Applied Energy 226 (2018) 631–643

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Risk-averse stochastic model predictive control-based real-time operation method for a wind energy generation system supported by a pumped hydro storage unit

Uğur Yıldıran*, İsmail Kayahan

Yeditepe University, Industrial and Systems Eng. Dep., Kayışdağı Cad., 34755, Kayışdağı/Ataşehir, İstanbul, Turkey

HIGHLIGHTS

- A real-time operation method is proposed for a wind producer having a PHS plant.
- The method is risk-averse stochastic model predictive control (SMPC) algorithm.
- The SMPC strategy is compared with alternative methods appeared in the literature.
- Real-time operation and bidding based performance estimates are compared.
- Effects of changing imbalance prices on real-time operation are analyzed.

ARTICLE INFO

Keywords:
Stochastic model predictive control
Real-time operation
Day-ahead bidding
Wind energy
Pumped hydro storage
Conditional value at risk

ABSTRACT

A wind energy producer participating in deregulated markets needs to make contracts on the energy it will supply in the next day. Deviations from the contracts, which could occur due to wind uncertainties, are compensated in real-time balancing markets at a considerable cost. Therefore, developing advanced day-ahead bidding and real-time operation strategies minimizing such imbalance costs constitutes an important problem. There are several works on finding optimal day-ahead bids but the real-time operation problem is not studied well. Motivated by this fact, we propose a new strategy in which the day-ahead bids are computed by solving a risk-averse stochastic program, and real-time operation is performed by a stochastic model predictive control-based algorithm with a risk control capability. The algorithm is applied to a realistic system composed of wind farms and a pumped hydro storage plant. Its performance is compared to a number of approaches appearing in the literature. Because the problem considered has two conflicting objectives of profit maximization and risk minimization, a Pareto optimality analysis is also conducted. Finally, the validity of a common practice followed in the literature, which is estimating the economic performance by bidding optimization, is investigated by comparing the estimate with the actual performance achieved by real-time operation methods.

1. Introduction

The penetration of wind energy has increased rapidly in the last decades worldwide. Environmental concerns along with decreasing capital costs, low operation costs, and improvements in turbine efficiencies constitute the driving forces behind this growth. In addition, there are currently incentives in many countries for supporting renewable sources. Energy is bought at a constant tariff rate ignoring variations in production. However, such subsidies are valid for a limited period after which generation companies are expected to join deregulated markets. The intermittent nature of wind makes energy trading in the market environment a difficult task.

The problem faced by wind energy producers can be understood by investigating the operation principles of the market. Consider a company participating in a day-ahead market and compensating its deviations in a real-time balancing market. The associated timing diagram is depicted in Fig. 1. As can be observed from the figure, the market trading can be separated into two phases. In the first phase, which is day-ahead bidding, the company is required to submit its production offers for each hour of the next day (day D) at the gate closure time in day D-1. These contracts are to be made under uncertainty, as the wind production that will occur in the future cannot be predicted perfectly, and energy prices, which are determined after the market clearing, are not known. In the second phase, which is real-time operation, the

* Corresponding author.
E-mail addresses: uyildiran@yeditepe.edu.tr (U. Yıldıran), ismail.kayahan@yeditepe.edu.tr (İ. Kayahan).

https://doi.org/10.1016/j.apenergy.2018.05.130
Received 3 October 2017; Received in revised form 17 May 2018; Accepted 31 May 2018
0306-2619/

Nomenclature

Indices and index sets

k scenario index
t time index (h)
$\Omega(n, t)$ set of indices of scenarios passing through scenario tree node (n, t)

Exogenous variables

$\lambda(k, t)$ day-ahead market price in period t and scenario k (TL)
$W(k, t)$ total wind power in period t and scenario k (MW)
$\pi(k, t)$ probability of scenario k in period t
$V_{initial}$ initial water volume in the reservoir at the start of the day (m^3)

State/Decision variables

$P_d^c(k, t)$ power generated by turbine c in period t and scenario k (MW)
$P_p^c(k, t)$ power consumed by turbine c in period t and scenario k (MW)
$q_d^c(k, t)$ water discharged by turbine c in period t and scenario k (m^3/h)
$q_\delta^c(k, t)$ deviation of water discharge from its technical minimum for turbine c in period t and scenario k (m^3/h)
$q_p^c(k, t)$ water pumped by turbine c in period t and scenario k (m^3/h)
$u_d^c(k, t)$ discharge status (on-off) of turbine c in period t and scenario k
$u_p^c(k, t)$ pumping status (on-off) of turbine c in period t and scenario k
$l(k, t)$ logic variable for preventing simultaneous pumping and generation in period t and scenario k
$y_d^c(k, t)$ startup status for discharge of turbine c in period t and scenario k
$y_p^c(k, t)$ startup status for pumping of turbine c in period t and scenario k
$z_d^c(k, t)$ shutdown status for discharge of turbine c in period t and scenario k
$z_p^c(k, t)$ shutdown status for pumping of turbine c in period t and scenario k
$V(k, t)$ water level in the upper reservoir in period t and scenario k (m^3)
$W_{grid}(k, t)$ wind energy supplied to the grid in period t and scenario k (MWh)
$W_{pump}(k, t)$ wind energy consumed by turbines in pumping mode in period t and scenario k (MWh)
$P_{grid}(k, t)$ energy drawn from the grid in period t and scenario k (MWh)
$P_T(k, t)$ total energy exchange with the grid in period t and scenario k (MWh)
$B(k, t)$ day-ahead market bid in period t and scenario k (MWh)
$\Delta^+(k, t)$ positive deviation of the generation from the contract in period t and scenario k (MWh)
$\Delta^-(k, t)$ negative deviation of the generation from the contract in period t and scenario k (MWh)
$IC(k, t)$ imbalance cost in period t and scenario k (TL)
$SUSD(k, t)$ total startup/shutdown cost in period t and scenario k (TL)
$CVaR_\mu$ conditional value at risk
ζ value at risk
$\tau(k)$ auxiliary variable for computing CVaR in scenario k

Parameters

β risk-control weight
μ confidence level for CVaR
$\overline{V}$, $\underline{V}$ maximum and minimum water volume of the upper reservoir (m^3)
K total number of scenarios
M order of the wind speed SARIMA model
T optimization horizon (h)
C number of reversible turbines
r^+ penalty ratio for positive imbalance
r^- penalty ratio for negative imbalance
α_d^{up} startup cost for discharging (TL)
α_p^{up} startup cost for pumping (TL)
α_d^{down} shutdown cost for discharging (TL)
α_p^{down} shutdown cost for pumping (TL)
$\overline{q}_d^c$ maximum water discharge of turbine c (m^3/h)
$\underline{q}_d^c$ minimum water discharge of turbine c (m^3/h)
$\widetilde{q}_p^c$ water pumped by turbine c in pumping mode (m^3/h)
$\overline{P}_d^c$ maximum power generation of turbine c (MW)
$\underline{P}_d^c$ minimum power generation of turbine c (MW)
$\widetilde{P}_p^c$ power consumption of turbine c in pumping mode (MW)
$\underline{\eta}_d^c$ efficiency of turbine c at minimum flow in discharge mode
$\overline{\eta}_d^c$ efficiency of turbine c at maximum flow in discharge mode
η_p^c efficiency of turbine c in pumping mode
η_T transmission efficiency
δ^c energy coefficient (MWh/m^3)

company should decide on how much energy to supply at each hour. If there are discrepancies between the supplied energy and the production contracts determined during the day-ahead bidding stage, they are compensated in the balancing market. These deviations could lead to significant economic losses because in the balancing market, the buying price is higher and the selling price is lower than the day-ahead market price.

As can be inferred from the preceding discussion, appropriate bidding and real-time operation algorithms should be devised in order to maximize profits of wind producers by avoiding imbalances as much as possible. There are several studies in this direction, a review of which is given below.

1.1. Literature review of day-ahead bidding methods

The simplest approach to the day-ahead bidding problem is to compute point forecasts of wind generation and submit them as production contracts. The success of this method depends on the accuracy of the predictions. There is a rich literature on wind forecasting [1,2]. The proposed methods range from primitive persistence forecasts to more advanced techniques such as autoregressive integrated moving average-based time-series methods [3], artificial neural networks [4], and numerical weather prediction models [5]. However, there is a limit on the accuracy of these tools [6]. Although improvements have been achieved over time, according to recent figures, the estimation errors of the state of art methods are no less than 10% for day-ahead timescales [1,7].

Another idea is to make use of probabilistic methods [8]. Instead of point forecasts, the probability distribution of uncertainty, such as the Weibull distribution [9], can be employed to formulate the bidding as an expectation maximization problem. For simple systems only composed of wind farms, analytical solutions that provide optimal contracts