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Application of model predictive control to profit-based dynamic economic dispatch

By

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Abstract:

Recently many countries have gone through deregulation and restructuring of the electrical power systems with the aim of improving economic efficiency. In the deregulated environment, the generation company (GENCO) finds the optimum schedules of its energy to be sold in the market by running the profit-based dynamic economic dispatch (PBDED) problem with its aim to maximize its own profit (revenue minus generation cost). The objective of the PBDED is to maximize the GENCO's own profit based on the forecasted energy demand and prices, while satisfying the generators' ramp rate constraints and various other constraints. In [11], model predictive control (MPC) method has been proposed for the periodic implementation of the optimal solutions for the dynamic economic dispatch (DED) problem with periodic demand. In this paper we applied the MPC approach proposed in [11] for the PBDED problem under the assumption that both the energy price and demand is periodic. The convergence and robustness of the MPC algorithms are demonstrated through the application of MPC to the PBDED problem with a six-unit system.

Keywords: Dynamic economic dispatch, Electricity market, Model predictive control.

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1. Introduction:

In a vertically integrated monopolistic environment, the dynamic economic dispatch (DED) problem is formulated to determine the optimal scheduling of the committed generating unit's output so as to meet the load demand over a dispatch period at minimum operating cost while satisfying various constraints (see the review [12]). In this environment, utilities are obliged to server all customers and meeting all demands. After deregulation of the electricity markets, the DED has evolved from a minimum cost-based to a maximum profit-based, giving rise to the new profit-based dynamic economic dispatch (PBDED) problem. The objective function of the PBDED can be formulated to maximize the generation company's (GENCO's) own profit from selling energy into the market [1]. Therefore, the GENCO can choose to sell energy less than the predicted values if a higher profit is realized. The PBDED problem can be used to create the decision criteria for the GENCO. The first purpose of our paper is to introduce formulation to produce electricity with minimum operating cost and sell it with maximum profit.

Both DED and PBDED formulations and their solving algorithms suffer from the deficiency of not allowing to compensate for inaccuracies originating from modeling uncertainties, external disturbances, and unexpected reactions of some of the power system components. In the terminology of control theory, these formulations are in fact open-loop systems and there is no way to feedback account for the inaccuracy information so that the solutions can be compensated. In other words, these formulations are not closed-loop systems. A possible solution to this problem is to apply the model predictive control (MPC) method. This method obtains a feedback control by solving a finite horizon optimal control problem at each sampling instant using the current state of the plant as the initial state for the optimization and applying only ``the first part'' of the optimal control [6]. MPC method has emerged and been successfully applied particularly in the process control industry since 1970's. Theoretical properties such as stability and robustness of the MPC have been studied by many authors since the early work of Kleinman [5]. Up to present, MPC has become one of the most widely used multivariable control algorithms in various industries including chemical engineering, food processing, automotive, aerospace applications [10], and recently in power systems [9], [11]. This is due to its facility of handling constraints, being able to use simple models, and its closed-loop stability and inherent robustness. Moreover, MPC solves optimal control problem *on-line* for the current state of the plant which is a mathematical programming problem and is much simpler than determining the feedback solution by dynamic programming [6].

MPC has been proposed for the periodic implementation of the optimal solutions for the DED problem in [11]. It has been shown theoretically that the closed-loop MPC solutions asymptotically approach the optimal solution of the DED problem and the

MPC algorithm is also robust under certain disturbances and uncertainties. The second purpose of this paper is to apply the MPC approach proposed in [11] to the PBDED problem.
The remainder of this paper is organized as follows: In Section 2, we introduce the DED and PBDED formulations. In Section 3, we outline the MPC approach for the DED problem. The simulation results for the application of MPC to the PBDED problem are given in Section 4. The last section is the conclusions.

2. Problem Formulation:

In this section we introduce the DED and PBDED formulations. For a sampling period T, the dynamic dispatch problem is considered over dispatch intervals, $[iT,(i+N)T)$ where the optimization is considered, for $i \ge 0$, N is a fixed positive integer, and NT is the dispatch period. For simplicity, we make the convention throughout the paper that $[i,j)$ denotes the time interval $[iT, jT)$. Assume that n is the number of committed units, P_i^k is the generation of unit i during the k-th time interval $[k-1,k)$; $C_i(P_i^k)$ is the generation cost for unit i to produce P_i^k; D^k, SP^k are the demand and energy price at time k (i.e., the k-th time interval); the control variable u_i^k is the ramp rate of the unit i at time k; UR_i and DR_i are the maximum ramp up/down rates for unit i; $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum capacity of unit i respectively. For any $m \ge 0$, $k \ge 1$ define $\mathrm{P}^m = \left(P_1^{m+1}, P_2^{m+1}, \ldots, P_n^{m+1}, P_1^{m+2}, P_2^{m+2}, \ldots, P_n^{m+2}, \ldots, P_1^{m+N}, P_2^{m+N}, \ldots, P_n^{m+N}\right)$ and $P^k = \left(P_1^k, P_2^k, \ldots, P_n^k\right)'$. Define $U = \left(u_1^1, u_2^1, \ldots, u_n^1, u_1^2, u_2^2, \ldots, u_n^2, \ldots, u_1^{N-1}, u_2^{N-1}, \ldots, u_n^{N-1}\right)$, $D = \left(D^1, D^2, \ldots, D^N\right)'$ and $SP = \left(SP^1, SP^2, \ldots, SP^N\right)'$. The total fuel cost from all units and over the dispatch period $[m, m+N)$ is denoted by $C(\mathrm{P}^m)$. The demand D^k and energy price SP^k are assumed to be periodic with period N. This periodic assumption is made to reflect the cyclic consumption behavior and seasonal changes over the dispatch interval. The following convention is also made:

$$\sum_{i=j}^{k} x_i = \begin{cases} 0 & if \quad j > k \\ x_j + x_{j+1} + \ldots + x_k & if \quad j \le k \end{cases}$$

2.1 Dynamic Economic Dispatch

The objective of the DED problem is to determine the generation levels for the committed units which minimize the total fuel cost over the dispatch period $[0, NT]$, while satisfying a set of constraints ([11], [12]). The DED can be mathematically stated as follows:

$$\min_{\mathrm{P}^0} C(\mathrm{P}^0) = \sum_{t=1}^{N}\sum_{i=1}^{n} C_i(P_i^t)$$
$$\text{subject to } P_i^t \in \Omega_{DED}(\mathrm{P}^0), \qquad i = 1,2,...,n,\ t = 1,2,...,N \tag{1}$$

where the feasible domain $\Omega_{DED}(\mathrm{P}^0)$ is defined to be the set of $(P_i^t,\ i = 1,2,...,n,\ t = 1,2,...,N)$ satisfying the following constraints:

(i) Power balance constraint

$$\sum_{t=1}^{N} P_i^t = D^t, \qquad t = 1,2,...,N, \tag{2}$$

(ii) Generation limits

$$P_i^{\min} \le P_i^t \le P_i^{\max} \qquad i = 1,2,...,n,\ t = 1,2,...,N, \tag{3}$$

(iii) Generating unit ramp rate limits

$$-T \bullet DR_i \le P_i^{t+1} - P_i^t \le T \bullet UR_i \qquad i = 1,2,...,n,\ t = 1,2,...,N-1, \tag{4}$$

$$-T \bullet DR_i \le P_i^1 - P_i^N \le T \bullet UR_i \qquad i = 1,2,...,n. \tag{5}$$

In this paper we consider for simplicity, the cost functions in quadratic forms:

$$C_i(P_i^t) = a_i + b_i P_i^t + c_i (P_i^t)^2$$

where a_i, b_i and c_i are the fuel cost coefficients of generator *i* and they are constants. The constraints (2)-(4) are usually used in the conventional DED problem. Since the demand and constraints are periodic, one may obtain the solution of the conventional DED problem (1)-(4) over e.g. 24 hours ($N = 24$ and $T = 1$) then this solution is implemented not only for the first day, but also for all the other week days. Sometimes such an optimal solution is not able to be practically implemented, or in other words, the solution is not practically feasible. The ramp rate constraint may be violated when the generators are moved from the 24-th hour of a day to the first hour of the next day. This problem can be resolved by including the ramp limit on the difference between P_i^{24} and $P_i^{25} = P_i^1$. This can be achieved by adding the constraint (5) to the conventional DED problem [11].

We note that the above DED problem can be solved over the dispatch period $[m, m+N]$ for any $m \ge 0$ and it can be formulated as:

$$\min_{\mathrm{P}^0} G(\mathrm{P}^m)$$
$$\text{subject to } P_i^t \in \Omega_{DED}(\mathrm{P}^m), \qquad i = 1,2,...,n,\ t = 1,2,...,N$$

Since the demand and the energy price are periodic and $P_i^{\min}, P_i^{\max}, UR, DR_i,$ and T do not change over time, then $P_i^{m+1} = P_i^{m+1+N}$ and Ω_{DED} satisfies

$$\begin{aligned}\Omega_{DED}(\mathrm{P}^{m+1}) &= \Omega_{DED}(P_i^{m+2}, P_i^{m+3}, ..., P_i^{m+1+N}) \\ &= \Omega_{DED}(P_i^{m+2}, P_i^{m+3}, ..., P_i^{m+1}) \\ &= \Omega_{DED}(\mathrm{P}^m)\end{aligned}$$

then Ω_{DED} is shift-invariant (see [13]). The shift-invariant property of Ω_{DED} is needed for

the application of the MPC approach to the PBDED problem.
The solution of the DED problem will give the amount of power to be generated by the committed units with minimum total fuel cost. But after deregulation, the GENCO has the goal to produce electricity with minimum operating cost and sell it with maximum profit, therefore, to take into account the profit in the dynamic dispatch problem we shall formulate a new dynamic dispatch problem under deregulated electric power system.

2.2 Profit-Based Dynamic Economic Dispatch

The objective of the PBDED problem is to determine the generation levels for the committed units which maximize the profit (revenue minus generation cost) over the dispatch period $[0, NT]$, while satisfying a set of constraints [1]. The PBDED can be mathematically stated as follows:

$$\max_{P^0} \underbrace{\sum_{t=1}^{N}\sum_{i=1}^{n} SP^t \bullet P_i^t}_{revenue} - \underbrace{\sum_{t=1}^{N}\sum_{i=1}^{n} C_i(P_i^t)}_{\cos t}$$

or (6)

$$\min_{P^0} G(P^0) = \sum_{t=1}^{N}\sum_{i=1}^{n} C_i(P_i^t) - \sum_{t=1}^{N}\sum_{i=1}^{n} SP^t \bullet P_i^t$$

$$\text{subject to } P_i^t \in \Omega_{PBDED}(P^0), \qquad i = 1,2,...,n,\ t = 1,2,...,N$$

where the feasible domain $\Omega_{PBDED}(P^0)$ is defined to be the set of $(P_i^t,\quad i = 1,2,...,n,\ t = 1,2,...,N)$ satisfying the following constraints:

$$\sum_{t=1}^{N} P_i^t \le D^t, \qquad t = 1,2,...,N, \tag{7}$$

$$P_i^{\min} \le P_i^t \le P_i^{\max} \qquad i = 1,2,...,n,\ t = 1,2,...,N, \tag{8}$$

$$-T \bullet DR_i \le P_i^{t+1} - P_i^t \le T \bullet UR_i \qquad i = 1,2,...,n,\ t = 1,2,...,N-1, \tag{9}$$

$$-T \bullet DR_i \le P_i^1 - P_i^N \le T \bullet UR_i \qquad i = 1,2,...,n. \tag{10}$$

where SP^t is the forecasted energy price at time t.
We note that the constraints in the DED did not changed except the constraint (2) which has been changed into constraint (7). Constraint (7) means that under the deregulated environment, GENCO is not obliged to serve all demand, but may sell its energy at less than the system's forecasted demand equilibrium.

2. MPC approach to DED:

In this section, we outline the MPC approach proposed in [11] and give a review on the results obtained in [11]. We first introduce the control variables u_i^t as (see [7], [8]):

$$u_i^t = \frac{P_i^{t+1} - P_i^t}{T}, \quad i = 1,2,...,n, \quad t = 1,2,...,N-1 \tag{11}$$

where u_i^t is the ramping action of unit i at time t. This equation is actually defined coordinate transformation between the variables $P_i^t,\ i = 1,2,...,n,\ t = 1,2,...,N$ and the variables $u_i^t,\ i = 1,2,...,n,\ t = 1,2,...,N-1$. It is obvious that the inverse coordinate transformation is given by

$$P_i^t = P_i^1 + \sum_{j=1}^{t-1} T u_i^j, \qquad t = 2,3,...,N. \tag{12}$$

The optimal solution of the DED problem is implemented repeatedly at instants which equal to multiples of N. To introduce the MPC approach, let us consider the DED problem starting at an arbitrary instant $t = m$ and over a dispatch interval $[m, m+N]$. Then the optimization variables are changed into $\{P_i^{m+1}, P_i^{m+2},..., P_i^{m+N},\ i = 1,2,...,n\}$. By the transformation defined in (12), the optimization variables $\{P_i^{m+1}, P_i^{m+2},..., P_i^{m+N},\ i = 1,2,...,n\}$ are transformed into $\{P_i^{m+1}, u_i^{m+1}, u_i^{m+2},..., u_i^{m+N-1},\ i = 1,2,...,n\}$.

In an MPC approach, a finite-horizon optimal control problem is repeatedly solved and the input is applied to the system based on the obtained optimal open-loop control. In our case, the horizon is chosen to be N. Instead of solving the DED problem with $\{P_i^{m+1}, u_i^{m+1}, u_i^{m+2},..., u_i^{m+N-1},\ i = 1,2,...,n\}$ as the optimization variables, the MPC algorithm solves the following problem:

Problem MPCDED ($P^{m+1}, u, [m, m+N]$) Given $n, N, P_i^{\min}, P_i^{\max}, UR_i, DR_i, i = 1,2,...,n, D, P^{m+1}$, let

$$P_i^1 := P_i^{m+1},\ \ u_i^j := u_i^{m+j},\ D^t := D^{t+m},\ i = 1,2,...,n, \quad t = 1,2,...,N,\ j = 1,2,...,N-1 \tag{13}$$

and solve the following minimization problem

$$\min_{\mathrm{U}} \sum_{t=1}^{N}\sum_{i=1}^{n} C_i\Big(P_i^1 + \sum_{j=1}^{t-1} T u_i^j\Big)$$

$$\text{subject to } u_i^j \in \Omega_D(P^1, U), \qquad i = 1,2,...,n,\ \ j = 1,2,...,N-1,$$

where the feasible domain $\Omega_D(P^1, U)$, is defined to be the set of $\{P_i^1, u_i^1, u_i^2,..., u_i^{N-1},\ i = 1,2,...,n\}$

$$\sum_{t=1}^{N}\left(P_i^1 + \sum_{j=1}^{t-1} T u_i^j\right) = D^t, \qquad t = 1,2,...,N,$$

$$P_i^{\min} \le P_i^1 + \sum_{j=1}^{t-1} T u_i^j \le P_i^{\max} \qquad i = 1,2,...,n,\ t = 1,2,...,N,$$

$$-DR_i \le u_i^j \le UR_i \qquad i = 1,2,...,n,\ \ j = 1,2,...,N-1,$$

The notation **Problem MPCDED** ($P^{m+1}, u, [m, m+N]$) denotes the optimization problem is solved over the interval $[m, m+N]$ with variables u_i^j and for known inputs P^{m+1}, $i = 1,2,...,n$, $j = m+1, m+2,..., m+N-1$.

In order to make the above **MPCDED** problem solvable, the following hypothesis is needed as in [3], [4] and [11].

Feasibility Hypothesis: After the change of variables in (13) over any dispatch interval $[m, m+N]$ with $m \geq 0$, the set $\Omega_D(P^1, U)$ is not empty.

This hypothesis ensures the solvability of the problem **MPCDED** ($P^{m+1}, u, [m, m+N]$). Denote the optimal solution of **MPCDED** for given initial generation $\overline{P}^{m+1}$ by $\bar{\mathrm{u}}^m(\overline{P}^{m+1}) = \{\bar{u}_i^{m+j}(\overline{P}^{m+1}), i = 1,2,...,n, \ j = 1,2,..., N-1\}$. In the model predictive control method the optimal solution $\bar{\mathrm{u}}^m$ is applied only in the first sampling period $[m, m+1]$ that is, $\bar{u}_i^{m+1}(\overline{P}^{m+1})$ is applied to the state $\overline{P}_i^{m+1}$. Since the optimal controller $\bar{\mathrm{u}}^m(\overline{P}^{m+1})$ depends on $\overline{P}^{m+1}$, in this way a feedback can be obtained. We define the MPC feedback controller by $v_i^m := \bar{u}_i^{m+1}$. The closed-loop solution $\overline{P}_i^{m+2}$ given by $\overline{P}_i^{m+2} = \overline{P}_i^{m+1} + Tv_i^m(\overline{P}_i^{m+1})$ is actually executed over the time period $[m+1, m+2)$.

The above ideas can be strictly formulated into the following MPC algorithm.

MPC Algorithm Initialization: Input the initial status $\overline{P}^1 \stackrel{\Delta}{=} P^1 = (P_1^1, P_2^1, ..., P_n^1)$ and let $m = 0$.

(1) Compute the open-loop optimal solution $\bar{\mathrm{u}}^m$ to the **MPCDED** ($P^{m+1}, u, [m, m+N]$).

(2) The (closed-loop) MPC controller v_i^m is applied to the plant in the sampling interval $[m, m+1)$ to obtain the closed-loop MPC solution

$$\overline{P}_i^{m+2} = \overline{P}_i^{m+1} + Tv_i^m(\overline{P}^{m+1}) \tag{14}$$

over the period $[m+1, m+2)$.

(3) Let $m := m+1$ and go to step (1).

Theorem 1 [11] Suppose Feasibility Hypothesis holds, P^* is the globally optimal solution of the DED problem, and the initial power output P^1 at time $t = 1$ satisfies $P^1 \in \Omega_D(P^1, U)$, then MPC Algorithm converges to P^*.

Now we consider the inherent robustness properties of the MPC algorithm (IRP-MPC). For simplicity, suppose that disturbance happens only in the execution of the controller. That is, the disturbance happens only in Step (2) of MPC Algorithm so that when the control v_i^m is applied to the plant in the sampling interval $[m, m+1)$, the system actually execute

$$\overline{P}_i^{m+2} = \overline{P}_i^{m+1} + Tv_i^m(\overline{P}^{m+1}) + Tw_i^{m+1} \tag{15}$$

over the period $[m+1, m+2)$, where w_i^{m+1} is the disturbance. We assume that, the disturbances satisfy the following bound

$$\left\| w_i^{m+1} \right\| < \varepsilon, \quad \varepsilon > 0, \ \ i = 1,2,...,n, \ \ \forall m \geq 0. \tag{16}$$

Theorem 2 [11] Suppose Feasibility Hypothesis holds, P^* is the globally optimal solution of the DED problem, the norm of the gradient of the fuel cost function of DED problem has the upper bound L on Ω_{DED}, δ is a small enough positive constant, c is a positive constant which is less than δ, (15) is executed in Step (2) of MPC Algorithm instead of (14), the constant disturbance w_i^k satisfies (16) where ε is small enough so that $\varepsilon < \min\{c/L, (\delta - c)/L\}$, then there exists an integer N_0 such that for any $k > N_0$, the optimal MPC solution $\overline{P}^{k+1}$ of the *k*-th loop in MPC Algorithm belongs to the domain $\overline{\Omega} := \{P : \|P - P^*\| < c\}$.

Theorems 1 and 2 are based on the assumption that the objective function *C* of the DED problem is strictly convex and differentiable over the set Ω_{DED} which is bounded.
Since the fuel cost function is assumed to be quadratic, then function G is strictly convex and differentiable over the set Ω_{PBDED}. Also since the demand and energy price are assumed to be periodic then the set Ω_{PBDED} is shift invariant. Therefore, Theorems 1 and 2 are valid for the PBDED problem.

4. Simulation Results:

In this section we present the results of PBDED problem with a six-unit system. The demand and energy price are assumed to be periodic over a dispatch period of one day and the sampling period is chosen to be one hour. The initial P_i^1 is chosen such that $\sum_{i=1}^{n} P^1 \le D^1$. We apply MPC approach to the periodic implementation of the optimal solutions of the PBDED. Also we show the convergence and robustness properties of the MPC algorithm to the PBDED problem. The technical data of the units and the demand are taken from [2]. The optimization problem is solved by the fmincon code of the MATLAB Optimization Toolbox.

The result of the optimization is dependent on the energy price data. Indeed, minor changes in the energy price may give a significant change in the power generation of thermal units. Hence, the influence of price forecasting on the optimal solution of the PBDED is analyzed. We consider three different energy price profiles which are given in Table 1. The effect of the energy prices on the total amount of power which produced by the total generators is shown in Table 1. It will be noted that, for price-I and price-II, the total power is less than the demand except some intervals as shown by bold font in Table 1. For price-III, the total power satisfies the demand over the whole dispatch period. We note that, the profit increases according to the energy prices. Figures 1, 2 and 3 show that the MPC closed-loop solutions asymptotically approach the optimal solutions of the PBDED problem for the three price profiles.

To show the IRP-MPC for the PBDED problem, let (15) be executed, and the disturbance w_i^m is generated by $w_i^m = -\varepsilon_i + 2\varepsilon_i r(m)$ where the parameters $r(m)$'s are uniformly distributed random numbers on $[0,1]$ and ε_i's are chosen as

$\varepsilon_1 = 10,\ \varepsilon_2 = 5,\ \varepsilon_3 = 4, \varepsilon_4 = 2,\ \varepsilon_5 = 3,$ and $\varepsilon_6 = 2$.

. In this case the initial P_i^1 for the MPC are chosen as the optimal solution of the PBDED problem at $t = 1$, i.e., $P_i^1 = \overline{P}_i^1$. From Figure 4, we can see that, the IRP-MPC can keep the disturbed system around the optimal solutions of the PBDED problem.

Table 1: The results of PBDED for three prices

	Price-I	$\sum_{i=1}^{6} P_i^t$	Profit	Price-II	$\sum_{i=1}^{6} P_i^t$	Profit	Price-III	$\sum_{i=1}^{6} P_i^t$	Profit
Hour	($)	(MW)	($)	($)	(MW)	($)	($)	(MW)	($)
1	10.314	565.3	800.7918	11.46	747.6	28868	13.752	**955**	93941
2	10.888	627		12.00	883.9		14.40	**942**	
3	11.556	753.4		12.84	**935**		15.408	**935**	
4	9.486	485.5		10.54	620.5		12.648	**930**	
5	10.890	630.5		12.10	876.6		14.52	**935**	
6	11.862	845		13.18	**963**		15.816	**963**	
7	12.42	**989**		13.80	**989**		16.56	**989**	
8	11.214	802.8		12.46	1020.9		14.952	**1023**	
9	13.248	**1126**		14.72	**1126**		17.664	**1126**	
10	13.446	**1150**		14.94	**1150**		17.928	**1150**	
11	13.374	**1201**		14.86	**1201**		17.832	**1201**	
12	13.914	**1235**		15.46	**1235**		18.552	**1235**	
13	11.736	814.5		13.04	**1190**		15.648	**1190**	
14	12.420	1009		13.80	**1251**		16.56	**1251**	
15	10.980	651.4		12.20	943.5		14.64	**1263**	
16	10.188	549.3		11.32	734.1		13.584	**1250**	
17	11.25	704.8		12.50	1012.4		15.00	**1221**	
18	12.258	906.1		13.62	**1202**		16.344	**1202**	
19	9.792	545.6		10.88	696.2		13.056	**1159**	
20	11.034	661.1		12.26	952.2		14.712	**1092**	
21	11.196	692.8		12.44	1014.9		14.928	**1023**	
22	12.222	941		13.58	**984**		16.296	**984**	
23	11.43	740.4		12.70	**975**		15.24	**975**	
24	10.278	560.7		11.42	738		13.704	**960**	

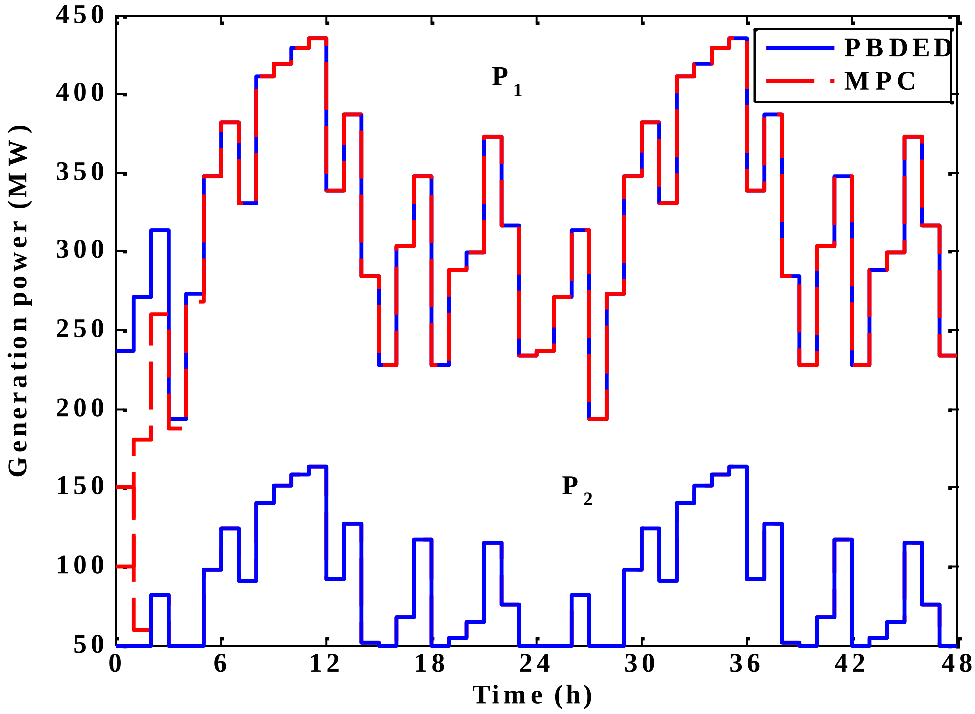

Fig. 1. Convergence of the closed-loop MPC solutions to those of PBDED for price-I.

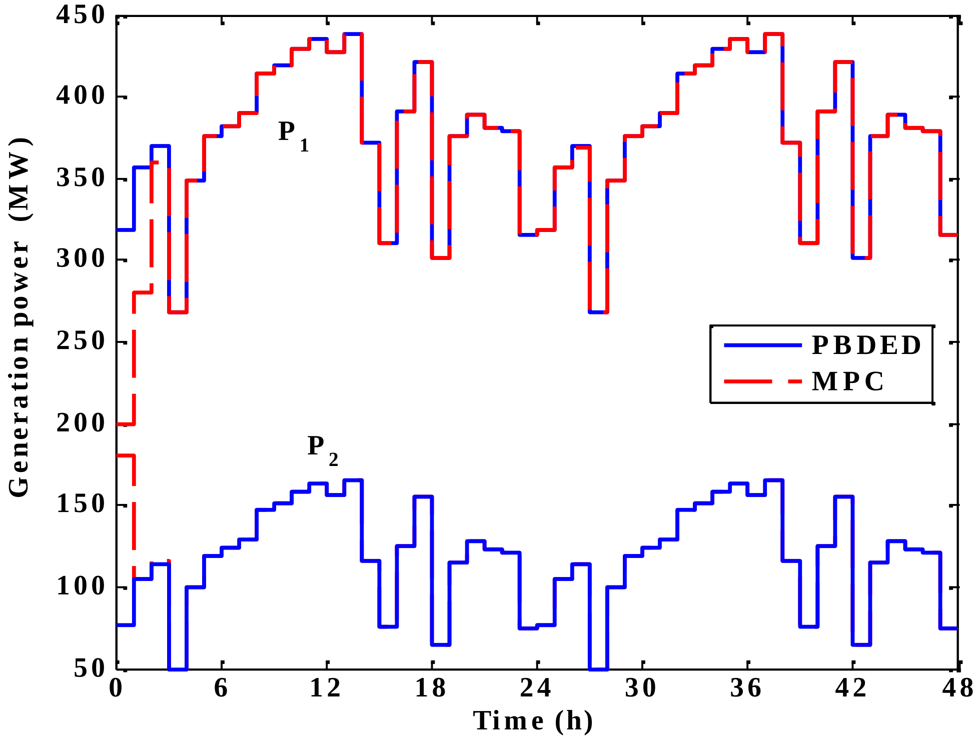

Fig. 2. Convergence of the closed-loop MPC solutions to those of PBDED for price-II.

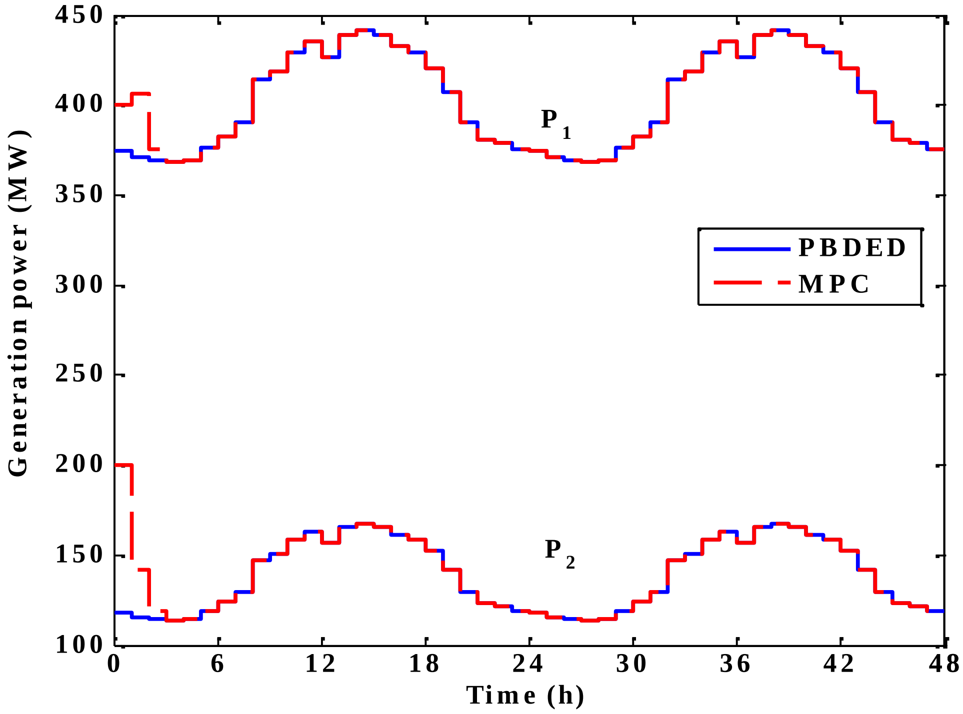

Fig. 3. Convergence of the closed-loop MPC solutions to those of PBDED for price-III.

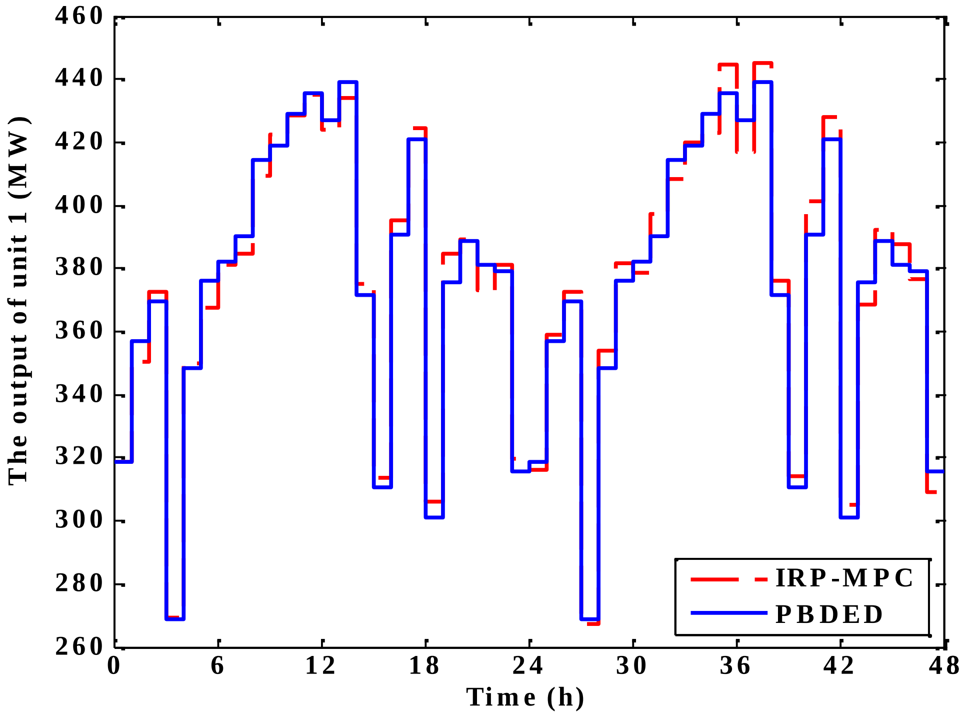

Fig. 4. The generation output of the unit 1 under PBDED and IRP-MPC for price-II.

6. Conclusions:

This paper presents an extension of the work of [11] to include profit-based considerations for operations in a deregulated market. The proposed model predictive control method is tested on a six-unit system with three different energy prices and shown to approach the optimal solutions of the profit-based dynamic economic dispatch. The method is finally tested robustness under disturbance conditions and shown to keep the disturbed system about the optimal solutions.

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