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Multiobjective optimization for carbon market scheduling based on behavior learning

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Abstract

With advances of smart grid, the responsibility of carbon emission reduction can be fairly allocated to each participant in power networks through bidirectional communications. This paper proposes a hierarchical carbon market scheduling model to effectively realize carbon emission reduction. The policy makers in the upper level aim to maximize the effects of carbon emission reduction. They set out appropriate monetary incentives and emission allowances for both customers and generators. Considering restrictions from policy makers, both generators and customers in lower levels seek to minimize their operational costs and payment bills, respectively. To achieve these objectives, a multiobjective problem is formulated by forecasting market trends from a behavior learning model. The simulation results demonstrate that through the proposed approach the renewable penetration increases and the carbon emissions decrease. The benefits for each participant are analyzed as well.

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Keywords: Behaviour learning; carbon market scheduling; demand response; multiobjective problem; smart grid.

1. Introduction

The global warming problem has been recognized as a result of greenhouse gas (GHG) emissions. Electricity sector accounts for 29% of the GHG emission in the UK in 2015. It is therefore important to regulate energy generation and consumption [1]. For generators, they need to consider the emission allowances while minimizing their operational costs. For customers, they can adjust their behaviors to save payment bills, consequently reducing the emissions [2]. In the UK, for example, the Department of Energy and Climate Change (DECC) is responsible for scheduling primary energy sources and providing monetary incentives from funded schemes for carbon reductions, such as the Green Deal [3]. Meanwhile, Office of Gas and Electricity Markets (Ofgem), serving as a government regulator, takes the consumer's interests as a whole responsibility, including their interests in the reduction of GHG

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[4]. The Big Six Energy Suppliers, serving as a retailer, buys the electricity from wholesale market and pays the policy costs before charging customers electricity bills [5]. For simplicity, this paper takes generators and retailers as a whole so that the operational costs and emission constraints can be considered at the same time.

For the electricity generation and demand, uncertainties such as the variations of fuel prices and climate conditions should be considered. There are a number of studies in literature focused on the short-term and long-term forecasting of electricity generation and demand [6, 7]. However, the analysis of fuel uses in electricity generation by major producers that can elementally mitigate the emissions from the very beginning of carbon cycles is rarely seen. Therefore, it could be useful to apply this approach to the behavior learning and optimization. A more dedicated study for behavior learning, multiobjective optimization, and allocating carbon emission targets for each participant in energy market should be proposed to address the carbon market scheduling problem. The contributions of this paper can be summarized as follows: 1) The carbon market scheduling is involved in the hierarchical model, and the responsibility of each participant can be identified; 2) The behavior learning approach takes the uncertainties into account to support a prediction for carbon market scheduling.

2. Behavior Learning Models

This section describes the behavior learning models for both generation and demand sides. The autoregressive function is used to learn the stochastic process for the variations of uncertain variables. A linear regressive function is adopted to describe the relationship between the forecasting objectives and uncertain variables.

2.1. Generation side behavior learning

The prices of coal, smokeless fuels, and heating oils can impact on the fuel usages. The price set is defined as $p(t) = \{p_c(t),\ p_f(t), p_o(t)\}$ representing the prices of coal, smokeless fuels, and heating oils, respectively, in observation period $t = \{1,\ 2,\ \ldots,\ T\}$. The fuel usage in electricity generation by major producers is $g(t) = \{g_c(t), g_o(t), g_g(t), g_n(t),\ g_h(t), g_w(t), g_b(t), g_s(t)\}$, where the subscripts correspond to the producers of coal, oil, gas, nuclear, hydro, wind, bioenergy and solar. The future prices of coal, smokeless fuels, and heating oils fluctuate stochastically on the basis of present and previous values [8]. Therefore, they can be modelled using autoregressive model as:

$$p(t) = \sum_{n=1}^{t-1} \alpha(n)p(n) + \varepsilon_p \tag{1}$$

where $\alpha(n)$ is the system coefficient, and ε_p is the model error. The fuel usage function in which how a major electricity producer responds to price signals can be subsequently established as:

$$g(t) = \sum_{n=1}^{t-1} \beta(n)p(n) + \varepsilon_g \tag{2}$$

where $\beta(n)$ is the system coefficient, and $\varepsilon_g$is the model error. These coefficients can be learned from historical observations and determined through evaluating the minimal squared differences between the forecasts and the actual values [9].

2.2. Demand side behavior learning

Similar to the generation side behavior learning, the temperatures and electricity can impact on electricity consumption. The future temperature h(t) and electricity bill b(t) can also be forecast by using an autoregressive model: