A comprehensive study of economic unit commitment of power systems integrating various renewable generations and plug-in electric vehicles

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ABSTRACT

Significant penetration of renewable generations (RGs) and mass roll-out of plug-in electric vehicles (PEVs) will pay a vital role in delivering the low carbon energy future and low emissions of greenhouse gas (GHG) that are responsible for the global climate change. However, it is of considerable difficulties to precisely forecast the undispatchable and intermittent wind and solar power generations. The uncoordinated charging of PEVs imposes further challenges on the unit commitment in modern grid operations. In this paper, all these factors are comprehensively investigated for the first time within a novel hybrid unit commitment framework, namely UCsRP, which considers a wide range of scenarios in renewable generations and demand side management of dispatchable PEVs load. UCsRP is however an extremely challenging optimisation problem not only due to the large scale, mixed integer and nonlinearity, but also due to the double uncertainties relating to the renewable generations and PEV charging and discharging. In this paper, a meta-heuristic solving tool is introduced for solving the UCsRP problem. A key to improve the reliability of the unit commitment is to generate a range of scenarios based on multiple distributions of renewable generations under different prediction errors and extreme predicted value conditions. This is achieved by introducing a novel multi-zone sampling method. A comprehensive study considering four different cases of unit commitment problems with various weather and season scenarios using real power system data are conducted and solved, and smart management of charging and discharging of PEVs are incorporated into the problem. Test results confirm the efficacy of the proposed framework and new solving tool for UCsRP problem. The economic effects of various scenarios are comprehensively evaluated and compared based on the average economic cost index, and several important findings are revealed.

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1. Introduction

Global warming due to extensive consumption of fossil fuels has been a major challenge that mankind is facing in the past decade. The global agreement forged in the Paris Climate Conference 2015 set a target to limit the maximum temperature rise within 2 °C by the end of this century [1]. To achieve this goal, significant reduction of the GHG emissions from both major contributors of emissions, namely the power generation and transportation is ultimately a key approach [2], which could only be fulfilled by adopting significant RGs and low carbon vehicles. Therefore, the intelligent scheduling of power system for seamless integrating the intermittent RGs and PEVs is a crucial solution in delivering future low carbon energy future.

Unit commitment (UC) is a mixed-integer often nonlinear NP-hard problem in power system operation. It requires simultaneously determination of the binary on/off status of power generation units and the real valued power output of on-line units, while obeying various constraints such as power balance, capacity limit, and minimum up/down time limited. Extensive researches have been conducted over the past decades to solve the problem, leading to the proposal of numerous conventional methods, intelligent methods, and hybrid or analytical methods. Conventional methods such as dynamic programming (DP) [3], Lagrangian relaxation (LR) [4], branch and cut (BC) [5], Benders decomposition (BD) [6], priority list (PL) [7] as well as some other mix-integer programming solvers [8] have successfully been utilised in solving conventional UC problems with thermal generation units only.

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However, the significantly increased system complexity due to the introductions of a number of new players into the power system in recent years such as various types of distributed generations, bring considerable computational requirements on these conventional approaches, making them technically less appealing. On the other hand, intelligent meta-heuristic algorithms such as genetic algorithm (GA) [9], harmony search (HS) [10], particle swarm optimisation (PSO) [11], firefly algorithm [12] and teaching learning based optimisation (TLBO) [13] have been employed to solve UC problems and achieved some good results. These methods however require a large number of iterations to ensure the algorithm convergence, which may reduce their computational efficiency. Some hybrid algorithm frameworks have also been proposed, combining binary meta-heuristic methods such as binary particle swarm optimisation (BPSO) [14], quantum-inspired particle swarm algorithm (QPSO) [15] and binary gravitational search algorithm (BGSA) [16] with the lambda iteration method to trade off the accuracy and convergence speed. However, significant intermittent RGs and large number of PEVs have brought even more remarkable challenges to the power system operation, appealing for new problem formulation frameworks and novel solving tools.

The dramatic increase of wind and solar power generations leads them to play significant roles in the wholesale energy markets and reducing fossil fuel consumption. However, the intermittent natures of wind and solar power generations, normally treated as negative loads, bring high fluctuations to the original load curve and are likely to cause frequent ramping and start-ups/shut-downs for thermal units [17]. Though numerous methods have been proposed to predict wind and solar power generation [18,19], the uncertainty arising from the renewable power prediction however is still significantly enough that cannot be neglected due to the unpredictable natural inherent natural conditions in renewable generations. It is therefore important to evaluate the uncertainty and intelligently provide appropriate UC schedules to guarantee power balance and spinning reserve while minimising the economic cost, especially for power systems with low dispatching flexibility dominated by coal or peat units. In recent studies, the original UC has been separately or comprehensively investigated considering wind power [20–22] and solar power [23,24] generations. In [25], stochastic programming, robust optimisation as well as stochastic dynamic programming are reviewed as key approaches for solving UC problems considering system stochastics. Moreover, the fuzzy set method [26] and model predictive control [27] are also employed to handle uncertain factors. Among these approaches, the scenarios based method, which transfers stochastic RGs to multiple deterministic scenarios rather than a single scenarios tree, is an alternative technique of low computational cost and provides alternative deterministic scheduling options for system operators. The scenarios in these approaches have been achieved by sampling methods such as Monte Carlo (MC) [28], Latin Hypercube Sampling (LHS) [20,22,29], importance sampling [30] and other approaches. These sampling methods are associated with scenario reductions [31] for trading off the accuracy and computational cost, and with perturbation methods [29] to control the scenario correlations. In addition, the whole scenario based method has been utilised within the framework to deal with the uncertainty of wind [29], RGs [21], and RGs with stochastic load [23]. However, mass roll-out of electric vehicles (EVs), as key players in future grid given the great potentials in reshaping the power demand curve and relief of the uncertainty of RGs, remain to be considered in the scenarios impact evaluation [32].

Plug-in electric vehicles, referring to both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) [33] are utilised together with intermittent RGs at different system levels. In some studies, the PEVs are aggregated [34] and used to countermeasure the uncertainty of wind power generation [35]

or to minimise the operational cost in distribution network [36,37] or micro-grid [38], however none of them considers the UC perspective. In [26], PEVs work together with other demand responses to match the stochastic wind power generation. The economic cost is evaluated in UC benchmarks using a fuzzy set method, and the resultant optimum is conservative. Some researchers evaluate the economic or environmental impacts of PEVs charging and discharging in the UC problem with [39] or without [40–42] the association to deterministic RGs. The uncertainty of wind and PEVs have also been analysed in the security-constrained unit commitment [43]. However, very few publications have addressed the unit commitment problem considering the uncertainties of both wind and solar generations and in association with the load shaping demand side management (LSDSM) of PEVs. This is however an extremely challenging optimisation problem not only due to the large scale, mixed integer and nonlinearity, but also due to the double uncertainties relating to the renewable generations and PEV charging and discharging.

In this paper, a new computational framework is first proposed to seamlessly integrate the scenario generation based RGs and flexible charging and discharging of PEVs in the UC problem, namely the UCsRP problem (UC stands for unit commitment, R stands for scenario based renewable generation, P stands for PEVs). To improve the reliability of power generation scheduling, a new multi-zone sampling (MZS) approach, which samples from three sections of the distribution probabilities of both the wind and solar generations, is proposed to generate scenarios of intermittent RGs. To solve the UCsRP problem, a hybrid novel parallel optimisation tool integrating the hybrid topology binary particle swarm optimisation (HTBPSO), self-adaptive differential evolution (SaDE) and the lambda iteration method is proposed. In numerical studies, the economic evaluation of UCsRP integrating 10 scenarios of typical wind in two seasons and solar power in three weather conditions are comprehensively studied, and intelligent PEVs charging and discharging (e.g. LSDSM of PEVs) is further integrated into the problem. The impacts of uncertainties of wind and solar generations as well as intelligent scheduling of PEVs on the economic cost are comprehensively analysed for the first time and the average power costs are compared for illustrating the efficacy of the proposed whole framework and solving tool, and several important findings are revealed in this study.

The rest of the paper is organised as follows: the new UCsRP problem is formulated in Section 2; Section 3 proposes a new multi-zone sampling method for generation of uncertain renewable energy generation scenarios; the hybrid meta-heuristic method is proposed in Section 4 for solving the UCsRP problem; in Section 5, scenarios of wind power generation in two specific seasons and solar power generation in three weather conditions are generated respectively and integrated in the UCsRP problem, where four cases including UC integrated with LSDSM of PEVs, UC integrated with uncertain wind power generation in two seasons and LSDSM of PEVs, UC integrated with uncertain solar power generations in three weather conditions and LSDSM of PEVs as well as UC integrated with deterministic both wind and solar power and LSDSM of PEVs scenarios are comprehensively analysed; Section 6 summarises and concludes the paper.

2. Problem formulation

2.1. Objective function

The objective function of the UCsRP problem is the economic cost of power generations which is similar to the conventional UC problem [9], including two parts namely the fossil fuel cost and the start-up cost respectively.