International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-4, November 2019

A MOPSO-Based Optimal Demand Response Management System for the Integration of Wind-PV-FC-Battery Smart Grid

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Abstract**:** ***This paper proposes the Multi-Objective Particle Swarm Optimization to optimize the performance of hybrid Wind-PV-FC-Battery smart grid to minimize operating costs and emissions. The demand response strategy based on the real-time pricing program with the participation of all kinds of consumers such as residential, commercial and industrial consumers is utilized in order to resolve the power generation uncertainty of renewable energy sources. The multi-objective particle swarm optimization based energy management programming model will be leveraged to reduce the operation costs, emission of pollutants, increase the micro grid operator's demand response benefits and at the same time satisfying the load demand constraints amongst the others. For the purpose of validating the proposed model, the simulation results are considered for different cases for the optimization of operational costs and emissions with/without the involvement of demand response. The simulation results precisely concluded the impact created by the demand side management in reducing the effects of uncertainty that prevails in forecasted power generation through solar cells and wind turbines.***

Index Terms**:** ***Renewable energy sources, Particle swarm optimization, Energy management, Load management, Energy storage.***

I. INTRODUCTION

The limited life of fossil-based fuels and the adjoining concerns raised upon the conventional energy sources on environment coupled with ever increasing demands across the globe led to the exploration of Renewable Energy Sources (RES) [1]. Integrated utilization of different renewable energy resources may overcome the drawbacks of single technology based system and helps in increasing power reliability with the reduction of system cost and amount of energy storage [2]. However, it is challenging to predict the penetration of irregular patterns of such decentralized RES such as solar radiation and wind speed which is a major drawback associated with the power balancing between the consumption and the production [3]. In order to successfully maintain power balance between production and consumption, any increase of the installed capacities of intermittent RES must be accompanied by the corresponding changes in management strategy of other power plants within power system, primarily conventional power plants [4]. So, for the purpose of facilitating the process in which the available renewable energy potential are harvested in an affordable way and at the same time, flexible enough to the electricity grid using the concept of smart grid. Being introduced with advanced control and communication components, the smart grids can be helpful in optimizing the energy generation, distribution-consumption, energy efficiency, power quality and finally the system reliability [5-6]. Generation Side Management (GSM) and Demand Response (DR) are the most important aspects in smart grid operation to represent possible solution for a large-scale integration of RES [7]. Previous studies [8] have investigated smart grids in terms of structures, components, how to execute optimal operations and how to control it. The literature has suggested that the power flow in grids can be managed in an efficient manner only when the consumption profiles of industrial, commercial and residential loads are obtained and analysed [9]. A number of studies conducted earlier explored smart grid management in terms of reducing energy cost and carbon di oxide emission [10], reducing the operational costs incurred and enhancement of economic performance [11], achieving green energy management through various measures such as reducing emission of pollutants, increasing the penetration of renewable energy and minimizing the energy costs [12], enhancing the dynamic performance through economic aspects [13], reducing the environmental pollution and increasing the smart grid revenue [14] and enhancing the reliability of the smart grid [15]. A solution can be optimal for the optimization problem proposed in the energy management of smart grid using various and different kinds of optimization algorithms or intelligent methods, powerful and flexible mathematical methods such as multi-layer ant colony optimization [16], GA [17], Artificial Neural network and modified bacterial foraging algorithm [18], hyper-heuristic algorithms [19], multi period Artificial Bee Colony combined with Markov chain [21], and multiperiod gravitational search algorithm [21]. When there is a DR, it changes the patterns of electricity consumption by the end-user customer from the normal customer according to the changes brought in the electricity price over time or in accordance to the incentive payments which are specifically decided to reduce the electricity consumption at times of high wholesale market prices or when the system reliability of jeopardized [22-23]. When the DR programs are included in the process, it enhances the operations cost, reliability of the smart grid, optimum operating conditions at both ends such as supplier and the consumer, enables grid flexibility and it further aids in risk mitigation of unpredictable, intermittent RES [24-25].

Manuscript published on November 30, 2019.
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A number of important studies were conducted recently towards the proper implementation of DR programs and modelling their roles played in bringing the balance between generation and consumption of energy from the RES due to its stochastic behaviour [26-28]. Various issues were addressed in the literature with regards to heating-cooling systems being an efficient structure in the management of energy [29], reserve and energy scheduling methods [30], DR coordination in real micro grid conditions for various demands and implementation [31], followed by consumer effects in complete systems such as production of carbon [32]. Further, in micro grid energy management, uncertainty is one of the primary concerns to be noted down [33, 34]. Generally, the probability of discrepancy rise between the real and the forecasted value, otherwise termed as uncertainty [35], is the major issue here. According to a study [36], solar radiation, loads and wind speed are the most prominent parameters that are modelled by normal (Gaussian) or Weibull distribution functions. Multi-objective operation planning in a smart distribution grid with wind and solar resources was evaluated in Ref. [37] as a probabilistic model to reduce operational costs and emissions; Rayleigh and beta Probability Density Functions (PDFs) were used for modelling variations in the wind speed and solar radiation, respectively. In Ref. [38], using demand response programs was proposed for controlling the frequency of a smart microgrid with renewable generation. A multi-objective function has become a single objective function, and Mixed Integer Liner Programming (MILP) method is used to solve the proposed model. The use of demand side management in a smart grid, considering the wind power generation (wind farm) and the resulting uncertainty, was studied by Cicke et al. in Ref. [39] in order to increase social welfare. In this research, the authors don't consider the use of solar power generation and do not use incentive-based DR programs that can cause consumers the motivation to participate. Using a stochastic planning approach based on the Monte Carlo method was suggested in Ref. [40] for modelling the stochastic behavior of wind and DR considering the influence of wind power as an operational storage in an energy market. Demand response programs were used in Ref. [41] to manage the operation of a smart micro-grid with wind and solar resources, and Particle Swarm Optimization (PSO) algorithm was applied to solve the proposed model so that the pollution emission function was not considered in modelling the micro-grid management. Ref [42] has proposed a probabilistic multi-objective modelling of wind, solar, and wind-solar powers using the MOPSO method by considering Pareto criterion and fuzzy-based mechanism to find the optimal operation of the smart microgrid with the purpose of minimizing operational costs and emissions and considering the concept of DR in smart grids. A study conducted earlier [43] containing a unique augmented Epsilon-constraint method in which multi-objective and stochastic programming in the management of energy was suggested in order to optimize both cost and pollution simultaneously with the help of potable RES at the demand side so as to increase the flexibility in the microgrid performance.

This paper aims to find the optimal operation of the smart micro grid with the purpose of minimizing operational costs and emissions and increase flexibility of the smart micro grid performance and considering the concept of DR in smart grids for covering the uncertainty caused by wind and solar power generation and taking into account the stochastic natural behavior. Since consumer's participation in these programs is considered to be completely voluntary, an incentive-based DR method is proposed to be implemented in industrial, homes and business entities. As an outcome, the consumer is able to give back to the energy even at the instance when smart micro grid is unable to meet the expectations. The smart microgrid is generally capable of functioning as a standalone system or in connection with the main grid and it is allowed to import or export power from the main grid into the smart micro grid. The model developed has the capability to provide grid flexibility and support in mitigating the effects of intermittent RES and at the same time, DR is also used in order to relieve the system. With the help of Multi-Objective Particle Swarm Optimization (MOPSO) method, the proposed multi-objective model is solved, provided it meets the Pareto criterion with nonlinear-sorting based on fuzzy mechanism.

II. TYPICAL SMART GRID SYSTEM

Smart grid, the future of energy network is the most convenient, potent and efficient player, a result of power systems engineering, communications and information technology. The features of these components enable the utilities to foresee, observe and control the electricity flows in an accurate manner across the grid. Bidirectional communication is enabled in smart grid which provides real-time metering for customers. Further, the consumer loads can also be controlled by the utility in smart grids so that the system parameters are within the safer limits. After acquiring the user’s power profile and usage through smart meter, the utility levies the tariff to the consumer. When analysing such consumption data, power generation plants can predict the peak demand periods and respond to it through smart ways. By planning for higher production during peak times and wrap up production when there is less usage, power plants can reduce costs, energy and time. By leveraging data analytics, technology, computers, communications, smart grids can be the next-generation grids through enhanced and efficient methods compared to traditional grid. It also can open new channels of development using intermittent renewable energy sources such as wind, solar and new stresses to the network, for example electric vehicle. At certain period, it becomes the need of the hour for the grid to handle an additional amount of energy production during the instance of usage spikes that might happen. The figure 1 shows the various components in a smart grid system such as control unit and related communication tools, storage devices, various energy sources and electrical appliances The smart micro-grid has three types of consumers: residential, commercial, and industrial, along with power generation resources such as Wind Turbine (WT), Photovoltaic (PV) cell, Fuel Cell (FC), and battery and diesel generators; therefore, this grid has the capacity to exchange energy with the utility. In most of the cases, micro grid generates its own energy through RES such as wind turbine and solar Photovoltaic (PV) panels. Either it stores the energy generated or exports the additional energy to batteries and Electric Vehicle (EV) through charging station.

In smartgrid, the real time monitoring enables the end-users keep updated with information on instant, daily and monthly energy production and consumption values of each load. Through this feature, the consumers are much aware about the consumption of electricity through real-time feedback and also get to know on how to save energy. Further, the data collected in the smart grid can be retrieved through web-based application so that remote monitoring and device management status is made possible. In the proposed smart building, there are options available for smart plus and local controller that can monitor and control the energy consumption of electrical appliances in accordance to the pricing of the electricity and battery condition. Smart plugs can measure the power of the appliances and forward the information to local controller. They have the capability to receive signals from the local controller that can instruct either to start or stop or otherwise switch between the battery and the grid for operating the electrical appliances. The aim of the local controller in HEMS is to choose the best operation i.e., either battery or the grid, for electrical appliances in order to optimize the electricity price during day time based on the price charged in the grid to the user comfort.

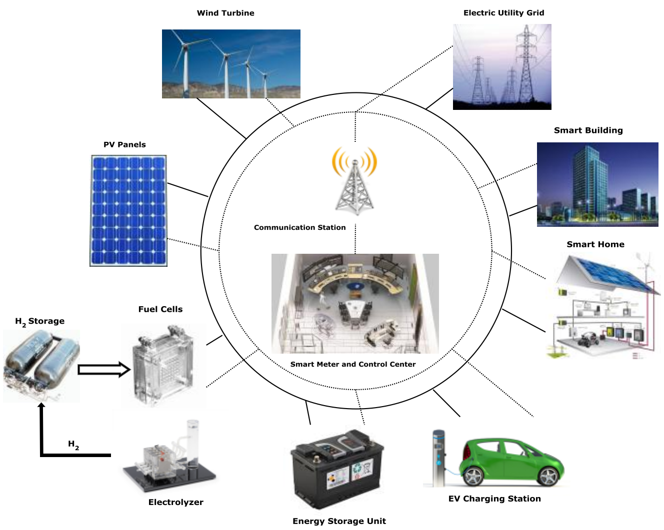

Figure 1. General scheme of the smart micro-grid system

III. DEMAND RESPONSE STRATEGY

DR can be explained as the incentive payments designed for the purpose of triggering less electricity usage by the consumers at the time when the wholesale market rates are high or when the system reliability is in question. DR is inclusive of any kind of purposeful modifications brought to reduce the electricity consumption by the end-use customers whose intention is to alter the timing, level of instantaneous demand level or the level of overall electricity consumption. In terms of utility, there are drastic changes experienced in electricity usage patterns whereas the demand is found to be minuscule. The controller modifies the user profile of the consumer based on the smart meter readings about the demand time from the utility. Through regular inspection of responses, the controller suggests the optimum time for every appliance to be used in a day so as to achieve minimum usage, thus minimum demand at a time. Imagine a scenario in which one utility company serves a number of residential consumers. Initially, the utility company analyses the demand for electricity for some hours and sets different price for different hours. After setting these prices, the utility company markets the prices to the consumers through digital communication network. Each user chooses best scheduling for their appliances and consumes energy according to the price information received from the utility. This is a methodology followed in the dominance game played by the user which has two categories. The first part contains the utility side tariff generation. According to the prevailing demands from the consumers in terms of units, the utility generator decides different tariff according to different hours in a day. This tariff is informed to the consumer in a-day-ahead-schedule manner. Using this information, the user has the liberty to modify the load profile distributed towards the hour during which there is less tariff or best utilize most of the loads in non-peak hours. With the help of this algorithm being optimized according to the day ahead schedule, the user now will be able to get the benefit of minimum rates for consumption. For the smart home which has an $\mathbf{m}_{sh}$ number of appliances, let N_{sish}, N_{snish}, N_{rsh} are sets of shiftable interruptible appliances, shiftable uninterruptible appliances, and regular appliances, respectively. Then all these loads are scheduled in 24 h time horizon. The Shiftable interruptible appliances can be shifted to any time slot and can be interrupted when required. Let P_{sish} is the power rating of each appliance in the smart home. Then total energy consumption per day (E_{sish}) is represented by:

$$E_{sish} = \sum_{t=1}^{T} P_{sish} \times \alpha(t) \tag{1}$$

Where α (t) = [0, 1] shows appliance ON/OFF status. Total cost per day of all shiftable interruptible appliances in time interval T can be obtained by following formula:

$$E_{sish}^{total} = \sum_{t=1}^{T} P_{sish} \times \alpha(t) \times \rho_{sh}(t) \tag{2}$$

Here, ρ_{sh}(t) represents the Real Time Pricing signal for the smart home at each time interval. Let N_{sish} be the set of uninterruptible appliances and n_{sish} represents each appliance. Similarly, cost per hour of interruptible loads is:

$$CPH_{sish}^{t} = \sum_{n_{sish} \in N_{sish}}^{T} P_{sish} \times \alpha(t) \times \rho_{sh}(t) \qquad \forall t = 1:T \tag{3}$$

We minimize cost per hour of each appliance, as a result overall cost is reduced. The Shiftable uninterruptible appliances can be shifted to any time slot but once start their operation, they must complete their operation without interruption. Let N_{snish} be the set of uninterruptible appliances and n_{snish} represents each appliance. If the power rating of each appliance is P_{snish} then, total energy consumption E_{snish} per day is represented by:

$$E_{snish} = \sum_{t=1}^{T} P_{snish} \times \alpha(t) \tag{4}$$

As these appliances are uninterruptible so they must complete their length of operation. This continuous operation of appliances may increase the cost which can be calculated by the following Eq.:

$$E_{snish}^{total} = \sum_{t=1}^{T} P_{snish} \times \alpha(t) \times \rho_{sh}(t) \tag{5}$$

cost per hour of shiftable uninterruptible appliances is calculated as follows:

$$CPH_{snish}^{t} = \sum_{n_{snish} \in N_{snish}}^{T} P_{snish} \times \alpha(t) \times \rho_{sh}(t) \quad \forall t = 1:T \tag{6}$$

The operation of the Regular appliances or thermostatically controlled appliances depends on temperature. Let N_{rsh} be the set of regular appliances and n_{rsh} represents each appliance. Let P_{rsh} is the power rating of each appliance and E_{rsh} is the total energy consumption per day which is represented by Eq.:

$$E_{rsh} = \sum_{t=1}^{T} P_{rsh} \times \alpha(t) \tag{7}$$

Regular appliances have a large length of operation to fulfil user requirements. Cost of such appliances in time interval T is:

$$E_{rsh}^{total} = \sum_{t=1}^{T} P_{rsh} \times \alpha(t) \times \rho_{sh}(t) \tag{8}$$

Cost per hour of regular appliances can be calculated by Eq.:

$$CPH_{rsh}^{t} = \sum_{n_{rsh} \in N_{rsh}}^{T} P_{rsh} \times \alpha(t) \times \rho_{sh}(t) \quad \forall t = 1:T \tag{9}$$

Let E_{sh} represents the total load consumed by the smart home in time interval T.

$$E_{sh}^{total} = E_{sish}^{total} + E_{snish}^{total} + E_{rsh}^{total} \quad \forall t = 1:T \tag{10}$$

Hence, to calculate the total cost per hour, total load consumed in each hour is multiplied by price rate at that hour. Eq. (11) shows cost per hour of total load.

$$CPH_{sh\_total}^{t} = \sum_{n_{sh} \in N_{sh}}^{T} E_{sh}^{total} \times \rho_{sh}(t) \quad \forall t = 1:T \tag{11}$$

Similarly, to find the cost per day we sum up all values of cost per hour for time T. Eq. (12) represents total cost per day of all appliances.

$$CPD_{sh\_total} = \sum_{t=1}^{T} \left(\sum_{n_{sh} \in N_{sh}}^{T} E_{sh}^{total} \times \rho_{sh}(t) \right) \quad \forall t = 1:T \tag{12}$$

For the smart commercial building of $\mathbf{m}_{sb}$ number of loads, let N_{nsb} represents a set of appliances, and N_{sisb}, N_{snisb}, N_{rsb} are sets of shiftable interruptible appliances, shiftable uninterruptible appliances, and regular appliances, respectively. Let P_{sisb} is the power rating of each load in the commercial smart building. Then total energy consumption per day (E_{sisb}) is represented by the following Eq.

$$E_{sisb} = \sum_{t=1}^{T} P_{sisb} \times \alpha(t) \tag{13}$$

Total cost per day of all shiftable interruptible appliances in time interval T can be obtained by following formula:

$$E_{sisb}^{total} = \sum_{t=1}^{T} P_{sisb} \times \alpha(t) \times \rho_{sb}(t) \tag{14}$$

Let N_{sisb} be the set of uninterruptible appliances and n_{sisb} represents each appliance. Similarly, cost per hour of interruptible appliances is

$$CPH_{sisb}^{t} = \sum_{n_{sisb} \in N_{sisb}}^{T} P_{sisb} \times \alpha(t) \times \rho_{sb}(t) \quad \forall t = 1:T \tag{15}$$

We minimize cost per hour of each appliance, as a result overall cost is reduced. Let N_{snisb} be the set of uninterruptible appliances and n_{snisb} represents each appliance. If the power rating of each appliance is P_{snisb} then, total energy consumption E_{snisb} per day is represented by the following Eq.

$$E_{snisb} = \sum_{t=1}^{T} P_{snisb} \times \alpha(t) \tag{16}$$

The cost can be calculated by the following Eq.:

$$E_{snisb}^{total} = \sum_{t=1}^{T} P_{snisb} \times \alpha(t) \times \rho_{sb}(t) \tag{17}$$

cost per hour of shiftable uninterruptible appliances is calculated as follows:

$$CPH_{snisb}^{t} = \sum_{n_{snisb} \in N_{snisb}}^{T} P_{snisb} \times \alpha(t) \times \rho_{sb}(t) \quad \forall t = 1:T \tag{18}$$

Let N_{rsb} be the set of regular appliances and n_{rsb} represents each appliance. Let P_{rsb} is the power rating of each appliance and E_{rsb} is the total energy consumption per day which is represented by Eq.:

$$E_{rsb} = \sum_{t=1}^{T} P_{rsb} \times \alpha(t) \tag{19}$$

Regular appliances have a large length of operation to fulfil user requirements. Cost of such appliances in time interval T is:

$$E_{rsb}^{total} = \sum_{t=1}^{T} P_{rsb} \times \alpha(t) \times \rho_{sb}(t) \tag{20}$$

Cost per hour of regular appliances can be calculated by Eq.:

$$CPH_{rsb}^{t} = \sum_{n_{rsb} \in N_{rsb}}^{T} P_{rsb} \times \alpha(t) \times \rho_{sb}(t) \quad \forall t = 1:T \tag{21}$$

Let E_{sb} represents the total load consumed by the smart home in time interval T.

$$E_{sb}^{total} = E_{sisb}^{total} + E_{snisb}^{total} + E_{rsb}^{total} \quad \forall t = 1:T \tag{22}$$

Hence, to calculate the total cost per hour, total load consumed in each hour is multiplied by price rate at that hour. The cost per hour of total load is:

$$CPH_{sb\_total}^{t} = \sum_{n_{sb} \in N_{sb}}^{T} E_{sb}^{total} \times \rho_{sb}(t) \quad \forall t = 1:T \tag{23}$$

Similarly, to find the cost per day we sum up all values of cost per hour for time T. The total cost per day of all loads is represented by:

$$CPD_{sb\_total} = \sum_{t=1}^{T} \left(\sum_{n_{sb} \in N_{sb}}^{T} E_{sb}^{total} \times \rho_{sb}(t) \right) \quad \forall t = 1:T \tag{24}$$

For the charging station of capacity $\mathbf{m}_{cs}$ number of electric vehicles, let N_{ncs} represents a set of appliances, and N_{sics}, N_{snics}, N_{rcs} are sets of shiftable interruptible appliances, shiftable uninterruptible appliances, and regular appliances, respectively. Let P_{sics} is the power rating of each appliance in the charging station. Then total energy consumption per day (E_{sics}) is represented by the following Eq.

$$E_{sics} = \sum_{t=1}^{T} P_{sics} \times \alpha(t) \tag{25}$$

Total cost per day of all shiftable interruptible appliances in time interval T can be obtained by following formula:

$$E_{sics}^{total} = \sum_{t=1}^{T} P_{sics} \times \alpha(t) \times \rho_{cs}(t) \tag{26}$$

Let N_{sics} be the set of uninterruptible appliances and n_{sics} represents each appliance. Similarly, cost per hour of interruptible appliances is

$$CPH_{sics}^{t} = \sum_{n_{sics} \in N_{sics}}^{T} P_{sics} \times \alpha(t) \times \rho_{cs}(t) \quad \forall t = 1:T \tag{27}$$

We minimize cost per hour of each vehicle; as a result overall cost is reduced. Let N_{snics} be the set of uninterruptible appliances and n_{snics} represents each appliance. If the power rating of each vehicle is P_{snics} then, total energy consumption E_{snics} per day is represented by:

$$E_{snics} = \sum_{t=1}^{T} P_{snics} \times \alpha(t) \tag{28}$$

The cost can be calculated by the following Eq.:

$$E_{snics}^{total} = \sum_{t=1}^{T} P_{snics} \times \alpha(t) \times \rho_{cs}(t) \tag{29}$$

cost per hour of shiftable uninterruptible appliances is calculated as follows:

$$CPH_{snics}^{t} = \sum_{n_{snics} \in N_{snics}}^{T} P_{snics} \times \alpha(t) \times \rho_{cs}(t) \quad \forall t = 1:T \tag{30}$$

Let N_{rcs} be the set of regular appliances and n_{rcs} represents each appliance. Let P_{rcs} is the power rating of each vehicle and E_{rcs} is the total energy consumption per day which is represented by Eq.:

$$E_{rcs} = \sum_{t=1}^{T} P_{rcs} \times \alpha(t) \tag{31}$$

Regular loads have a large length of operation to fulfil user requirements. Cost of such appliances in time interval T is:

$$E_{rcs}^{total} = \sum_{t=1}^{T} P_{rcs} \times \alpha(t) \times \rho_{cs}(t) \tag{32}$$

Cost per hour of regular appliances can be calculated by Eq.:

$$CPH_{rcs}^{t} = \sum_{n_{rcs} \in N_{rcs}}^{T} P_{rcs} \times \alpha(t) \times \rho_{cs}(t) \quad \forall t = 1:T \tag{33}$$

Let E_{cs} represents the total load consumed by the smart home in time interval T.

$$E_{cs}^{total} = E_{sics}^{total} + E_{snics}^{total} + E_{rcs}^{total} \quad \forall t = 1:T \tag{34}$$

Hence, to calculate the total cost per hour, total load consumed in each hour is multiplied by price rate at that hour. The cost per hour of total load is:

$$CPH_{cs\_total}^{t} = \sum_{n_{cs} \in N_{cs}}^{T} E_{cs}^{total} \times \rho_{cs}(t) \quad \forall t = 1:T \tag{35}$$

Similarly, to find the cost per day we sum up all values of cost per hour for time T. The total cost per day of all loads is represented by:

$$CPD_{cs\_total} = \sum_{t=1}^{T} \left(\sum_{n_{cs} \in N_{cs}}^{T} E_{cs}^{total} \times \rho_{cs}(t) \right) \quad \forall t = 1:T \tag{36}$$

IV. MOPSO DEMAND RESPONSE ALGORITHM

The objectives of the DR based strategy are: minimize the operational cost and emissions in a smart micro-grid, minimizing the electricity bill, minimizing the use of power from the grid, or minimizing the electricity cost to benefit both consumer and utility. These objectives can be achieved by shifting load from on-peak hours to off-peak hours to reduce the electricity bill. The aim of the problem formulation is to find out an effective and efficient automated load selection that optimizes the overall energy utilization, thus resulting in electricity consumption cost reduction. To minimize total cost, optimization algorithm reschedules the loads and avoids turning on during on-peak hours. The objective function to minimize cost per day is as follows:

$$\text{minimize} \sum_{t=1}^{T} \left(\sum_{n_{sh} \in N_{sh}}^{T} E_{sh}^{total} \times \rho_{sh}(t) \right) + \sum_{t=1}^{T} \left(\sum_{n_{sb} \in N_{sb}}^{T} E_{sb}^{total} \times \rho_{sb}(t) \right) + \sum_{t=1}^{T} \left(\sum_{n_{cs} \in N_{cs}}^{T} E_{cs}^{total} \times \rho_{cs}(t) \right) \tag{37}$$

The second objective function is to minimize the power used from the grid Σ $P_{Grid}(t)$ so as to optimize the cost spent on consuming electricity. When the loads are operating on battery mode, it is represented through Negative value in $P_{Battery}$ whereas the positive value denotes that the battery is being charged through grid.

$$\text{minimize} \sum_{t=1}^{T} P_{Grid}(t) = \sum_{t=1}^{T} E_{sh}^{total}(t) + \sum_{t=1}^{T} E_{sb}^{total}(t) + \sum_{t=1}^{T} E_{cs}^{total}(t) - \sum_{t=1}^{T} P_{PV}(t) - \sum_{t=1}^{T} P_{Wind}(t) - \sum_{t=1}^{T} P_{FC}(t) \pm \sum_{t=1}^{T} P_{Battery}(t) \tag{38}$$

The third objective function is to minimize the pollution emissions caused by the grid at the time of electricity purchase and the pollution emissions caused the renewable energy sources. The pollutants include carbon dioxide (CO_2), sulphur dioxide (SO_2) and nitrogen oxides (NO_x), and the mathematical model of the average pollution caused by the grid and the renewable energy sources can be calculated as follows:

$$\text{minimize} \sum_{t=1}^{T} \left[\left(\sum_{i=1}^{n} E_{CO_2}^{DG}(i) + E_{SO_2}^{DG}(i) + E_{NO_x}^{DG}(i) \right) \times P_i^{DG}(t) + \right. \\ \left. + \sum_{t=1}^{T} \left(E_{CO_2}^{Grid} + E_{SO_2}^{Grid} + E_{NO_x}^{Grid} \right) \times P_{Grid}(t) \right] \tag{39}$$

where $E_{CO_2}^{DG}(i), E_{SO_2}^{DG}(i), E_{NO_x}^{DG}(i)$ indicate the amount of CO_2, SO_2, and NO_x, pollution caused by the ith DG, respectively, that kg/MWh is its measurement unit. The typical smart microgrid is assumed to operate with the following constraints.

$$\left(E_{sh}^{total} + E_{sb}^{total} + E_{cs}^{total} \right) \le \left(KW_{grid} \right) \tag{40}$$

The maximum power which is drained from the grid is controlled by the algorithm proposed in the study. Therefore the total load demand of each group of loads should be less than or equal to the grid capacity (KW). The value of grid capacity (KW) is defined by the electricity providing company to ensure the reliability of the grid. The power consumption constraint guarantees that the total power consumption before and after scheduling remains same. It also ensures that length of operation of each load must not be affected by scheduling. Maximum and minimum power generations by each renewable energy source should be maintained and can be expressed as follows:

$$P_{PV\_\min} \le P_{PV}(t) \le P_{PV\_\max} \tag{41}$$

$$P_{Wind\_\min} \le P_{Wind}(t) \le P_{Wind\_\max} \tag{42}$$

$$P_{FC\_\min} \le P_{FC}(t) \le P_{FC\_\max} \tag{43}$$

Simultaneous minimization of operational costs and emission functions with renewable generation, and DG and DR which are carried out using the algorithm of Multi-Objective Particle Swarm Optimization (MOPSO). Application of the concept of Pareto optimization algorithm to the problem is considered in this paper. The developed MOPSO control algorithm starts with defining the input data such as the available power from each renewable energy source, the required power by each load, the selling and buying price of grid electricity, the SOC of the battery. The value of $P_{Utility}$, P_{Wind}, $P_{Battery}$, P_{PV} and P_{FC} will be symbolized as the possible position or solution for the particles array for the optimal power generation. In addition, the value of P_{Smart_home}, $P_{Smart\_building}$ and $P_{Cahrging\_station}$ will present the possible position or solution for the particles array for the optimal load demand. Each particle represents a specific configuration and will be considered as a possible solution of the energy management problem.

A vector of the objective functions which are functions of the encoded values of $P_{Utility}$, P_{Wind}, $P_{Battery}$, P_{PV}, P_{FC}, P_{Smart_home}, $P_{Smart\_building}$ and $P_{Cahrging\_station}$ will be produced using the encoded value of each particle. The optimal objective functions vector and the associated best particle will be determined by comparing the different objective function values. The assessment of the objective functions is executed on the vector of the produced particles and will be saved in *pbest* vector structure and all "non-dominated" arrangements are saved in the "Pareto Archive".

V. SIMULATION RESULTS

The numerical results are presented in this section to demonstrate the performance of the proposed method. In the simulation results the smart grid community consists of a set of renewable energy sources, energy storage system, and load systems that can be operated independently or in conjunction with the utility grid. The load system includes three types of consumers: four residential smart homes, commercial smart building and EV charging station of 10 EVs capacity. The power generation includes Wind Turbine (WT), Photovoltaic (PV) cell, Fuel Cell (FC), and battery; therefore, the smart grid has the capacity to exchange energy with the utility. The 24 hours energy demands and the load profile for different user are assumed and simulated which is given in Fig 2. The maximum electricity demand of the aggregated residential smart homes, commercial smart building and EV charging station are 200 kW, 100 kW and 300 kW, respectively. The real-time electricity pricing data used in the simulations is shown in Fig. 3. The time framework is considered to be T=24 hours, divided into hourly time-slots. Capacity of EV's battery used in simulation process is 20 kWh. Availability of EVs is shown in Fig. 3. While parked, EVs is connected to the microgrid. Typical daily travelled distance and energy consumption for their life style is showed in Fig. 4. The proposed model has been implemented in MATLAB software on a PC (2.6 MHz with 4 GB of RAM). The amount of greenhouse gas emissions caused by each renewable energy source and utility are presented in Table 1. To evaluate the effect of planning for energy level, energy storage, and the effect of the demand response in the operational costs and pollution emissions function, the problem is considered in three different scenarios: The first scenario, where the demand response was not implemented. The second scenario is based on single objective particle swarm optimization integrated with the proposed demand response. Finally, the third scenario includes multi-objective optimization of operational costs and emissions integrated with the proposed demand response. In the first scenario, the operational cost and emission are minimized using the SOPSO without considering the demand response. The optimal allocation of the power generation of the units for minimizing the operational cost and emissions is shown in Fig. 7. The results of Fig. 7 suggest that in the early hours, when the price of energy is low, the battery starts to be charged, and from 8 to 15, when energy prices are high, the utility purchases energy from the smart microgrid in which the power consumption is provided by DGs with the priority of offered price. Since wind and solar power are devoid of any pollution most of the time, these resources reach almost their maximum power generation when energy prices are high to reduce the pollution emission. However, since the offered price of these resources is higher than that of other power generation resources, they cannot receive much attention when energy prices are low to minimize the optimal operational cost. In the second scenario, operational cost and emissions are minimized with the involvement of demand response. The optimal allocation of power generation of units for minimizing operational cost and emissions is shown in Fig. 8. Comparison of the results presented in Figures 7 and 8 show that, in the case of using demand response programs, wind power generation is reduced by 9.34 %, FC power generation is reduced 15.34 % and solar power generation is reduced from 22.45%. In the third scenario, the optimal power allocation of the units is carried out for the minimization of operational cost and emissions using the MOPSO with/without the involvement of demand response. Since the objectives of operational cost and emissions are conflict, the operation of low cost leads to more pollution and operation of low pollution leads to higher cost. Therefore the optimal operation point can be determined by the MOPSO. Fig. 9 shows the optimal allocation of power generation of units with the MOPSO minimization of the operational cost and emissions objective functions when demand response programs are implemented. The results of Fig. 9 indicate that, in the case of using demand response programs, it is possible to improve the optimal operation point such that the operational cost and pollution emissions are reduced by 23% and 18%, respectively. Figures (10-13) shows the load demand reductions for the residential smart home, the commercial smart building and the charging station. According to results in Figures (10-13), it can be said that, the demand response rearranged the demand from peak periods during hours with high electricity prices to off-peak periods during hours with low electricity prices. Appliances which are time-bound such as clothes washer-dryer and dishwasher are rescheduled to morning and afternoon periods instead of afternoon and night time. Appliances which are power-shiftable such as laptop, water boiler and heat-pump are rescheduled when there is high penetration of renewable energy source. In the above case, when the customers are part of the DR program who is open to reduce their electricity usage in the defined hour, the system operator is allowed to reduce the scheduled power of generating units.

TABLE I. EMISSIONS COEFFICIENT OF THE DG SOURCES

	CO_2 (g/KWh)	SO_2 (g/KWh)	NO_x (g/KWh)
WT	39	0.0004	0.0012
PV	79	0.0006	0.0023
FC	460	0.003	0.0075
Battery	10	0.0002	0.001
Grid	950	0.5	2.1

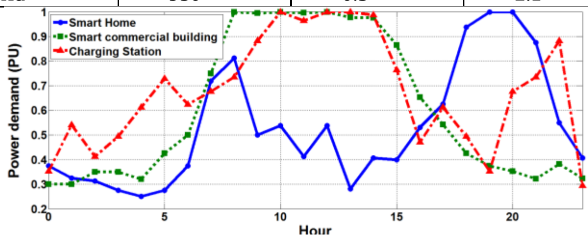

Figure 2. Average Load Demand profile for a typical day by smart home, Smart commercial building and charging station

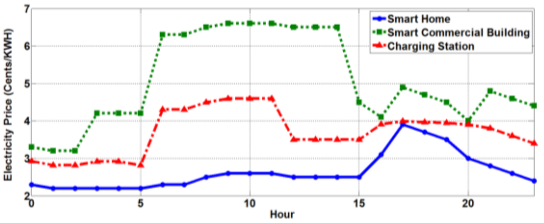

Figure 3. Grid Electricity price for a typical day for smart home, Smart commercial building and charging station

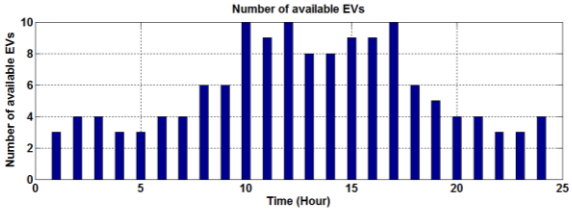

Figure 4. Availability of EVs

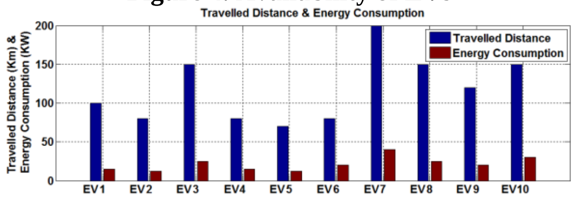

Figure 5. Typical daily EV travelled distance and energy consumption

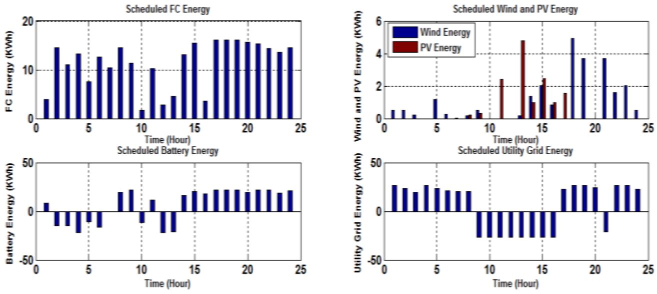

Figure 6. First scenario - optimal allocation of power generation of units

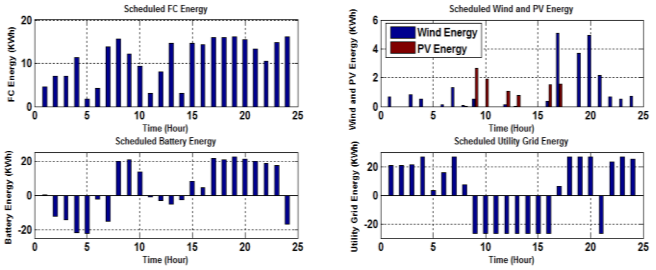

Figure 7. Second scenario - optimal allocation of power generation of units

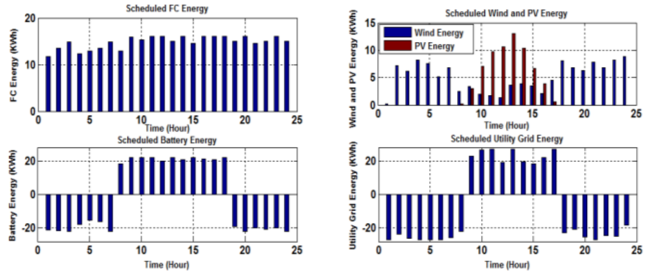

Figure 8. Third scenario - Optimal allocation of power generation of units

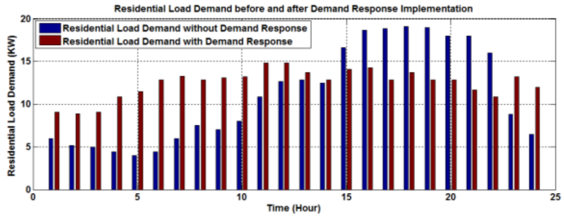

Figure 9. Residential Smart home Load Demand pre and post DR Implementation

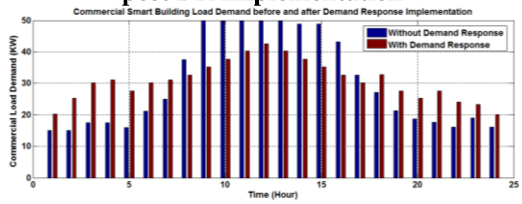

Figure 10. Commercial Smart Building Load Demand with/without DR.

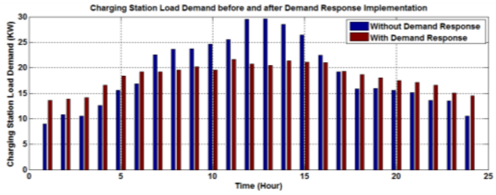

Figure 11. Charging Station Load Demand with/without DR.

VI. CONCLUSION

In this research article, an integrated renewable energy system that comprises FC, PV, wind and battery bank storage incorporated with DR program was studied in order to introduce the optimization at demand side of the micro grid. The MOPSO technique was implemented to solve and achieve an optimal DR for the smart micro grid with the possibility of energy exchange with the utility. The pollution together with total operational cost of the micro grid were optimized. Here, the main purpose is to minimize the cost incurred on conventional generators and the transaction cost which is spent on trading the transferable power. Further, the other goal is to enhance the DR benefit of the grid operator. The optimization model proposed in the study contains a scheduling interval of 24 hours which decides various elements such as the schedule for optimal power generation using conventional generators, optimal customer incentive, optimal power curtailed, optimal power which is to be transmitted from the main grid to micro grid and vice versa. It has been observed that significant amount of savings in system operation cost are obtained with DR strategy compared to system without DR reducing operational cost and pollution emissions by 21% and 14%, respectively. Results show that MOPSO based DR controller has improved the system in term of pollution reduction and operation cost reduction.

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