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Distributed Model Predictive Control for Hybrid Energy Resource System With Large-Scale Decomposition Coordination Approach

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ABSTRACT Due to the large-scale and distributed characteristics of increasing renewable energy resources, dynamic economic emission dispatch (DEED) of hybrid energy resource system becomes more and more important in the power system operation. This paper proposes a distributed model predictive control (DMPC) method for hybrid energy resources system of dynamic economic optimal dispatch with large-scale decomposition coordination approach. First, the DEED model of hybrid energy resources is converted into predictive control model, which can provide rolling optimization mechanism for dealing with intermittent energy resources optimization. Second, predictive control model is decomposed into several subsystems with Lagrangian multipliers for coordinating those subsystems, which can greatly decrease the computational complexity. Third, due to the randomness or uncertainty of intermittent power generation, model predictive control can dynamically optimize random or uncertainty problem with rolling optimization mechanism. Furthermore, adaptive dynamic programming is utilized to solve those subsystem optimization problems, which can optimize the random or uncertain problem in real-time condition. In the optimization process, probability constraint is converted into deterministic constraint with its probability density function, and system load balance can be properly handled with coupled coarse-fine constraint-handling technique. According to the obtained results in the case studies, the proposed DMPC can optimize the DEED of hybrid energy resources well combining with the large-scale decomposition-coordination approach, while greatly decreasing the optimization complexity and computation time, which reveals that the proposed method can provide an alternative way for solving the DEED problem of hybrid energy resources.

INDEX TERMS Renewable energy resources, dynamic economic emission dispatch, model predictive control, large-scale decomposition-coordination.

I. INTRODUCTION

Dynamic economic dispatch (DED) plays an important role in power system operation, which mainly optimizes the outputs of those generator units with satisfying the predicted load demands in the incoming time periods. In comparison to economic dispatch (ED), DED takes the ramp rate limits of generator units between time intervals, which makes DED a more accurate formulation of economic dispatch problem in the face of more difficult optimization challenges [1]. Generally, DED takes the economic factor as its only objective in the problem formulation, and many efficient methods are proposed to properly solve the DED problem. Some intelligent algorithms are proposed to solve those dynamic economic problems, such as interior point method [2], quadratic programming [3], neural network [4], genetic algorithm [5], particle swarm optimization (PSO) [6], [7] and differential evolution (DE) [8].

With the increase concern about environmental problem, the clean air act amendments ordered the electricity utility industry to modify their operational strategies to reduce the emission pollutants by power generations [9]. Though the installation for reducing clean equipment can reduce the emission pollutants, it is still a long-term option. In the short-term view, an efficient way is that emission and cost are both to be minimized, which also promotes the DED problem to extend to the dynamic economic emission dispatch (DEED) problem. Then, several weighted and constrained methods are proposed to solve this DEED problem, generally DEED is converted into single objective optimization problem. In literature [10], only the economic objective is optimized while treating the emission as a constraint. In literature [11]–[13], economic objective and emission objective are weighted to convert the DEED into the single objective optimization problem.

Actually, to reduce the emission pollutant of thermal units, the wind and solar power have been taken into considerations as potential renewable energy sources especially when economic and environmental apprehensions are rapidly increasing in those thermal power generations. However, numerous challenges need to be overcome to integrate wind and solar power into the thermal power systems, the power generation process depend on the climate situations [14]–[20]. Furthermore, wind and solar energy source have small power generation capacity, large scale of wind and solar energy sources are needed to meet the load demand requirements [21], [22]. Therefore, the uncertainty, dynamic and high-dimension characteristics need to be considered in the whole optimal model, which brings great challenge in the optimization process [23], [24].

In the past few years, some methods have been proposed to solve the economic emission problem with incorporating renewable power generations [25]–[34]. In literature [26], a model predictive control-based MPPT and model predictive control-based droop current regulator is proposed to interface PV in smart dc distribution systems. Literature [30] presents a dynamic discrete-time piecewise affine (PWA) model of a wind turbine for the optimal active power control of a wind farm. In literature [33], a market-oriented energy management system (EMS) for a hybrid power system composed of a wind energy conversion system and a battery energy storage system is presented with a real-time MPC system.

This paper proposes a distributed model predictive control (DMPC) method to solve the dynamic economic emission dispatch problem of hybrid energy resource system. The proposed DMPC mainly has three main procedures: (1) It converts DEED model of hybrid energy resources into predictive control model, which can deal with stochastic or uncertain characteristics of intermittent energy resources with real-time correction mechanism; (2) In comparison to conventional DMPC, it decomposes above predictive control model into several subsystems with large-scale decomposition coordination method, which coordinates each subsystem with Lagrangian operator, this procedure can decrease the computational complexity of total predictive control model; (3) It utilizes ADP to solve each subsystem model problem with its real-time optimization mechanism, which can satisfy its requirement of rolling optimization. Furthermore, the obtained results of two test systems prove the efficiency of proposed DMPC for solving DEED problem of hybrid energy resources.

II. PROBLEM FORMULATION

The hybrid energy system is mainly consisted of three different energy resources: wind turbines, solar panels and thermal units. To ensure the economic efficiency, environmental conservation and cost of BESS in the hybrid energy resource system, the power balance, output constraint, ramp rate limits and BESS charging limits are taken into consideration, and the joint optimal model of multiple energy resources can be properly created [35].

A. OBJECTIVE FUNCTIONS

1) POWER GENERATION COST

$$\begin{aligned} f_1 = \min\{\sum_{t=1}^{T}[\sum_{i=1}^{N_w}(a_{wi}x_{wit}^2 + b_{wi}x_{wit} + c_{wi}) \\ + \sum_{j=1}^{N_p}(a_{pj}x_{pjt}^2 + b_{pj}x_{pjt} + c_{pj}) \\ + \sum_{m=1}^{N_c}(a_{cm}x_{cmt}^2 + b_{cm}x_{cmt} + c_{cm})]\} \end{aligned} \tag{1}$$

Where T is the length of whole time period, x_{wit}, x_{pjt}, x_{cmt} are the wind power output, photovoltaic power output and thermal output at the t-th time period, N_w, N_p, N_c are the number of wind turbines, solar panels and thermal units, and $a_{wi}, b_{wi}, c_{wi}, a_{pj}, b_{pj}, c_{pj}, a_{cm}, b_{cm}, c_{cm}$ are the cost coefficients of wind turbines, solar panels and thermal units.

2) POLLUTANT EMISSION

Since more and more concerns have been taken over the environmental problem, society demand requires not only adequate and secure electricity at cheapest price, but also at minimum level of pollutant emission. The pollutant emission is mainly discharged by thermal units, the major effect of pollutant emission is composed of nitric oxide and sulfur oxide, and only nitric oxide can be considered from the viewpoint of environmental conservation. Generally, emission amount can be formulated with function of thermal output, which is expressed as the summation of a quadratic function and an exponential function.

$$\begin{aligned} f_2 = \sum_{t=1}^{T}\sum_{m=1}^{N_c}[\alpha_{cm} + \beta_{cm} * x_{cmt} + \gamma_{cm} * x_{cmt}^2 \\ + \eta_{cm} * \exp(\delta_{cm} * x_{cmt})] \end{aligned} \tag{2}$$

Where $\alpha_{cm}, \beta_{cm}, \gamma_{cm}, \eta_{cm}, \delta_{cm}$ are the coefficients of emission rate in each thermal unit.

3) OPERATION COST OF BATTERY ENERGY STORAGE SYSTEM (BESS)

Since large-scale intermittent power generators are integrated, BESS is needed to keep the stability of power system.

The charging and discharging operation will bring operation cost to power system, it can be generally described as follows:

$$f_3 = \sum_{d=1}^{N_B}\sum_{t=1}^{T}(\prod_{d,t} \cdot \left|P_{d,t}^B\right|) \tag{3}$$

Where N_B is the number of batteries, $\prod_{d,t}$ is the coefficient of operation cost at the dth battery at the t-th time period, which also means operation cost ($) per each KWh, $\left|P_{d,t}^B\right|$ is the discharging output or charging output at the dth battery at the t-th time period.

B. CONSTRAINTS

(1) System load balance limits

System load balance is a crucial constraint limit in the DED problem, it ensures that load demand can be properly satisfied in each time period. In hybrid energy system, the output of all power generators and BESS are provided to meet the load demand, which also connects different power generators together.

$$\sum_{i=1}^{N_w} x_{wit} + \sum_{j=1}^{N_p} x_{pjt} + \sum_{m=1}^{N_c} x_{cmt} + \sum_{d=1}^{N_B} P_{d,t}^B = L_t + P_{loss,t} \tag{4}$$

Where L_t is the system load at the t-th time period, $P_{loss,t}$ is the transmission loss at the t-th time period. The transmission loss is mainly related to the thermal units, and it can be expressed in quadratic form of thermal output, which can be formulated as:

$$P_{Loss,t} = \sum_{m_1=1}^{N_c}\sum_{m_2=1}^{N_c} x_{cm_1t}B_{m_1m_2}x_{cm_2t} + \sum_{m_1=1}^{N_c} B_{0m_1}x_{cm_1t} + B_{00} \tag{5}$$

Where $B_{m_1m_2}$, B_{0m_1}, B_{00} are the coefficients of transmission loss at each thermal unit.

1) THE OUTPUT LIMITS

Since power generation of renewable energy has strong random characteristics, it is difficult to formulate the constraint limits of intermittent power generation in the deterministic way, constraint limits of wind and solar power output can be described with probability characteristics. The output limits of wind turbine, solar panel and thermal unit are described as follows:

$$\begin{cases} \Pr ob(P_{wi\min} \le x_{wit} \le P_{wi\max}) \ge \rho, & i = 1, 2, \ldots, N_w \\ \Pr ob(P_{pj\min} \le x_{pjt} \le P_{pj\max}) \ge \rho, & j = 1, 2, \ldots, N_p \\ P_{cm\min} \le x_{cmt} \le P_{cm\max}, & m = 1, 2, \ldots, N_c \end{cases} \tag{6}$$

Where $P_{wi\min}, P_{pj\min}, P_{cm\min}$ represent the minimum output of the i-th wind turbine, the j-th solar panel and the m-th thermal unit. $P_{wi\max}, P_{pj\max}, P_{cm\max}$ represent the minimum output of the i-th wind turbine, the j-th solar panel and the m-th thermal unit, $\Pr ob(\cdot)$ is the probability function, $\rho \in [0.5, 1)$.

2) RAMP RATE LIMITS

Since adjustment ability of each power generator has a certain limit, the deviation of output between current time period and next time period is limited, which also means that the allowed up-ramp rate and down-ramp rate must be controlled in certain feasible domain. The allowed ramp rate of each energy resource can be described as follows:

$$\begin{cases} Z_{wi\min} \le x_{wi,t+1} - x_{wit} \le Z_{wi\max}, & i = 1, 2, \ldots, N_w \\ Z_{pj\min} \le x_{pj,t+1} - x_{pjt} \le Z_{pj\max}, & j = 1, 2, \ldots, N_p \\ Z_{cm\min} \le x_{cm,t+1} - x_{cmt} \le Z_{cm\max}, & m = 1, 2, \ldots, N_c \end{cases} \tag{7}$$

Where $Z_{wi\min}, Z_{pj\min}, Z_{cm\min}$ are the minimum ramp rate of the i-th wind turbine, the j-th solar panel and the m-th thermal unit. $Z_{wimax}, Z_{pj\max}, Z_{cm\max}$ are the maximum ramp rate of the i-th wind turbine, the j-th solar panel and the m-th thermal unit.

3) CONSTRAINT LIMITS OF (BESS)

Due to the fixed storage of batteries, the discharging and charging output must satisfy storage limits, which is presented as follows [27]:

$$\begin{cases} V_{i,t+1}^B = V_{i,t}^B + \eta_i P_{i,t}^B * \Delta t \\ V_{i,\min}^B \le V_{i,t}^B \le V_{i,\max}^B \\ P_{i,t}^B = P_{i,t}^{dis}, \quad if\ P_{i,t}^B \ge 0 \\ P_{i,t}^B = -P_{i,t}^{cha}, \quad if\ P_{i,t}^B < 0 \\ 0 \le P_{i,t}^{dis} \le P_{i,\max}^{dis} \\ 0 \le P_{i,t}^{cha} \le P_{i,\max}^{cha} \end{cases} \tag{8}$$

Where $P_{i,t}^{dis}$, $P_{i,t}^{cha}$ are the output of discharging and charging state, $P_{i,\max}^{dis}$, $P_{i,\max}^{cha}$ are the maximum discharging and charging output in the ith battery at tth time period. The state of charge (SOC) is also taken into consideration, $V_{i,t}^B$ is the storage of the ith battery at tth time period, $V_{i,\min}^B$, $V_{i,\max}^B$ are the minimum and maximum storage of the ith battery, $\eta_i \in (0, 1]$ represents the efficiency of SOC.

III. THE PRINCIPLES OF MODEL PREDICTIVE CONTROL METHOD

The model predictive control (MPC) is a popular optimization approach for those constrained systems by its optimizing the future plant behavior with explicit prediction model, it mainly contains the discrete-time system and continuous-time system. In the practical application, the discrete-time system is often used for rolling optimization, the linear discrete model for model predictive control can be generally described as follows [36]:

$$\begin{cases} J(y(k)) = \sum_{j=1}^{N}(\Delta y^T(k+q|k)Q_{\Delta u}\Delta y(k+q|k) \\ \qquad + y^T(k+q|k)Q_u y(k+q|k)) \\ x(k+1) = Ax(k) + Bu(k) \\ y(k) = Du(k) + G \\ Cu(k) + E \ge 0 \end{cases} \tag{9}$$

And $J(\cdot)$ is the performance index function, which controls the optimal process in a stable way, $y(k)$, $u(k)$ are presented as:

$$\begin{cases} y(k) = [y^T(k+1|k), y^T(k+2|k), \cdots, y^T \\ \qquad \times (k+1+q|k), \cdots, y^T(k+N|k)]^T \\ u(k) = [u^T(k|k), u^T(k+1|k), \cdots, u^T \\ \qquad \times (k+q+1, k), \cdots, u^T(k+N|k)]^T \end{cases} \tag{10}$$

Where N is the prediction length, $y(q|k)$, $u(q|k)$ are the predictive value of output variable and controlled variable at k-th step in the $q+1$-th control period, A, B, C, D, E, G are the parametric matrixes and vectors.

Generally, the control variable needs to satisfy the following constraints:

$$\begin{cases} u_{\min} \le u(q|k) \le u_{\max} \\ \Delta u_{\min} \le \Delta u(q|k) \le \Delta u_{\max} \\ \Delta u(q|k) = u(q|k) - u(q-1|k) \end{cases} \tag{11}$$

Where $u_{\min}$, $u_{\max}$ are the minimum and maximum limits of control variables, $\Delta u_{\min}$, $\Delta u_{\max}$ are the minimum and maximum limits of the deviations between two time periods.

In the real-time optimization process, the predictions depend on the system model $x(k+1) = F(x(k), u(k))$, and the performance index measures the difference between the predictive behavior and desirable behavior of discrete system. The variables $x(k+q|k)$ and $u(k+q|k)$ represent the predictive state and predictive control at the $k+q$-th time period based on the information at the k-th time period, $u(k+q|k) = u(k)$ especially when $q = 0$, then the next control action needs to be found by repeating the above process.

IV. THE IMPLEMENTATION OF THE PROPOSED DISTRIBUTED MODEL PREDICTIVE CONTROL BASED VIRTUAL POWER PLANT ECONOMIC OPTIMAL METHOD

On the basis of MPC presented in section III, the proposed DMPC includes three procedures: (1) Converting economic optimal model of hybrid energy resource into predictive control model; (2) Decomposing the predictive model into several subsystem models with Large-scale decomposition coordination method; (3) Solving the subsystem problems with adaptive dynamic programming. The details of each procedure has been presented in following sections.

A. THE PREDICTIVE MODEL OF DYNAMIC ECONOMIC EMISSION DISPATCH MODEL

For properly tackling with stochastic or uncertain characteristics of intermittent energy resources, predictive control model can be a good choice for its rolling optimization and real-time correction mechanism. Therefore, it is necessary to convert DEED model into predictive control model, and this section mainly takes the measurement of increment cost method. According to objective functions introduced in the section II-A, the emission pollutant merely depends on the thermal units, it can be controlled well by properly allocating the output of thermal units. Here, the incremental cost of power generation cost at energy resource is utilized to convert the DEED model into the predictive control model.

It is assumed that $f = f_1 + f_2$, the increment cost of power generation can be calculated ($\delta_{cm} = 0$) as follows:

$$\begin{cases} \dfrac{\partial f}{\partial x_{wit}} = 2a_{wi}x_{wit} + b_{wi} = u_{wit} \\ \dfrac{\partial f}{\partial x_{pjt}} = 2a_{pj}x_{pjt} + b_{pj} = u_{pjt} \\ \dfrac{\partial f}{\partial x_{cmt}} = 2a'_{cm}x_{cmt} + b'_{cm} = u_{cmt} \\ u(q|k) = [u_{wik}, u_{pjk}, u_{cmk}], \quad k \le q \le k+N \\ a'_{cm} = a_{cm} + \gamma_{cm} \\ b'_{cm} = \beta_{cm} + b_{cm} \end{cases} \tag{12}$$

The optimal incremental cost of each energy resource needs to be obtained, it can be labeled as $u_k^* = [u_{wk}^*, u_{pk}^*, u_{ck}^*]$. The predictive model can be created according to the predictive control model introduced in section III.

With the incremental cost criterion, it needs to follow [37]:

$$\begin{cases} u_k = u_k^*, & u_k \in \Omega \\ u_k \le u_k^*, & u_k = \bar{\Omega} \\ u_k \ge u_k^*, & u_k = \underline{\Omega} \end{cases} \tag{13}$$

The limits of control rate can be obtained with the output limits:

$$\begin{cases} 2a_w P'_{wi\min} + b_w \le u_{wik} \le 2a_w P'_{wi\max} + b_w \\ 2a_p P'_{pj\min} + b_p \le u_{pjk} \le 2a_p P'_{pj\max} + b_p \\ 2a'_c P_{cm\min} + b'_c \le u_{cmk} \le 2a'_c P_{cm\max} + b'_c \end{cases} \tag{14}$$

Since generation process of wind power and solar power has strong randomness, those uncertainty constraints in formula (6) need to be converted into certainty constraints, the details of converting process is presented in section IV-D3, $P'_{wi\min}$, $P'_{wi\max}$, $P'_{pj\min}$, $P'_{pj\max}$ are those obtained maximum, minimum output.

The change of control variable needs to satisfy the corresponding limits:

$$\begin{cases} 2a_w Z_{wi\min} \le \Delta u_{wik} \le 2a_w Z_{wi\max} \\ 2a_p Z_{pj\min} \le \Delta u_{pjk} \le 2a_p Z_{pj\max} \\ 2a'_c Z_{cm\min} \le \Delta u_{cmk} \le 2a'_c Z_{cm\max} \end{cases} \tag{15}$$

The power balance limits in formula (4) can be converted as:

$$\begin{cases} \dfrac{1}{2a_w}\sum_{i=1}^{N_w} u_{wik} + \dfrac{1}{2a_p}\sum_{j=1}^{N_p} u_{pjk} + \dfrac{1}{2a'_c}\sum_{m=1}^{N_c} u_{cmk} + \sum_{d=1}^{N_B} P_{d,t}^B \\ = L_t + P_{loss,t} + M \\ M = \dfrac{b_w}{2a_w}N_w + \dfrac{b_p}{2a_p}N_p + \dfrac{b'_c}{2a'_c}N_c \end{cases} \tag{16}$$

B. THE DECOMPOSITION OF MPC

According to the above analysis, the key to solve the dynamic optimal dispatch problem is to discover the common optimal incremental cost, which means that the differences of the incremental cost between these generator units need to be minimized.

The performance index function can be deduced with the Lagrangian operator as follows:

$$J_L(u(k)) = J(y(k)) + \lambda_k(\frac{1}{2a_w}\sum_{i=1}^{N_w} u_{wik} + \frac{1}{2a_p}\sum_{j=1}^{N_p} u_{pjk} + \frac{1}{2a'_c}\sum_{m=1}^{N_c} u_{cmk} + \sum_{d=1}^{N_B} P^B_{d,t} - L_t - M) \quad (17)$$

According to the large system decomposition-coordination theory, the main performance index function can be presented as the summation of several functions as follows:

$$\min(J_L(u(k))) = \min(J_{L,w}(u_{wk})) + \min(J_{L,p}(u_{pk})) + \min(J_{L,c}(u_{ck})) \quad (18)$$

Where $J_{L,w}(\cdot)$, $J_{L,p}(\cdot)$, $J_{L,c}(\cdot)$ are the performance index functions of the subsystems of wind power generation, photovoltaic power generation and thermal power generation, these subsystems can be described as follows:

1) THE SUBSYSTEM OF WIND POWER GENERATION

$$\begin{cases} \min J_{L,w}(u_{wik}) \\ y_{wi}(k) = D_{wi}u_{wik} + G_{wi} \\ x_{wi,k+1} = A_{wi}x_{wi,k} + u_{wik} \\ 2a_{wi}P'_{wi\min} + b_{wi} \le u_{wik} \le 2a_{wi}P'_{wi\max} + b_{wi} \\ 2a_{wi}Z_{wi\min} \le \Delta u_{wik} \le 2a_{wi}Z_{wi\max} \end{cases} \quad (19)$$

2) THE SUBSYSTEM OF PHOTOVOLTAIC POWER GENERATION

$$\begin{cases} \min J_{L,w}(u_{pjk}) \\ y_{pj}(k) = D_{pj}u_{pjk} + G_{pj} \\ x_{pj,k+1} = A_{pj}x_{pjk} + u_{pjk} \\ 2a_{pj}P'_{pj\min} + b_{pj} \le u_{pjk} \le 2a_{pj}P'_{pj\max} + b_{pj} \\ 2a_{p}Z_{pj\min} \le \Delta u_{pjk} \le 2a_{pj}Z_{pj\max} \end{cases} \quad (20)$$

3) THE SUBSYSTEM OF THERMAL POWER GENERATION

$$\begin{cases} \min J_{L,w}(u_{cmk}) \\ y_{cm}(k) = D_{cm}u_{cmk} + G_{cm} \\ x_{cm,k+1} = A_{cm}x_{cm,k} + u_{cmk} \\ 2a'_{cm}P_{cm\min} + b'_{cm} \le u_{cmk} \le 2a'_{cm}P_{cm\max} + b'_{cm} \\ 2a'_{cm}Z_{cm\min} \le \Delta u_{cmk} \le 2a'_{cm}Z_{cm\max} \end{cases} \quad (21)$$

The economic optimal dispatch problem is converted into several predictive control problem, where the robust characteristics can also be guaranteed in the optimization process.

C. ADAPTIVE DYNAMIC PROGRAMMING FOR OPTIMIZING SUBSYSTEM

The ADP is taken as an optimization tool in this manuscript, each divided subsystem is optimized with ADP under the MPC mechanism. The MPC can provide possible states of power generators especially intermittent power generations in next few periods, and ADP is utilized to optimize the DEED in these periods. Since MPC has a typical rolling optimization mechanism, this rolling mechanism requires optimization method optimize in real-time way. Hence, ADP can be a good choice as a real-time optimization method. The adaptive dynamic programming proposed by Werbos can adaptively find the optimal solution for forward-in-time due to its strong ability of self-learning mechanism. On the basis of dynamic programming (DP), ADP has three networks: control network, model network and critic network. Here, the heuristic dynamic programming is utilized to solve the above subsystem obtained in section IV-B, its working principle is shown in Fig. 1 as follows [38]:

The value of cost function $J(x(k))$ is produced from the critic network, action network reflects the relationship between the state variable $x(k)$ and control input $u(k)$, and model network estimates the state of system $x(k+1)$ in the next time period. In the discrete nonlinear system, the cost function of interacted system can be presented as follows:

$$\begin{aligned} \min_u\ J &= \theta[x(T), T] + \sum_{k=1}^{T-1} \Phi[x(k), u(k), k] \\ \text{s.t. } x(k+1) &= f(x(k), u(k), k) \\ x(k) &= x_k,\ x(T) = x_T \end{aligned} \quad (22)$$

It can be concluded that the minimum cost function value in system state $x(k)$ is obtained in formula (23).

$$J^*[x(k), k] = \min_{u(k),u(k+1),\cdots,u(T-1)} \{\theta[x(T), T] + \sum_{k=1}^{T-1} \Phi[x(k), u(k), k]\} \quad (23)$$

With consideration of the discount factor, the Bellman recurrence equation can be also presented:

$$J^*[x(k), k] = \min_{u(k)}\{\Phi[x(k), u(k), k] + \gamma J^*[x(k+1), k+1]\} \quad (24)$$

Where $\Phi[\bullet]$ is the utility function, γ is the discount factor. The optimization process takes the iteration in formula (24) to approximate the optimal value from the state variable $x(T)$ to $x(0)$. According to above ADP approach, each dynamic subsystem model can be established as follows:

1) WIND POWER SUBSYSTEM

$$\begin{cases} \min \sum_{k=1}^{T} J_{L,w}(u_{wk}) = \min \sum_{k=1}^{T-1} J_{L,w}(u_{wk}) + J_{L,w}(u_{wT}) \\ y_{wi}(k) = D_{wi}u_{wik} + G_{wi} \\ x_{wi,k+1} = A_{wi}x_{wi,k} + u_{wk} \\ \frac{1}{2a_w}\sum_{i=1}^{N_w} u_{wik} + \frac{1}{2a_p}\sum_{j=1}^{N_p} u_{pjk} + \frac{1}{2a'_c}\sum_{m=1}^{N_c} u_{cmk} + \sum_{d=1}^{N_B} P_{d,t}^B \\ = L_t + P_{loss,t} + M \\ 2a_w P'_{wi\min} + b_w \le u_{wik} \le 2a_w P'_{wi\max} + b_w \\ 2a_w Z_{wi\min} \le \Delta u_{wik} \le 2a_w Z_{wi\max} \end{cases} \tag{25}$$

2) PHOTOVOLATIC POWER SUBSYSTEM

$$\begin{cases} \min \sum_{k=1}^{T} J_{L,p}(u_{pk}) = \min \sum_{k=1}^{T-1} J_{L,p}(u_{pk}) + J_{L,p}(u_{pT}) \\ y_{pj}(k) = D_{pj}u_{pjk} + G_{pj} \\ x_{pj,k+1} = A_{pj}x_{pj,k} + u_{pjk} \\ \frac{1}{2a_w}\sum_{i=1}^{N_w} u_{wik} + \frac{1}{2a_p}\sum_{j=1}^{N_p} u_{pjk} + \frac{1}{2a'_c}\sum_{m=1}^{N_c} u_{cmk} + \sum_{d=1}^{N_B} P_{d,t}^B \\ = L_t + P_{loss,t} + M \\ 2a_{pj} P'_{pj\min} + b_{pj} \le u_{pjk} \le 2a_{pj} P'_{pj\max} + b_{pj} \\ 2a_{pj} Z_{pj\min} \le \Delta u_{pjk} \le 2a_{pj} Z_{pj\max} \end{cases} \tag{26}$$

3) THERMAL POWER SUBSYSTEM

$$\begin{cases} \min \sum_{k=1}^{T} J_{L,c}(u_{cmk}) = \min \sum_{k=1}^{T-1} J_{L,c}(u_{cm}) + J_{L,c}(u_{cT}) \\ y_{cm}(k) = D_{cm}u_{cmk} + G_{cm} \\ x_{cm,k+1} = A_{cm}x_{cm,k} + u_{cmk} \\ \frac{1}{2a_w}\sum_{i=1}^{N_w} u_{wik} + \frac{1}{2a_p}\sum_{j=1}^{N_p} u_{pjk} + \frac{1}{2a'_c}\sum_{m=1}^{N_c} u_{cmk} + \sum_{d=1}^{N_B} P_{d,t}^B \\ = L_t + P_{loss,t} + M \\ 2a_{cm} P'_{cm\min} + b_{cm} \le u_{cmk} \le 2a_{cm} P'_{cm\max} + b_{cm} \\ 2a_{cm} Z_{cm\min} \le \Delta u_{cmk} \le 2a_{cm} Z_{cm\max} \end{cases} \tag{27}$$

During the real-time optimization process, initial state of each subsystem is known, terminate state is in the range of feasible region, which is also known. In above subsystem models, optimal scheme can be calculated according to Bellman recurrence equation on the objective function.

D. CONSTRAINT HANDLING METHOD

Since dynamic economic optimal dispatch is often presented as a nonlinear, complex-constrained problem, the constraint handling efficiency can affect the optimization results directly.

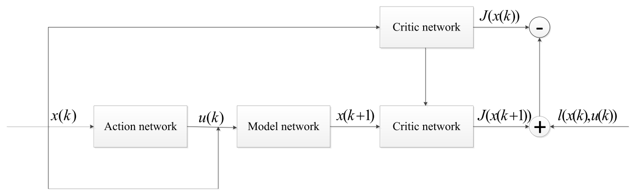

FIGURE 1. The framework of heuristic dynamic programming.

1) FEASIBLE DOMAIN OF DECISION VARIABLE

Since the decision variables can not avoid violating those constraint limits during the optimization process, these variables are forced into the feasible domain by formulation (28) as follows:

$$x'_i = \begin{cases} \min_i, & if\ x_i < \min_i \\ x_i, & if\ \min_i \le x_i \le \max_i \\ \max_i, & if\ x_i > \max_i \end{cases} \tag{28}$$

2) INITIALIZATION OF DECISION VARIABLES

Since the ramp rate constraint of each energy resource is considered, the maximum and minimum output of each time period can't be easily described by formula (7). For each time period, the feasible interval can be modified as follows:

$$[x_{i,t,\min}, x_{i,t,\max}] = [x_{i,\min}, x_{i,\max}] \cap [x_{i,t-1} - DR_i, x_{i,t-1} + UR_i] \tag{29}$$

Where $x_{i,t,\min}$, $x_{i,t,\max}$ are the minimum and maximum bounds of output of i-th energy resource at t-th time period, DR_i, UR_i are the up-ramp and down-ramp limits of those different energy resources.

3) THE PROBABILITY CONSTRAINT HANDLING TECHNIQUE

Since the wind power generation process is random, dynamic economic optimal dispatch model can be taken as the stochastic model, which brings great challenge for solving this problem. Thus, dynamic economic optimal model needs to be converted to the deterministic model with the probability density function, the probability constraint can be properly handled as follows:

Firstly, the value of wind output needs to be normalized with $\eta_{it} = x_{wit}/x_{wi\max}$, it assumes that η_{it} follows the Beta distribution [39], and its probability density function is described as:

$$f(\eta_{it}) = \frac{1}{B(\alpha_t, \beta_t)}\eta_{it}^{\alpha_t - 1}(1-\eta_{it})^{\beta_t - 1}, \quad 0 \le \eta_{it} \le 1 \tag{30}$$

Then its distribution function can be obtained:

$$F(\xi_{it}) = \frac{\int_0^{\xi_{it}} \varpi_{it}^{\alpha_t - 1}(1-\varpi_{it})^{\beta_t - 1} d\varpi_{it}}{B(\alpha_t, \beta_t)}, \quad 0 \le \xi_{it} < 1 \tag{31}$$

It equals 0 when $\xi_{it} \le 0$, and equals 1 when $\xi_{it} \ge 1$. The $B(\cdot)$ represents the beta function with its two parameters α_t, β_t. Secondly, combined with method in literature [39], it can obtain that minimum output is smaller than

$x_{wi\max} * F^{-1}(1-\rho)$ and maximum output is larger than $x_{wi\max} * F^{-1}(\rho)$, then the following probability constraint of output limits can ensure the feasibility.:

$$\begin{cases} x_{wi\max} * F^{-1}(1-\rho) \leq x_{wit} \leq x_{wi\max} * F^{-1}(\rho) \\ x_{pj\max} * F^{-1}(1-\rho) \leq x_{pjt} \leq x_{pj\max} * F^{-1}(\rho) \end{cases} \tag{32}$$

4) THE CONSTRAINT HANDLING FOR NONLINEAR POWER BALANCE CONSTRAINT

The power balance constraint plays an important role in the dynamic economic dispatch due to its nonlinear and complex characteristics, and the transmission loss is also taken into consideration, the constraint handling technique for this nonlinear equality constraint has great influence on the efficiency for solving this problem. For reducing BESS cost, BESS is started merely when power balance is not properly satisfied, BESS cost can be controlled into a limited area, in which limited value is very small. Here, let those thermal units equally bear the power balance violation, some measurements are taken in consideration of its nonlinear characteristics:

$$\Omega = \sum_{i=1}^{N_w} x_{wit} + \sum_{j=1}^{N_p} x_{pjt} + \sum_{m=1}^{N_c} x_{cmt} + \sum_{d=1}^{N_B} P_{d,t}^B - L_t - P_{loss,t} \tag{33}$$

Replace $P_{loss,t}$ with formula (4), the balance violation can be described as follows:

$$\Delta\Omega = \sum_{i=1}^{N_c} (1-B_{0i}) \frac{\partial x_{cit}}{\partial x_{cit}} \Delta x_{cit} - 2 \sum_{i=1}^{N_c} \sum_{j=1}^{N_c} \frac{\partial x_{cit}}{\partial x_{cit}} B_{ij} x_{cjt} \Delta x_{cit} \tag{34}$$

Equally adjust the thermal output, which means $\Delta x_{cit} = \Delta x_{cjt} (i \neq j)$, let $m = \Delta x_{cit}$, it obtains:

$$m = \frac{\Delta\Omega}{\sum_{i=1}^{N_c} (1-B_{0i}) - 2 \sum_{i=1}^{N_c} \sum_{j=1}^{N_c} B_{ij} x_{cjt}} \tag{35}$$

Therefore, the nonlinear equality constraint can be adjusted coarsely with the formula (33), and it can be properly handled combined with fine tuning technique in literature [40]. In the assignment of output violation, wind power and photovoltaic power are prior to thermal power, which can cause the fuel cost and emission pollutant, the priority strategy can take full advantages of renewable energy resource, and reduce the emission pollutant and fuel cost of thermal units.

E. THE FLOWCHART OF THE PROPOSED DISTRIBUTED MODEL PREDICTIVE CONTROL METHOD FOR VIRTUAL POWER PLANT DYNAMIC ECONOMIC OPTIMAL DISPATCH

After the dynamic economic optimal dispatch model is created, the model can be converted into the predictive control model with the incremental cost technique. Due to the large scale and nonlinear characteristics of the optimization system, the obtained predictive control model can be divided into several subsystems with each agent for each subsystem by the large scale decomposition-coordination method. Each subsystem is managed in each agent, control command of each subsystem is mainly made in each agent, and all those agents coordinate each other with coordination factors. Then, the adaptive dynamic programming is utilized to solve those subsystem optimization problem, and obtains the final results for the whole dynamic economic optimal dispatch. In addition, stability and convergence of the proposed DMPC can also be properly analyzed. For stability, since performance index function is positive definite quadratic and feasible region is convex, the proposed DMPC satisfies lemma 1 and lemma 2 in literature [41], which can establish the exponential closed-loop stability result. For convergence, Bellman recurrence equation mainly promotes the optimization process, convergence ability has been proved in literature [42], [43]. The whole procedures can be summarized in Figure.2.

V. CASE STUDY

In real world, energy resources mainly include wind power, solar power, hydro power and thermal power, wind power and solar power are typical intermittent energy resources, thermal units have the most stable power generation ability. In this section, the test system mainly consists of several numbers of above three energy resources, test system 1 is consisted of three wind generator, three solar panels and four thermal units, test system 2 is consisted of nine wind generators, nine solar panels and twelve thermal units.

Two test systems are taken to verify the efficiency of the proposed DMPC, the analysis on convergence process and optimization results can be taken in comparison to centralized dynamic programming (CDP), the obtained results of two test systems can reveal that the proposed DMPC can have excellent results while decreasing the computational complexity especially in the large-scale hybrid energy resource system.

A. TEST SYSTEM 1

In this test system, three wind farms, three photovoltaic groups, four thermal units and single BESS compose the hybrid energy resource system, the BESS mainly contains single battery with storage capacity 100MW, and all the data details about different power generators are shown in Table. 1. Since emission pollutant is mainly caused by the thermal units, it needs to take full advantages of these clean energy resources, thermal power is mainly utilized to ensure the system load balance in the hybrid energy resource systems. According to the problem formulation in section II, power generation cost, emission pollutant and transmission loss can be taken as the criterions for verifying the final results, the comparison results are shown in Table. 2. Transmission loss is the summation of transmission loss in the 24 time period, and BESS cost represents total cost of BESS in the whole time period. The obtained results reveal that the

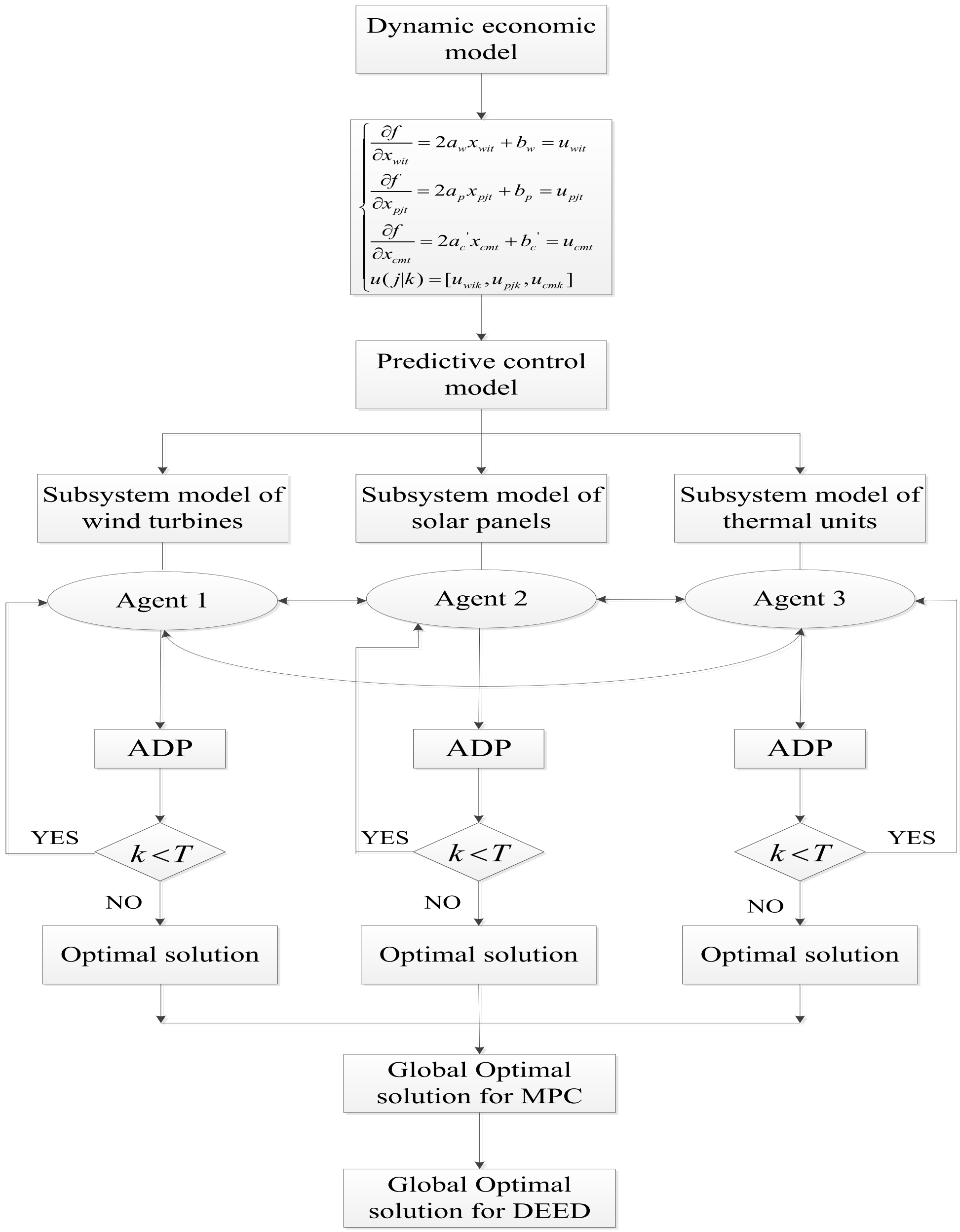

FIGURE 2. The framework of the proposed distributed model predictive control for dynamic economic emission dispatch problem.

TABLE 1. The output limits of hybrid energy resource system.

Limits	P_1	P_2	P_3	W_1	W_2	W_3	C_1	C_2	C_3	C_4
Minimum output (MW)	47	20	10	73	57	20	150	135	73	60
Maximum output (MW)	140	70	75	150	150	138	480	490	480	450
Minimum ramp rate (MW)	30	30	30	50	50	50	80	80	80	80
Maximum ramp rate (MW)	30	30	30	50	50	50	80	80	80	80

proposed DMPC can minimize the power generation cost, emission pollutant and transmission loss simultaneously in shorter period of time.

Further analysis is taken on the convergence process of the proposed DMPC, final results are obtained after 200 iterations, the convergence process of the proposed DMPC on

TABLE 2. The comparison between CDP and the proposed DMPC in test system 1.

Methods	Cost ($)	Emission (lb)	Transmission loss (MW)	BESS cost ($)	Time(s)
CDP	2543331	254570	1305.911	13582	73s
The proposed DMPC	2534045	250787	1304.896	13147	60s

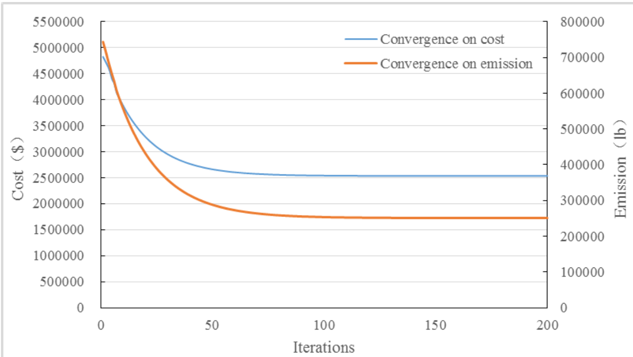

FIGURE 3. The convergence on cost and emission by the proposed DMPC.

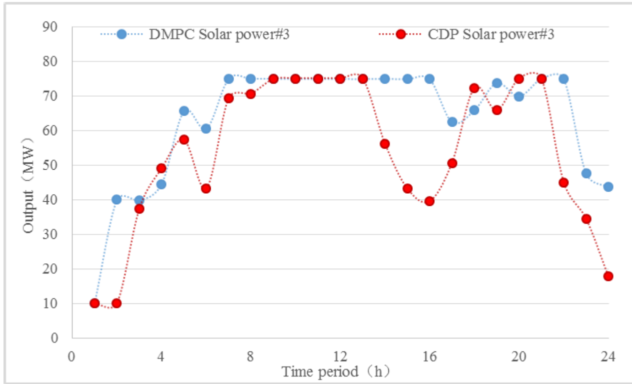

FIGURE 5. The comparison of solar power #3 by proposed DMPC and CDP.

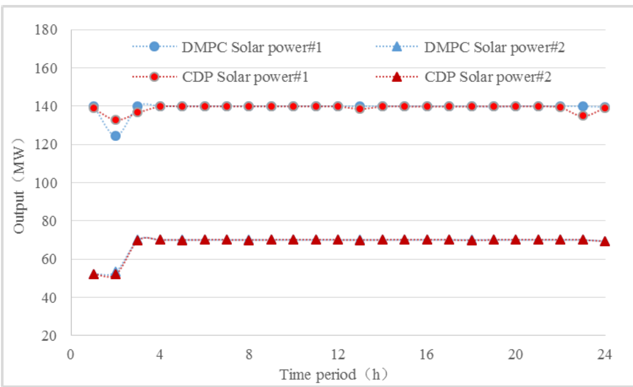

FIGURE 4. The comparison of solar power #1 and solar power #2 by proposed DMPC and CDP.

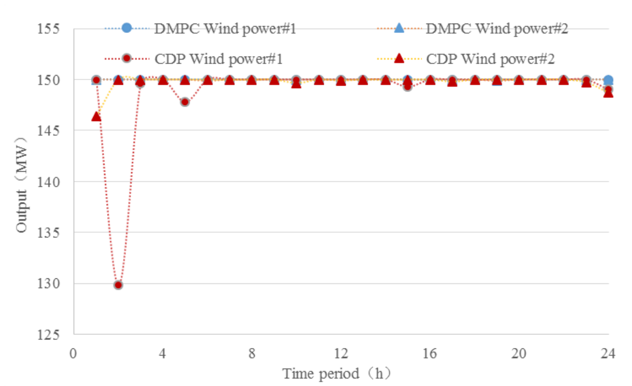

FIGURE 6. The comparison of wind power #1 and wind power #2 by proposed DMPC and CDP.

the power generation cost and emission pollutant are shown in Figure.3, it can be seen that cost converges after about 70 generations while emission converges after about 100 generations. The convergence process of cost and emission is relative stable and converges well near to the optimal scheme. In the obtained optimal scheme, the comparisons between CDP and the proposed DMPC are taken in those hybrid energy resources. In the Figure.4, the output process obtained by CDP and the proposed DMPC have the similar shape, there is not large deviation of solar power output in the solar power#2, while the proposed DMPC has larger output than that of CDP in solar power#1 during the whole time period, which also reveals that solar power #1 can be fully used in the obtained optimal scheme by the proposed DMPC. In the Figure.5, the comparison of output process between CDP and the proposed DMPC are taken in solar power#3, it can be seen that the output obtained by the proposed DMPC is larger than that of CDP in the most time period, solar power#3 has been fully used in the hybrid energy resource system. The wind power plays the similar role with the solar power in the hybrid energy resource system, full use of them can decrease the emission pollutant caused by thermal power. In the Figure.6 and Figure.7, the output process of wind power are shown in the whole time period, it can be seen that the wind power#1 and wind power#2 by the proposed DMPC can be fully used in comparison to that obtained by CDP in the Figure.6. In the Figure.7, it can be seen that the output process of wind power#3 by the proposed DMPC is not obviously larger than that of CDP, the result by DMPC is larger than that of CDP merely in several time periods, which reveals that they both can't play full use of the wind power#3.

Thermal power is different from solar power and wind power, since the emission pollutant is mainly caused by thermal power, satisfactory result needs to maximize the solar

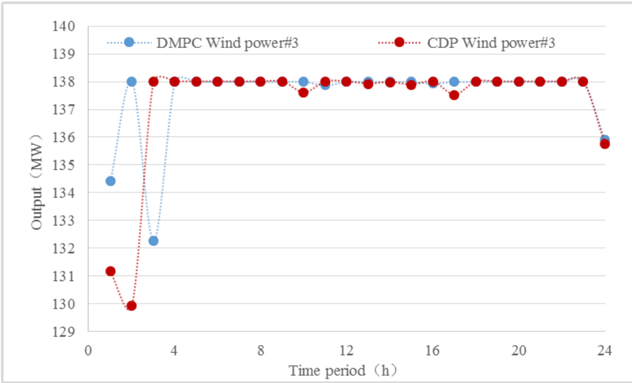

FIGURE 7. The comparison of solar power #3 by proposed DMPC and CDP.

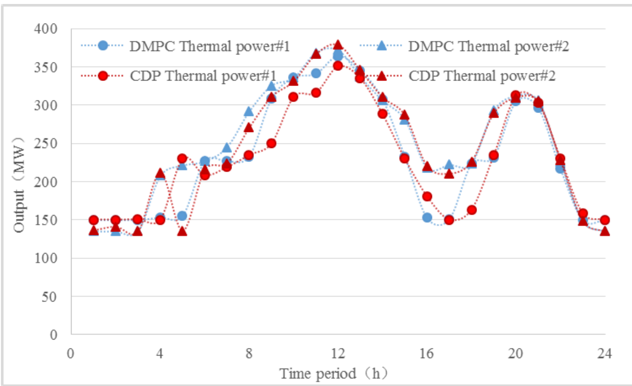

FIGURE 8. The comparison of thermal power #1 and thermal power #2 by proposed DMPC and CDP.

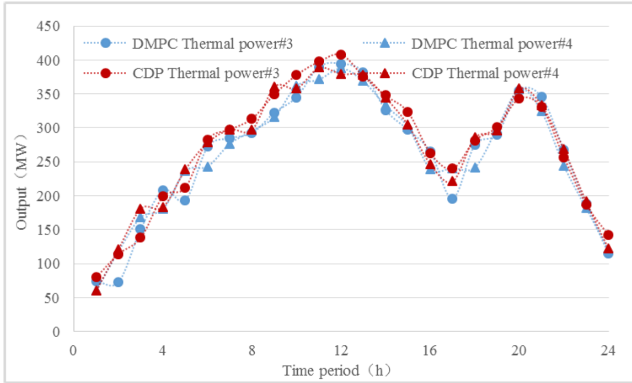

FIGURE 9. The comparison of thermal power #3 and thermal power #4.

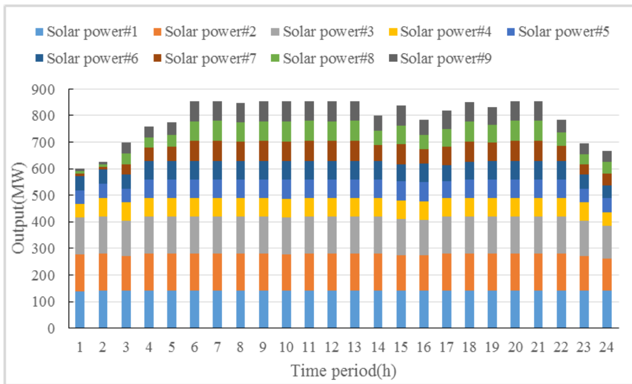

FIGURE 10. The output of all the solar power resources by the proposed DMPC.

power and wind power while minimizing the thermal output during the whole time period. According to the above analysis on results of wind power and solar power, the output of wind power and solar power by the proposed DMPC is larger than that of CDP, those renewable energy resources can be fully used in comparison to CDP. The obtained results are shown in Figure.8 and Figure.9, the results of thermal power#1 and thermal power#2 are presented in Figure.8, and the results of thermal power#3 and thermal power#4 are presented in Figure.9. In the Figure.8, the output of thermal power#1 and thermal power#2 by the proposed DMPC is smaller than that obtained by CDP in most time periods, which can promote to decrease the emission pollutant. In the Figure.9, it can't be clearly seen that the obtained output of thermal power#3 and thermal power#4 by the proposed DMPC are smaller than that of CDP.

However, since the output of solar power and wind power by the proposed DMPC can be more fully used in the whole time period in comparison to that of CDP, and system load at each time period is a certain value, the output of thermal power by DMPC is obviously smaller than that of CDP, which can prove that the proposed DMPC can optimize the dynamic economic emission dispatch problem of hybrid energy resource system well.

B. TEST SYSTEM 2

To verify the decreasing computational complexity of large-scale system in the proposed DMPC, this test system extends to the triple scales of test system 1, the number of each wind power, solar power, thermal power and capacity of BESS enlarges to three times in test system 1, and the data details are the same as it is shown in Table.1. The CDP is also used to take comparison with the proposed DMPC, the obtained results are shown in Table.3. It can be seen that the proposed DMPC can optimize the power generation cost, emission pollutant and BESS cost better with less transmission loss in shorter period of time. In comparison with the obtained results in test system 1, the proposed DMPC has obvious advantages in power generation cost, emission pollutant, transmission loss and time consumption, which can become remarkable as the scale of hybrid energy resources becomes large.

Further analysis is taken on the obtained optimal scheme by the proposed DMPC. The output of all the solar power resources is presented in Figure.10, it can be seen that most solar power resources has maximum output during the whole time period, only the solar power#9 has relative low output at several time periods, the solar power can be fully used in the dynamic economic emission dispatch of hybrid energy resources. The output of all the wind power resources is

TABLE 3. The comparison between CDP and the proposed DMPC in test system 2.

Methods	Cost ($)	Emission (lb)	Transmission loss (MW)	BESS cost ($)	Time(s)
CDP	8416732	831694	42997	4013	275s
The proposed DMPC	8032191	781367	42651	3911	132s

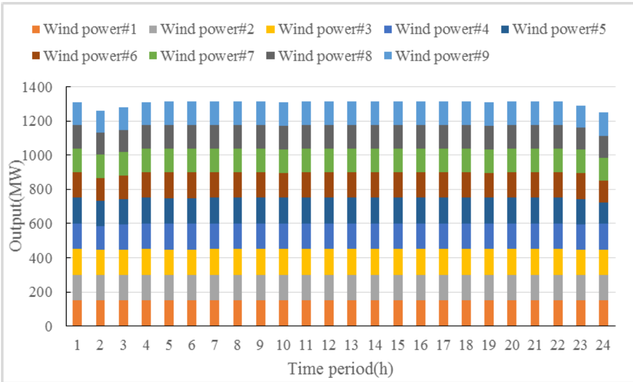

FIGURE 11. The output of all the wind power resources by the proposed DMPC.

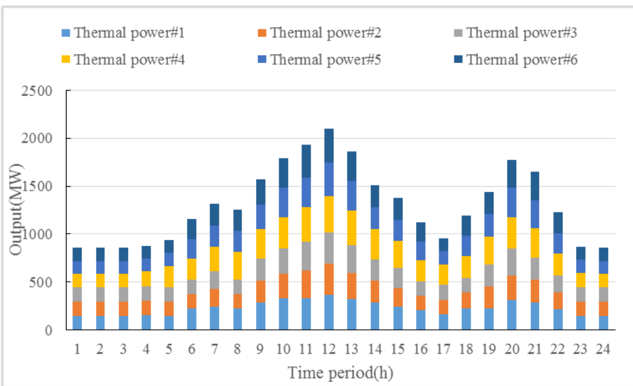

FIGURE 12. The output of the thermal power #1-6 by the proposed DMPC.

presented in Figure.11, it can be seen that the output limits of each wind power at each time period is properly handled, and most of the wind power resources have maximum load operation during the whole time period, which also reveals that wind power has been fully used by the proposed DMPC method. In comparison to solar power and wind power, thermal power is mainly utilized to adjust system load balance while trying to maximize the output of the solar power and wind power. The output of thermal power #1-6 is shown in Figure.12. It is seen that the output of thermal power #1-6 is evenly distributed at each time period, which reveals that the consensus in formula (12) is properly obtained, and they evenly bear the system load at each time period. The output of thermal power #7-12 is similar to that of thermal power #1-6, the system load at each time period is evenly bear by those thermal power resources, as it is shown in Figure.13. It can be seen that the limit of each thermal power at each time period

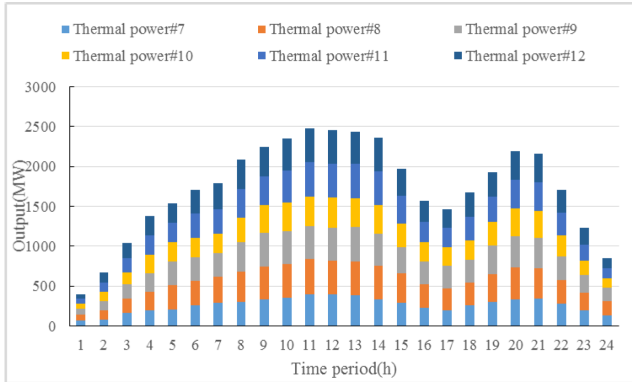

FIGURE 13. The output of the thermal power #7-12 by the proposed DMPC.

is properly satisfied, and the constraint of system load balance has been properly handled at each time period.

According to the above obtained results, it proves that the proposed DMPC can optimize the test system 1 and test system 2 well while satisfying all the constraint limits at each time period. In the test system 1, the proposed DMPC can divide the hybrid energy resource system into three subsystems, and optimizes each subsystem well with properly handling those output limits and system load balance constraints. To verify the optimization efficiency on those large-scale hybrid energy resource system, the scale of test system 2 is extended to triple scale of test system 1, the obtained results have obvious advantages in comparison to CDP both on the results and computational time, computational complexity is obviously decreased especially when hybrid energy resource system has large scale, which reveals that the proposed DMPC can optimize the dynamic economic emission dispatch of hybrid energy resource system well and have remarkable advantages especially when the scale of hybrid energy resource system is large.

VI. CONCLUSION

Due to large-scale and intermittent characteristics of increasing renewable energy resources, the dynamic economic emission dispatch of hybrid energy resources system brings great challenge for energy optimal management. This paper proposes a distributed model predictive control method to optimize hybrid energy resource system with considering BESS. In order to tackle with stochastic or uncertain characteristics of intermittent energy resources, DEED model of hybrid energy resources is converted into predictive control model with incremental cost method. In comparison to conventional

DMPC, the predictive control model is decomposed into three subsystems with large-scale decomposition coordination approach, which decreases the optimization computational complexity. Simultaneously, ADP is utilized to solve each subsystem model problem with its real-time optimization mechanism due to rolling optimization requirement of MPC, and probability constraint handling technique properly handles stochastic constraints in the optimization process. The efficiency of proposed DMPC is also proved by those obtained satisfactory results in two test systems, which also reveals that the proposed DMPC can be a viable way for solving DEED problem of hybrid energy resources.

REFERENCES

[1] Y. Gu and L. Xie, "Stochastic look-ahead economic dispatch with variable generation resources," *IEEE Trans. Power Syst.*, vol. 32, no. 1, pp. 17–29, Jan. 2017.

[2] A. R. Balbo, M. A. da Silva Souza, E. C. Baptista, and L. Nepomuceno, "Predictor-corrector primal-dual interior point method for solving economic dispatch problems: A post optimization analysis," *Math. Problem Eng.*, vol. 2012, Apr. 2012, Art. no. 376546.

[3] M. J. Morshed and A. Asgharpour, "Hybrid imperialist competitive-sequential quadratic programming (HIC-SQP) algorithm for solving economic load dispatch with incorporating stochastic wind power: A comparative study on heuristic optimization techniques," *Energy Convers. Manage.*, vol. 84, pp. 30–40, Aug. 2014.

[4] T. Ganesan, P. Vasant, and I. Elamvazuthi, "Hopfield neural networks approach for design optimization of hybrid power systems with multiple renewable energy sources in a fuzzy environment," *J. Intell. Fuzzy Syst.*, vol. 26, no. 5, pp. 2143–2154, 2014.

[5] J.-C. Lee, W.-M. Lin, G.-C. Liao, and T.-P. Tsao, "Quantum genetic algorithm for dynamic economic dispatch with valve-point effects and including wind power system," *Int. J. Elect. Power Energy Syst.*, vol. 33, no. 2, pp. 189–197, Feb. 2011.

[6] S. Ce, S. Dipti, and R. Thomas, "An improved particle swarm optimisation algorithm applied to battery sizing for stand-alone hybrid power systems," *Int. J. Elect. Power Energy Syst.*, vol. 74, pp. 104–117, Jan. 2016.

[7] B.-F. Bahman, F. Ebrahim, and A.-A. Rasoul, "An efficient scenario-based and fuzzy self-adaptive learning particle swarm optimization approach for dynamic economic emission dispatch considering load and wind power uncertainties," *Energy*, vol. 50, pp. 232–244, Feb. 2013.

[8] J. Jasper, R. S. Sivakumar, A. Victoire, and S. N. Deepa, "Cost optimization of power generation using a differential evolution algorithm enhanced with neighbourhood search operation," *Int. Rev. Elect. Eng.*, vol. 7, no. 5, pp. 5854–5865, Oct. 2012.

[9] R. Palma-Benhke, A. Philpott, A. Jofré, and M. Cortés-Carmona, "Modelling network constrained economic dispatch problems," *Optim. Eng.*, vol. 14, no. 3, pp. 417–430, Sep. 2013.

[10] K. Vaisakh, L. R. Srinivas, "A genetic evolving ant direction DE for OPF with non-smooth cost functions and statistical analysis," *Energy*, vol. 35, no. 8, pp. 3155–3171, Aug. 2010.

[11] M. Basu, "An interactive fuzzy satisfying method based on evolutionary programming technique for multiobjective short-term hydrothermal scheduling," *Elect. Power Syst. Res.*, vol. 69, nos. 2–3, pp. 277–285, May 2004.

[12] K. K. Mandal and N. Chakraborty, "Daily combined economic emission scheduling of hydrothermal systems with cascaded reservoirs using self organizing hierarchical particle swarm optimization technique," *Expert Syst. Appl.*, vol. 39, no. 3, pp. 3438–3445, Feb. 2012.

[13] C.-C. Kuo, "Wind energy dispatch considering environmental and economic factors," *Renew. Energy*, vol. 35, no. 10, pp. 2217–2227, Oct. 2010.

[14] C. Chun-Lung, C. Zih-Yan, and L. Tsung-Ying, "Multi-area economic generation and reserve dispatch considering large-scale integration of wind power," *Int. J. Elect. Power Energy Syst.*, vol. 55, pp. 171–178, Feb. 2014.

[15] Y. Zhang, H. H.-C. Iu, T. Fernando, F. Yao, and K. Emami, "Cooperative dispatch of BESS and wind power generation considering carbon emission limitation in Australia," *IEEE Trans. Ind. Informat.*, vol. 11, no. 6, pp. 1313–1323, Dec. 2015.

[16] H. M. Dubey, M. Pandit, and B. K. Panigrahi, "Hybrid flower pollination algorithm with time-varying fuzzy selection mechanism for wind integrated multi-objective dynamic economic dispatch," *Renew. Energy*, vol. 83, pp. 188–202, Nov. 2015.

[17] Y. Zhang, F. Yao, H. H. C. Iu, T. Fernando, and H. Trinh, "Wind–thermal systems operation optimization considering emission problem," *Int. J. Elect. Power Energy Syst.*, vol. 65, pp. 238–245, Feb. 2015.

[18] A.-A. Rasoul, N. Taher, A. B. Mohammad, and Z. Mohsen, "Coordination of combined heat and power-thermal-wind-photovoltaic units in economic load dispatch using chance-constrained and jointly distributed random variables methods," *Energy*, vol. 79, pp. 50–67, Jan. 2015.

[19] W. Kehe and Z. Huan, "A multi-agent-based energy-coordination control system for grid-connected large-scale windŰphotovoltaic energy storage power-generation units," *Solar Energy*, vol. 107, pp. 245–259, Sep. 2014.

[20] Y. Mimoun, K. Fouad, and K. R. Lakhdar, "Multi-objective economic emission dispatch solution using hybrid FFA (firefly algorithm) and considering wind power penetration," *Energy*, vol. 67, pp. 595–606, Apr. 2014.

[21] K. Wang, H. Gao, X. Xu, J. Jiang, and D. Yue, "An energy-efficient reliable data transmission scheme for complex environmental monitoring in underwater acoustic sensor networks," *IEEE Sensors J.*, vol. 16, no. 11, pp. 4051–4062, Jun. 2016.

[22] H. Jiang, K. Wang, Y. Wang, M. Gao, and Y. Zhang, "Energy big data: A survey," *IEEE Access*, vol. 5, pp. 3844–3861, 2016, doi: 10.1109/ACCESS.2016.2580581.

[23] M. Ammar, P. Jagadeesh, K. Tamer, and E. Wilfried, "A review of process and operational system control of hybrid photovoltaic/diesel generator systems," *Renew. Sustain. Energy Rev.*, vol. 44, pp. 436–446, Apr. 2015.

[24] Y. S. Mohammed, M. W. Mustafa, and N. Bashir, "Hybrid renewable energy systems for off-grid electric power: Review of substantial issues," *Renew. Sustain. Energy Rev.*, vol. 35, pp. 527–539, Jul. 2014.

[25] X. Liu and W. Xu, "Economic load dispatch constrained by wind power availability: A here-and-now approach," *IEEE Trans. Sustain. Energy*, vol. 1, no. 1, pp. 2–9, Apr. 2010.

[26] M. B. Shadmand, R. S. Balog, and H. Abu-Rub, "Model predictive control of PV sources in a smart dc distribution system: Maximum power point tracking and droop control," *IEEE Trans. Energy Convers.*, vol. 29, no. 4, pp. 913–921, Dec. 2014.

[27] M. Mahmoodi, P. Shamsi, and B. Fahimi, "Economic dispatch of a hybrid microgrid with distributed energy storage," *IEEE Trans. Smart Grid*, vol. 6, no. 6, pp. 2607–2614, Nov. 2015.

[28] U. Krishnasamy and D. Nanjundappan, "A refined teaching-learning based optimization algorithm for dynamic economic dispatch of integrated multiple fuel and wind power plants," *Math. Problems Eng.*, vol. 2014, Apr. 2014, Art. no. 956405.

[29] H. T. Jadhav and R. Roy, "Gbest guided artificial bee colony algorithm for environmental/economic dispatch considering wind power," *Expert Syst. Appl.*, vol. 40, no. 16, pp. 6385–6399, Nov. 2013.

[30] H. Zhao, Q. Wu, Q. Guo, H. Sun, and Y. Xue, " Distributed model predictive control of a wind farm for optimal active power control part I: Clustering-based wind turbine model linearization," *IEEE Trans. Sustain. Energy*, vol. 6, no. 3, pp. 831–839, Jul. 2015.

[31] W. Wei, W. Cheng-Yi, and H. Jenn-Jiang, "Scenario-oriented design of an MFC/PV/Battery based hybrid power generation system," *Int. J. Elect. Power Energy Syst.*, vol. 65, pp. 34–40, Feb. 2015.

[32] A. R. Abul'Wafa, "Optimization of economic/emission load dispatch for hybrid generating systems using controlled Elitist NSGA-II," *Elect. Power Syst. Res.*, vol. 105, pp. 142–151, Dec. 2013.

[33] H. H. Abdeltawab and Y. A.-R. I. Mohamed, "Market-oriented energy management of a hybrid wind-battery energy storage system via model predictive control with constraint optimizer," *IEEE Trans. Ind. Electron.*, vol. 62, no. 11, pp. 6658–6670, Nov. 2015.

[34] J. Runhai, L. Bo, L. Yuancheng, and Z. Lingzhi, "An enhanced quantum-behaved particle swarm algorithm for reactive power optimization considering distributed generation penetration," *Math. Problems Eng.*, vol. 2015, Jan. 2015, Art. no. 342080.

[35] K. Wang, Z. Ouyang, R. Krishnan, L. Shu, and L. He, "A game theory-based energy management system using price elasticity for smart grids," *IEEE Trans. Ind. Informat.*, vol. 11, no. 6, pp. 1607–1616, Dec. 2015.

[36] N. I. Nwulu and X. Xia, "Implementing a model predictive control strategy on the dynamic economic emission dispatch problem with game theory based demand response programs," *Energy*, vol. 91, pp. 404–419, Nov. 2015.

[37] Y. Xu, Z. Yang, W. Gu, M. Li, and Z. Deng, ''Robust real-time distributed optimal control based energy management in a smart grid,'' *IEEE Trans. Smart Grid*, vol. PP, no. 99, pp. 1–12, Oct. 2015. DOI: 10.1109/TSG.2015.2491923.

[38] F.-Y. Wang, H. Zhang, and D. Liu, ''Adaptive dynamic programming: An introduction,'' *IEEE Comput. Intell. Mag.*, vol. 4, no. 2, pp. 39–47, May 2009.

[39] Z. Haifeng, G. Feng, W. Jiang, and L. Kun, ''A dynamic economic dispatching model for power grid containing wind power generation system,'' *Power Syst. Technol.*, vol. 37, no. 5, pp. 1298–1303, 2013.

[40] L. Youlin, Z. Jianzhong, Q. Hui, W. Ying, and Z. Yongchuan, ''A hybrid multi-objective cultural algorithm for short-term environmental/economic hydrothermal scheduling,'' *Energy Convers. Manage.*, vol. 52, no. 5, pp. 2121–2134, May 2011.

[41] A. N. Venkat, I. A. Hiskens, J. B. Rawlings, and S. J. Wright, ''Distributed MPC strategies with application to power system automatic generation control,'' *IEEE Trans. Control Syst. Technol.*, vol. 16, no. 6, pp. 1192–1206, Nov. 2008.

[42] Q. Wei, D. Liu, G. Shi, and Y. Liu, ''Multibattery optimal coordination control for home energy management systems via distributed iterative adaptive dynamic programming,'' *IEEE Trans. Ind. Electron.*, vol. 62, no. 7, pp. 4203–4214, Jul. 2015.

[43] X. Xie, D. Yue, H. Zhang, and Y. Xue, ''Control synthesis of discrete-time TŰS fuzzy systems via a multi-instant homogenous polynomial approach,'' *IEEE Trans. Cybern.*, vol. 46, no. 3, pp. 630–640, Mar. 2016.

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