

# A Demand Response Framework to Overcome Network Overloading in Power Distribution Networks<sup>\*</sup>

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**Abstract:** This paper considers the problem of network overloading in the power distribution networks of Pakistan, often resulting from the inability of the transmission system to transfer power from source to end-user during peak loads. This results in frequent power-outages and consumers at such times have to rely on alternative energy sources, e.g. Uninterrupted Power Supply (UPS) systems with batteries to meet their basic demand. In this paper, we propose a demand response framework to eliminate the problem of network overloading. The flexibility provided by the batteries at different houses connected to the same grid node is exploited by scheduling the flow of power from mains and batteries and altering the charging-discharging patterns of the batteries, thereby avoiding network overloading and any tripping of the grid node. This is achieved by casting the problem in an optimal control setting based on a prediction of power demand at a grid node and then solving it using a model predictive control strategy. We present a case study to demonstrate the application and efficacy of our proposed framework.

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## 1. INTRODUCTION

The economic and social impact of an unreliable power generation and distribution system can be huge. For example, in Pakistan, the annual loss is estimated to be 4.5 billion dollars (1.7% of gross domestic product), while more than 50 million still remain off the grid (Samad and Zhang (2018)). The demand-supply gap results in an average of six to eight hours of outages per day during hot summers when the demand peaks and the existing infrastructure cannot sustain the power flow from generation to end users. With the increase in energy demand to sustain economic growth and more people connecting to the grid, the existing infrastructure is going to be more strained. Replacing or upgrading the transmission and distribution system is either costly or infeasible, hence necessitating more innovative solutions to the problem of network overloading.

During the power-outages, consumers usually rely on Uninterrupted Power Supply (UPS)<sup>1</sup> systems together with

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<sup>1</sup> UPS is a power-converter that ensures a smooth flow of power to the critical loads from the associated battery, in case of interruption of the mains power supply. It also charges and discharges the battery depending on the availability of the power.

electric batteries to meet their most essential requirements. Due to planned and unplanned outages in the country, almost every household in Pakistan has a UPS-battery system installed. In this paper, the availability of such a resource is exploited, and a Demand Response (DR) based approach is proposed to address the network overloading problem by utilizing the flexibility of the energy storage devices at the consumers' premises. Based on a forecast of power demand at a given grid node, the flow of power is scheduled from the grid and storage batteries to houses connected to the same node, while altering the charging periods of the batteries to off-peak hours. This smart coordination of the electric batteries with the grid helps to keep the overall load on the grid node within its limits, and thus reduces overloading and power-outages. All of this is achieved by posing the problem in an optimal control framework and solving it in a receding horizon fashion using a Model Predictive Control (MPC) setting. The optimal strategy eliminates the peaks in consumption at a given node and ensures continuous flow of power to all the consumers connected to that node.

The purpose of DR is to enable the consumers to contribute to the operation of the electric grid by reducing or shifting their electricity usage to off-peak hours, thus giving some relaxation to the grid. Various DR techniques have been proposed in the literature. Consumer partici-

pation, however, usually comes with an incentive such as subsidised rates during the off-peak hours (Ballenger et al. (2017), Mahmood et al. (2014)). In (Ma et al. (2012), Avci et al. (2013), Conejo et al. (2010)), an MPC approach is proposed to minimize the daily electricity costs of the consumers. In (Vrettos et al. (2013), Qureshi et al. (2014), Bianchini et al. (2016)), an MPC controller that enables optimization of building's thermal load operation in the presence of day-ahead and real-time prices was proposed. (Oldewurtel et al. (2010)) considers building climate and incorporates an electricity tariff directly into the cost function of an MPC setup to reduce the peak demand. (Li et al. (2011)) solve for an optimal price policy that not only reduces the consumers' individual electricity bill but also benefits the whole system. (Zhang et al. (2014)) explicitly models the dynamic nature of specific appliance preferences and their short term evolution to solve for an optimal price policy.

This paper presents a DR framework that addresses the network overloading problem by adopting demand side management, where the flexibility provided by the energy storage devices is exploited in conjunction with a demand forecast. The problem is posed in an optimal control framework where the optimal strategy alters the charging/discharging times of the batteries, based on a demand forecast, and optimally schedules the flow of power from the grid and the batteries to meet the consumers demand. With the proposed approach, the discharged batteries are scheduled to charge during the off-peak hours, and in such a way that the simultaneous charging of the batteries at all houses is avoided to evade network overloading events, e.g., consider a case where all batteries have been fully discharged during the peak hours. In the usual scenario, where DR is not implemented, all batteries will begin charging right after the power-outage is recovered. This can cause overloading as soon as the power supply is resumed. However, an optimization based technique, as proposed in this paper, ensures that the charging time of the batteries is distributed through out the off-peak hours in such a way that the batteries are charged without overloading the network. The efficacy of the proposed framework is shown in simulations. It is demonstrated that the proposed approach optimally regulates the flow of power, thereby eliminating network overloading and thus power-outages during peak hours.

The main contribution of this paper can be summarized as follows:

- (1) A DR based strategy is proposed to overcome and minimise network overloading events in a power grid.
- (2) A framework of the DR based strategy is presented, where a Model Predictive Control (MPC) strategy is employed to control charging and discharging of the batteries.
- (3) The proposed strategy is implemented on the demand profiles of an average house in Las Vegas and San Francisco (Data source: EERE (2019)).

The paper focuses on the special case of Pakistan (where UPS-battery setups already exists), however, due to unavailability of consumption data of houses, authors are using available data from a foreign country. The proposed framework is quite general and extendable to any power grid with battery based resources such as electric vehicles,

houses with solar systems etc. Additionally, appliances with major consumption such as air-conditioners can also be incorporated into DR framework to fully exploit the flexibility of the load.

The rest of the paper is organized as follows. Section 2 presents the problem formulation. An MPC based optimal control strategy is presented in Section 3 to solve the problem over a finite horizon. In Section 4, simulation results are provided to demonstrate the working of the proposed framework. Section 5 concludes the paper.

## 2. PROBLEM FORMULATION

In this section, we first present a setup that is amenable to the application of our demand response framework. We then present the mathematical models for batteries, power consumption and demand forecasts and then propose cost functions to achieve the objective of minimizing network overloading.

### 2.1 Network Control Architecture

Consider a typical household with a UPS-battery setup and connected to grid as shown in Figure 1. The house can take power from the grid or from the UPS-battery unit in case the grid is down. Figure 2 shows the proposed control overlay over the existing network architecture for the implementation of our framework. In this setup, a communication link is established between a central controller and UPS-battery units at homes to allow for exchanges of information such as battery's State-Of-Charge (SOC) and control signals for charging and discharging of batteries. We assume that the appliances at homes can be powered by grid and UPS-Battery units simultaneously e.g. using multi-port power converters.

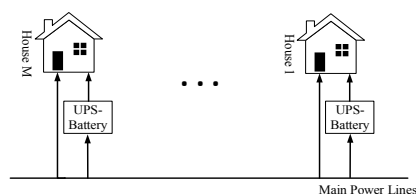


Fig. 1. Current status of the power distribution network in Pakistan.

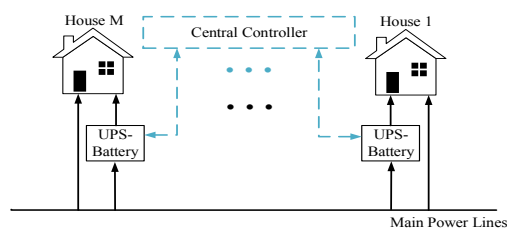


Fig. 2. Proposed upgrade for the power distribution network in Pakistan.

### 2.2 System Modeling and Constraints

Consider a cluster of  $N$  houses attached to a grid node, out of which  $M$  houses are equipped with UPS-Battery

setups, as shown in Figure 2. The dynamics of a battery, inspired by (Patrinos et al. (2011)), can be represented as

$$x_j(k+1) = a_j x_j(k) + b_j u_j(k), \quad (1)$$

where  $j = 1, 2, \dots, M$  denotes the battery in the respective house. Here  $x_j$  represents the State-Of-Charge (SOC), while the coefficients  $a_j$  and  $b_j = [\eta_j^c \ \eta_j^d]$  represent dissipation factors, and the charging and discharging coefficients of the  $j^{\text{th}}$  battery. The input  $u_j$  to each respective battery is assumed to be of the form  $u_j(k) = [u_j^c(k) \ u_j^d(k)]^T$ , where  $u_j^c$  and  $u_j^d$  represent the charging and discharging inputs respectively. To obtain a more compact representation, we concatenate the equations in (1) to obtain the following state space model:

$$X(k+1) = AX(k) + BU(k), \quad (2)$$

where

$$X(k) = [x_1(k) \ x_2(k) \ \dots \ x_M(k)]_{M \times 1}^T, \quad (3)$$

$$U(k) = [u_1(k) \ u_2(k) \ \dots \ u_M(k)]_{2M \times 1}^T, \quad (4)$$

and

$$A = \begin{bmatrix} a_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & a_M \end{bmatrix}_{M \times M}, \quad B = \begin{bmatrix} b_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & b_M \end{bmatrix}_{M \times 2M}.$$

If we let

$X_L = [x_{1,l} \ \dots \ x_{M,l}]_{M \times 1}^T$  and  $X_H = [x_{1,h} \ \dots \ x_{M,h}]_{M \times 1}^T$  denote the minimum and the maximum SOC allowed for the batteries, we then have the constraint

$$X_L \leq X(k) \leq X_H. \quad (5)$$

Similarly, there is a constraint on the inputs

$$U_L \leq U(k) \leq U_H, \quad (6)$$

where

$U_H = [u_{1,h} \ \dots \ u_{M,h}]_{2M \times 1}^T$  and  $U_L = [u_{1,l} \ \dots \ u_{M,l}]_{2M \times 1}^T$  contain the maximum and minimum charging and discharging limits for the inputs respectively. Since each input further has a charging and discharging component, we let

$$U_c(k) = [u_1^c(k) \ u_2^c(k) \ \dots \ u_M^c(k)]_{M \times 1}^T, \quad (7)$$

$$U_d(k) = [u_1^d(k) \ u_2^d(k) \ \dots \ u_M^d(k)]_{M \times 1}^T. \quad (8)$$

where  $k$  denotes the time index. At any given time, a UPS can either charge or discharge a corresponding battery, but can't do both i.e. both  $u^c$  and  $u^d$  cannot be positive simultaneously. Alternatively, each battery can remain in an idle state with no charging or discharging happening. This constraint on charging and discharging of batteries can mathematically be written in succinct form using the Hadamard product (Horn (1990)) as

$$U_c(k) \circ U_d(k) = \mathbf{0}_{M \times 1}, \quad (9)$$

where  $\mathbf{0}_{M \times 1}$  is a vector of zeros of size  $M \times 1$ .

### 2.3 Power Consumption

The total power flow from the grid node to the cluster can be modeled as

$$P(k) = \sum_{j=1}^N d_j(k) + \sum_{j=1}^M u_j^c(k) - \sum_{j=1}^M u_j^d(k), \quad (10)$$

where  $d_j(k)$  represents the actual consumption of the  $j^{\text{th}}$  house measured by a smart meter, while  $u_j^c(k)$  and  $u_j^d(k)$

either adds to or subtracts from the load. There is an upper limit on the total available power to the node imposed by the operators to avoid network overloading. This limit is imposed by the ratings of the transmission wires and the transformers tasked to supply power to the given node, and can be represented by the following inequality constraint

$$P(k) \leq P_{\max}. \quad (11)$$

Whenever the demand exceeds the constraint, the electricity providers disconnect the entire power supply to avoid any damage to the associated electrical systems in the network.

### 2.4 Demand Forecast

To be able to determine the optimal charging and discharging inputs  $u_j^c$  and  $u_j^d$  at time  $k$ , we need a demand forecast in such a way that  $P(k)$  never exceeds  $P_{\max}$ . For our problem, we use the following Auto Regressive (AR) predictor, inspired by (Fan and Hyndman (2012)), as the demand forecast model for a single house:

$$\hat{d}(k) = a_1 d(k-1) + a_2 d(k-2) + a_3 d(k-3) + a_4 d(k-24) + a_5 d(k-48). \quad (12)$$

Here  $\hat{d}(k)$  is the predicted demand at time  $k$ , the sampling time is 1 hour and  $a = [a_1, a_2, a_3, a_4, a_5]$  denotes the model parameters. ' $k-24$ ' and ' $k-48$ ', in (12), represent the time instants yesterday and the day before yesterday. The unknown parameters in  $a$  are estimated by the method of least squares using historical data.

### 2.5 Objective Function

To avoid network overloading, we consider the following two cost functions:

*Cost Function 1- Peak Shaving:* Network overloading can be avoided by minimising the maximum of the total consumption at a given node. Mathematically this min-max problem can be formulated using the infinity norm,

$$\min_{U(1), U(2), \dots, U(T)} \left\| [\hat{P}(1) \ \hat{P}(2) \ \dots \ \hat{P}(T)]^T \right\|_{\infty} \quad (13)$$

over the sequence of control actions,  $U$ , as defined in (2), for a finite time horizon,  $T$ , and  $\hat{P}(k)$  is defined as follows:

$$\hat{P}(k) = \sum_{j=1}^N \hat{d}_j(k) + \sum_{j=1}^M (u_j^c(k) - u_j^d(k)). \quad (14)$$

The above objective function shaves off the peaks in  $\hat{P}$ .

*Cost Function 2 - Peak Shaving and Valley Filling:* Network overloading can also be avoided by shifting the demand to a carefully chosen power consumption  $\gamma$  for the node, which is always less than  $P_{\max}$ , e.g., consider the following objective function:

$$\min_{U(1), U(2), \dots, U(T)} \sum_{k=1}^T (\hat{P}(k) - \gamma)^2, \quad (15)$$

where  $\gamma$  can be chosen as the mean of the consumption at a node obtained from historical data. This objective function also shaves off the peaks in  $\hat{P}$  but additionally fills in the valleys in load profiles. The results for the two choices of the objective function are compared in the sequel.

### 3. MPC BASED DEMAND RESPONSE FRAMEWORK

The objective functions in (13) and (15), subject to the constraints in (2), (5), (6), (10), (9) and (11), is solved in a receding horizon fashion. To be precise, the following Model Predictive Control (MPC) problem is solved:

$$\begin{aligned} & \min_{U(m), U(m+1), \dots, U(m+T-1)} \sum_{k=m}^{m+T-1} (\hat{P}(k) - \gamma)^2, \\ \text{subject to} \quad & X(k+1) = AX(k) + BU(k), \\ & \hat{P}(k) \leq P_{\max}, \\ & X_L \leq X(k) \leq X_H, \\ & U_L \leq U(k) \leq U_H, \\ & U_c \circ U_d = O, \\ & m = 1, 2, \dots \end{aligned} \quad (16)$$

The proposed discrete-time optimal control problem is quadratic in cost and linear in constraints, and as such, it is amenable to the use of commercially available solvers for computing the optimal sequence of actions. For our case, we solve the MPC problem (16) we use Gurobi (Gurobi Optimization (2018)), via YALMIP (Lofberg (2004)), in MATLAB.

### 4. SIMULATIONS

To demonstrate the application, and consequently the effectiveness of the proposed DR framework, a cluster of 100 houses is considered in this section for a simulation based study. The cluster consists of houses with both large and small demand. All houses satisfy the assumptions stated in problem formulation (Section 2).

#### 4.1 Power Demand Data

The consumption data of the houses is taken from the dataset in (EERE (2019)). The dataset contains the load profiles of the major cities Las Vegas and San Francisco in the United States of America, sampled on hourly basis. This is because the climate of these cities resembles the climate of most of the cities in Pakistan. The load profiles contain the consumption data for a single residential building for a whole year. To use it for 100 houses, the data of the two cities is divided into 50 chunks each, and every chunk is assumed to be the actual consumption of a house. The data of a large house is obtained by further incrementing the consumption of the house by 75%.

#### 4.2 Simulation Parameters

For simulations, it is assumed that all houses in a cluster are participating in the DR program and all batteries have the same dissipation factor,  $a_j = 0.95$ , and the same charging and discharging coefficients,  $\eta_j^c = \eta_j^d = 0.85$ . There are 30 large houses and 70 small houses. The large and small houses are equipped with batteries of 1800 Wh and 1200 Wh storage capacities respectively. The initial SOC for all large batteries is set to 900 Wh while that of all small batteries is set to 600 Wh. The maximum power ratings of the corresponding UPS-battery setups are assumed to be 1200 W and 1000 W respectively. These

values correspond to the commonly used UPS-battery units in Pakistan. A lower limit of 200 Wh on the SOC of all batteries has also been set to ensure that it never gets fully discharged which conforms to the precautions taken for longer battery life.

Parameters of the demand forecast model, (12), are estimated by the method of least squares using the historical data (EERE (2019)). The estimate  $\hat{a}_{SF}$  is,

$$\hat{a}_{SF} = [-0.0035, -0.0164, 0.0486, 0.7888, 0.1673]$$

for the first 50 houses, obtained from the San Francisco dataset, and the estimate  $\hat{a}_{LV}$

$$\hat{a}_{LV} = [0.0159, -0.0188, 0.0197, 0.9766, 0.0127]$$

for the remaining 50 houses obtained from the Las Vegas dataset. The identified models are then used to predict the consumption for every house. Figure 3 shows the performance of the estimated model on the dataset. It

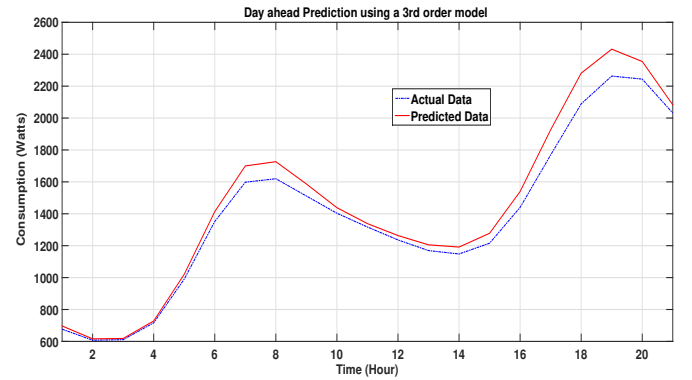


Fig. 3. Day ahead consumption, predicted by a model obtained from the historical data.

can be noted that the model has predicted the short term consumption trends quite well, which coincides with our requirements for MPC based control strategy. In the proposed strategy, a noise of zero mean and a standard deviation of 50 watts, which ranges between 2 to 12 percent of the consumption of the houses, is also added to the predicted demand to account for the consumers' unpredictable behavior.

The maximum allowed power consumption,  $P_{\max}$ , was set in the range 85–95% of the maximum value of the demand profile. The following simulation results are shown for  $P_{\max} = 86\%$ , which is the minimum value that eliminated any network overloading. The reference consumption,  $\gamma$  in (15), is chosen to be the average of the demand profile. The time horizon,  $T$ , is set to be 6 hours in (16), and the simulations are carried out for  $R = 48$  MPC steps (1 MPC step = 1 hour).

#### 4.3 Results

The simulation results for 48 hours are shown in Figures 4 and 6. Figure 4 shows the simulation results for the infinity norm based cost function. The red (solid) line shows the cluster's original demand while the blue (dashed) line shows the optimized consumption resulting from the proposed technique. The demand curve exceeds the  $P_{\max}$  constraint two times (from 18<sup>th</sup> to 22<sup>th</sup> and 32<sup>th</sup> to 46<sup>th</sup> hours) indicating network overloading and hence power-outages. The optimized consumption resulting from the

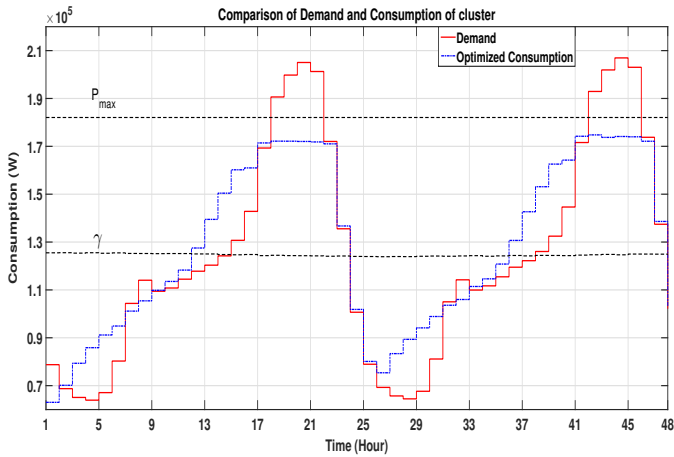


Fig. 4. Figure shows the demand and the optimized consumption of the cluster. The DR framework performs demand side management in such a way that the optimized consumption always remains below  $P_{max}$ .

optimization based DR framework, however, is always within the limits, thereby successfully avoiding network overloading for the entire duration and highlighting the efficacy of the proposed approach.

The improvement, as shown in Figure 4, is made possible by the contribution of each house in the cluster. Figure 5 shows the response of a randomly chosen house (House 30). The first two subplots demonstrate the behavior of the battery. The battery is charged when the charging input (red (solid) line in subplot 2) is non-zero and the SOC of the battery rises (in subplot 1). Similarly, the battery is discharged when the discharging input (blue (dashed) line in subplot 2) is non-zero and the SOC of the battery drops (in subplot 1). The SOC of the battery, however, is always greater than or equal to the minimum SOC value, so that the constraint on SOC is always satisfied. Similar response has been observed for the remaining houses (not shown to avoid repetition). The third subplot shows the demand (solid red line) and the consumption as a result of the proposed technique (optimized consumption, blue dashed line) of the house. While the optimized consumption is different from the demand for a given house, the combined effect of all houses resulted in the avoidance of network overloading at the node, as shown in Figure 4.

Figure 5 shows that there is a rapid charging and discharging behavior of the battery. This is not good for the battery health and it also adds huge fluctuations in terms of from where the load is served (grid or battery) in a house. Moreover, in Figure 4, the off-peak hours are not fully exploited. These problems are however circumvented by using the objective function in (15) instead of (13). Figure 6 shows the simulation results for the cost (15). It can be seen that both consumption peaks are reduced and the flexible load has been shifted to off-peak hours. Figure 7 shows the corresponding response of House 30, where the frequent charging and discharging of the battery has also been reduced. In summary, the optimization problem in (16) puts some additional load on the grid during the off-peak hours to charge the batteries, while during the peak hours, the optimal scheduling shifts some of the load from

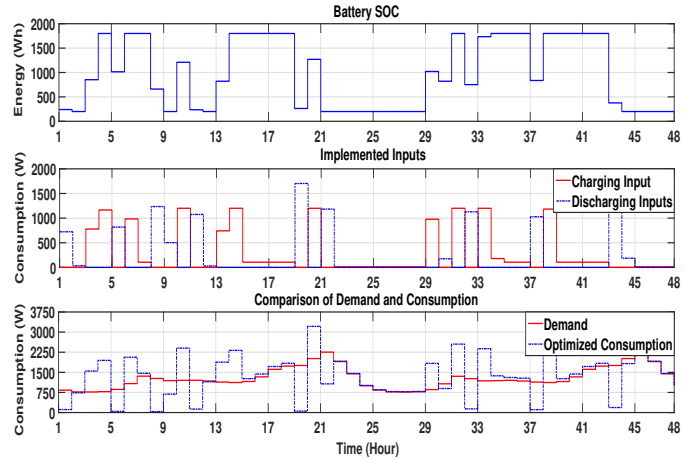


Fig. 5. Figure shows the power flow at house 30. The battery is charged to provide a backup for a component of the house demand thereby reducing the load on the grid during the peak hours.

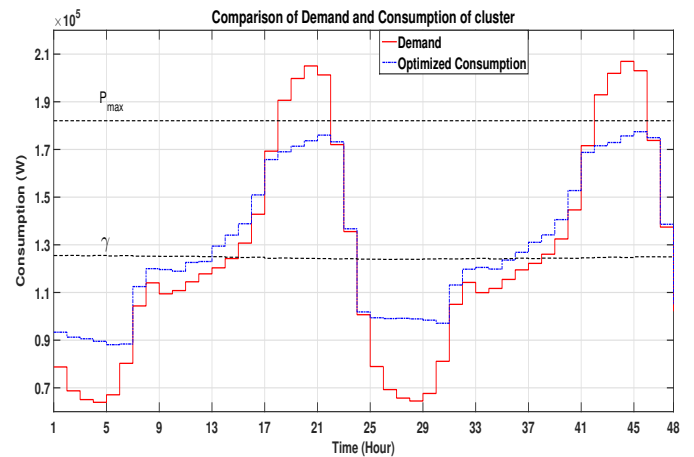


Fig. 6. Figure shows an improvement in the profile of the optimized power consumption with the use of (15). The overall consumption is now closer to the reference level  $\gamma$ .

the grid to the charged batteries, thus keeping the overall consumption of the cluster below  $P_{max}$ .

Figure 8 shows an analysis of the proposed technique in view of number of participants in the DR technique. One can see that as the number of participants increase, load shedding decreases. It can be noticed that only 45% participation rate can reduce the load shedding to half its maximum value while 80% participation results in complete elimination of load shedding.

## 5. CONCLUSIONS

In this paper, a DR based technique is utilized on the UPS-battery units to reduce overloading on the grid. The proposed formulation is practically viable for developing countries like Pakistan, where such units are available in almost every house. Whenever load on the grid exceeds a certain threshold, some of the load, corresponding to each house, is shifted to the batteries associated with those houses, and as a result providing a relief to the grid. Later the batteries are charged again during the off peak hours. The charging and discharging decisions are taken



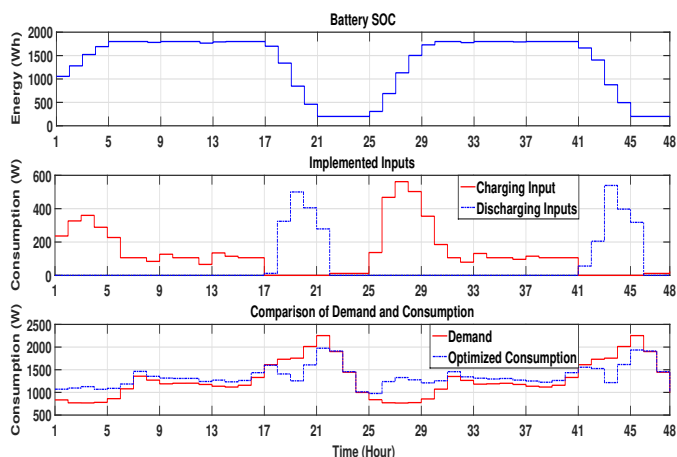


Fig. 7. Figure shows the power flow at the same house 30 with the objective function of (15). The frequent switching between charging and discharging has been reduced.

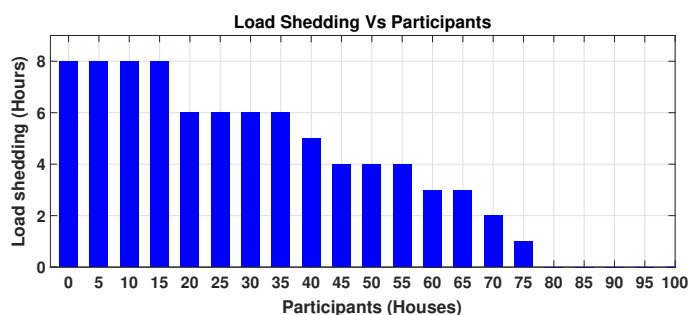


Fig. 8. Figure shows that increasing number of participants (UPS-Battery setups) successfully manages to reduce the magnitude of load shedding.

on the basis of a demand forecast and the UPS-battery units are controlled by a control signal from the electricity provider. The technique is simulated on a cluster of 100 houses of large and small sizes. The simulation results show reduction in the peak consumption of the cluster and demonstrate how much a flexible load, such as a UPS-battery unit, can play a role in the avoidance of network overloading.

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