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Model predictive control to two-stage stochastic dynamic economic dispatch problem

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ABSTRACT

A multi-stage model predictive control approach is proposed to compensate the forecast error in a scenario-based two-stage stochastic dynamic economic dispatch problem through a feedback mechanism. Reformulating the problem as a finite moving-horizon optimal control problem, the proposed approach decelerates the growth of the number of scenarios by updating the system as uncertainties are gradually realized. Consequently, the computation time is reduced, and the problem is solved without the need for using scenario reduction techniques that compromise the accuracy of the solution. To exhibit the computational efficiency of the proposed approach, numerical experiments are conducted on the IEEE 118-bus system.

1. Introduction

One of the very important objectives of the power system operation is to maintain the balance between supply and demand at all times with the lowest possible cost. Considering power system constraints, the problem of finding an economical solution by determining the optimal generation level of many generators is called Economic Dispatch problem (ED). In other words, ED is an optimization problem which is formulated to minimize the cost of electricity generation, subject to various constraints such as power balance between generation and demand, the generator output limits, and ramp constraints. ED can be formulated either as a static or dynamic problem (Wood, 1982). Unlike static-ED, dynamic-ED (DED) has the capability of considering the complete prediction of demand profile over the dispatch period. This enables DED to prepare generators for the upcoming demand to achieve an optimal and robust solution. Therefore, the DED solution is more realistic and accurate than the static-ED solution since it has a look-ahead capability (Wood, Wollenberg, & Sheble, 2013; Xia & Elaiw, 2010). DED can be further classified as deterministic or stochastic. The main drawback of the deterministic DED formulations is that its solution is suboptimal or even infeasible when the demand forecast has considerable error. To overcome this issue, a stochastic DED formulation can be developed to consider demand, and potentially, renewable generation uncertainties.

Many publications include the stochastic DED problem as a subproblem of a two-stage stochastic unit commitment problem, where the first stage determines the commitment status of generators, and in the second stage, the economic dispatch is obtained (Wang, Shahidehpour, & Li, 2008; Wu, Shahidehpour, & Li, 2007; Zheng, Wang, & Liu, 2014). The other possible approach is that the unit commitment problem is already solved, and stochastic DED problem is viewed as a one stage problem, which attempts to minimize the cost considering the expected value of uncertain variables (Liu, Guo, Huang, Wang, & Wang, 2013; Patrinos, Trimboli, & Bemporad, 2011; Peng, Sun, Guo, & Liu, 2012). However, since uncertain variables such as renewable generation availability and actual demand will be known over time, the system operator will be able to correct his/her decisions accordingly through a recourse action. This approach requires a two-stage formulation for the stochastic DED problem. Another advantage is that the first stage solution prepares the generators for the forecasted demand and the second stage solution determines the exact amount of required generation once uncertainties are revealed (Gangammanavar, Sen, & Zavala, 2016; Lee & Baldick, 2013; Liu & Nair, 2016; Yang, Zhang, Han, & Cheng, 2014).

Robust optimization and stochastic programming have been the most applied approaches to tackle the power system optimization problems under uncertainties (Alqurashi, Etemadi, & Khodaei, 2016; Warrington, 2013; Zheng et al., 2014). Robust optimization approach ensures feasibility of the solution under the worst case scenario, but produces very conservative, and consequently, costly solutions. On the other hand, in stochastic programming, the variability and uncertainty are

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Nomenclature

Indices

g	Generator index, $1 \leq g \leq G$
t	Time interval, $0 \leq t \leq NT$
s	Scenario index, $1 \leq s \leq S$

Parameters

x_g^{min}/x_g^{max}	Minimum/maximum capacity
UR_g/DR_g	Maximum up/down ramp rate
a_g, b_g, c_g	Fuel cost coefficients
z_g	Reserve price
v	Penalty factor for load shedding
D^t	Demand at t for deterministic model
d^t	Expected demand at time t
d_s^t	Demand at time t of scenario s
W^t	Expected wind generation at time t
W_s^t	Wind generation at time t of scenario s
x_g^0	Initial generation at $t = 0$
T	Sampling period
ω_s	Represents the uncertain data with known distribution
π_s	Probability of scenarios
H	Length of the horizon window of the multi-stage MPC

Variables

u_g^t	First stage control actions of the generator g at time t
$r_{g,s}^t$	Second stage control actions of the generator g for time t of scenario s
L_s^t	Amount of load shedded at time t of scenario s

included directly in the formulation as probability-weighted scenarios. Resource allocation based on probability of a given scenario reduces solution costs, at the expense of small tolerable reduction of security. In stochastic DED, scenarios are generated to capture all possible combinations of load/generation variations. Clearly, this results in a large number of scenarios. Scenario reduction techniques (Heitsch & Römisch, 2003; Römisch, 2009), such as forward and backward algorithms, are typically used to overcome this problem, leading to less required computational power and time; however, solution optimality and accuracy might be compromised as a result (Conejo, Carrión, & Morales, 2010). To overcome the problem of large number for scenarios without the need of using a scenario reduction technique, a multi-stage model predictive control (MPC) approach is proposed to reformulate the two-stage stochastic DED problem as a finite moving-horizon optimal control problem.

In general, MPC predicts the response of the system over a finite moving-horizon and produces optimal inputs for the system, while constantly collecting necessary information to update the solution (Mayne, Rawlings, Rao, & Scokaret, 1999). The potential of applying MPC to optimize a conventional power plant generation was introduced in Edlund, Bendtsen, Børresen, and Mølbak (2008) and Gallestey, Stothert, Antoine, and Morton (2002). The application of MPC to optimal-control-based DED problem was first proposed in Xia, Zhang, and Elaiw (2009) and Xie and Ilic (2008), demonstrating advantages such as reduced problem size, ease of implementation, fast convergence, and ability to take into account disturbances in real-time. References (Elaiw, Xia, & Shehata, 2012; Kim, Gui, Lee, & Chung, 2012) later applied MPC to the DED problem; however similar to Xia et al. (2009), they did not consider uncertainties either. An MPC-based stochastic DED problem, considering wind uncertainty was proposed in Gui, Kim, and Chung (2013) and Kim, Gui, Chung, and Kang (2013), relaxing the power balance constraint by including it in the objective function with an appropriate weighting factor. Using the point forecast method, (Xie & Ilic, 2008, 2009) apply MPC to solve the DED problem of power system that includes intermittent resources. However, loads and intermittent generation are assumed to be accurately predictable. The stochastic DED problem is formulated in Patrinos et al. (2011) as a single stage stochastic problem, and stochastic-MPC is applied. In their proposed stochastic-MPC, a scenario reduction method has to be applied to solve the problem. Therefore, the accuracy of the solution is compromised.

In this paper, a scenario-based two-stage stochastic programming model for the optimal control dynamic economic dispatch (OC-DED) problem considering demand and wind generation uncertainties is proposed. A multi-stage MPC approach is proposed to compensate the forecast error through a feedback mechanism. Compared with the existing work, our main contributions are the following:

- The existing deterministic OC-DED formulation is extended to consider demand and renewable generation uncertainties, and formulate it as a two-stage stochastic optimization problem. To obtain a more accurate solution, quadratic generator cost functions are included in the objective. The first stage determines the optimal control actions based on the forecasted demand and wind generation, while the second stage control actions redispatch generation to obtain a better solution as uncertainties are revealed.
- The proposed multi-stage MPC reformulates the two-stage stochastic OC-DED problem as a finite moving-horizon optimal control problem. The moving-horizon decelerates the growth of number of scenarios by updating the information in each time step, resulting in reducing computational time to solve the problem. Hence, using the proposed approach obviates the need for using scenario reduction techniques in the proposed OC-DED formulation. To the best of our knowledge, the multi-stage MPC-based solution of a two-stage stochastic OC-DED problem has not been reported in the existing literature.

The rest of this paper is organized as follows: Section 2 presents deterministic and stochastic OC-DED models; Section 3 describes the methodology used in this paper to construct scenarios and how the proposed approach deals with the large number of scenarios. Section 4 describes the proposed multi-stage MPC approach to solve the stochastic OC-DED problem; Section 5 presents numerical case studies using a standard six-unit system and the IEEE-118 bus system. Section 6 concludes the paper.

2. OC-DED formulation

In this section, first the deterministic OC-DED problem is explained. Then, it is expanded to obtain the two-stage stochastic OC-DED formulation.

2.1. Deterministic OC-DED formulation

The dynamics of power generation can be considered as a discrete time control system (Ross & Kim, 1980; Travers & Kaye, 1998) as $x_g^{t+1} = x_g^t + T.u_g^t$. The inverse coordinate transformation of this equation is $x_g^t = x_g^0 + \sum_{j=0}^{t-1} T.u_g^j$, where the generation increment/decrement, u_g^j, is the control variable ($0 \leq j \leq NT - 1$), while the generation level of each generator x_g^t is the state variable and x_g^0 is the initial value. Given the initial value x_g^0, where $\sum_g x_g^0 = D^0$, and by applying the inverse coordinate transformation equation, the deterministic OC-DED problem is formulated as (Xia, Zhang, & Elaiw, 2011):

$$\min F(u_g^j) = \sum_{g,t} [F_g(x_g^0 + \sum_{j=0}^{t-1} T.u_g^j)] \tag{1}$$

subject to

$$\sum_g (x_g^0 + \sum_{j=0}^{t-1} T.u_g^j) = D^t \quad \forall t \tag{2}$$