Stochastic Gradient Descent Optimization Model for Demand Response in a Connected Microgrid

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Abstract

Smart power grid is a user friendly system that transforms the traditional electric grid to the one that operates in a co-operative and reliable manner. Demand Response (DR) is one of the important components of the smart grid. The DR programs enable the end user participation by which they can communicate with the electricity service provider and shape their daily energy consumption patterns and reduce their consumption costs. The increasing demands of electricity owing to growing population stresses the need for optimal usage of electricity and also to look out alternative and cheap renewable sources of electricity. The solar and wind energy are the promising sources of alternative energy at present because of renewable nature and low cost implementation. The proposed work models a smart home with renewable energy units. The random nature of the renewable sources like wind and solar energy brings an uncertainty to the model developed. A stochastic dual descent optimization method is used to bring optimality to the developed model. The proposed work is validated using the simulation results. From the results it is concluded that proposed work brings a balanced usage of the grid power and the renewable energy units. The work also optimizes the daily consumption pattern thereby reducing the consumption cost for the end users of electricity.

Keywords: Smart grid, Demand Response, Stochastic dual descent, renewable energy sources

1. Introduction

The increase in energy consumption across the globe and environmental impact created by traditional power generation sources insists the need to move towards alternative renewable sources of energy. Smart grid enables a way for integration of green energy in to the traditional power grid. A micro grid is a small independent grid system which has a control capability and act as a major source of power supply of small residential units [1]. In grid connected mode of micro grid operation it attempts to purchase from or sell back the excess power to the macro grid. The power from main grid will be completely cut off in off grid mode. When the main utility grid is located at a larger distance the micro grid operates completely independent in an isolated mode.

There are numerous research works done on standalone micro grid operation. The isolated self-sufficient grid micro grid (where demand is less than the power generated at residential unit) with an active solar and wind energy generation units and a passive storage batteries has been discussed [2]. Since this is practically infeasible because of the intermittent nature of renewable energy sources and increase in load demand this work is not suited for applications which produces a preplanned constant load demand profile. The ever increasing demand for electricity with the growing population paved a way to research on alternative renewable energy sources (RESs) because of their environmental friendly nature and zero depletion rate. Smart power systems attempt to integrate the RESs in to the traditional power system to make it reliable and efficient. Micro grid has maximum efficiency in a grid connected mode where it can utilize the energy from the grid when needed and sell back the excess energy towards the grid. The method of shifting the demand to different time periods to achieve smooth energy demand is common approach in smart grid. The load shifting is achieved by formulating a demand response (DR) optimization problem which can be a linear programming (LP), dynamic programming (DP) or multi variable objective functions [3-5]. These formulations suffer from a disadvantage of inability to program the dynamic energy consumption patterns and there is a difficulty in incorporating different sets of home appliances. A different approach using stochastic and heuristic optimization techniques to minimize the consumption cost has also been discussed [6-11] in which the authors attempt to overcome the disadvantages of existing micro grid optimization approaches.

Besides incorporating various demand response approaches for energy savings, smart grid also gives an option to combine in home energy storage and energy generation units for saving grid energy. Since RESs are a better alternative to depleting energy sources, it is a major research area in smart grid and there are numerous research proposals which focus on integration of RESs in to smart grid in a cost efficient manner. The process of integrating RESs in to traditional power grid system induces many challenges at both ends. The dynamicity of climatic conditions causes an intermittent nature in RESs electricity generation and this variable nature causes voltage fluctuations in the power grid side. To overcome the variable nature of RESs, storage of generated energy and scheduling the in home demand can be a best option which is discussed in the literature [12-14].

The technical challenges in integrating the renewable sources in to traditional electric grid has been investigated in [15] which attempts to achieve the following objectives: (i) guaranteed utility grid reliability, (ii) usage cost minimization for consumers. The variable nature of RESs is a problem in achieving the smooth integration. There are several research works which discuss a variety of algorithms for achieving an efficient integration. An IREMS (intelligent residential energy management system) is proposed to optimally schedule shiftable loads and size RESs in [16]. The work uses genetic algorithm (GA) for optimization. Even though the work achieves cost savings, it does not provide any model to motivate consumers to sell the excess renewable power and achieve other related benefits. The research in [17] discussed some methods to smooth out the fluctuating nature of RESs. The first method is to use battery energy storage system (BESS) which makes RE smoother one. The other scheme is to incorporate coordination among RE generating customers. The results prove the energy efficient integration of RESs and minimize cost of energy sharing within the grid.

The work in [18] discusses methods to handle power quality problems created due to integration of RESs in to traditional power grid system. The work in [18] can be divided in to twofold: (i) analyzing the power quality problems due to integration RESs such as solar panel and wind turbine, and (ii) discusses various approaches to handle these challenges such as FACTS and VSM. Even then the work does not take in to consideration the appliances working schedule and a communication between various RESs. The energy management and load scheduling for a residential unit with the integration of RESs has been discussed in [19] in which stochastic optimization method is used to handle the intermittent nature of renewable energy source. Appliance scheduling to a desirable time slot along with battery storage is achieved by a real time scheduling algorithm. The efficiency of the proposed approach is determined by simulation studies. However, the appliance classification and co-operation between different RE consumers are not considered. Heuristic optimization model for home energy management system with RESs has been discussed in [20]. The optimization problem is formulated in the type of multiple knapsack problem. The optimization approach is effective in consumer cost savings, reduction of PAR and maintaining the user convenience. By reducing the PAR the proposed method increase the grid stability. However, the following issues are not addressed by the authors: (i) frequency of interruption of RESs, and (ii) smoothening of the demand curve. A price incentive based load scheduling method for residential units is proposed in [21]. The method adopts pricing scheme based on time of use (TOU) and the load scheduling is achieved using particle swarm optimization. This work optimally uses the RESs in order to increase the bill savings for consumers. The system does not model the user satisfaction and also does not address the issues in integration of renewable energy sources. The study of efficient integration of renewable energy sources specially PV panels has been discussed by the authors in [22-23]. These works concentrate on minimizing energy losses in large scale distribution systems during PV integration. They also give a frame work for determining an efficient PV module for integration using different machine learning and soft computing methods. However the authors does not address anything about load forecasting and appliance scheduling. A real time case study with novel integration of variable renewable energy units is studied by authors in [24]. The research put forth a production cost model for achieving DR in real test bed. The method is efficient since the authors have modelled a real time constraints for the DR optimization problem. The results are presented with reference to real time scenario. However an explicit modelling of DR optimization problem is missing in the work.

The research in [25] studies the demand response by using various heuristic and hybrid approaches like genetic algorithm, grey wolf optimizers etc. The authors have taken a single home scenario with two renewable energy generation units and one battery storage unit. A RTP scheme has been used with varying prices for every time slot. The authors have achieved an optimal PAR and cost reduction. However the user convenience has not been modelled and traditional disadvantages of heuristic algorithms like increased computational complexity remains the same. Hence for same scenario we attempt to study the possible mathematical models which has reduced complexity.

A detailed survey on possible mathematical models for demand response paradigms has been presented in [26]. The authors discusses a variety of mathematical optimizations methods for different scenarios of demand response which are listed as follows: i) Convex optimization for utility maximization problems, ii) Game theory models for enabling a healthy interaction between service provider and consumers, iii) Dynamic programming which gives an option for multistage optimization, iv) Stochastic programming by which uncertain scenarios can be modelled. Out of the above models listed dynamic programming suffers from a disadvantage of high memory utilization. The convex optimization methods imposes strict constraints on structure of optimization problem (functions must be strictly convex). Game theory can be used to model an economic behavior of group of consumers and individual consumer level modelling cannot be done efficiently. Since our proposed work aims to efficiently model the individual consumer demand response with an integrated RESs we choose stochastic programming as a best option for our DR model. So the proposed work uses a stochastic dual descent algorithm to study the DR of a connected micro grid.

Because of the intermittent nature of renewable sources and to introduce more flexibility in the demand the proposed approach uses stochastic optimization method. The proposed algorithm optimizes the consumption cost for residential users and their peak to average (PAR) ratio while providing an option for integrating RESs from the residential unit to the grid. The proposed system uses a flexible real time pricing (RTP) for calculating the consumer's usage cost. The major contributions of the proposed work can be listed as follows:

- We use grid-connected micro grid and a residential unit with different sets of home appliances and two different types of renewable energy sources.
- A mathematical model for a micro grid has been derived.
- Stochastic online algorithm has been developed for consumption scheduling
- The simulations have been done to validate the results.

2. A mathematical model for proposed system

A mathematical formulation of a smart home integrated with renewable energy sources is modeled in this section. We take a single home scenario connected to a service provider and the user is equipped with smart meter which has ability to control and schedule the user loads. The intended time of working is divided into T equal length time slots, where $T \triangleq |t|$ and t is the set of all time slots and it is 24 hours of the day. For any user A denote the set of appliances where $a \in A$ and 'a' is any appliance in home. For all given set of appliances$a \in A$, their energy consumption needs are defined as a vector $X_a \triangleq (x_a^1, \dots \dots \dots \dots . x_a^T)$. In the defined energy consumption vector x_a^t gives the energy consumption of specified appliances a in the specified time slot t. An optimum and feasible selection of this scheduling vector is done by proposed scheduling algorithm

The feasible set of energy consumption scheduling is defined by some constraints in a residential unit. The constraints include desired operational slots, energy required for each appliance and so on. In our proposed work we define two constraints for scheduling which include desired start and end time of operation of appliance and the maximum and minimum energy required for operation. For each appliance $a \in A$ let $\alpha_a \in t$ be the desired starting time and $\beta_a \in t$ be the ending time of appliance operation. Thus for proper operation of appliance we have

$$\sum_{\alpha_a}^{\beta_a} x_a^t = E_a \tag{1}$$

and

$$x_a^t = 0, \forall\, t \in T \setminus T_a \tag{2}$$

where E_a is the energy needs of any appliance a and $T_a \triangleq \{\alpha_a, \dots \dots \dots \dots \beta_a\}$ and we always have $\alpha_a \leq \beta_a$. For each appliance $a \in A$, minimum and maximum power levels are defined as γ_a^{min} and γ_a^{max} respectively. Therefore we have

$$\gamma_a^{min} \leq x_a^t \leq \gamma_a^{max} \tag{3}$$

Hence the feasible set of power consumption for any user is given as follows

$$X = \left\{ \begin{matrix} x \mid \sum_{t=\alpha_a}^{\beta_a} x_a^t = E_a, & x_a^t = 0, \forall\, t \in T \setminus T_a \\ \gamma_a^{min} \leq x_a^t \leq \gamma_a^{max}, \forall\, t \in T_a, \forall\, a \in A & \end{matrix} \right\} \tag{4}$$

where $X = X_1 \times \dots \dots \times X_T$ is the feasible set of consumption of a user for all time slots.

2. 1 Energy Cost Model

There are two basic constraints which influences the decision of the scheduling algorithm. The constraints are as follows (i) The complete set of user appliances and their desired working periods are known at the beginning of every time slot. (ii) The scheduling approach finds a set of shiftable appliances and attempts to shift the operation of those appliances to different time slot so as to reduce consumption cost. The shift operation is done in response to varying electricity prices.

As we know the energy consumption scheduling vectors for each time slots $x_1, \dots \dots \dots \dots x_T$ and the energy consumption needs for each appliance in each time slot, the optimization problem for minimizing the peak to average ratio can be formulated as follows:

$$\underset{x \in X}{\text{minimize}} \quad \frac{t \max_{t \in T} (\sum_{a \in A} x_a^t)}{\sum_{a \in A} E_a} \tag{5}$$

In the equation (5) the value of t and the $\sum_{a \in A} E_a$ are fixed for a time slot and independent of scheduling vector *x* hence the equation (5) can be reduced as follows:

$$\underset{x \in X}{\text{minimize}} \; \max_{t \in T} (\sum_{a \in A} x_a^t) \tag{6}$$

The optimization problem in equation (6) is minimization problem with maximization term hence to make it as a complete minimization problem an auxiliary variable Γ is introduced. Hence the problem in equation (6) can be reformulated as follows:

$$\underset{\Gamma, x \in X}{\text{minimize}} \quad \Gamma$$
$$\text{subject to } \Gamma \geq \sum_{a \in A} x_a^t \qquad \forall\, t \in T \tag{7}$$

The solution to minimization of peak to average ratio (PAR) indirectly benefits the customers with the cost minimization. In this approach we consider real time pricing (RTP) were the prices of electricity tend to change for all the time slots. By equation (4) we can formulate the energy consumption of all the appliances in a given time slot l_t as:

$$l_t = \sum_{a \in A} x_a^t \tag{8}$$

A quadratic cost model is obtained with three different cost coefficients to reflect the increasing cost for every rime slot [27-28]. If a consumer consumes l_t units of electricity in any given time period t then the usage cost is denoted by $C_t(l_t)$. The quadratic cost equation is given as follows:

$$C_t(l_t) = c_1^t\, l_t^2 + c_2^t l_t + c_3^t \tag{9}$$

In the above equation (9) c_1^t, c_2^t, c_3^t represents the cost coefficients which vary for different time periods. These values are set by service provider based on their historic demand profiles. Hence the objective function to minimize consumption cost can be given as follows

$$\underset{x \in X}{\text{minimize}} \sum_{t \in T} C_t(l_t) \tag{10}$$

From equation (8) the minimization problem in equation (10) can be reformulated as follows:

$$\underset{x \in X}{\text{minimize}} \sum_{t \in T} C_t\left(\sum_{a \in A} x_a^t\right) \tag{11}$$

From the equation (8) the total energy consumption of a user E_{total} can be defined as follows:

$$E_{total} = \sum_{t \in T} \sum_{a \in A} x_a^t \tag{12}$$

2. 2 Waiting Time Minimization

In the proposed scheme, the user convenience is considered as important as the minimization of consumption cost. In general the consumers need their demand to be satisfied as soon as possible. The consumers will express minimum interest for waiting. The level of user satisfaction can be described as an inverse of waiting time. Here we model the waiting of any appliance $a \in A$ in any given slot using a waiting parameter ρ_a^t. The waiting time can be calculated only if desired time of operation of any appliance 'a' is known. Hence at the beginning of every operating period when consumer submits their energy needs we also request the desired operating time periods $[\alpha_a, \beta_a]$ for all appliances. Now the waiting parameter can be modelled as follows:

$$\rho_a^t = 0, \forall\ t < \alpha_a \ and \ t > \beta_a \tag{13}$$

and

$$\rho_a^t = (\delta_a)^{t-\alpha_a} \quad \forall\, a \in A \ \ and \ \ t \in [\alpha_a, \beta_a] \tag{14}$$

where $\delta_a \geq 1$ is a delay parameter. When the value of δ_a is maximum then there will be a prolonged waiting time for an appliance to complete its operation.

Now the objective of energy consumption scheduling optimization problem can be defined as the cost minimization problem with a minimum wait time for all appliances. Thus the optimization problem is defined as given below:

$$\underset{x \in X}{\text{minimize}} \quad \left(\omega \sum_{t \in T} C_t \left(\sum_{a \in A} x_a^t\right)\right) + ((1-\omega) \sum_{t \in T} \sum_{a \in A} (\delta_a)^{t-\alpha_a}$$

subject to

$$l_t \leq \gamma_{max}^t, \tag{15}$$

A wait factor ω has been introduced to the objective function in equation (15) and γ_{max}^t is the maximum power need for a consumer at time slot t. The importance of the objective functions is determined by the wait factor and $0 \leq \omega \leq 1$.

2. 3 PV Generation

The residential unit is fitted with a solar panel since solar energy is less costly and abundantly available energy source compared to other forms of renewable energy sources like bio gas, bio mass etc.. Our planet earth has an exposure to maximum percentage of solar radiation. Although the radiation may vary across the globe India has a nominal insulation levels in the range of 150-300 W/m^2. From the stated references [29-31] the power generated from the solar unit is defined as follows:

$$E_{PV} = E_N + \left(\frac{G}{G_{ref}}\right) \times \left[1 + K_T\left(T_c - T_{ref}\right)\right] \tag{16}$$

The total energy generated by solar unit is given as E_{PV}. The power generated by PV panel depends on many factors as constituted in equation (17). The solar irradiation at ideal conditions is given by $G_{ref} = 1000\ W/m^2$. There is always in variation in irradiation and the radiation at given moment is described as by G (W/m^2). The other factors includes K_T the temperature coefficient ($K_T = -3.7 \times 10^{-3}(1/{}^0C)$) and the cell temperatureT_c. The present cell temperature can be calculated as in the equation (17).

$$T_c = T_{amb} + (0.0256 \times G) \tag{17}$$

where the ambient PV cell temperature is given by T_{amb}. The ambient temperature varies anywhere between 16^0 C to 26^0C and maintaining an average of 20 ^{0}C.

2. 4 Wind Generation

In countries like India wind is an easily available source of renewable energy. The energy generated from the wind turbines can be given by the following equation (18) [32].

$$E_{rated} = 0.5 A_{rs} \sigma V^3 P_{coff} \tag{18}$$

where A_{rs} is the blade area expressed in m^2, σ in kg/m^2 is the air density, V in m/s is the average wind speed and the power coefficient is expressed as P_{coff}(maximum value is 0. 59). The generated power from wind turbine is directly proportional wind speed and is determined as in by equation (20) as in [33].

$$E_{wp}=\begin{cases} 0\,, & v \le v_{cut-in}\,, v \ge v_{cut-out} \\ \frac{(v-v_{cut-in})}{(v_{rated}-v_{cut-in})} E_{rated}, & v_{cut-in} \le v \le v_{rated} \\ E_{rated}, & v_{rated} \le v \le v_{cut-out} \end{cases} \tag{19}$$

where v_{rated}, v_{cut-in}, $v_{cut-out}$ are the wind speed rated, and cut-out and cut –in wind speed

2. 5 Formulation of Scheduling Objective Function

The reduced energy consumption cost with minimized waiting time is the basic objective of the proposed work. We considered a single residential unit and it is consuming electricity from the commercial electric utility grid and self-owned renewable energy units. Let E_{grid}^{t} be the power available from the grid for any time slot *t*. From equation (8) l_t is the total energy consumption of residential unit in any time slot *t*. E_{PV}^{t} , E_{wp}^{t} are the power from PV generation and wind turbines respectively for any time slot *t*. The total energy consumed by a home for any time slot is explained in equation (20)

$$l_t - \left(E_{PV}^{t} + E_{wp}^{t}\right) \tag{20}$$

The optimization function must minimize the consumption cost with optimal waiting time for schedulable loads. Let C_t^{pv} and C_t^{wp} be the cost of PV generation and wind power at time *t* respectively. The objective function for cost minimization for a home with small renewable energy generation can be given as follows:

$$\underset{x \in X}{\text{minimize}} \quad (((\ \omega \sum_{t \in T} C_t (\sum_{a \in A} x_a^t)) + ((1-\omega) \textstyle\sum_{t \in T} \sum_{a \in A} (\delta_a)^{t-\alpha_a} \quad)) - (\textstyle\sum_{t \in T}((E_{PV}^{t} \times C_t^{PV}) + (E_{WP}^{t} \times C_t^{WP}))))$$

Subject to

$$l_t \le E_{grid}^{t} + E_{PV}^{t} + E_{WP}^{t} \tag{21}$$

In equation (21) to have a balance between the energy demand and supply the constraint is introduced. The proposed optimization problem is in deterministic in nature and it is solved using stochastic dual descent method.

2. 6 Stochastic Optimization with Dual Descent

Let X denote all the scheduled energy consumption vectors x_a^t for all $a \in A, t \in T$. The minimization problem in equation (21), is associated with the dual variables λ_t then the lagrangian for the optimization problem can be written as

$$L(X,\lambda) = (((\omega \sum_{t \in T} C_t (\sum_{a \in A} x_a^t)) + ((1-\omega) \textstyle\sum_{t \in T} \sum_{a \in A} (\delta_a)^{t-\alpha_a})) - (\textstyle\sum_{t \in T} \lambda_t ((E_{PV}^{t} \times C_t^{PV}) + (E_{WP}^{t} \times C_t^{WP})))) \tag{22}$$

where λ collects the variables $\{\lambda_{t_{t\in T}}\}$. The dual function can be written as

$$D(\lambda) = \min_{x\in X} L(X,\lambda) = \sum_{t=1}^{T} D^t(\lambda) \tag{23}$$

Where X collects the sets x_a^t for all $t \in T$ and $a \in A$. Now

$$D^t(\lambda)= \min_{x_a^t\in X_a^t} (\omega(\sum_{a\in A}\mu_{t\times}x_a^t) + ((1-\omega)\sum_{a\in A} (\delta_a)^{t-\alpha_a}) - \lambda_t((E_{PV}^t \times C_t^{PV}) + (E_{WP}^t \times C_t^{WP})) \tag{24}$$

The final dual problem is formulated as follows:

$$D = \min_{\lambda>0} \sum_{t=1}^{T} D^t(\lambda) \tag{25}$$

The solutions for primal and dual optimal problems be denoted as x_a^{t*} and λ^* respectively. The traditional sub gradient algorithm has the following iterations, which starts at an arbitrary $\lambda_t$and for all $t \in T$.

$$[\hat{x}_a^t]_{t=1}^T \coloneqq \arg \max_{x_a^t \in X_a^t} [\sum_{t\in T} C_t (\sum_{a\in A} x_a^t))) + ((1-\omega)\sum_{t\in T}\sum_{a\in A} (\delta_a)^{t-\alpha_a})) - [\lambda_t(\sum_{t\in T}(E_{PV}^t \times C_t^{PV}) + (E_{WP}^t \times C_t^{WP}))]] \tag{26}$$

$$\lambda_{t+1} = \lambda_t + \epsilon \sum_{t=1}^{T}(\hat{x}_a^t - x_a^t) \tag{27}$$

where $\epsilon > 0$ is the step size parameter or learning parameter. From the above set of equations we can derive iterates for dual descent algorithm as follows:

$$\hat{x}_a^t = \arg \max_{x_a^t \in X_a^t} \left(\omega\left(\sum_{a\in A}\mu_{t\times}x_a^t\right) + (1-\omega)\sum_{a\in A} (\delta_a)^{t-\alpha_a}\right) - (\lambda_{t-1}((E_{PV}^t \times C_t^{PV}) + (E_{WP}^t \times C_t^{WP}))) \tag{28}$$

$$\lambda_t = \lambda_{t-1} - \epsilon[\hat{x}_a^t - x_a^t] \tag{29}$$

$$\lambda_0 = \lambda_T \tag{30}$$

The important characteristic feature of the online consumption scheduling algorithm is that its dual variable λ_t gets incremental update over a total a total of T time slots. The incremental update rule allows us to calculate the stochastic sub gradient of $D^t(\lambda)$ using the realizations of $\{x_a^t, C_t\}$ at any given time slot *t*. Since the primal iterates $\hat{x}_a^t$ are readily available at each time slot, it is used in the scheduling as in dual descent method. The complete algorithm for online energy consumption scheduling is given as Algorithm 1

Algorithm 1: Online Usage Energy Consumption Scheduling

1: Initialize λ_0 for all $x_a^t \in X_a^t$,
2: for $t = 1\ to\ T$
3: Input $x_a^t, C_t, E_{PV}^t, C_t^{PV}, E_{WP}^t, C_t^{WP}$
4: Calculate $\hat{x}_a^t$ from equation(28) and load scheduling is done accordingly.
5: Update dual variables λ_t using equation (29)
6: end
7: t:=t+1.

3. Results and Discussions

The proposed approach has been validated using Matlab simulations. The toolboxes of Matlab gives a flexible environment for mathematical modelling and simulation [34]. We need a set of appliances their desirable operating periods their energy needs and price of electricity for every time block to proceed with the simulation. **Table 1**. lists the set of appliances selected for simulation.

We attempt to depict a typical moderate Indian household for simulation. Hence we follow the guidelines presented by Indian service provider [35] for selecting appliances and their needs for the purpose of simulation. The appliances listed in Table I are identical to our previous research [36]. We assumed that the customer has minimum of 10 appliances. There are three categories of consumer appliances as listed as follows : i) Non-shiftable loads, these are appliances whose demand must be satisfied immediately. ii) Shiftable loads, these are appliances whose demands can be scheduled to low price slots. There is a waiting time for demand satisfaction but which can be compromised by reduction in consumer cost. iii) Must run loads, these are appliances which must be in a ready to run condition at any time. To satisfy these appliances there is always a guaranteed minimum power flow from the grid to the residential unit at all times. As discussed in Section II at the beginning of every time period the energy consumption scheduling vector of all the appliances are known. The coefficients of quadratic cost function are determined as follows: $c_2^t = c_3^t = 0. \forall t \in T$ and $c_1^t = 1.5$ rupees at peak time (8:00am to 12:00 pm and 6:00pm to 12:00pm) and $c_1^t = 1.0$ rupees during the night and the day after(12:00pm to 8:00am and 12:00 pm to 6:00pm)[37].

Table 1. Appliance profile of residential unit

Appliance index (a)	Name	Type	Operating period	Hourly power Consumption (kWh)
1	Washing Machine	shiftable	9am to10am 5pm-6pm	1
2	Electric Stove	Non-shiftable	6 am-9am 7 pm-8pm	1
3	Freezer	Non shiftable	24 hours	0. 12

4	Electric water Heater	shiftable	5 am-7 am 8 pm – 9 pm	1.5
5	Air Conditioning	shiftable	10 pm-5 am	1
6	Electric Cooker	Non shiftable	7 am-8pm 7 pm-8 pm	0.5
7	Home Lightings	Non shiftable	24 hours	0.25
8	Fans	Must Run Loads	24 hours	1.06
9	Television	Must Run Loads	24 hours	0.7
10	Optional lightings	Must Run Loads	24 hours	0.25

The smart home management system in the residential unit has the ability to schedule and update the appliance loads for every time slot. The consumer has two options for energy consumption one from the utility grid and other from the owned renewable units. In the proposed model we have two readily available cost efficient renewable sources wind and solar power. The capacity of the installed RESs at home is listed in **Table 2**.

Table 2. Power rating of renewable energy units

Source	Rating
Wind turbine	10 kW
Solar panel	230 W

3. 1 Installed Wind and Solar Energy Statistics

The **Fig. 1**. gives the energy generation scenario of installed wind turbines. As it is said already the wind speed has a direct effect on wind energy generation when the speed of the wind is maximum in the range of 15m/s at time slots 11-20 there is a maximum power generation up to 3.5 kWh with the peak attained at time slot 12. The minimum power generated is 0.5 kW and it is recorded at two different intervals one is at 1-6 and other is at 21-24.

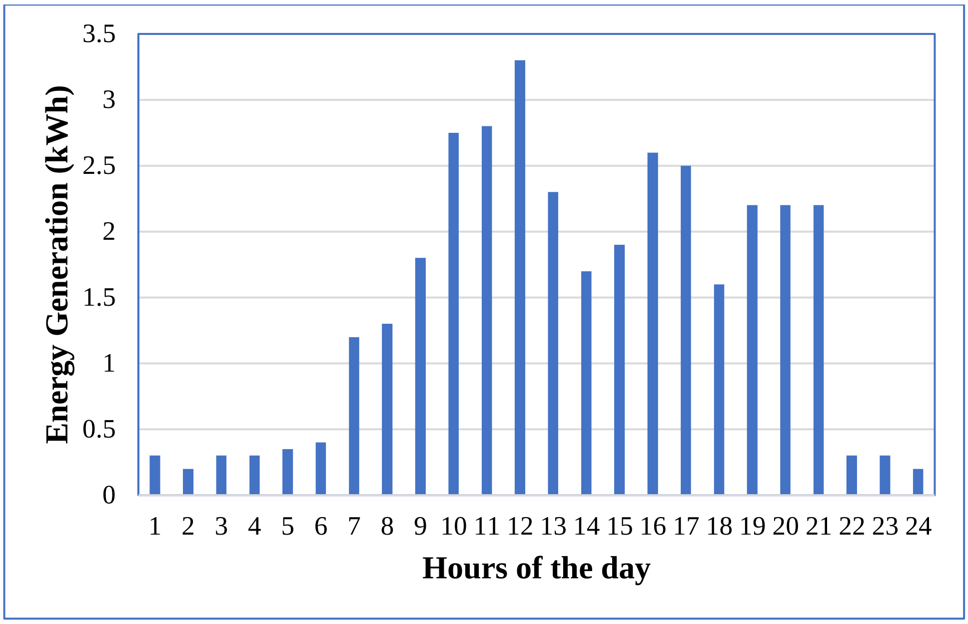

Fig. 1. Power generation from wind turbine

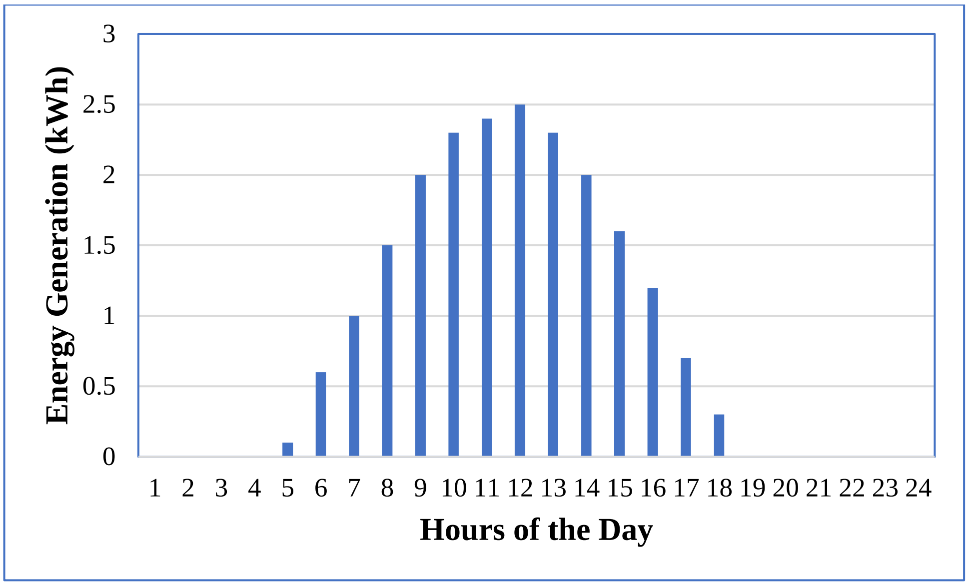

Fig. 2. Power generation from PV panel

The solar energy statistics is depicted in the **Fig. 2**. The solar energy is expected only at day time slots because the solar energy generation has a direct relation with the temperature and solar radiation. So the possible time slots for energy generation is between 5-18 hours and thus contributing only 13 active hours of generation. In this duration we can expect a maximum generation at peak day time hours that is normally 4-5 hours. The generation pattern can be well understood from the **Fig. 2**. When the temperature drops below 20 ^{0}C the solar power generation will be ideally zero.

3. 2 House hold Energy Usage Statistics

The energy usage statistics of different appliances in each slot is discussed here. There is an arbitrary threshold determined for limiting maximum energy consumption. The determined thresholds are listed as follows with the availability to be 15 kW (i) the high peak is 12–14 kW (ii) the average is 5–8 kW (iii) the minimum to be 3–5 kW and (iv) ignorable is 1–2 kW. The energy consumption scenario can be discussed in three folds one is without scheduling, second is with scheduling load and the final to be scheduled with RESs as given in **Fig. 3**. The proposed system simulates a scenario of 66% percent energy usage from utility grid and the remained 34% can be consumed from owned RESs. The **Fig. 3**. indicates that during the peak cost period of 6-9 hours the maximum hourly load of 4. 88kW is attained in a unscheduled normal house hold scenario and during off peak hours of 13-16 a minimal load of 1.8kW is indicated. The peak to average ratio (PAR) is calculated as 1.7 for an unscheduled house hold.

The scheduled house hold energy consumption for a single home without RESs integration can also compared from **Fig. 3**. From the graph series it can be seen that loads are distributed and it is prevented from load attaining maximum during peak hours. After Scheduling the PAR reduces to1.45 (14% less). From the **Fig. 3**. we can also see the energy consumption profile of a residential unit from the grid after renewable energy integration. The graph series depicts that almost 34% of daily consumption from grid is satisfied by renewable energy units. The peak power demand is 3. 13 kWh during 4 hours which is an off peak hour. We can see that PAR has value of 1.3 (24 % less) which is less than scheduled energy consumption.

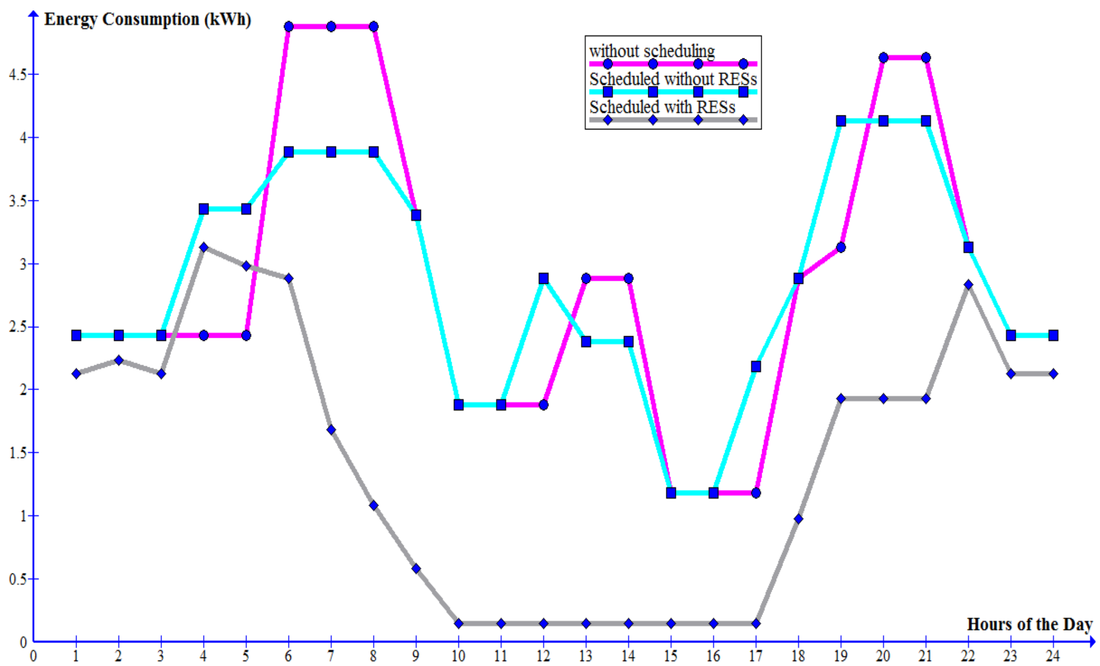

Fig. 3. Energy consumption from the grid.

3. 3 Consumption Cost Statistics

The cost reduction achieved by the proposed scheduling algorithms will be discussed here. As discussed in consumption scenario the associated cost has three different dimensions one is actual cost without scheduling, the second is scheduled cost and the third is scheduled cost with RESs integration as shown in **Fig. 4**.

The actual cost without scheduling is high at intervals 8-10 and is minimum at two different intervals 15-17 and 1-4. The daily energy consumption cost for an unscheduled load is around 290 rupees per day. The cost of scheduled load during time slots 6-9 and 19-21 is at its peak and at the intervals 2–3, 15–16 and 23–24 is low. The cost of daily consumption of scheduled load is around 270 rupees per day. The cost is further reduced by RESs, integration and its curve is very smooth, as shown in **Fig. 4**. Since the demand during peak hours is satisfied by RESs the cost is reduced by nearly 70% which is 83 rupees per day.

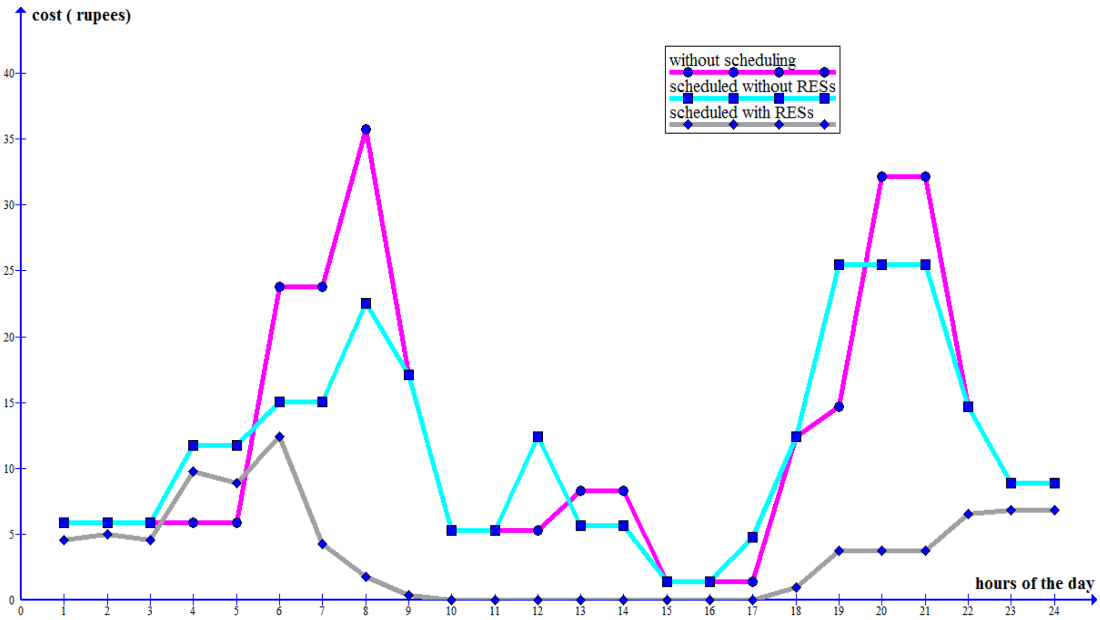

Fig. 4. Daily consumption cost

3. 4 Energy Consumption and Cost Statistics for N=3 consumers

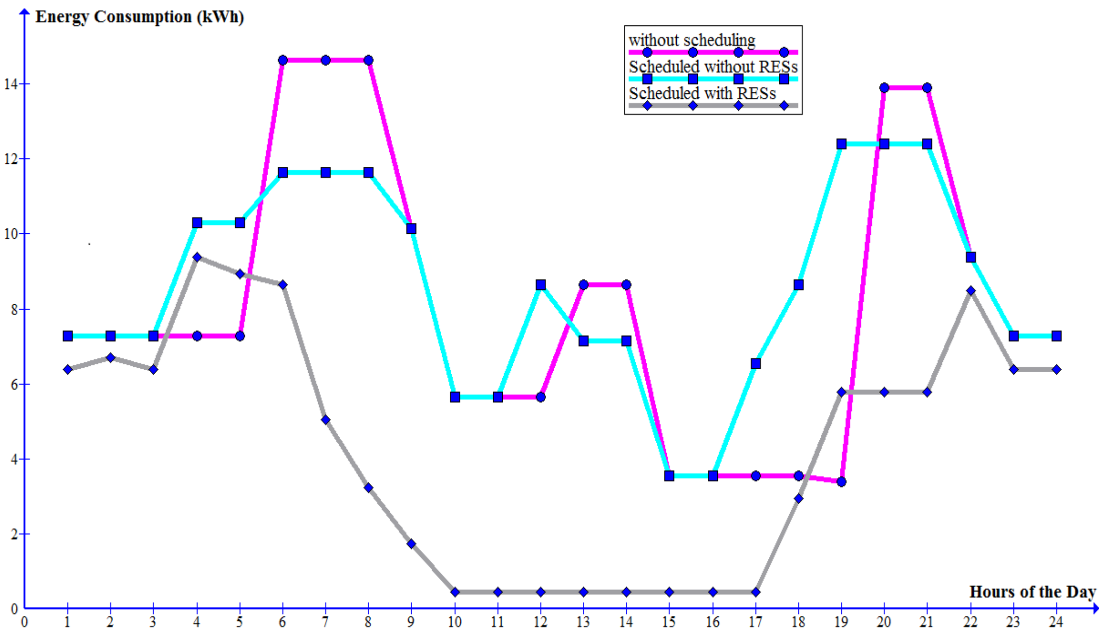

Fig. 5. Energy consumption from the grid (N= 3 consumers)

In this section we attempt to study the efficiency of the proposed work for increased number of consumers. We have simulated a scenario for three consumers not necessarily with an identical set of appliances but near equal demands. The aggregated consumption profile of three consumers for a day is depicted in **Fig. 5**. From the figure we can see that PAR of unscheduled average load is 2.06 which drops to 1.45 (29.6 % less) with a scheduled load which is very close to single consumer scenario. This indicates that algorithm goes for a fair share scheduling even with increased number of consumers. The PAR of scheduled aggregated load with RESs integration further drops to 1.19 which is 42.2% less than the unscheduled load.

The average cost curve for three consumers for a month is shown in **Fig. 6**. It is clear from the figure that compared to the unscheduled curve the scheduled cost drops by about 6.8%. This is further reduced by 71.3% by integrating RESs.

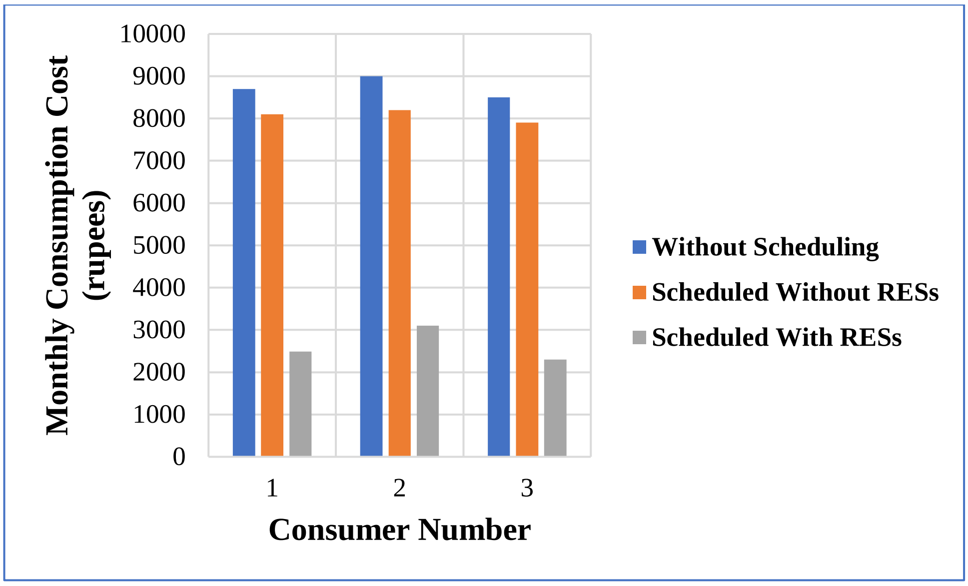

Fig. 6. Monthly average consumption cost (N=3 consumers)

3. 5 Comparative analysis

In general there is an extensive amount research articles which discuss the use of soft computing algorithms for optimization of micro grids. The base for the proposed work is drawn from the literature [25] which studies the demand response in a connected micro grid using a group of soft computing algorithms. The idea of using mathematical algorithms for demand response modelling has been decided as a best alternative after analyzing the disadvantages of traditional soft computing algorithms like genetic algorithm, swarm optimization etc. The drawbacks of these algorithms can be discussed in two folds. First the increased number of iterations which is fixed as 50 for every schedule in [25] and the number of iterations tend to increase with increase in population size. In our model the number of iterations are dynamic and the iteration necessarily stops when the learning parameter ϵ approaches zero. The number iterations by simulation is 450 for the entire 24 hours duration by which we can conclude that there is approximately 18 iterations needed to determine schedule for every time slot which is much less when compared to fixed iteration numbers. Moreover in our proposed stochastic descent we go for a random sampling of the input to compute the sub gradient $D^t(\lambda)$ by which we update the consumption schedule $\hat{x}_a^t$. By the simulation we have seen that computation cost of each iteration necessarily drops from O(n) to O(1) which is a constant.

Secondly the soft computing methodologies do not have explicit learning strategies which makes them to conclude at local optima rather than reaching the global optimum value in most of the cases which can be proved by numerical results. We compared the simulation results for our proposed model and the set of soft computing algorithms discussed in [25] for the same scenario. It can be seen that both the works achieve 66% of consumption from grid and 34% of consumption from integrated RESs. The maximum cost reduction achieved for daily consumption by using soft computing algorithms is 44% and which is nearly 70% for our proposed work. The literature does not explicitly quote any reduction in PAR only by scheduling and achieves a lowest PAR of nearly 1.3 by scheduling with RESs integration. The stochastic model in our approach achieves a PAR of 1.45 only with scheduling and PAR by scheduling with RESs is 1.3 which is same as the one using soft computing algorithms. From the above discussions we conclude the stochastic model achieves a better optimal schedule for demand response with minimum computational cost.

4. Conclusion

The control and optimization of in home energy usage will help consumers to better understand their energy profile which will help them to minimize energy wastage also achieve some cost savings. A mathematical model for appliances scheduling has been formulated with two objective variables one is cost and another is waiting time for operation. The formulated optimization problem is a minimization problem. The proposed model also attempts to form a grid connected minimal micro grid environment by integrating two renewable sources in to the residential utility grid. This helps to reduce the direct consumption from utility grid and thus offering more grid stability at service provider side and cost reduction for consumers. An online stochastic gradient algorithm is used to solve the formulated optimization problem. A comparison between our proposed scheduling approach with RESs integration and without scheduling and RESs integration is presented and our proposed schemes optimizes the consumption profile and hence reducing the consumption cost and smoothens the peak load. The simulation studies validates the efficiency of the proposed algorithm. Scheduling the house hold appliance load with the integration of RESs minimizes the consumption cost by nearly 70% and the PAR is minimized by 23%respectively. In the proposed approach we have neglected the cost of renewable generation, in future a model incorporating the dynamic pricing of renewable power will be developed. We also plan to model and study the stability of grid in terms injecting excess renewable energy from residential units into the grid.

Conflict of Interest: On behalf of all authors, the corresponding author states that there is no conflict of interest.

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