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Clustering based unit commitment with wind power uncertainty

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ABSTRACT

Wind power generation is continuously increasing around the world, but due to uncertainty in wind power generation, the unit commitment problem has become complex. In this paper, scenario generation and reduction techniques are used to consider wind power uncertainty on system operation. Also, a new approach is developed for creating clusters of unit status associated with a probability of occurrence from an initial set of large wind power generation scenarios. And then a model of wind-hydro-thermal coordination problem along with the pumped storage plant is established. Combination of proposed weighted-improved crazy particle swarm optimization along with a pseudo code based algorithm and scenario analysis method is utilized to solve above problem. The effectiveness and feasibility of the proposed method is tested on systems with and without pumped storage plant integration. The results are analyzed in detail, which demonstrate the model and the proposed method is practicable in solving the unit commitment.

1. Introduction

Wind power generation has been one of the rapidly growing energy conversion systems in the last few decades. It plays major role in meeting the load demand and environmental protection. Due to stochastic nature and uncertain behavior of wind power generation, daily generation scheduling becomes a challenging task in modern energy management systems. Large wind power penetration puts an increased burden on the system operation due to intermittency of wind power output. An accurate wind power forecasting tool to mitigate the undesirable effects, in the growing wind penetration scenario, is, there, very much essential. Various wind power forecasting techniques have been developed, in the past, to forecast the wind power output [1], but wind power generation cannot be forecasted with a great accuracy for dispatching purposes [2]. There is an unavoidable random error between the actual wind power output and its forecasted value. Hence, the major challenge is to deal with its impacts on Unit Commitment (UC).

Unit commitment in a power system is a problem to schedule the operation of the generating units in order to satisfy the load demand, in addition to the reserve requirements, such that the total operating cost over the scheduled time horizon is minimum, subjected to the many system and operational constraints [3]. The unit commitment is a non-linear mixed integer programming problem. The problem becomes further complex due to the inclusion of wind power generations, which impose additional reserve requirements. Therefore, unit commitment is taken as model to investigate the impact of wind penetration on power system operation [4].

To solve UC problem, various optimization techniques have been proposed such as, Priority List (PL) [5], in this technique load is satisfied by committing low cost unit first. It is simple and fast, but high operation cost is the major concern of this technique. Authors in [6] proposed Advanced Three-Stage (ATHS) approach which utilizes three different stages based on priority list, optimization technique and solution modification process to reach optimum solution. Dynamic Programming (DP) [7] approach has dimensionality problem. It may leads to more mathematical complexity and increase in computation time by increasing the problem size. Branch and Bound Method (BBM) [8] is utilized to solve a discrete variable problem by solving a sequence of simpler problems derived from the original problem. On the other hand, Lagrangian Relaxation (LR) suffers from sub optimality problems as the degree of optimality is measured by the relative duality gap which may not always reduce to zero [9], these methods are known as classical or conventional optimization techniques.

The performance of the conventional methods is not satisfactory, when the objectives function/constrains is discontinuous and very complex. They also requite close initial guess. Therefore, meta-heuristic techniques are proposed to solve such problems such as, Genetic Algorithm (GA) [10], operation is based on genetic

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Nomenclature

a_i, b_i, c_i	cost coefficients of the ith generating unit
de/ue	percentage of wind generation contributing to down/up spinning reserve requirement
CSC_i	cold start cost of ith thermal unit
CSH_i	cold start hour
D_t	system load demand at hour t
$F_{i,t}(P_{s,i,t})$	fuel cost function of ith thermal unit at hour t in scenario s
FC_s	total fuel cost of scenario s
F_T	total operation cost over the scheduling horizon
HSC_i	hot start cost of ith thermal unit
$I_{i,t}$	schedule state of ith thermal unit at hour t
$N_{T,H,W}$	number of thermal, hydro and wind units
N_s	number of reduce scenarios
MDT_i/MUT_i	minimum down/up time of ith unit
$Ph_{k,t}$	generation of kth hydro unit at hour t
$P_{s,i,t}$	output of ith thermal unit at hour t in scenario s
$\overline{P}_i/\underline{P}_i$	maximum/minimum output power of unit i
$\overline{P}_{s,i,t}/\underline{P}_{s,i,t}$	maximum/minimum generation of ith thermal unit at hour t in scenario s
$\overline{P}_{P,G}/\underline{P}_{P,G}$	maximum/minimum output power of PSP
$P_{(P,t)\ (G,t)}$	pumping and generation of PSP unit at hour t
$P_{L,t}$	power network losses at hour t
$P^{wind}_{f,t}$	forecasted wind generation at hour t
$P^{wind}_{s,t}$	total actual wind generation at hour t in scenario s
$P^j_{s,t}$	generation of jth wind unit at hour t in scenario s
P_{WN}	rated wind power output
RU_i/RD_i	ramp-up/down rate of unit i
S	total number of wind scenarios
$\overline{SR}^s_t/\underline{SR}^s_t$	up/down spinning reserve at time t in scenario s
$ST_{i,t}$	startup cost of ith thermal unit
$SO_{k,t}/TO_{k,t}$	spilled/turbine out flow for the reservoir k during hour t
$\overline{TO}_k/\underline{TO}_k$	max/min turbine out flow of water for reservoir k
T	number of time interval (hr)
$T^{off}_{i,t}/T^{on}_{i,t}$	time period that ith thermal unit has been continuously down/up till period t
$\overline{Vh}_k/\underline{Vh}_k$	max/min volume of water for hydro reservoir k
$Vh_{k,t}$	volume of water for reservoir k during hour t
$V_{psp,t}$	volume of reservoir in PSP during hour t
$\overline{V}_{psp}/\underline{V}_{psp}$	max/min volume of reservoir in PSP
$v^s_w(t)$	wind speed at hour t in scenario s
v_1, v_2, v_3	cut-in, rated and cut-out wind turbine speed
$WI_{k,t}$	water inflow to the reservoir k during hour t
ω_s	probability of scenario s
ρ_k	input/output characteristics of kth hydro units

operators, they are random in nature therefore it causes infeasible solution with excessive computational time. Evolutionary Programming (EP) [11] has same process as GA, but candidates' selection mechanism for reproduction and solution coding is different. In [12], Evolving Ant Colony Optimization (EACO) employs GA for finding optimal set of ACO parameters, while ACO solves the UC problem. New integer-code algorithm is proposed in [13], which is based on foraging behavior of E-coli Bacteria presents in the human intestine. Authors in [14], developed second order conic reformulations of the UC problem based on the convex hull description of mixed integer set defined by nonlinear. Discrete Binary Differential Evolution (DBDE) [15] works on mutual operation of meta-heuristics approach and some of the logical/simple stages. The unit-scheduling problem is handled by DBDE and the Lambda-iteration method is used to solve the economic load dispatch problem.

Compared with other techniques, the PSO is easy to implement to find a number of high quality solutions, and has stable convergence characteristics. Furthermore, PSO also has a flexible and well-balanced mechanism for improving and adjusting the global and local search capabilities. Particle Swarm Optimization (PSO) [16] is widely used to solve the power system problems, such as reactive power and voltage control considering voltage security assessment [17]. Extended Optimal Power Flow (OPF) with additional rotor angle inequality constraints is formulated for Transient Stability Constrained OPF (TSCOPF) problem [18]. In [19], authors solve the unit commitment problem which deals the economic aspect of the power system, proper scheduling of the generating units to minimize the total operating cost and gain maximum profit, etc. A survey of PSO applications in power systems is presented in [20].

In the past, several new improvements have been suggested for getting the better and faster solutions, such as Hybrid Particle Swarm Optimization (HPSO) [21], which utilizes Binary PSO (BPSO) for UC problem, while Real Coded PSO (RCPSO) solves the economic load dispatch problem. Both algorithms are run simultaneously, adjusting their solutions in search of a better solution. Improved Particle Swarm Optimization (IPSO) [22] employs the idea of collecting maximum information from large number of particles to control the mutation process, similar to the social community where group leaders could take better decisions. Authors in [23] developed fuzzy controlled and multi-population based Binary Clustered Particle Swarm Optimization (BCPSO) to solve short term thermal generation scheduling problem incorporating uncertainties regarding total cost, spinning reserve and forecasted demand, etc. Most of these techniques are used for hydro-thermal scheduling and did not consider the impact of Wind Power Generation (WPG) on system operation.

In order to investigate wind power uncertainty, overall uncertainty modeling can be divided into three types: scenarios reduction, uncertainty sets, and probabilistic constraints. Many different optimization models use scenarios to deal with the uncertainty related to economic and environmental parameters [24]. Each scenario corresponds to a particular outcome of the random quantity, i.e., scenarios are the realizations (trajectories) of a certain multidimensional stochastic process and the data process of the optimization model. In Refs. [25], an author provides robust day-ahead unit commitment schedule for thermal units under wind output uncertainties with the objective of minimizing the total cost under the worst wind power output scenarios. Robust unit commitment with methodological framework for scenario based uncertainty model for wind power application is proposed in [26], which is divided into three dependent phases. Authors, in [27] proposed different methods to solve UC with wind power integration. The special reserve constraints were established to protect the system security (without considering the system operation) at a required level. In Refs. [28], authors applied a chance constrained programming formulation to deal with the wind variations, assuming certain distribution of wind power output. However, the constraints, which contained wind power output, were be described as probability inequalities in this method and the system reliability was too much affected by the predetermined probability level. Moreover, [29] presents a computational framework for integrating a state-of-the-art Numerical Weather Prediction (NWP)