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Application of nonlinear model predictive control based on swarm optimization in power systems optimal operation with wind resources

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ABSTRACT

With the increased share of power generation based on wind energy, the complexity of the unit commitment (UC) and economic dispatch (ED) problems increases due to the stochastic nature of wind power. Therefore, an accurate and fast optimization method is needed when the generation process involves large quantities of wind sources to effectively manage generation mix and load requirements. In this paper, model predictive control (MPC) is used to solve power system UC/ED problems with the presence of wind energies. Because the UC/ED problem is nonlinear, non-convex and mixed integer problem, the MPC must be used as nonlinear. To produce a nonlinear MPC (NMPC), MPC must be integrated with a fast optimization methodology. This paper presents a generic mathematical formula for a NMPC, integrated with swarm optimization technique to describe the nonlinear behavior in the mathematical formulation. This new formulation will be called swarm model predictive control (SMPC) optimization. The control model will be able to address the effect of the system disturbances and fluctuations using a controlled autoregressive integrated moving average (CARIMA). A general form of future predictions can be expressed as a function of input and output past data, and a future control sequence, and the degree of freedom in the SMPC problem. Also, the prediction part improves the swarm technique, because it identifies the size of search space in a better way. In this paper, UC schedule is designed using the swarm technique offline, while ED is solved using the proposed SMPC optimization method on real-time basis and fed into the automatic generation control system. There is no load deficit in real time ED results in less spinning reserve requirements compared with swarm optimization and dynamic program techniques used discretized load. The system under study is a standard IEEE 30 bus modelled in MATLAB environment, with all data from the city of Florida, USA.

1. Introduction

A main function of the smart electrical power system is to coordinate and control power generation from both conventional and renewable sources including wind power. When solving unit commitment (UC) and economic dispatch (ED) problem for large power system, a high computational capacity is required to the system. Single optimization approaches cannot achieve this goal, so combination techniques were introduced to integrate two or more optimization techniques in order to benefit from their strengths and overcome the weakness in solving the optimization problems. There is a rich literature on hybrid methods as in [1–4]. Although these combinations are better than single approaches, some combination methods' computational effort represents a burden. Also, none of the currently available optimization techniques are able to avoid shortage or surplus of wind power by solving the dispatch problem with a high frequency, e.g., every 2–4 min. UC/ED problems quickly become very complex and extremely difficult to solve within a limited time.

Thus, to account for the variations in power supply from the wind energy sources, and solve UC/ED problems within limited times, this paper introduces an improved model predictive control (MPC) method. MPC has been popular since the 70's of the past century [5]; and in the 90's, it has become a standard advanced control technique in many petrochemical processes [6]. Recently, the application scope for

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MPC has expanded and covers not only the petrochemicals and refining fields, but also food processing, automotive, metallurgy, aerospace and defense industries [7]. The main advantages of MPC are its ability to predict performance over the future horizon, its quick processing capacity that enables it to tackle changing patterns within very short timelines, and its being suited for multivariable control operations. In addition, the superior performance of MPC in systematically handling constraints, through incorporating the constraints directly into the objective functions, makes it theoretically a perfect real-time optimal control paradigm equipped with process integration ability. Real-time is mean that MPC can solve the dispatch problem with a high frequency.

Even though MPC has been used for a long time as a standard control in industry, its utilization is limited in electrical systems and is still the subject of many researches. Electricity is a vital economic sector that requires an accurate control model such as MPC to reach optimal operation. Therefore, numerous researches are being carried out with the aim of improving the performance of MPC algorithms or addressing the weakness of MPC such as the stability and robustness issues in electrical systems. Authors in [8] solved the dynamic ED problem using MPC in both regulated and deregulated systems. Authors in [9] presented potential benefits of applying MPC to solve the multi-objective economic dispatch problem in electric power systems with intermittent resources in order to minimize generation costs. A predictive economic dispatch algorithm is utilized as an optimization strategy that computes the dispatch schedules by minimizing marginal dispatch costs. Authors in [10] incorporated stochastic problem with MPC scheme to further compensate the uncertainty though the feedback mechanism. Authors in [11] investigated the German power system for high penetration levels of wind and solar energy and used MPC to manage storage units charging from renewable source. Authors in [12] combined optimization of the UC problem and the economic MPC problem, for optimal operation of power systems with the increased share of intermittent renewable energy sources in the power supply.

In this paper, MPC is used to solve power system UC/ED problems on the presence of high wind energy penetration. The fluctuating behavior of wind power generation is addressed by developing a forecasting model using autoregressive integrated moving average (ARIMA) [13]. Most of the MPC software available in the market uses linear models, whereas most processes are nonlinear. Because the UC/ED problem is nonlinear, non-convex and mixed integer problem, the MPC must be used as nonlinear. Papers [8–12] solved UC/ED problem using standard MPC by linearization of the problem, while the problem must be solved as nonlinear to reach the most accurate analysis.

To produce a nonlinear MPC (NMPC), MPC must be integrated with an optimization methodology as in [14,15]. In this paper, a NMPC is developed to resolve the problem using simultaneous methods [5], where the system is reduced to algebraic equations through a weighted residual method. To avoid defects of simultaneous methods, where the valid iteration for the system takes a considerably shorter time than the optimization, the MPC is integrated with fast optimization techniques, e.g. particle swarm. In addition, NMPC prediction horizon is made longer than optimization time. To sum up, this paper presents an MPC model that is modified to be a swarm algorithm based model predictive control. This new formulation is generic for several industrial purposes. In electrical generation problems, this paper introduces the NMPC to minimize operation cost by calculating the generation capacity of the generating units to satisfy all constraints. So, the new formula is used in solving the optimal dispatch problem. Swarm model predictive dispatch (SMPD) decisions are based on UC schedules that record the daily ordering of the units on/off [16] in the system, to match the anticipated load with the forecasted wind power using swarm technique. Also, SMPC is enhanced by inputting disturbance rates to achieve best optimization in limited timelines, where the disturbance effect is calculated by using the prediction model. Disturbance in electrical systems can be due to factors including fluctuation of renewable sources, variation of the load demand, and response of the automatic generation control (AGC), etc. Controlled autoregressive integrated moving average (CARIMA) is used to predict the disturbance, and enhance the swarm performance by better identifying search areas. The main advantage of SMPD is its mathematical formulation as a real-time optimization problem solver that computes the dispatch actions. The real-time optimization decisions are subject to AGC to manage the machine's generation level.

The rest of the paper is organized as follows: Section 2 introduces the multi-objective UC formulation; Section 3 introduces the swarm optimization methodology; Section 4 introduces the new generic formulation of NMPC; Section 5 illustrates NMPC application in electrical field; Section 6 introduces the framework models implemented in Matlab; finally, Section 7 illustrates numerical case studies. The system under study in this paper is a standard IEEE 30 bus, with wind power data of the city of Florida, USA. The values of total power generation from wind farms are representing a penetration of 35%.

2. Unit commitment formulation

The objective of this paper is to minimize the total operation cost which contains fuel cost (FC_i^t), operation and maintenance cost (OMC_i^t), and start-up cost (SUC_i^t) as shown in Eq. (1). The objective function is subject to multi-constraints. These constraints are: the power balance constraint, the generation limits constraint, and the ramp rate constraint as shown in Eq. (2) [17].

$$\text{Minimize} \sum_{t=1}^{T} \left\{ \left[FC_i^t + OMC_i^t + SUC_i^t \left(1 - U_i^{t-1}\right)\right].U_i^t \right\}_{i=1}^{N} \tag{1}$$

$$FC_i^t = a_i P_i^2 + b_i P_i + c_i \tag{2a}$$

$$OMC_i^t = m.P_i^t.\Delta t + R^t.r_p \tag{2b}$$

$$SUC_i^t = (C_b.t_b.F_i) + C_c\left(1 - e^{-t_c/\gamma}\right).F_i + C_f \tag{2c}$$

$$\text{Subject} < \text{ to } L^t = \sum_{l=1}^{N_L} g_l[V_x^2 + V_y^2 - 2V_xV_y\cos(\delta_x - \delta_y)] \tag{2d}$$

$$\sum_{i=1}^{N} \left(P_i^t + P_W^t\right) \geq D^t + L^t + R^t \tag{2e}$$

$$P_{i,\min} \leq P_i^t \leq P_{i,\max} \tag{2f}$$

$$P_i^{t-1} - P_i^t \leq \nabla_i \tag{2g}$$