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Load Scheduling of Smart Net-Zero Residential Buildings Based on Pandemic Situation

S. M. Mahfuz Alam [1] and Mohd. Hasan Ali [2,*]

[1] Department of EEE, Dhaka University of Engineering & Technology (DUET), Gazipur 1707, Bangladesh; mahfuz@duet.ac.bd
[2] Department of ECE, The University of Memphis, Memphis, TN 38152, USA
* Correspondence: mhali@memphis.edu

Abstract: Load scheduling is an effective way of utilizing loads of smart residential buildings according to the preferences of the inhabitants or grid demands, while reducing the cost of energy. This work proposes objective functions for load scheduling to confine the cost of energy within the consumers' preference range while keeping the load consumption closer to the load demand as possible, to minimize system loss during normal and pandemic condition such as COVID-19 periods, fulfilling the unique features of a net-zero energy building. The proposed objective function is implemented by considering the realistic grid power cost, levelized cost of renewable sources, battery, and incentives offered by the utility system existing in California, USA. In addition to three different types of days such as normal working days, weekends and pandemic situations, brown out power outages are considered as operating conditions. Particle swarm optimization (PSO) is utilized in all considered operating conditions. Two terms that account for the total energy cost savings and the total delayed/scheduled load over a fixed time horizon are formulated as performance indices to illustrate the effectiveness of the proposed objective functions for load scheduling. All of the cases are optimized by the Paticle Swarm Optimization (PSO) and non-optimized systems are simulated in the MATLAB environment. It is evident from the simulation results that the proposed objective function is very efficient in tackling the energy resources, loads and grid power to maximize cost savings and minimize shifting of loads for later hours for normal and pandemic situations in net-zero energy buildings. Moreover, it is equally effective in responding to any emergency situations such as brown out energy crisis situations, which are not considered in the literature so far. In all cases, the performance index also validates the effectiveness of the proposed objective function-based scheduling system for net-zero energy buildings.

Keywords: battery energy storage; load scheduling; renewable energy sources; COVID-19

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1. Introduction

Residential buildings consume almost 30–40% of the total energy production in the world [1]. With advancements in technology, the consumers' comfort demands have been continuously increasing over the last decade, which have also been the reason behind the increase in residential power consumption. The increase in residential power puts a huge burden on the grid system as it is responsible for delivering power along with ensuring safety, stability, and reliability. The installation of renewable energy sources such as solar, wind, etc., in residence, and implementation of demand-side management (DSM) can be prominent solutions to this problem. Driven by this fact, the department of energy (DoE), USA has been encouraging the installation of renewable energy sources in buildings. It has also been offering incentives to encourage consumers to participate in demand response in terms of load scheduling according to the grid demands or electricity price [2].

Load scheduling is a key element for the DSM system to actively participate in the demand response program. It also ensures the effective utilization of residential load to increase the efficiency of the system, minimization of the energy cost while maintaining the consumers' comfort demand to the utmost levels. It also helps the grid provide power with minimum energy source utilization during peak power [3]. Therefore, different scheduling schemes have been proposed in the literature. Among them, the load scheduling to reduce the energy cost has been most popular [1,4–8].

The second type of scheduling for residential building, that is found in the literature, is facilitated with both grid power and battery energy storage [9–11]. In this case, a hybrid electric vehicle can be considered as a battery storage system. The battery energy storage is operated in such a way that it charges during the off-peak hour when the electricity price is low and tries to give power to the load whenever possible or mostly in peak hours when the electricity price is high. In ref. [10], although the battery operating cost is claimed to be assumed, the levelized cost of battery energy storage, which represents the cost of battery operation in terms of kWh, has not been considered so far in the literature, and therefore needs to be considered as the battery has an operating life and degradations.

The last type of load scheduling is for the buildings that are facilitated with renewable energy sources such as solar, wind power, and grid power with or without battery energy storage [2,12–18]. In this case, load scheduling is mainly conducted with available renewable energy without taking grid power or taking minimum grid power and a battery acts as a secondary device. In most of the research [12,13,15,16], the grid power is minimized to reduce the cost of energy without considering the levelized cost of renewable energy and battery energy storage. In some work [2], PV and Wind cost is taken from online for micro-grid, which is not realistic in terms of the annual cost. In ref. [14], the cost of renewable energy is simply assumed. The authors in [17] have considered the cost of PV energy. However, it is never mentioned how the cost is obtained and no such value is found. The cost of PV energy is again assumed in [18]. Moreover, the renewable energy cost should be presented in terms of levelized cost of energy as it takes into account the installation cost, bank loan, operation, and maintenance cost, and productivity during the lifespan of the energy sources. That is the reason the DoE and national research laboratories in the USA always express the renewable energy expenses in terms of levelized cost of energy as it is realistic. The costs of renewable energy that are found in the above-mentioned literature are either assumed or from the data obtained online that are not levelized costs of energy as well. Therefore, the cost of renewable energy and battery energy storage should be expressed in levelized cost of energy for cost calculation with a view to reducing the cost of energy while scheduling to be realistic.

Moreover, the energy consumption or load pattern of a residential building depends on the normal working days, weekends, and special days [19,20]. The special day is a day when the energy consumptions will be much higher than that of working days or weekends, although it can be working days or weekends. It varies from family to family based on their culture, habits, etc. Therefore, while load scheduling the strategy should be different for normal working days, weekends, and special days. The load scheduling, based on the three different days mentioned above, has not been considered in the literature for a residential building to the best of our knowledge. Moreover, COVID-19 has a great impact on energy consumption in residential buildings as the inhabitants are forced to stay at home [21,22] and the energy consumption not only increased but also the pattern has significantly shifted [23–25]. This has an influential impact on the power grid as well [26]. Therefore, the load scheduling, during COVID-19 pandemic situations, needs further investigations.

Due to renewable energy penetration, the grid has suffered brown out power failures, which keep the consumers without grid power for several hours. Effective scheduling in residential buildings equipped with renewable sources, battery energy storage and electric vehicles can be an effective tool to not only have power in the buildings but also to deliver some power to the grid as emergency backup. To the best of our knowledge, such a situation is not considered in the literature.

Based on the above-mentioned discussion, it is obvious that a practical time of use bill, that is offered by the utility service provider, is needed in consideration for the practical implementation of load scheduling. Moreover, commercially available renewable energy sources and battery energy storage should be considered for load scheduling. Additionally, the levelized cost of practically available energy sources, battery energy storage should be used for actual calculation of the cost of energy in residential building as it is the norm of calculation for national laboratories in the USA. The realistic incentive should be also considered that is provided by the utilities or federal government for installation of the renewable energy sources and battery energy storage in smart buildings as it contributes to the cost of these systems. So far, to the best of our knowledge, no work has considered an incentive for renewable energy or energy storage cost calculation. Moreover, no work is proposed on load scheduling during COVID-19 pandemic situations.

Having been motivated by the fact, this work proposes an efficient load scheduling intending to confine the cost of energy within the consumers' preference range while considering the realistic grid power cost, levelized cost of renewable sources, battery, and incentives. The main contributions of this work are as follows:

i. Load scheduling is conducted for a smart building to keep the cost of energy within the consumers' desire levels while keeping the load consumption closer to the demand. To fulfill the scheduling objectives, objective functions are formulated, which are very efficient and practically implementable. The objective function is also developed to fulfill the performance of the net-zero energy building along with the objective mentioned above. The objective function is implemented by considering the cost of energy, the levelized costs of commercially available renewable energy sources and battery energy storage system to make the scheduling realistic and practically implementable. Different electricity TOU rates, that are offered by Pacific Gas and Electric (PG&E), are analyzed for scheduling to obtain the best rates for the smart buildings.

ii. As the load pattern is different for normal working days, weekends, and special days, the scheduling is conducted considering the different load patterns and each combination of energy resources, which has not been considered so far in the literature to the best of our knowledge. Also, the load scheduling during the COVID-19 pandemic situation considering the load pattern change from normal working days is not analyzed anywhere in the literature. Moreover, effective scheduling in case of brown out power failure due to large penetrations of renewable sources is considered. Two performance indices are formulated to find the best strategy for each mode of operation. The proposed objective is effective in scheduling load optimizing all of the aspects mentioned above. In the literature, an incentive is considered as a financial benefit to the consumers. However, in this study, the consumers are liable for both benefit and penalty from the utility service provider for participation in the demand response, which is a realistic practice.

All of the operations are optimized by the well-known particle swarm optimization (PSO) technique. All of the conditions are optimized in MATLAB and the performance indices are tabulated.

The rest of the paper is organized as follows. In Section 2, the motivation behind this work is described as a problem statement. The calculations of levelized cost of renewable resources and battery energy storage are discussed in Section 3 considering all the feasible aspects. The formulations of objective function along with considered constraint and optimizing algorithms are explained in Section 4. In Section 5, the effectiveness of the proposed objective function in load scheduling by keeping the desired features as close as possible for both normal and COVID-19 situations are investigated with simulation results and performance indices. Finally, the discussion and conclusion are provided in Section 6.

2. Problem Statement

The load scheduling is an essential element in net-zero residential buildings for providing power to consumers maintaining a balance between the cost of energy and the consumer's demand. The cost of renewable energy is assumed in the literature in most cases, which is unrealistic. Therefore, the cost of energy should be represented in terms of levelized cost of energy, which is realistic and recommended by the department of energy, USA. Moreover, the energy consumption in a residential building depends on the day type and scheduling strategy should be different for different days. Another feature of net-zero buildings is to manage loads with renewable energy and battery energy, taking almost no power from the grid. However, the building should be able to provide power to the grid in case of emergency conditions such as brown out conditions as part of a demand response program. Therefore, a new scheduling methodology should be developed that can be effectively implemented under not only different loading conditions such as day type but also work efficiently with change in the loading pattern during office hours of the day during COVID-19 periods as compared to normal working conditions. Moreover, it should be implementable for demand response programs under emergency conditions. These facts motivate the proposed work.

3. Calculation of Levelized Cost of Energy for Net-Zero Smart Residential Buildings

The smart building is a building with a centralized controller that can access the generation information from renewable energy sources, and the charging/discharging condition of the battery energy storage with available energy to be stored or dispatched. The centralized controller will have control over the operations of all of the loads and battery energy storage, and bi-directional communication between the centralized controller, and the loads and battery energy storage would be additional features. Moreover, having been connected to the grid through the smart meter, the smart meter will have the electricity price information or can acknowledge any demand request offered by the grid at any given time. Also, the smart building has a future prediction system for energy sources and loads and therefore can be scheduled effectively with available sources or demand preferences of the consumer. The smart residential building can effectively control the loads' energy consumption, operations, etc.

Figure 1 shows a smart building that is considered for this work having renewable energy sources, and the battery energy storage. The building is also connected to the grid through a smart meter that controls the bi-directional power flow to and from grids. The residential building in this work is assumed to have been situated in California. Therefore, climate data such as wind speed and solar irradiance data are considered suitable for California [27]. The ratings of the PV and wind turbine are selected to be 6.2 kW and 10 kW [28,29]. The two-battery energy storage was considered to have ratings of 14 kWh each that is practically available [30,31]. The distribution company considered for this is PG&E for TOU electricity price, the incentive for solar, wind turbine and battery energy storage installation, and incentive for the demand response program participation.

The levelized cost of energy (LCOE) of any system can be defined as shown below [27]:

$$LCOE = \frac{ICC \times FCR + AOE}{AEP} \tag{1}$$

where ICC, FCR, AOE, AEP represent the installed capital cost, fixed charge rate (%), annual operating expenses and annual energy production, respectively. The fixed charge rate, FCR, can be defined by the following Equation (2) shown below [32]:

$$FCR = \frac{d(1+d)^n}{(1+d)^n - 1} \times \frac{1 - \left(T \times PV_{dep}\right)}{1 - T} \tag{2}$$

where, d, T, PV_{dep} represent, interest rate (%), effective tax rate, and the present value of depreciation (%), respectively. These are the two equations that have been used for LCOE calculation to be considered in scheduling.

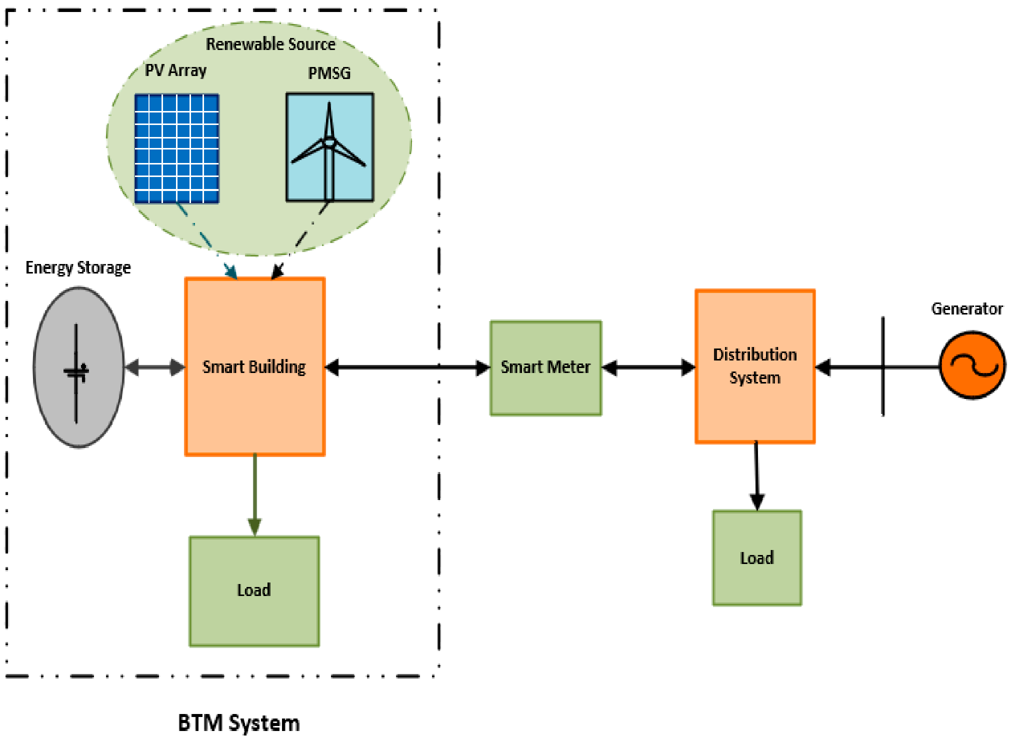

Figure 1. Components of a smart building connected to smart grid through smart meter.

3.1. LCOE of PV System

According to [24], the residential solar system ranges from 3 to 10 kW. The average solar system rating is 6.2 kW. Therefore, for this work, a 6.2 kW solar system is considered for residential buildings. In ref. [28], the installed cost ($/W) is reported to be 2.70. The federal tax rate of 21%, California state tax rate of 7%, a total lifetime of the solar system is 30 years, 4% interest loan, etc., are considered for this installed cost calculation. The operational and maintenance cost is reported to be 22 $/kW-yr [28]. Moreover, a solar panel of 1 kW peak dc capacity is reported to produce an average of 1642 kWh annually in California [33]. Therefore, using Equation (1), the levelized cost of residential PV system, which is considered for this work, is found to be 0.0681 $/kWh.

3.2. LCOE of Wind System

The wind turbine system, which is considered in this work, has a rating of 10 kW as in [23]. Although a lot of wind turbines are available, for this work, the Excel 10 of Bergey wind power company is considered [34]. The installation cost of this wind turbine requires around $60,000 as found on the manufacturer's website. Considering 30% incentive by the federal government and 90 $/W incentive self-generation incentive program by PG&E [35] in California, the initial installation cost becomes $33,000. Moreover, considering 1.3% interest for 25 years with federal and state tax rates as same as the PV system, the FCR value was found to 0.0654. The maintenance cost is considered to be 40 $/yr. Moreover, Excel 10 is capable of producing 13,800 kWh/yr for a location where the average wind speed is 5 m/s [36]. From the NASA toolbox, locations are selected where the average wind speed over the last two years is found to be slightly more than 5 m/s at 100 feet above sea-level. Therefore, the levelized cost of wind energy is found to be 0.1593 $/kWh according to (1).

3.3. LCOE of Battery Energy Storage System

The battery energy storage system, as discussed in the system description section, has a rating of 28 kW of which 27 kW is practically available. From the manufacturer's website, the installation cost is found to be around $16,100. Again, considering the 30% incentive from the federal government and 0.25 $/Wh incentive by PG&E in California for residential energy storage, the equivalent installation cost reduces to $4270. Moreover, 2.5% interest is considered for 10 years for which the FCR value is found to be 0.1586. The warranty period for the battery storage is 10 years as mentioned on the manufacturer's website. Therefore, the operation and maintenance cost is considered 0 $/yr. Again, considering the daily operation of 35.1 kWh per day, the annual operating energy becomes 12,811.5 kWh/yr. Therefore, the levelized cost of battery energy storage for both charging and discharging condition is calculated to be 0.05289 $/kWh.

4. Load Scheduling Methodology

4.1. Formulation of Objective Function

In this work, the first proposed objective function keeps the cost of energy per hour within the desired value of the consumers while keeping the consumptions closer to the demand as possible for both normal and COVID-19 situations. The objective function is for a smart net-zero building that is equipped with both grid power, renewable energy sources as well as battery energy storage. In this case, the proposed objective function can be expressed as:

$$f_{obj} = \sqrt{K_3 A^2 + K_4 B^2 + K_5 C^2 + K_6 P_g + \frac{P_{sys_{loss}}(h)}{P_e(h)}} \tag{3}$$

where

$$A = C_e(h) - C_{g\_actual}(h)$$

$$B = \left(\frac{P_{l\_actual}(h) - P_e(h)}{1000} \right)$$

$$C_e = \lambda_g(h) P_g(h) + \lambda_s P_s(h) + \lambda_w P_w(h) + \lambda_{batt} |P_{batt}(h)|$$

$$C = \frac{P_w(h) + P_s(h) + |P_{batt}(h)| - P_e(h)}{1000}$$

And

$$P_{sys_{loss}}(h) = 0.01 P_e(h) + P_{batt_{loss}}$$

where, λ stands for cost of energy and P stands for power. The subscript s, w, batt stand for solar, wind and battery, respectively. The first term represents the difference between the system cost of per hour and the desired cost. The second term corresponds to the difference between the actual load demand and load consumption. The third term is the difference between the available renewable energy, battery energy storage and consumed loads. λ_g, P_g and C_g actually represent the per unit grid energy cost, received grid power and the maximum bill the consumers want to pay in dollars, respectively. P_s and λ_s represent solar power generation and per unit (kWh) solar power cost. Similarly, P_w and λ_w represent wind power generation and per unit (kWh) wind power cost. P_l, P_e, $Psys_{\_loss}$ represent load demand at any hour (h), and the actual load consumed at that hour and system power loss, respectively. K_3 and K_4 are the contributing factor that determines the consumers preference of cost and load consumption over the desired cost of energy and the load demands. Higher value of K_3 means the difference in the first term should be small to minimize the objective function, which in fact keeps the consumption cost closer to the desired cost as much as possible. Therefore, this objective function would be minimum if the system cost would be close to the desired cost and the difference between the demand and actual consumption. Moreover, in order to have minimum value, the consumption should be close to the available renewable sources and battery energy storage while taking less power to the grid (P_g positive) and giving maximum power to the grid (P_g negative) if possible. In addition, the load loss and battery energy loss should be minimum for minimum value of the objective function. Therefore, this objective function should satisfy every aspect of net-zero energy buildings' function to have minimum value. The PSO optimization algorithm will try to minimize the above objective function shown in (3) subject to:

$$K_3 + K_4 = K_5 + K_6 = 1$$

$$P_e(h) + P_d(h) = P_g(h) + P_s(h) + P_w(h)$$

$$P_{l\_actual}(h) - P_e(h) \geq 0$$

$$P_{sys_{loss}}(h) = 0.01 P_e(h) \leq 0.8 \text{ kW}$$

$$0 \leq C_e(h) \leq 4C_g(h)$$

Moreover, battery energy level, Be and the percentage state of charge (%SOC) can be expressed by the following two equations [37,38]:

$$B_e(h) = B_e(h-1) + P_d \Delta h \eta \tag{4}$$

$$\%\ SOC(h) = \frac{B_e(h)}{B_{e_{rated}}} \times 100 \tag{5}$$

where, the charging and discharging efficiencies, η of the battery system is assumed to be 95% and 90%, respectively. The value Δh is considered to be 1 h for all cases. The constraints considered for this objective function are the same as it has been considered for (3). In addition, the constraints that are considered are:

$$-5 \text{ kW} \leq P_d \leq 5 \text{ kW}$$

$$2.7 \text{ kWh} \leq B_e \leq 24.3 \text{ kWh}$$

In all conditions, the load scheduling objective functions are optimized/minimized by the particle swarm optimization (PSO) technique. Its application, in different fields such as energy management [37,38], load predictions [39,40], etc., are proposed in the literature.

4.2. PSO Algorithm

In the PSO, a random number of particles are considered for search space and the objective function is formulated. Based on the cost function, at each iteration each particle tries to find it optimal position and value. Then, by sharing the information of personal best value and position, the group's optimal best values and positions are selected.

$$v_i^{k+1} = wv_i^k + c_1 r_1 \left(p_i^k - x_i^k\right) + c_2 r_2 \left(p_g^k - x_i^k\right) \tag{6}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{7}$$

The PSO algorithm is governed by the two-model equations of velocity and position vector in an N-dimensional solution space [37–42] as shown above where v_i^{k+1} represents i^{th} particle velocity of $(k+1)^{th}$ iteration of N dimensional search space. Similarly, x_i^k corresponds to i^{th} particle velocity of k^{th} iteration. p_i^k and p_g^k correspond to the individual best position of i particle and global best position of the swarm, respectively. Moreover, r_1 and r_2 are chosen randomly and they are uniformly distributed between 0 and 1. The learning factors (c_1, c_2) controls the significance of the best solution. The values for both learning factors are considered to be 2 in this work. The value for the inertia co-efficient, w for each iteration number is calculated using the following equation:

$$w = w_{max} - \frac{t(w_{max} - w_{min})}{MaxI} \quad (8)$$

where, w_{max} and w_{min} represent the upper and lower value of w and t, $MaxI$ indicate current iteration number and maximum iteration number, respectively.

The whole procedure of determining the loads for any hour is shown in Figure 2. At any hour, the load demand, available solar, wind power, available battery energy, time of use (TOU) of electricity, demand response request, parameter for the objective function ($K_1, \ldots, K_6$) are gathered. After achieving all of the information, the parameters of the PSO such as number of particles with their initial positions, number of iterations, etc., are initialized for load power (P_e). After the parameter initialization, the proposed objective functions as shown in Equation (3) are evaluated based on the constraints selected. Finally, after the objective function evaluations, based on the personal best and global best values of all the particles, each particle's position and velocity vectors are updated based on Equations (6)–(8) for load power (P_e). After this stage, if the maximum number of iterations is not reached, then the procedures start repeating. Once the maximum number is reached, the global best value, which is the loads value (P_e), is used for load scheduling and parameters of renewable sources, TOU price, etc., are gathered for the next hours' load selection.

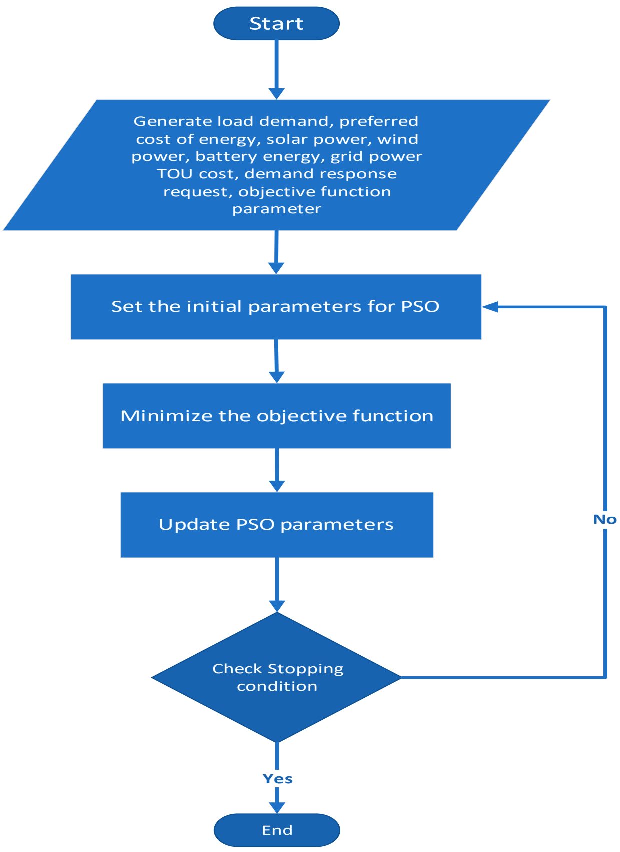

Figure 2. The PSO algorithm flowchart.

The performance of the PSO, in reaching the optimized value for a given case, under different parameter conditions is shown in Figure 3. Among the considered six cases, in first three cases (case 1 to case 3), only number of particles was changed (10, 30 and 50 respectively) while maximum iteration (150), w_{max} (0.9) and w_{min} (0.2) values were kept constant. For the last three considered cases, w_{max} values were changed (0.9, 0.7, and 1, respectively). Similarly, w_{min} values were changed (0.2, 0.1, and 0.4, respectively) while keeping number of particles (30) and number of iteration (150) constant. In all considered cases, the PSO obtained the optimized objective function value (1.1802) within 15 iterations, although in all cases the starting point was different as the initial positions and velocity vectors were randomly generated.

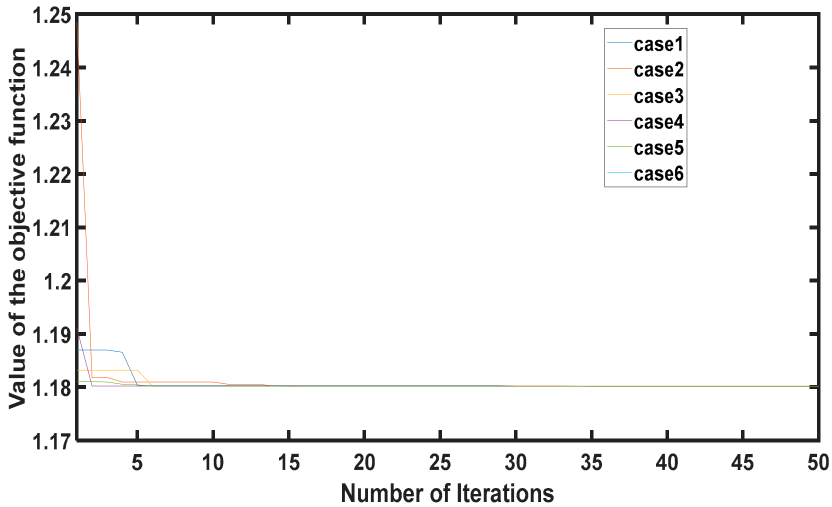

Figure 3. Performance of the PSO under different parameter consideration.

5. Simulation Results

In this work, extensive simulations have been performed to show the effectiveness of the proposed methodology. Simulations have been performed by using Matlab 2023b software. Several scenarios such as smart building operations with renewable energy sources, battery energy storage under normal, COVID-19, and emergency conditions like brown outs are considered. The details of these simulation scenarios, results, and associated descriptions are provided below.

5.1. Smart Net-Zero Building Operated by Renewable Energy Sources, Grid Power and Battery Energy Storage under Normal Conditions

For the system having renewable sources, battery energy storage and grid power are considered for normal conditions. The objective function in (3) is used for optimization considering all of the constraints and during the peak and off-peak hours, $K_3 = 0.7$, $K_5 = 0.5$ values are considered. For all cases, the desired cost (C_g) per hour for off-peak and peak hours are considered to be \$1 and \$1.75 (\$28.5 per day), respectively, as it is calculated that the cost of loads before the considered cases was \$30 per day. Therefore, the objective of choosing the value is to reduce the load cost per day by 5%. Moreover, if the energy cost, C_e of one hour is less than C_g, then the difference between the C_g and energy cost can be added with the next hour C_g to utilize more load if required. Similarly, if the load utilized in any hour, P_e is less than the actual load demand, P_l, then the difference between the actual demand and consumed load is added with the demand of the next hour. The above two conditions are expressed in Equations (9) and (10), respectively.

$$C_{g\_actual}(h) = C_g(h) + \left(C_g(h-1) - C_e(h-1)\right) \quad (9)$$

$$P_{l\_actual}(h) = P_l(h) + (P_l(h-1) - P_e(h-1)) \quad (10)$$

As previously discussed, PG&E has been considered for this work as a utility service provider. PG&E has three TOU electricity rates [43] as shown in Figures 4 and 5 for normal working days and weekend respectively that the consumer can choose. Therefore, E-TOU option-B, has been considered for our work as it is the most economical among the offered electricity prices.

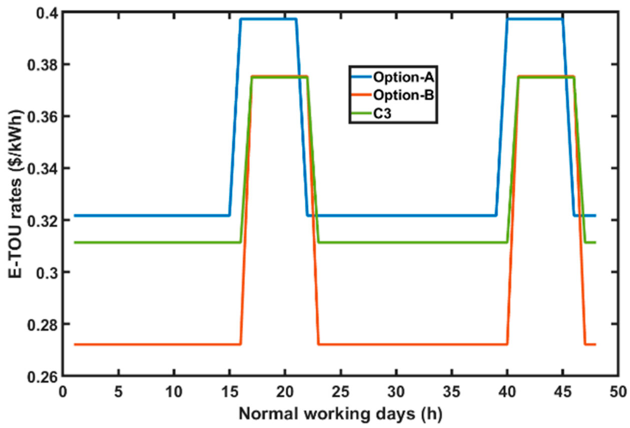

Figure 4. Three different E-TOU rate options on working days.

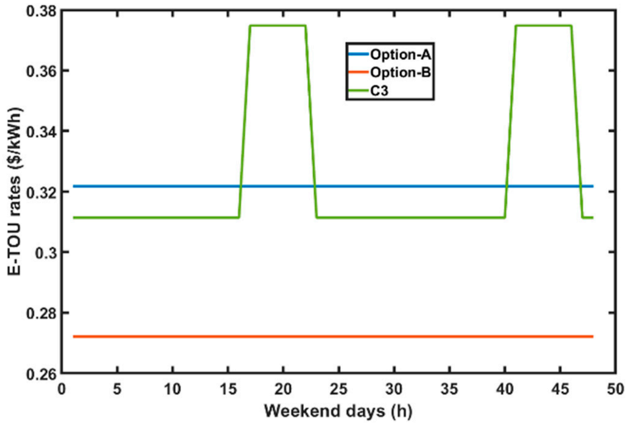

Figure 5. Three different E-TOU rate options on weekend days.

Figure 6 shows the solar and wind power available for the considered normal working days with the load demands. Figure 7 shows the unscheduled (demand) and load consumption for the considered scheduling scheme. In normal cases, the difference between the demand and generation is provided by the grid power. For the considered case, the battery energy storage provides the discrepancy between the renewable energy and load demand and fulfilling the concept of net-zero buildings. Therefore, no scheduled load is required.

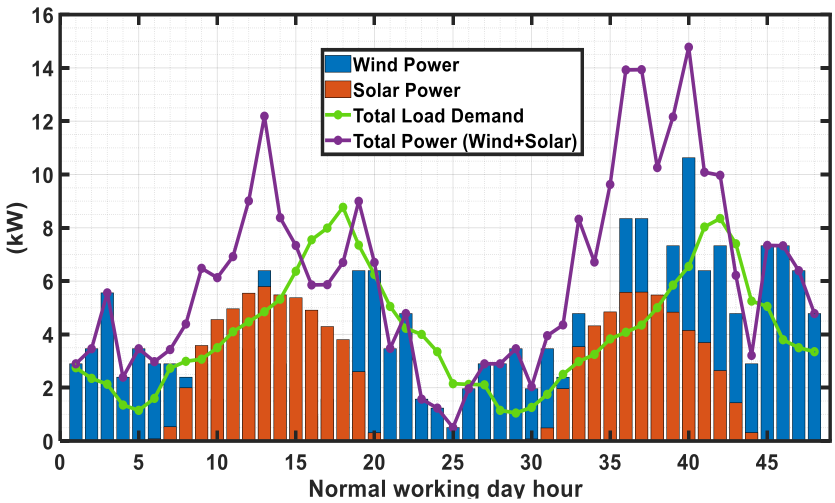

Figure 6. Renewable source power and load considered for normal working days.

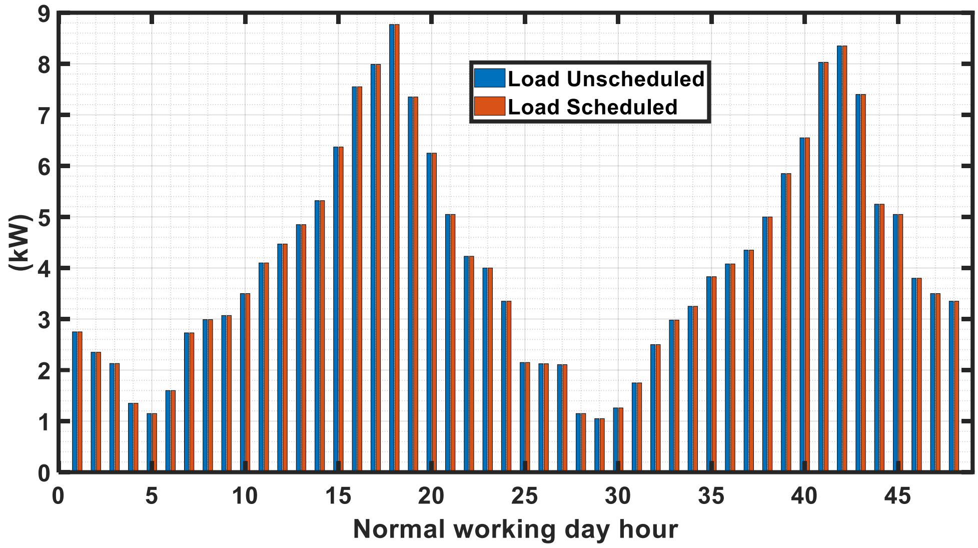

Figure 7. Load scheduling for different cases for normal working days using renewable sources and with battery energy storage.

Moreover, the grid power requirement for all of the cases is shown in Figure 8. In Figure 8, the unscheduled grid power represents the power that is required from the grid if all the demands are supplied by the grid only. The load requires considering the scheduling algorithm and is fulfilled with renewable energy available and battery energy storage taking less power from the grid as shown in Figure 8. Moreover, the residential building provides power to the grid whenever possible.

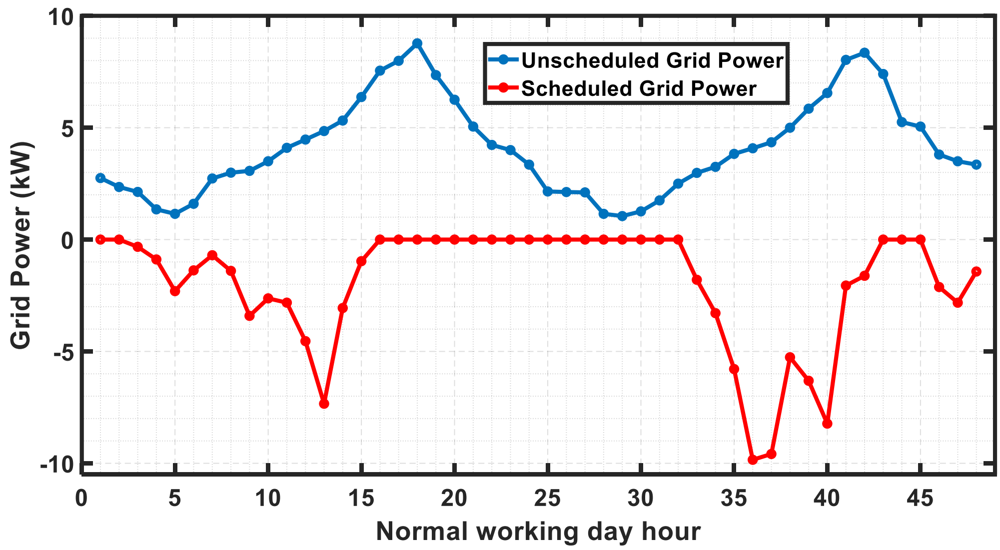

Figure 8. Grid power required for normal working days using renewable sources and with battery energy storage.

Figure 9 represents the system cost for normal working days. The system cost in unscheduled cases is higher as compared to scheduled cases, as it utilizes more grid power and the grid power cost is higher than the wind and solar power for both peak and off-peak hours.

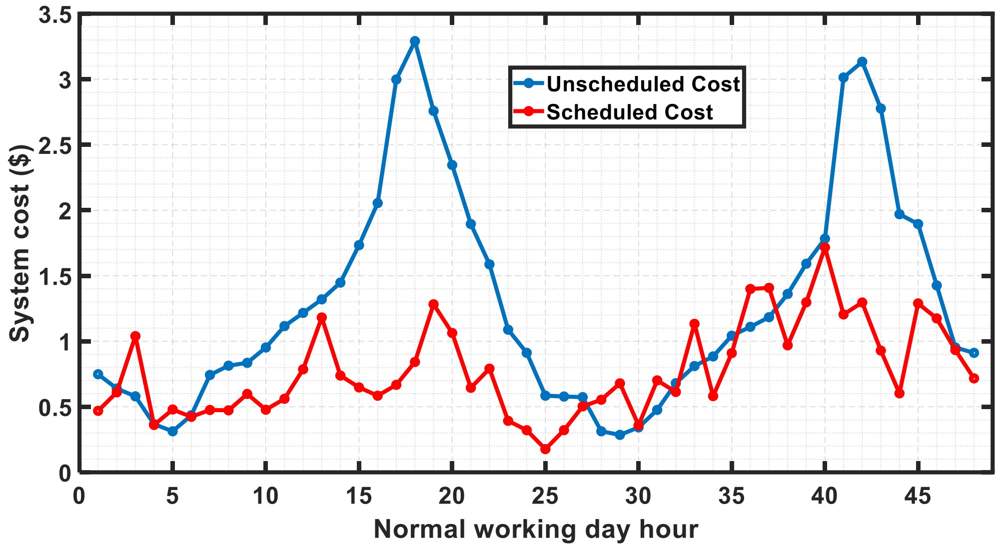

Figure 9. Cost of the system for normal working days using renewable sources and with battery energy storage.

The charging and discharging operation for battery energy storage in case of load scheduling is shown in Figure 10. The positive battery power indicates the charging of the battery when the generated power is less than the demand, which will increase the battery stored energy.

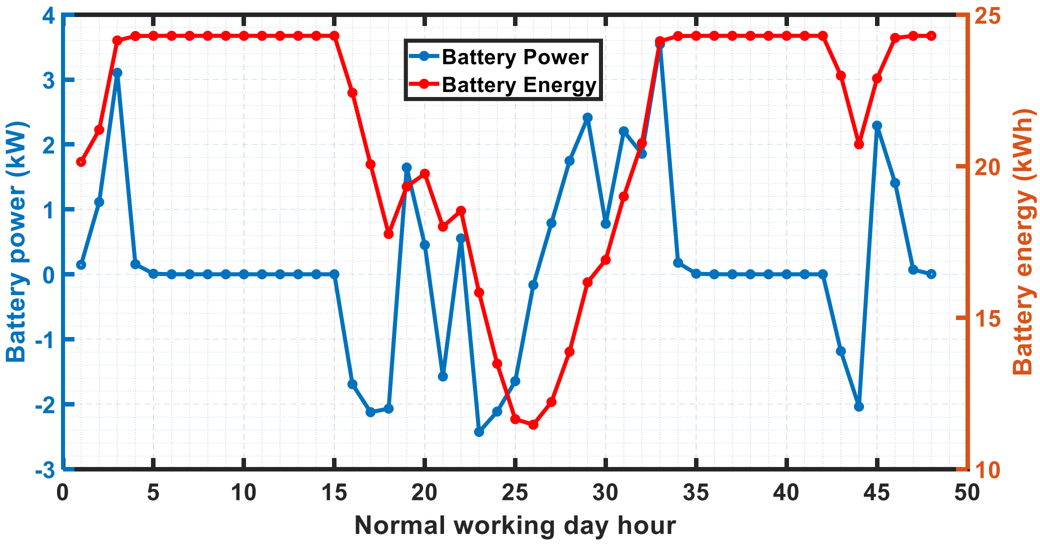

Figure 10. Battery power and energy for normal working days.

The renewable energy along with the load demand for the considered weekend days is shown in Figure 11, which are different than the considered cases as shown in Figure 6. Like normal working days, both unscheduled and scheduled cases are considered for weekend days. The unscheduled load and the load consumption for the scheduled case are shown in Figure 12 followed by the scheduled loads shown in Figure 13. From Figure 13, it is evident that the required load to be scheduled for later hours is higher in unscheduled conditions than that in scheduled cases where the load to be scheduled for later hour is zero for all hours as the difference of power is supplied by the grid. But in case of scheduling, the load is determined each hour by the objective functions.

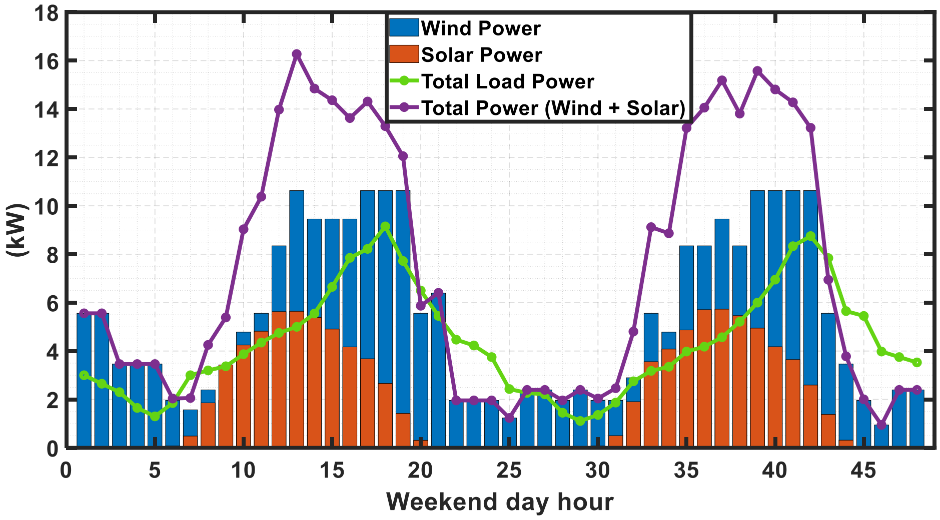

Figure 11. Renewable source power and load considered for weekend days.

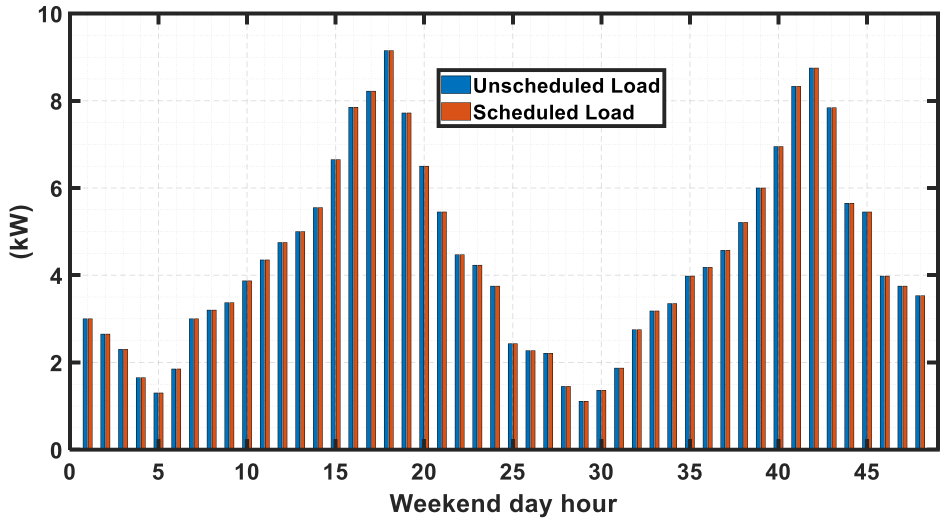

Figure 12. Load scheduling for different cases for weekend days using renewable sources and with battery energy storage.

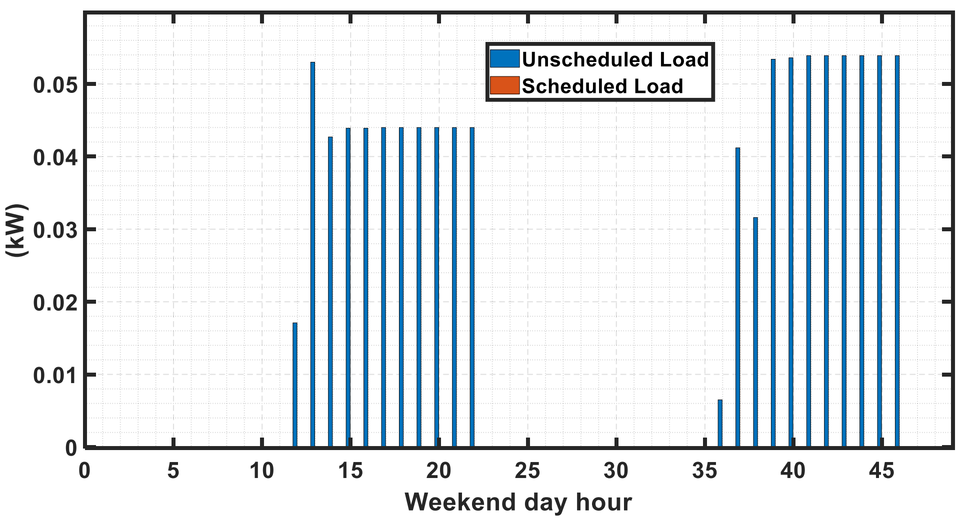

Figure 13. Scheduled loads for different cases for weekend days using renewable sources and with or without battery energy storage.

Figure 14 indicates that in the case of scheduled loading no grid power is taken, as the battery energy storage supplied the extra power required in addition to the renewable power available and satisfies the unique features of net-zero smart buildings.

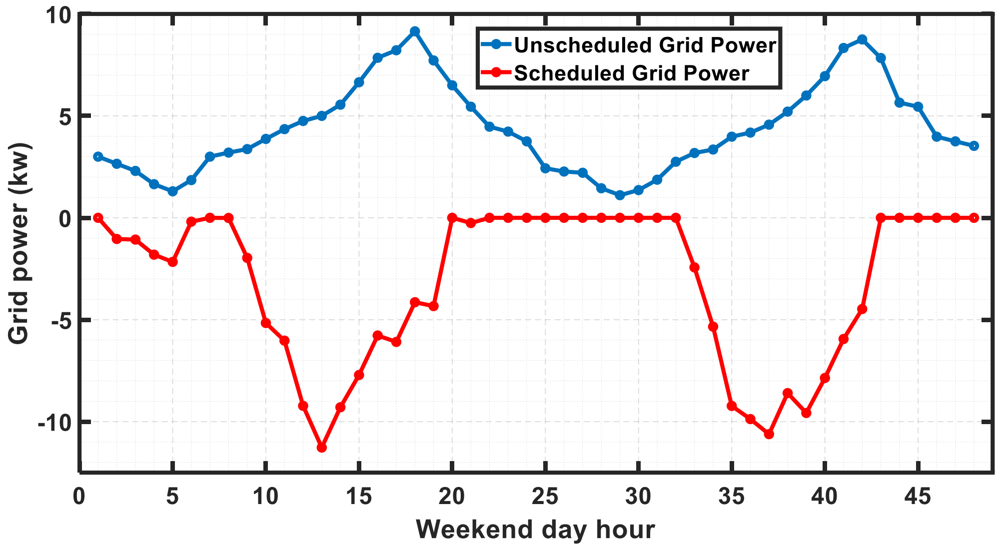

Figure 14. Grid power required for weekend days using renewable sources and with or without battery energy storage.

Moreover, in order to compare the performances of the considered cases, two terms are defined as in shown in Equations (8) and (9). Equation (8) represents the total cost saving that is the summation of maximum desired cost (C_g) and the consumed cost (C_e). The higher value of C_{saving} means lower energy cost over the considered days. Similarly, Equation (9) represents the total load delayed or re-scheduled, that is the summation of maximum desired demand (P_l) and the consumed cost (P_e). The higher value of $P_{delayed}$ means more loads have been re-scheduled for the considered days. Moreover, the k value for normal working days and weekends are considered 48. The higher value of C_{saving} and lower value of $P_{delayed}$ represent the better performance. Both C_{saving} and $P_{delayed}$ are tabulated in Table 1 for all working and weekend days.

$$C_{saving} = \sum_{h=1}^{k} \left(C_g(h) - C_e(h)\right) \tag{11}$$

$$P_{delayed} = \sum_{h=1}^{k} \left(P_l(h) - P_e(h)\right) \tag{12}$$

Table 1. C_{saving} and $P_{delayed}$ summary.

Day Type	Performance Index	Scheduled Case
Working Days	C_{saving}	19.62
	$P_{delayed}$	0.0
Weekends	C_{saving}	12.68
	$P_{delayed}$	0.0

For the unscheduled cases, the scheduled load is 0 as difference of power is supplied by the grid power, which increases the cost of energy consumption for the day. However, for the scheduled case considered for the normal working days, the scheduled load is 0, which indicates that no load is left for the next days. Therefore, our proposed objective functions perform well for normal working days. In terms of cost saving, the scheduled case also performs better as compared to the unscheduled case. Moreover, in terms of load delayed or cost savings for the weekend days, the scheduled system with the proposed algorithm performs better.

5.2. Smart Net-Zero Building Operated by Renewable Energy Sources, Grid Power and Battery Energy Storage under COVID-19 Pandemic Conditions

As for the COVID-19 pandemic situation, people are forced to stay at home. Therefore, load consumptions are assumed to be similar for both normal working days and weekends. The energy consumption will be higher for the working day under COVID-19 situation as compared to the normal working day as the people will stay at home during office hours [21,22], as shown in Figure 15. The solar energy and wind energy are considered to be the same as shown in Figure 6.

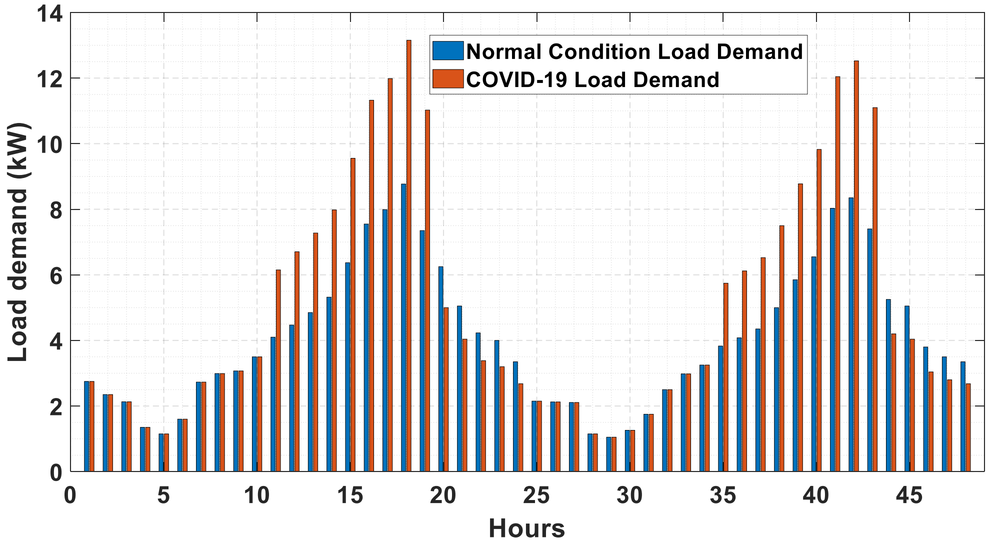

Figure 15. Comparison of load consumption for working day during normal and COVID-19 pandemic situation.

As for the scheduling, the renewable sources and battery storage are used for scheduling loads using the objective function proposed in Equation (3). Figure 16 shows the scheduled loads and percentage of demand fulfilment by the proposed scheduling method where more than 75% demand is fulfilled at all times. The load is kept for the next hours to have minimum objective function as proposed in Equation (3).

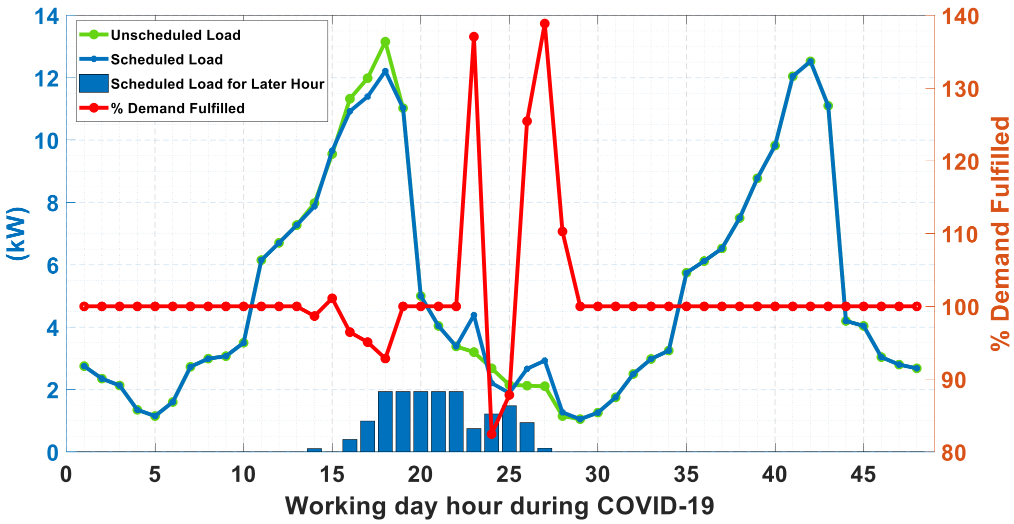

Figure 16. Scheduled loads and demand fulfilment during COVID-19 situation.

Figure 17 represents the system cost during COVID-19 situation, which indicates that the system cost is much less as compared to the unscheduled cases; as for unscheduled cases, the extra load demand is fulfilled by the grid power. Moreover, most of the time for scheduled cases the energy cost is close to the desired cost of $1 during off-peak hours and $1.75 during peak hours.

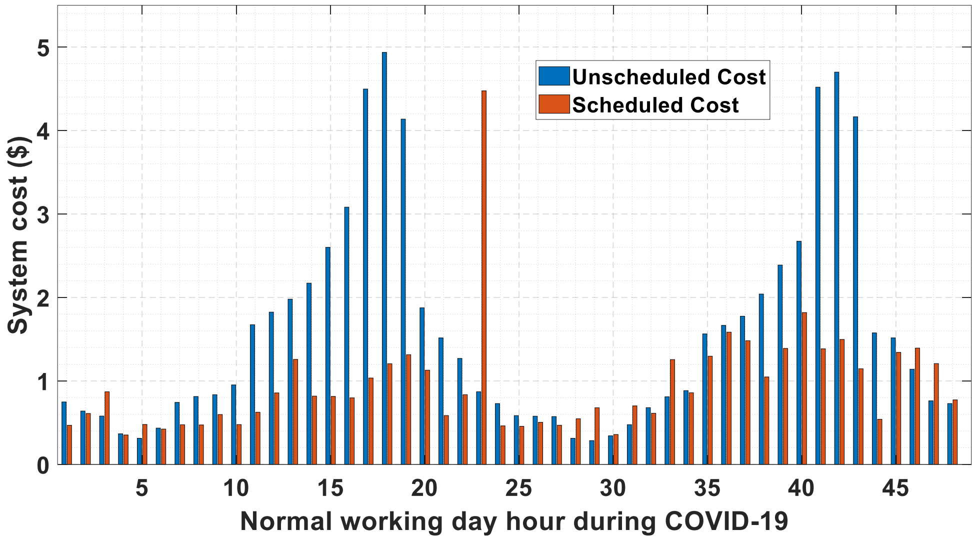

Figure 17. System cost during COVID-19 situation.

The grid power received during the pandemic situation with the battery power exchange and battery energy is shown in Figure 18. It is clear from Figure 18 that very few times power is imported from the grid, whereas frequently power is exported to the grid.

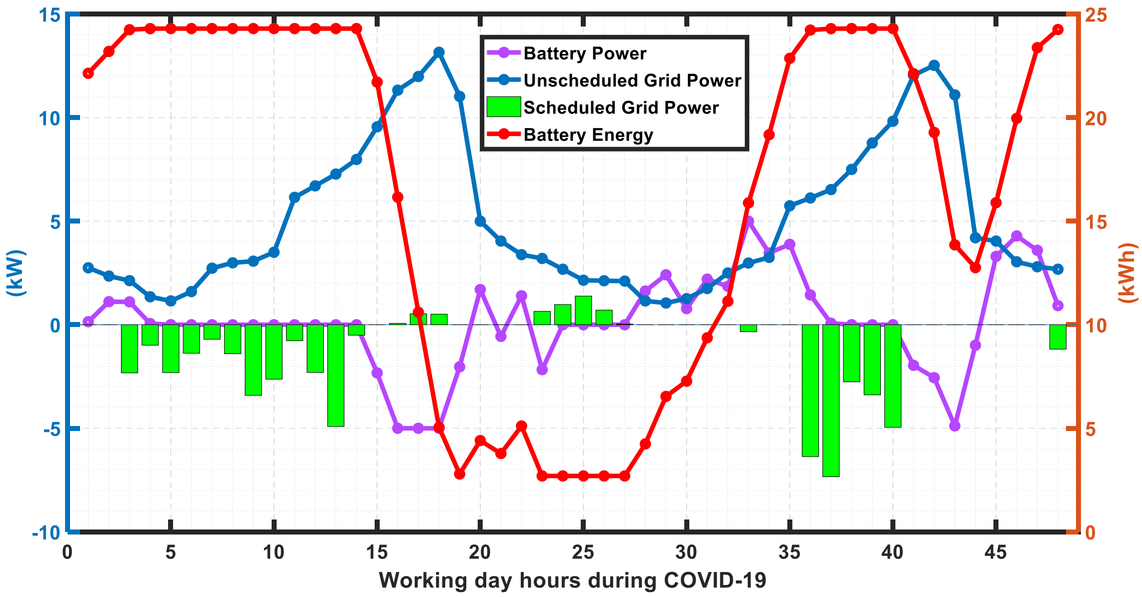

Figure 18. Grid power, battery power and energy during COVID-19 situation.

The saving of costs during COVID-19 is shown in Table 2. From Table 2, it is evident that the proposed algorithm is effective in saving costs, although the energy consumptions have been increased significantly during office hours. This is achieved by scheduling loads effectively each hour using Equation (3), as shown in Figure 16, and the saving of costs is achieved by exporting power to the grids, as shown in Figure 18.

Table 2. C_{saving} and $P_{delayed}$ summary for COVID-19 situation.

Day Type	Performance Index	Scheduled Case
Working/Weekend Days	C_{saving}	11.20
	$P_{delayed}$	0.0

5.3. Smart Building Operated by Renewable Energy Source, Grid Paper with Battery Energy Storage Considering Demand Reponse Situation during Brown out Crisis Conditions

In this section, the building is considered to be involved in demand response. Therefore, the building must comply with the utility demands. It is assumed that at least 4 h before, the building will be given information about curtailment or addition of load. It is assumed that if the building complies with the demand, they will give incentives during demand period and also be benefitted after the demand period. If it fails to do so, an extra $2/h will be charged as a penalty.

At first, it would take a day to consider the demand response implementation. On the 10th hour, the utility provider informs the building owner that from the 15th to 19th hours no power can be taken from the grid due to sudden brown out conditions. If the building can provide power during that period, it will obtain incentives equal to 60% of the electricity price at that time and will enjoy a 60% off-peak price for the next five hours. Otherwise, the building will be penalized by $2/h for failing to cope with the utility demand. The load and renewable energy available from the chosen day is shown in Figure 19.

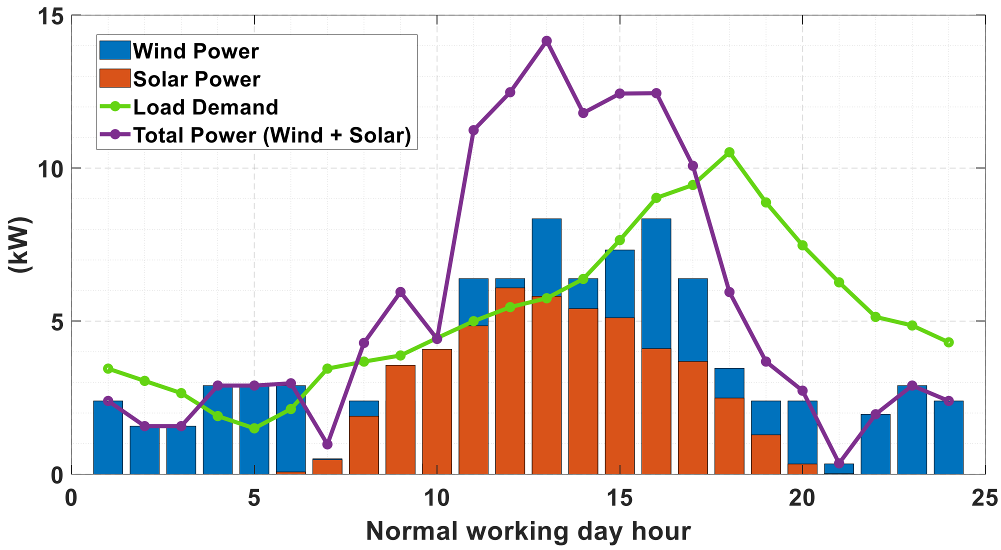

Figure 19. Renewable source power and load considered for special day considering brown out.

Figure 20 shows the scheduled loads and percentage of demand fulfilment for the special day under demand response during brown power outage from 15th to 19th hours, where the demand is almost 100% fulfilled during the response periods. As shown in Figure 20, the percentage of demand is less than 100% fulfilled during the 21st to 24th hour because of the optimization of load power based on Equation (3) to keep the closest balance between the desired cost of energy per hour and demand of the loads; although, during that period, the grid power was also taken as an incentive for participating in demand response from the 15th to 19th hour.

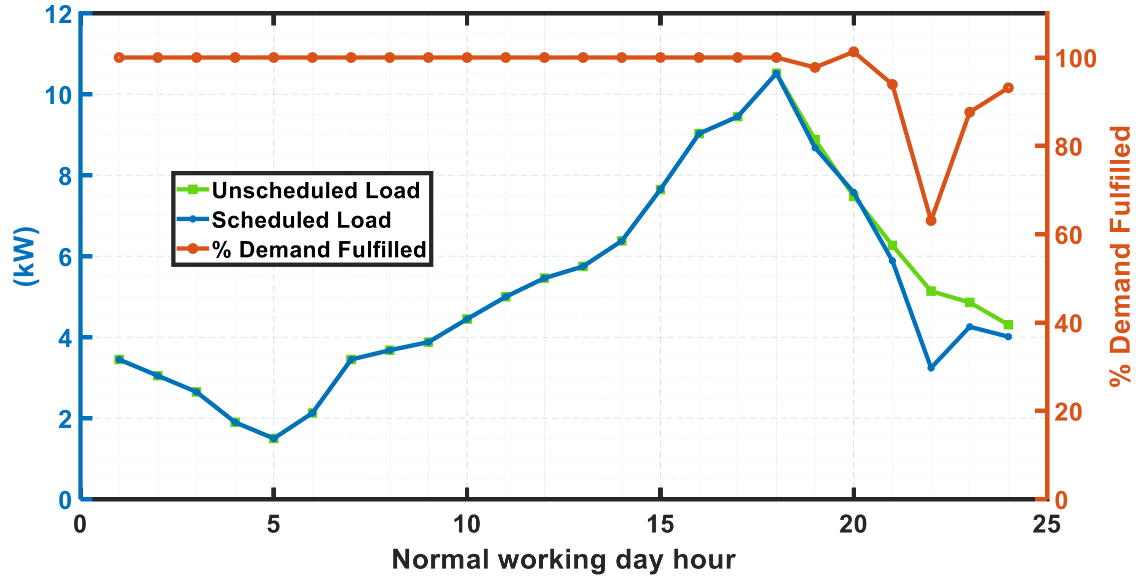

Figure 20. Scheduled loads and demand fulfilment under demand response during brown out conditions.

As for grid demands during demand response periods, no power was taken during the 15th to 19th hour, as shown in Figure 21. Rather, by providing power during brown out situations from the 15th to 17th hours, an incentive is achieved. Moreover, the charging and discharging power of battery energy storage is kept within 5 kW and is considered as constraint battery energy is kept at 2.7 kWh at its minimum energy level the battery can have from the 21st to 24th hour, as shown in Figure 21.

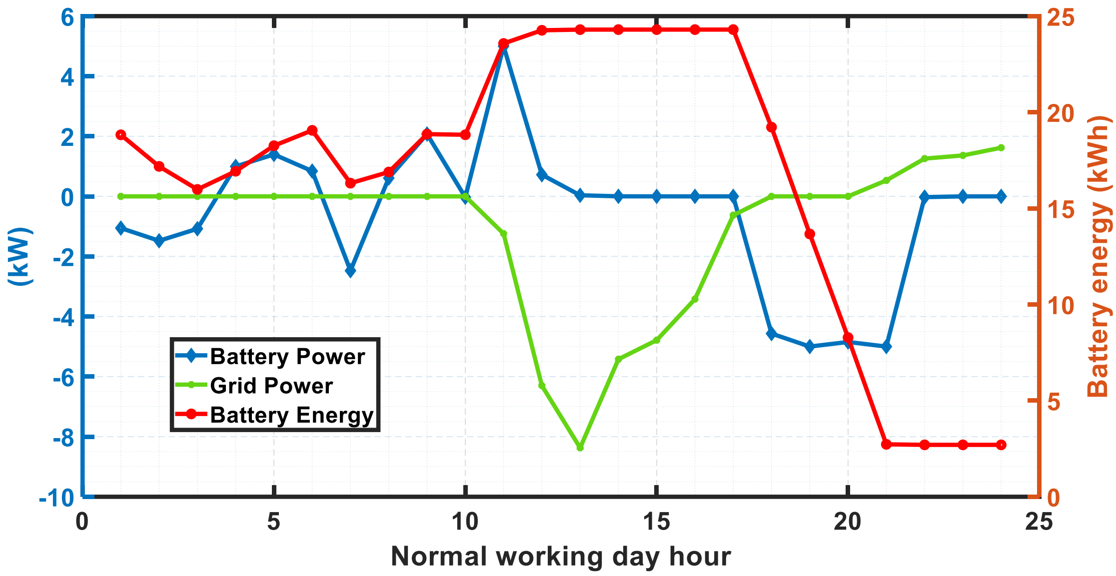

Figure 21. Grid power, battery power and energy under demand response for brown out conditions.

The performance index expressed in Equations (11) and (12) are utilized and tabulated in Table 3. Therefore, proper scheduling of load and energy resources, based on demand response, can provide not only benefit to the grid during brown out conditions but also the residential building consumer because of obtaining an incentive, which is evident from Table 3. The cost saving is higher with incentives as compared to that of without incentives. Moreover, scheduled loads after both days are lesser than that of normal days because of obtaining grid power with a lesser electricity rate as a bonus for participating in the demand response.

Table 3. C_{saving} and $P_{delayed}$ summary for brown out conditions.

Day Type	Performance Index	Demand Response Program	
		With Incentive	Without Incentive
Working Days	C_{saving}	10.07	8.99
	$P_{delayed}$	3.28	3.54

5.4. Smart Building Operated by Renewable Energy Source, Grid Power with Battery Energy Storage on Working Days Participating in Demand Response during COVID-19 and Brown out Situation

Because of lockdown conditions during the COVID-19 situation, the energy consumption has increased and because of the sudden rise in demand, several brown outs happened in California in the recent past [44]. Therefore, considering this case, a demand response condition was developed and analyzed.

The first working day, under COVID-19 conditions, was considered for demand response implementation. On the 10th hour, the utility provider informed the building that from the 14th to 18th hour no power could be taken from the grid because of brown outs. Rather, the building had to provide at least 2 kW power during that period to obtain an incentive equal to 60% of the electricity price at that time and enjoy a 60% off-peak price for the next five hours. Otherwise, the building would be penalized by $2/h for failing to cope with the utility demand. The load and renewable energy available from the chosen first day is the same as shown in Figure 19 (0 to 24 h).

Figure 22 shows the load consumption, scheduled loads and percentage of demand fulfilment of load. The load value during the 14th to 18th hours was less than the demand as an extra 2 kW was provided to the grid, which was also evident from the percentage of demand response. Therefore, the proposed scheduling scheme and objective function are efficient in responding to the emergency conditions as demanded and load was scheduled effectively for the later hours (from the 19th to 23rd hours).

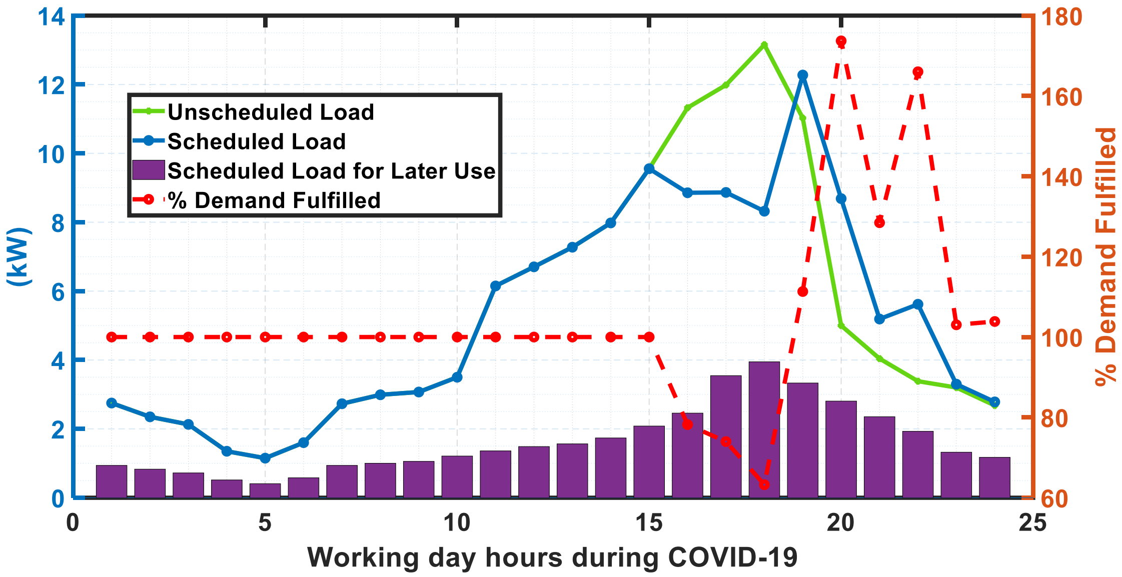

Figure 22. Scheduled loads and demand fulfilment under demand response during COVID-19 and brown out conditions.

As per grid demands, at least 2 kW power was provided during the 14th to 18th hours as shown in Figure 23 and therefore, the incentive was achieved although load was scheduled for the later hours. The battery discharges from the 14th to 18th hours to provide load power and to provide the extra power required for the load and grid demand.

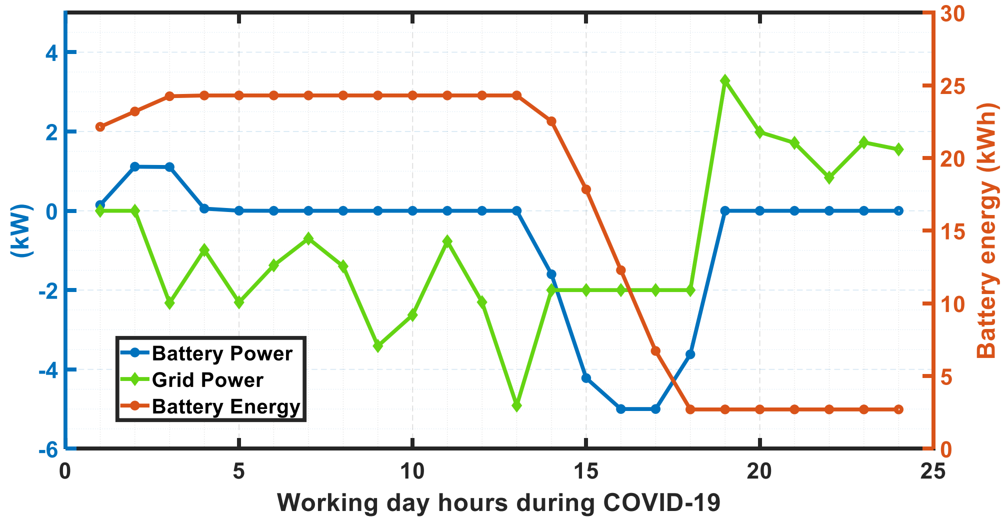

Figure 23. Battery power, grid power, battery energy under demand response during COVID-19 and brown out conditions.

Table 4 indicates that participating in demand response is beneficial in terms of cost saving. However, more loads are scheduled for later hours to compensate the energy that are provided to the grid.

Table 4. C_{saving} and $P_{delayed}$ summary for brown out conditions with or without incentive.

Day Type	Performance Index	Demand Response Program With Incentive	Demand Response Program Without Incentive
Working Days	C_{saving}	10.07	8.99
	$P_{delayed}$	3.28	3.54

6. Discussion and Conclusions

This work proposes an efficient new load scheduling system optimized by the PSO with a view to keeping the cost of energy within the consumers preference range, meeting consumers' demand as closely as possible, minimum load loss while considering the realistic grid power cost, levelized cost of renewable sources, battery and incentives offered by the utility system existing in California, USA. The proposed new objective function is implemented to facilitate the load scheduling in a smart net-zero smart building. In addition, the existing literature does not consider three different types of days such as normal working days, weekend, COVID-19 pandemic situations, and brown out conditions as operating conditions. All of these conditions are considered in this work. The PSO is utilized to minimize the objective function with the given constraints in all operating conditions to optimize load consumption, the operation of battery storage and the bi-directional power flow to or from the grid. The performance is compared in terms of performance index. All the cases are optimized by the PSO and simulated in the MATLAB environment. Based on the simulation results and analysis, the following conclusions can be made:

- The proposed objective functions are very effective in saving costs, meeting consumer demands, minimizing system loss and fulfilling the features of net-zero energy buildings for different day types during normal operating conditions.
- Although the load consumption patterns have changed significantly, the proposed scheduling system defined by (3) can schedule the load effectively taking no power from the grid, rather providing power to the grid whenever possible.
- The proposed objective function not only responds effectively to any sudden emergency condition such as a brown out power crisis, but also enables the consumer

to earn incentives by participating in the demand response program. Therefore, the proposed scheduling system is robust and can be incorporated in future smart net-zero residential buildings.

In future, new operating conditions along with new optimization techniques will be applied for load scheduling in smart buildings.

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