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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.

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

[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, …, 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. Tthe 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:

$$h(t) = \sum_{n=1}^{t-1} \alpha'(n)h(n) + \varepsilon_h, \;\; b(t) = \sum_{n=1}^{t-1} \alpha''(n)b(n) + \varepsilon_b \tag{3}$$

where $\alpha'(n)$ and $\alpha''(n)$ are system coefficients, and ε_h and ε_b are the model errors. The demand function can be subsequently established:

$$\mathrm{d(t)} = \sum_{n=1}^{t-1} \beta'(n)b(n) + \sum_{n=1}^{t-1} \beta''(n)b(n) + \varepsilon_d \tag{4}$$

where $\beta'(n)$ and $\beta''(n)$ are system coefficients, and ε_d is the model error. These coefficients can be learned from the same method used by the generation side.

3. Multiobjective Approach

In this section, the proposed carbon market scheduling problem is modelled on the basis of the forecasts. This scheduling problem consists of three objectives. The objective for customers is to minimize the payment bills, considering emission compensation from policy makers. The objective for generators is to minimize the operational costs, considering carbon allowances. The objective for policy makers is to minimize the carbon emissions.

3.1. Optimal payment bills scheduling for consumers

The optimization problem of payment bills is illustrated as the basic payment subtracting emission compensation plus the incurred dissatisfactions. The load curtailments of demand response (DR) are adopted in this paper as an approach for carbon emissions reduction. The higher level of load curtailments contributes to more significant effects on carbon emissions reduction [10]. Since the amount of compensation to consumers increases as the emission reduction increases, the compensation can be modelled as a linear increasing function [11]

$$\begin{aligned} &f_c(t) = m(t) \sum_{i=1}^{n} \left(e_i g_i(t) - e_i {g_i}^{DR}(t)\right) \\ &s.t. \;\; m(t) \geq 0, \quad \textstyle\sum_{t=1}^{T}\sum_{i=1}^{n} e_i {g_i}^{DR}(t) \leq \sum_{t=1}^{T}\sum_{i=1}^{n} e_i g_i(t), \quad 0 \leq g_i \leq {g_i}^{max} \end{aligned} \tag{5}$$

where $f_c(t)$ is the compensation function, $m(t)$ is the carbon compensation rate, e_i is the carbon emissions factor for electricity generation by major producer i, $g_i(t)$ is the original fuel usage, ${g_i}^{DR}(t)$ is the fuel usage after load curtailment, and ${g_i}^{max}$ is the maximum fuel usage. A dissatisfaction function is also introduced to capture the inconvenience for consumers caused by the deviation from the original consumption. Since the dissatisfaction of consumers increases as the emissions reduction increases, the dissatisfaction function can be modelled as:

$$\begin{aligned} &\mathrm{f}_d(t) = n(t)\left(d(t) - d^{DR}(t)\right)^2 \\ &s.t. \;\; n(t) \geq 0, \;\; d^{min} \leq d \leq d^{max} \end{aligned} \tag{6}$$

where $\mathrm{f}_d(t)$ is the dissatisfaction function, $n(t)$ is the inelasticity parameter of satisfaction for consumers, $d(t)$ is the original electricity demand from consumption side, $d^{DR}(t)$ is the electricity demand after load curtailment, d^{min} is the minimal demand required from consumption side, and d^{max} is the maximal demand that can be provided form the generation side. The payment bills optimization problem for the consumption side can be modelled as

$$\min \sum_{t=1}^{T} \{d(t)b(t) - f_c(t) + f_d(t)\} \tag{7}$$

3.2. Optimal operational cost scheduling for generators

The optimization problem of operational cost is described as the basic cost with an additional cost introduced by altering generation units due to the restriction of carbon emissions. Since the costs of generators increase as the amount of carbon emissions decreases, the operational costs of generators can be modelled as [11]

$$f_a(t) = r(t)\sum_{i=1}^{8}\left(e_i g_i(t) - e_i {g_i}^{s}(t)\right)$$
$$s.t.\quad \textstyle\sum_{t=1}^{T}\sum_{i=1}^{8} e_i {g_i}^{s}(t) \le \sum_{t=1}^{T}\sum_{i=1}^{8} e_i g_i(t),\quad 0 \le g_i \le {g_i}^{max},\quad \frac{\sum_{t=1}^{T}\sum_{i=1}^{8} g_{i,r}(t)}{\sum_{t=1}^{T}\sum_{i=1}^{8} g_i(t)} \ge R \tag{8}$$

where $r(t)$ is the inelasticity parameter of operational cost, ${g_i}^{s}(t)$ is the fuel usage after load curtailment and carbon market scheduling, $g_{i,r}(t)$ is the fuel usage in electricity generation by renewable energy, and R is the minimum percentage of renewable energy penetration regulated by policy maker. This percentage of renewable energy penetration is also considered as a constraint according to the government policies, because higher percentage of renewable energy contributes to lower carbon emissions [12]. Therefore, the operational cost optimization problem for generators can be modelled as:

$$min\left\{\sum_{t=1}^{T}\left(\sum_{i=1}^{n} c_i g_i(t) + f_a(t)\right)\right\} \tag{9}$$

where c_i is a coefficient that transfers the fuel usage into corresponding power generation cost.

3.3. Optimal carbon emissions reduction scheduling for policy makers

With the objective of maximizing the reduction of carbon emissions, the optimization problem for policy maker can be described as:

$$max\sum_{t=1}^{T}\sum_{i=1}^{n}\left(e_i g_i(t) - e_i {g_i}^{s}(t)\right)\ . \tag{10}$$

3.4. Algorithm

If the proposed multiobjective problem (MOP) is feasible, there would exist a possible fuel usage scheduling satisfying all the requirements. Table 1 presents the artificial immune algorithm used to solve the MOP problem [13, 14]. The terminology "antibody" is used to represent a point in the decision variable space.

Table 1. Pseudocode of the Artificial Immune Algorithm.

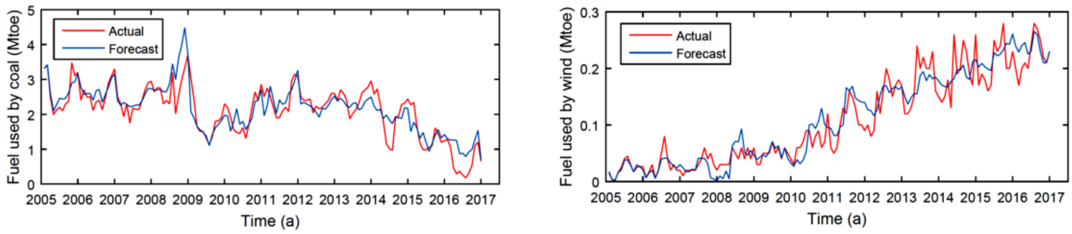
Algorithm
1: Generate a group of antibodies $g_i(t)$ over $\left\|g_i^{min}, g_i^{max}\right\|$ as initial population that represent the fuel usages of major sources.
2: Remove dominated antibodies.
3: Perform mutations over the nondominated antibodies.
4: Repeatly remove dominated antibodies until the remaining antibodies are all nondominated.
5: Evaluate the remaining antibodies on the basis of their objective values and remove infeasible antibodies.
6: If the population size is larger than the nominal size, it needs to be shrunk to the nominal size.
7: Repeat steps 3—7 until the maximum iteration is reached.
8: A solution that maximizes the minimum improvement in all dimensions is selected as the output.

4. Case Studies

Case studies are conducted to demonstrate the proposed model. The behaviour learning on generators and consumers for each month in 2017 is performed through the use of the UK historical data [15, 16]. With the help of the forecasting results and corresponding carbon emissions, the optimal scheduling results are obtained.

4.1. Behavior learning

The UK monthly prices of coal, smokeless fuels, and heating oils in the unit of million tons of oil equivalent (Mtoe) from January, 2005 to December, 2016 are implemented as an input of the regressive model. The corresponding fuel uses in electricity generation by major sources during the same time period are implemented as an output. Fig. 1 shows the learning results of the regressive model in which coal and wind serve as conventional and renewable sources, respectively.

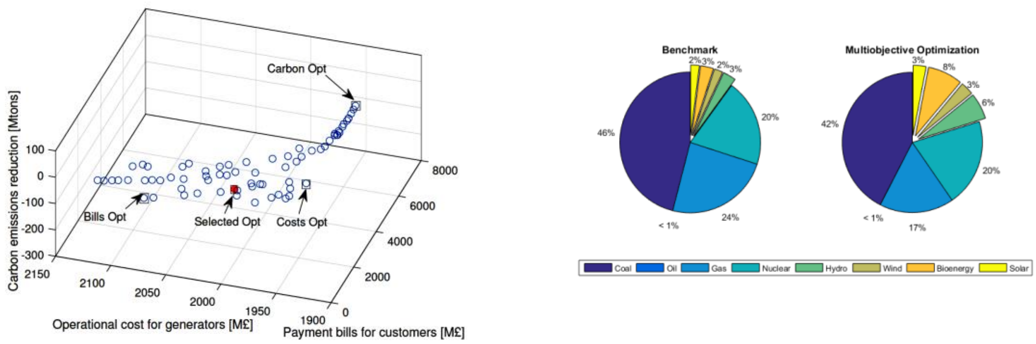


(a) (b)

Fig. 1. Comparison between actual and forecasting fuel uses in electricity generation by (a) coal; (b) wind.

4.2. Carbon market scheduling

Scheduling is performed on a monthly basis in 2017. The monetary compensation rate 18 £/ton is adopted, which is the current UK carbon tax [17]. The optimization result in October, 2017 is presented as an example. The results from behavior learning are defined as a benchmark. Fig. 2(a) illustrates the interactions among three objectives. It can be seen that the selected optimal solution corresponds to the vector located at the center of all possible outcomes, which means that the proposed multiobjective model is able to obtain a fair scheduling solution. Table 2 shows the detailed value of three objectives from different solutions.



(a) (b)

Fig. 2. (a) Example of possible solutions; (b) Comparison between optimization and benchmark results.

Fig. 2 (b) shows the comparison results in terms of the percentage of major producers between benchmark and optimal schedules. Detailed values can be found in Table 2. It is clear that using the proposed approach increases the percentage of renewable sources significantly, while decreasing the percentage of coal and gas. This illustrates that our approach can help to realize the UK emissions and renewable targets.

Table 2. Results of system performance.

Objective\ Method	Benchmark	Selected Opt.	Carbon Opt.	Costs Opt.	Bills Opt.
Carbon Reduction [Mtons]	0	128.52	200.76	1.10	170.44
Operational Costs [M£]	1940.84	1173.26	2142.22	1940.70	2085.94
Payment Bills [M£]	1507.18	1598.90	2227.83	6039.11	1578.34

5. Conclusion

This paper proposed multiobjective carbon market scheduling based on the behavior learning on both generation and consumption sides. A hierarchical framework consisting of policy makers, generators, and customers was designed. Compared with the benchmark results, the proposed approach improved the percentage of renewables penetration, addressed the carbon reduction required by policy makers, and reduced operational costs of generators and payment bills of customers.

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