization algorithms are not able to deal with all provided constraints [13]-[15].

In addition, these authors suggested that robust optimization algorithms can be effectively utilized with any pricing scheme in such systems to attain an optimal solution. Also, these studies have explored the possibilities of effective utilization of renewable energy sources to reduce energy consumption costs and keep a balance between demand and supply. Further, to the same objective, three more hybrid optimization algorithms, like Wind-Driven Genetic Algorithm (WDGA), Wind-Driven Grey Wolf Optimization (WDGWO) and wind-driven binary particle swarm (WBPSO), are utilized by the authors of the papers [16], [17] and [18]. But these authors have given more priority to consumer satisfaction. So, to ease the scheduling process, two groups of home appliances, namely, schedulable and non-schedulable, are used. They utilized both time of use and dynamic (RTP) pricing schemes to identify the best and most suitable pricing for such home environments. The TOU pricing scheme has lesser overall energy consumption costs than the dynamic pricing. Also, they discuss the feasibility of using renewable energy sources (solar) with a battery in the residential environment.

Similarly, in recent years, most researchers have explored the effective utilization of alternative energy sources and the usage of energy-storing devices (batteries) that provide better results in the optimization process. The authors of [19] and [20], have proposed an energy management system that includes Renewable Energy Sources (RES) and storage devices for the optimal scheduling of residential loads. The effective utilization of alternative energy sources and the usage of energy-storing devices (batteries) will provide better results in the optimization process. Therefore, the authors have effectively utilized charging and discharging actions of storing devices to decrease the peak load demand problem under the TOU pricing scheme. The authors of [21] and [22] considered consumer satisfaction and the effectiveness of TOU, RTP and CPP schemes in their load scheduling problem. According to these authors, the RTP pricing strategy benefits consumers more during the frequent variations in electricity prices and intermittent RES power generation. But the literatures [23]-[27] has given their observations that the TOU price is more effective with any optimization algorithms. This is because of the availability of price information well before the actual energy consumption begins and guaranteed energy consumption cost reduction compared to the RTP pricing.

In recent days, due to increased electrical energy demand, balancing electricity demand and supply is the biggest challenge to the utility control center. In this regard, the energy forecasting technique assists the home energy management system in making effective decisions to balance the energy demand and supply [28]-[30]. Hence, to have efficient energy management, both the consumers and control center has to update mutually about their energy demand and consumption information at regular intervals without any errors and delays. With the support of computing and communications technology, consumers and utility control centers can share information/data regarding power demand and generation. But in certain cases, like the non-availability of any historical data or erroneous forecasted information, the reinforcement learning method is the suitable strategy [31]. Thus, it is necessary to have adequate data aggregation; hence the sensors are employed effectively with wired/wireless communication networks to collect information on energy generation and demand. Actually, because of the huge size of data, it is a tedious job to process and store without any loss. Therefore, big data/cloud computing methods are employed extensively for effective home energy management [32], [33].

This investigation was carried out based on the inferences obtained by the author’s research work [7], [28], [34], [35], and [36]. From the literature, it is understood that every algorithm has its advantages and disadvantages. Hence, this paper gives importance to the robustness of an algorithm to identify the suitable optimization algorithm for the home energy management system.

From the recent literatures, it is further understood that most of the researchers were focusing on residential microgrid and the prevalent pricing scheme; the TOU price, which has three pricing periods: peak, off-peak, and mid-peak period prices during the course of a day. The authors of [37] have presented an optimal energy management system for a residential microgrid that employs both RTP and TOU pricing schemes. The results show that the TOU pricing scheme assures lower operational costs and higher energy exchange with the grid than the RTP scheme. Regarding the power generation system for residential microgrids and renewable-energy-based smart homes against the backdrop of COVID-19 is extensively discussed in [38] and [39].

Furthermore, a residential microgrid is considered with energy storage system, an electric vehicle, and renewable energy sources [40]. The authors have used PSO algorithm and attained an optimal solution to the problem that aims to minimize the energy consumption cost.

As discussed above, energy management in residential buildings has been a critical research issue for decades. Researchers have used different metaheuristic algorithms for the reduction of energy consumption costs using various pricing schemes. Most of them have achieved low cost by shifting the load from peak to off-peak periods by compromising on user comfort. In this regard, pricing schemes plays an important role in energy consumption costs.

Thus, the authors have investigated on four meta-heuristic techniques (GA, WDO, GWO, and SSA) and without a scheduling technique with the four (RTP, TOU, CPP, and DAP) pricing schemes to achieve the objective of minimizing energy consumption costs, reducing PAR, and maximizing user comfort. Consequently, the problem is formulated by considering a home with multiple smart appliances that operate with and without RES support on a summer day, with a one-hour time gap between each set of operations.

III. Problem Formulation

This section gives detail about the objective function and associated constraints. The eighteen smart appliances are divided into three categories: schedulable (SA), non-schedulable (NSA), and controllable (CA). Table I shows the complete classification of appliances.

The results obtained using GA, WDO, GWO, and without scheduling with the RTP scheme are considered from [16].

TABLE I: Classification of Appliances

Non-Schedulable Appliances (NSA)	Controllable Appliances (CA)	Schedulable Appliances (SA)
Domestic lightings	Heater (Water)	Ceiling fans
celling Fan	Electric vehicle	Other lightings
Exhaust fan	Iron box	Towel driers
Desktop (PC)	Water Pump	Computer
Energy storage system	Fridge	TV
Washing machine	Garden lightings	Electric watch

This section defines the objective function and constraints for reducing electricity prices and PAR. A battery with RES (wind and solar) power generation is considered. Scheduling is done for one day, represented by *D* (24 hours). A day is divided equally into 24 sub-intervals (each one hour), represented as $t_1, t_2, \cdots, t_{24}$.

This article uses the TOU, RTP, CPP, and DAP tariffs to establish a daily power price. Let γ^{t_i} and P^{t_i} be the real-time price and the power consumption (kWh) in t_i interval, γ and P be the price and the power consumption in normal price intervals, γ^+ and P^+ the price and the power consumption in peak price intervals, and γ^- and P^- the price and the power consumption in off-peak price intervals, the cost of energy consumption is calculated as

$$\begin{aligned}\text{Electricity bill} &= \gamma^{t_i} P^{t_i} \\ &= \gamma P + \gamma^+ P^+ + \gamma^- P^-\end{aligned} \tag{1}$$

For consumers' convenience, users in a residential area are allowed to classify their appliances as SA, NSA, or CA. The group of (SA, NSA, and CA) appliances is called set formulation, (*W*). Each individual appliance are represented as $a_1, a_2, a_3, \cdots, a_n$.

A. Decision Variable

In general, the load profile is a real and continuous decision variable. A binary β =0, 1 variable can be considered as a decision variable to specify "1" (ON) and "0" (OFF) for each scheduled appliance and the non-scheduled appliance of the day that equals the total number of times to be operated.

The objective of this paper is to minimize the total energy consumption costs, the cost calculation is based on a given 24-hours of four different electricity tariffs, such as TOU, RTP, CPP and DAP. Let γ^{t_i} denote the electricity tariff for the time slot t_i. The total electricity cost for operating all appliances (SA, NSA, CA) is given in the following equation (2).

$$\left(\sum_{t=1}^{24} \gamma^{t_i} \left(\sum_{a=1}^{a_n} \sum_{W=1}^{W_n} P_{\text{Total}}^{\text{ON}}\right)\right) \tag{2}$$

During the scheduling process, energy consumption by each group of appliances in a particular time slot t_i and total energy consumed by all appliances for a given day is as defined in equations (3)-(6).

$$P^{\text{NSA}^{\text{ON}}} = \sum_{t=1}^{24} \left(\sum_{W=1}^{W_{\text{NSA}}} P_{a_n t_n}^{\text{NSA}}\right) = \left(P_{a_1 t_1}^{\text{NSA}} + P_{a_2 t_2}^{\text{NSA}} + \cdots + P_{a_n t_{24}}^{\text{NSA}}\right) \tag{3}$$

$$P^{\text{SA}^{\text{ON}}} = \sum_{t=1}^{24} \left(\sum_{W=1}^{W_{\text{SA}}} P_{a_n t_n}^{\text{SA}}\right) = \left(P_{a_1 t_1}^{SA} + P_{a_2 t_2}^{\text{SA}} + \cdots + P_{a_n t_{24}}^{\text{SA}}\right) \tag{4}$$

$$P^{\text{CA}^{\text{ON}}} = \sum_{t=1}^{24} \left(\sum_{W=1}^{W_{\text{CA}}} P_{a_n t_n}^{\text{CA}}\right) = \left(P_{a_1 t_1}^{\text{CA}} + P_{a_2 t_2}^{\text{CA}} + \ldots + P_{a_n t_{24}}^{\text{CA}}\right) \tag{5}$$

$$P_{\text{Total}}^{\text{ON}} = P^{\text{NSA}^{\text{ON}}} + P^{\text{CA}^{\text{ON}}} + P^{\text{SA}^{\text{ON}}} \tag{6}$$

where W_{NSA}, W_{SA}, and W_{CA} are the group/set of appliances NSA, SA and CA, $P^{\text{NSA}^{\text{ON}}}$, $P^{\text{SA}^{\text{ON}}}$ and $P^{\text{CA}^{\text{ON}}}$ are the total power consumed by non-schedulable, controllable appliances, and schedulable appliances respectively, $P_{\text{Total}}^{\text{ON}}$ is the total power consumed by all appliances.

B. Constraints

This section describes the two groups of constraints: timing constraints and energy constraints.

1) Timing constraints

Non-Schedulable Appliance (NSA) - 24 hours operation: Every NSA appliance must be turned ON for the entire day, whether it is a peak period or not. Thus, the constraint is given in equation (7) and the entire set of non-schedulable appliances is represented within the operator (|·|).

$$\sum_{t=1}^{24} D = \left(\left|W^{\text{NSA}^{\text{ON}}}\right|\right) \tag{7}$$

where *D* is the total number of time intervals of the day.

2) User Comfort Level: Both schedulable and controllable appliances are to be scheduled appropriately to avoid overloading during peak hours. Also, keeping in mind the user's comfort level and satisfaction, the appliances have to be scheduled optimally and distribute the energy according to the price of the time slot. The appliances are operated for the desired number of times K, which is defined in equation (8).

$$\sum_{t=1}^{24} K_{\mathrm{app}_x t_i} = k_{\mathrm{app}_x, N} \tag{8}$$

where $K_{\mathrm{app}_x t_i}$ is the total number of times that a given appliance is operated. app_x is the appliances type (i.e., NSA, CA, SA). $k_{\mathrm{app}_x, N}$ is the frequency of preference given by the consumers which ensures that all appliances are operated for the desired number of times and that can be formulated as shown in equation (9):

$$\sum_{t=1}^{n} k_{\mathrm{app}_x, t} + k_{\mathrm{app}_x, t_i+1} + k_{\mathrm{app}_x, t_i+2} + \cdots + k_{\mathrm{app}_x, t_i+(N-1)} = K_{\mathrm{app}_x, t_i} \tag{9}$$

C. Energy Constraints

1) Maximum energy consumption ($E_{\max}$): The total power $P_{\mathrm{Total}}^{\mathrm{ON}}$ consumed by SA, NSA and CA appliances for a given day should be less than or equal to the threshold limit ($E_{\max}$=15kW), that is

$$P_{\mathrm{Total}}^{\mathrm{ON}} \le E_{\max} \tag{10}$$

2) Total energy consumption: In order to ensure that the scheduling process has fulfilled their total energy demand E_{a_n, w_n} of 156.5 kW, the following constraint is imposed:

$$\sum_{t=1}^{24} P_{\mathrm{Total}}^{\mathrm{ON}} = E_{a_n, w_n}, \forall a_n, w_n, t_i \tag{11}$$

3) Peak average ratio (PAR): During peak hours, the peak average ratio (PAR) must be reduced. Consequently, the calculation of PAR is illustrated in (12) to (14):

$$P_{\mathrm{peak}} = \max\left(\sum_{t=1}^{24} (P^{\mathrm{ON}}(t))\right) \tag{12}$$

$$P_{\mathrm{avg}} = \frac{P_{\mathrm{Total}}^{\mathrm{ON}}}{D} \tag{13}$$

$$\mathrm{PAR} = P_{\mathrm{peak}} / P_{\mathrm{avg}} \tag{14}$$

where P_{peak} is the maximum load demand for a time slot t_i and P_{avg} is the average power consumption (from t = 1 to 24 hours). PAR represents a consumer's electricity consumption behavior and is directly related to utility control center activity during peak periods. Minimizing the PAR helps both consumers and utility control centers to balance demand and supply.

4) Objective function: Once the group (set) of appliances satisfies the given constraints, then that set of appliances will undergo the optimized load scheduling process. Accordingly, the objective function is defined as shown in equation (15).

$$\begin{aligned}\mathrm{OF} = \min\Bigg\{&\sum_{T=1}^{24} (P_{\mathrm{Total}}^{\mathrm{ON}}) - \Big[\left(P^{\mathrm{grid}} + P^{\mathrm{wind}}(t)\right) + \\ &\left(P^{\mathrm{solar}} + \mathrm{BT}(t)\right)\Big]\Bigg\} \gamma^{t_i} + \min(\mathrm{PAR})\end{aligned} \tag{15}$$

where OF is the objective function, $P_{\mathrm{Total}}^{\mathrm{ON}}$ is the total power consumption by all sets of appliances in the ON state for scheduling in an appropriate time slot. P^{wind} is the power supported by wind, P^{solar} is the power supported by solar, BT is the power supported by the battery, and γ^{t_i} is the energy consumption cost.

D. Renewable Energy Sources (RES) in Residential Buildings

The home environment considered in this paper consumes, generates and stores energy while being connected either with the support obtained from a grid or renewable energy sources. Hence, the home taken for analysis is equipped with renewable energy sources (wind and solar), a grid supply, and a battery, as discussed in [16]. Using stored energy during peak hours is a benefit to both consumers and utility control centers. It is to be noted that RES and grid supply are there to support batteries for storing and discharging their energy, but this paper does not discuss about battery control unit.

Solar and Wind energy generation: A 230W fixed array solar panel and a battery (1.2 kwh) are considered to meet the load demand. The capacity of the battery (BT(t)) is calculated by equation (16) in the time interval (t).

$$\mathrm{BT}(t) = \frac{L_{\mathrm{demand}} H}{\eta_v \eta_B D_{\mathrm{discharge}}} \tag{16}$$

where L_{demand} is the daily energy consumption by the consumers, H is the number of autonomy hours. η_v and η_B are the voltage and battery efficiency respectively, and $D_{\mathrm{discharge}}$ is the allowable depth of discharge. The battery charging and discharging during time intervals (t–1) to t can be determined by,

$$\mathrm{BT}_{\mathrm{Capacity}}(t) = \mathrm{BT}_{\mathrm{Capacity}}(t-1)(1-\wp) + P_{\mathrm{BT_{bank}}}(t)$$

where $\mathrm{BT}_{\mathrm{Capacity}}(t)$ and $\mathrm{BT}_{\mathrm{Capacity}}(t-1)$ is the amount of energy available in a battery (which may be consumed by the consumer) at time intervals t and (t–1) hours, $\wp$ is the battery self-discharge rate (0.002A) and power supported from the battery $P_{\mathrm{BT_{bank}}}(t)$ at time interval t. This paper considers the depth of battery discharge as 50%. The minimum and maximum capacity of the battery are $\mathrm{BT}_{\min}$ and $\mathrm{BT}_{\max}$, respectively, given as

$$\mathrm{BT}_{\min} \le \mathrm{BT}_{\mathrm{Capacity}} \le \mathrm{BT}_{\max} \tag{17}$$

As the solar panel produces its power from the sun, the irradiance that reaches the surface of the Earth can vary substantially based on the geographic location, altitude, time of day, time of year, and the concentration of atmospheric gases and particles. The Earth receives a considerable amount of solar radiation, and most populated places have insulation levels of 150 to 300 variability in irradiance. The reference solar irradiance spectra are typically used in the calculation. The solar panel output power is measured as shown in equation (18).

$$P_{\text{solar\_out}} = P_{\text{solar\_nominal}} \frac{\psi}{\psi_{\text{ref}}} \left[1 + K_T (T_c - T_{\text{ref}})\right] \\ T_c = T_{\text{ambient}} + (0.256\psi) \tag{18}$$

where $P_{\text{solar\_out}}$ is the total power generated by solar panel (kW), $P_{\text{solar\_nominal}}$ is the nominal power of solar panel (kW), ψ is the solar radiation (W/m^2), ψ_{ref} is the solar radiation at reference conditions (1000 W/m^2), whereas K_T =–3.7×10^{-3} (1/°C). T_c is cell temperature (°C), T_{ref} is the cell temperature reference (25°C) and T_{ambient} is the ambient temperature (°C).

An AC-AC converter integrates a 10 kW wind turbine generator into this same home environment. Weather-related factors such as wind speed ($P_{\text{wind-speed}}$) and air density influenced the energy produced by wind generators, as defined in equations (19) and (20),

$$P^{\text{wind}} = 0.5\Gamma_{\text{rotor}}\sigma V^3 P_{\text{coefficient}} \tag{19}$$

$$P_{\text{wind-speed}}(V) = \begin{cases} 0, & V \le V_{\text{cin}}, V \ge V_{\text{cout}} \\ \dfrac{V - V_{\text{cin}}}{V_{\text{rtd}} - V_{\text{cin}}} P_{\text{rtd}}, & V_{\text{cin}} \le V \le V_{\text{rtd}} \\ P_{\text{rtd}}, & V_{\text{rtd}} \le V \le V_{\text{cout}} \end{cases} \tag{20}$$

where Γ_{rotor} is the rotor swept area of a wind turbine, σ (m^2) is the density of air (kg/m^2), V is the average wind velocity (m/s). The power coefficient for wind turbine efficiency and it is denoted as $P_{\text{coefficient}}$. The output of a wind turbine purely depends on what kind of wind speed (m/s) it is rated for (V_{rtd}), the turbine's cut-in (V_{cin}) speed and cut-out (V_{cout}) speed. The power produced by the wind generator is denoted as, P^{wind}. Finally, the most challenging task for the utility control center is to balance the demand and supply as defined in equation (21), for which the net power source of the smart home is,

$$P_{\text{Total}}^{\text{ON}} \le P^{\text{grid}} + P^{\text{wind}}(t) + P^{\text{solar}}(t) + \text{BT}(t), \ \forall 1 \le t \le 24 \tag{21}$$

IV. Optimization Technique for Reducing Energy Consumption Cost

For reducing energy consumption cost, this section describes the inspiration and performance of four bio/nature-based algorithms: genetic, grey wolf, wind-driven, and salp-swarm optimization algorithm. The suggested salp-swarm optimization technique (SSA) efficiently shifts the appliance demand from peak to off-peak. The results of SSA under various pricing schemes such as TOU, RTP, CPP, and DAP are compared and validated with the outcomes of genetic, grey wolf, wind-driven optimization algorithms and without scheduling technique.

A. Genetic Algorithm (GA)

In genetic algorithm, the fittest individuals are selected for the reproduction of the next generation. The process commences by identifying a group of individuals named as population. An individual has categorized by a set (group) of parameters (set of appliances) identified as Genes. Genes are a group of strings to form a Chromosome (solution). Every individual is the solution (appliances) to the problem that must be solved (kept ON or OFF). Usually, a group of chromosomes is represented as a string of binary values (0s and 1s). It indicates the appliance in ON (1s) or OFF (0s) state. This length of the binary-coded chromosome represents the number of appliances in the ON or OFF state [16], [32], [41].

$$\text{Chromosome} = [C_1, C_2, \cdots, C_n] \tag{22}$$

where C_n is the length of chromosomes in binary and n is the number of chromosomes. After determining the number of chromosomes, the fitness function $f(x)$ is assessed by calculating the objective function (OF) using (23):

$$f(x) = \frac{1}{1 + \text{OF}} \tag{23}$$

where OF is the objective function of the problem. A mutation operator P_m is used for random modification of the chromosomes from 0 to 1. Each bit in every chromosome is checked for possible mutation by generating a random number between 0 and 1. If this number is less than or equal to the given mutation probability (P_m=1), then a gene is mutated from its unique state. Most of the literature studies show that better results are achieved by a crossover probability between 0.65 and 0.90 which ensures the probability of a selected chromosome surviving to the next generation remains unchanged. Therefore, the authors of this paper have chosen the probability of crossover P_c as shown in (25) so that premature convergence that leads to a sub-optimal solution can be eliminated. If crossover probability is 100%, then all chosen chromosomes are used for new generation reproduction. For 0%, the entire new generation will be an exact copy of the parent chromosomes.

$$P_c = 0.9 \tag{24}$$

In natural genetic systems, the probability of mutation P_m is too low; thus, an optimal mutation rate for optimization problems is given in equation (25).

$$P_m = 1 - P_c \tag{25}$$

Towards the end of crossover and mutation operation, the fitness of newly created population is compared with the current population and stores the best solution. After initializing the population, the objective function is determined through the fitness function. The new generation is generated by implementing the crossover and mutation process using parameters given in Table II.

Table II: Parameters used in GA

Parameters	Value
Size of the Population	200
Iterations	50
Mutation probability P_m	0.1
Crossover probability P_c	0.9
n	18

B. Wind-Driven Optimization Algorithm (WDO)

The wind-driven optimization technique works by tracking air particle movement. Air particles travel in the same direction (forward) when the wind blows from high pressure to low pressure zones. The WDO algorithm's velocity and position vectors are upgraded using Newton's second law of motion [42]. Various forces acting on air particles are represented using (26) to (29):

$$F_{\mathrm{Cr}} = -2\Omega v \tag{26}$$

$$F_{\mathrm{Gv}} = \eta \cdot \delta \mathrm{v} \cdot g \tag{27}$$

$$F_{\mathrm{prg}} = -\Delta\eta \cdot \delta \mathrm{v} \tag{28}$$

$$F_{\mathrm{Fr}} = -\eta \Phi v \tag{29}$$

where F_{Cr} is the Coriolis Force, Ω is the earth rotation, v is the velocity of wind and F_{Gv} is the gravitational force, η is the density of air, δv represents a finite volume of air with gravity g. F_{pr} is the pressure gradient force and Δ is the pressure gradient with Frictional force F_{Fr} and Φ is the friction coefficient.

Velocity and position of the air particles are updated using (30) and (31):

$$x^p_{(i+1)} = x^p_i + v^p_{(i+1)} \tag{30}$$

$$v^p_{(i+1)} = \left((1-\Phi)v^p_i - g x^p_i + \left[\mathrm{RT}\left|\frac{1}{r} - 1\right| (x_{g_{best}} - x^p_t \right] + \left[\frac{F_{\mathrm{Cr}} v^p_i}{r} \right] \right) \tag{31}$$

where v^p_i is the current velocity of air particles, $v^p_{(i+1)}$ is the new velocity of air particles and x^p_i is the current position of air particles. x^p_{i+1} and $x_{g\mathrm{best}}$ represents the new position of air particles. and the global best position respectively. r is the ranking value of air particles. R and T is the universal gas constant and temperature respectively.

The optimal solution is generated by evaluating the velocity and fitness function of air particles. WDO uses the term "pressure" to describe the fitness function and the parameters involved in algorithm are given in Table III.

TABLE III: PARAMETERS USED IN WDO

Parameters	Value
Size of the Population	200
Iterations	50
n	18
dimMin, dimMax	-5, 5
vmin, vmax	-0.3, 0.3
universal gas constant	3
Gravity	0.2
Friction Coefficient	0.4

TABLE IV: SOCIAL HIERARCHY OF GREY WOLVES

Level of Hierarchy	Category Name	Administration level of the Pack
I	Alpha (α)	leader, it orders the final decision to the pack
II	Beta (β)	mentor to alpha, it upholds discipline in the pack
III	Delta (δ)	observing the territory/ border-it acts as caretaker of sick and injured wolves
IV	Omega (ω)	follows the leading wolves- It eats after all the powerful wolves complete their food

C. Grey Wolf Optimization Algorithm (GWO)

The GWO was proposed by Seyedali Mirjalili *et al.* [43] and it is based on the grey wolf hunting hierarchy (Table IV). The pack of wolves always live with a hierarchy. Hunting has four primary steps: searching (exploration), chasing, surrounding, and assaulting the prey (exploitation).

The mathematical representation of encircling the prey is given in equations (32) and (33).

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_P(t) - \vec{X}(t) \right| \tag{32}$$

$$\vec{X}(t+1) = \vec{X}_P(t) - \vec{A} \cdot \vec{D} \tag{33}$$

where t is the current iteration, $\vec{D}$ is the distance between the prey and wolf $\vec{A}$ and $\vec{C}$ is the coefficient vectors $\vec{X}_P(t)$ is the position vector of prey, $\vec{X}(t)$ is the position vector of predator (grey wolf). In equations (34) to (38), the operator "·" represents the dot product and the operators "+" and "-" are the normal arithmetic addition and subtraction operators.

Equation (34) to (39) updates each wolf's location in the n-dimensional search space. Table V shows the parameters used in the GWO simulation.

$$\vec{D}_\beta = | \vec{C}_2 \cdot \vec{X}_\beta - \vec{X} | \tag{34}$$

$$\vec{D}_\delta = | \vec{C}_3 \cdot \vec{X}_\delta - \vec{X} | \tag{35}$$

$$\vec{X}_1 = | \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha | \tag{36}$$

$$\vec{X}_2 = | \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta | \tag{37}$$

$$\vec{X}_3 = | \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta | \tag{38}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{39}$$

TABLE V: PARAMETERS USED IN GWO

Parameters	Value
Size of the population	200
Iterations	50
$\vec{a}$	2 to 0
Random vectors (r_1, r_2)	[0, 1]
n	18

D. Salp Swarm Optimization Algorithm (SSA)

Salp Swarm Optimization Algorithm (SSA) models salps' navigation and foraging behaviour (family of Salpidae). Salp is similar to jellyfish with a transparent barrel-shaped body. A salp chain is a network (swarm) of salps that develop in the deep sea. SSA is a nature-inspired, evolutionary, robust, and, stochastic optimization algorithm to solve computationally hard optimization problems. The paper [44] presented the salp swarming mathematical model. The swarms (salp chain) are grouped as leader and followers. The first salp in the chain is the leader, and the others are followers. The leader salp communicates either directly or indirectly with the follower salps using search directions. The positions of all salps are defined as, $(x_1^1, y_1^1, \cdots, x_m^n, y_m^n)$ where $d = 1, 2, \cdots, n$, n is the number of salps and $j = 1, 2, \cdots, m$, m is the number of variables. The SSA considers the food source (F) as a target and that is in the search area. It has three components: direction, personal best, and team-best.

$$X_j^1 = \begin{cases} F_j + c_1((\text{ub}_j - \text{lb}_j)c_2 + \text{lb}_j), & c_3 \geq 0 \\ F_j - c_1((\text{ub}_j - \text{lb}_j)c_2 + \text{lb}_j), & c_3 < 0 \end{cases} \tag{40}$$

where X_j^1 and F_j are the position of leader salp and the position of food at j^{th} dimension on search space respectively. c_1, c_2, and c_3 are the random numbers, ub_j and lb_j are the upper bound and lower bound of j^{th} dimension. The controlling parameter c_1 is a significant coefficient factor in SSA to balance the exploration and exploitation as given in (41), it is the constant number having natural of the helical shape of salp swarm:

$$c_1 = 2e^{-}\left(\frac{4l}{L}\right)^2 \tag{41}$$

where l is the current iteration and L is the maximum number of iterations. The controlling parameter c_1 is decreased adaptively over the course of iteration so that the SSA algorithm first explores and then exploits it in the search space.

The coefficient factors c_2 and c_3 are consistently generated random numbers, where c_2 is in the range of [0, 1] which is responsible for widening the search space. And c_3 is to indicate whether the next position of current leader salp and follower salps are within the boundary or not. If $c_3<0.5$, the salps are moving out of the boundary on a negative scale while for $c_3 \geq 0.5$, salps are going on a positive scale with respect to food. Thus, c_2 and c_3 help to decide the next position of salp in j^{th} dimension of search space. Additionally, the coefficient factors c_1, c_2, and c_3 together are used to reposition the solutions that goes outside the search space. The position of salp followers is updated using (42) and it depends on salps speed, velocity and distance moved, and worth noting that this equation follows the Newton law of motion.

$$x_j^d = \frac{1}{2}at^2 + v_o t \tag{42}$$

where x_j^d is the position of d^{th} follower salp in j^{th} dimension on search space, v_0 is the initial speed, a is the acceleration, t is the time, and $v_{\text{final}} = (x - x_0)/t$ is the final velocity. Considering $v_0=0$ the above equation can be expressed as follows.

$$x_j^d = \frac{1}{2}\left(X_j^d + X_j^{d-1}\right) \tag{43}$$

Equation (44) portrays how to bring back the salp into the search space.

$$X_j^d = \begin{cases} \text{lb}_j, & \text{if } X_j^d \leq \text{lb}_j \\ \text{ub}_j, & \text{if } X_j^d \geq \text{ub}_j \\ X_j^d, & \text{otherwise} \end{cases} \tag{44}$$

The SSA optimization starts by initializing the salps in a random position. Consequently, the fitness of each salp is dictated by the distance between the food source and the salp. For each dimension, with the help of coefficient factors, the position of both leader and follower salps are updated frequently. The X_j is considered the optimum load scheduling for the cost-saving of a day. The salp chain exploits the search space to get the most appropriate global optimum solution and avoid the local solution. The salp swarm chain's velocity, distance and fitness function are evaluated. Table VI shows the SSA simulation parameters.

TABLE VI: PARAMETERS USED IN SSA

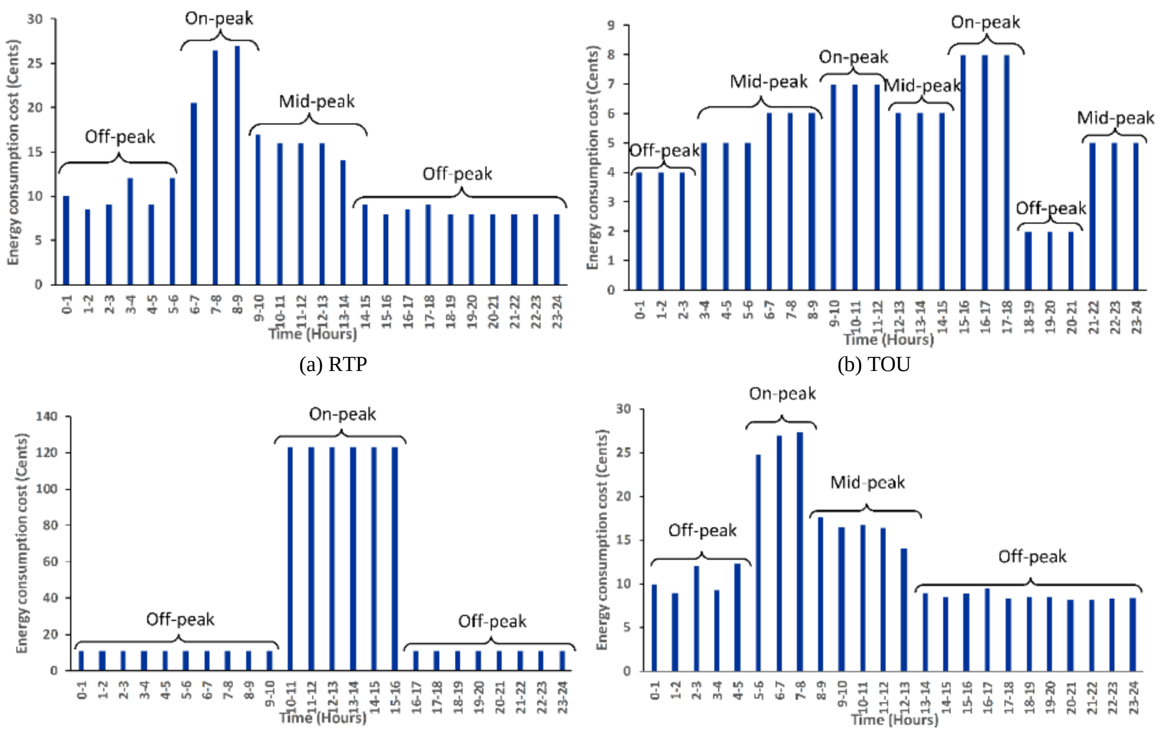
Parameters	Value
Size of the Population	200
Iterations	50
lb and ub	0 to 15
c_2	[0, 1]
c_3	[0, 0.5]
n	18
dim	24

V. RESULTS AND DISCUSSION

The outcomes of the genetic, grey wolf, wind-driven algorithms and without scheduling technique to the SSA technique under four different pricing schemes are compared. Also, this paper evaluates the impact of integrating renewable energy sources with the battery. Fig. 3 (a) represents real-time pricing similarly, Fig. 3 (b) to Fig. 3 (d) depict the time of use, day-ahead, and crucial peak prices that are adapted from [8], [12], and [45]. All the discussed techniques are implemented with these prices with and without RES integration.

Both solar and wind power generation are shown in Fig. 4 (a) and Fig. 4 (b). The power generation from these sources are high during mid of the day (summer).

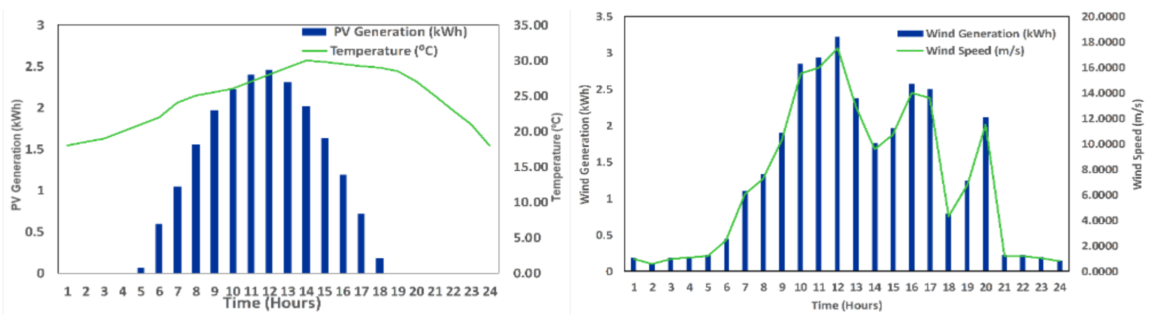
The simulation is carried out in MATLAB (R2017a) for 18 appliances with a total demand of 156.5 kW in the summer. The desktop/laptop used for simulation: Processor Intel(R) Core (TM) i3-7020U CPU @ 2.30GHz; RAM-12.0 GB; System type-64-bit operating system; x64-based processor. The GA, WDO, GWO, SSA and manual (without any scheduling) techniques are simulated under four pricing systems (RTP, TOU, DAP, and CPP) with the constraints discussed in section III. The scheduling of loads is shown in Fig. 5. It is also to be noted that this scheduling pattern is limited to a maximum energy (threshold) limit of 15 kW to decrease the peak load and energy usage costs.



(a) RTP (b) TOU

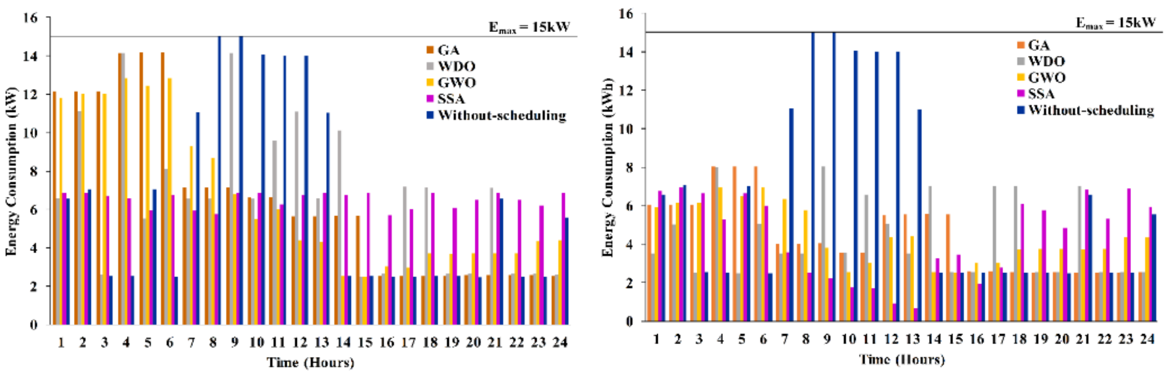
(c) CPP (d) DAP

Fig. 3. Electricity tariff schemes.



(a) Solar power generation (b) Wind power generation

Fig. 4. Renewable energy sources.



(a) Without RES (b) With RES

Fig. 5. Comparison of demand scheduling.

A. *Demand Comparison*

Fig. 5 (a) and Fig. 5 (b), shows the load that are scheduled in each time slot using the RTP pricing scheme by all the algorithms. Fig. 5 (a) (without RES) during the t_1 slot shows that both the without-scheduling (manual operation) technique and the WDO algorithm have scheduled 6.5 kW, whereas GA and GWO have scheduled 12 kW for RTP pricing schemes. But SSA schedules the load demand of 6.8 kW. Similarly, for the t_4 slot, the GA and WDO have shown a demand of 14 kW and GWO with 12 kW. But SSA has selected a group of appliances that has a demand of 6.5 kW.

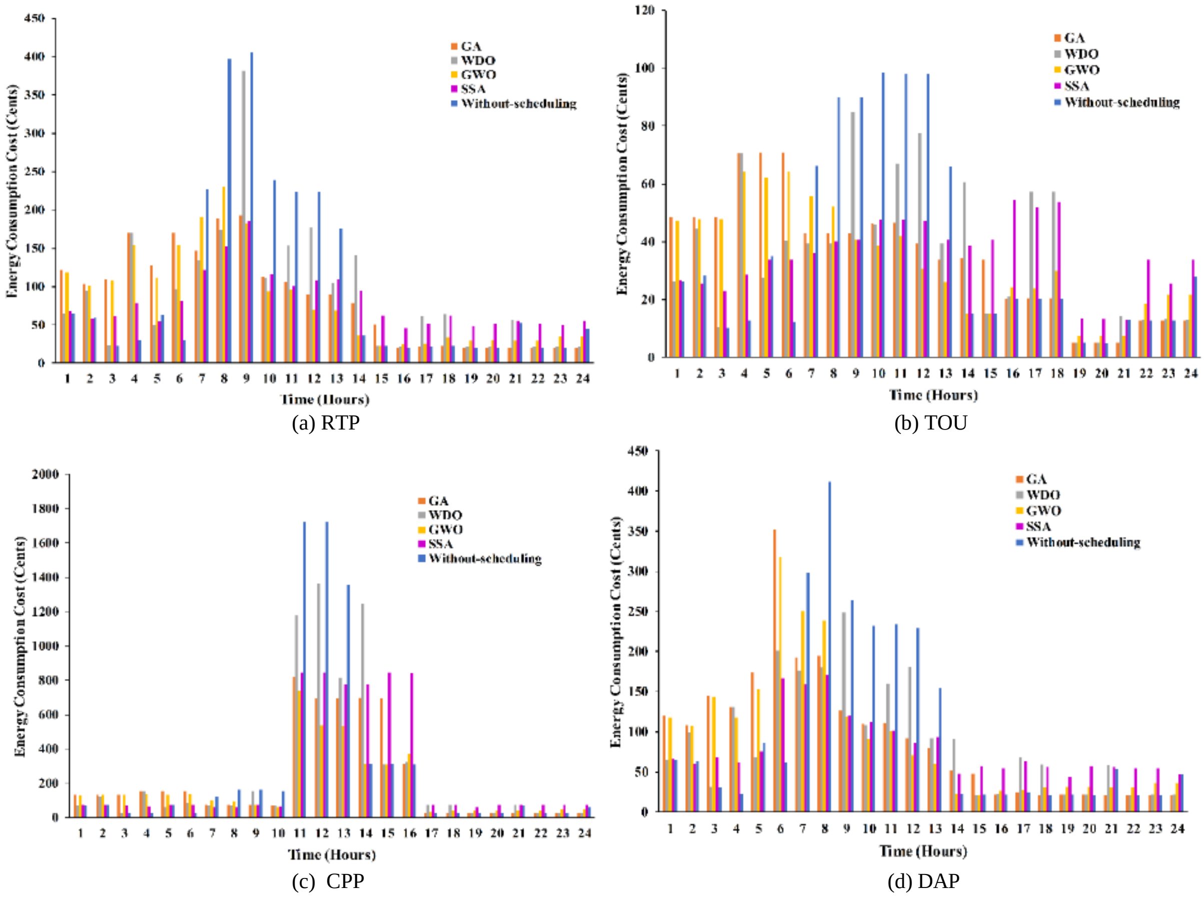
Considering the eighth time slot t_8 (high electricity price time slot), the GA has scheduled a 7 kW demand, WDO with 6.5 kW, GWO schedules up to 8.5 kW, but SSA schedules with a demand of 5.7 kW only. While the SSA has reduced the energy usage costs, it has also met the total demand of 156.5 kW by distributing the appliance in all time slots. This comparison shows that except for SSA, all other algorithms scheduled high-demand appliances in low-tariff time slots resulting in low-cost energy usage. Notably, the SSA does not surpass 15 kW at any time of the day. The 2.5 kW of non-schedulable appliances is also satisfied.

By utilizing renewable energy sources, the energy usage cost is reduced and the same is illustrated in Fig. 5 (b). Also, this figure proves that the SSA schedules the load effectively by satisfying the minimum demand of 2.5 kW and not exceeding the E_{max} value. The comparison shows that all optimization approaches schedule the loads by satisfying the constraint specified in equation (7). In time intervals t_{15} to t_{24}, the GA, WDO, and GWO have scheduled the demand between 3 kW and 7 kW, while the SSA has scheduled the demand between 3 kW and 5 kW. From the utility control center and consumer perspectives, the SSA algorithm efficiently schedules the home appliances and manages the peak demand problems.

B. Cost Comparison

1) Without RES Integration

Fig. 6 (a) to Fig. 6 (d) show the cost comparison of SSA with GA, WDO, GWO, and without scheduling. Considering Fig. 6 (a) with the RTP pricing scheme, at the high-cost time slot t_8, the SSA algorithm attains the energy usage cost of 152.8 Cents. While, the GA, WDO, GWO, and without-scheduling operations schedule with the cost of 189.16 Cents, 174.1 Cents, 230.5 Cents and 397.5 Cents, respectively. Similarly, the time slot t_9 is also a high-cost period of the day and observes similar performance by the approaches such as GA, WDO, GWO, and without-scheduling operations with 192.82 Cents, 381.8 Cents, 183.22 Cents, and 405 Cents respectively. From the comparison, the SSA schedules the demand with least energy usage cost of 184.71 Cents in the t_9 time slot.



(a) RTP (b) TOU (c) CPP (d) DAP

Fig. 6. Cost comparison without RES

2) With RES Integration

Fig. 7 (a) to Fig. 7 (d) compares the energy consumption cost using four pricing strategies with RES integration. With the SSA technique, energy consumption cost has drastically reduced during the t_8 and t_9 time slots. It is understood from the results that the energy usage cost using CPP scheme is higher than the cost obtained using RTP, TOU, and DAP schemes. From the results, both the TOU and DAP schemes effectively reduce energy consumption costs.

3) Total Cost Comparison

Table VII and Table VIII present the comparison on percentage of cost difference with respect to the SSA technique. The SSA attains 1401.03 Cents which is lesser cost than the cost obtained from GA, WDO, GWO, and without-scheduling methods, i.e., 2032.40, 2257.70, 1869.90, and 2494.80 Cents, respectively (Fig. 8 (a)). The GA, WDO, GWO, and without-scheduling techniques with the RTP scheme and without RES have attained higher energy usage costs than SSA. It is to be noted that all the algorithms have satisfied the total demand of 156.56 kW, hence 100% of the user comfort level is achieved (Table VII). Note that by all techniques, the demand of non-schedulable appliances (2.5 kW) is also satisfied.

With RES integration, the SSA using RTP scheme has attained 1182.26 Cents which is lesser cost than the cost obtained from GA, WDO, GWO and without-scheduling techniques, i.e., 1341.90, 1237.40, 1287.40 and 1781.08 Cents respectively (Fig. 8 (b)). The percentage cost difference obtained using GA, WDO, GWO, and without-scheduling technique with respect to SSA (with RTP scheme and RES) is 11.90%, 4.46%, 8.17% and 33.62%, respectively (Table VIII). Likewise, the remaining pricing schemes are compared with and without RES and it is evident that SSA has outperformed other techniques in all pricing schemes. In particular, the SSA technique with the TOU price has a remarkable cost-saving compared to other pricing schemes. Thus, the TOU pricing scheme is more effective than other pricing schemes in reducing energy consumption costs.

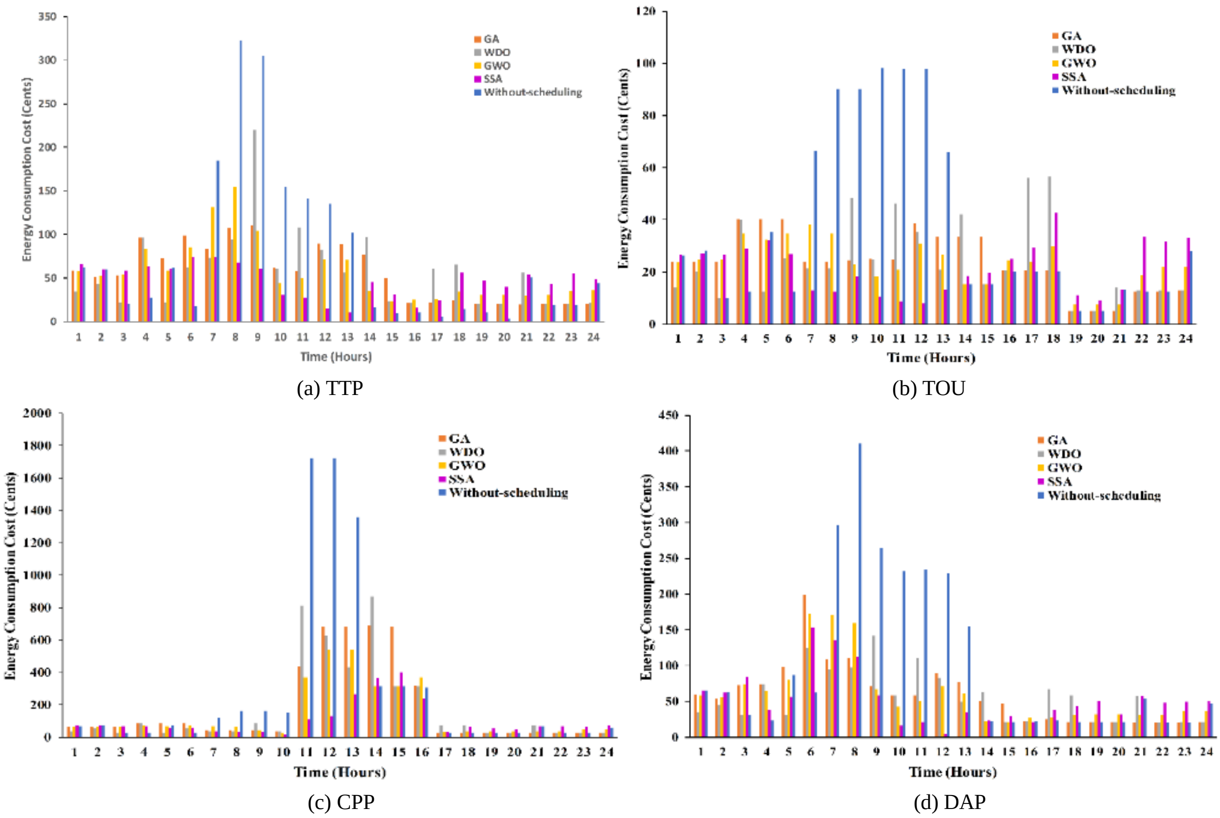


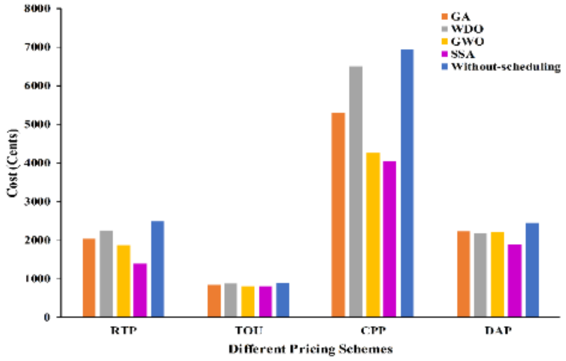
Fig. 7. Cost comparison with RES.

TABLE VII: ENERGY CONSUMPTION COST COMPARISON - WITHOUT RES

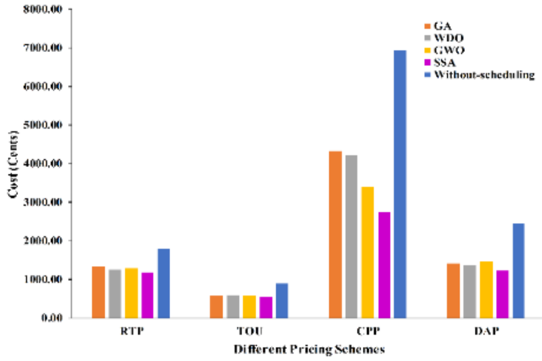
Price	Description	SSA	GA	WDO	GWO	Without scheduling algorithm
RTP	Cents	1401.03	2032.40	2257.70	1869.90	2494.80
	Percentage of Cost difference from SSA	-	31.07	37.94	25.07	43.84
TOU	Cents	801.03	835.61	889.25	812.33	898.90
	Percentage of Cost difference from SSA	-	4.14	9.92	1.39	10.89
CPP	Cents	4051.22	5289.31	6489.67	4260.86	6931.58
	Percentage of Cost difference from SSA	-	23.41	37.57	4.92	41.55
DAP	Cents	1881.57	2228.78	2171.89	2213.81	2447.23
	Percentage of Cost difference from SSA	-	15.58	13.37	15.01	23.11

TABLE VIII: ENERGY CONSUMPTION COST COMPARISON - WITH RES

Price	Description	SSA	GA	WDO	GWO	Without scheduling algorithm
RTP	Cents	1182.26	1341.90	1237.40	1287.40	1781.08
	Percentage of Cost difference from SSA	-	11.90	4.46	8.17	33.62
TOU	Cents	549.45	569.26	593.81	560.33	898.90
	Percentage of Cost difference from SSA	-	3.48	7.47	1.94	38.38
CPP	Cents	2734.83	4333.18	4220.52	3401.81	6931.58
	Percentage of Cost difference from SSA	-	36.89	35.20	19.61	60.55
DAP	Cents	1235.11	1425.92	1370.83	1453.07	2447.25
	Percentage of Cost difference from SSA	-	13.38	9.90	15.00	49.53



(a) Scheduling without RES



(b) Scheduling with RES

Fig. 8. Total cost comparison

TABLE IX: PEAK AVERAGE RATIO (PAR) EVALUATION UNDER DIFFERENT PRICING SCHEMES

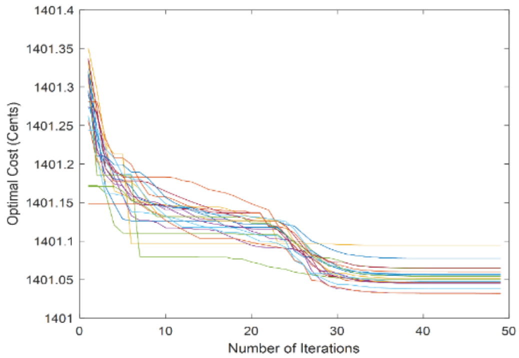
Price	Renewable source	Without scheduling algorithm	GA	WDO	GWO	SSA
RTP	Without RES	5.2915	4.6095	5.2915	4.2426	1.0381
	With RES	5.2915	1.8199	2.5024	1.6265	1.0443
TOU	Without RES	2.6254	2.0363	2.2898	1.8971	1.0507
	With RES	3.0212	1.6954	2.2797	1.6313	1.0579
CPP	Without RES	5.9656	3.7168	5.0465	4.1680	1.0411
	With RES	7.6035	3.8023	4.9332	3.8240	1.0547
DAP	Without RES	4.0295	3.7807	2.7543	3.4473	1.0731
	With RES	4.6749	3.3518	2.4829	2.8328	1.0677

4) *Peak Average Ratio (PAR) Comparison*

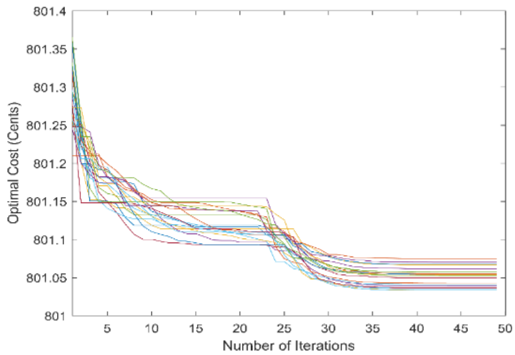
This section discusses the peak-average ratio (PAR) with and without RES integration. From Table IX, a significant PAR difference is observed after load scheduling in all four pricing schemes. When comparing the PAR values attained by scheduling and without-scheduling techniques, it is clear that the without-scheduling (manual operation) technique has achieved the highest PAR. Moreover, the result shows that the SSA algorithm has attained the lowest PAR (with and without RES) among the scheduling techniques.

VI. ROBUSTNESS OF SSA TECHNIQUE

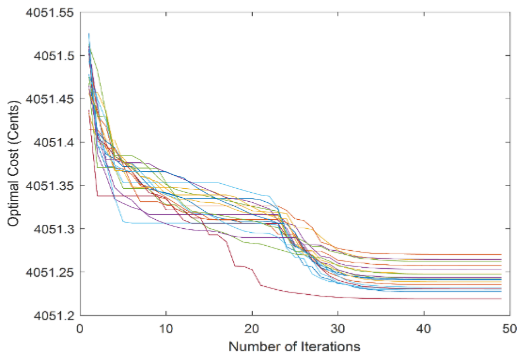
Fig. 9 and Fig. 10 show the SSA technique convergence curves for 20 trial runs in load scheduling. The figures show that as the number of iterations reaches 25, the SSA approach starts to attain the optimal value. These results strongly prove that the SSA technique helps to avoid local solutions. After every trial run, the algorithm reaches the fitness value, indicating that the convergence curve is substantially closer to the optimal energy usage cost. Thus, the SSA algorithm achieves the best results with the TOU price among the four pricing schemes.



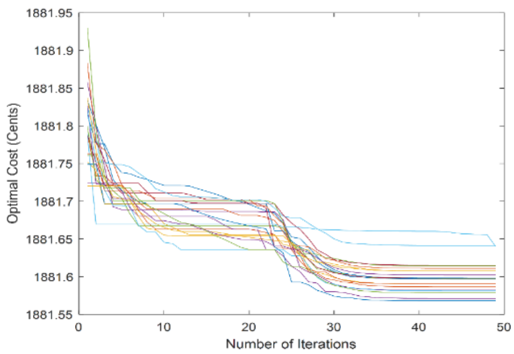
(a) RTP



(b) TOU

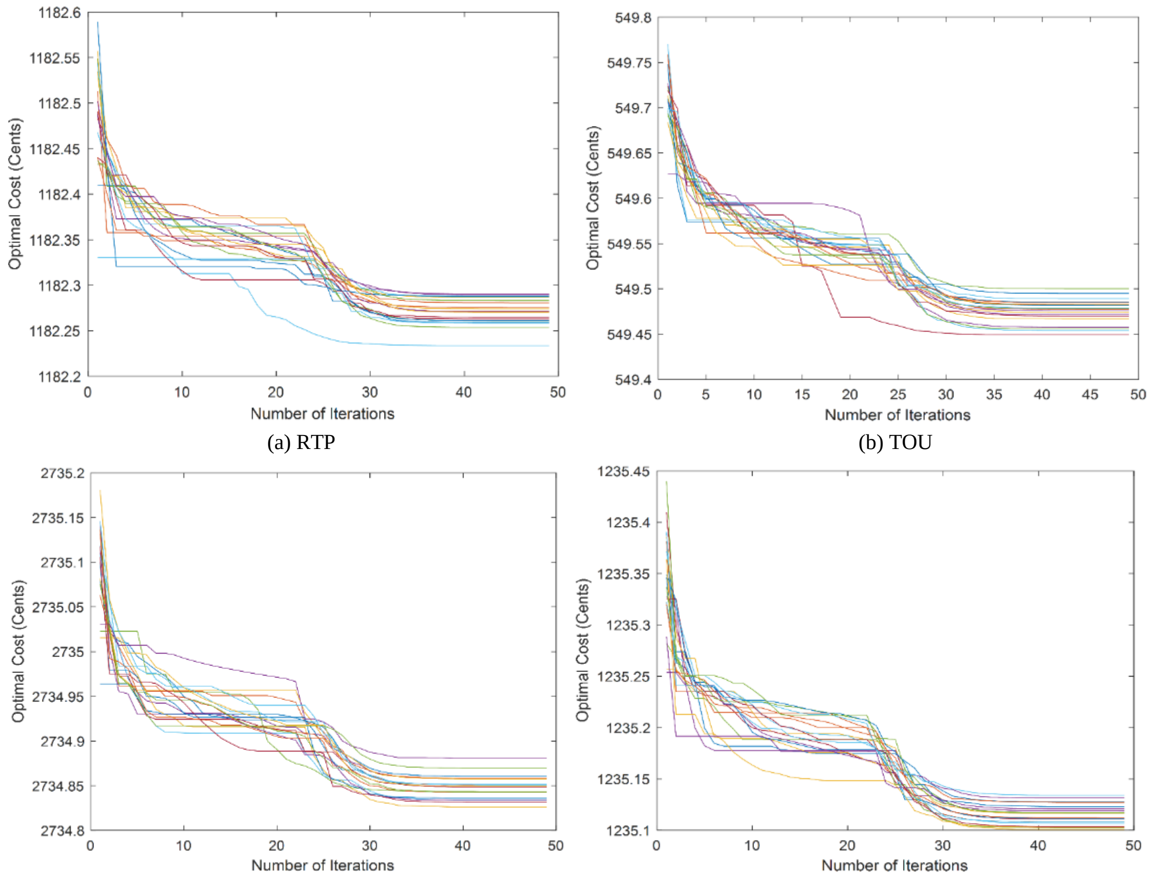


(c) CPP



(d) DAP

Fig. 9. SSA algorithm optimal cost convergence curve without RES-20 Trail runs



(a) RTP (b) TOU (c) CPP (d) DAP

Fig. 10. SSA algorithm optimal cost convergence curve with RES-20 Trail runs

TABLE X: BEST, MEDIAN, AND WORST VALUES OF SSA

Price	Renewable source	Best (Cents)	Average (Cents)	Worst (Cents)	Standard deviation
RTP	With RES	1182.2336	1182.2704	1182.2897	0.0150
	Without RES	1401.0332	1401.0543	1401.0945	0.0133
TOU	With RES	549.4493	549.4756	549.5001	0.0135
	Without RES	801.0332	801.0518	801.0749	0.0128
CPP	With RES	2734.8285	2734.8512	2734.8808	0.0156
	Without RES	4051.2192	4051.2438	4051.2706	0.0136
DAP	With RES	1235.1081	1235.1171	1235.1342	0.0196
	Without RES	1881.5681	1881.5981	1881.6605	0.0153

The results of SSA algorithm (with RES) outperform the results obtained by without RES in terms of the specified performance measures, such as the best, average (median), and worst values of optimized energy costs (Table X). From the obtained standard deviation, confirms the SSA technique accuracy and robustness.

The unique features of SSA algorithm which makes it popular in the field of optimization problems are:

The number of parameters involved are less compared to other optimization techniques like GA, WDO and GWO. Further it can be implemented to a wider range of optimization problems,

a) The extensive property of SSA is elitism which helps to find the best solution with in the search space,

b) Furthermore, the convergence of the system is insensitive to the parameter selection which helps in reducing the tuning time of the parameters for a specific problem,

c) In addition, SSA is more stochastic and robust for most of the optimization problems compared to the other meta-heuristic algorithms like GA, WDO and GWO algorithms etc., and

d) In SSA, the leader salp is used to update the position with respect to the food source in search space for generating new candidate solutions which makes the randomization process more efficient.

In addition to the above features of SSA, most of the recent literatures have proven that SSA is potentially more efficient than other metaheuristic algorithms. Taking all the above factors into account, the authors have chosen SSA as the method for optimizing the energy consumption cost and the PAR of residential buildings through load scheduling.

VII. CONCLUSION

This paper investigates four meta-heuristic optimization algorithms like SSA, GA, WDO, GWO algorithms and without scheduling technique used for load scheduling under four pricing (TOU, RTP, CPP, DAP) schemes in a common home environment (with/without RES).

The home environment consists of eighteen different appliances. Minimization of energy usage cost, PAR reduction and increasing the user comfort level are the main objectives of this paper. Simulation results prove that the SSA algorithm efficiently schedules the appliances and attains reduced energy usage cost and PAR with maximum user comfort level than other techniques.

The energy usage cost attained by SSA algorithm with TOU price is minimized by 10.89% (without RES) and 38.88% (with RES), also the PAR has been reduced by 59.97% (without RES) and 64.98% (with RES) from the cost obtained by without scheduling technique. Thus, the simulation results prove that the SSA algorithm with TOU pricing is the most promising algorithm by meeting all the constraints.

Thus, it is clear that renewable energy generation has potentially supported in reduction of energy consumption costs and PAR, which helps the control center to balance the energy demand and supply effectively. In future work, the same home environment can be considered with the real-time scheduling process. In addition, cases like power injection from RES into the grid (both forward and reverse operation), and the usage of an electric vehicle as one of the appliances (vehicle to grid/grid to vehicle) can be included.

Conflict of Interest

None of the authors have any financial or non-financial competing interests with respect to this manuscript.

Author Contributions

Senthil Prabu Ramalingam and Dr. Prabhakar Karthikeyan Shanmugam have conceived the idea and converted it in to an article. The authors confirm their contribution to the paper as follows: Dr. Prabhakar Karthikeyan Shanmugam encouraged to investigate and supervised the findings of this work. Senthil Prabu Ramalingam developed the theory and performed the computations, verified the analytical methods and drafted the article.

Acknowledgment

The authors thank the Management of Vellore Institute of Technology, Vellore, Tamil Nadu, India for their constant support and encouragement to carry out the research work.

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