applied sciences

MDPI

Article

Exploiting Multi-Verse Optimization and Sine-Cosine Algorithms for Energy Management in Smart Cities

Ibrar Ullah [1], Irshad Hussain [1,*], Peerapong Uthansakul [2,*], M. Riaz [1], M. Naeem Khan [1] and Jaime Lloret [3]

1 Faculty of Electrical & Computer Engineering, University of Engineering and Technology Peshawar, Peshawar 25000, Pakistan; ibrarullah@uetpeshawar.edu.pk (I.U.); m.riaz@uetpeshawar.edu.pk (M.R.); naeembannu@uetpeshawar.edu.pk (M.N.K.)

2 School of Telecommunication Engineering, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand

3 Instituto de Investigacion para la Gestion Integrada de Zonas Costeras, Universitat Politecncia de Valencia, 46730 Grao de Gandia, Valencia, Spain; jlloret@dcom.upv.es

* Correspondence: ee.irshad@gmail.com (I.H.); uthansakul@sut.ac.th (P.U.)

Received: 4 February 2020; Accepted: 16 March 2020; Published: 20 March 2020

Abstract: Due to the rapid increase in human population, the use of energy in daily life is increasing day by day. One solution is to increase the power generation in the same ratio as the human population increase. However, that is usually not possible practically. Thus, in order to use the existing resources of energy efficiently, smart grids play a significant role. They minimize electricity consumption and their resultant cost through demand side management (DSM). Universities and similar organizations consume a significant portion of the total generated energy; therefore, in this work, using DSM, we scheduled different appliances of a university campus to reduce the consumed energy cost and the probable peak to average power ratio. We have proposed two nature-inspired algorithms, namely, the multi-verse optimization (MVO) algorithm and the sine-cosine algorithm (SCA), to solve the energy optimization problem. The proposed schemes are implemented on a university campus load, which is divided into two portions, morning session and evening session. Both sessions contain different shiftable and non-shiftable appliances. After scheduling of shiftable appliances using both MVO and SCA techniques, the simulations showed very useful results in terms of energy cost and peak to average ratio reduction, maintaining the desired threshold level between electricity cost and user waiting time.

Keywords: cost minimization; energy management system; multi-verse optimization algorithm; sine-cosine algorithm; smart universities; smart grid; scheduling

1. Introduction

The advent of modern technology has paved the way for efficient and effective utilization of energy resources through smart appliances and applications. It is necessary to utilize the energy resources in a better way using smart appliances in residential, commercial and industrial sectors. Unlike conventional power grids, the smart grid (SG) ensures optimum utilization of energy in a better and affordable way. A SG is actually an intricate structure composed of many sections. An opportunity is offered by the SG's demand side management (DSM) in which the appliances are scheduled according to time-based electricity rates. This is financial motivation which compels the users to shift appliances from peak time slots to off-peak time slots. DSM provides two functionalities: energy management and demand response. Energy management focuses on the intelligent utilization of energy. Demand Response (DR) can be achieved through two programs: incentive based [1] and price based [2]. In incentive-based programs, the utility can wirelessly switch the state of the user's appliance from the on to the off-state by sending a short message to the load unit (LU) or smart building's (SB) energy management controller (EMC) whenever it senses the peak. Thus, in such a way the utility can automatically decrease the peak to average ratio (PAR). In the price-based program, the user is motivated to use their appliances during off-peak hours. If the user shifts appliances to off-peak hours, then as a result, he will be charged less for the single unit and will bring a dramatic decrease in his electricity bill. Actually, there is some kind of trade-off between electricity cost and the user's waiting time. Thus, scheduling can disturb the user comfort if the scheduling is not intelligent. The consumer can decrease the electricity cost, PAR and electricity consumption via interactive relationship between the smart meter (SM) and the utility [3]. According to [4] electricity consumption can be decreased 10%–30% by scheduling of appliances intelligently. It means that scheduling can perform well toward the objective of using energy efficiently. SG also integrates renewable energy resources (RES) and sensors to make the procedure easier and more transparent [5]. RES are used in emergencies and catastrophic situations. A smart meter is basically a platform for the users and utilities to interact via two way communication [6]. The smart Meter (SM) functions as a bridge between the SB or SH and the utility provider. SM sends information to the utility server after some interval of time informing the utility about the running load, previous hour information, etc. DSM was developed in the early 1980s, to balance the varying requirements of the end users and the generation capacities of power systems. After that genetic algorithm (GA) was used for the scheduling of appliances to reduce electricity cost and peak to average ratio (PAR) [7]. But objectives were obtained at the cost of user discomfort. For fulfilling the daily electricity requirement, the smart grid is becoming more and more familiar after every passing day. At the same time, a devoted and worthy electrical power system is very important to satisfy the user's energy demand. There is an utmost need for natural resources and assets. Globally, the main problem is the mismatch between consumer need and utility supply. The smart grid has a very important role in reducing the user's electricity cost; however, it increases consumer frustration in terms of waiting time to switch on their appliances.

Optimization problems can be solved through a natural phenomenon. Mostly, these problems are probabilistic and occur randomly. Some random solution is taken initially for solving a problem. After creating a random solution, it is then collected and passed through some steps. It is approximately the whole design of optimization problems. One algorithm changes from another only how to collect, shift and elaborate the possible solution. For example, particle swarm optimization's [8] inspiration was thinking of birds while flying in the air. It is the responsibility of that bird to fly around that specific area in accordance with its own best position acquired up to that point. The genetic algorithm (GA) [9] uses the concept of might is right. It means that only those entity will survive which are the fittest, and it then collects them depending on their chromosomes.

There are two approaches for solving optimization problems: based on a specific solution, mainly for a single problem, and the residential sector. On the basis of a single solution, first the process is initiated and then passed through some predetermined steps. Those algorithms which are based on a single solution are clear and less compilation is required. However, local optima are disturbed in this case. Additionally, every compilation includes a single solution; there is no information exchange; and the algorithm gives rise to many complications. Those algorithms which are based on residential sector start the procedure by creating random solutions and then enhance their performances. Many well-known algorithms follow this procedure, such as particle swarm optimization (PSO) and ant-colony optimization (ACO). Such algorithms have the benefit of there being a connection among the different solutions. That is why these algorithms are superior to the single based solution and can overcome further consequences. Population based algorithms are very complex and more compilation is required. After too much research it was revealed that single solution algorithms could be replaced by population-based algorithms because of many advantages. Primarily, inspiration is required to initiate an algorithm. An algorithm can be inspired from creature behavior, a natural occurrence or the social behavior of individuals. Different models are then designed to implement an algorithm. In this area the parameters of algorithm are modeled in such a way as to achieve exploration and exploitation in a better way. A best search space must be selected during the exploration phase. For this purpose, it is necessary to equip the algorithm in the best possible manner. Actually, in this phase desirable regions are selected. There should be focus on the targeted area in the exploitation phase. There are no similarities in the exploration and exploitation. They are opposites to each other and cannot be modeled mathematically. It is necessary that the exploration phase occurs first and then exploitation; however, when there exist local optima, then re-exploration of the search space is needed. A problem takes place during changeover from exploration to exploitation in the algorithm plotting. A predefined or specific rule does not exist which defines the transition periods of exploration and exploitation, because they both have different search spaces. Many algorithms have been proposed for the transition between exploration and exploitation evenly. While designing a new algorithm, the designer must give due consideration to challenges discussed above.

Exploration and exploitation are two familiar notions which exist for optimization problems. Exploration is the time in which an algorithm struggles worldwide to find a suitable region. Exploitation is the second phase in which an algorithm finds the best place among those regions, which are selected in the first phase of exploration. In order to get the global optimum, these two must be balanced. It is a need of the current day to make the existing algorithms more efficient or propose new algorithms for solving optimization problems. The optimization field became more famous when the no free lunch algorithm (NFL) [10] was introduced. This theorem has proven that there is no technique that can solve all optimization problems at the same time. The NFL theorem has kept the area open for the researchers; they have been permitted to enhance the existing algorithms or come up with new ideas and then matched the results for further improvement. Here we are proposing two optimization algorithms, the multi-verse optimization (MVO) algorithm and the sine-cosine algorithm (SCA), which are based on population.

The key contributions of this research work are summarized as follows:

1. We have explored and analyzed two new algorithms for energy optimization problem, i.e., MVO and SCA.
2. For analysis and validation of the proposed nature inspired algorithms, we applied these algorithms in a new scenario of university campus for two time sessions of load, morning session and evening session in twenty four hours.
3. Through simulations, we have shown that, the proposed optimization algorithms outperform in terms of minimization of:
    - **(a)** Total energy cost;
    - **(b)** Waiting time of the user appliances;
    - **(c)** Peak to average power ratio (PAR).
4. We integrated renewable energy sources (RESs) for further minimization of total load and its cost.
5. We also used constraints on user appliances' starting times and operation ending times to get maximum comfort level of the end user.
6. We used the day ahead pricing (DAP) electricity pricing signal to make the system practicable.

This paper commences with an introduction followed by relevant literature; in subsequent sections the problem is highlighted and then formulated in a proper way. The next section proposes the methodology by presenting two different algorithms for solving the desired problem. The Simulations and Results section presents the results of our simulated algorithms for the energy management system of smart cities. At the end the paper is a summary, followed by references.

2. Literature Review

In the past few decades, particularly in the last two decades, a lot of work has been carried out on energy optimization. Different algorithms have been developed and deployed successfully in the realm of energy optimization. In all this work, the goals that we want to achieve are the reduction of electrical cost, reduction in PAR and maximized user comfort. All of the algorithms that were used to achieve the objectives showed beneficial results.

Numerous researchers everywhere in the world are exploring various techniques to fulfill the energy demands of consumers by using smart meters (SM). For implementing different optimization techniques and making efficient use of natural resources, various algorithms have been proposed. In [11] with the help of the mixed integer linear programming approach, the authors have suggested a way for balancing the load and minimizing the cost by adopting scheduling methods for residential and populated areas. The prescribed algorithm has efficiently reduced the peak to average ratio and cost. However, they have not given due consideration to user comfort. In [12], mix integer non linear programming is used for reducing both PAR and cost. With this technique they were able to reduce the cost, but PAR was not given any importance. In [13], the authors used meta-heuristic techniques to achieve the objectives mentioned above. They used three meta-heuristic techniques; i.e., the harmony search algorithm (HSA), enhanced differential evolution (EDE) and the bacterial foraging algorithm (BFA) to efficiently utilize the available energy resources. In the end, their results are analyzed. HSA surpasses BFA and EDE in terms of cost. HSA reduced the cost of electricity well in comparison with the other two algorithms and BFA achieved the highest cost. However, the cost of the each individual algorithm is less than the unscheduled cost. The algorithm schedules appliances according to the day ahead pricing (DAP) signal provided by the utility. In every price signal, there are some peaks and dips, designed according to the energy consumption pattern of overall users. Algorithms try to move the user's appliances to off-peak hours where they can enjoy electricity for less per unit compared to occupied hours. It is shown that the maximum energy consumption in the unscheduled case is 12.0750 kWh. After algorithms executed their actions, the new values were 9.0152, 9.4750 and 9.7750 kWh in cases of HAS, EDE and BFA respectively. PAR comparison of algorithms reveals that EDE performed well. BFA did well in terms of user comfort which was assessed using waiting time as an estimating factor.

Some of the researchers also used hybrid techniques by combining the steps of different algorithms to optimize the problem. In [14], the authors used a hybrid version of the genetic algorithm and moth-flame optimization algorithm and proposed the time-constrained genetic moth-flame optimization (TG-MFO) algorithm for achieving better results in terms of cost and PAR reduction. Likewise, in [15], BFA and the genetic algorithm (GA) are used to make a hybrid algorithm for energy optimization. The hybrid algorithm is a merged form of two or more algorithms. Thus, throughout the optimization process, different algorithms will be working inside a coordinated environment. The main focuses of this algorithms are cost minimization, PAR minimization and load balancing on the DSM side. The graph of the cost per day explicated that the price in case of hybrid is less compared to GA and BFA. Using the hybrid approach, 10% of the unscheduled cost is saved. Similarly, the graph of PAR showed that the PAR for BFA is low but the cost is high which shows the trade-off between cost and PAR in BFA and GA. The PAR achieved by hybrid approach is less than that achieved by GA. Thus, regarding PAR, the hybrid approach performed well. Similarly, waiting time response is better in the case of the hybrid approach. In [16], the authors have used the grasshopper optimization algorithm (GOA) and cuckoo search algorithm (CSA) for optimum scheduling of an industry machines, to reduce cost and PAR. They divided the total industry into different load units according to their running operations. The simulation results show that cost and PAR are reduced.

In [17], the authors used the cuckoo search (CS) algorithm to do energy optimization. In this paper, all the parameters that are considered are based on home energy consumption pattern. In this paper, the concept of energy management controller (EMC) is used and it is assumed that each home's appliance can communicate with the EMC. The main focus here is the same as in the previous case. Simulation results showed very beneficial output. The results of CS are compared with GA. Results showed that electricity cost is minimized in both the CS and GA. GA decreases electricity by 12.64% and CS decreases costs by 13.96%. Similarly, PAR reduction in case of GA is 17.41% and in CS

12.94%. We know that technology is progressing very rapidly. In the field of energy, many types of equipment, pieces of machinery, peripherals and measuring devices have been designed. Similarly, in the generation of power, many useful types of machinery have been designed and introduced to the industry that can be used to obtain energy from renewable energy sources. Solar panel and windmills are the leading sources that can generate energy from renewable energy sources. In [18], the authors have used GOA and the bacterial foraging algorithm (BFA) for an efficient energy management system in an office. They scheduled different office appliances to reduce the cost and PAR. In [19], renewable energy sources (RESs) are integrated into the SG system to make the utility more stable, reduce electricity cost and reduce waiting time. SG provides the consumer the opportunity to integrate RESs to play significant role DSM. The authors have used an energy management controller unit (EMCU) to schedule home appliances efficiently and integrate RESs. When results were compared regarding costs, the algorithm that brought about higher costs was the GA, and genetic wind driven optimization (GWDO) showed a lesser value for the cost than all the others. Likewise, in [20–23], the authors proposed DSM models for multiple-home areas. They evaluated the requirements of the project using three algorithm: GA, binary particle swarm optimization (BPSO) and ant colony optimization (ACO). They used the combined form of two pricing schemes: time of use (TOU) and inclined block rate (IBR). EMC was also introduced in this system. Their simulation exposed that in terms of cost and PAR, the genetic algorithm (GA) worked well compared to other two algorithms; i.e., BPSO and ACO. In [24], the authors used a dominance-based evolutionary algorithm for a set of Pareto-optimal solutions of the given problem. They considered economical, environment friendly and user comfortable solutions of the given problem. In [25,26], the authors proposed chance-constrained programming (CCP) for reducing the renewable energy consumption cost. The problem is formulated using mixed-integer linear programming (MILP) by considering the uncertainties in the renewable energy generation. In all these studies, the researchers tried to reduce the energy costs and maximize user comfort.

3. Problem Statement

The essential issues that need to be addressed in power distribution are:

1. Cost minimization;
2. Minimization of the peak to average power ratio (PAR);
3. Minimization of user discomfort in terms of waiting time.

With the rapid increase in the world's population the energy consumption is increasing day by day. The Traditional Grids (TGs) are not enough to fulfill the electricity needs of the modern world. The reason behind this is that TGs are unstable to fulfill this need and require high cost for their regular maintenance. To meet the consumer's need and increase power generation, we must integrate renewable energy sources (RES) to our generation systems and this is not possible in TG. For solving this difficulty, the researchers introduced the concept of the smart grid (SG). The SG is very friendly with the environment. The SG does not pollute the environment; consumes energy efficiently and intelligently among consumers; and does not include extra energy generation from other resources. One advantage of the smart gird is that it can integrate the RES to the generation which fulfills the needs of the people. In SGs, different optimization techniques are used for resolving the issues addressed in the power distribution, which are: multi-verse optimization (MVO) and the sine-cosine algorithm (SCA). We analyzed MOV and SCA and compared their simulation results for a university load units during morning session and evening session.

4. Problem Formulation

4.1. Proposed System Model Architecture

DSM is the entity responsible for the productive and smooth performance of a smart grid. The main function of DSM is the management of energy and controlling of all those activities which take place on consumer side. In this model, we are working on a university campus. Thus, to handle load scheduling in a proper manner, we have divided the university campus load into two sections, morning session and evening session. The morning session is further divided into offices, laboratories, classrooms, lavatories, main halls, a canteen and a library; meanwhile, the evening session consists of a staff hostel, student hostels, a canteen and searchlights, as given in the Table 1.

As is clear from the model, the campus receives a dedicated line from the distribution grid. In our proposed scheme, we assume that the university campus receives a price signal from the utility according to which it schedules its appliances in order to obtain aforementioned objectives. As mentioned earlier, we have divided the campus into blocks. Labs, classes and offices have some non-shiftable appliances, such as fans, tube lights, energy saver lights and exhaust fans. These appliances cannot be shifted from one-time slot to another time slot during scheduling. Similarly, there are some shiftable appliances, such as geysers, exhaust fans, laboratory equipment, tube well water pumps and water coolers. In order to reduce PAR and electricity cost, we have divided the time horizon of 8 h (the morning session time 8 a.m.–4 p.m.) into eight slots, and the evening session time of 16 h (4 p.m.–8 a.m.) in to 16 slots. Shifting of appliances is basically some kind of trade-off between users waiting time and cost. If a user uses an appliance during peak hours then he must pay a lot. Smart meters are allocated in each apartment for hourly computation of power consumption. The smart meters are responsible for exchanging mutual information between the end users and a utility. For example, the price information will be conveyed from the utility side to the user and corresponding energy consumption data will be sent from demand side to utility. A set of appliances is considered $App_n = App_1, App_2, \ldots, App_n$. It is assured that every appliance is able to keep its connection with EMC uninterruptedly, and according to the time slots scheduled for the appliances. It is necessary for every appliance to complete its operation in the given time slot. The time duration of the earliest starting time and the latest finishing time must be followed. We make twenty four (24) time-slots for one day; one slot shows one hour. Our suggested system architecture is shown in Figure 1.

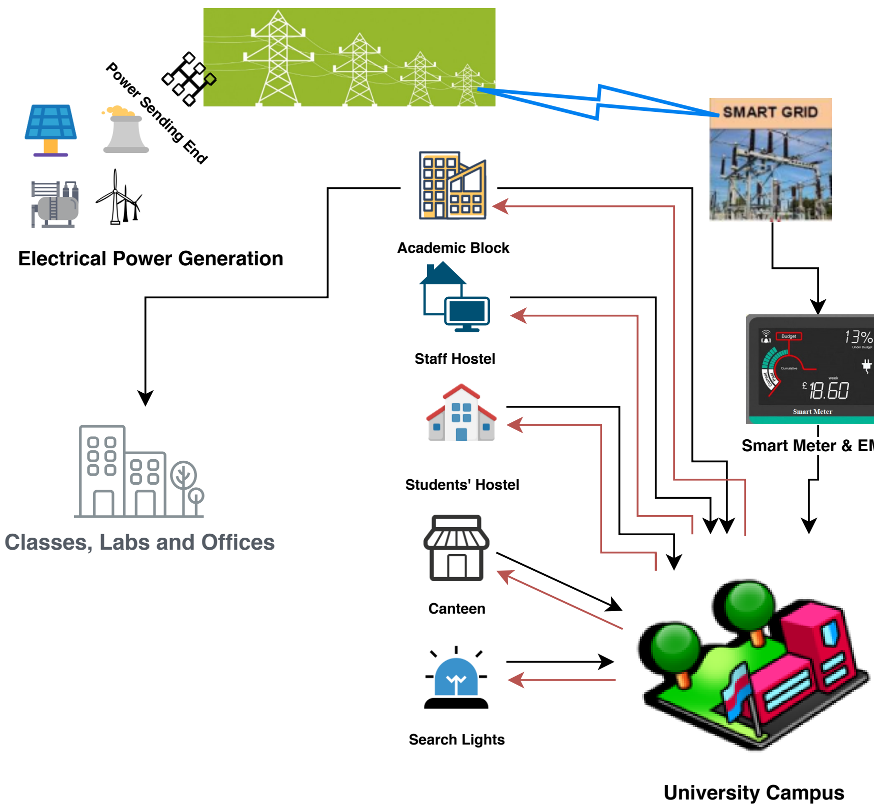


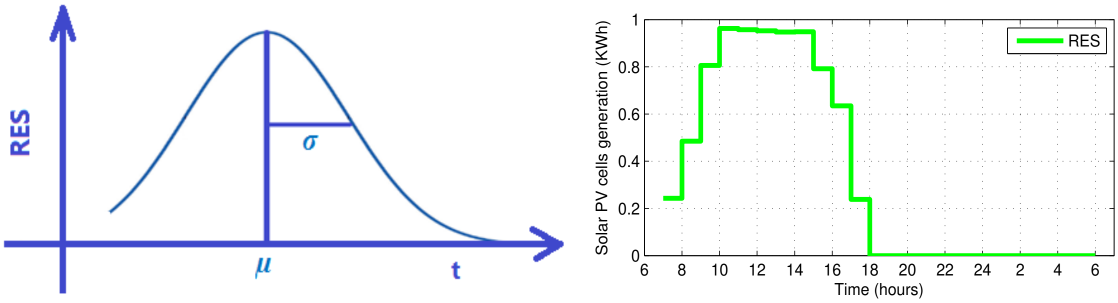
Figure 1. Architecture of our model.

4.2. RES for Generation of Local Energy

Solar PV cells are used for generation of local power to reduce the energy demand and to further reduce the electricity cost. Figure 2a depicts a local Gaussian function, while Figure 2b depicts the approximate PV generated curve used for the calculation of RES energy using Equation (1) as follows:

$$RES(t, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\left(-\frac{(t-\mu)^2}{2\sigma^2}\right)} \tag{1}$$

where t denotes the prospection variable (time), μ is the mean or central value and σ is the standard deviation.



(**a**) (**b**)

Figure 2. (**a**) Gaussian function representing approximate PV cells' renewable energy resources (RES) generation (KWh). (**b**) Approximate RES used for RES energy calculation.

One condition for the RES generated energy is that the total daily-based energy from such sources should be larger than zero.

$$0 \leq RES \leq RES_{(max)} \tag{2}$$

where $RES_{(max)}$ is that RES energy which could be achieved at maximum. If the RES generated energy exceeds the consumer's requirements, then the extra energy is stored in the battery bank for night use. The charging and discharging conditions of the battery bank, i.e., X_{bat}, can be modeled using Equation (3) as follows:

$$X_{bat} = \begin{cases} 1 & \text{for charging} \\ 0 & \text{for discharging} \end{cases} \tag{3}$$

4.3. Load Categorization

In the practical scenario of our proposed system model, we have classified our campus total load into two classes: class A and class B. Class A appliances are named shiftable appliances, and class B appliances are named non-shiftable appliances. Let $App_n = A_s + A_{ns}$, show the set of all appliances, which consists of two classes of appliances, shiftable = A_s and non-shiftable = A_{ns}. These appliances are scheduled in the 24-h time-duration, as follows:

$$t \in T, \forall, T = \{t_1, t_2, t_3, ...t_{24}\} \tag{4}$$

Table 1 depicts the considered load units power rating, starting time, operation finishing time, time-span and time constraints in the form of LOT (length of operational time). LOT of the given load units tells us how much the required time is for completion of its operation. For example, LOT of serial number 1 (offices) is equal to 6 h out of total morning session time slot of 8 h. Thus, for maximum efficiency of the given system, different offices time slots can be shifted with in this time span, as for at least 2 h each faculty member will be in class. Similarly, laboratories and classrooms are alternatively scheduled to minimize the total load and energy cost.

Table 1. Appliances and their constraints.

Time Sessions	Load Units	Power Rating (λ_s) (KW)	Starting Time (T_s)	Finishing Time (T_f)	Time-Span ($T_f - T_s$) (h)	Average LOT (h)
Morning Session	1. Offices	25.38	08	16	8	6
	2. Labs	20.23	08	16	8	4
	3. Classrooms	12.20	08	16	8	4
	4. Library	05.41	08	16	8	8
	5. Main hall	08.24	08	16	8	2
	6. Lavatories	05.30	08	16	8	7
	7. Canteen	10.32	08	16	8	6
Evening Session	1. Staff hostel	33.36	16	08	16	12
	2. Student hostels	31.14	16	08	16	14
	3. Searchlights	10.48	16	08	16	10
	4. Canteen	12.10	16	08	16	12

4.3.1. Shiftable Appliances

Shiftable appliances are those appliances which can be shifted to other time slots during their operation and can be interrupted during the operation. We have placed toasters, TVs, microwave ovens, laptops, ACs, vacuum cleaners, dish washers, washing machines and electric heaters, electric jugs, classroom projectors, different laboratory equipment and water pumps used in the campus in this class. Let a_s show any of these members of class A; i.e., shiftable appliance set; then, mathematically it can be given as follows (Equation (5));

$$a_s \in A_s \tag{5}$$

The entire power usage of shiftable appliances in one day is given by the following equation (Equation (6)):

$$''_s = \sum_{a_s \varepsilon A_s} \left(\sum_{t=1}^{24} \lambda_s \times \alpha_s(t) \right) \tag{6}$$

Here λ_s represents the power rating of each appliance of class A.

Total per day cost of single load unit is given as (Equation (7)):

$$\delta_{a_s}^{Total} = \sum_{a_s \varepsilon A_s} \left(\sum_{t=1}^{24} \lambda_s \times \rho(t) \times \alpha_s(t) \right) \tag{7}$$

Total per day cost of all units is given as (Equation (8)):

$$\varphi_{a_s}^{Total} = \sum_{loadunit=1}^{all} \left[\sum_{a_s \varepsilon A_s} \left(\sum_{t=1}^{24} \lambda_s \times \rho(t) \times \alpha_s(t) \right) \right] \tag{8}$$

where α_s(t) represents the ON/OFF states of shiftable appliances and $\rho(t)$ represents the price of an electrical unit.

4.3.2. Non-Shiftable Appliances

Non-shiftable appliances are those appliances which cannot be shifted nor interrupted from their execution time. Non-shiftable appliances can be switched on in their predefined time slots for the completion of their operations. We placed the refrigerator and interior lighting in the class of non-shiftable appliances. Let a_{ns} show each appliance in the set of non-shiftable appliances. Then, $a_{ns} \in A_{ns}$. The energy consumption of this class can be calculated by the following equation (Equation (9)):

$$\varepsilon_{ns} = \sum_{a_{ns} \varepsilon A_{ns}} \left(\sum_{t=1}^{24} \lambda_{ns} \times \alpha_{ns}(t) \right) \tag{9}$$

Due to the uninterrupted nature of refrigerator and interior lightening, users pay maximum cost, because in the case of non-shiftable appliances the PAR increases very much. For maintaining the balance between energy generation and energy consumption, the utility charges huge prices per unit energy consumption. The cost of one load unit for non-shiftable appliances can be calculated by the following equation (Equation (10)):

$$\delta_{a_{ns}}^{Total} = \sum_{a_{ns} \varepsilon A_{ns}} \left(\sum_{t=1}^{24} \lambda_{ns} \times \rho(t) \times \alpha_{ns}(t) \right) \tag{10}$$

The total per day energy cost of all load units for shiftable appliances can be calculated by the following equation (Equation (11));

$$\varphi_{a_{ns}}^{Total} = \sum_{loadunits=1}^{all} \left[\sum_{a_{ns} \varepsilon A_{ns}} \left(\sum_{t=1}^{24} \lambda_{ns} \times \rho(t) \times \alpha_{ns}(t) \right) \right] \tag{11}$$

where α_{ns}(t) represents the ON/OFF state of non-shiftable appliances and $\rho(t)$ represents the unit price.

4.4. A Consumer's Waiting Time (τ_w)

The consumer's frustration due to the an appliance operational starting time delay is usually undesirable. Therefore, the choice of an algorithm mainly depends on the condition of how this waiting time can be reduced. For this purpose, "time constrains" are set to avoid or at lest minimize user discomfort. Figure 3 shows different solutions of how to divide the time span for achieving our objectives. In the figure, t_1 is the initial time, when a user wants to start an appliance, t_2 is the final time, upto which the operation must be finished, and τ_{LOT} is the total length of operational time (LOT). In this example, we took offices 6 h LOT in the total 8 h time span. Here, 2 h waiting time does not constitute a problem, so the 6 h LOT is divided according to different solutions, as, **a, b, c, d, e or f**. In case of solution **a**, no waiting time is involved. Therefore, the running algorithm checks whether this 6 h slot is economical for the offices' 6 h LOT. If not, then the algorithm will check for other economical solutions. However, the algorithm is confined to schedule the offices' 6 h LOT in the specified 8 h time span.

Now, since,

$$(t_2 - t_1) \geq \tau_{LOT} \tag{12}$$

Therefore, the maximum waiting time could be 2 h in our case. The normalized waiting time of an appliance can be calculated using Equation (13) as follows:

$$\tau_w = \frac{t - t_1}{(t_2 - \tau_{LOT}) - t_1} \tag{13}$$

Equation (13) tells that the range of τ_w can be from "0" (when $t = t_1$) to "1" (when $(t_2 - \tau_{LOT}) = t$).

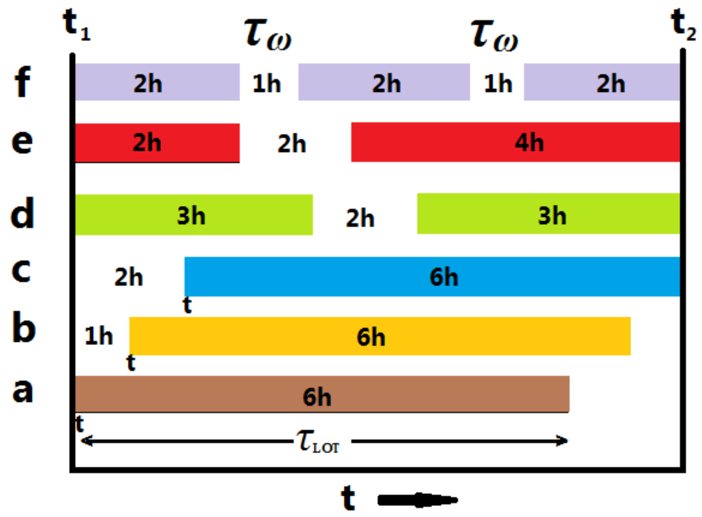


Figure 3. Starting time, waiting time, ending time and length of operational time (LOT).

4.5. PAR

PAR is the ratio of the peak load ($Load_{peak}$) in a given interval of time to the average load ($Load_{avg}$) and can be calculated as follows (Equation (14)):

$$PAR = \frac{Load_{peak}}{Load_{avg}} = \frac{Load_{peak}}{\frac{1}{T}\sum_{n=1}^{T} Load_{t,n}} \tag{14}$$

5. Objective Functions

Three main objectives of this work are summarized as follows:

1. Minimization of consumer's electricity bill;
2. Minimization of consumer's waiting time due to scheduling of their appliances;
3. Minimization of PAR.

The mathematical formulations of our objective functions are given by Equations (15)–(17) respectively as follows:

$$min\left(\varphi_{a_s}^{Total} = \sum_{loadunit=1}^{all} \left[\sum_{a_s \varepsilon A_s} \left(\sum_{t=1}^{24} \lambda_s \times \rho(t) \times \alpha_s(t)\right)\right]\right) \tag{15}$$

$$min\left(\tau_w = \frac{t - t_1}{(t_2 - \tau_{LOT}) - t_1}\right) \tag{16}$$

$$min\left(PAR = \frac{Load_{peak}}{Load_{avg}} = \frac{Load_{peak}}{\frac{1}{T}\sum_{n=1}^{T} Load_{t,n}}\right) \tag{17}$$

6. Proposed Schemes

All the parameters, such as smart meter, smart load units and EMC are interconnected in smart grid. Power station and electricity users remain in contact with each other via an EMC and a SM. For minimizing the cost, users are informed to shift the load from high pricing hours to low pricing hours. Here a problem may occur while shifting the loads, that peaks can be produced in low pricing hours. In the last decade different approaches were made to solve such problems. In this work, we have used two techniques, i.e., MVO and SCA, for solving such issues.

6.1. Multi-Verse Optimizer (MVO)

Inspiration of the Multi-Verse Theory:

According to the big bang theory [27], the evolution of the universe occurred due to a huge explosion. According to the stated theory, there was not even a single creature in the world. The big bang is the reason for the existence of all the things in the world. Physicists have proposed a new and famous theory called multi-verse [28]. It is stated in the multi-verse theory that not only did a single big bang take place, but many big bangs occurred and each one give birth to a new universe. It is concluded that many other universes also exist other than our universe [29]. There also exists the probability that these different universes may strike one another. In this paper, we take white holes, black holes and wormholes as inspiration for solving the optimization problem. It is believed that the white holes are the main factor for the origin of the universe, and they have actually never been observed. The white hole itself is claimed as a big bang. When two concurrent universes collide with each other, they originate a big bang. White holes are totally different from black holes. The property of the black hole is that it drags every little thing towards itself with its immense gravitational force. Different universes remain in contact with each other due to worm holes. In the theory of multi verse worm holes are responsible for moving objects from one universe to another, or within the same universe. The universe is expanded in the space due to its constant rate called inflation. Meanwhile, when constructing different bodies such as planets and stars, the rapidness of inflation rate is necessary. For attaining a balanced condition in the different universes, it is necessary for them to remain in contact through black, white and wormholes.

MVO algorithm should follow these rules for optimization.

1. White holes will exist in large quantities, if the rate of inflation is high.
2. If the rate of inflation is higher, black holes existing will be unlikely.
3. Objects will be sent via white holes if the inflation rate of the universe is high.
4. Objects will be received via black holes if the inflation rate of the universe is low.
5. Without considering the inflation rate, objects can move to the best universe via wormholes randomly.

When adopting the roulette wheel mechanism, all the terms like black holes, white holes and tunnels can be modeled mathematically. We arrange the universes at each iteration for selecting white hole through the roulette wheel mechanism. We will perform below steps to implement our work. Assume that

$$Y = \begin{pmatrix} x_1^1 & x_1^2 \ldots & x_1^s \\ x_2^1 & x_2^2 \ldots & x_2^s \\ \vdots & \vdots & \vdots \\ x_n^1 & x_n^2 \ldots & x_n^s \end{pmatrix} \tag{18}$$

where "s" shows the no of parameters, while n indicates the number of universes.

$$x_i^j = \begin{pmatrix} x_k^j & r_1 \leq NI(YI) \\ x_i^j & r_1 \geq NI(YI) \end{pmatrix} \tag{19}$$

In this case, the j_{th} term of the i_{th} universe is represented by x_i^j, the i_{th} universe is indicated by YI, the normalized inflation rate is shown by $NI(YI)$, r_1 is produced randomly, it can be either 0 or 1, while, j_{th} term of the k_{th} universe is represented by x_k^j.

The selection procedure of white holes is dependent on inflation and is performed through roulette wheel mechanism. If the rate of inflation is high, there will be a higher probability to send objects via the white or the black hole tunnels. It should be noted that for maximization problems, $-NI$ and NI can be interchanged. Using this technique exploration can be confirmed, as the universes need to transfer objects and deal with sudden variation so that one can explore the search space. For making changes locally in a universe while keeping the probability high of enhancing the inflation rate through wormholes, we assume the wormhole channels are fixed between best and the new universe. Following are the steps for implementing this technique.

$$x_i^j = \begin{cases} \begin{cases} X_j + TDR \times ((ub_j - lb_j) \times r_4 + lb_j) & \text{r3} < 0.5\ ,\ \text{r2} < \text{WEP} \\ X_j - TDR \times ((ub_j - lb_j) \times r_4 + lb_j) & \text{r3} \geq 0.5\ ,\ \text{r2} \geq \text{WEP} \end{cases} \\ x_i^j \end{cases} \tag{20}$$

X_j is the j_{th} term of the best universe produced up to now; TDR and WEP are the two coefficients; lb_j and ub_j indicate the lower and upper bounds respectively; r2, r3 and r_4 appear randomly which may be 1 or 0.

Traveling distance rate (TDR) and the wormholes-existing probability (WEP) are two prime coefficients. WEP must be increased linearly during optimization. TDR tells us about the object which is deported by the wormhole to the best universe.

Mathematically, WEP and TDR are given as follows (Equation (21)):

$$WEP = \min + l \times \left(\frac{\max - \min}{L} \right) \tag{21}$$

We have kept the value of min = 0.2 in this paper; max = 1, l is the recent iteration; and L indicates max iterations.

$$TDR = 1 - \frac{l^{1/p}}{L^{1/p}} \tag{22}$$

In this paper we have kept the value of p equal to 6 and it shows the accuracy of exploitation. Algorithm 1 shows the stepwise process, whereas Figure 4 depicts the step by step process of the proposed (MVO) algorithm via a flow chart.

Algorithm 1: Pseudocode of the proposed multi-verse optimization algorithm

```
Parameters initialization: WEP, TDR, maximum size of the pop. , number of iterations etc.
 Input: DAP (ρ(t)), λ_s, λ_ns, T_s, T_f Specify LOTs for all machines Specify power ratings of all
 appliances in a load unit while Numbers of iterations < population size do
    for i =1: X do
        for j =1: Y do
        end
        Find used-energy price Evaluate the price of all LOTs for consumer smart appliances in
          a load unit Evaluate P_best Assign P_best to L_best New solution is evaluated Update LOTs
          of appliances Find P_best and L_best Assign L_best to G_best
    end
end
Output: φ_{a_s}^{Total}, PAR
```

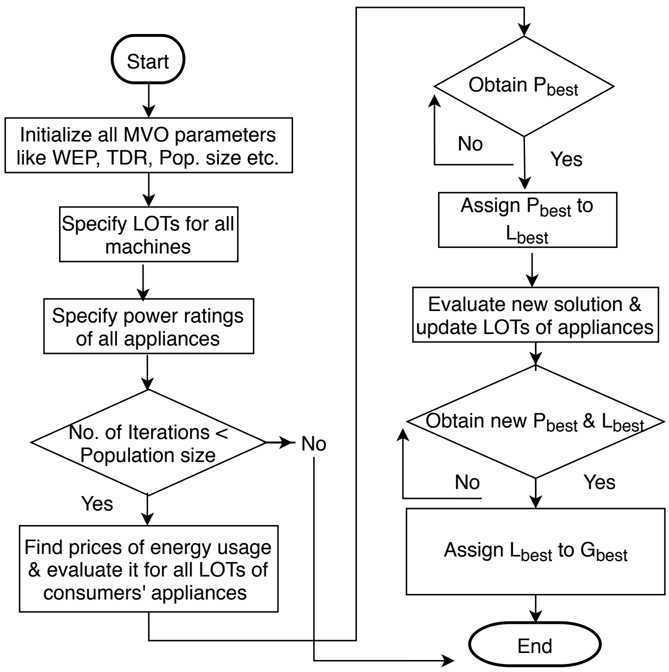


Figure 4. MVO algorithm step by step process/flow chart.

6.2. Sine-Cosine Algorithm (SCA)

We are working on a university campus solution. For that, we have divided the campus into sections—an academic block, a hostel, a staff hostel, a canteen and searchlights, to deal with each block separately. Each block is treated as a smart building (SB). A smart building is connected to the EMC and EMC is further connected to the smart meter (SM). SM establishes the connection with the SG. In this study, we propose that each section of the campus will be connected to separate EMC. EMC automatically schedules all shiftable appliances, while a smart meter establishes a two-way link between SG and SB. Thus, to utilize energy efficiently on the campus and to make the electricity cost per month minimal, and to reduce PAR, we used the population-based optimization algorithm called the sine cosine algorithm (SCA). We took electricity cost and PAR our main objectives keeping user discomfort within the threshold. SCA uses sine and cosine functions to move and fluctuate the random candidate solution towards the best solution. Several other parameters and variables can be integrated into this algorithm to make the search for the optimal solution easier, faster, more accurate and more precise. According to [30], SCA is able to explore the different regions of search space, avoid local optima and converge toward the global optimum. Initially, the SCA algorithm proposes a set of the random candidate solution. After that, through iterations, the algorithms try to improve those randomly selected solutions. As we know that the population-based algorithms move towards the optima stochastically, so there is no information about the iteration number in which optima will occur. However, by increasing the number of search agents and iterations, the probability of success increases. In our study, we used the following position updating equations (Equations (23) and (24)):

$$X_i^{t+1} = X_i^t + r_1 \sin(r_2) \times \left| r_3 p_i^t - X_i^t \right| \tag{23}$$

$$X_i^{t+1} = X_i^t + r_1 \cos(r_2) \times \left| r_3 p_i^t - X_{ii}^t \right| \tag{24}$$

A random number r_4 will be generated with values [0 1]. The value of r_4 will decide to choose which one of the above two equations will be operated. Thus, r_4 is basically a switching parameter between the sine and cosine functions. The remaining three parameters r_1 , r_2 and r_3 basically dictate SCA to the different regions of search. The parameter r_1 dictates the movement direction, while r_2 specifies the overall span of the movement. In the above positioning updating equations, X_i^t is the position of the current solution in i_{th} dimension at t_{th} iteration. P_i is the position of the destination point in i_{th} dimensions. In SCA we initially define the number of iterations. During each iteration the randomly selected candidate solution set is improved. At the last iteration the best value is returned. If the algorithm delays a particular appliance, it may disturb the classes, offices and laboratories. Thus, to make the algorithm more intelligent, we integrated some constraints into the algorithm to start and finish the operation with in the specified interval.

7. Results and Discussion

Our proposed algorithms MVO and SCA showed very useful results in terms of either cost or PAR reduction or both. As mentioned earlier, appliances have been divided into two categories based on their operational nature, shiftable or non-shiftable. The detail discussions of each result is given as follows:

7.1. Pricing Signal

The day ahead pricing (DAP) signal (Figure 5), issued by the utility [31], is reproduced and used for the manipulation of consumed energy bill. SM is responsible for the communication of this DAP signal to a consumer. There are many national and international energy providing operators in the world. They issue a new and updated unit pricing signal every day which contains 24 different price values for 24 h. This feature of SM may become beneficial for both users and the utility. Due to rise and fall in RTP unit price, users modify their daily needs according to the RTP. The SM feeds the DAP to the EMC, while, EMC schedule appliances according to the proposed algorithm.

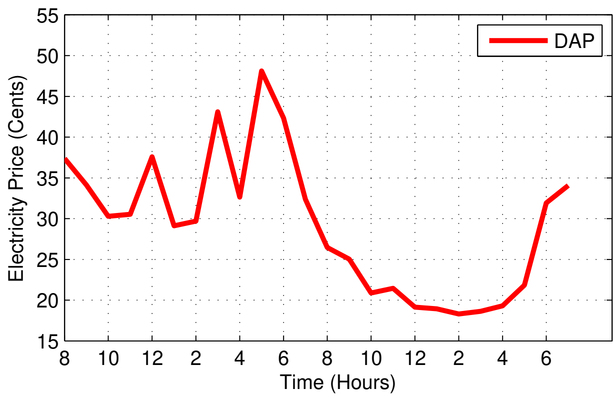


Figure 5. Day-ahead pricing (DAP) signal [31].

7.2. Per Hour Power Consumption

Figure 6 shows the graph of hourly power consumed by different load units of the campus. The consumption pattern shows that in the unscheduled case, more power is consumed with high demand timing, thereby creating the peak load. After the scheduling of the load through algorithms, power consumption in high demand timing is shifted to low-demand hours. From the graph it is clear that the MVO-scheduled load pattern is a bit uniform and is low during high price hours, as per the DAP signal shown in the Figure 5. Figure 6 depicts that, SCA-scheduled load pattern shows a bit of a variable response. The load is not totally shifted from high price hours; however, both algorithms have reduced the PAR in the morning session.

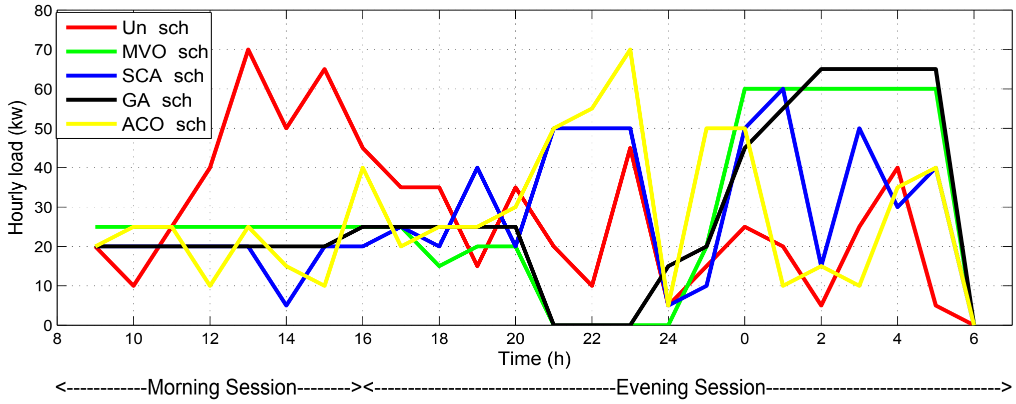


Figure 6. Hourly load.

7.3. The Hourly Consumed Energy Price

Figure 7 elaborates the graph of per hour consumed energy price. The result illustrates that in unscheduled case, the company has to pay more because the peak load is created in peak hours. In the scheduled-load case, the load is shifted from the timing of high load demand to low demand hours, and thus reduces the cost per hour. MVO-scheduled load per hour cost is again a bit uniform due to its load pattern, and gives a reduced total cost, as is shown in Figure 8. However, due to the variable nature of the SCA-scheduled load pattern, its total cost is a bit more than MVO-scheduled load cost, but still it is less than unscheduled load cost.

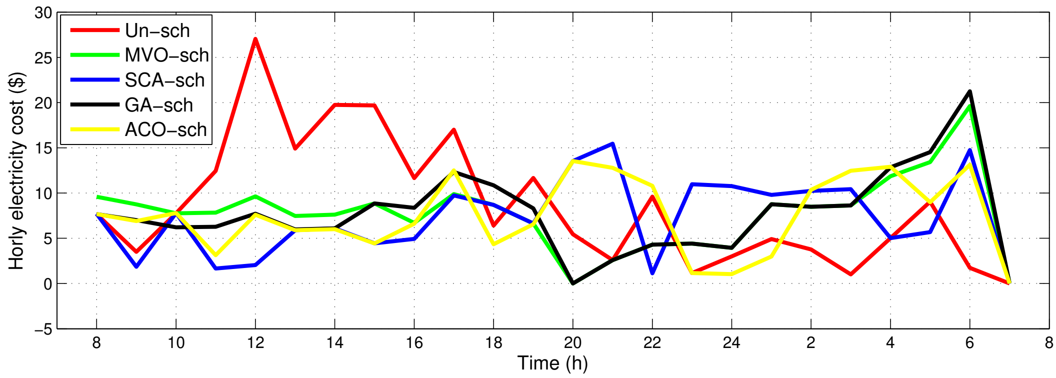


Figure 7. Hourly consumed energy price.

7.4. The Total Electricity Cost

Figure 8 shows the electricity cost for the unscheduled and scheduled (with MVO, SCA, GA, and ACO) loads. The results show that the electricity cost of the meta-heuristic algorithm-based scheduled load is very low compared to the unscheduled load cost. In Figure 8a, the operation of morning session of the campus for a single day is considered. In this case, MVO-based scheduling shows better results compared to all scheduled and unscheduled costs. Similarly, in Figure 8b the operation of evening session of the campus for a single day is considered. In this case, MVO has reduced it compared to all scheduling techniques, except GA.

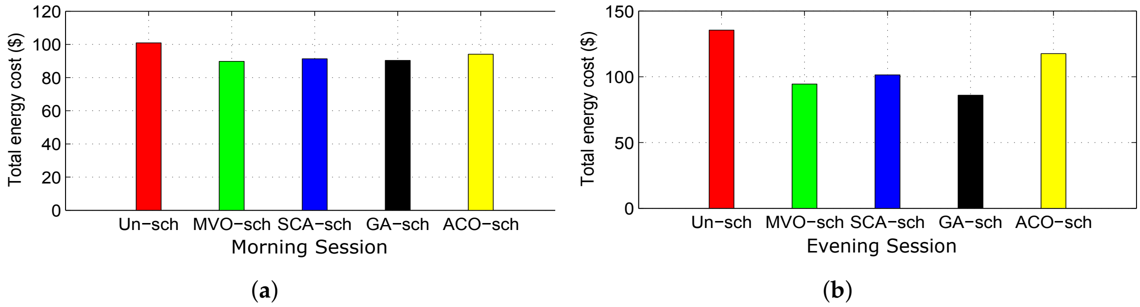


Figure 8. Total cost for un-scheduled load and scheduled with MVO, SCA, GA and ACO algorithms. (**a**) Total cost for morning session of the campus for 1 day. (**b**) Total cost for evening session of the campus for 1 day.

7.5. PAR

Figure 9 shows PAR results, which show the stability of a grid. When the PAR value increases or decreases, it affects the stability of a grid. Due to the reduction in cost, PAR is not reduced. MVO-scheduled load reduces the PAR, as for an unscheduled load, all scheduling techniques considered in this work do. The figure also depicts a comparison of the proposed algorithm's PAR with the most modernistic optimization algorithms, such as GA and ACO. However, using the same scenario, the MVO-scheduled load PAR is the least out of all the algorithms.

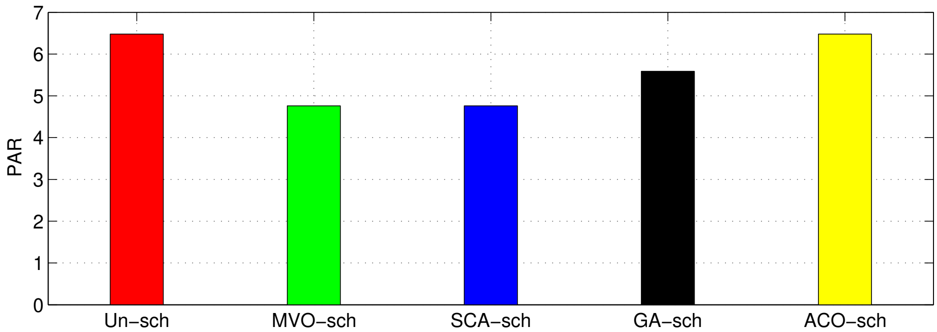


Figure 9. Peak to average ratio (PAR).

7.6. Waiting Time

Figure 10 shows the average waiting times of machines for each technique. It is that time interval wherein a consumer switches on an appliance, but due to scheduling for the reduction of cost, the appliance does not start. Thus, the consumer has to wait for a specific amount of time T_w. The figure shows that the waiting time of MVO is very much less compared to SCA. It shows that MVO has not reduced the cost too much; however, it has far less waiting time in the morning session of the campus load. In case of evening session, MVO is not too good. In this case, SCA showed better results compared to all techniques. Thus, for those consumers who want to reduce their waiting time, SCA-scheduling is good. Figure 10 also depicts a comparison of the proposed algorithms with GA and ACO algorithms. SCA gives better results in the case of waiting time.

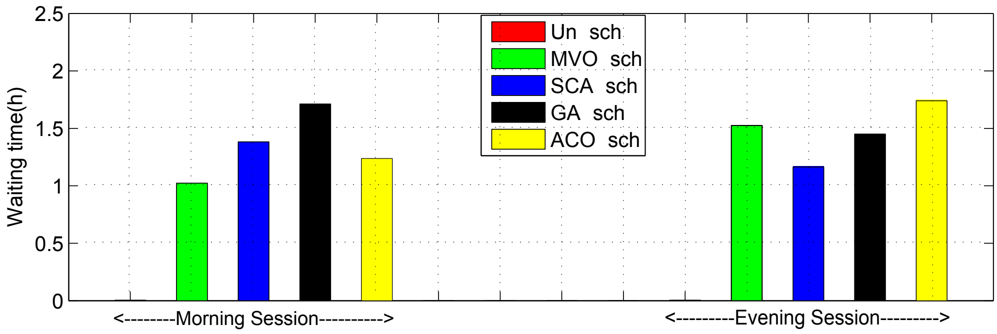


Figure 10. Waiting time.

7.7. The Total Daily Average Load

Figure 11 shows that the total daily average load is the same in the case of unscheduled and scheduled with different algorithms. It is clear from the figure that, irrespective of the scheduling algorithms, the total daily load remains the same. Scheduling algorithms only shift the load to low cost or low demand hours; however, they do not reduce the total daily load of the campus.

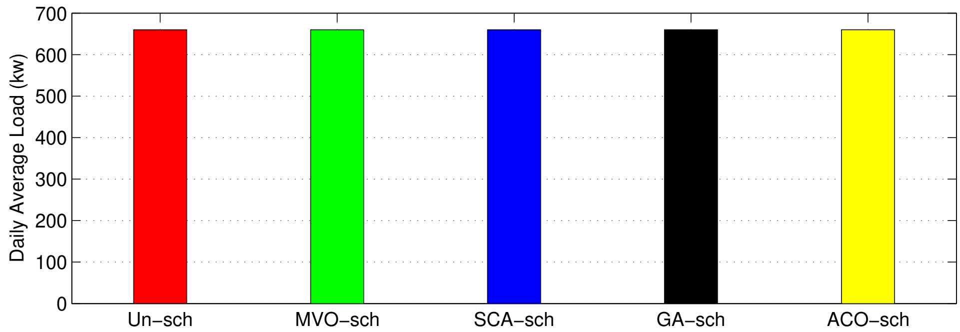


Figure 11. The total daily average load.

7.8. Hourly Power Demand with and without RES

Figure 12 depicts the unscheduled load curve along with the generated RES and battery bank charging and discharging. It is clear from the figure that the extra stored energy is used during night time to further reduce the electricity cost.

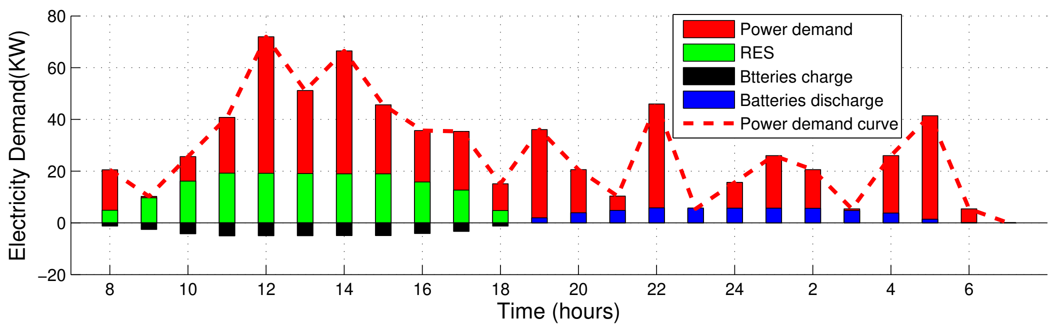


Figure 12. Unscheduled load with renewable energy sources and the battery bank.

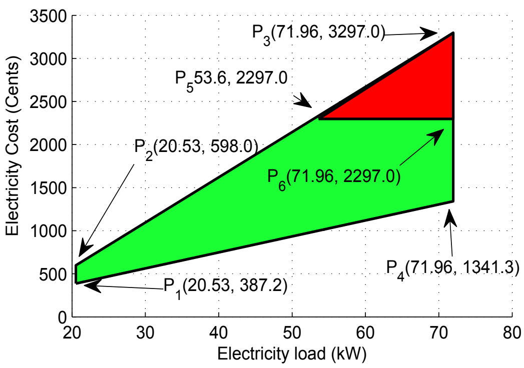
Table 2 depicts a comparison of the proposed algorithms with the unscheduled load in terms of minimization of consumed energy price, PAR and average user wait time. A comparison of the proposed algorithms with recently applied algorithms like GA and ACO algorithms is also shown in the table.

Table 2. An evaluation of the anticipated algorithm for appliance scheduling in terms of unscheduled load and scheduled load with MVO, SCA, GA and ACO algorithms.

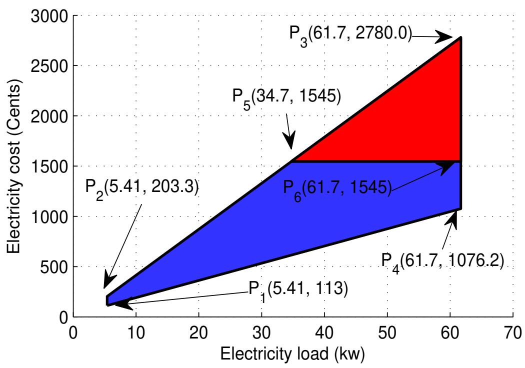
Time Sessions	Techniques	Cost ($)	Cost Reduction	PAR	PAR Reduction	Waiting Time (h)
Morning Session	Un-scheduled	101.32	–	6.49	–	–
	MVO-scheduled	88.47	12.68%	4.73	27.11%	1.01
	SCA-scheduled	90.03	11.14%	4.73	27.11%	1.37
	GA-scheduled	88.71	12.44%	5.52	14.94%	1.69
	ACO-scheduled	93.24	07.97%	6.49	0.0%	1.22
Evening Session	Un-scheduled	131.41	–	6.49	–	–
	MVO-scheduled	89.39	31.98%	4.73	27.11%	1.52
	SCA-scheduled	102.16	22.26%	4.73	27.11%	1.18
	GA-scheduled	77.53	41.00%	5.52	14.94%	1.42
	ACO-scheduled	121.49	07.55%	6.49	0.0%	1.71

7.9. Feasible Regions

A feasible region is a set of all possible points. Due to the scheduling of the load, cost minimization is decided on the bases of the pricing signal issued by the utility, using different algorithms. We have considered the DAP signal for our calculations. Figure 13a shows the feasible region for the MVO algorithm. Point P_1(20.53, 387.2) gives the minimum load with minimum cost, and point P_2(20.53, 598.0) gives the minimum load with maximum cost in any interval of time. It usually happens when the minimum load is running in peak hours with high energy cost. Similarly, point P_3(71.96, 3297.0) gives the maximum load with maximum cost in the case of the unscheduled load. Point P_4(71.96, 1341.3) gives the maximum load during off peak hours with minimum cost. P_5(53.6, 2297.0) puts a threshold on the maximum cost after scheduling with MVO. It continues until point P_6 (71.96, 2297.0) is reached, which gives a point of the maximum load with reduced cost. Figure 13b shows all these points for SCA scheduling. It is clear from these figures that SCA performs better compared to MVO in the case of cost minimization.



(**a**)



(**b**)

Figure 13. Feasible regions. (**a**) Feasible region for the MVO-scheduled load; (**b**) feasible region for the SCA-scheduled load.

Table 3 depicts the computational times of the proposed algorithms, MVO and SCA, using an Intel (R) Core (TM) i5 processor, with 4.00 GB of installed memory (RAM) and the 32-bit Windows 7 Operating system.

Table 3. Computational times of the proposed multi-verse optimization (MVO) algorithm and the sine-cosine algorithm (SCA) for load scheduling.

Proposed Algorithm	Computational Time (s)
MVO	19.183
SCA	17.271

8. Conclusions, Challenges and Future Work

Demand side management strategy for the energy optimization problem has been addressed in this work. The electrical load of the university is divided into various units of (electrical) load for which two bio-inspired algorithms, i.e., MVO and SCA, have been proposed and applied (practically). The function of these algorithms was to schedule the shiftable appliances as per the pricing (i.e., day ahead pricing) signal provided by the electricity suppliers. The performance of the proposed schemes was compared to the unscheduled load, which is judged on the basis of PAR, total energy consumption, cost and users' comfort (in terms of time to wait). Moreover the performances of well-known algorithms, i.e., GA and ACO, have been compared with our proposed solution and it could be seen from the results that our proposed algorithms efficiently minimized the price of energy consumption without disturbing their operation, via shifting of some load to certain low-demand hours. This in-turn reduces the PAR and maximizes user comfort, which causes in reduction of burden over the utilities.

Due to the random number generation at the beginning, and the stochastic nature of the bio-inspired algorithms, every time the algorithm runs, it will give a new solution. Therefore, an infinite number of solutions is possible, as in each iteration, the algorithms look for local best, and then assign that best solution to the previous one achieved and store the global best solution if applied. Therefore, the performance of an algorithm is measured upon taking an average of more than ten (10) repetitions in different consumer scenarios. Based on this strategy, the proposed algorithms may take more time. In future, other, better techniques and methodologies will be adopted for commercial, residential and educational sectors by using some other bio-inspired algorithms; moreover, renewable energy sources will be encountered for further reduction in peak-to-average ratio (PAR) and energy prices.

Author Contributions: I.U. and I.H. designed the system model and wrote the manuscript; I.U. and I.H. did the editing; M.R. and M.N.K. developed the methodology; J.L. and P.U. technically supervised the whole work. All of the authors equally contributed, edited, revised and approved the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: The authors would like to thank Suranaree University of Technology, for supporting this work from SUT Research and Development Funds.

Acknowledgments: The authors are extremely thankful to Suranaree University of Technology and Govt. of Thailand for it's esteemed support.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Avci, M.; Erkoc, M.; Rahmani, A.; Asfour, S. Model predictive hvac load control in buildings using real-time electricity pricing. *Energy Build.* **2013**, *60*, 199–209. [CrossRef]
2. Yang, J.; Zhang, G.; Ma, K. Matching supply with demand: A power control and real time pricing approach. *Int. J. Electr. Power Energy Syst.* **2014**, *61*, 111–117. [CrossRef]
3. Hu, W.; Chen, Z.; Bak-Jensen, B. Optimal operation strategy of battery energy storage system to real-time electricity price in Denmark. In Proceedings of the Power and Energy Society General Meeting, Providence, RI, USA, 25–29 July 2010; pp. 1–7.
4. Tascikaraoglu, A.; Boynuegri, A.; Uzunoglu, M. A demand side management strategy based on forecasting of residential renewable sources: A smart home system in turkey. *Energy Build.* **2014**, *80*, 309–320. [CrossRef]

5. Logenthiran, T.; Srinivasan, D.; Shun, T.Z. Demand side manage- ment in smart grid using heuristic optimization. *IEEE Trans. Smart Grid* **2012**, *3*, 1244–1252. [CrossRef]
6. Saad, W.; Han, Z.; Poor, H.V.; Basar, T. Game-theoretic methods for the smart grid: An overview of microgrid systems, demand-side management, and smart grid communications. *IEEE Signal Process. Mag.* **2012**, *29*, 86–105. [CrossRef]
7. Zhao, Z.; Lee, W.C.; Shin, Y.; Song, K.-B. An optimal power scheduling method for demand response in home energy management system. *IEEE Trans. Smart Grid* **2013**, *4*, 1391–1400. [CrossRef]
8. Kennedy, J.; Eberhart, R.C. Particle swarm optimization. In Proceedings of the ICNN'95-International Conference on Neural Networks, Perth, Australia, 27 November–1 December 1995; IEEE Service Center: Piscataway, NJ, USA, 1995; Volume IV, pp. 1942–1948; .
9. John, H. *Holland, Adaptation in Natural and Artificial Systems*; MIT Press: Cambridge, UK, 1992.
10. Wolpert, D.H.; Macready, W.G. No Free Lunch Theorems for Optimization. *IEEE Trans. Evolut. Comput.* **1997**, *1*, 67. [CrossRef]
11. Naraharisetti, P.K.; Karimi, I.A.; Anand, A.; Lee, D. A linear diversity constraint application to scheduling in microgrids. *Energy* **2011**, *36*, 4235–4243. [CrossRef]
12. Huang, Y.; Tian, H.; Wang, L. Demand response for home energy management system. *Int. J. Electr. Power Energy Syst.* **2015**, *73*, 448–455. [CrossRef]
13. Irshad; Aamir; Ullah, I.; Khan, N.; Riaz, M. Reliable and Secure Advanced Metering Infrastructure for Smart Grid Network. In Proceedings of the 2018 International Conference on Computing, Electronic and Electrical Engineering (ICE Cube), Quetta, Pakistan, 12–13 November 2018; pp. 1–6, 10.1109/ICECUBE.2018.8610995. [CrossRef]
14. Ullah, I.; Hussain, S. Time-Constrained Nature-Inspired Optimization Algorithms for an Efficient Energy Management System in Smart Homes and Buildings. *Appl. Sci.* **2019**, *9*, 792. [CrossRef]
15. Khalid, A.; Javaid, N.; Mateen, A.; Khalid, B.; Khan, Z.A.; Qasim, U. Demand Side Management Using Hybrid Bacterial Foraging and Genetic Algorithm Optimization Techniques. In Proceedings of the 2016 10th International Conference on Complex, Intelligent, and Software Intensive Systems (CISIS), Fukuoka, Janpan, 6–8 July 2016; pp. 494–502.
16. Ullah, I.; Hussain, I.; Singh, M. Exploiting Grasshopper and Cuckoo Search Bio-Inspired Optimization Algorithms for Industrial Energy Management System: Smart Industries. *Electronics* **2020**, *9*, 105. [CrossRef]
17. Aslam, S.; Bukhsh, R.; Khalid, A.; Javaid, N.; Ullah, I. An Efficient Home Energy Management Scheme Using Cuckoo Search. In *Advances on P2P, Parallel, Grid, Cloud and Internet Computing*; Springer International Publishing: Cham, Switzerland, 2018; pp. 167–178.
18. Ullah, I.; Khitab, Z.; Khan, M.N.; Hussain, S. An Efficient Energy Management in Office Using Bio-Inspired Energy Optimization Algorithms. *Processes* **2019**, *7*, 142. [CrossRef]
19. Javaid, N.; Hafeez, G.; Iqbal, S.; Alrajeh, N.; Alabed, M.S.; Guizani, M. Energy Efficient Integration of Renewable Energy Sources in the Smart Grid for Demand Side Management. *IEEE Access* **2018**, *6*, 77077–77096. [CrossRef]
20. Hussain, I.; Ullah, M.; Ullah, I.; Bibi, A.; Naeem, M.; Singh, M.; Singh, A.D. Optimizing Energy Consumption in the Home Energy Management System via a Bio-Inspired Dragonfly Algorithm and the Genetic Algorithm. *Electronics* **2020**, *9*, 406. [CrossRef]
21. Hernández, L.; Baladrón, C.; Aguiar, J.M.; Calavia, L.; Carro, B.; Sánchez-Esguevillas, A.; Sanjuán, J.; González, Á.; Lloret, J. Improved short-term load forecasting based on two-stage predictions with artificial neural networks in a microgrid environment. *Energies* **2013**, *6*, 4489–4507. [CrossRef]
22. Hernández, L.; Baladrón, C.; Aguiar, J.M.; Calavia, L.; Carro, B.; Sánchez-Esguevillas, A.; García, P.; Lloret, J. Experimental analysis of the input variables' relevance to forecast next day's aggregated electric demand using neural networks. *Energies* **2013**, *6*, 2927–2948. [CrossRef]
23. Hernandez, L.; Baladron, C.; Aguiar, J.M.; Calavia, L.; Carro, B.; Sanchez-Esguevillas, A.; Perez, F.; Fernandez, A.; Lloret, J. Artificial Neural Network for Short-Term Load Forecasting in Distribution Systems. *Energies* **2014**, *7*, 1576–1598. [CrossRef]
24. Li, Y.; Yang, Z.; Zhao, D.; Lei, H.; Cui, B.; Li, S. Incorporating energy storage and user experience in isolated microgrid dispatch using a multi-objective model. *IET Renew. Power Gener.* **2019**, *13*, 973–981. [CrossRef]

25. Li, Y.; Wang, C.; Li, G.; Wang, J.; Zhao, D.; Chen, C. Improving operational flexibility of integrated energy system with uncertain renewable generations considering thermal inertia of buildings. *Energy Convers. Manag.* **2020**, *207*, 112526. [CrossRef]
26. Monteiro, C.; Santos, T.; Jimenez, L.A.F.; Rosado, I.J.R.; Olarte, M.S.T. Short-Term Power Forecasting Model for Photovoltaic Plants based on Historical Similarity. *Energies* **2013**, *6*, 2624–2643. [CrossRef]
27. Mirjalili, S.; Mirjalili, S.M.; Hatamlou, A. Multi-Verse Optimizer: A nature-inspired algorithm for global optimization. *Neural Comput. Appl.* **2016**, *27*, 495–513. [CrossRef]
28. Khoury, J.; Ovrut, B.A.; Seiberg, N.; Steinhardt, P.J.; Turok, N. From big crunch to big bang. *Phys. Rev. D* **2002**, *65*, 086007. [CrossRef]
29. Tegmark, M. Parallel universes. In *Science and Ultimate Reality: Quantum Theory, Cosmology, and Complexity*; Barrow, J.D., Davies, P.C.W., Harper, C.L., Jr., Eds.; Cambridge University Press: Cambridge, UK, 2004; pp. 459–491.
30. Mirjalili, S. Sca: A sine cosine algorithm for solving optimization problems. *Knowl.-Based Syst.* **2016**, *96*, 120–133. [CrossRef]
31. Day-Ahead Pricing (DAP). NYISO (New York Independent System Operator). Available online: http://http://www.energyonline.com/Data/GenericData.aspx?DataId=2&ISO-NE___Day-Ahead_Energy_Price (accessed on 7 January 2020).