Wind Power Capacity Planning in Enterprise's Microgrid based on Approximation Expectation of Operation Cost

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***Abstract*—Electricity cost constitutes an important part of the total energy cost for some energy-intensive enterprises (EIEs). For such EIEs, an effective way to reduce the electricity cost is to integrate the renewable energy, such as wind power, into their energy systems. In this paper, the problem of optimal wind power capacity planning in EIEs with self-generation power plants (SGPP) is considered. A two-level method framework is proposed in which the optimal electricity cost is obtained at the low level while the wind capacity planning decision is updated at the high level. The procedure is then repeated till the optimal capacity is obtained. Especially, a robust optimization-based formulation is established to guarantee the robustness and nonanticipativity of the low-level subproblem. And, the approximated expectation of operation cost is obtained without using the detailed probability distribution information. Numerical testing is performed for a real system and the results suggest the method is effective.**

***Keywords*—Microgrid, wind power, capacity planning, robust optimization, nonanticipativity**

NOMENCLATURE

A. Indices and Sets:

t	Index of time period, $t = 1,...T$.
s	Index of scenarios, $s = 1, 2, ..., S$.
BS	Base scenarios set.
SVS	Selected vertex scenarios set.

B. Parameters:

β_s	Weighting factor of scenario *s*.
λ_t^{in}	Electricity price at time *t* when enterprise purchases electricity from main grid ($/MWh).
λ_t^{out}	Electricity price at time *t* when enterprise sells electricity to main grid ($/MWh).
τ	Length of each time period (h).
$\overline{w}_t, \underline{w}_t$	Original upper and lower bounds of the available wind power at time *t* (MW).
$\overline{d}_t, \underline{d}_t$	Upper and lower bounds of the uncertain load demand of EIE at time *t* (MW).
$\overline{g}_t, \underline{g}_t$	Allowable range of load/power injection of the microgrid from/to the main grid (MW).
$\overline{p}, \underline{p}$	Upper and lower bounds of the power outputs of the SGPP (MW)
Δ	Ramp-rate of the SGPP power output (MW/h).

C. Decision Variables and random variables:

p_t	Power output of the SGPP (thermal unit) (MW)
$p_t^{\max}, p_t^{\min}$	Two ancillary variables related with bounds of power outputs of the SGPP (MW)
w^{pla}	Planning capacity of wind power (MW)
h_t	Wind curtailment level at time *t* (MW)
w_t	Uncertain wind power output (MW)
w_t^{real}	Real accommodated wind power (MW)
d_t	Uncertain load demand (MW)
g_t	Uncertain load (positive) /power injection (negative) of the enterprise's microgrid from/to the main grid (MW)
D_t	Uncertain net load (MW)

D. Functions:

$C(\cdot)$	Fuel cost of thermal units ($)
$E(\cdot)$	Expectation function

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I. INTRODUCTION

Electricity cost constitutes an important part of the total production cost of energy-intensive enterprises (EIEs) [1],[2]. For such EIEs, an effective way to reduce the electricity cost is to integrate renewable energy such as wind and/or photovoltaic energy into the energy system. The EIE with self-generation power plant (SGPP) and wind power installations have a typical microgrid structure [3]-[5] with conventional/uncertain power generations and uncertain loads. The problem of optimal wind capacity planning in microgrid then arises naturally since the solution to this problem gives the optimal installation capacity to make full use of wind energy in microgrid ([6]-[13]).

Consider an EIE with SGPP, for example, an iron and steel plant ([4], [5]). Since its large range of load fluctuation, this kind of enterprise microgrid usually has several features as follows: (1) the microgrid of such EIE is usually grid-connected and the power/electricity exchange with the main grid is allowed. However, the exchange must be limited in an interval because high punishment prices are set when the limitations are violated [4],[5] and we call this constraint the gateway power bound limits (GPBLs). (2) Energy storage system cannot be used as the main equipment to reduce the large range of load fluctuation. (3) To encourage the enterprise to keep balance as well as possible in its electricity generation and consumption, the price of buying electricity from the main grid is usually higher than that of selling electricity to the main grid.

For such EIEs, the integration of renewable energy can reduce the electricity cost and at the same time, increase the aggregated uncertainties. Thus, feasible and optimal capacity planning is quite important for such EIEs. Therefore, capacity planning problems for microgrid have attracted great attention recently. According to the structure of these methods, they can be divided into two categories: multi-level methods and one-level methods.

In the multi-level methods (usually two-level) ([6]-[10]), the optimal operation cost is obtained at the low level for the trial planning decision and the planning decision is updated at the high level to reduce the total cost. The process is then repeated till the stopping criterion is satisfied. In [6], the low level subproblem is solved by using CPLEX and the high level problem is solved by using particle swarm optimization (PSO). In [7], robust optimization is used to solve the low level subproblem and an optimality cut is also generated and added to the high level master problem. Similar decomposition based two-stage approaches are adopted in [8] to solve the transmission and energy storage expansion planning problem and in [9] to solve the optimal planning of combined cooling, heating, and power (CCHP) microgrid. In [10], a Benders' decomposition based method is proposed to solve the wind power investment problem.

In the one-level methods ([11]-[13]), the optimal planning decision and the optimal operation scheduling (for a finite number of scenarios) are obtained at the same time by solving a single level mathematical programming problem. In [11], a one-level method is used to solve the capacity expansion planning problem of energy storage system in remote microgrids. Markovitz (mean-variance) objective function is adopted in [12] in the one-level method framework to minimize risk in microgrid planning. Differential evolution method is used in [13] to solve the optimal planning of access location and access capacity of wind power plants.

Calculation of optimal operation cost is one of the main difficulties in solving all kinds of planning problems. However, to the best of our knowledge, robustness and nonanticipativity are not fully considered in the related literature on planning problem in computing the operation cost. In [14] and [15], it is pointed out that without consideration of nonanticipativity of the dispatch decisions, the results obtained may be infeasible in real operation. Besides, the real operation cost is difficult to be evaluated accurately when the realization of uncertainty is unknown.

Therefore, in this paper, the problem of wind power capacity planning is considered in an EIE with SGPP. Main contributions of the paper are summarized as follows.

(1) A formulation of wind capacity planning in a grid-connected microgrid is established considering the real operation cost with GPBLs.

(2) An approximated expectation of the operation cost is obtained without using the detailed probability distribution information of the uncertainties.

The rest of the paper is organized as follows. The formulation of wind capacity planning problem is proposed in Section II. A robust optimization-based formulation for obtaining the optimal operation cost under a trial planning capacity is established in Section III. The approximation method for calculating the expectation of operation cost is given in Section IV. Numerical testing is analyzed in Section V and the paper is concluded in Section VI.

II. Wind Power Capacity Planning Method

A. Wind Power Capacity Planning: Framework

To solve the problem of optimal wind power capacity planning problem, a two-level method framework is proposed in this section. The flow diagram is shown in Fig.1.

In the two-level method framework, the optimal operation cost is obtained at the low level for the trial planning decision and the planning decision is updated at the high level to reduce the total cost.

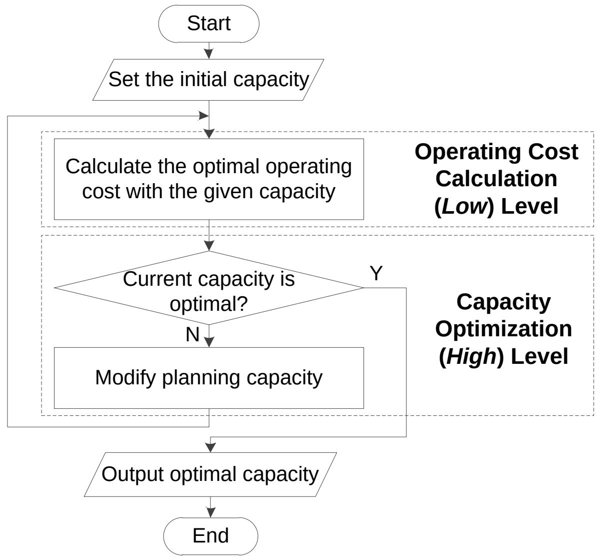

Fig. 1 Wind power capacity planning flow diagram

B. Capacity planning model

Operation cost J_t^{ED} is obtained at the low level and used in the high level. The capacity planning model is then formulated as follows:

$$\min_{w^{pla}} \left(\frac{C_{co}^w}{N} + (C_{om}^w - C_{su}^w)\tau T\right)\cdot w^{pla} + \sum_{t=1}^{T} E(J_t^{ED}) \qquad (1)$$

s.t.
$$0 \le w^{pla} \le \max\{\overline{w}_t\} \qquad (2)$$

The objective (1) consists of investment and operation cost [6]-[10] (in one year). C_{co}^w is the construction cost of unit capacity, and total investment return periods are $N \times T$ periods. For example, if investment needs to be recovered in 10 years ($10\times 8760h$), then $T = 8760/\tau$, $N = 10$. C_{om}^w is the operation and maintenance cost of unit capacity, and C_{su}^w is the subsidy from the government for unit wind installation capacity. It is required by (2) that the planned capacity is no more than the original upper bound of available wind power and this is also the constraint to avoid unnecessary and idle installed capacity.

Since the realization of uncertain wind power and load is unknown, the accurate operation cost cannot be obtained. Therefore, the expectation of operation cost is used to evaluate the operation cost. In the following sections, firstly, the calculation of optimal operation cost is proposed, which is a function of the realization of uncertainty (wind power and load); Secondly, the approximation method for obtaining the expectation of the operation cost is given.

III. Calculation of Optimal Operation Cost

A. Optimal Operation Cost Calculation: Framework

A robust optimization-based scheduling formulation and an economic dispatch (ED) model are established to obtain the optimal operation cost in this section. The framework of the solution procedure is shown in Fig.2.

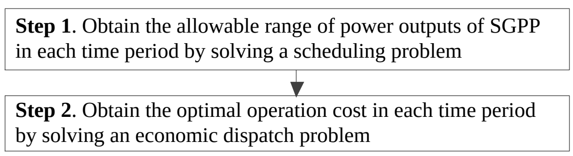

Fig. 2. Framework for obtaining the optimal operation cost

B. Formulation of Scheduling Problem

Suppose the trial planning capacity is w^{pla} then the formulation of the scheduling problem is given as follows.

$$\min_{\substack{p_t^{\max}, p_t^{\min}, h_t, \\ p_t^s, w_t^{s,real}, g_t^s}} J^{SC} = \sum_{s=1}^{S} \beta_s \left(\sum_{t=1}^{T} C(p_t^s) + \sum_{t=1}^{T} \lambda_t^{in} \tau \max\{g_t^s, 0\} \right) + \sum_{s=1}^{S} \beta_s \left(\sum_{t=1}^{T} \lambda_t^{out} \tau \min\{g_t^s, 0\} \right) \quad (3)$$

s.t. $$p_t^s + w_t^{s,real} + g_t^s = d_t^s; \forall t; s \in BS, SVS \quad (4)$$

$$\underline{g}_t \le g_t^s \le \overline{g}_t; \forall t; s \in BS, SVS \quad (5)$$

$$\underline{p} \le p_t^s \le \overline{p}; \forall t; s \in BS, SVS \quad (6)$$

$$p_t^{\min} \le p_t^s \le p_t^{\max}; \forall t; s \in BS, SVS \quad (7)$$

$$| p_t^{\min} - p_{t-1}^{\max} | \le \Delta; \forall t \quad (8)$$

$$| p_t^{\max} - p_{t-1}^{\min} | \le \Delta; \forall t \quad (9)$$

$$w_t^{s,real} = \min\left\{ w^{pla} - h_t, w_t^s \right\}; \forall t; s \in BS, SVS \quad (10)$$

$$0 \le h_t \le w^{pla}; \forall t \quad (11)$$

In the objective function (3), the weighted sum of operating costs is minimized. The first, second, and third term in (3) correspond to the generation cost of SGPP, the cost of buying electricity from the main grid, and the income of selling electricity to the main grid respectively.

In (3)-(11), two kinds of selected scenarios are included: the base scenario (BS) and the selected vertex scenarios (SVS). The BS is included to guarantee the economic performance of the solution, which corresponds to the (point) forecasts of load demand and wind power output as defined below.

$$d_t^s = E(d_t), \ w_t^s = E(w_t); \ \ for\ s = BS \quad (12)$$

The SVS are included to guarantee the robustness and nonanticipativity of the solution. The proof is omitted due to the length limit. Similar proof can be found in [15]. Two scenarios are included in the SVS set and they are defined as follows.

$$\begin{cases} d_t^s = \underline{d}_t, w_t^s = \overline{w}_t; & for\ s = SVS1 \\ d_t^s = \overline{d}_t, w_t^s = \underline{w}_t; & for\ s = SVS2 \end{cases} \quad (13)$$

According to (13), SVS1 is, in fact, the scenario with the minimum net load demand and SVS2 is the one with the maximum net load demand.

(4) is the power balance equation. (5)-(6) are the GPBLs and the power output bound limits of SGPP. (7)-(9) are the proposed nonanticipative constraints (NCs) which are closely related with ramp-rate of the SGPP power output. $p_t^{\max}, p_t^{\min}$ represent the maximum and minimum allowable power outputs of SGPP at t period respectively. (10)-(11) correspond to the wind accommodation/curtailment decision under the trial planning capacity. The essence of h_t is the difference between the planning capacity and the upper bound of the optimal accommodation interval at t period.

The optimal feasible range of SGPP outputs ($p_t^{*\max}, p_t^{*\min}$) and the optimal wind curtailment level (h_t^*) are obtained by solving the scheduling problem, which are substituted into the dispatch problem as known values.

C. Economic Dispatch (ED) Model

For convenience, the net load demand $D_t = d_t - w_t^{real}$ is introduced ($w_t^{real} = \min\{w^{pla} - h_t^*, w_t\}$) and the economic dispatch problem at time period t is defined as follows.

$$J_t^{ED} = \min_{p_t, g_t} \ C(p_t) + \lambda_t^{in} \tau \max\{g_t, 0\} + \lambda_t^{out} \tau \min\{g_t, 0\} \quad (14)$$

s.t. $$p_t + g_t = D_t \quad (15)$$

$$\underline{g}_t \le g_t \le \overline{g}_t \quad (16)$$

$$p_t^{*\min} \le p_t \le p_t^{*\max} \quad (17)$$

Similar to (3), the objective function (14) includes fuel cost and the electricity transaction (purchase/sell) cost with the main grid at time period t. (15)-(16) are the power balance equation and the GPBLs respectively. (17) is the allowable range of power outputs of the SGPP which is very important in guaranteeing the nonanticipativity and robustness of the solution.

Only one thermal unit is considered in (3)-(11) for two reasons. First, there are several identical thermal units in the background EIE considered in this paper and they can be easily aggregated as one unit. Second, the method proposed in this paper can be generalized to the case with several different units.

IV. APPROXIMATION EXPECTATION OF OPERATION COST

The optimal objective value of the dispatch problem is a function with respect to the uncertain net load D_t. The accurate expectation of $J_t^{ED}(D_t)$ depends on the detailed probability distribution information of D_t and it cannot be obtained in the planning process. Therefore, usually, Monte Carlo simulations are used to approximate the expectation of operation cost. However, at the same time, it means a heavy computing burden. In this section, an approximation method for calculating the expectation of the operation cost is given based on the convexity of the dispatch problem.

A. Analysis on the Operation Cost Function

For real systems, it holds that $\lambda_t^{out} \le \lambda_t^{in}$. Meanwhile, the cost function $C(p_t)$ of the SGPP can be well formulated by convex function. Then, it is found that (14)-(17) is a convex programming problem and this result is stated as the following proposition.

Proposition 1. If $\lambda_t^{out} \le \lambda_t^{in}$ and $C(p_t)$ is convex, then:

(i) The gateway electricity cost $\lambda_t^{in} \tau \max\{g_t, 0\}$ $+\lambda_t^{out} \tau \min\{g_t, 0\}$ is a convex function of g_t.

(ii) The objective function in (14) is convex with respect to p_t and g_t.

The conclusions of the proposition are easy to be obtained and the proof is omitted due to the length limit.

Based on Proposition 1, we now prove that the optimal dispatch cost $J_t^{ED}(D_t)$ is a convex function with respect to D_t. For simplicity of presentation, (14)-(17) is rewritten as follows.

$$\begin{cases} f(D) = \min\limits_{x,y} F(x,y) \\ s.t. \quad x + y = D \\ \quad\quad \underline{x} \le x \le \overline{x} \\ \quad\quad \underline{y} \le y \le \overline{y} \end{cases} \quad (18)$$

Proposition 2. Suppose $F(x,y)$ is a convex function of x and y then $f(D)$ is a convex function when $D \in [\underline{x} + \underline{y}, \overline{x} + \overline{y}]$.

Proof. It is clear that (18) has feasible solution if and only if $D \in [\underline{x} + \underline{y}, \overline{x} + \overline{y}]$. Suppose D_1 and D_2 $\in [\underline{x} + \underline{y}, \overline{x} + \overline{y}]$ and the corresponding optimal solutions of (18) are denoted as (x_1^*, y_1^*) and (x_2^*, y_2^*) respectively. That is,

$$f(D_1) = F(x_1^*, y_1^*) \ , \ f(D_2) = F(x_2^*, y_2^*) \ . \qquad (19)$$

We then have

$$\lambda x_1^* + (1-\lambda)x_2^* + \lambda y_1^* + (1-\lambda)y_2^* = \lambda D_1 + (1-\lambda)D_2 \qquad (20)$$

This suggests that $x = \lambda x_1^* + (1-\lambda)x_2^*$, $y = \lambda y_1^* + (1-\lambda)y_2^*$ give a feasible solution for $D = \lambda D_1 + (1-\lambda)D_2$ and therefore the objective value is no less than the optimal objective, that is

$$\begin{aligned} f(\lambda D_1 + (1-\lambda)D_2) &\le F(\lambda x_1^* + (1-\lambda)x_2^*, \lambda y_1^* + (1-\lambda)y_2^*) \\ &\le \lambda F(x_1^*, y_1^*) + (1-\lambda)F(x_2^*, y_2^*) \\ &= \lambda f(D_1) + (1-\lambda) f(D_2) \\ &= \lambda f(D_1) + (1-\lambda) f(D_2) \qquad (21) \end{aligned}$$

The proof is thus completed according to the definition of the convex function. **Q.E.D**

Then, according to the proposition 2, the conclusion that $J_t^{ED}(D_t)$ is a convex function with respect to D_t is obtained.

B. Approximation Method of Operation Cost Expectation

According to the above conclusion, the sketch of the optimal dispatch cost $J_t^{ED}(D_t)$ is shown in Fig. 3. Then, a simple upper bound of $J_t^{ED}(D_t)$ can be obtained as the red line segment in Fig.3 which links the two endpoints of the curve of $J_t^{ED}(D_t)$ in $[\underline{g}_t + p_t^{*\min}, \bar{g}_t + p_t^{*\max}]$. A simple lower bound can be obtained as the blue line segment in Fig.3 which is parallel to the red line and lies under the curve of $J_t^{ED}(D_t)$. The approximation of $J_t^{ED}(D_t)$ is then set as the dashed line (the mean of the upper and lower bounds).

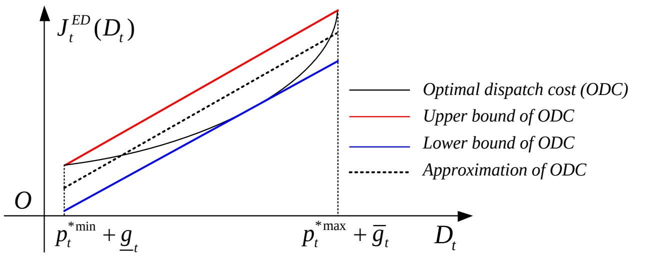

Fig. 3 Approximation of the optimal dispatch cost

Suppose the expression of the dashed line is $a_t D_t + b_t$ (a_t, b_t can be easily obtained) then we have:

$$E(J_t^{ED}(D_t)) \approx E(a_t D_t + b_t) = a_t E(D_t) + b_t \qquad (22)$$

(22) means that an approximation of the expectation of $J_t^{ED}(D_t)$ can be obtained based on $E(D_t)$. It is found in numerical testing that the approximation error is satisfactory and, in this way, a good enough approximation of the dispatch cost is obtained without using the detailed probability distribution information of D_t.

Thus, the $E(J_t^{ED})$ in (1) is obtained approximately and (1)-(2) can be solved very efficiently.

V. Numerical Testing

Numerical testing results for an EIE are analyzed in this section. All tests are implemented using Matlab R2014a and Gurobi 7.5.2 at Intel(R) Core(TM) i7-4790 CPU @ 3.60GHz PC with 8GB RAM.

A. Basic Information

There are 4 identical thermal units in the SGPP of the EIE with a total installed capacity of 1400MW. The four identical units are aggregated as one unit and basic information of the aggregated unit is shown in Table I. Load demands and original available wind power (and the upper/lower bounds) of a typical day (96 periods, 15min per period) are shown in Fig.4 and Fig.5 respectively, which are used in section IV.B for solving the scheduling problem. Large fluctuation of load demands is an important feature of the EIE microgrid as shown in Fig.4. One year data (35040 periods) is used in section IV.C and IV.D for solving the planning problem.

Table I
Basic Information of The Thermal Unit

$\bar{p}$ (MW)	$\underline{p}$ (MW)	Δ (MW/h)	α (\$/(MW·h)) *	γ (\$) *
1400	640	400	19.74	3979

*: $C(p) = \alpha p + \gamma$

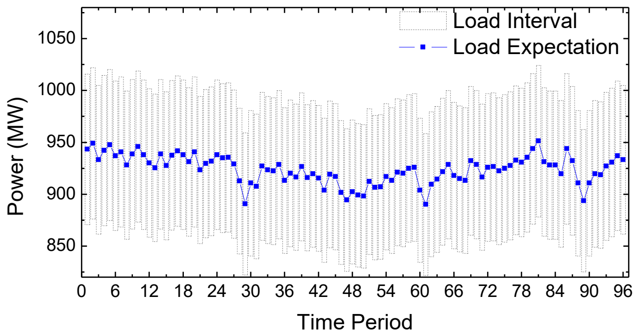

Fig. 4 Basic information of load demands

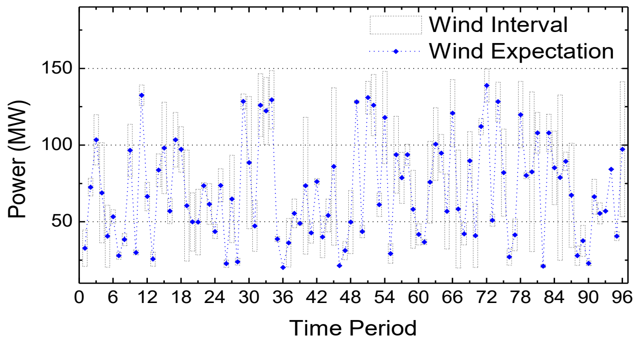

Fig. 5 Basic information of wind outputs

B. The Accuracy of Expectation Approximation Method

The approximation error of (22) is tested and analyzed in this subsection. The true expectation of the operation cost in one day is estimated by using Monte Carlo simulations (1000 samples) and the simulation data is generated randomly in the wind interval of Fig.5, including three distributions. All results are shown in Table II.

Table II
Comparison of Different Cost

Cost-type	**M-Cost ($\times 10^5$ \$)**	**M-Error (%)**	**O-Cost ($\times 10^5$ \$)**	**O-Error (%)**
Approximation	5.1376	/	5.3162	/
Normal	5.0681	1.35	5.2617	1.02
Uniform	5.1049	0.64	5.3045	0.22
Weibull	5.2162	1.53	5.4893	2.69

In Table II, "M-" means that the planning capacity is 150MW (maximum of original available wind power outputs in Fig.5). "O-" means that the planning capacity is 20MW (one of the optimal capacity obtained in later tests). "Error" means the relative error between the expectation of optimal operation cost under each distribution and the approximated expectation cost. It is seen that the approximation error is very small which suggests that the method in section IV is effective.

C. Effect of Wind Power Fluctuation on Planning Capacity

In this subsection, the original upper and lower bounds of available wind power are modified to test the effects of wind power fluctuation on optimal planning capacity. This problem is important since the bounds are different for different locations of wind plant. $\overline{w}_t^N$, $\underline{w}_t^N$ are the new upper and lower bounds and they are obtained based on the wind power fluctuation rate (WPFR) as shown in (23)-(24). Test results are shown in Fig. 6.

$$\overline{w}_t^N = \overline{w}_t + (\overline{w}_t - E(w_t)) \cdot \text{WPFR} \tag{23}$$

$$\underline{w}_t^N = \underline{w}_t - (E(w_t) - \underline{w}_t) \cdot \text{WPFR} \tag{24}$$

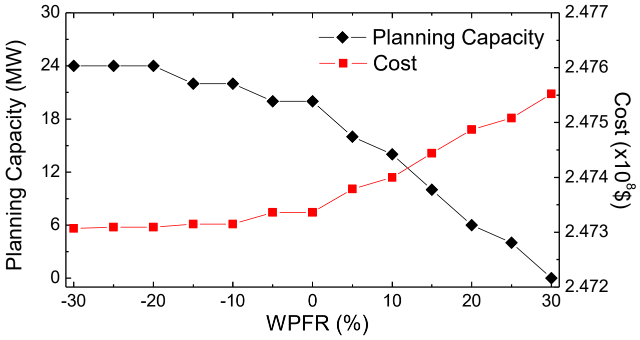

Fig. 6 Effect of the wind power fluctuation on the capacity planning result

From Fig. 6, the following conclusions are obtained: 1) The planning capacity decreases with the increase of WPFR. The planning capacity becomes zero when the WPFR is 30%, which shows that the installment of wind turbines is no longer an economic choice. 2) The total cost increases with the increase of WPFR. The results are useful in determining the installment positions of wind farms with different wind power outputs.

D. Effect of Load Change on Planning Capacity

In real operation, for EIEs, it is found that the lower/upper bounds of load demands vary with different production plan while the differences between the lower and upper bounds do not change significantly. Therefore, the effects of this kind of load change on optimal capacity planning are tested in this subsection. For this purpose, new bounds of load demand ($\overline{d}_t^N$, $\underline{d}_t^N$) are set based on the load change rate (LCR) as shown in (25). Test results are shown in Fig. 7.

$$\overline{d}_t^N = \overline{d}_t + \underline{d}_t \cdot LCR; \quad \underline{d}_t^N = \underline{d}_t + \underline{d}_t \cdot LCR \tag{25}$$

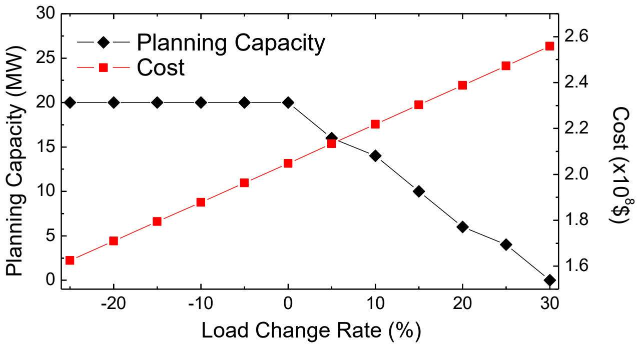

Fig. 7 Effect of the load change on the capacity planning

It is seen from Fig. 7 that the planning capacity is unchanged when LCR is between -20% and 0%, and then decreases with the increase of LCR. This is because the wind accommodation capacity is closely related to the ramp rate of SGPP. When LCR is small, the power output of SGPP is far away from its upper bound, $\overline{p}$, and can be adjusted in a large interval. When LCR is large, the power output of SGPP is close to its upper bound, and can only be adjusted in a small interval. Therefore, the wind accommodation capacity decreases when LCR increases. Moreover, the total cost increases nearly linearly with LCR since the fuel cost of SGPP is assumed to be an affine function.

VI. Conclusion

A wind power capacity planning method in grid-connected microgrid of EIE with GPBLs is presented in this paper. An approximation method for the expectation of operation cost is proposed to reduce the computing burden without using the detailed probability distribution information of the uncertainties. Numerical testing results for a real system suggest the method is effective.

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