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Generation scheduling in smart grid environment using global best artificial bee colony algorithm

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ABSTRACT

Generation scheduling is an important concern of the current power system which is suffering from many obstacles of limited generation resources, grown energy demand and fuel price, inconsistent load demand and fluctuations of available wind power in case of the thermal–wind system. Smart grid system has a great potential of tumbling existing power system difficulties with intelligent infrastructure and computation technologies. Three different distributed energy resources, namely, distributed generation, demand response and gridable vehicles are used in this paper to overcome the power system hitches. The classical generation scheduling is solved with insertion of the cost of demand response and the cost model pertaining to underestimation and overestimation of fluctuating wind power. The modified optimization problem is solved using an efficient Global best artificial bee colony algorithm for 10 generating units test system. Generation scheduling in the smart grid environment yields a significant reduction in the total cost.

Introduction

Future power system has to be competent to deal with growing energy demand, global environmental alarm and inconsistent load demand, which are the major concern of the current power system. Extensive penetration of distributed energy resources (DERs) and their appropriate handling in the scheduling of generating units could be the probable solution to lessen the existing power system difficulties. Three types of DERs such as distributed generation (DG), customer participation in demand response program (DRP) as a responsive load and vehicle to grid (V_2G) as an energy storage unit are considered in this paper [1,2]. V_2Gs can feed power to the grid by discharging the battery and also referred to as gridable vehicles (GVs) [3]. Traditionally generation scheduling (usually referred to as unit commitment) is a mixed integer, combinatorial two linked optimization problem which decides when to start-up and shut down the generating units (unit commitment) and how to dispatch committed generators over a scheduled time horizon (economic load dispatch) to minimize the operating cost while satisfying the load demand and multiple constraints.

Many researchers have developed several optimization techniques to solve unit commitment problem (UCP). The traditional methods include priority list method (PL) [4,5], branch and bound method (BB) [6], dynamic programming (DP) [7], mixed-integer programming (MIP) [8] and Lagrangian Relaxation (LR) [9,10]. The classical PL method is simple and fast but yields higher generation cost. DP and BB suffer from the dimensionality problem which results in excessive computation time as the number of generating unit increases. LR method has convergence problem and generates poor quality solution. Recently, some methods based on meta-heuristics approach are also available such as genetic algorithm (GA) [11,12], evolutionary programming (EP) [13], simulated annealing (SA) [14], fuzzy logic (FL) and particle swarm optimization (PSO) [15–18], tabu search [19] and ant colony optimization (ACO) [20]. These methods can execute complex problems with high quality resolution and can reach up to or near the global optimal solution. However, with the large-scale unit system all these algorithms adversely result in enormous computation time and some methods yield suboptimal solutions. With this perspective, recently established global best artificial bee colony algorithm (GABC) [21,22] is implemented to solve UCP to achieve the global optimum solution.

Moreover, several researches have been carried out to solve UCP with demand response and GVs individually to achieve an economic and ecological solution. The model of emergency demand response program (EDRP) and interruptible load contracts (ILC) in UCP is proposed in [23] to minimize the energy consumption during the critical or peak period of the day. Another UCP associated with demand response is suggested in [24] to study the environment and economic effect.

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GVs have great potential of emission reduction and reliability enhancement. The intelligent, cost-effective and eco-friendly study of UCP with GVs is discussed in [25]. Also, GVs can reshape the load demand by charging from the grid during off-peak hours and feeding (discharging) power to the grid during peak hours. Two novel techniques of load levelling and smart grid models of GVs for cost and emission reduction with UCP are presented in [26]. The vehicle to grid algorithm has been developed in [27] to optimize the scheduling of energy and ancillary services. The analysis of electric vehicle mobility in transmission constrained generation scheduling is given in [28]. Some research literature on the collective impact of demand response and GVs on generation scheduling are also published recently. In [2], reliability constrained UCP is solved considering the cost of demand response and GVs in the objective function. Moreover day-ahead resource scheduling with demand response and GVs is discussed in [29,30].

This paper has modified classical UCP formulation with the integration of the cost model of uncertain wind power in terms of overestimation and underestimation cost along with the cost of DRP. However, the cost model for economic load dispatch which considers overestimation and underestimation cost of wind generation has been discussed in [22,31], but in this paper the same concept is stretched for UCP. According to [32], among the different demand response models (linear, potential, exponential and hyperbolic), hyperbolic and potential demand models are unable to attain the optimum hourly solution. The most reasonable linear function model for UCP has been developed in [24]. Hence, this paper has chosen another moderate approach to exponential load economic model for exhaustive study of demand response. A well-known emergency demand response program (EDRP) is considered in this paper.

The main contribution of this work is as follows:

- The conventional UCP objective function is modified by including the direct cost, overestimation and underestimation cost of uncertain wind power generation.
- The exponential demand function is solved to comprehend the impact of EDRP on generation scheduling.
- The entire optimization problem is solved considering the impact of EDRP and GVs on generation scheduling along with uncertain wind power using an efficient global best artificial bee colony (GABC) algorithm.

The rest of the paper is deployed as follows: Section 'Distributed energy resources' deals with the essential framework of DERs considered in this paper. Section 'UC problem formulation' describes the modified UCP along with the cost model of DRP and uncertain wind power. A brief structure of the GABC optimization algorithm and its implementation is described in Section 'Overview of global best artificial bee colony optimization algorithm'. Section 'Results and discussion' deliberates the simulation results and comparison of different scenarios considered. The conclusion is drawn in Section 'Conclusion'.

Distributed energy resources

Three types of DERs are considered in this paper, namely, distributed generation (DG), emergency demand response program (EDRP) and gridable vehicles (GVs).

DG plays a significant role in the power system generation and operation. Upcoming wind energy has been identified as a new challenge in distributed generation due to unpredictable wind nature. This paper has considered a wind power generator as DG and its consequence on generation scheduling.

Federal Energy Regulatory Commission (FERC) order 719 has classified different DRPs into two main categories, namely, incentive based programs and time based programs [33]. The incentive based DRP offers cash or discount in bill to the customers for reducing their electricity consumption during peak hours or during periods of high electricity price. The well-known time based DRP motivates the customers to shift their load from peak hours to low load or off-peak hours. DRP has been proved as an organized approach to reshape the inconsistent load demand curve by reducing the load demand during peak period of the day in [34,35].

Electric vehicles with the competence of feeding power to the grid are usually referred to as gridable vehicles (GVs) and can be served as DER when GVs are parked. GVs charged during off-peak hours can insert power to the grid during peak hours which in turn results in peak hour saving. Occurrence of GV reduces the CO_2 emission and enhances the system reliability.

This paper has assumed three individual DER aggregators to communicate with the independent system operator (ISO). ISO will dispatch power according to the information gathered from these aggregators as shown in Fig. 1. Wind aggregator will collect information of wind power generation from wind farm owner and accordingly decide the associated overestimation and underestimation cost. DR aggregator will offer various incentive schemes to the customer for peak load reduction and keeps a record of the participating customer through smart metering. GV aggregator will maintain a history of registered vehicles, their grid connected timings and depth of charge level. This study has assumed the smart grid system which can assure appropriate operation and control of these DERs with the intelligent infrastructure and computational technologies.

Mathematical modelling

Wind probability distribution function

Uncertainty of wind speed can be modelled from the probability distribution function of wind power. It has been already proved that the Weibull distribution function [31,36] is proficient to characterize the uncertain wind speed and is given as:

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{(k-1)} \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \quad 0 < v < \infty \tag{1}$$

where function $f(v)$ gives the time span in which wind has a velocity of v m/s, c and k denote scale factor and shape factor of a particular location respectively. The probability of having wind velocity equal to or less than v m/s is defined as the cumulative distribution function and is described as:

$$F(v) = 1 - \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{2}$$

After mapping the inconsistent wind speed as a random variable, the wind power generated from the wind power generator [31] is calculated as:

$$\begin{aligned} P_W &= 0, \quad v < v_{ci} \text{ and } v > v_{co} \\ P_W &= P_{Wr}\frac{(v - v_{ci})}{(v_r - v_{ci})}, \quad v_{ci} \leqslant v \leqslant v_r \\ P_W &= P_{Wr}, \quad v_r \leqslant v \leqslant v_{co} \end{aligned} \tag{3}$$

where P_W and P_{Wr} are output and rated power of wind power generator respectively whereas v_{ci}, v_{co} and v_r are signified as cut-in, cut-out and rated speed of wind power generator respectively. From the Weibull probability distribution function [31], the probability of wind power being zero, rated and between zero and rated power can be formulated as (4)–(6) respectively: