Multi-objective Load Scheduling in a Smart Grid Environment

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Abstract—Smart grid is a remarkable development for managing the existing grids more efficiently. This paper deals with an integration of distributed energy resources and plug-in electric vehicles (PEVs) into an existing grid. There are significant impacts due to PEVs in the existing grid. However they also bring negative impacts to the grid if they are not coordinated properly. The continuous varying load and voltage fluctuations caused by their disordered charging behaviour can be detrimental to the grid. In order to overcome them, an intelligent load-scheduling strategy is applied in this paper. A multi-objective optimization strategy based on non-dominated sorting genetic algorithm (NSGA-II) is used in this paper to minimize two contradicting objective functions such as voltage deviation at buses and the total line loss simultaneously. The applied method is tested on IEEE 17-bus test system. Simulation results show the superiority of the applied method.

Index Terms—plug-in electric vehicles (PEVs), multi-objective optimization, Load scheduling.

I. INTRODUCTION

The increase in demand and the expectations of quality power supply pose major challenges to existing grids. Due to the depleting levels of fossil fuel storage and the rising energy cost, the interest is leading towards the utilization of renewable energy sources [1]–[3]. The advancement of technologies to integrate these renewable energy sources has resulted in a gradual change to the classical power grid [4]. In present times, distribution systems started incorporating distributed generations (DGs) to respond to the randomly varying consumer requirements. In addition to DGs, the integration of storage systems such as Data Centers (DCs) and Plug-in electric vehicles (PEVs) makes it possible to increase the demand response to get the most favourable operation of the grid.

DGs are essentially dedicated to the grid according to their availability of energy, whereas DCs and PEVs are loads and heterogeneous in nature. DCs’ growth is principally connected to the explosion of digital informatics [5]. PEVs are one of those, who are gaining fast popularity due to the advantages like independence from oil usage and pollution free. These kinds of loads need a large battery storage system to supply them, when they are not connected to the grid. DCs have battery storage systems to supply the server at the time of grid failure. Whereas, PEVs use the stored energy in their batteries for normal operation. Each PEV needs charging at specified times at specified rates based on its requirement.

The different necessities of those components of smart grid represent a challenge to operate them in coordination. However they will bring a lot of benefits if they are optimally operated. For that, the grid needs full flexibility in operational capabilities. Maintaining continuous and stable power supply to a large number of consumers with satisfactory levels of quality power, and lower energy cost are some general objectives associated with the optimum operation of the smart grid. Line loss and voltage fluctuations are serious problems, which deteriorate power quality and increase the cost of the energy received. Losses are very large in case of distributed systems. This loss is a major reason of low voltage. Although Line loss and voltage deviation objectives are individually important for the grid scheduling, but they are conflicting in nature. To handle such contradicting objective functions, multi-objective (MO) algorithms are suitable to get a set of optimal solutions called Pareto-optimal set.

Optimal scheduling of micro grid in multi-objective manner was discussed in [6]–[11]. In [6], [7], optimal energy management strategy was applied for economic consideration by minimizing cost and emission of a micro grid, incorporating generation and storage. Multi-objective optimization technique was applied to minimize environmental and economical cost in [8], including both active and reactive power resources. Optimal operation of micro-grid considering voltage security in presence of electric vehicles was applied in [9], as MO approach. A multi-objective economic dispatch model for micro-grid scheduling considering the fluctuations of energy resources was applied in [10], to minimize emission, customer outage and production cost. An operational and planning model for micro-grid scheduling was applied in [11] for minimizing cost and emission. An interesting study on DC integrated smart grid was described in [12], with multi-objective optimization to balance power load and minimize energy cost. A multi-objective scheduling approach of electric vehicle charging and discharging was studied in [13] to optimize economical and environmental objectives.

Several methods have been applied for multi-objective optimization problems. In [6], a combined artificial intelligence
and linear-programming technique has been applied. In [7] and [12], the weighted sum method has been used. Methods based on Fuzzy mathematics technique were used in [8], [10]. In [11], [13], the augmented \( n \)-constraint approach has been applied. However, the non-dominated sorting based genetic algorithm is much efficient in solving non-linear non-convex problems [14]. Moreover, NSGA-II has a better performance for multiple objectives and uses a natural evolution process to find a set of optimal solutions.

In this paper, a multi-objective based optimal load scheduling of smart grid technique is described considering DGs, DCs and PEVs. The voltage deviation at buses and the line loss are considered as the objectives in this paper. These two objectives are simultaneously optimized using the NSGA-II method. For a comparison purpose, these two objectives are also minimized individually. Simulation results of both single and multi-objective cases are compared. The organization of the paper is as follows. Section II explains the mathematical modelling of the problem. Section III explains the multi-objective problem formulation. The test system considered in this paper is explained in Section IV. Simulation results are given in section V. The paper concludes in section VI.

II. MATHEMATICAL MODELLING

A medium voltage (MV) smart grid is considered in this paper. This smart grid has an interconnected bus containing DGs, DCs, PEVs and loads. The smart grid operation is organized by a centralized control system (CCS), which forecasts the behaviour of all resources and loads. An unorganized charging behaviour of PEVs can create serious load fluctuations, which in return damage the economy and security of the grid. Voltage fluctuation, line losses, overload, increase in per unit cost of energy are the adverse effects due to the uncontrolled charging behaviour of PEVs. To minimize these types of effects, the multi-objective scheduling technique is applied to control the behaviour of PEVs’.

The scheduling technique is aimed to attain individual goals of those objectives while serving the grid properly. This strategy is applied to determine the active power absorbed by PEVs to operate the grid optimally. Inputs to the applied problem are the forecast of DGs’ power generation and the load demand of DCs.

A. Objective Functions

1) Node Voltage Deviation: The first objective is to minimize the grid’s node voltage deviation/fluctuation, with respect to it’s specified nominal voltage. It is calculated as follows:

\[
f_{obj_1} = \frac{1}{n_j} \sum_{j=1}^{n_j} \left[ \frac{1}{n_d} \sum_{i=1}^{n_d} (V_{i,j}^{sp} - V_{i,j})^2 \right]
\]  

\( V_{i,j} \) is the voltage of the bus bar \( i \) at time slot \( j \). \( V_{i,j}^{sp} \) is the specified nominal voltage of the \( i^{th} \) bus bar at the time slot \( j \).

2) Line Loss: The second objective is to improve the energy efficiency of the grid by minimizing line losses in the power system.

\[
f_{obj_2} = \sum_{j=1}^{n_j} P_{loss_j}
\]  

Here \( P_{loss_j} \) is the power loss at \( j^{th} \) time slot. Total power loss for a whole day is taken for loss minimization calculation.

This optimization model is developed for a day, divided into \( n_j \) periods. The optimization problem is solved for the total time slots. Both of the above mentioned objectives depend on the active and reactive power of the network. The voltage at all the bus bars is related to the reactive power and the loss is related to the active power demand. The total power demand of the system also depends upon the vehicles’ charging demand. PEVs’ power demand implicitly depends on the service provided by the grid to the PEV fleet. This work is done to visualize the effect of PEVs’ demand on the system for different operational objectives. By controlling the PEVs charging demand the overall demand of the system can be controlled. In this paper optimal charging rate of EVs is taken as control variable.

The objective functions considered in this paper Eq. (1) and Eq. (2) are minimized to find the optimal charging rate. Demand of PEVs through the fleet per time slot is controlling the objective functions considered in this paper. Minimization of the above mentioned objectives is subject to some constraints, which are described below.

B. Constraints

Load flow equations are the equality constraints. For the power flow equations, the PEVs’ active power and DGs’ reactive power are taken into account.

1) Generation Bus: Different characteristics and behaviours of DG units connected to the grid are available in [15]. Active and reactive power control of DGs are subjected to different conditions. Impact of DGs in the steady state behaviour of a distribution system is described in [16]. Here, only the non-dispatchable generating units with power converters are considered, for the sake of conciseness. This one is the most popular approach for the DG units in an advanced distribution system (i.e., photovoltaic and wind energy system). Here, the constraints related to the DG bus for load flow equations and the ratings for the converters are:

\[
P_{DG_{i,j}} = V_{i,j} \sum_{l=1}^{n} V_{i,j} [G_{i,l} \cos(\delta_{i,j} - \delta_{i,j}) + B_{i,l} \sin(\delta_{i,j} - \delta_{i,j})]
\]

\[
Q_{DG_{i,j}} = V_{i,j} \sum_{l=1}^{n} V_{i,j} [G_{i,l} \sin(\delta_{i,j} - \delta_{i,j}) - B_{i,l} \cos(\delta_{i,j} - \delta_{i,j})]
\]

\[
\left[ (P_{DG_{i,j}})^2 + (Q_{DG_{i,j}})^2 \right]^{1/2} \leq S_{DG_{i,j}}^{max}
\]

Where \( j = 1, 2, \ldots, n_j \), \( i \in \Omega_{DG} \). \( \Omega_{DG} \) represents the set of DG buses. \( P_{DG_{i,j}} \) is the active power injected to the bus through the DG. \( Q_{DG_{i,j}} \) is the reactive power injected to
the grid through the DG. $V_{i,j}$ is the bus voltage magnitude, and $\delta_{i,j}$ is the argument of the bus voltage. $G_{i,l}$ and $B_{i,l}$ are the $(i,l)$th term of the matrix representing conductance and susceptance value for the particular term. $S_{DG}^{max}$ is capacity of the converter in between bus and $i^{th}$ DG unit.

2) Load Bus: The constraints related to the load buses are only the power flow equations. They are not shown here. However they can be derived simply from Eq. (3) and Eq. (4), with change in $i \in \Omega_{L,D}$, the set of load buses, for active and reactive power injected to the buses.

3) PEV Aggregator Bus: PEV aggregator bus is a charging station for PEVs. This charging station has a number of PEV fleets which are used as charging connectors. The charging equipment (CE) is used to connect the vehicle to grid, and each CE is supposed to connect one vehicle battery at a time for charging. The aggregator bus active and reactive power supply have to fall in an admissible range. The aggregator active and reactive power constraints have to be considered in the smart grid load flow calculation which is shown as

\[
\left[(P_{AG_{i,j}})^2 + (Q_{AG_{i,j}})^2\right]^{1/2} \leq S_{AG_{i}}^{max}
\]

where $P_{AG_{i,j}}$ and $Q_{AG_{i,j}}$ are the active and reactive power of the aggregator bus, $i \in \Omega_{AG}$, $\Omega_{AG}$ represents the set of aggregator buses, and $j$ is the time slot $j = 1, 2, \ldots, n_j$.

The balance equations can get traced simply following Eq. (3) and Eq. (4), with change in $i \in \Omega_{AG}$, the set of PEV aggregator buses, for active and reactive power injected to the bus. Different charging/discharging modes for optimal behaviour of PEVs are studied in [17] [18]. In this paper, the method applied in [19] is used for PEVs.

It is assumed that $i^{th}$ aggregator has $n_{i}$ CE connected to it. It means at any time instant $j$, there will be $n_{i}$ number of vehichels connected to the $i^{th}$ aggregator. $i \in \Omega_{AG}$, $\Omega_{AG}$ represents the set of aggregator buses. The equality and inequality constraints imposed to the $m^{th}$ CE $(m = 1, \ldots, n_{i})$ of the $i^{th}$ aggregator. CE has some maximum power transfer limits and minimum threshold value, dependent on both the CE and PEV. Lower limit of CE is a point up to which the battery can be discharged, and upper limit is related to the CE capacity. When any PEV is not plugged in, the CE power will be zero.

\[
P_{CE_{i,m,j}}^{Min} \leq P_{CE_{i,m,j}} \leq P_{CE_{i,m,j}}^{Max} \quad t \in \Omega_{i,m,p}, p \in \Omega_{PEV,i}
\]

\[
P_{CE_{i,m,j}} = 0 \quad t \notin \Omega_{i,m,p}, p \in \Omega_{PEV,i}
\]

where $P_{CE_{i,m,j}}$ is the power input to the $m^{th}$ CE at $j^{th}$ time slot of the $i^{th}$ aggregator. $P_{CE_{i,m,j}}^{Max}$ and $P_{CE_{i,m,j}}^{Min}$ are respectively the maximum and minimum limit of power transfer through CE. $\Omega_{i,m,p}$ is the time slots set, where the $p^{th}$ PEV is connected to the $j^{th}$ CE of the aggregator $i$. $\Omega_{PEV,i}$ is the set of PEVs connected to the aggregator $i$.

4) Datacenter Bus: Datacenter bus bar has number of priviledged battery loads connected through the UPS system. The active and reactive power have to satisfy the balance equations which can be derived simply from Eq. (3) and Eq. (4), with small change in place of $i \in \Omega_{DC}$, $n_{UPS_{i}}$ is the number of UPSs parallely connected to the DC bus. Active power injected into the bus is the sum of active power injected to the UPSs connected to the bus.

\[
P_{DC} = \sum_{m=1}^{n_{UPS_{i}}} P_{UPS_{i,m,j}}
\]

III. MULTI-OBJECTIVE PROBLEM FORMULATION

A general non-linear, constrained, multi-objective optimization problem is defined as follows:

\[
\min \left[f_{obj_{1}}(x), f_{obj_{2}}(x), \ldots, f_{obj_{N_{f}}}(x)\right]
\]

subjecte to;

\[
g_{k}(x) = 0, k = 1, 2, \ldots, N_{ec}
\]

\[
h_{l}(x) \leq 0, l = 1, 2, \ldots, N_{inec}
\]

where $f_{1}(x), f_{2}(x), \ldots, f_{N_{f}}(x)$ are objective functions, $N_{f}$ is the total number of objective functions, and $x$ is the function variable or the optimization variable vector. $g_{k}(x), h_{l}(x)$ are the equality and inequality constraints, respectively and $N_{ec}, N_{inec}$ are the number of equality and inequality constraints, respectively.

Since the objective functions considered in this paper are contradictory in nature, they are simultaneously minimized by Non-dominated sorting genetic algorithm II (NSGA-II). NSGA-II is a population based evolutionary algorithm, which can handle multiple objectives [14]. In this multi-objective NSGA-II based scheduling algorithm, the demand of PEV fleet for each hour are taken as the control variables, and latter calculated it for twenty four hours. The number variables or population size, depends on the number of controllable PEV bus loads for a full day. Here, GA is used for single objective optimization.

This algorithm starts with an initialization of randomly generated population. Selection and crossover operation help produce a new offspring population. After evaluating the new offspring population, non-dominated shorting algorithm ranks all the parent and offspring solutions in a $2N$ population. From this $2N$ solutions, crowding distance shorting algorithm accepts only $N$ number of solutions [14]. In place of only one optimal solution for the single objective function, multi-objective NSGA-II gives a set of non-dominated solution set, where each solution is equally important.

A. Fuzzy optimization function

Fuzzy optimization function is used to select the best compromised solution from the set of N non-dominated solution set of the multi-objective problem [20]. It helps to normalize the the multi-objective values and model them by
The membership function and decision making tool are:

$$
\mu_r = \begin{cases} 
1 & \text{if } F_r(x) \leq F_r^{Min} \\
\frac{F_r^{Max} - F_r(x)}{F_r^{Max} - F_r^{Min}} & \text{if } F_r^{Min} < F_r(x) < F_r^{Max} \\
0 & \text{if } F_r(x) \leq F_r^{Max}
\end{cases}
$$

(13)

$F_r^{Min}$ and $F_r^{Max}$ are respectively the minimum and maximum value of the $r^{th}$ objective function $F_r(x)$, where $\mu_r$ is the $r^{th}$ objective function’s $(F_r(x))$ membership value.

$$
N_{\mu_q} = \frac{\sum_{r=1}^{N_{non}} \mu_r(q)}{\sum_q \sum_{r=1}^{N_{non}} \mu_r(q)}
$$

(14)

$N_{\mu_q}$ is the $q^{th}$ non-dominated solution’s normalized value of the membership function. $N_{obj}$ and $N_{nd}$ are respectively the number of objective functions and the number of non-dominated solutions present. The maximum of $N_{\mu_q}$ of all $N_{nd}$ non-dominated solutions decides the best compromised solution of the multi-objective problem.

IV. TEST SYSTEM

A MV test system consisting of 17 buses is considered in this work. It’s voltage and MVA rating are 12.5 kV and 10 MVA respectively. The on-line diagram of the system with DGs, DCs and PEVs is shown in Fig. 1. The network data and load rating are given in [21], [22]. This system is connected to a high voltage transmission network through a transformer of capacity 18 MVA. This smart grid has 3 DG units. Among them, two 1 MW photovoltaic (PV) systems and one 500 kW wind turbine (WT). It also has 2 PEV fleet aggregators and 2 DC bus loads. The DGs are connected to the grid buses through power converters. The DCs are connected to 1 MW load with an UPS system. The minimum state of charge (SoC) is larger than the back-up needed to serve. Batteries are charged during central hours of the day.

Each PEV aggregator contains 80 CE which are of fast charging type [23]. The charging equipment’s efficiency is about 98% and taken to work only in charging mode. By allowing the CE to charge and discharge both, some added benefits can be achieved. It seems that CE in charging mode gives a more consistent operation. Aggregator interfacing converter has a size of 2 MVA, and an efficiency of 95%. The PEV aggregator can connect more than 200 EVs with battery rating 24 kWh [23]. Arrival and departure time are considered as given in [17]. The state of charge for each battery is supposed to be at minimum at arrival and maximum at departure time.

The day is divided into 24 time slots each of 1 hour to solve the optimization problem. The forecast data for load, PV and WT is assumed available for each hour basis. A typical power profile is considered in this paper. Fig 2 shows the active power profile of Bus 7 and Bus 12. This is collected from the load profile of DCs [19], [24], [25]. Typical active power and reactive power profile of PV bus 15 and 17 are shown in Fig. 3 and Fig. 4 respectively. The generation power factor of the wind energy resource is considered as unity.

V. SIMULATION RESULTS

The performance of the optimization model is validated on three different cases to represent the behaviour of the other objective function when one is getting optimized. In case 1 the node voltage deviation and in case 2 the line loss are minimized individually using a single-objective optimization method. Where as, in case 3 both objectives are minimized simultaneously by the multi-objective optimization approach to find the Pareto-optimal set. Fuzzy optimization function is used to find the best compromised value from the set. All the load flow and optimization algorithms are implemented in
minimization and the corresponding value of voltage deviation for the same charging rate of EVs as a variable. The optimum value of line loss function is 12.06 kW, whereas for the same charging rate of EVs the value of voltage deviation is 0.001183 (P.U.).

**TABLE II**

<table>
<thead>
<tr>
<th>GA for Line loss</th>
<th>Voltage deviation (p.u.)</th>
<th>Line loss (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.001183</td>
<td>12.06734</td>
<td></td>
</tr>
</tbody>
</table>

**C. Case 3**

In case 1 node voltage deviation is minimized resulting an increase in the line loss. In case 2, the line loss is minimized resulting an increase in the node voltage deviation. In this case, both node voltage deviation and line loss function are minimized simultaneously. Multi-objective optimization is performed here to find the Pareto-optimal set for the two objectives in Table III. Fig. 5 shows the Pareto-optimal set. With the help of the fuzzy optimization technique, the best compromised value from the Pareto-optimal set is selected. Table IV shows the best compromised values of the two objective functions. The best compromised value for the voltage deviation is 0.001176 (P.U.) which is better than it’s value in Case 2 and close to its optimal value in Case 1. Similarly, the best compromised value for line loss is 12.4288 kW which is better than it’s value in Case 1 and close to its optimal value in Case 2. It is clear that the multi-objective optimization approach is able to give better results which are close to the optimal values of single objective cases.

**TABLE III**

<table>
<thead>
<tr>
<th>Voltage Deviation</th>
<th>Line Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0011728</td>
<td>12.6582</td>
</tr>
<tr>
<td>0.0011736</td>
<td>12.6500</td>
</tr>
<tr>
<td>0.0011744</td>
<td>12.5412</td>
</tr>
<tr>
<td>0.0011752</td>
<td>12.5132</td>
</tr>
<tr>
<td><strong>0.0011760</strong></td>
<td><strong>12.4288</strong></td>
</tr>
<tr>
<td>0.0011776</td>
<td>12.4151</td>
</tr>
<tr>
<td>0.0011784</td>
<td>12.3449</td>
</tr>
<tr>
<td>0.0011792</td>
<td>12.3229</td>
</tr>
<tr>
<td>0.0011800</td>
<td>12.3015</td>
</tr>
<tr>
<td>0.0011808</td>
<td>12.2612</td>
</tr>
</tbody>
</table>

**TABLE IV**

<table>
<thead>
<tr>
<th>Voltage deviation (p.u.)</th>
<th>Line loss (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>0.001176</strong></td>
<td><strong>12.4288</strong></td>
</tr>
</tbody>
</table>

**IV. Conclusion**

This paper proposes a multi-objective load scheduling approach to minimize the voltage deviation and the line loss in
a medium voltage microgrid. The applied strategy explores all the DG resources for the grid and optimizes two objectives simultaneously while satisfying various constraints. NSGA-II is used to minimize the objectives simultaneously. For comparison, the objectives are also minimized individually. Simulation results of both single objective cases and multi-objective case are compared. From the results, it is clear that the multi-objective method is able to give better values than the single objective cases.

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REFERENCES


