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An Intelligent Control Strategy of Battery Energy Storage System for Microgrid Energy Management under Forecast Uncertainties

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In the developing of smart grid, many new technologies and components such as energy storage and microgrid are playing more and more role for making the power system more reliable and efficient. A grid-connected microgrid consists of local controllers, local consumers, renewable energy generators and storage facilities will becoming an important part of future smart grid in integrating more renewable energy resources (RER), demand side response (DSR), reducing cost of transmission, increasing power quality and reliability, and so on. This paper concerns on efficient energy management of microgrid with RER integration and battery energy storage system (BESS) and in real-time electricity price (RTP) markets. A model predictive control (MPC) based scheduling and operation strategy for microgrid operator to minimize the operation costs under different forecast uncertainty levels of load demand, electricity price, and renewable energy generation outputs is proposed. Three other strategies are also discussed for evaluating the performance of strategy presented in this paper. Simulation results show that the proposed MPC-based strategy has better performance and more robust than the other strategies facing different prediction uncertainty levels.

Keywords: battery energy storage system (BESS); model predictive control (MPC); microgrid; renewable energy resources (RER); real-time price (RTP)

1. INTRODUCTION

As a vital factor for developing of every country, energy for power generation increasing year and year, but as the main part of energies, fossil fuels are depleting and increasing environmental problems, the power generation should enter in an evolution phase [1-3]. Environmentally friendly power generation technologies such as wind, solar and alike will play more and more important role in future power supply [4], and usually be conducted in the form of individual distributed generation (DG) systems in grid-connected or standalone configuration, and then researchers soon found out that customized DG may create problems as many as it solves, particularly in the case of high penetration level [5]. Therefore, after long time researching, microgrid was proposed to overcome the problems described above.

The concept of microgrid is a new approach to integrating RER reliably and efficiently. A microgrid is a small electric power system with one or more RER, load and energy storage, operated by smart energy management controllers, either in grid-connected or isolated form, which can represents a house, a community, or commercial center [6]. Because of the intermittence nature of many RER, only combined them in a system could not solve all the problems, energy storage is needed, especially in the case of real-time price electricity market. Among all the energy storage technologies, battery energy storage system with the characteristics of high power and energy density, fast response time, and scalability is drawing more and more attentions [7].

In literature, a lot of researches in studying microgrid configuration, characteristics, planning, evaluation, and control and optimization strategy. In currently, there are main two architectures of microgrid, that is, Consortium for Electric Reliability Technology Solutions (CERTS) architecture proposed by US and microgrids architecture presented by EU, all of them obliged to have the function of peer-to-peer and plug-and-play, CERTS is based on the concept of distributed control, however, microgrids mainly on the concept of central control [8-9].

As an important microgrid research problem, optimal sizing and selecting of RER draws massive concerns. Multiple objectives will be considered in chosen suitable units of a microgrid, such as capital costs, installing costs, operation and management costs, reliability, or environmental costs, even the life time of units should be included. Researchers in [10] presented a model to size a vanadium redox flow battery storage energy system for a midsized European town with considering to minimize grid purchase and reduce spilled wind energy by HOMER, reference [11, 12] studied the optimal size of wind, PV and BESS in a microgrid with tangent method and genetic algorithm, authors in [13] investigated the unit sizing and cost analysis problem a stand-alone microgrid with PSO methods.

After the sizing problems of microgrid solved, how to ensure the system work properly under uncertainties arise to be another vital issue. Authors in [14-17, 6] devoted themselves to controls of microgrid with energy storage, proposed a lot of strategies and optimization methods. [14] presented a hybrid operation strategy of an isolated microgrid, [15] proposed an optimization based control approach for microgrid energy management, [16] presented a generic mixed integer linear programming model to minimize the operating cost of residential microgrid, [17] investigated the economic/environmental operation management of microgrids, [6] studied the energy management of a microgrid considering reliability and economic constraints.

The model and analysis in this paper differ from the related work in the literature in several aspects. In [15], the RER connected to the BESS, this will propose higher request for BESS in capacity and power limit to fully utilize RER power generation, and not consider the uncertainties of forecast either. Our work is also different form the model in [19], there is no energy storage system is considered in system optimization. The work in [20] is under the conventional condition of distribution system, no RER integration is considered, and the electricity price market is different from this paper.

In the present paper, a novel computationally feasible and automated intelligent control strategy in a retail electricity market with real-time price and high forecast uncertainties of load demand, electricity price, and RER power output. The aim is to minimize the system operation cost of microgrid by optimally scheduling the charging and discharging of BESS, subject to the special constraints. Advanced communication network and smart meter are assumed equipped by the microgrid in this paper.

The rest of this paper is organized as follows. System model of microgrid studied in this paper is described in section Ⅱ. In section Ⅲ, mathematical models of the strategies are presented. Simulation and results are shown in section Ⅳ. The paper is concluded in section Ⅴ.

2. SYSTEM MODEL

In this section, a RTP environment configuration is presented in figure 1, where a number of generators, independent users, conventional distribution systems and microgrids are included, and they all participate in the system with local aggregator.

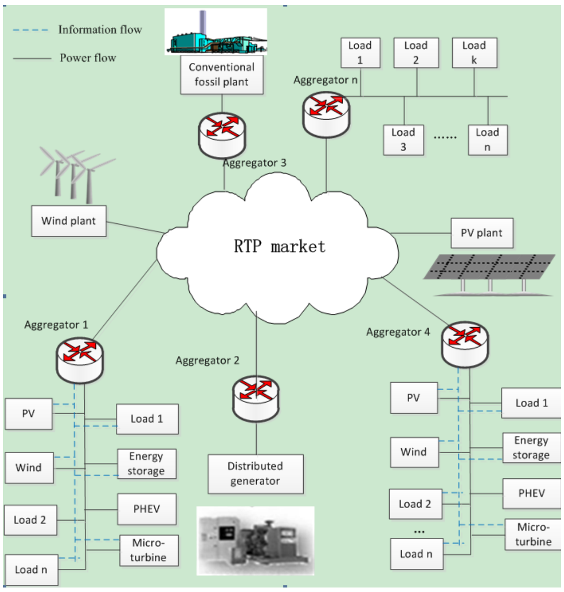

Figure 1. A simplified configuration of a wholesale electricity market

The RTP information reflects the wholesale price, which is determined by the total load demand of all users, and RER generation output in this market. The price information of electricity will be sent by advanced communication infrastructure. This paper concerns the optimal BESS scheduling and operation to minimize the operation cost and maximize the utilization of RER for local use, the scheme of a microgrid are presented as follows.

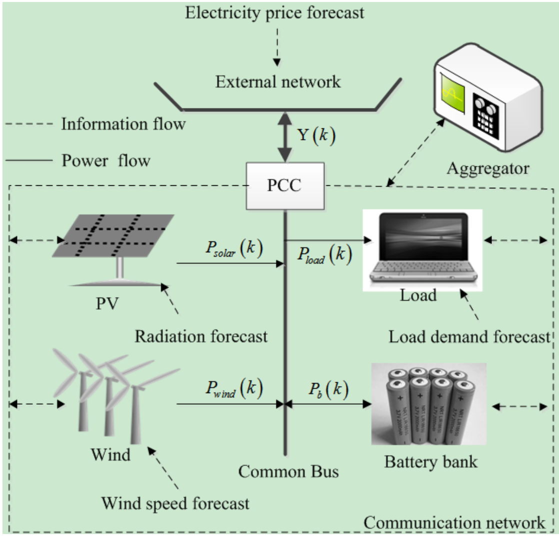

Figure 2. Simplified microgrid architecture

The microgrid consider in this paper, as shown in Fig. 2, which includes a few local consumers, some renewable energy generators, and a BESS. The operation of the microgrid is controlled by an aggregator through high quality communication network followed by the varying of conditions, such as price fluctuation, or RER generation randomness. Load demand in this paper is considered inelastic, that is the load cannot be deferred or interrupted. Load demand in period k is denoted by $P_{load}(k)$, PV generation and wind turbine generation in period k are represented by $P_{solar}(k)$ and $P_{wind}(k)$ respectively. $\mathrm{P}_b(k)$ represents the power exchanged between microgrid and BESS, when BESS charge power from microgrid, $\mathrm{P}_b(k)>0$, in the opposite case, when BESS discharges power into microgrid, $\mathrm{P}_b(k)<0$. The imported power from the external network is $\mathrm{Y}(k)$, which can be positive or negative. When $\mathrm{Y}(k)<0$, the external energy transferred to the external network with a cheap price, because these surplus power may cause unexpected oscillation of the external network, and will bring more complex management problems, when $\mathrm{Y}(k)>0$, aggregator purchase energy with normal price.

As to general optimization problems, intelligent control of BESS for microgrid energy management under different forecast uncertainties should conclude objective model and constraints, which can be formulated as follows.

2.1 Objective model

In mathematical terms, the objective model can be described as:

$$\min F(x)=\sum_{k=1}^{T}Cost\left(P_{netload}(k)\right) \tag{1}$$

$$s.t.\ G_{iL}(x)\le G_i(x)\le G_{iU}(x)\quad (i=1,2,\cdots,m)$$

where $F(x)$ denotes the objective function, $P_{netload}(k)$ refers the net-load of the microgrid. T represents the simulation horizon of this paper, $G_i(x)$ presents every constraint, $G_{iL}(x)$ and $G_{iU}(x)$

refers the lower and upper limit of *i*th constraint, m denotes the number of constraints, they all will be shown in the next.

	$P_{netload}(k) = P_{load}(k) - P_{solar}(k) - P_{wind}(k) + \mathrm{P}_b(k)$	(2)
	$\mathrm{P}_b(k) = \begin{cases} \eta_c \mathrm{P}_b(k), & \mathrm{P}_b(k) \geq 0 \\ \eta_d \mathrm{P}_b(k), & otherwise \end{cases}$	(3)

where η_c and η_d represent the BESS efficiency in charging and discharging respectively, and $0 \leq \eta_d, \eta_c \leq 1$. The electricity price in period k for microgrid is

	$\mathrm{P}_{rice}(k) = \begin{cases} \mathrm{P}_{ricerel}(k), if\ P_{netload}(k) \geq 0 \\ \beta_{extr}\, \mathrm{P}_{ricerel}(k), otherwise \end{cases}$	(4)

where $\mathrm{P}_{ricerel}(k)$ denotes the real-time electricity price of the RTP market in period k, $\beta_{extr}\, \mathrm{P}_{ricerel}(k)$ refers the sale price when RER generation exceed the load demand in period k, and $\beta_{extr} < 0$.

2.2 Constraints model

From the microgrid configuration shown in Fig. 2, several constraints on the state and control should be met, which are listed as follows:

1) Power balance constraint: the power imported in the microgrid should be equal to the net-load of microgrid, if transmission loss not be considered, namely

	$\mathrm{Y}(k) = P_{netload}(k)$	(5)

2) BESS constraints: the capacity and power at each period should not over the limit, which can be described as follows

	$SOC_{bmin} \leq SOC_b(k) \leq SOC_{bmax}$	(6)
	$\mathrm{D}_{max} \leq \mathrm{P}_b(k) \leq \mathrm{C}_{\max}$	(7)

where $SOC_b(k)$ represents the storage level of BESS at the end of period k, and $k = 1, 2, \cdots, T$, SOC_{bmin} and SOC_{bmax} denotes the minimum and maximum BESS available useful capacity respectively, however, they are not the capacity limit. We also could note that they are not normalized value, but the useful energy capacity (kWh). $\mathrm{C}_{\max}$ and D_{max} refers the BESS charge and discharge power limit respectively. In the present paper, we assume that there is only one BESS, therefore, the BESS cannot charge and discharge at the same time.

3) Other constraints of loads and generators: some upper and lower power limits should be considered when managing the microgrid.

	$0 \leq P_{wind}(k) \leq P_{wind} max$	(8)
	$0 \leq P_{solar}(k) \leq P_{solar} max$	(9)
	$0 \leq P_{load}(k) \leq P_{load} max$	(10)

As mentioned above, the optimal operation and control can be model as a linear programming problem, which can be formulated as

$$\min F\left(x\right)=\sum_{k=1}^{T}\mathrm{Y}\left(k\right)\mathrm{P}_{\mathrm{r}ice}\left(k\right)\Delta t \tag{11}$$

$s.t.(5)-(10)$

where Δt is the time duration of each time interval.

3. METHODOLOGY

The flexibility of microgrid is mainly determined by flexible units in microgrid such as energy storage, deferrable or/and interruptible loads, other units are inflexible, therefore, the operation of microgrid with no BESS is very limited, especially in the case of this paper. For better evaluation among the strategy proposed in this paper and strategies used before, detail mathematical model of the four strategies will be described, that are MPC-based scheduling and operation strategy, day-ahead programming strategy, load following strategy, and normal operation with no energy storage.

3.1 Normal operation with no BESS

When microgrid has no BESS integration, the operation is very limited, in addition that load in this paper is considered inelastic and scheduling beforehand has no difference with real-time operation. Therefore, the actual imported power in microgrid is represented as follow

$$Y\left(k\right)=P_{load}\left(k\right)-P_{solar}\left(k\right)-P_{wind}\left(k\right) \tag{12}$$

$s.t.(5),\left(8\right)-(10)$

where $k=1,2,\cdots,T$.

3.2 Load following strategy

Load following strategy is a real-time rule based strategy with the assistance of BESS [21]. The rule is: when RER generation exceed the load demand, BESS will charge as much as possible unless reaching the operation limits, the additional power still could not be consumed by microgrid will be transmitted to the external grid; in the opposite case, when RER generation could not support load demand of microgrid, BESS should discharge energy as much as possible unless reaching the operation limits, the energy insufficient would be imported in the microgrid from the external network; in other conditions, BESS will standby and do nothing. In this strategy, no prediction method or technology is needed, because it is a real-time rule based operation strategy. The detail mathematical model is described as follows:

$$P_b(k)=\begin{cases}\eta_c C_{\max} & C_{\max}\le P_{netload}(k), SOC(k)\le SOC_{b\max}\\ -\eta_c P_{netload}(k) & 0\le -P_{netload}(k)\le C_{\max}, SOC(k)\le SOC_{b\max}\\ {}^{1}\!/_{\eta_d}\, P_{netload}(k) & 0\le -P_{netload}(k)\le -D_{\max}, SOC(k)\le SOC_{b\max}\\ -{}^{1}\!/_{\eta_d}\, D_{\max} & -D_{\max}\le P_{netload}(k), SOC(k)\le SOC_{b\max}\\ 0, & otherwise\end{cases} \tag{13}$$

where $P_b(k)$ refers the power imported into or exported from BESS in period k, $k=1,2,\cdots,T$.

The power imported into microgrid in period k is

$$Y_{loadf}(k)=P_{netload}(k)+P_b(k) \tag{14}$$

The total operation cost of microgrid with load following strategy over the whole simulation horizon T can be formulated as

$$F_{loadf}(x)=\sum_{k=1}^{T}Y_{loadf}(k)P_{rice}(k)\Delta t \tag{15}$$

where $F_{loadf}(x)$ represents total cost of microgrid under load following strategy in the whole simulation horizon.

3.3 Day-ahead programming strategy

In this strategy, BESS will be scheduled day-ahead followed by the forecast data of RER generation, load demand, and real-time price of the next day, in addition, BESS will operate along with the scheduled value. There are massive researches about the forecasting of RER generation, load demand, and electricity price [22, 23]. As forecast methods are not the focus of this paper, simplified models are used for simulation instead in this paper. The detail process of this strategy can be described as follows.

The day-ahead programming objective function is

$$\min \hat{F}_j(x)=\sum_{i=1}^{N}\hat{Y}(i)\hat{P}_{rice}(i)\Delta t \tag{16}$$

$s.t.(5)-(10)$

$$\hat{Y}(i)=P_{load}(i)-\hat{P}_{solar}(i)-\hat{P}_{wind}(i)+\hat{P}_b(i) \tag{17}$$

where $F_j(x)$ represents the objective of day-ahead programming, $\hat{Y}(i)$ denotes the predicted imported power into the microgrid, $\hat{P}_{rice}(i)$, $P_{load}(i)$, $\hat{P}_{solar}(i)$, $\hat{P}_{wind}(i)$ refers the predicted RTP, predicted load demand, PV generation, wind generation about the time interval *i* of the next day. $\hat{P}_b(i)$ represents the scheduled charging and discharging power of BESS in time interval of i in the next day, N is the simulation periods of one day, which determined by the duration of simulation interval, *j* presents the day number. The actual cost of *j*th day could be formulated as

$$F_j(x)=\sum_{i=1}^{N}\left(P_{netload}(i)+\hat{P}_b(i)\right)P_{rice}(i)\Delta t \tag{18}$$

The total operation cost of microgrid of the whole simulation horizon T can be formulated as

$$F_{day}(x)=\sum_{j=1}^{M}F_j(x) \tag{19}$$

where $M*N=T$, $F_{day}(x)$ represents the total cost of microgrid under day-ahead programming strategy in the whole horizon.

3.4 MPC-based scheduling and operation strategy

The basic approach of MPC is a finite-horizon optimization determining the series of the optimal control operations solved before control step, but only the first control operation is implemented [24], nowadays it is found in the control rooms of almost every refinery and petrochemical plant [25]. The predictive model calculates the state series over the prediction horizon, and then the controller implements the first control action with the forecasting data and updated other information, in the next time interval the controller will repeat these operations once time until to the end of simulation horizon.

The exemplified structure of basic MPC is shown as follow.

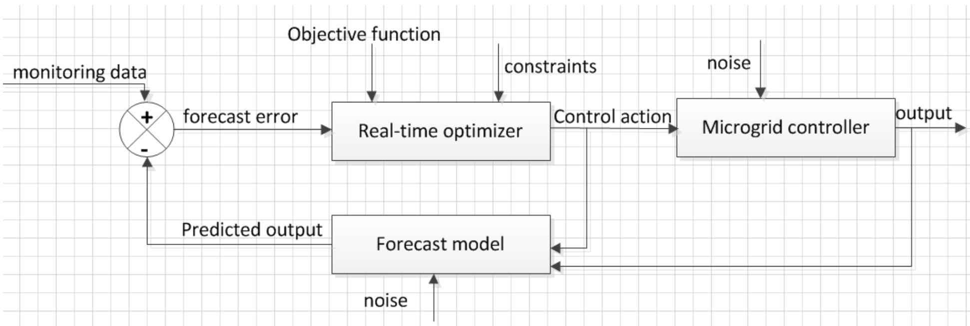

Figure 3. Scheme of basic MPC

The MPC-based scheduling and operation strategy at period i in this paper can be described as follows:

1) Initial the algorithm, set time interval $i=0$;
2) Choose a receding optimization horizon T_1. Utilize corresponding load, RER generation, electricity price predictive models to calculate the most updated data of load demand $P_{load}(i+d)$, PV generation $\hat{P}_{solar}(i+d)$, wind turbine generation $\hat{P}_{wind}(i+d)$, electricity forecast $P_{rice}(i+d)$ in time period $i+d$, where $d\in(1,T_1)$.
3) Calculate the optimization problem of microgrid cost shown in the following

$$\min \hat{F}_i(x)=\Upsilon(i)\mathrm{P}_{\mathrm{rice}}(i)\Delta t+\sum_{d=1}^{T_1}\hat{\Upsilon}(i+d)\hat{\mathrm{P}}_{\mathrm{r}ice}(i+d)\Delta t\gamma^d \tag{20}$$

$s.t.(5)-(10),(17)$

where $\hat{F}_i(x)$ denotes the objective of microgrid operation cost should be scheduled in the *i*th period.

$\mathrm{Y}(i)$ and $\mathrm{P}_{\mathrm{rice}}(i)$ represent the actual imported power into microgrid and electricity price respectively, $\hat{Y}(i+d)$ could be calculated by equation of (17), $\hat{\mathrm{P}}_{rice}(i+d)$ refers the predicted electricity price in $i+d$. $\gamma \in (0,1)$, the value depends on the forecast precision of all the variables needed in this paper, also has relationship with the interval cost will decrease more or less fast or not at all, its function is to adjust the impaction of prediction uncertainty to the optimization results.

4) Obtain the first period operation of BESS $\hat{\mathrm{P}}_b(i+1)$, which is solved from the optimization problem of (20), implement this control operation, and then Set $i = i+1$.

5) Update the prediction models with the newest information, then go back to step 2) until to the terminal time $i = T$ of this simulation in the present paper.

In the general case, short-term forecast will be more accurate than relatively longer term forecast. Therefore, the optimization horizon could not be too long.

4. CASE STUDY

In this section, the above four scheduling and operation strategies will be implemented in the microgrid shown in Fig. 2. For easy understanding, we assume the time interval of every period is 1hour, that is so N is 24, also we assume the optimization horizon of MPC strategy is one day, that is $\Delta t = 1h$, $T_1 = N = 24$, the charging efficiency η_c and discharging efficiency η_d is set as $\eta_c = \eta_d = 1$, thus there is no power loss when BESS charging or discharging. The penalty factor β_{extra} is set as $\beta_{extra} = 0.8$.

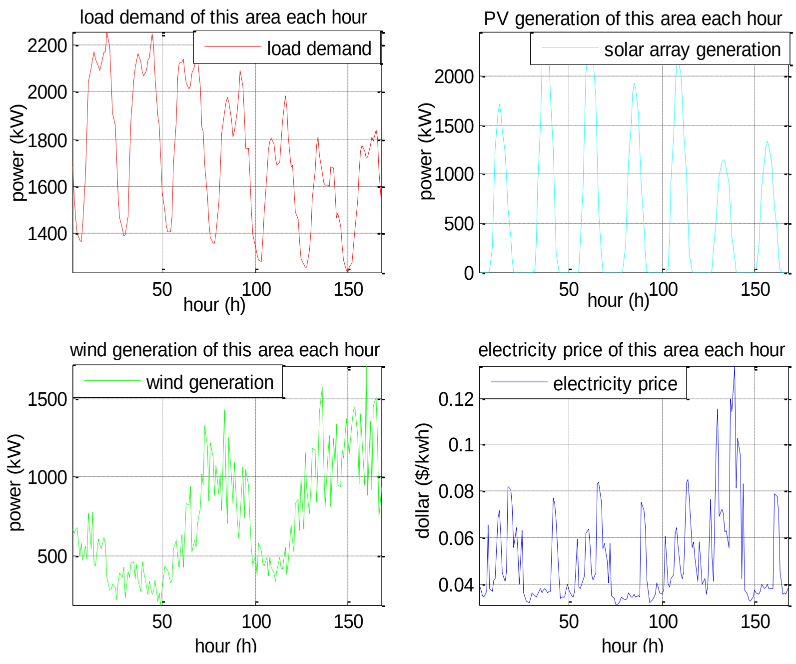

Figure 4. Actual data of Load demand, PV generation, wind generations and electricity price

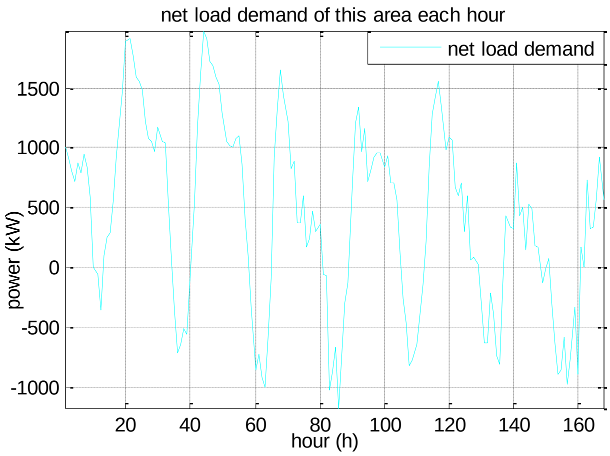

Figure 5. Data of net-load

The weighting factor γ is set as $\gamma = 0.98$. The BESS capacity limit is set as 600kWh, available BESS capacity is 480kWh, and power limit is set as 200kW. Actual data of load demand, PV generation, wind turbine generation and electricity price are shown in Fig. 4, net generation is shown in Fig.5.

Fig. 4 and Fig. 5 present the actual data of one week, namely $T = 168$. Fig. 4 (top left) shows the consumer power demand $P_{load}(k)$, Fig. 4 (top right) shows the power generation of solar arrays $P_{solar}(k)$, Fig. 4 (bottom left) depicts the power generation of wind turbines $P_{wind}(k)$, Fig. 4 (bottom right) depicts the RTP market price of electricity $\mathrm{P}_{rice}(k)$, where $k = 1, 2, \cdots, T$.

Fig. 5 shows the net-load of microgrid at each time period $P_{netload}(k)$, $P_{netload}(k) < 0$ means that the RER generation power is exceed the power demand of load in this microgrid, the surplus energy will be transmitted back to external network with a relative cheap price or store in the BESS and use in the later time period. From Fig. 4 we could find out the strong randomness and intermittence of RER generation output, and the volatile of electricity price is larger than load demand uncertainty. Comparing the load demand in Fig. 4 (top left) and net-load demand in Fig. 5, we note that the net-load curve is more volatile than only load curve, which means that more uncertainties arisen by RER integration.

Many new technologies are used for better integration RER, such as advanced digital communication network, prediction methods of RER generation, load demand, and electricity price, and newest devices [5, 8]. These methods progress the developing of smart grid, and RER integration, however, as the focus of this paper is on the scheduling and operation strategies of microgrid with the help of BESS, history data is simplified as real-time data instead, and the real-time forecast data of load demand, electricity price, PV generation, wind turbine generation are generated as follows.

	$\hat{P}_{load}(k) = P_{load}(k)\left(1 + \mathrm{E}_{Pl,\max} R_{Pl}\right)$	(21)
	$\hat{P}_{solar}(k) = P_{solar}(k)\left(1 + \mathrm{E}_{Ps,\max} R_{Ps}\right)$	(22)
	$\hat{P}_{wind}(k) = P_{wind}(k)\left(1 + \mathrm{E}_{Pw,\max} R_{Pw}\right)$	(23)

$$\hat{\mathrm{P}}_{\mathrm{rice}}(k) = \mathrm{P}_{\mathrm{rice}}(k)\left(1+\mathrm{E}_{Pr,\max} R_{Pr}\right) \quad (24)$$

where $\hat{\mathrm{P}}_{\mathrm{rice}}(k)$, $\hat{P}_{load}(k)$, $\hat{P}_{solar}(k)$, $\hat{P}_{wind}(k)$ are the forecast electricity price, load demand, PV generation and wind turbine generation in the time interval of period k respectively. $\mathrm{P}_{\mathrm{rice}}(k)$, $P_{load}(k)$, $P_{solar}(k)$, $P_{wind}(k)$ are the real-time data of electricity price, load demand, solar generation, wind generation in period k respectively R_{Pw}, R_{Ps}, R_{Pl}, R_{Pr}, are random vectors subject to uniform distribution, which are used for representing the forecast uncertainty, their mean value are 0 and variation are 1, $\mathrm{E}_{\mathrm{Pr},\max}$, $\mathrm{E}_{Pl,\max}$, $\mathrm{E}_{Ps,\max}$, $\mathrm{E}_{Pw,\max}$ denote the maximum forecast error percentage of electricity price, load demand, PV generation, and wind generation in the period of k respectively.

For better understanding the performance of the four strategies in different prediction error level, according to the past experience, we set three forecast error levels, namely low forecast error level, with load prediction error 3%, PV prediction error 8%, price prediction error 6%, and wind prediction error 10%; middle forecast error level, with load forecast error 6%, PV prediction error 16%, price forecast error 12%, and wind prediction error 20%; and high forecast error level, with load prediction error 9%, PV generation forecast error 24%, price prediction error 18%, and wind prediction error 30%. A simple example of comparison between real-time data and forecast data in different forecast error levels is described in Fig. 6, therein the red curves represent the real-time data of one day, green lines denote the prediction data with low forecast error level, blue lines present the prediction data of middle forecast error level, and cyan curves refer the prediction data with high forecast error level.

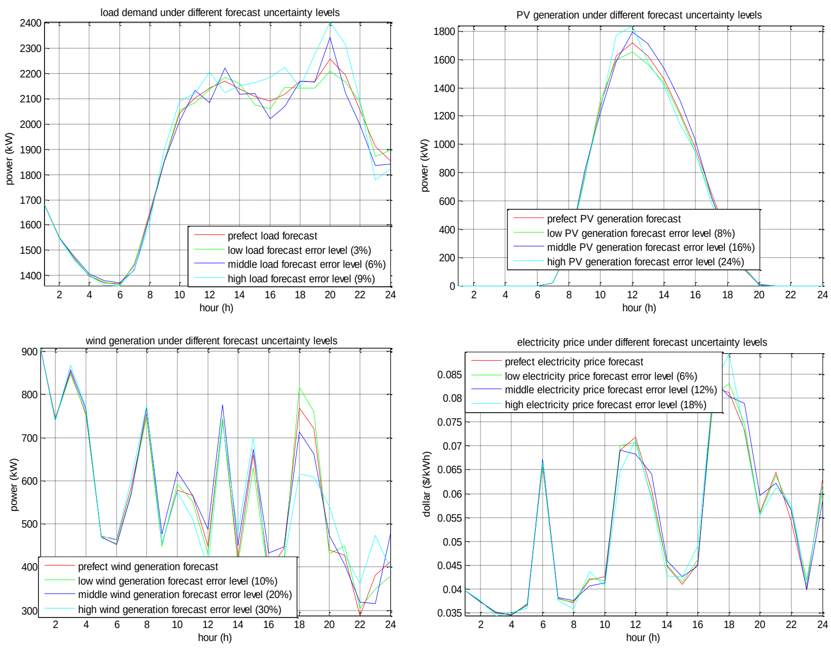

Figure 6. Load demand, wind generation, PV generation and electricity price data at different forecast error levels in day-ahead prediction

It is known to all that the higher forecast error level the harder to predict accurately, as shown in Fig. 6 that as the forecast error level increasing, the prediction uncertainty grows sharply. In this paper, for better comparing the different performances of the four strategies in different forecast error level, more detail forecast error level will be introduced as shown in equation (25), and some external numerical study will be implemented with these data.

$$\mathrm{E}_{Pj,\max} = K \cdot \mathrm{E}_{Pjbasic} \left(j = 1,2,3,4 \right) \quad (25)$$

where $\mathrm{E}_{Pj,\max}$ $\left(j = 1,2,3,4 \right)$ denotes the maximum forecast error percentage of load demand, electricity price, wind generation, and PV generation respectively, therein $\mathrm{E}_{P1,\max} = \mathrm{E}_{Pl,\max}$ presents the maximum forecast error of load, $\mathrm{E}_{P2,\max} = \mathrm{E}_{Pr,\max}$ presents the maximum forecast error of electricity price, $\mathrm{E}_{P3,\max} = \mathrm{E}_{Ps,\max}$ presents the maximum forecast error of PV generation, $\mathrm{E}_{P4,\max} = \mathrm{E}_{Pw,\max}$ presents the maximum forecast error of wind generation, $\mathrm{E}_{Pjbasic}$ represents the basic forecast percentage level of each unit of this microgrid, and according to the past experience, we assume that the basic value as shown in Tab. 1, K is a product factor, which refers the number of simulation.

Table 1. Parameters needed for simulation

Parameter	$\mathrm{E}_{P1basic}$	$\mathrm{E}_{P2basic}$	$\mathrm{E}_{P3basic}$	$\mathrm{E}_{P4basic}$	K
Value	2%	3%	4%	5%	11

From Tab. 1 we know that there are 10 levels of forecast error ($K = 1$ represents perfect forecast), the results of simulation are shown as follows.

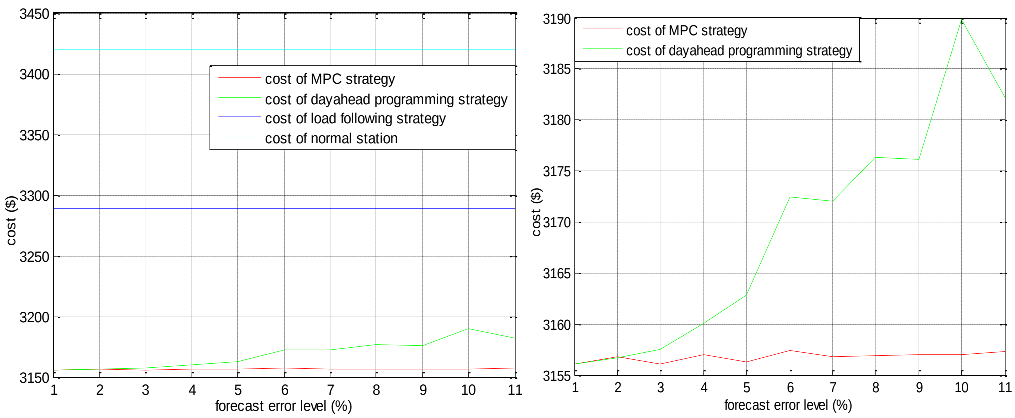

Figure 7. Microgrid operation cost of the four strategies under different forecast error levels

Several conclusions could be deduced from observing Fig. 7 (the left). Firstly, energy storage (BESS) can reduce the cost of microgrid in purchasing electricity energy, as depicted with blue line and other lines. Because the strategy of load following and normal operation with no BESS are both rule based real-time operation strategy, the cost of microgrid in these strategies have no difference with forecast error level, so they are two parallel curves. Secondly, BESS could play an more important role in microgrid operation if suitable strategies or methods are used, as shown in Fig. 7 (the left), there is a big difference of microgrid cost between load following strategy and day-ahead programming and

MPC based strategy, even though the cost of these strategies increasing as the forecast error level increases, nevertheless, the cost of them less than the cost of load following strategy. Last but not the least, as shown in Fig. 7 (the right), with the forecast error level increases, the cost of day-ahead programming increase faster than that under the strategy of MPC, and the increasing rate of cost under day-ahead programming strategy grows faster and faster when the value of forecast error level grows large, however, the cost under MPC based strategy grows not very fast.

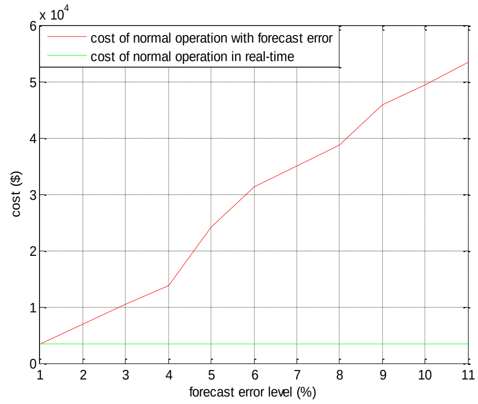

Figure 8. Cost of normal operation strategy under forecast error and perfect forecast case

As shown in Fig. 8, the cost of microgrid as forecast error level increasing under normal operation strategy with no BESS grows sharply. This phenomenon inflects the importance of accuracy prediction when considering economic dispatch of microgrid.

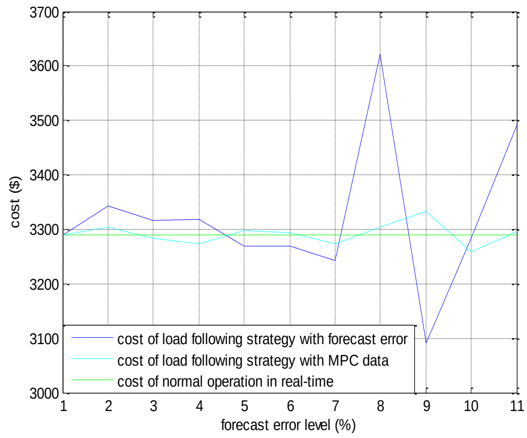

Figure 9. Cost of microgrid under load following strategy in three different cases (real-time data, day-ahead forecast data, and forecast data one period ahead)

It can be observed in figure 9 that the cost of microgrid under load following strategy with one period ahead forecast is more close to real-time operation cost, as the forecast level increasing, the randomness and cost of microgrid operation increase. As to the big difference between the cost of the same strategy with day-ahead forecast data and one period (one hour in this paper) ahead, because as the forecast horizon becomes long, the accuracy of it decrease. This conclusion also can be verified by the cost comparison between day-ahead strategy and MPC strategy and the supplied energy from external network in each period under these two strategies, which is shown in Fig. 10.

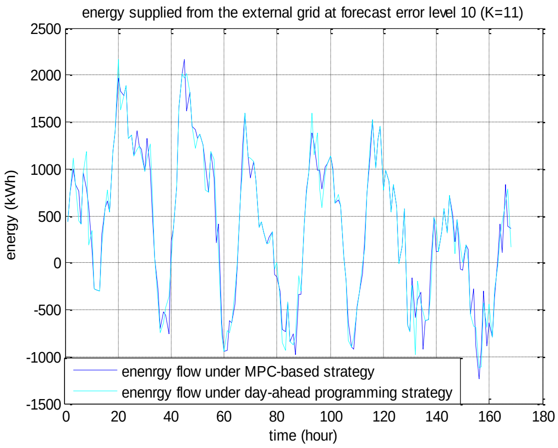

Figure 10. Energy supplied by external grid under MPC-based strategy and day-ahead programming strategy when forecast error level is 10 ($K = 11$)

5. CONCLUSIONS

In this paper, an intelligent control strategy based on model predictive control is proposed for microgrid operator for economic dispatching facing high forecast uncertainty of load demand, PV generation, wind generation, and electricity price in real time price market along with a battery energy storage system. It has been shown that the proposed operation and schedule strategy can lead to an improved microgrid economic dispatch with the help of BESS. Moreover, the simulation study results of comparison between the strategy proposed in this paper and strategies used before show that the proposed control strategy is more flexible and robust as the forecast error level increases when BESS capacity fixed.

Future work will focus on multi-objective dispatching of microgrid, and higher efficient optimization methods suitable for microgrid operation and control.

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