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A critical review of robust self-scheduling for generation companies under electricity price uncertainty

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ABSTRACT

For a generation company trading in an electricity market, efficient control of the financial risks and robustness is as vital as maximizing profit. A robust approach is preferred since the generation company can obtain an optimal self-schedule considering price volatility as a source of uncertainty. The goal of this paper is to implement and compare different robust approaches such as robust optimization methods with different uncertainty sets, conditional value-at-risk based stochastic programming, and information gap decision theory for self-scheduling of generation companies. Moreover, all robust methods are applied to test cases with different price behaviors in the long-run to demonstrate the performance and features of each method. Finally, the different self-scheduling strategies based on the price data and the generation company's desired robustness level are proposed.

1. Introduction

1.1. Background and motivation

In a competitive market environment, a generation company (GenCo), as a decision-maker, not only tries to attain a profitable bidding strategy, but also strives to achieve a robust position (i.e. a strategy hedged against any realization of the uncertainty as the difference between the forecasted and actual values). The self-scheduling of a GenCo is a complex and difficult optimization problem, not only due to the need for meeting all equality and inequality constraints of the generating units during the entire scheduling period, such as minimum on/off duration, generation capacity limits, ramping up/down limits of generating units, but also due to all issues affecting electricity market prices and increasing their volatility, such as system load forecasting, predicting rival GenCos bidding strategies, and transmission congestion. In other words, electricity market prices and their volatility are the key factors complicating the self-scheduling problem of a GenCo. The price signal forces the on/off status of a generation unit and its volatility significantly affects the self-scheduling problem of a GenCo. Since the forecasted electricity market prices are subject to uncertainty due to their high volatility [1], it is necessary to characterize the uncertainty of the forecasted electricity market prices aiming at hedging the self-schedules of GenCos against different realizations of uncertain electricity market prices. In other words, a GenCo should adopt optimization methods considering uncertainty for its self-scheduling approach. This has led to a growth in non-deterministic self-scheduling methods. These methods include robust optimization (RO) with different uncertainty sets [2–5], conditional value-at-risk based stochastic programming (CVaR-SP) [6,7], and information gap decision theory (IGDT) [8,9].

The RO methodology models uncertainty sets as bounded intervals, such as box, ellipsoidal, and polyhedral uncertainty sets [10]. The ellipsoidal uncertainty set has been applied to the self-scheduling problem leading to a second-order cone model in [2]. An ellipsoidal RO method has also been used in [3] to determine the worst-case robust profit of the self-scheduling problem. Besides, there is some research work concentrated on the combination of the uncertainty sets with each other. The combination of the box and polyhedral uncertainty sets for RO as a linear optimization framework has been presented in [11]. Moreover, this combined uncertainty set has been used to construct the offer curve of a generation company in [4]. The RO approach presented in [11] has been implemented to construct the bidding strategy of a wind farm and energy storage devices in [5]. In addition, the combined box and ellipsoidal uncertainty set for RO has been introduced in [12]. In RO methods including various uncertainty sets, a decision-maker can change the robustness of the solution by changing a specific parameter named the degree of robustness (DR).

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Nomenclature

Function

$f_u(\cdot)$ generation cost function of unit u

Parameters

CSC_u cold startup cost of unit u ($)
A_u coefficient of the piecewise linear generation cost function of unit u
a_u, b_u, c_u coefficients of the quadratic generation cost function of unit u
$B_{ut}^{ss'}$ binary parameter for unit u in hour t, which is zero if $e_{ts} = e_{ts'}$ and one otherwise
$Diff_t$ difference between maximum and minimum prices of each price interval in hour t ($/MWh)
$Diff_{DP}$ difference between maximum and minimum deterministic profits of each profit interval ($)
E_t predicted electricity price for hour t ($/MWh)
E_{ts} electricity price of hour t in scenario s ($/MWh)
$\widehat{E}_t$ respective range of $\widetilde{E}_t$ ($/MWh)
$E_t^{\max}$, $E_t^{\min}$ upper and lower limit E_t ($/MWh)
HSC_u hot startup cost of unit u ($)
i, j loop counters
J set of uncertain electricity market prices
$|J|$ number of elements for the uncertainty set J
MD_u, MU_u minimum down and up time of unit u, respectively (h)
N_i number of electricity price intervals
N_j number of profit intervals
N_u^l number of blocks of the piecewise linear generation cost function of unit u
N_s number of scenarios
P_u^l upper limit of block l of the piecewise linear generation cost function of unit u (MW)
$P_u^{\max}$, $P_u^{\min}$ upper and lower limit for unit u, respectively (MW)
S_{lu} slope of block l of the piecewise linear generation cost function of unit u
RD_u, RU_u ramp down and ramp up limit of unit u, respectively (MW/h)
SDR_u, SUR_u shutdown and startup ramp limit of unit u, respectively (MW/h)
$SU_{u\tau}$ startup cost of unit u after τ hours down time ($)
T_u^{cold} required time to cool down unit u (h)
T total hours of the scheduling period
U total number of units
Ψ_B degree of robustness for the box uncertainty set
Ψ_E degree of robustness for the ellipsoidal uncertainty set
Ψ_P degree of robustness for the polyhedral uncertainty set
λ a non-negative weight factor that weighs conditional robust profit against expected profit
Π_s probability of scenario s
α per unit confidence level
σ profit deviation factor

Variables

h_t, q_t, v continuous auxiliary robust modeling variables
$m_{ut}^{ss'}$ non-negative auxiliary variable used for modeling non-decreasing constraints
p_{ut} power offered by unit u in hour t for energy auction; p_{uts} is p_{ut} value in scenario s (MW)
pb_{lut} power in block l of the piecewise linear generation cost function of unit u in hour t (MW)
$r_{ut}^{ss'}$ free auxiliary variable used for modeling non-anticipativity constraints
u_{ut}^{su} startup cost of unit u in hour t ($)
x_{ut}, y_{ut} binary variables indicating startup and shutdown status of unit u in hour t, respectively
z_{ut} binary variable indicating status of unit u in energy auction in hour t (1/0 for accepted/not-accepted)
$\widetilde{e}_t$ uncertain electricity price in hour t ($/MWh)
β_s continuous auxiliary stochastic modeling variable
μ value-at-risk (VaR)
θ uncertainty parameter for information gap decision theory

The stochastic programming (SP) approach uses scenarios to model uncertainty sources [13]. In this method, the scenarios are generated by using the probability distribution function (PDF) of uncertain variables. Also, to model the financial risk, conditional value-at-risk (CVaR) index has been used in the stochastic framework [14]. The CVaR-SP has been applied to the weekly self-scheduling and offering problem of a GenCo in [5]. In this model, a forward contract is considered as the first-stage of the CVaR-SP framework and pool market as the second-stage. The CVaR-SP method has also been used to model the day-ahead self-scheduling of a GenCo for multi-auction markets in [7]. The presented methodology simultaneously models two uncertainty sources of electricity market prices and unavailability of units. In both models, the producer, who is the decision-maker, can adjust the financial risk of the framework and switch from risk-averse to risk-seeker GenCo and vice versa, only by changing the weight factor of the CVaR index. In other words, CVaR-SP has the capability to control the robustness of the solution.

The information gap decision theory (IGDT) expounds that the decisions made under severe uncertainty should not require more information than what is dependably provided by the decision-maker [15]. Moreover, the IGDT obtains optimal values of the uncertain variables with a guarantee that the objective function (OF) does not become worse than a definite threshold. In [8], the IGDT has been used to model non-deterministic self-scheduling problem considering electricity price uncertainty. The IGDT has been applied to the bidding strategy problem of a GenCo in which demand response is also modeled [9]. Note that the IGDT, like the RO approaches and CVaR-SP, can control the robustness of the problem by changing the horizon of uncertain variables.

1.2. Contributions

The main contributions of this paper are:

1. The mathematical formulations of different robust approaches including Box RO (BRO), Ellipsoidal RO (ERO), Polyhedral RO (PRO), Box and Ellipsoidal RO (BERO), Box and Polyhedral RO (BPRO), CVaR-SP, and IGDT models are proposed. Also, the characteristics of the uncertainty sets corresponding to BRO, ERO, PRO, BERO, and BPRO are presented by means of relevant theorems and proofs. Previous research work in this area have either only used these approaches [2–9] or compared these methods without any mathematical proof [16]. Accordingly, to the best of our knowledge, there is no existing research work that mathematically characterizes the robust approaches.
2. Various self-scheduling strategies based on the robust approaches are proposed for GenCos to participate in an electricity market considering the price data and desired robustness level.
3. To correctly analyze and compare the performance of these robust methodologies in the uncertain environment of self-scheduling, a