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Optimal scheduling and demand response implementation for home energy management

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ABSTRACT

The optimal scheduling of the loads based on dynamic tariffs and implementation of a direct load control (DLC) based demand response program for the domestic consumer is proposed in this work. The load scheduling is carried out using binary particle swarm optimization and a newly prefaced nature-inspired discrete elephant herd optimization technique, and their effectiveness in minimization of cost and the peak-to-average ratio is analyzed. The discrete elephant herd optimization algorithm has acceptable characteristics compared to the conventional algorithms and has determined better exploring properties for multi-objective problems. A prototype hardware model for a home energy management system is developed to demonstrate and analyze the optimal load scheduling and DLC-based demand response program. The controller effectively schedules and implements DLC on consumer devices. The load scheduling optimization helps to improve PAR by a value of 2.504 and results in energy cost savings of ₹ 12.05 on the scheduled day. Implementation of DLC by 15% results in monthly savings of ₹ 204.18. The novelty of the work is the implementation of discrete elephant herd optimization for load scheduling and the development of the prototype hardware model to show effects of both optimal load scheduling and the DLC-based demand response program implementation.

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1. INTRODUCTION

Domestic consumers account for a significant portion of the power utility's overall load demand in India. Due to the increased use of a variety of appliances by the consumer, the power demand is increasing exponentially, which creates demand generation imbalances and stability issues in the grid. Effective mechanisms are needed for scheduling and controlling domestic consumer loads so that peak power reduction, grid stability, and grid efficiency can be improved. The scheduling of the residential consumer loads helps the consumers to take benefit of different alternatives of using energy and reducing the energy cost. This can be achieved by implementing demand response (DR) actions like shifting the devices used during low energy price periods, interrupting the working cycle for certain periods, and altering parameters of certain loads like temperature settings in the case of an air conditioner or electric water heater. Some devices like electric water heaters, and air conditioners have high energy consumption rates and if these devices operate coherently by different consumers, it can cause voltage quality issues at the remote end of the feeder. Load Scheduling is used to organize the operation of a set of loads into various time slots while minimizing electricity cost and peak to average ratio (PAR).

Technologies that allow automatic adjusting of demand by some programmed or learned rules in response to price signals while maintaining consumer comfort is known as optimal load shifting [1]. By enabling consumers to plan their shiftable load, demand side management increases their participation in helping the power utility achieve system objectives [2]. The utility's various dynamic pricing schemes for consumers can help to manage electricity costs, peak load reduction, and peak to average ratio improvement. Real time pricing (RTP) based DR program when implemented for home energy management systems helps to decrease the consumer's electricity costs [3]. The DR program helps to protect the grid from the risk of outages during peak periods, balances demand and supply, improves the reliability of the grid and reduces the usage of the spinning reserves [4]. The application of the home energy management system (HEMS) is to schedule the different categories of loads as per the consumer's priority to reduce the electricity bill [5]. The demand-side management technique of scheduling the end consumer home appliances that use power from the utility and the rooftop solar units helps to reduce the energy bill and PAR [6]. The direct load control (DLC) based DR program is an incentive-based program in which the power utility can control the power consumption of the consumer remotely. The utility notifies the consumer ahead of time, and an incentive is paid to him for his contribution [7].

Three different categories of devices were selected for our proposed model. Shiftable, curtailable, and fixed operation devices are selected for simulation and in the hardware model of the proposed work. The optimization code schedules the usage times of eight different devices in a house with different power requirements. The convenience of the consumer is taken into consideration by considering the preferred time interval for the optimal operation of the devices. The effective utilization of solar photovoltaic systems and energy storage can also help the utility and consumers effectively manage the load. Consumers' willingness to respond to a load schedule is influenced by a variety of factors, including the price of power, the time of day, the priority of use, and knowledge of extreme situations. The scheduling problem needs to consider economic optimization while satisfying varying levels of technical constraints. The controller controls the operation of devices based on the optimization algorithm meeting the conditions.

The first part of this work is to develop a system that will reduce energy consumption and minimize the cost function considering the user's time preference and comfort by using the heuristic binary particle swarm optimization (BPSO) and discrete elephant herd optimization (DEHO) algorithms. The model considers various types of home appliances with operations related to RTP. The optimization scenarios with the integration of a photovoltaic system for more efficient load scheduling are also considered in the model. The various constraints, including daily energy requirements and consumer preferences, are considered. The mathematical model used to decide the schedule and the cost function is implemented in MATLAB using the BPSO and DEHO techniques. The load schedule seeks to determine the best time to use an appliance based on its power and the hourly variation of the electricity price. The second part of the work is the implementation of direct load control-based DR programs that help the utility manage peak loads, improve the peak-to-average ratio, and minimize the power procurement cost. The prototype hardware model is developed to demonstrate the effect of optimal load scheduling and DLC DR from both the consumer and utility point of view.

In the literature review, the study and analysis of different scenarios, including developing the hardware model, are not reported in a single work. The focus of this work was to develop the simulation as well as the hardware model which can demonstrate the savings that can be achieved due to DR implementation. Our approach with optimization helps to reduce energy costs, and PAR, considering user priority which is also demonstrated by the prototype hardware model results.

The primary contributions of the work are to i) Analyze the benefits of both optimal load scheduling and DLC-based demand response program; ii) Help to balance demand and supply to minimize electricity costs and minimize PAR; iii) Develop a prototype of a HEMS considering consumer preferences; and iv) Promote energy, cost savings, and efficiency improvement with participation of a large number of consumers based on the findings from the paper. The results indicate that the optimal load scheduling model minimizes the total electricity cost and PAR benefiting both the consumer and the utility. The effect of integrating photovoltaic (PV) systems into the utility supply grid also helps to reduce energy costs and peak power, benefiting both the consumer and the utility.

2. LITERATURE REVIEW OF RELATED WORKS

Optimization studies are available in the literature that focus on a single optimization goal of reducing total electricity costs by scheduling the operation of consumer devices. A multiperiod consumer management methodology is proposed for scheduling the loads, considering different types of demand response and supply options under a dynamic pricing scheme [8]. To reduce costs under the time of use (TOU) pricing plan, mixed integer linear programming (MILP) is utilized to schedule residential appliances optimally while taking solar PV and battery energy storage system (BESS) installation into account [9]. To reduce the overall cost of the microgrid system, an updated particle swarm optimization (PSO) algorithm is employed to generate the best schedule strategy for the variable loads in the microgrid [10]. To optimally schedule the different loads based on time-varying pricing and user priority, a home automation system is designed and developed [11]. Smart load scheduling modeling using mixed integer nonlinear programming for a microgrid with PV systems is developed with the objective of either minimizing the peak load or the electricity cost [12]. An optimization strategy for the optimal energy management of the home considering thermostatic loads like an electric water heater, and solar photovoltaic (SPV) systems along with a BESS is presented in [13]. An optimization framework is developed in [14] for the best demand response scheduling at the residential community level, considering smart loads, BESS, electric vehicle (EV), and renewable sources using residual load modeling. For the energy management of smart homes, MILP-based optimization is used, taking into account the integrated approach of BESS, EV, smart loads, and renewable sources, which considers the requirements of both supply and demand sides [15]. A heuristic DR technique is adopted for scheduling the appliances to reduce the peak-to-average ratio with a focus on maintaining consumer confidentiality. To schedule the appliances on a flexible schedule without needing individual appliance consumption, the suggested solution uses a hopping strategy [16]. The shiftable home loads are scheduled using a cuckoo search optimization technique to balance the load curve and reduce costs [17]. In study [18], grey wolf optimization is used for the optimal scheduling of the household appliances of two different houses with TOU and RTP tariff schemes.

Different DR contracts like load curtailment, load shifting, and onsite generation power are considered for the price-based self-scheduling model using the MILP optimization technique to obtain optimal DR schedules for the consumers in the day ahead energy markets [19]. To plan and regulate the power consumption of the air conditioner, electric water heater, washing machine, and refrigerator of the domestic consumer to lower the electricity bills by taking into account the DR signals, an artificial neural network (ANN)-based home energy management controller is simulated in MATLAB [20]. For the residential community considering aggregated air-conditioning loads, an energy management strategy is proposed to minimize energy consumption by using the MILP technique [21]. In study [22], load scheduling problem is formulated as a constrained multi-objective problem with minimizing energy cost and maximizing overall utility, and a modified version of the multi-objective optimization evolutionary algorithm based on decomposition using a differential evolution operator is adopted. MILP is adopted for optimizing the simultaneous demand and cost mitigation for five residential users using time of use rates with user time preference as the constraint [23]. A new RTP technique is presented in [24] that can be used to implement DR programs in order to reduce the peak load and the energy expenditure which is validated by simulation results. The Cuckoo search and symbiotic organisms search algorithms are used to efficiently schedule time-shiftable loads in a task scheduling-based DR technique, and the results obtained are compared. The basic hardware model for the DR implementation for consumer loads has been developed by the authors in [25], but the results are obtained without optimization. PLC-based advanced metering infrastructure and the OpenADR 2.0 protocol are used for developing the automated demand response system for the control of residential loads. To verify the performance of the protocol simulation tests are performed [26]. For a microgrid with SPV system, wind energy, battery storage, and load energy management is implemented using Arduino and internet of things (IoT) based system. the Arduino microcontroller senses the environmental parameters and gives to IoT system for energy management and minimizing energy costs [27]. A genetic algorithm is proposed in [28] for household energy management to reduce energy costs and PAR. The user comfort and integration of renewable energy are not considered in their work. A multi-objective genetic algorithm is proposed by Ullah *et al.* [29] to minimize operating costs and reduce carbon emissions with incentives for consumers, but consumer comfort is not considered. In [30] the load scheduling scheme for the price-based DR program for IoT-enabled smart homes is suggested to minimize the energy cost and PAR. Mixed integer quadratic programming is proposed for the HEMS which is driven by a thermal source to reduce the electricity bill [31]. In study [32], a prototype hardware model is developed for appliance power scheduling and DR implementation, but the optimization is not carried out for scheduling of the consumer appliances. An improved binary bat algorithm is proposed in [33] to schedule the load demand of smart homes, reduce operation costs, and control energy generation from the distributed generator for a microgrid system.

Elephant herd optimization (EHO) is the population-based swarm intelligence nature-inspired metaheuristic algorithm. In base EHO algorithm searching strategy generates continuous variables, so the algorithm needs to be adapted to the binary search space to solve the scheduling problem. In DEHO the encoding scheme, cross-over, and moving operators in updating and separating phases need to be considered to solve the optimization problem. In this paper, DEHO is adopted to solve the scheduling problem as it provides the advantages of having few control parameters, faster convergence, and high solution accuracy.

The currently available literature in this field focuses mostly on unique or partially related aspects. It is observed from the review and analysis that all the scenarios with grid power, and the SPV energy system including implementing the strategies on the hardware model are not reported in a single work. In most previous works, only optimization or simulation studies are carried out to see the effect of load scheduling there is no focus on developing the hardware model. This work develops a prototype hardware model to show how to schedule loads efficiently while controlling devices and implementing an emergency DLC DR program. The HEMS is designed and developed to optimally schedule the devices based on RTP rates, considering consumer satisfaction based on user-defined time preferences. HEMS also carries out control of the devices to implement the emergency DLC DR program. Scenarios with optimal load scheduling using the DEHO heuristic algorithm considering only grid power, grid, and SPV power with the prototype hardware model with grid power supply are analyzed and addressed in this paper. The heuristic algorithm BPSO and DEHO are used to obtain the output considering the cumulative nature of the devices i.e., only one vector for a large number of devices used in formulating the objective function and the constraints. Our approach to optimization helps reduce energy costs, and PAR, considering consumer priority which is demonstrated by the prototype hardware model.

3. PROPOSED METHOD FOR FORMULATION OF LOAD SCHEDULING AND DR MODEL

The consumer's interests and needs determine how much electricity they use throughout the day; therefore, the consumption pattern is not consistent and flat. The consumer must manage the power consumption pattern of time-shiftable devices for higher energy efficiency and reduced energy expenses. Different types of home devices are taken into consideration for the model simulation based on their power consumption patterns as shown in Table 1. The devices under consideration are divided into fixed, time, and power-shiftable categories. Devices that are required and must operate constantly for 24 hours or for a specific number of hours each day, such as refrigerators, are referred to as fixed or nonflexible devices. The users of power-shiftable devices are encouraged to complete a task within a certain time frame that is designated in the operation schedule. The third type consists of time-shiftable appliances, whose operation time can be changed to any other time slot without compromising performance, but the demand must be met without an interruption in between.

Table 1. Details of consumer devices considered in the model

Type of device	Power rating (watts)	Start point (Hour)	Finish point (Hour)	Energy requirement per day (kWh)
Dishwasher	1,000	11	19	2
Electric water heater	2,000	8	22	4
Air conditioner	1,000	9	23	5
Washing machine	500	9	17	1.5
Electric vehicle	2,000	22	8	10
Non-flexible loads	600	1	24	12
Water Pump	400	1	13	1.2

Total energy consumption and total energy cost for a day is given by (1) and (2) respectively.

$$\text{TEC}=\left(\sum_{j=1}^{Q} P_j^t X_j^t\right) + \left(\sum_{i=1}^{D} P_i^t X_i^t\right) \tag{1}$$

$$\text{TC}=\sum_{t=1}^{M} R^t \left[\left(\sum_{j=1}^{Q} P_j^t X_j^t\right) + \left(\sum_{i=1}^{D} P_i^t X_i^t\right)\right] \tag{2}$$

where *TEC* is the total energy consumption, *TC* is the total energy cost, P_j is a shiftable type of device, P_i is a fixed type of device, Q is the total fixed type of devices, D is total nonflexible devices, X indicates the status of operation i.e., on or off, R^t is the real-time energy price prevailing at that time slot.

The optimization of the electricity cost is realized using BPSO and DEHO methods. The results obtained using DEHO are presented in the paper and it can be established that the proposed DEHO has exhibited better conquest solutions. In load scheduling formulation it is assumed that the power utility provides the RTP tariff to the consumer one day in advance so the scheduling can be performed with the objective of minimizing the energy cost and PAR. For the implementation of a DLC-based DR program, it is assumed that the curtailment signal is provided by the power utility two hours in advance to the consumer. The optimization is implemented to schedule the usage of eight different appliances each with a distinct amount of energy consumption. The appliances are power-shiftable, so optimization can schedule power usage throughout various hours while maintaining a steady supply of energy. The output vector consists of the hourly schedule of each schedulable device. The mathematical model is based on a set of discrete variables, and it needs to be optimized by minimizing an objective function. The objective functions formulated are linearly dependent on the decision variables under a given set of constraints. The first objective is to minimize the energy cost as given in (3), the second objective is to minimize PAR as per (4) and the third is the overall multiobjective function as per (5) is to minimize the energy cost and PAR. The functions used as objectives in the BPSO and DEHO algorithms are subject to constraints. The objective functions $F1$ and $F2$ are normalized to solve the multiobjective optimization function $F3$.

$$F1 = Min\left[\sum_{t=1}^{M} R^t \left[\left(\sum_{j=1}^{Q} P_j^t X_j^t\right)\right) + \left(\sum_{i=1}^{D} P_i^t X_i^t\right)\right)\right]\right] \quad (3)$$

$$F2 = Min\left[\frac{Max \sum_{t=1}^{M}\left(\sum_{j=1}^{Q} P_j^t X_j^t\right)\right)+\left(\sum_{i=1}^{D} P_i^t X_i^t\right)\right)}{\sum_{i=1}^{n}\sum_{i=1}^{n}\left(\frac{P_j^t X_j^t + P_i^t X_i^t}{M}\right)}\right] \quad (4)$$

Objective functions $F1$ and $F2$ are normalized by dividing with the unoptimized maximum value, and the normalized functions are used in solving multiobjective function $F3$ considering the weight factors α_1 and α_2. Conflicting performance metrics generate a trade-off which is formulated as a constrained multiobjective optimization problem.

$$F3 = Min(\alpha 1 F1 + \alpha 2 F2) \quad (5)$$

The objective functions are subjected to equality, inequality, and upper and lower bounds as constraints. Four parameters S_d, F_d, P_d, and E_d are used in the modeling of each type of device that can be scheduled. Here the S_d stands for the starting point of operation of the device, F_d is the finishing time, P_d is the power rating of the device, and E_d is the total energy requirement. The constraints related to the mandatory energy requirement, device operating window, power rating, and type of load (dimmable, shiftable) are considered. The formulations for scheduling of power shiftable, continuous operation devices, and alternate time slot operation are also considered in the analysis. For analysis, the values of α_1 and α_2 are taken as 0.6 and 0.4 as more priority is given to the objective of minimizing the cost and less priority to the PAR. The optimization can also be carried out with different values of α_1 and α_2. The result of the algorithm gives the total energy cost and the optimal schedule of the devices, representing their operation time and power consumption with consumer preference. The optimization using an algorithm is carried out for both 24 as well as 96-time blocks for hourly and 15-minute time scheduling respectively.

3.1. Optimal scheduling of loads by DEHO algorithm

In this section, the performance of the proposed DEHO derived from a population-based swarm intelligence nature-inspired metaheuristic algorithm is analyzed. It has been used to tackle many power system optimization problems and has proven to be quite successful in finding global or almost global solutions. EHO has good convergence characteristics and the potential to find the optimal solution. When compared to many other nature-inspired algorithms, this one can explore significantly better optimal solutions. EHO has a strong search ability and can find the fittest solution [34]–[36].

The exploration and exploitation characteristics of the global optimization technique are mathematically modeled using the behavior of the clan's elephants. The matriarch is the oldest female elephant in each elephant family and guides the other elephants. The matriarch is considered the most suitable elephant in the family, which indicates the clan updating operator and is used to model and solve an optimization problem. As the base EHO algorithm search strategy generates continuous values to solve binary optimization problems, the EHO algorithm should be adopted to the binary search space. To solve the device scheduling problem DEHO algorithm is adopted. Proper encoding scheme, crossover, and moving operators in updating and separating phases need to be considered in the DEHO algorithm.

The following steps are normally taken to implement the algorithm. First get the addresses of the initialization, cost function, and feasibility functions. Initialize the elephant population next, make sure there are no duplicates, compute the cost for each individual, order the population based on how well it fits the criteria, and calculate the average cost in subsequent steps [35], [37].

All the elephants in the clan act as search agents in an elephant community of size 's' in the surrounding region. The vector 'pe' as in (6) gives the population of each elephant 'e' at iteration 'j' and (7) gives the population of size 's' with dimension 'c' at iteration 'j'. The following steps were adopted in order to solve the optimization problem.

Step 1: The position of each elephant in different clans except the matriarch and male elephant that holds the best and worst solution in each clan are updated.

$$p^j e = [p^j e, 1p^j e, 2p^j e, 3 \ldots\ldots\ldots\ldots\ldots\ldots p^j e, d] \quad (6)$$

where e=1.2.3 ... s and j=1,2,3 … $jmax$

$$p = \begin{pmatrix} pe, 1^t & \ldots & pe, d^t \\ \vdots & \ddots & \vdots \\ ps, 1^t & \cdots & ps, d^t \end{pmatrix} \quad (7)$$

Depending on the matriarch's position, each elephant in the clan pe will shift positions. In the following iteration, pe will update the position for the elephant in the clan as per (8).

$$pe^{j+1} = pe^j + \rho * (pbest^j - pe^j) * r \quad (8)$$

$pe^{j+1}{}_1$ and pe^j are the newly updated and old positions for the elephant e in the clan pe respectively. ρ € [0,1] is the scale factor that determines the impact of the matriarch in clan pi on the elephant e. The distribution r € [0,1] is considered to be uniform.

Step 2: Updates the position of each clan's fittest elephant

The best elephant can modify its position as per (9).

$$pbest^{t+1} = \beta * pcenter^t \quad (9)$$

where scale factor β € [0,1] influences the $pbest$. The $pcenter$ is in the middle of clan pe.

Step 3: Separating the worst male elephants

The single worst inferior elephant is used as a separation operator at each iteration to separate from the clan in accordance with (10). This is done to increase the searching ability of EHO.

$$peworst^t = p\,min + (p\,max - p\,min + 1) * rand \quad (10)$$

$$peworst^t = round(p\,min + (p\,max - p\,min + 1) * rand) \quad (11)$$

where $pmin$ and $pmax$ are the upper and lower bound of the individual elephant position respectively. $peworst$ is the worst elephant in the clan, rand is the random number, and the $round()$ function that rounds each of the randomly generated vector components in continuous space to the nearest integer. The upper and lower bounds are equal to 1 and 0 since each of them can take binary values in the DEHO algorithm.

Step 4: Convergence

Clans are recombined after the separation phase to begin the next iteration of the clan update phase. Until the convergence condition is met, steps 1-4 are repeated. The DEHO algorithm is able to optimize the combination of the product of the scheduling vector with the power rating of devices.

The procedure followed for coding the load scheduling optimization problem is as follows. All the residential devices with their power rating are represented by vector '*X*.' So, the vector gives the power consumption of a device at any instant of time. For hourly scheduling in a day, the number of the elements in the vector is the product of 24 and the number of devices that are scheduled. If the time slots for the day are given by '*T* and the number of devices considered is '*D*'. The number of elements in the vector is considered as *T**D*. The first *T* elements of the vector will be the status of device 1 multiplied by its power rating P_1, and the second *T* elements will be the status of device 2 multiplied by its power rating and this continues till all the devices are covered. The real-time price data for 24 hours or 15 minutes time block is obtained from the state power utility is considered with *T* number of elements in vector based on the number of devices.

Now for solving the problem using DEHO the objective function with a set of constraints is considered, one related to the preferred time interval of operation and the other related to the total energy that the device can consume. The DEHO code file contains parameters like the number of particles/clans, scaling factor, a random value, upper bound, and lower bounds of '*X*'. The output of the DEHO code file generates a random vector '*X*' with 0 and 1 indicating the off and on status of the devices. The status obtained is then fed to the objective function file to find whether it obeys the constraints and the value of the objective function is saved to obtain the best position of the elephants. A similar procedure is repeated for all the elephants in the clan. Then the vector position is changed by altering the position of the matriarch separating the worst elephant and using predefined constants. This new vector is also fed to the objective function file and values are compared to that of randomly generated '*X*'. The most desirable value and its corresponding index are saved and it replaces the inferior elephants in clans in '*X*'. This procedure is repeated for a user-defined number of iterations, to get the best scheduling pattern for meeting the objective function. The desired '*X*' value obtained is separated based on the number of devices into T elements. The device rating is then multiplied by the optimal status of the devices to obtain the total power consumption and the load curve.

4. RESULTS AND DISCUSSION

4.1. Load scheduling optimization and simulation

Both BPSO and DEHO techniques are employed in the simulation to optimally schedule the consumer devices to reduce the peak load and energy expenses. The results obtained from both algorithms are then compared and analyzed. In the unoptimized case, the consumer has complete control over the functionality of his device and makes the decision about switching on and off the devices without any concern about the cost. In this work, it is assumed that the consumers turn on the load at the first or the second time slot of the specified time preference set decided as per their convenience. This type of switching results in a higher cost of energy and also a higher PAR for the utility. The energy bill of the consumer increases and the utility has to purchase power at a higher cost from the energy market due to unoptimized scheduling of the devices. The two scenarios are considered for the optimization based on either utilization of only the grid power and both grid power and SPV power to operate the consumer loads.

4.2. Scenario 1: consumer devices operating on utility grid supply

Consumer devices in this case just use the grid supply for their operation and are scheduled based on the RTP signal. Consumer devices operate in accordance with the load scheduling algorithm based on RTP rates. The scheduling algorithm optimizes the operation of the devices based on the (3), (4), and (5), as stated in the previous section. The results of scheduling obtained based on the DEHO algorithm are shown in Figure 1. Table 2 lists the parameters used for carrying out the load scheduling optimization. For 15 minutes time period or 96 blocks in a day the results of the optimization carried out are shown in Figure 2. In comparison to the unoptimized scheduling of the devices, the operation of the devices has shifted to different time intervals with optimization. After simulation, it is observed that the device's operation is spread throughout a 24-hour time horizon with the goal of minimizing the cost and PAR. Table 3 shows the outcomes of various scenarios used to model the system, and Table 4 compares alternative optimization techniques based on the objectives.

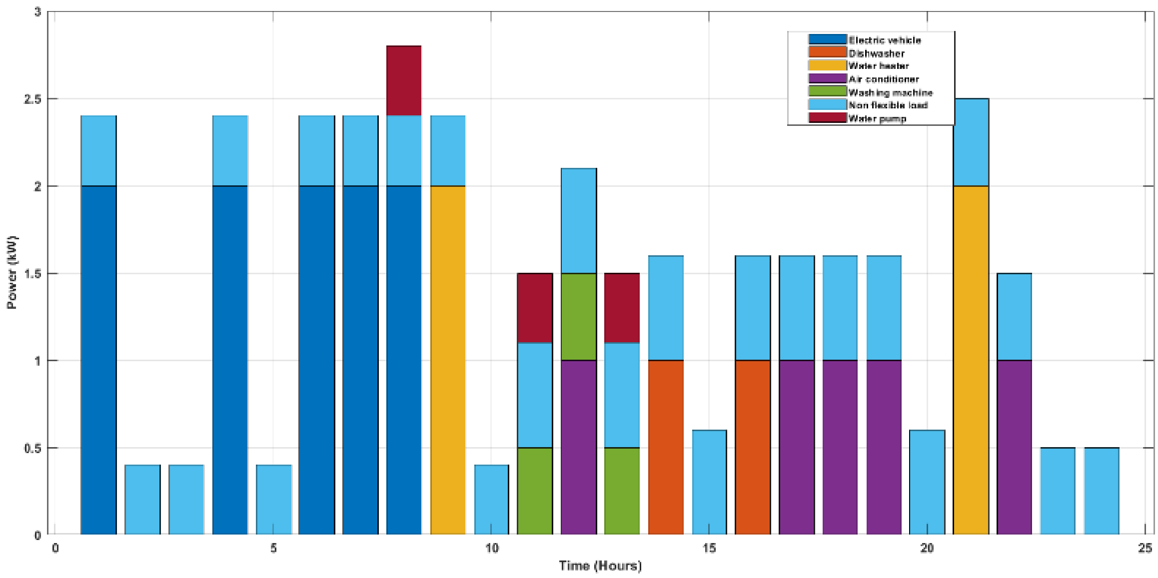

Figure 1. Optimal scheduling of devices using the DEHO algorithm

Table 2. Parameters of the optimization algorithm

Optimization type	Parameters	Parametric values
DEHO	No. of particles/Clans	150
	Scaling factor	0.1
	Maximum iterations	100
	Random value	0.5

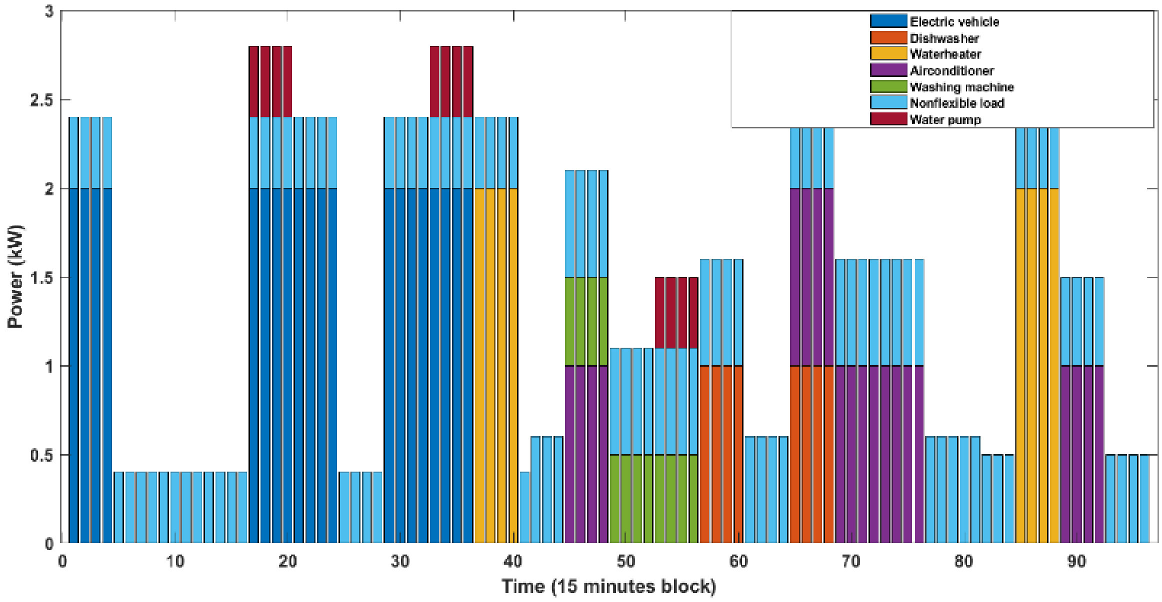

Figure 2. Optimal scheduling of devices using the DEHO algorithm for 96 blocks

Table 3. Modeling scenario comparison

Scenario considered	Cost in (₹)	PAR
Unscheduled	117.86	2.91
Only Grid Power	105.81	2.506
Grid+ SPV Power	63.14	1.887

Table 4. Evaluation of different optimization strategies

Optimization type	Cost in (₹)	Savings (₹)
Unoptimized	117.86	--
BPSO	109.60	8.26
DEHO	105.81	12.05

4.3. Scenario 2: consumer devices utilizing both utility grid supply and SPV power

In this scenario, it is assumed that the consumer owns an SPV system that produces electricity, thus lowering the amount of electricity required from the grid as well as the amount of electricity purchased each day. The consumers own generation from SPV is represented as a negative load based on the projected generation pattern for the following day. The SPV output profile is included in the optimization problem for the period of the scheduling horizon. During simulation, the SPV system of a 5 kWp roof-mounted PV system of the consumer is considered. The energy yield of an SPV system is obtained using PV*SOL software based on the location of the consumers residential site. The projected SPV output for the day is utilized for the optimization to find the most suitable time to schedule the devices, as per the objective functions shown in (12) to (13). The SPV generation's installed capacity is considered less than the total connected load. This approach helps consumers automatically establish the optimum operation schedules while taking into consideration consumer convenience, dynamic RTP pricing, and SPV energy yield. Power obtained from the utility electricity is used to optimize the device schedule, and because there is no storage, solar power is fed quickly. To reduce their electricity expenditure, the user schedules their appliances obtained from the optimization as illustrated in Figure 3. DEHO algorithm schedules the operation of the devices throughout the day to achieve optimal consumption, hence lowering the cost and PAR.

$$F1 = Min\left[\sum_{t=1}^{M} R^t\left[\left(\sum_{j=1}^{Q} P_j^t X_j^t\right) + \left(\sum_{i=1}^{D} P_i^t X_i^t\right) - \left(SPV^t\right)\right]\right] \tag{12}$$

$$F2 = Min\left[\frac{Max\sum_{t=1}^{M}\left(\sum_{j=1}^{Q} P_j^t X_j^t\right)+\left(\sum_{i=1}^{D} P_i^t X_i^t\right)-\left(\left(SPV^t\right)\right)}{\sum_{t=1}^{M}\sum_{j=1}^{Q}\sum_{i=1}^{D}\left(\frac{P_j^t X_j^t + P_i^t X_i^t - \left(SPV^t\right)}{M}\right)}\right] \tag{13}$$

$$F3 = Min(\alpha 1F1 + \alpha 2F2) \tag{14}$$

4.4. Analysis of direct load control DR program implementation

The power utility implements the DLC DR program for residential customers in response to contingency events and during periods of high wholesale electricity prices. When the utility encounters system contingencies, it directly controls the consumer devices in the case of a DLC-based DR program. The control signal is sent from the utility to the consumer's HEMS via smart meters, and the devices are controlled. The energy consumption pattern data of one of the domestic consumers was analyzed over six months for the proposed implementation. The consumer's last 10 weekly days of recorded power usage data are used to estimate reference or baseline consumption. The baseline consumption is calculated using the average 24-hour readings over the previous ten days. For the day on which the DLC program is to be implemented, the calculated baseline consumption for the day is shown, and the average load for that day is computed. When the power utility wants to execute load curtailment, it sends a control signal to the consumer, who subsequently manages his devices via a controller and a series of relays. We have simulated the cases where 5%, 10%, and 15% curtailment is applied based on the consumption during peak hours. The amount of curtailment is decided based on the computed average and measured power. If the detected power exceeds the computed average power, the load is reduced based on the priority of the devices' operation. The detailed implementation of this is explained further in the prototype hardware model. Figures 4 and 5 represent the results of simulations of the implementation of a DLC-based DR program regarding curtailment for two periods from 8:00 to 10:00 hours and 19:00 to 22:00 hours, respectively.

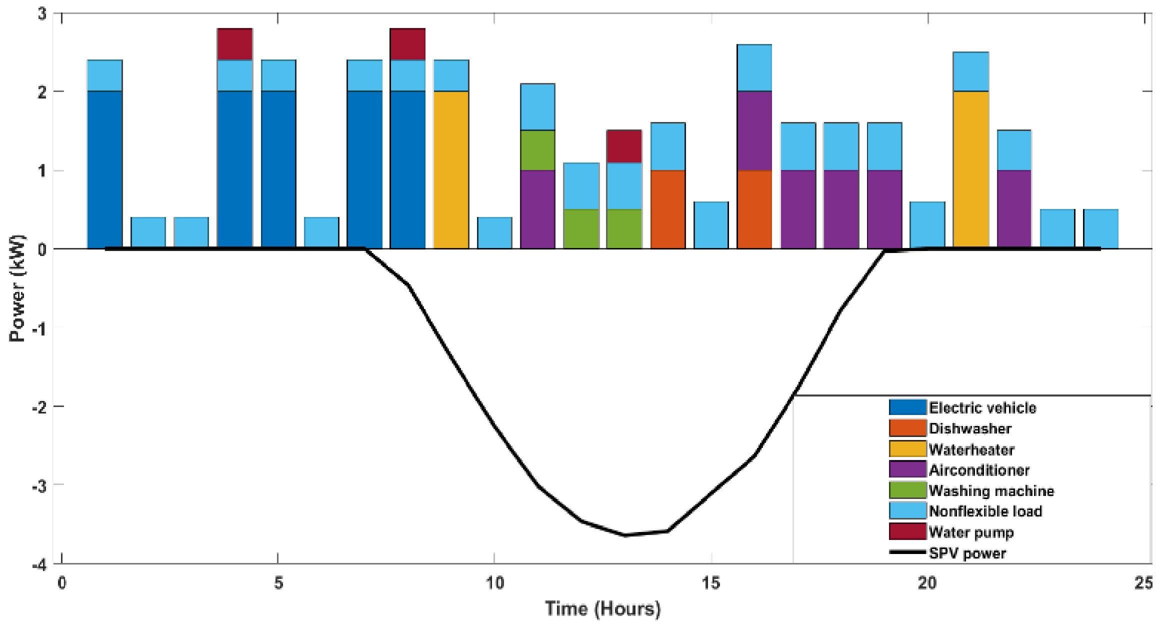

Figure 3. Scheduling of devices considering both grid and 5 kW SPV power

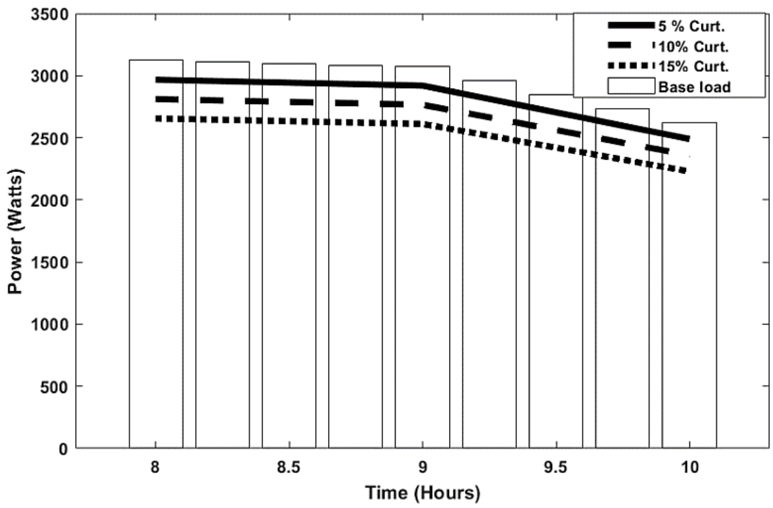

Figure 4. Comparison of predicted baseline load and objective load demand from 8:00 to 10:00 hours

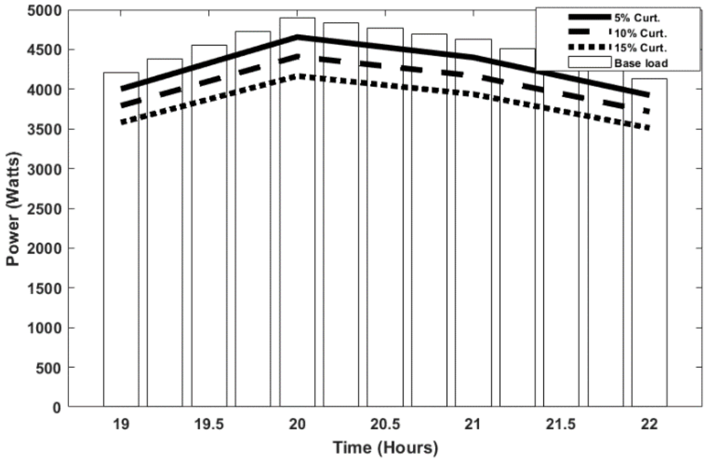

Figure 5. Comparison of predicted baseline load and objective load demand from19:00 to 22:00 hours

4.5. Hardware model design and development

Lack of effective building automation systems to manage the loads and lack of knowledge among the consumers to respond to the dynamic prices are major barriers to the effective implementation of DR programs for residential consumers. This problem is addressed by proposing the optimal and automated residential energy consumption framework which attempts to achieve the desired tradeoff between minimizing the electricity bill payment and the convenience of the consumers considering the operation of the household appliances under the RTP. The optimization strategy is developed first and then converted into code and then used to configure the Arduino-based controller. In case of the load scheduling the optimization code intelligently monitors the load during different pricing periods and accordingly sends the signal to control the operation time of the devices. A better and more efficient load devices scheduling plan is obtained.

Emulating household devices like refrigerators, washing machines, air conditioners, electric vehicles, and nonflexible loads like lighting incandescent bulbs have been used in prototype hardware. Table 5 indicates the rating of the various devices used for emulating it on the prototype hardware model. The devices are classified into three different categories based on power consumption patterns fixed, variable, and shiftable type. The incandescent bulbs of different power ratings are used to represent the devices on the hardware model. Figure 6 indicates the methodology followed in the work to obtain the solution for load scheduling optimization and DR implementation. The hardware model developed provides consumers the ability to automatically perform the device controls based on utility prices, consumer convenience, consumer load priority, and reliability issues faced by the utility.

The load shifting, controlling, and curtailing operations of the devices can be carried out as all these operations are programmed in the controller and are triggered when the load control signal is encountered. Basically, in the hardware model, there are two circuits namely the power circuit and the control circuit decided based on the voltage level. Figure 7 shows the power and the control circuit for the HEMS. All the loads are powered through a single-phase 230 V supply. The smart meter is used here only for measurement of the energy consumption. The power bank is used to obtain the DC supply to Arduino and node microcontroller unit (MCU). A DC power supply of 5 V is obtained for their operation. The control circuit is for controlling the loads using node MCU. Optocouplers are used in hardware circuits to provide isolation between the power circuit and the control circuit as well as for protection. All the loads are connected to the pins of Arduino with the help of relays and sensors which are powered accordingly. The voltage and current sensors are used for measurement of the voltage and current and further for computing the power and energy consumption based on the device operation. An app named load manager is developed for the consumer's smartphone that uses the Blynk platform to implement load scheduling and DLC DR program. The app designed is named load manager is shown in Figure 8. The app makes it convenient for consumers to participate in load scheduling and DR programs for device operation. As the node MCU can connect to a Wi-Fi router and keep an internet connection, the consumer can manage loads using a smartphone and the Blynk IoT platform's app. Using the voltage and current sensors, the controller determines the voltage, current, and power, and the power data is then shown on the app. The tariff rates of the utility are also displayed on the app. The controller unit is linked with the app for manual operation as well as notifications sent from the mobile application. The relays are used to control the operation of different devices based on instructions received from the controller.

Table 5. Device emulation in a prototype hardware

Name of device	For optimization rating (watts)	For hardware prototype rating (watts)
Dishwasher	1,000	100
Electric water heater	2,000	200
Air conditioner	1,000	100
Washing machine	500	50
Electric vehicle	2,000	200
Non-flexible loads	600	60
Water Pump	400	40

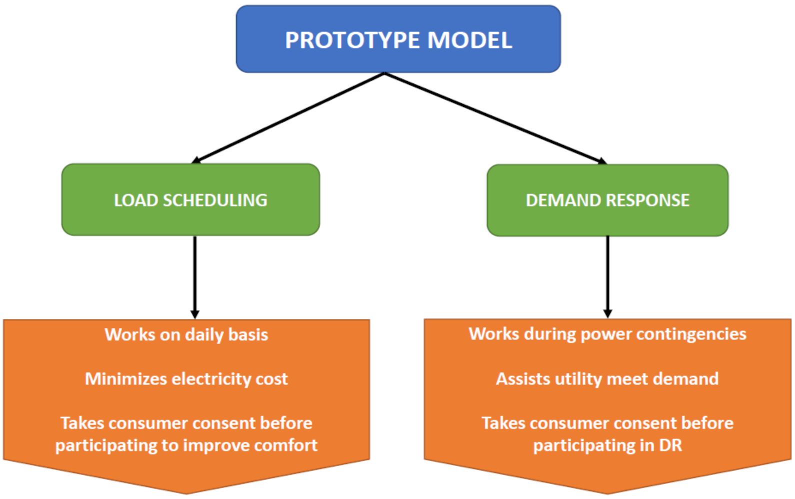

Figure 6. Methodology to prototype system model solution

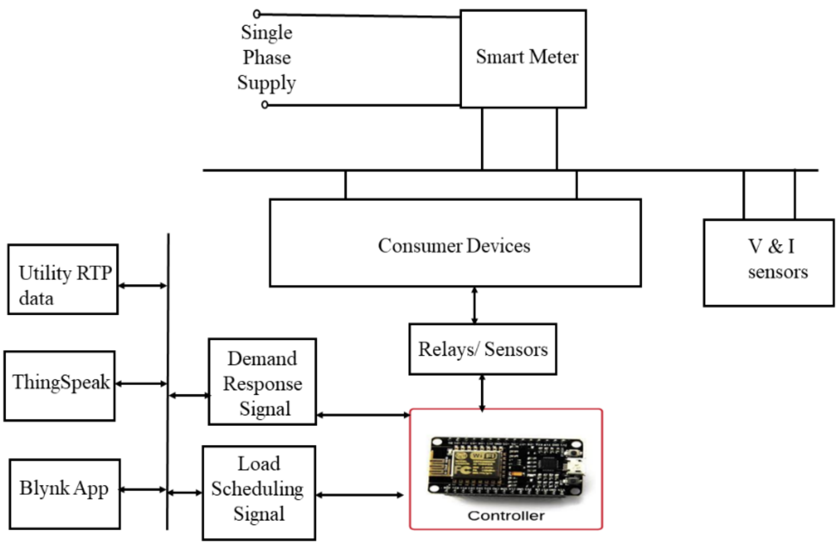

Figure 7. Block diagram of the prototype HEMS model

The prototype model is designed, developed, and coded in such a way that consumers have the option of participating in both optimal load scheduling and DLC-based DR programs based on their priority and preference. The state of devices with feedback features, such as washing machines, is examined so that the operation is not interrupted, as this will affect consumer satisfaction and processing items. For coding the consumer can feed the data such as start time, finish time, total energy usage, and number of devices based on which best schedule of operation of the devices will be obtained. Figure 9 shows the prototype hardware model with a set of loads, controllers, sensors, and smart meters.

Figure 8. Load manager app

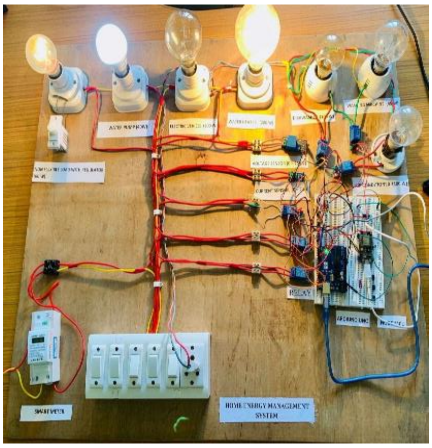

Figure 9. Developed prototype model

In this work, it is assumed that the consumer receives information on RTP rates, emergency DLC signals, and price incentives for demand reduction from the power utility via the registered cell phone. In the optimization code, the RTP rates are applied to minimize the cost and peak-to-average ratio. For implementation of the DR program by the utility, the consumer registers his name, smart meter ID, email ID, and smartphone number with the database of the utility. The information of the consumers willing to participate in the program is uploaded on the utility server. Every consumer can be monitored in real-time by the utility. ThingSpeak, an IoT service, is used in the work to replicate the power utility's analysis of consumers' power consumption for metering and to provide incentives. The MATLAB code for load scheduling and DR is executed in ThingSpeak for data processing, analysis, and visualization. ThingsSpeak securely gathers power consumption data from the controller device. The website presents data graphically and in real-time. Since each channel has a unique channel ID, data is sent to that channel. Consumers can download data from a channel as a CSV file from the ThingSpeak website.

4.6. Implementation of load scheduling optimization on prototype hardware

A smartphone application that allows users to schedule and manage device operations is created using the Blynk platform. Based on the notification received the consumer can decide whether to participate in the DR program. The switch is also used on the hardware module to control the manual or automatic operation. The consumer has to accord his consent before the scheduling of the devices as per the optimization algorithm code begins. The optimization code is sent to the Arduino-based node MCU for further implementation. The objective function, constraints, consumer preferences, and control parameters for scheduling the devices are sent to the controller via personal computer (PC) for the devices to be optimally scheduled. The device operation will be based on the output of the DEHO optimization code which generates the device operation vector for the node MCU to control the relays. The optimization code's output vectors are aggregated to form a matrix with dimension $T \times D$, where T is the number of time slots and D is the number of devices. The device vectors are transformed to digital 0's and 1's, indicating whether the device is turned on or off. The relays operating the device are normally open, and for timeslots where the device vector elements become greater than zero, the control signal to the relay is set high to connect the corresponding device. During the entire period, the Arduino/Node MCU should remain connected to the relays controlling the device operation. For remote operation of the devices, an internet (Wi-Fi) connection is needed.

To simplify and for analysis purposes, the load consumption computation during prototype model development, a reference day has been divided into 72 time slots. The power utilized by the devices is measured using the voltage and current sensors using the microcontroller, and the data is then transferred to the ThingSpeak platform for monitoring and records. The real-time operation with a record of consumption is shown in Figure 10. The instantaneous values of voltage, current, and power at a certain instant are shown in Figure 11. The instantaneous values are the direct values without any multiplying factor for power measurement or the current measurement. Whereas the readings shown in Figure 10 are with multiplying factor to replicate with the simulation model.

The data is collected regularly to keep track of how much power the devices utilize. Real-time energy consumption data can be received via a ThingSpeak service on the website. ThingSpeak enables the controller to deliver data to a specified channel. During the coding process, the channel ID and authentication credentials are provided to the controller. After establishing the channel ID and authentication information, real-time data on instantaneous and average power values can be retrieved. The collected data is sent to a server of the power utility to examine it for further study of energy billing and deciding on consumer incentives. The power consumption data is to determine the energy savings achieved over a period. The proposed hardware model, which is based on optimization code, can achieve device operating time within the customers' preferred time window, resulting in minimal power consumption while retaining consumer convenience.

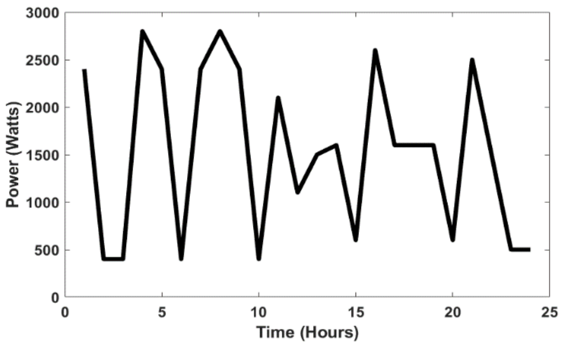

Figure 10. Measured power based on optimal device scheduling

Figure 11. Actual instantaneous values of electrical parameters

4.7. Implementation of DLC DR program on prototype hardware

Implementation of the DLC DR program by the state power utility for the domestic consumer is demonstrated with the hardware. DLC DR program is implemented only when the utility faces issues related to a power shortage, contingency situation or the wholesale electricity prices become very high on a particular day or a particular time of the day. The communication between the power utility and the consumers is must regarding power and information flow for implementation of DLC DR program. Whenever the power utility wants to implement this it sends the notification to the consumers one or two hours in advance. In the notification, all the information related to the start time, duration of the event, and the curtailment percentage needed is specified. The consumer choice is included in the programming code to indicate whether he wants to participate in DR or not. If the consumer gives his consent to participate then only the curtailment and control of his device operation can be done. The load curtailment value is decided from the average load data obtained from the baseline value. The average value of the load of the consumer is computed by taking the last 10 days daily hourly consumption excluding DR event days. The actual value of measured power is then compared with the average value of baseline power. Only if the actual measured value of the power is more than the average value then the load curtailment is carried out by controlling the operation of the devices based on the priority of the operation of the devices set by the consumer. The consumer decides the priority of the operation of devices based on his convenience and need.

The signal for DLC DR instructs every consumer who has signed a contract with the power utility to curtail his power requirement in exchange for the incentives. This is achieved through our algorithm which adequately curtails the load and the power. The required reduction needed is determined along with the value of the objective power. The current state of all the devices and the potential for the curtailment of the power is reviewed after computing the power difference. Consumers specify the order of priority for scheduling the devices, which is provided in the code. In the code for controlling the operation of the devices, the shiftable loads are given priority followed by curtailable and controllable loads.

In this paper working on the algorithm for the model, 5%,10%, and 15% curtailment volume from the average load value is demonstrated. The model is tested for two peaks of the load curve one during the morning peak and the other during evening peak hours. For a certain DR event day, the working of the DR algorithm on the model is tested. Figure 12 shows the load manager app developed for displaying the notification to the consumer for DR implementation. Once the signal is received based on the code the node MCU's transmitter and receiver will decide the operation of particular devices to manage the load.

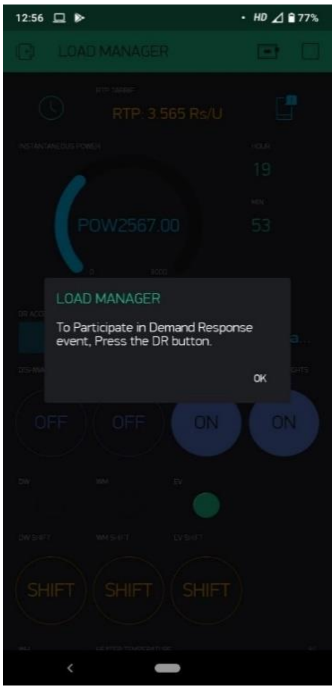

Figure 12. Developed app for load management and consumer notification

The power utilized by the devices before and following curtailment is recorded on the ThingSpeak service. The code includes a multiplying factor of 10 for getting measurement data to correlate the simulation and hardware results. The instantaneous values of voltage, current, and power values without any multiplying factor can also be obtained on the meter connected to the circuit. The measured value of the average power considered over a time period is sent to the ThingSpeak server. Since the time block of 15 minutes on average leads to precise energy billing and gives reliable data for the analysis, it is considered. Figure 13 shows the readings obtained on the ThingSpeak server platform. Through the ThingSpeak platform, the information of every consumer participating in the DR program can be uploaded to the power utility database for analysis of energy consumed and providing incentives for participation in the DR program. The power curtailment volume is determined using the power before and load curtailment depending on device operation. The load curtailment value is also utilized by the power utility to provide monetary incentives to the consumers for assisting the utility in managing load demand. Figures 14 and 15 depict power before and after DR implementation for two time periods, namely morning and evening peak hours.

Figure 13. ThingSpeak server showing the average power consumption

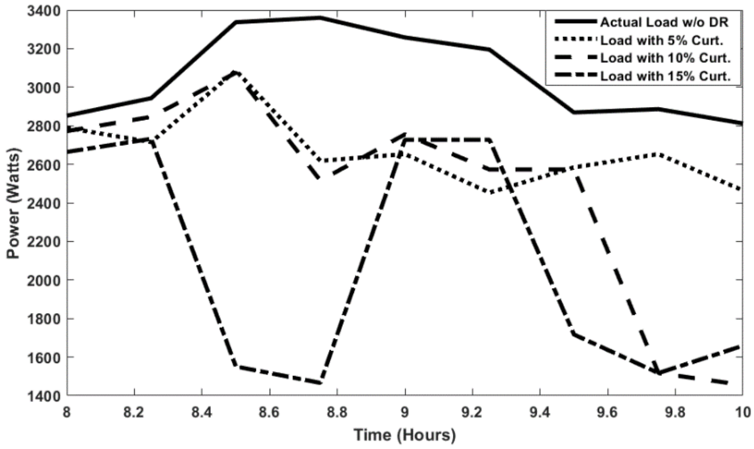

Figure 14. DLC implementation on actual load in a prototype model from 8:00 to 10:00 hours

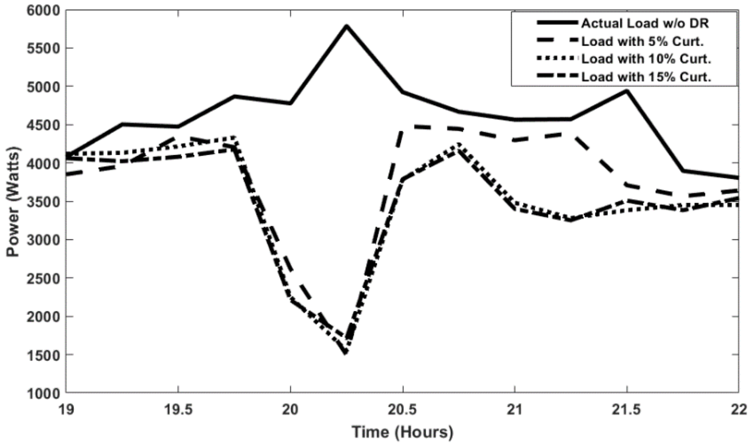

Figure 15. DLC implementation on actual load in a prototype model from 19:00 to 22:00 hours

As previously mentioned, the DLC DR was implemented on the hardware model for two time periods per day. Table 6 shows the results achieved for a day with RTP rates on that day. Similarly, the analysis was carried out for DLC DR deployment on 5 days with RTP rates in effect on those specific days; the results obtained are provided in Table 7. The power utility can also determine the amount of consumer incentives that can be provided based on the amount of load reduction achieved.

Table 6. Implementation of DLC DR for 1 day

Demand Curtailed (%)	Energy Saved (kWh)	Money Saved (₹)
5	3.59	15.08
10	4.91	35.7
15	5.83	39.85

Table 7. Implementation of DLC DR for 5 days in the month

Demand Curtailed (%)	Energy Saved (kWh)	Money Saved (₹)
5	18.39	77.26
10	25.13	182.93
15	29.85	204.18

5. CONCLUSION

The DEHO algorithm proposed optimizes device scheduling based on user time preferences, resulting in significant cost savings and PAR reduction. The results of simulations and optimization show that load scheduling benefits both the power utility and the consumer. The prototype hardware implementation validates the simulation model. For different time durations, DLC-based DR implementation for the consumer is demonstrated using prototype hardware. Adoption of the proposed approach results in effective load control, reduced peak load, and improved load factor, all of which benefit both the consumer and the utility. If the proposed concept is adopted on a wide scale by the state power utility for domestic consumers, it has the potential to improve the security and reliability of the distribution system network of the power utility.

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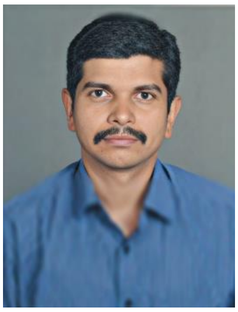

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