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Multi-objective biogeography-based optimization for dynamic economic emission load dispatch considering plug-in electric vehicles charging

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ABSTRACT

The climate change is addressing unprecedented pressures on conventional power system regarding the significant fossil fuel consumptions and carbon emissions, which largely challenges the conventional power system operation. This paper proposes a novel dynamic non-dominated sorting multi-objective biogeography-based optimization (Dy-NSBBO) to solve multi-objective dynamic economic emission load dispatch considering the mass integration of plug-in electric vehicles (PEVs), namely MO-DEELDP problem. First, a real-world economic emission load dispatch considering PEVs charging is first formulated as a constrained dynamic multi-objective optimization problem. Then a new multi-objective BBO is proposed adopting the non-dominated solution sorting technique, change detection and memory-based selection strategies in the multi-objective BBO method to strengthen the dynamic optimization performance. The proposed Dy-NSBBO is applied to solve three different dynamic economic emission load dispatch cases integrating four plug-in electric vehicle charging scenarios respectively. Comprehensive analysis shows that the novel algorithm is promising to bring considerable economic and environmental benefits to the power system operators and provides competitive charging strategies for policy makers and PEVs aggregators.

1. Introduction

Economic emission load dispatch (EELD) problem is one of fundamental issues of power system operation. The objective of EELD is to simultaneously achieve the optimal generation cost and the least emission of power systems while satisfying equality and inequality constraints encompassing power balance, generator capacity, ramping rate constraints and etc. In other words, EELD is a multi-objective optimization problem that determines the optimal power production of power systems by minimizing the generation cost and emission cost [2,14].

Several classical optimization methods, such as gradient-based method and linear programming, have been applied to solve different EELD problems [15]. However, these methods are lack of feasibility and accuracy due to non-convex and nonlinear characteristics of the objective functions and constraints. In the recent decade, meta-heuristic algorithms, such as genetic algorithms (GAs) [5], harmony search algorithm (HSA) [16], gravitational search algorithm (GSA) [24], teaching-learning based optimization (TLBO) [26], biogeography-based optimization (BBO) [18], artificial bee colony (ABC) [19] and flower pollination algorithm (FPA) [1] have been used to solve EELD problems. However, very few concerns have been addressed on new participants of power system such as stochastic renewable energy generations and electric vehicles, which significantly perplex the load dispatch tasks.

Some new attempts have been made to tackle with EELD problems integrated with new participants. In ref. [10], the EELD problem of power system was combined with solar photo voltaic generation solved by particle swarm optimization (PSO). In ref. [11], the authors used stochastic multi-objective optimization for EELD with uncertain wind power and distributed loads. In ref. [4], a

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dynamic EELD problem considering load and wind power uncertainties was optimized by an efficient scenario-based and fuzzy self-adaptive learning particle swarm optimization approach.

Modern plug-in electric vehicles (PEVs) are potentially flexible load demand and promising to replace the fossil fuel powered vehicles due to less exhaust gas emission ([29,27]). On the other hand, the remarkable charging load required from PEVs to maintain the daily commutes would significantly challenge the facility capacity and operation stability of traditional power systems. Simultaneous charging for the household chargers and large-scale PEVs will possibly result in ripples and spikes on the daily power demand. It is therefore important to dispatch economic emission loads under different time intervals and PEVs charging allocations.

However, very limited publications have concerned EELD problem considering the integration PEV charging. The charging load uncertainty of PEVs addresses more complexity for the power system scheduling tasks such as unit commitment and optimal power flow [23]. Yang et al. [28] studied the economic unit commitment of power systems integrating various renewable generations and plug-in electric vehicles, where only economic factor is considered. In ref. [7], an energy storage model was proposed with gridable vehicles for economic load dispatch in the smart grid, and the authors used weighing coefficients to transform two objectives into a single objective function. In ref. [26], the authors use the same transform method to solve dynamic economic/environmental dispatch considering multiple plug-in electric vehicle loads. However, the appropriate selection of these weights remains to be a key issue for system operators. It is necessary to perform dynamic multi-objective optimization to solve EELD problem considering multiple PEVs charging scenarios, providing a Pareto front with a series of optimal results.

The key contributions of this paper are as follows. Firstly, a novel multi-objective dynamic economic emission load dispatch problem namely MO-DEELDP is established, for the first time combining PEVs charging scenarios. Secondly, a novel dynamic non-dominated sorting multi-objective biogeography-based optimization (Dy-NSBBO) method is proposed, which combines change detection and memory-based selection strategies to strengthen the dynamic optimization performance. Further, the proposed Dy-NSBBO method is adopted to seek the optimal solutions of the MO-DEELDP problem without and with considering the penetration of PEVs charging scenarios, and the comprehensive analysis on the economic and environmental impact of various PEV charging scenarios on the MO-DEELDP problem is finally addressed.

The remainder of this paper is organized as follows. Section 2 formulates a novel mathematical model of the MO-DEELDP problem under PEV charging, followed by Section 3 where a new Dy-NSBBO to solve dynamic multi-objective optimization problem is proposed. Section 4 applies Dy-NSBBO to solve the MO-DEELDP problem, and then comprehensively evaluate the performance of the proposed method by comparing with other algorithms. Section 5 concludes the paper and presents future works.

2. Problem formulation of MO-DEELDP

This section first presents the problem formulation of MO-DEELDP (Section 2.1), and then describes four plug-in electric vehicle charging scenarios (Section 2.2).

2.1. Dynamic economic emission load dispatch

The mathematic model of the MO-DEELDP problem is formulated as a multi-objective optimization problem, which has two objectives: the generation cost and the emission cost should be minimized, and it is defined as follow.

$$\min F(P,t) = \text{Minimize}(F_1(P,t), F_2(P,t)) \tag{1}$$

where t is time, $P = (P_1, \cdots, P_n)$ is the power outputs of generation units and n is the number of generation units in power system, $F(P, t)$ represents the set of two objective functions with respect to the time t. $F_1(P, t)$ denotes the dynamic economic load dispatch, and $F_2(P, t)$ denotes the dynamic emission load dispatch.

In Equation (1), the MO-DEELDP problem is required to depend only on the time t at the time interval $[t, t+1)$, it keeps no change within such interval. By this way, the MO-DEELDP problem is composed of a series of interconnected static optimization problems, that is, at the tth time interval, it corresponds to the tth static optimization problem. This MO-DEELDP problem is a new mathematic model, and its task is to rapidly and effectively seek a balance between generation cost and emission cost for each time interval.

2.1.1. Dynamic economic load dispatch

The dynamic economic load dispatch is expressed as minimization of the generation cost of power system, which is defined as

$$\begin{aligned} F_1(P,t) = \sum_{i=1}^{n} F_i^{eco}(P_{it}) = \sum_{i=1}^{n} \Big[\left(a_i P_{it}^2 + b_i P_{it} + c_i \right) \\ + \left| d_i \sin\left(e_i \left(P_i^{\min} - P_{it} \right) \right) \right| \Big] \quad (\$/\text{h}) \end{aligned} \tag{2}$$

where P_{it} is the power output of the ith generation unit at the tth time interval and $P_i^{\min}$ is the minimum power output limit of the ith generation unit, $F_i^{eco}(P_{it})$ is the generation cost function of the ith generation unit and is usually expressed as a quadratic polynomial added sinusoidal function, which denotes valve-point loading effect [30], and a_i, b_i, c_i, d_i and e_i are the generation cost coefficients of the ith generation unit.

2.1.2. Dynamic emission load dispatch

The dynamic emission load dispatch is expressed as minimization of the emission cost released by power systems, which is defined as

$$\begin{aligned} F_2(P,t) &= \sum_{i=1}^{n} F_i^{emis}(P_{it}) \\ &= \sum_{i=1}^{n} \left[\left(\alpha_i P_{it}^2 + \beta_i P_{it} + \gamma_i \right) + \eta_i \exp(\delta_i P_{it}) \right] \quad (\text{Kg/h}) \end{aligned} \tag{3}$$

where $F_i^{emis}(P_{it})$ is the emission cost function of the ith generation unit and is usually expressed as a quadratic polynomial associated with an exponential term [17], and α_i, β_i, γ_i, η_i and δ_i are the emission cost coefficients of the ith generation unit.

2.1.3. Constraints

Furthermore, two objective functions must satisfy the following constraints.

a) Real power balance constraint

The sum of the generated power of all generation units at each time interval t must be equal to the sum of power demand response by the various loads and the total transmission network loss in the corresponding time interval.

$$\sum_{i=1}^{n} P_{it} = P_{Dt} + P_{Lt} + L_{Et} \tag{4}$$

where the loads include the general traditional load demand P_D and