Stochastic model predictive control based economic dispatch for hybrid energy system including wind and energy storage devices

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***Abstract*—In this paper, a stochastic model predictive control (SMPC) approach is proposed to schedule a hybrid energy system (HES) which composes a battery energy storage system (BESS) and a wind farm. The SMPC is used to control the charge and discharge of the BESS to minimize the operation costs and maximum the selling power revenue for the HES owner with considering wind production and electricity price forecast uncertainties. Case study is employed to assess the performance of the SMPC approach and simulation results show that this approach proposed in this paper is effective and feasible.**

I. Introduction

In recent years, as the increase of energy demand and the depletion of fossil resources, the share of wind power capacity installed is increasing throughout the world [1]. As one of the most fast-growing new electricity generation capacities, wind power has been considered as a free, clean, and sustainable energy resource. However, wind power production is high variability and intermittent, and it will introduce increasingly difficult when the wind power penetration level increases to significant percentages [2]. The traditional control of wind power is limited to curtailing it, or increase the use of reserve power [3]. One other technical feasible way is integrate energy storage system with the wind farms to mitigate the stochastic behavior of wind power.

The hybrid energy system (HES) composes of wind farm and energy storage system can improve the power quality, system reliability, wind power availability and increase wind farm owner's revenue [4]. Among various energy storage technologies, battery energy storage system (BESS) is a suitable choice to maximize wind farm owner's benefit due to it has been utilized support reserves, defer network upgrades and achieve price arbitrage [5]. As a result, BESS is focused in this paper.

During the recent years, various efforts have been made to control wind power farm dispatchable by using BESS. A game-theoretic oriented analysis is implemented in [6] under the electricity market model of German. Stochastic programming framework is chosen to optimal operation of energy storage and determine reserve bids to keep profitability of the investment on storage units [7]. A wind power stabilization system is discussed in [8] by different kinds of storage devices.

MPC method is widely used in industry as it has been recognized as an effective and practical control strategy that uses a prediction of system evolution to establish an updated control response. Authors in [9] and [10] presented MPC based approaches to smoothing wind power fluctuation with BESS. The objective is to minimize the deviation between the forecasted value and real production. In [5], sizing and control of BESS method is discussed to mitigating wind power intermittency and reducing the operation cost to the wind farm owner. A MPC based coordinated scheduling framework for variable wind generation and BESS is presented in [11], short-term forecast of wind generation and price information is considered to determine the net power injection to the electric power grid. However, as the penetration level of wind power is high, the traditional MPC methods based on point forecast cannot mitigate the wind fluctuation effectively enough.

The objective of this paper is to discuss the control of BESS to mitigate the wind power intermittency and increase the revenue of wind farm owner using BESS and SMPC control method. SMPC method is more effective in reducing the operation cost and wind power intermittency than the traditional MPC methods and day ahead programming methods.

The remainder of this paper is organized as follows: Section II provides the brief problem formulation; Section III introduces the SMPC policy and optimization model; Simulation and conclusions are shown in Section IV.

II. Problem formulation

The basic structure of the HES considered in present paper is illustrated in Fig.1. The HES includes a wind farm and a BESS. The energy provided by the HES is sold to the electricity grid. The SMPC based control system should forecast the wind power production and electricity price and then calculate the appropriate amount of BESS charging/discharging power with considering the BESS constraints, wind power and electricity forecasts to maximize the wind farm owner's revenue. The forecast uncertainties of wind power production and electricity price are presented by scenarios.

The optimization of HES can be considered as an optimization problem for determining the optimal charging/discharging power of BESS. The mathematical formulations are shown as follows:

This research is financially supported by National Natural Science Foundation of China (No. 61403404, 71571187, 71401167) and the National University of Defense Technology (No. JC14-05-01).

978-1-4799-7560-0/15 $31.00 © 2015 IEEE
DOI 10.1109/SSCI.2015.181

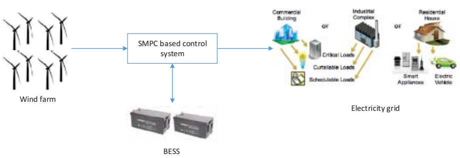

Fig. 1. Schematic diagram of the grid-connected HES

For mitigating the intermittency of wind power to the electricity grid, the power provided by the HES must be scheduled before. The over produced power of the wind farm correspond to the scheduled value can be curtailed or stored, and in the opposite case, the inadequate power can be discharged by the BESS or purchased from the electricity market with higher price.

The objective is to maximize the expected cost of the HES over the next T periods. The uncertain power production of wind and variable electricity price are modeled by different paths of scenario trees.

$$F_1 = min \sum_{s=1}^{S} \pi^s \sum_{t=1}^{T} P_{grid}^s(t) Pr^s(t) \Delta t; \ \ t \in [1, T] \quad (1)$$

where s is an auxiliary variable, and $s \in [1, S_{po} * S_{pr}]$, S denotes the number of scenarios, S_{po} is the number of RERs generation scenarios, S_{pr} is the number of electricity price scenarios. T is the control horizon, π^s is the probability of scenario s, $P_{grid}^s(t)$ is the generation of wind farm at time t in scenario s, $Pr^s(t)$ is the basic price in electricity market at time t in scenario s, and Δt is the time interval of two sequential time samplings.

When the HES energy optimization scheme is applied, the total cost over the next T periods is calculated as in Eq. (1). The first term is the electricity buying cost from electricity grid; the second term is the revenue from electricity selling to the electricity grid. The power exchange between the HES and electricity grid can be indicated as:

$$P_{grid}^s(t) = P_{wind}^s(t) + P_{Ed}^s(t) - P_{Ec}^s(t); t \in [1, T] \quad (2)$$

where $P_{Ed}^s(t)$, $P_{Ec}^s(t)$ are the discharge and charge power of the BESS at time t in scenario s, respectively. $P_{grid}^s(t)$ is the power interaction between the external grid and HES.

As the penetration level of wind power grows high, reduce the negative impacts of wind production and keep the electricity grid reliability is vital. One of the most important measure is to set the purchasing price higher than the basic price in electricity market and the selling price lower the basic price in electricity market at same time [12]. Therefore, purchasing electricity price $Pr_O^{S_{po},S_{pr}}(t)$ and selling electricity price $Pr_I^{S_{po},S_{pr}}(t)$ can be denoted as Eq. (3).

$$\begin{aligned} Pr_I^s(t) &= \rho_{buy}(t) Pr^s(t); t \in [1, T] \\ Pr_O^s(t) &= \rho_{sell}(t) Pr^s; t \in [1, T] \end{aligned} \quad (3)$$

where $\rho_{buy}(t)$, $\rho_{sell}(t)$ are the purchasing and selling coefficients with the following setting: $\rho_{buy}(t) \geq 1$ and $\rho_{sell}(t) \leq 1$. $Pr_I^s(t)$, $Pr_O^s(t)$ are the purchasing and selling energy price at time t in scenario s, respectively.

The dynamic model and constraints of the BESS are:

$$\begin{aligned} E_{E_e}^s(t+1) = E_{E_e}^s(t) + \eta_{Ec_e} P_{Ec_e}^s(t) \Delta t \\ - {}^1/_{\eta_{Ed_e}} P_{Ed_e}^s(t) \Delta t - \varphi_E \Delta t \end{aligned} \quad (4)$$

$$E_{E_{min}} \leq E_{E_e}^s(t) \leq E_{E_{max}}; t \in [1, T] \quad (5)$$

$$P_{Ec_{min}} \delta_{Ec}^s(t) \leq P_{Ec_e}^s(t) \leq P_{Ec_{max}}; t \in [1, T] \quad (6)$$

$$P_{Ed_{min}} \delta_{Ed}^s(t) \leq P_{Ed}^s(t) \leq P_{Ed_{max}}; t \in [1, T] \quad (7)$$

$$\delta_{Ed}^s(t) + \delta_{Ec}^s(t) \leq 1; t \in [1, T] \quad (8)$$

where $E_{E_e}^s(t)$ is the BESS energy level at time t in scenario s, η_{Ec_e}, η_{Ed_e} are the charge and discharge efficiency of BESS, respectively, φ_E is the self-discharge loss of BESS, $\delta_{Ed}^s(t)$, $\delta_{Ec}^s(t)$ are the discharge and charge status of the BESS, $P_{Ec_{min}}$, $P_{Ec_{max}}$ are the minimum and maximum charge power, $P_{Ed_{min}}$, $P_{Ed_{max}}$ are the minimum and maximum discharge power, respectively.

Eq. (4)-(8) are the BESS dynamic model, capacity constraint, charging power limit, discharging power limit, operation status constraint, respectively. The BESS model in present paper can avoid introducing extra auxiliary variables and extra models to describe the hybrid dynamics of the energy storage as shown in [12] and can effectively control the minimum charging/discharging power and charging/discharging cycles.

The power interaction between the HES and electricity grid and the wind power capacity constraint also should be satisfied.

$$P_{gridmin} \leq P_{grid}^s(t) \leq P_{gridmax}; t \in [1, T] \quad (9)$$

$$0 \leq P_{wind}^s(t) \leq P_{wind_{max}}; t \in [1, T] \quad (10)$$

where $P_{gridmin}$, $P_{gridmax}$ are the minimum and maximum power can be exchanged between HES and external grid, respectively. $P_{wind_{max}}$ is the capacity of the wind farm.

III. SMPC BASED OPTIMIZATION

As the penetration level of RERs grows high, the impaction of RERs forecast uncertainty is significant. Traditional day-ahead programming based energy control strategy and classical MPC formulations do not provide a systematic way to deal with model uncertainty and disturbances, which are often completely neglected in the prediction model [13]. Robust MPC schemes which consider the worst case are too conservative. The SMPC based control methods which can fully use the statistical information of the forecast error are concerned by more and more researchers. SMPC can be considered as a closed loop based method which is iteratively compute a sequence of decision variables over a future certain horizon with different wind production scenarios and then update the HES state. The detail process of this method is shown in Fig.2.

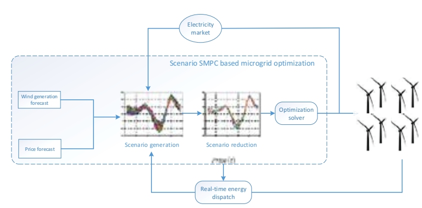

Fig. 2. SMPC based HES optimization

A. Scenario generation and reduction

The uncertainty of wind production and electricity price can be illustrated as

$$P_{wind}^s(t) = P_{wind}^{pre}(t) + \varepsilon_{wind}^s(t); t \in [1, T] \quad (11)$$

$$Pr^s(t) = Pr^{pre}(t) + \varepsilon_{pre}^s(t); t \in [1, T] \quad (12)$$

where $P_{wind}^{pre}(t)$, $Pr^{pre}(t)$ are the forecasted wind generation and basic electricity price at time t in scenario s, respectively. According to [14] and [15], the forecast error of wind power production and electricity price can be described by Gaussian distribution. Hence, the stochastic scenarios can be generated according to Eq. (11) and (12) with Lattice Monte Carlo Simulation over the control horizon.

We note that the number of primitive scenarios generated by Lattice Monte Carlo Simulation is very huge, large computation burden will be produced if all be considered. Scenario-reduction techniques must be used to delete the common scenarios, only typical scenarios are enough to represent the stochastic nature of the HES. However, the efficiency of traditional simultaneous backward method is not very high, cannot satisfy the online control operation requirement of HES. Therefore, a new fast scenario reduction method is implemented in present paper:

1) Generated N_{sce} scenarios with LMCS method as initial set;
2) Divide the N_{sce} scenarios into N_{pice} units uniformly, and consider N_{p_s} as the amount of saved scenarios in each unit, and S scenarios are finally saved, while meet $S \leq N_{p_s} \leq {N_{sce}}/{N_{pice}}$;
3) Use simultaneous backward method to delete scenarios in each unit, and collect these save scenarios from each unit to compose a new scenario set, which has $N_{p\_s} \cdot N_{pice}$ scenarios;
4) Use simultaneous backward method again to choose the final S scenarios from the new scenario set.

B. SMPC based HES optimization

For making the SMPC based HES optimization implemented effectively, some additional non-anticipativity should be satisfied in the root node.

$$P^s_{wind}(1) = P^s_{wind}(1); \tag{13}$$
$$P^s_{Ec}(1) = P^{s+1}_{Ec}(1); \tag{14}$$
$$P^s_{Ed}(1) = P^{s+1}_{Ed}(1); \tag{15}$$

IV. Simulation and Results

A. Test description

In order to verify the proposed control approach, extensive simulations for assessing different methods are carried out based on the actual wind farm and electricity price. The data of wind generation is collected and modified form ELIA [16], Belgium's electricity transmission system operator, the maximum generation capacity is 20MW; the electricity price is based on the actual of New York [17], as shown in Fig.2.

For reducing the negative impacts of wind intermittency and making the HES more dispatchable, the extra selling power price is ruled to lower than the extra purchasing price in real-time operation, therefore $\rho_{bI} = 1.2$ and $\rho_{bO} = 0.8$. The charge power rate is from 50kW to 500kW, energy level is 1MWh, the available depth of charge is 75%, the charge and discharge efficiency are both 0.95, and the self-discharge rate is 0.02kW/h. The operation cost of the battery energy storage is $0.6€ct/kWh$, charge-to-discharge operation cost and discharge-to-charge operation cost both are $1.1€ct$, and the initial energy capacity of the battery is $500kWh$. The maximum power can be exchanged between the HES and electricity grid is 2MW.

The sampling time duration is $0.5h$, and the control horizon is $24h$. The length of the simulation in this paper is over four days.

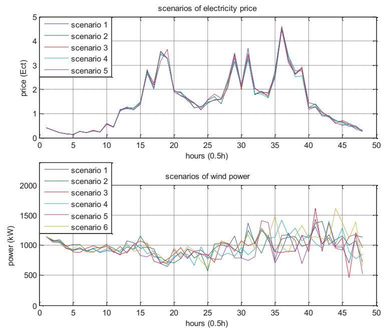

Fig. 3. Scenarios of electricity price and wind power production in the first day

B. Control strategies

In order to analyze the superiority of the SMPC based energy control strategy, two other strategies are used.

1) Deterministic MPC based strategy (D-MPC strategy): The control framework is the same as the SMPC strategy, however, it is an energy control strategy uses point forecasts of wind, solar, load, and electricity price [12]. The mismatch wind power between the
2) Deterministic day-ahead programming based strategy (D-DA strategy): It is a traditional two-stage open-loop energy control strategy based on point forecasts of wind, solar, load, and electricity price [18]. The charge and discharge routines are determined in schedule stage, and the mismatch wind power between the schedule stage and actual data are compensated by the electricity grid.

The energy dispatch in all the above four strategies have two stages: scheduling stage and real-time adjustment stage. In the scheduling stage, the control sequences of the controllable units in microgrid are determined based on forecasts to avoid the shortsightedness of real-time operation. However, due to the forecasts are imperfect for wind power production and electricity price, compensate measures should be employed at real-time to keep the power balance in actual operation. In real-time adjustment stage, the power compensate policy is determined and implemented [18] [19].

C. Results

All simulations were run on an PC with Intel(R) Core(TM) i5-3470 CPU @3.2GHz and 8.00GB memory. The ILOG's CPLEX v.12 optimization solver is utilized for solving the MIQP model.

The operation routines of microgrid units with all the four strategies are demonstrated in this section. Two main discussions are implemented: 1) performance comparing between the deterministic based control strategies (D-DA, D-MPC) and stochastic based control strategies (SMPC); 2) performance comparing between the open loop based energy control strategies (D-DA) and close loop based energy control strategies (S-MPC, D-MPC). Other results also discussed, such as computation complexity of all the four strategies, different spinning reserve requirements for different strategies, and the operation cost.

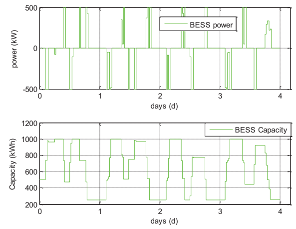

Fig. 4. BESS power and capacity for D-DA strategy

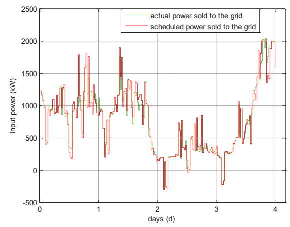

Fig. 5. Scheduled and actual wind power sold to the electricity grid for D-DA strategy

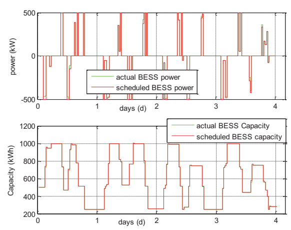

Fig. 6. BESS power and capacity for D-MPC strategy

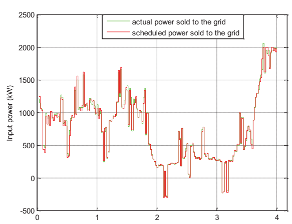

Fig. 7. Scheduled and actual wind power sold to the electricity grid for D-MPC strategy

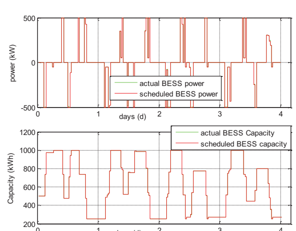

Fig. 8. BESS power and capacity for SMPC strategy

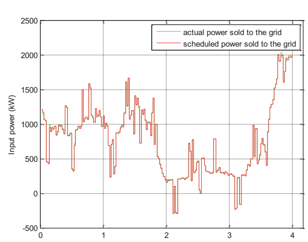

Fig. 9. Scheduled and actual wind power sold to the electricity grid for SMPC strategy

TABLE I. COMPARISON OF MICROGRID OPERATION STRATEGIES

Strategies	**Total cost (10^5€)**	**Correction cost (€)**
SMPC strategy	-2.6322	280.56
D-MPC strategy	-2.5247	590.74
D-DA strategy	-1.6666	5930.5

TABLE II. MODEL STATISTICS AND COMPUTATION TIMES

strategies	**Scenario reduction time (s)**	**Average number of variables**	**Average solving time (s)**
SMPC strategy	4.36	5760	7.35
D-MPC strategy	0.31	144	1.68
D-DA strategy	0.3	144	0.5

The results of D-DA strategy are presented in Figs. 3-4. Due to the BESS for D-DA strategy does not take part in the real-time power balance adjustment, which result in the actual BESS operation power is the scheduled BESS operation power, as shown in Fig. 4. Also bring about severe fluctuation between the scheduled power interaction and actual power interaction between the HES and the electricity grid, as shown in Fig.5. Moreover, the open-loop nature of D-DA strategy make the correction cost in real-time operation stage is much larger than D-MPC and SMPC strategy, as shown in Tab.1. The total HES power selling revenue for D-DA strategy is the least in the three strategies.

The results of D-MPC strategy are presented in Figs. 6-7. Due to the close loop nature of MPC strategy, the BESS operation power in schedule stage and actual power operation have not big difference, as shown in Fig.6. And there is no severe fluctuation between the scheduled power interaction and actual power interaction between the HES and the electricity grid, as shown in Fig.7. The fluctuation in Fig.6 is more intense is just because much more power purchased or sold in real-time stage optimization. Better performance of D-MPC strategy than D-DA strategy can be deduced according to the comparing between Figs 6-7 and Figs. 8-9, and this results also can be proved by the results in Table 1.

The results of SMPC strategy are presented in Figs. 8-9. Comparing the Figs 4-9, we could find that the performance of the SMPC strategy is the best in the three strategies. The fluctuation between the scheduled power interaction and actual power interaction between the HES and the electricity grid is the lowest, the differences of the BESS operation power between the schedule stage and actual operation is also the least. Moreover, the results in Tabl.1 shows that the HES power selling revenue for SMPC strategy is the highest, the revenue of SMPC increase 4.26% to the D-MPC strategy. Though the computation time of SMPC strategy is longer than D-MPC strategy, as shown in Table 2, this time is much shorter than the sampling time 0.5hour.

V. CONCLUSIONS

This present paper proposes a SMPC approach to maximum the revenue of a HES which include a wind farm and a battery energy storage system. The forecast error of the wind power production and electricity price are represented by scenarios generated by Lattice Monte Carlo Simulation method, and a new two stage scenario reduction method proposed in this paper. The operation optimization problem of the HES at each time sampling is modeled as a mixed integer linear programming problem, and a model predictive control based framework is used to mitigate the impaction of wind power production and electricity price forecast uncertainty. Two other strategies: D-MPC strategy and D-DA strategy are utilized to assessing the performance of the control strategy proposed in present paper. Simulation results show that the strategy proposed in this paper is superiority and feasible.

Future work will be focused on applying the SMPC strategy to a more complicated microgrid with more actual condition.

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