Economic Dispatch with Ramp Constraints Concerning Wind Power Uncertainty

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***Abstract*—This paper aims to solve an economic dispatch problem concerning wind power using a Bacterial Swarm Algorithm (BSA). The massive installation of the wind turbines in power system presents a challenge for the conventional economic dispatch. With increasing wind power penetration, the ramp capability of wind farms correlates with the uncertain wind speed rather than a fix ratio as conventional generators. Therefore, the ramp constraints of the economic dispatch can be extended to a probability which is related to the wind speed. In order to solve the constrained optimization problem, this paper employs the BSA to reduce the fuel cost by selecting suitable control variables governing the power systems. The proposed method has been evaluated using an IEEE 30-bus test system. Simulation results indicate that the proposed method significantly reduces the fuel cost and satisfies the ramp constraints.**

Keywords*—*wind power, economic dispatch, ramp constraints, bacteria swarm optimizer.

I. INTRODUCTION

ECONOMIC dispatch aims to achieve the minimization of fuel cost based on a model of power system by adjusting the control variables of the system, while satisfying a set of operational and physical constraints. As a result, the economic dispatch is formulated as a non-linear constrained optimization problem. Although economic dispatch has been widely studied over last few decades, most dispatch studies are based on a deterministic scheme, which consists of a deterministic objective function and associated constraints. Conventional dispatch assumes that the the model of the power system is invariant within the dispatch actions taken around an hour.

Recently, as the utilization of wind power has increased, uncertainties of wind power generation have attracted much attention [1]. With the fast increased rate of wind power penetration, the intermittent nature of wind power becomes a risk factor to the grid, where its uncertainty greatly affects the economic dispatch and the system stability. To preserve the system stability and to optimize the running costs, dispatch problems are extended to wind power integrated power systems, in which operators evaluate the system status with the consideration for wind power uncertainty. Although the running cost of wind power is lower than conventional generators, the spinning reserve cost rises due to the uncertainty. The wind power varies significantly during a dispatch period, especially during the ramp period. If the wind farm fails to follow the ramp rate as scheduled when the actual wind speed is different from the forecast value, the imbalance of the power in the grid will cause instability and the chain actions may further cause black out [2].

To deal with the wind speed uncertainty, some research adopts multi-stage features of preventive and corrective measures. By initially generating a large number of feasible stages with varieties on wind speed probability density, the optimized operation policy could be determined in connection with different stages. However, instantly switching operation policy based on real-time measurements of the wind speeds in application is still a difficult task to perform. In this paper, a novel ramp constraint is designed, where a lower and an upper ramp rate margin for the wind turbines is generate from the distribution of wind speed. The constraint proposed forces the operation policy of economic dispatch following the lower and upper ramp rate margin and the system stability is therefore guaranteed.

In this paper, an improved optimization algorithm, BSA, is introduced to solve the economic dispatch problem [3]. Instead of simply describing chemotaxis behavior in Bacterial Foraging Algorithm (BFA), BSA involves further details of bacterial behaviors, and incorporates the mechanisms of metabolism and quorum sensing. In BSA, two features of bacterial behaviors are incorporated, which are chemotaxis and quorum sensing. Chemotaxis comprises two basic foraging patterns, tumble and run, which form the basic searching strategy of BSA. Quorum sensing enables BSA to escape from local optima. This is a two-fold operation that can either attract a bacterium to the optimal location or repel it away from the location where bacteria are concentrated.

This paper also presents the simulation studies which are undertaken using an IEEE 30-bus test system. Compared with conventional dispatch schemes, the dispatch scheme proposed in this paper not only has an optimized fuel cost, but also satisfies the ramp constraint on both wind turbine and conventional generator. By applying the control strategy to the power system, even if the wind speed is different from forecast value, the ramp rate of entire system will still be guaranteed in most cases.

978-1-4799-6415-4/14/$31.00

II. Economic Dispatch Model

The economic dispatch problem discussed in this paper aims to reduce the fuel cost of the power system. To achieve this objective, the algorithm introduced is applied to optimize the control variables of the power system, including the power and voltages of each generator except the slack bus, the tap ratios of transformers and the reactive power of volt-ampere reactive (var) sources in the grid. Once these control variables have been decided, the state variables are calculate using power flow evaluation, which determines the values of the real power of the slack bus, the load bus voltage, the generator reactive power output, and the network power flows. Besides the objective functions, the constraints of the dispatch problem are also considered in this paper, which are inequality constraints limiting of the control variables and state variables, and equality constraints of the power flow equations. Moreover, the constraints are extended with a ramp rate which guarantees the increase of the actual power for each generator follow the requirement.

A. Objective function

The objective function of economic dispatch can be formulated as a minimization problem, described as follows:

$$\min \quad F(Y,X) \tag{1}$$
$$\text{s.t.} \quad G(Y,X)=0 \tag{2}$$
$$H(Y,X)>0, \tag{3}$$

where $F(Y,X)$ is the optimization objective function, which is concerned with fuel cost, $G(Y,X)$ is a set of equality constraints, and $H(Y,X)$ is a set of formulated inequality constraints; Y is the vector of dependent variables, which is expressed as:

$$Y^{\intercal}=[P_{\mathrm{G1}}\ V_{\mathrm{L1}}\cdots V_{\mathrm{L}N_{\mathrm{G}}}\ Q_{\mathrm{G1}}\cdots Q_{\mathrm{G}N_{\mathrm{G}}}\ S_1\cdots S_{N_{\mathrm{E}}}], \tag{4}$$

which includes the slack bus power P_{G1}, the load bus voltage V_{L}, generator reactive power outputs Q_{G}, and the apparent power flow S_{k}; X is the set of control variables:

$$\begin{aligned} X^{\intercal} \;=\; & [P_{\mathrm{G2}}\cdots P_{\mathrm{G}N_{\mathrm{G}}}\ V_{\mathrm{G1}}\cdots V_{\mathrm{G}N_{\mathrm{G}}} \\ & T_1\cdots T_{N_{\mathrm{T}}}\ Q_{\mathrm{C1}}\cdots Q_{\mathrm{C}N_{\mathrm{C}}}], \end{aligned} \tag{5}$$

which includes the generator real power output P_{G} except slack bus P_{G1}; the generator voltages V_{G}, the transformer tap setting T, and the reactive power generations of var source Q_{C}. The detailed notations and formulation for equality constraints and inequality constraints are given in [4].

The objective function, F, aims to optimize the fuel cost of the generators. The mathematical expectation of the fuel cost is expressed as:

$$F=\sum_{i=1}^{N_{\mathrm{G}}} f_{\mathrm{cost}_i}, \quad i=1,2,\cdots N_{\mathrm{G}}, \tag{6}$$

where

$$f_{\mathrm{cost}_i}=a_i+b_iP_{\mathrm{G}_i}+c_iP_{\mathrm{G}_i}^2, \tag{7}$$

where N_{G} indicates the number of generators, f_{cost_i} indicates the fuel cost ($/h) of the i^{th} generator, a_i, b_i and c_i are fuel cost coefficients of that generator, and $P_{\mathrm{G}ij}$ is the real power output generated by the i^{th} generator.

The inequality constraints $G(Y,X)$ are limits of control variables and state variables. Control variables are chosen according to these inequalities and are used for solving the power flow equations in each iteration of the dispatch process. Dependent variables in Y are calculated based on the control variables by power flow evaluation. Moreover, the voltage V, reactive power Q, and apparent power flow S for all buses are also limited during the entire OPF process, which if formulated as constraints of the objective function as [4].

B. Wind power uncertainty

Weibull distribution is commonly used to describe long-term wind speed stochastic behavior such as one month or one year [5]. When the wind speed follows the Weibull distribution, the wind speed at the i^{th} bus, $v_i\in\mathbb{R}$, is expressed as:

$$\mathrm{P}(v_i;\lambda,k)=\frac{k}{\lambda}\left(\frac{v_i}{\lambda}\right)^{k-1}e^{-(v_i/\lambda)^k} \tag{8}$$

where k and λ are the parameters of the Weibull distribution. In this study, k is set to be 2, which makes the wind uncertainty distribution close to the Rayleigh distribution such that the wind speed is always greater than zero [6].

The power output distribution of the wind turbine connected to the i^{th} bus is determined by the wind speed at that location. A relationship between the power generated and the wind speed was proposed in [7]. The active power output of a wind turbine is given as:

$$P_{\mathrm{W}_i} \;=\; \begin{cases} 0 & 0\le v_i<v_{\mathrm{ci}} \\ a+bv_i^3 & v_{\mathrm{ci}}\le v_i<v_{\mathrm{ra}} \\ P_{\mathrm{ra}} & v_{\mathrm{ra}}\le v_i<v_{\mathrm{co}} \\ 0 & v_i\ge v_{\mathrm{co}} \end{cases}, \tag{9}$$

where

$$a=\frac{P_{\mathrm{ra}}v_{\mathrm{ci}}^3}{v_{\mathrm{ci}}^3-v_{\mathrm{ra}}^3} \quad \text{and} \quad b=\frac{P_{\mathrm{ra}}}{v_{\mathrm{ra}}^3-v_{\mathrm{ci}}^3}, \tag{10}$$

where v_i is the wind speed, v_{ci} the cut-in wind speed, v_{ra} the rated wind speed, v_{co} the cut-out wind speed, and P_{ra} is the rated power of wind turbine. In this paper, the rated power of a wind power generator is set to be 2 MW, the rated wind speed is set to be 12.5 m/s, and the cut-in and cut-out wind speeds are set to be 4 m/s and 20 m/s, respectively.

C. Ramp rate constraints

This research assumes that the dispatch is performed every one hour. Therefore, the ramp rate is expressed as the difference of real power between the dispatch interval. Assuming the load at the i^{th} bus has an initial real power demand $\bar{P}_{\mathrm{D}_i}$ before the dispatch action. When the dispatch strategy is performed, the demand is updated to P_{D_i}. Therefore, the difference of the real power demand between the dispatch interval is expressed as:

$$\Delta P_{\mathrm{D}_i}=P_{\mathrm{D}_i}-\bar{P}_{\mathrm{D}_i}. \tag{11}$$

And the ramp demand of the power system is expressed as:

$$P_{\mathrm{ramp}}=\sum_{i=1}^{N_{\mathrm{B}}}\Delta P_{\mathrm{D}_i}, \tag{12}$$

where N_{B} indicates the number of buses in the power system. The ramp demand, P_{ramp}, is the total demand increase required by the load on each bus, and this amount of demand should be covered by the real power output of the generator. Similar as load, $\bar{P}_{\mathrm{G}_i}$ and P_{G_i} indicate the real power output of the i^{th} generator before and after the dispatch action. Therefore, the difference of the real power generated between the dispatch interval is expressed as:

$$\Delta P_{\mathrm{G}_i} = P_{\mathrm{G}_i} - \bar{P}_{\mathrm{G}_i}. \tag{13}$$

Therefore, the ramp rate constraint is expressed as:

$$\sum_{i=1}^{N_{\mathrm{G}}} \Delta P_{\mathrm{G}_i} > P_{\mathrm{ramp}} \tag{14}$$

$$\Delta P_{\mathrm{G}_i} < \Delta P_{\mathrm{GUB}_i}, \tag{15}$$

where $\Delta P_{\mathrm{GUB}_i}$ indicates the upper margin of the ramp rate of the i^{th} generator. By adding the above ramp rate constraints to the objective function, the solution obtained will guarantee that the ramp demand can be covered by all generators, and the ramp rate for each generator is limited within the ramp ability.

The ramp rate constraints for wind power is also considered in this research, which aims to provide a lower and upper margin to describe the maximal increase or decrease of the wind power output. Assuming the i^{th} wind turbine follows the Rayleigh distribution, the Cumulative Distribution Function (CDF) is expressed as:

$$C(v_i) = 1 - e^{-x^2/2\lambda^2}. \tag{16}$$

The ramp rate constraint proposed aims to satisfie most possible cases from entire wind speed distribution. Therefore, the lower and the upper CDF margins at the i^{th} wind turbine are introduced as C_{lb_i} and C_{pb_i}, respectively. By introducing these two margins, $C_{\mathrm{pb}_i} - C_{\mathrm{lb}_i}$ percent of the wind speed is included in this constraint. As a result, the lower and upper wind speed margins, v_{lb_i} and v_{pb_i}, are expressed as:

$$v_{\mathrm{lb}_i} = \sqrt{-2\lambda^2 \ln C_{\mathrm{lb}_i}} \tag{17}$$

$$v_{\mathrm{ub}_i} = \sqrt{-2\lambda^2 \ln C_{\mathrm{ub}_i}}. \tag{18}$$

Once the lower and upper wind speed margins are obtained, the lower and upper wind power margins, P_{Wlb_i} and P_{Wub_i}, can be calculated by using (9). The wind power margins can be integrated to the ramp rate margin as:

$$\sum_{i=1}^{N_{\mathrm{G}}} \Delta P_{\mathrm{G}_i} + \sum_{j=1}^{N_{\mathrm{T}}} (\bar{P}_{\mathrm{W}_i} - P_{\mathrm{Wlb}_i}) > P_{\mathrm{ramp}}, \tag{19}$$

where $\bar{P}_{\mathrm{W}_i}$ indicates the wind power output of the i^{the} before the dispatch action. If the system power demand is decreasing with time, the P_{Wlb_i} in ramp rate constraint is replaced by P_{Wub_i}.

III. Bacterial Swarm Optimizer

A. Chemotaxis

The chemotaxis behavior can be modeled by a tumble-run process that consists of a tumble step and several run steps. The tumble-run process follows a gradient searching principle, which indicates that the position of the bacterium is updated in the run steps by the gradient information provided by the tumble step. Determining the rotation angle taken by a tumble action in an n-dimensional search space can be described as follows. Suppose the p^{th} bacterium, in the tumble-run process of the k^{th} iteration, has a current position $X_p^k \in \mathbb{R}^n$. The objective of the optimization is to find the minimum of $F(X_p^k)$. The bacterium also has a rotation angle $\varphi_p^k = \left(\varphi_{p1}^k, \varphi_{p2}^k, ..., \varphi_{p(n-1)}^k\right) \in \mathbb{R}^{n-1}$ and a tumble length $D_p^k(\varphi_p^k) = \left(d_{p1}^k, d_{p2}^k, ..., d_{pn}^k\right) \in \mathbb{R}^n$, which can be calculated from φ_p^k via a polar-to-cartesian coordinate transform:

$$\begin{aligned} d_{p1}^k &= \prod_{i=1}^{n-1} \cos\left(\varphi_{pi}^k\right), \\ d_{pj}^k &= \sin\left(\varphi_{p(j-1)}^k\right) \prod_{i=p}^{n-1} \cos\left(\varphi_{pi}^k\right) \quad j = 2, 3, ..., n-1, \\ d_{pn}^k &= \sin\left(\varphi_{p(n-1)}^k\right). \end{aligned} \tag{20}$$

In the polar-to-cartesian coordinate transform, an arbitrary vector in the n-dimensional space can be represented by $n-1$ angles and a normalized distance to the original point.

The maximal rotation angle $\varphi_{\max}$ is related to the number of the dimensions of the objective function, which can be formulated as:

$$\varphi_{\max} = \frac{\pi}{\lfloor \sqrt{n+1} \rfloor}, \tag{21}$$

where n is the number of dimensions and $\lfloor \cdot \rfloor$ denotes the operation which rounds the element to the nearest integer towards minus infinity. By introducing (21), the maximal rotation angle is restricted with the increase of dimension. As a result, the algorithm is easier to converge to the optima in high-dimensional environment, when it finds a heading angle with an effective direction.

In the tumble-run process of the k^{th} iteration, the p^{th} bacterium generates a random rotation angle, which falls in the range of $[0, \varphi_{\max}]$. A tumble action takes place in an angle expressed as:

$$\hat{\varphi}_p^k = \varphi_p^k + r_1 \varphi_{\max}/2, \tag{22}$$

where $r_1 \in \mathbb{R}^{n-1}$ is a uniform random sequence with a range of $[-1, 1]$. The run action immediately follows the tumble action. Because the run action will be performed more than once, the position X_p^k is recorded as $\hat{X}_p^{k,0}$, which indicates the position of the p^{th} bacterium at the beginning of the k^{th} iteration.

Once the angle is determined by the tumble step, the bacterium will run for a maximum of N_{c} run steps. If at the $N_{\mathrm{f}}^{\mathrm{th}}$ ($N_{\mathrm{f}} < N_{\mathrm{c}}$) run step, the bacterium finds a position which has a better fitness value than the current one, the run process also stops. The position of the p^{th} bacterium is updated at the h^{th} ($h \geq 1$) run step in the following way:

$$\hat{X}_p^{k,h} = \hat{X}_p^{k,h-1} + r_2 D_p^k(\hat{\varphi}_p^k), \tag{23}$$

where $r_2 \in \mathbb{R}$ is a normally distributed random number generated from $\mathcal{N}(0, D_{\max})$, $D_{\max}$ is the maximal step length of a run, and $\hat{X}_p^{k,h}$ is the position of the p^{th} bacterium after the h^{th} run step. For convenience of description, the position of the p^{th} bacterium beginning immediately after the tumble-run process of the k^{th} iteration is denoted by $\hat{X}_p^{k,N_{\mathrm{f}}}$, $N_{\mathrm{f}} \leq N_{\mathrm{c}}$.

TABLE I. NUMBER OF WIND TURBINES AND WIND SPEED PARAMETERS IN THE IEEE 30-BUS SYSTEM

Node	2	7	10	16	24
Number of turbines	3	10	5	3	8
λ	10.3	7.5	8.6	3.7	9.5

The rotation angle is updated after each iteration. The tumble angle of the p^{th} bacterium at the beginning of the $(k+1)^{\text{th}}$ iteration is expressed as φ_p^{k+1}, which has the same value as $\hat{\varphi}_p^k$.

B. Quorum sensing

Inspired by Particle Swarm Optimizer (PSO), the positions of the bacteria moving by attraction are updated as follows:

$$X_p^{k+1} = \hat{X}_p^{k,N_{\text{f}}} + r_3(X_{\text{best}} - \hat{X}_p^{k,N_{\text{f}}}), \tag{24}$$

where $r_3 \in \mathbb{R}$ is a normally distributed random number with a range of $[-1, 1]$, which describes the strength of bacterial attraction, and X_{best} indicates the position of the current best global solution updated after the evaluation of each function.

In BSA, a small number of the bacteria are randomly selected to be repelled. To measure the degree of repelling, a repelling rate is defined by ζ, *i.e.*, in each iteration, 100ζ percent of the bacteria are processed by repelling. Accordingly the attraction rate is $100(1-\zeta)$ percent. The repelling process is based on the random searching principle. If the p^{th} bacterium shifts into the repelling process, a random angle in the range of $[0, \pi]$ is generated. The bacterium is thereby "moved" to a random position following this angle in the search space, which can be described as:

$$X_p^{k+1} = \hat{X}_p^{k,N_{\text{f}}} + r_4 D_p^k(\hat{\varphi}_p^k + \pi/2), \tag{25}$$

where $r_4 \in \mathbb{R}^n$ is a normally distributed random sequence which drawn from $\mathcal{N}(0, D_{\text{range}})$, and D_{range} is the range of the search space.

IV. EXPERIMENTAL STUDIES

A. Experimental setting

The simulation studies are carried out on an IEEE 30-bus system [8]. The present experimental study assumes five groups of wind turbines are installed on buses 2, 7, 10, 16 and 24, respectively. The number of wind turbines on each bus and the corresponding parameters in (8) are listed in Table I.

The experiment assumes the real power demands of all buses are increased by 10% from their original values. Therefore, the optimized real power output should be increased as well. The constraint parameters for conventional generators are listed in Table II, which include the bus number of the generator, the initial real power output before the dispatch ($\bar{P}_{\text{G}_i}$) and the ramp rate margin (ΔP_{GUB_i}). Among these generators, generator on bus 1 is the slack bus generator. Generator on bus 2 is defined to be a base load generator, which has a small ramp rate margin. The other 4 generators are defined to be peak load generators, and the ramp rate margins are set at higher values. For the ramp constraint, C_{lb_i} and C_{pb_i} are set to 5% and 95% to make the constraints cover 90% of the wind speed distribution.

TABLE II. RAMP RATE CONSTRAINTS FOR CONVENTIONAL GENERATORS

Generator number	Bus number	P_{G_i} (MW)	ΔP_{GUB_i} (MW)
0	1	90.00	20.00
1	2	50.00	2.00
2	5	35.00	10.00
3	8	20.00	5.00
4	11	10.00	5.00
5	13	10.00	5.00

In the experimental studies, BSA is compared with PSO [9], which has been widely studied and compared in the past few years [9]. For the parameters of PSO, the inertia weight ω is set to be 0.73, and the acceleration factors c_1 and c_2 are both set to be 2.05. The number of iterations for PSO to solve stochastic dispatch is set to be 3×10^2, as suggested in [10]. There are 50 individuals in PSO, and each individual is evaluated by 200 simulations with different combinations of environmental uncertainties in each iteration. Therefore, the total number of function evaluations for PSO is set to be 3×10^6. The number of BSA is set to be 50, and the maximal number of function evaluation is set to be 3×10^6 as well.

B. Optimization of fuel cost

The first objective function adopted in this experiment aims to optimize the fuel cost of the system without adding the ramp rate constraint. The wind turbines are assumed to be running under a fixed wind speed, which is the λ value in Table I. Once a control policy is obtained after the optimization, it is applied to the power system model 2,000 times with different wind speeds generated from a Weibull distribution. The mathematical expectation of the fuel cost (F) and the ramp rate for each generator can be calculate from these 2,000 samples. Meanwhile, a margin is defined to describe the spare power support provided to wind turbines from conventional generator, $\widehat{P}_{\text{W}}$, which is expressed as:

$$\widehat{P}_{\text{W}} = \Delta P\text{G}_0 - \Delta P_{\text{GUB}_i} - \Delta P_{\text{G}_i} - \sum_{j=1}^{N_{\text{T}}} \bar{P}_{\text{W}_i}. \tag{26}$$

A positive value of $\widehat{P}_{\text{W}}$ means the system is able to provide enough ramp power when the output of wind turbines reaches a lower value, which covers 95% of the total possible wind speed distribution. When $\widehat{P}_{\text{W}}$ is a negative value, the system may fail to provide enough ramp power.

According to the results listed in Table III, the solution obtained by BSA has a lower fuel cost than PSO. Because the ramp rate constraint is not included in the objective function, the ramp rate of most generators exceeds the margin. Running the system under this control policy will make the system unstable. Meanwhile, the solutions obtained by the two algorithms both successfully meet the requirement of ramp rate for the wind turbines. This is because the generator on the slack bus has a large ramp rate to balance the power.

C. Optimization with ramp rate constraints

Following the previous experiment, this experiment aims to enhance the economic dispatch objective function with a ramp rate constraint. The wind turbines are assumed to run under uncertain wind speed, which is generated using the Weibull

TABLE III. MATHEMATICAL EXPECTATION OF FUEL COST AND RAMP RATE OBTAINED WITHOUT CONSTRAINT

Algorithm	F ($/h)	ΔP_{G_1} (MW)	ΔP_{G_2} (MW)	ΔP_{G_3} (MW)	ΔP_{G_4} (MW)	ΔP_{G_5} (MW)	$\widehat{P}_W$ (MW)
PSO	910.55	**4.66**	**12.27**	2.85	**11.46**	**5.92**	15.83
BSA	907.43	**2.08**	**12.31**	**9.84**	4.84	3.87	11.53
Margin	-	2.00	10.00	5.00	5.00	5.00	0.00

TABLE IV. MATHEMATICAL EXPECTATION OF FUEL COST AND RAMP RATE OBTAINED WITH CONSTRAINT

Algorithm	F ($/h)	ΔP_{G_1} (MW)	ΔP_{G_2} (MW)	ΔP_{G_3} (MW)	ΔP_{G_4} (MW)	ΔP_{G_5} (MW)	$\widehat{P}_W$ (MW)
PSO	910.72	1.98	9.98	4.98	4.91	4.22	10.70
BSA	908.17	1.99	9.99	4.99	4.99	4.31	9.49
Margin	-	2.00	10.00	5.00	5.00	5.00	0.00

distribution with the λ value in Table I. The mathematical expectation of the fuel cost (F) and the ramp rate for each generator are listed in Table IV.

According to the results, it can be found that the fuel costs obtained by PSO and BSA are both increased. After integrating the ramp rate constraint to the objective function, the feasible space of the control variable is shrunk as well. Therefore, the cost of running the system under the control policy is increased. However, it also can be found that the ramp rate of these conventional generators are all secured within the margin. Meanwhile, these ramp rates are close to the margin, which maximize the performance of each generator. A lower value of $\widehat{P}_W$ also indicates the generator on slack bus has sufficient real power to support the ramping of wind power.

V. CONCLUSION

This paper extends the conventional economic dispatch objective function by employing a ramp rate constraint, which not only aims to minimize the running cost of the system, but also guarantee the ramp rate of each generator is secured within the margin. In order to solve this constrained optimization problem, a population based algorithm, BSA, has been employed. To evaluate the ramp rate constraint proposed in this paper, IEEE 30-bus test case is introduced and integrated with wind power. BSA and PSO are applied to the test case to analysis the system running cost and ramp rate constraint. Simulation results indicate that although the fuel cost of the system is increased after considering the ramp rate constraint, the ramp rate of conventional generator is limited in the margin, and therefore the ramp progress is stable. Meanwhile, the system optimized is also able to provide sufficient support to the ramp rate of wind power.

ACKNOWLEDGEMENT

This research is jointly supported by Guangdong Natural Science Foundation (No. S2013040016964), National National Key Basic Research Program of China (No. 2012CB215100) and Guangdong Innovative Research Team Program (No. 201001N0104744201).

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