Solving DOPF in VSWGs Integrated Power System Using Improved Evolutionary Programming

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***Abstract*—Wind turbine can be divided into two categories: fixed speed wind generators (FSWGs) and variable speed wind generators (VSWGs) . VSWGs's bus can be dealt with as PV-bus or PQ-bus in power flow calculation because reactive power compensation can be performed. Dynamic optimal power flow (DOPF) in VSWGs integrated power system is a typical complex multi-constrained non-convex non-linear programming problem when considering the valve-point effect of conventional generators. In this paper, an improved evolutionary programming (IEP) is proposed to solve DOPF in VSWGs integrated power system. In the methodology, the well-known evolutionary programming (EP) is used as a basic level search, which can give a good direction to the optimal global region. Then, a local search (LS) procedure is adopted as a fine tuning to determine the optimal solution. The modified IEEE 30-bus system is used to illustrate the effectiveness of the proposed method compared with those obtained from EP algorithm. In order to verify algorithm effectiveness in more complex power system, IEEE 39-bus system is used test system. It is shown that the proposed method is capable of yielding higher-quality solutions.**

***Index Terms*— wind power generation, variable speed wind generators, dynamic optimal power flow, improved evolutionary programming**

I. INTRODUCTION

Wind energy is the world's fastest growing renewable energy source. With the increasing levels of wind generator penetration in modern power systems, one of major challenges in the present and coming years is the optimization control, such as optimal power flow including wind farms [1].

Wind turbine can be divided into two categories: fixed speed wind generators (FSWGs) and variable speed wind generators (VSWGs) . FSWGs are still widely use in power system. The disadvantages of FSWGs are as follows.

When wind speed jump, huge wind force will pass through wind turbine blade, hit wind generator components including the main shaft, gearbox, engines, and so on. FSWGs mean that wind speed fluctuations are directly translated into electromechanical torque variations. This will bring in great mechanical stress and cause high fatigue damages on the components, and may result in swing oscillations between turbine and generator shaft. Also the periodical torque dips because of the tower shadow and shear effect are not damped by speed variations and result in higher flicker. Furthermore, the turbine speed cannot be adjusted with the wind speed to optimise the aerodynamic efficiency and wind energy utilization coefficient.

Compared with FSWGs, VSWGs turbine speed can be adjusted with wind speed. Mechanical stress is reduced, and gust energy can be absorbed by the means of inertia; wind energy utilization coefficient is improved, and reactive power compensation can be performed. So, VSWGs's bus can be dealt with as PV-bus or PQ-bus in power flow calculation.

In this paper, the problems of dynamic optimal power flow (DOPF) including VSWGs are researched. The expectation model of wind generators' active power outputs is adopted. DOPF is a typical complex multi-constrained non-convex non-linear programming problem in wind power integrated system when considering the valve-point effect of conventional generators. Both lambda-iterative and gradient technique methods in conventional approaches to the problems are calculus-based techniques and require a smooth and convex cost function and strict continuity of the search space.

In the field of global optimization, evolutionary programming (EP) was investigated and proved to be powerful in solving these problems in the last decades.

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Project supported by the Science Research Program of Education Bureau of Hubei Province under Grant No.D20092906.

doi:10.4304/jcp.6.3.556-563

EP is a stochastic search technique with biological foundations. However, One disadvantage of EP in solving some of the multimodal optimization problems is its slow convergence to a good near-optimum[2, 3, 4].

In this paper, a new improved evolutionary programming (IEP) methodology is proposed for solving DOPF in VSWGs integrated power system; A simple EP [5] is applied as a basic level search, which can give a good direction to the optimal global region, and a local search (LS) procedure [6, 7] is used as a fine tuning to determine the optimal solution at the final. IEP methodology enhances the computational accuracy and accelerates convergence rate at the later period of the searching by adopting LS operator which is invoked if fitness evaluation improves.

The modified IEEE 30-bus system and IEEE 39-bus system are used to illustrate the effectiveness of the proposed method for solving the established DOPF model in VSWGs integrated power system compared with those obtained from EP algorithm. It is shown that the proposed method is capable of yielding higher-quality solutions.

II. DOPF MODEL IN VSWGS INTEGRATED POWER SYSTEM

Due to the random variation of the wind velocities and load demands, it is difficult to research the DOPF in the power system including wind farms. For simplifying this problem, the dividing-stage strategy is adopted in this paper. Wind power generated by wind turbines has intimate relationship with wind speed. Wind speed is converted into power through characteristic curve of a wind turbine. According to the wind velocity forecasting curves and the load forecasting curves in the planning horizon, the expectations of wind generators' power outputs and the load demands at dispatch interval can be calculated.

A. Constraints

Constraints include equality and inequality constraints. The equation constraint is the power flow formulation constraint while inequality constraints including generator power output, ramp rate and bus voltage are as in(1) -(3) . The constraints of real power generation limit and the ramp rate are taken into account as in (1) .

$$\left\{\begin{array}{c} \max\left(P_{i,\min}, P_i^{t-1} - D_{Ri}\Delta T\right) \le P_i^t \le \min\left(P_{i,\max}, P_i^{t-1} + U_{Ri}\Delta T\right) \\ i \in N_{gen} \end{array}\right. . \tag{1}$$

$$Q_{Gi,\min} \le Q_{Gi}^t \le Q_{Gi,\max}, i \in N_{gen} \ . \tag{2}$$

$$V_{i,\min} \le V_i^t \le V_{i,\max}, i \in N \ . \tag{3}$$

where $P_{i,min}$ and $P_{i,max}$ are the maximum and minimum limits of the power generation of unit i, P_i^t is the real power output of unit i at the tth interval, $P_i^{t-1}$is the real power output of unit i at the t-1th interval; U_{Ri} is the up-ramp limit of the ith generator (in units of MW/time-period) ,and D_{Ri} is the down-ramp limit of the ith generator (in units of MW/time-period) ;$\triangle T$ is time interval, N_{gen} is the number of conventional generating units, and N is the number of system buses (excluding slack bus) ; V_i^t is the voltage magnitude output of bus i at the tth interval; Q^t_{Gi} is the reactive power output of conventional generating unit i at the tth interval; *max* is the maximum value of the variable, *min* is the minimum value of the variable.

After calculating the power flow, the state variables, power loss and real power output of the slack bus generator corresponding to the current control variables are available. The real power output of the slack bus generator will be set to the limit if it violates the limit. After handling overlimit of the real power output of the slack bus generator, the system power balance constraints as in(4) must meet, otherwise adding (4) as penalty terms to the objective function to form a generalized objective function. Details of the generalized objective function used in this paper are given in section C.

$$\Delta P^t = \sum_{i=1}^{N_{gen-1}} P_i^t + P_{sl}^t + P_{w,av}^t - P_{ls}^t - P_{ld}^t = 0 \ . \tag{4}$$

where ΔP^t is the unbalance of the real power at the tth interval,N_{gen}-1 represents the number of conventional generating units excluding the slack bus, P_{sl}^t is the real power output of the slack bus generator after handling its overlimit at the tth interval, P_{ls}^t is the total power loss at the tth interval, P_{ld}^t is the total load expectation at the tth interval, $P^t_{w,av}$ is the expectation of wind generators' real power outputs at the tth interval.

B. Objective Function

Due to the fact that wind generation does not consume the fuel, the utility must purchase all the energy produced by wind generating units. Consequently, the objective is to minimize the following total incremental fuel cost function F associated to N_{gen} dispatchable units for T intervals in the given time horizon, subject to the above-mentioned equality and inequality constraints.

$$\min F = \sum_{t=1}^{T} \sum_{i=1}^{N_{gen}} F\left(P_i^t\right) \ . \tag{5}$$

The inclusion of valve-point loading effects makes the modeling of the fuel cost function of the unit more practical. This increases the non-linearity and local optima in the solution space. Also the solution procedure can easily trap in the local optima in the vicinity of optimal value. The fuel cost function of the ith unit F (P_i^t) with valve-point loadings are represented as follows

$$F\left(P_i^t\right) = a_i + b_i P_i^t + c_i P_i^{t2} + \left| e_i \sin(f_i(P_{i,\min} - P_i^t) \right| \cdot \tag{6}$$

where a_i, b_i, and c_i are cost coefficients and e_i, f_i are constants from the valve-point effect of the ith generating unit.

C. Evaluation Function

We must define the evaluation function for evaluating the fitness of each individual in the population. In the most of the nonlinear optimization problems, the constraints are considered by generalizing the objective function using penalty terms.

To sum up, the above problems are generalized as follows

$$\begin{aligned} min\{ & \sum_{t=1}^{T}\sum_{i=1}^{N_{gen}} F\left(P_i^t\right) + K_V \sum_{t=1}^{T}\sum_{i\in N_{PQ}} (V_i^t - V_i^{\lim})^2 + \cdots \\ & + K_Q \sum_{t=1}^{T}\sum_{i\in N_{gen}} (Q_{Gi}^t - Q_{Gi}^{\lim})^2 + K_D \sum_{t=1}^{T}\left(\Delta P^t\right)^2 \} \end{aligned} . \tag{7}$$

where K_V, K_Q and K_D are variable overlimit penalty coefficients, V_i^t is the voltage magnitude of bus i at the tth interval (excluding the slack bus and PV bus) ; $Q^t{}_{Gi}$ is the reactive power output of generator i at the tth interval; V_i^{lim} and $Q_{Gi}{}^{lim}$ denote the violated upper or lower limits.

In this paper, K_V, K_Q are set to 1, 1 respectively. Because the unbalance of the real power ΔP is hard to meet, an adaptive penalty function to handle penalty coefficient K_D is adopted, $K_D=k\sqrt{k}\ \gamma\beta^{\alpha}$, where k is the algorithm's current iteration number; β is a relative violated value of the constraints, γ is a multi-stage assignment value, a is the power of the penalty value.

Meanwhile, several experiments have been done in order to obtain the penalty parameters. In this study, if $\beta\le 1$ then $a=1$, otherwise $a=2$. Furthermore, if $\beta\le 0.001$, then $\gamma=1$, else, if $\beta\le 0.01$ then $\gamma=10$, else, if $\beta\le 0.1$ then $\gamma=30$, else, if $\beta\le 1$ then $\gamma=100$, otherwise $\gamma=300$.

III. IEP AND IMPLEMENTS

A. Evolutionary Programming

EP is a powerful global optimization technique, has proved itself effective to handle complex optimization problems [2,3,4].EP starts with a population of randomly generated candidate solutions and evolves towards the better solutions over a number of iterations. It uses probabilistic rules to explore the complex search space. Hence, it is more suitable to effectively handle complex optimization problems. The main stages of EP include initialization, mutation, and competition and selection. The generalized mapping procedure of the EP technique is as follows

1) Representation and initialization

For DOPF problem including VSWG, there are T dispatches by $N_{gen\text{-}1}$ conventional generating units. An individual array of control variable arrays is

$$\boldsymbol{P} = \begin{pmatrix} P_1^1 & P_1^2 & \cdots & P_1^t & \cdots & P_1^T \\ P_2^1 & P_2^2 & \cdots & P_2^t & \cdots & P_2^T \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ P_{n-1}^1 & P_{n-1}^2 & \cdots & P_{n-1}^t & \cdots & P_{n-1}^T \\ P_n^1 & P_n^2 & \cdots & P_n^t & \cdots & P_n^T \end{pmatrix} . \tag{8}$$

$$\boldsymbol{P} = 1,2,\cdots g\ . \tag{9}$$

where $\boldsymbol{P}$ is individual vector, g is the number of population individuals, $P_n{}^t$ is the real power output of nth generating unit at the tth interval.

For the complete g population individuals, the candidate solution of each individual is randomly initialized within the feasible range in such a way that it should satisfy the constraint given by (1) .

2) Power flow and fitness calculation

Through the power flow calculation including wind farms, the state variables, power loss and real power output of the slack bus generator corresponding to the current control variables have been able to get. The real power output of the slack bus generator will be set to the limit if it violates the limit. After handling overlimit of the real power output of the slack bus generator, the system power balance constraints as in(4) must meet, otherwise adding (4) as penalty terms to the objective function to form a generalized objective function. In this paper, (7) is used as the fitness or evaluation function. This is a generalized fitness function used to evaluate the fitness of the candidate solution of each individual. Also, record the individual's position with the global best fitness as gBest, record the current position of each individual as its current pBest. Set the iteration count k=0.

3) Creation of offspring

The value of each decision variable in the individuals of the offspring population is obtained by perturbing the corresponding variable $p_{i,j}$ in the individuals of the parents population according to

$$p'_{i,j}[k] = p_{i,j}[k] + \sigma_{i,j}[k]\cdot N_{i,j}(0,1)[k]\ . \tag{10}$$

where $\sigma_{i,j}[k]$ denotes the corresponding strategy parameter of $p_{i,j}[k]$ and $N_{i,j}(0,1)$ $[k]$ is a Gaussian random value generated anew at each time of mutation. If the $p'_{i,j}[k]$ is outside the range, it is fixed to the boundaries.

$$\sigma_{i,j}[k] = \beta[k]\frac{F_i[k]}{F_{\max}[k]}(p'_{j,\max} - p'_{j,\min})\ . \tag{11}$$

where $F_i[k]$ denotes the fitness value of the ith individual in the kth generation; $F_{max}[k]$ and $F_{min}[k]$ denote the maximum and minimum fitness in the kth generation.
where β is a scaling factor, which can be tuned during the process of search for optimum. The value of β used here was suggested by [3,4].

4) Selection and Competitio*n*

The q-tournament selection scheme is adopted in this paper. Each individual is assigned a score s_i according to

$$s_i = \sum_{l=1}^{q} s_{i,l}\ . \tag{12}$$

$$s_{il} = \begin{cases} 1 \ , & if \quad F_i < F_l \\ 0 \ , & if \quad F_i > F_l \end{cases} . \tag{13}$$

where F_i is the fitness of individual i, F_l is the fitness of an opponent individual randomly selected from the whole $2N$ individuals, and q is called the tournament size. The N individuals with higher scores are selected to form the parent population of the next generation. Tournament size q is set to $0.9N$ in this paper.

B. LS Subroutine

EP is a powerful global optimization technique, has proved itself effective to handle complex optimization problems. However, the standard EP convergence rate is very slow [2,3,4]. Consequently, the IEP of blending the standard EP with the following LS is proposed.

The LS procedure is outlined below [6,7].

The initial search point is taken as $P_G{}^0$, $P_G{}^0 = [x_{g1}{}^0\ x_{g2}{}^0, \ldots, x_{Gd}{}^0]^T$ and the evaluation function value at $P_G{}^0$ is $F^0{}_{gbest}$. where D is the number of dimension.

Step 1) The initial LS range is selected around $P_G{}^0$ as follows

$$Y^{\min} = P'_{\min} + (P_G^0 - P'_{\min}) \times \beta \ . \tag{14}$$

$$Y^{\max} = P'_{\max} - (P'_{\max} - P_G^0) \times \beta \ . \tag{15}$$

$$R^0 = Y^{\max} - Y^{\min} = (P'_{\max} - P'_{\min})(1-\beta) \ . \tag{16}$$

where Y^{min} and Y^{max} are the lower and upper boundaries of the local search region; β is the local area parameter which is set to 0.4; $P'_{\max}$ and $P'_{\min}$ are the vectors of decision variables limits; and R^0 is the initial LS range.$P^0{}_{Gbest}$ (best search point at the beginning of LS) and P_{opt} (optimum search point) are set to $P_G{}^0$.

Step 2) The N_L LS points are randomly generated as follows

$$P_n^m = P_{Gbest}^{m-1} + R^{m-1} \times \mathbf{r}(D,1), \quad n = 1,2,\cdots,N_L \quad . \tag{17}$$

where r(D,1) is a random number vector of length D, whose elements are randomly generated between -1 and 1 in this paper. If any LS point violates the limits, it is forced within the boundaries. N_L is the number of LS points which is set to 5.

Step 3) For each LS point, the evaluation function values are calculated. Then the minimum evaluation function among all is taken as $F^m{}_{gbest}$, and the corresponding P_G is taken as $P^m{}_{Gbest}$. The optimum values are updated as follows

IF $F^m{}_{gbest} < F^{m-1}{}_{gbest}$ then $F_{opt} = F^m{}_{gbest}$ and $P_{opt} = P^m{}_{Gbest}$
Otherwise $F_{opt} = F^{m-1}{}_{gbest}$ and $P_{opt} = P^{m-1}{}_{Gbest}$.

Step 4) The search range is reduced as

$$R^m = R^{m-1} \times (1-\eta) \ . \tag{18}$$

where η is the range reduction parameter which is set to 0.05.

Step 5) m=m+1,if maximum iteration for LS is not reached, the iteration count is incremented by one and the above procedure is repeated from *step 2*,otherwise, F_{opt} and P_{opt} are taken as the optimum results found by the LS algorithm.

C. IEP and Computational Procedure

The overall procedure of the proposed solution methodology can be summarized as follows

1) Get the initial data;

2) Initialize randomly the initial population in the feasible range and iteration count k=0; Evaluate the initial population and identify the $F_{min}(0)$ and the best initial individual;

3) k=k+1,creation of new population by mutation, competition and selection;

4) Evaluate the fitness score for each individual. Identify the $F_{min}(k)$ and the best individual of the current iteration k;

5) If $F_{min}(k) < F_{min}(k\text{-}1)$

6) Solve the DOPF in VSWGs integrated power system using the LS subroutine with the individual of $F_{min}(k)$ of the EP as starting point;

7) Replace $F_{min}(k)$ of the EP with the final solution obtained using the LS;

8) Repeat for generations until the terminal conditions $k_{\max}$=150 being satisfied.

So, it is beneficial not only for global optimization in the early evolution but also for the computational accuracy and convergence rate in the later period of the searching.

The above strategies are clearly illustrated in Fig. 1.

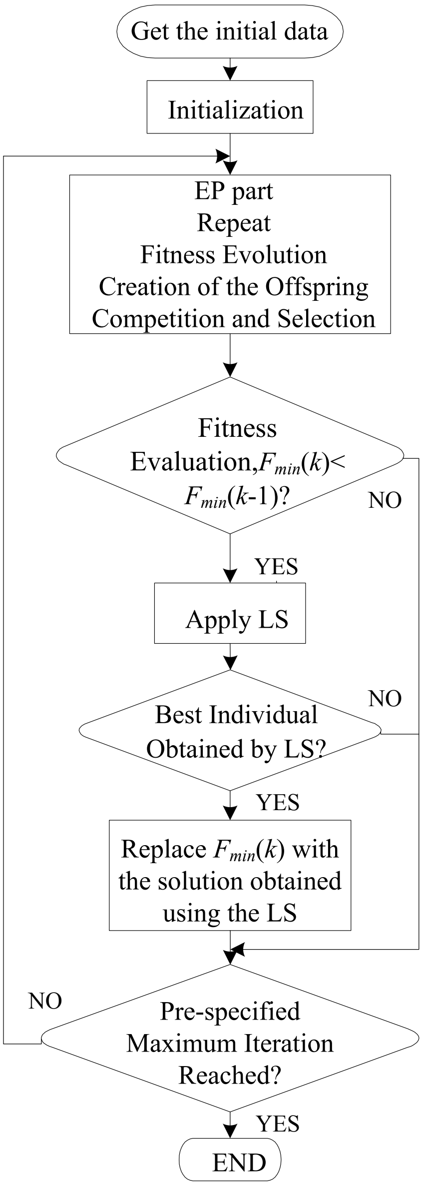

Fig. 1. Flow chart for the proposed method

IV. NUMERICAL RESULTS

To verify the effectiveness and efficiency of the adopted IEP for DOPF problems including VSWGs, The modified IEEE 30-bus system (see Fig.2) and IEEE 39-bus system (see Fig.3) are used as the test systems. The procedure has been implemented in Matlab 7.0 programming language and numerical tests are carried on a Pentium 4 2.4G computer. The wind farm including 60 wind generators with the same type, the rating power of which reaches 36MW, are connected to the system at the bus 6 for the modified IEEE 30-bus system and at the bus 22 for IEEE 39-bus system respectively. For simplifying the analysis, the load size is considered invariable in the planning horizon. The planning horizon is divided into 9 intervals for the modified IEEE 30-bus system and 12 intervals for IEEE 39-bus system respectively, and every interval is 1hr. The wind generators' outputs are shown in Tab. I for the modified IEEE 30-bus system and Tab. II for IEEE 39-bus system respectively. The modified IEEE 30-bus system data are given in [8]. The modified IEEE 30-bus system parameters of the conventional generating units are shown in Tab. III and Tab. IV [8, 9]. IEEE 39-bus system data are given in[8]. The IEEE 39-bus system parameters of the conventional generating units are shown in Tab. V and Tab. VI [8, 10].

TABLE I
THE WIND FARM DATA IN DIFFERENT PERIODS IN THE MODIFIED IEEE 30-BUS SYSTEM

Stage	1	2	3	4	5	6	7	8	9
$P^t_{w,av}$(MW)	0	4.5	9	13.5	18	22.5	27	31.5	36

TABLE II
THE WIND FARM DATA IN DIFFERENT PERIODS IN THE IEEE 39-BUS SYSTEM

Stage	1	2	3	4	5	6	7	8	9	10	11	12
$P^t_{w,av}$(MW)	9	12	15	18	36	36	36	36	0	10	14	19

TABLE III
THE PARAMETERS OF CONVENTIONAL GENERATING UNITS IN THE MODIFIED IEEE 30-BUS SYSTEM

Generator	a_i ($/h)	b_i ($/MWh)	c_i ($/MW^{2}h)	D_{Ri} (MW/h)	U_{Ri} (MW/h)	P_i^0 (MW)	e_i ($/h)	f_i (rad/MW)
G_1	0.0	2.00	0.0200	21.6	21.6	23.54	300	0.2
G_2	0.0	1.75	0.0175	18	18	60.97	200	0.22
G_{22}	0.0	1.00	0.0625	14.4	14.4	21.59	150	0.42
G_{27}	0.0	3.25	0.00834	10.8	10.8	26.91	100	0.3
G_{23}	0.0	3.00	0.0250	14.4	14.4	19.2	200	0.35
G_{13}	0.0	3.00	0.0250	18	18	37	200	0.35

TABLE IV
THE LIMITS OF CONVENTIONAL GENERATING UNITS IN THE MODIFIED IEEE 30-BUS SYSTEM

Generator	$Q_{i,max}$ (MVAr)	$Q_{i,min}$ (MVAr)	$V_{i,max}$ (p.u.)	$V_{i,min}$ (p.u.)	$P_{i,max}$ (MW)	$P_{i,min}$ (MW)
G_1	150	-20	1.05	0.95	80	0
G_2	60	-20	1.05	0.95	80	0
G_{22}	62.5	-15	1.05	0.95	50	0
G_{27}	48.7	-15	1.05	0.95	55	0
G_{23}	40	-10	1.05	0.95	30	0
G_{13}	44.7	-15	1.05	0.95	40	0

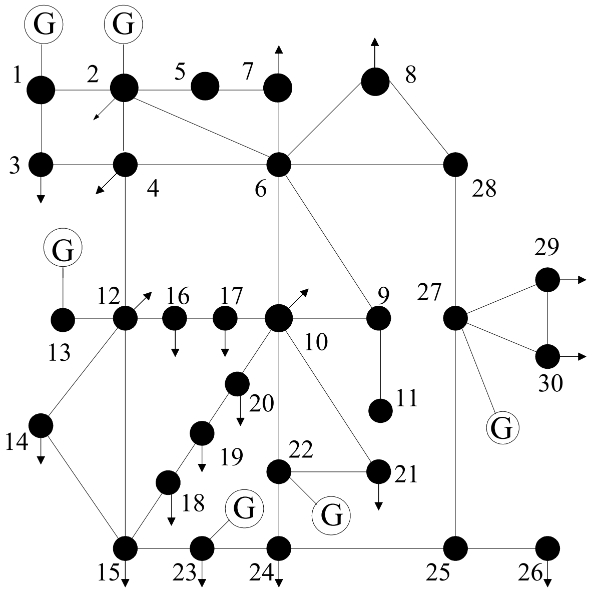

Fig.2. The modified IEEE 30-bus system

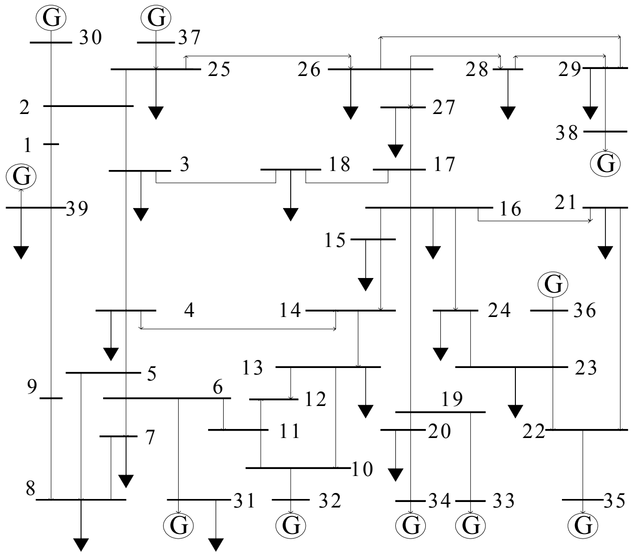

Fig.3. The 39-bus, 10-generator, IEEE system

TABLE V
THE PARAMETERS OF CONVENTIONAL GENERATING UNITS IN THE IEEE 39-BUS SYSTEM

Generator	a_i ($/h)	b_i ($/MWh)	c_i ($/MW^{2}h)	D_{Ri} (MW/h)	U_{Ri} (MW/h)	P_i^0 (MW)	e_i ($/h)	f_i (rad/MW)
G_{30}	0.2	0.3	0.01	80	80	250	450	0.041
G_{31}	0.2	0.3	0.01	80	80	572.9	600	0.036
G_{32}	0.2	0.3	0.01	80	80	650	320	0.028
G_{33}	0.2	0.3	0.01	50	50	632	260	0.025
G_{34}	0.2	0.3	0.01	50	50	508	280	0.063
G_{35}	0.2	0.3	0.01	50	50	650	310	0.048
G_{36}	0.2	0.3	0.01	30	30	560	300	0.086
G_{37}	0.2	0.3	0.01	30	30	540	340	0.082
G_{38}	0.2	0.3	0.006	30	30	830	270	0.098
G_{39}	0.2	0.3	0.006	30	30	1000	380	0.094

TABLE VI
THE PARAMETERS AND LIMITS OF CONVENTIONAL GENERATING UNITS IN THE IEEE 39-BUS SYSTEM

Generator	$Q_{i,max}$ (MVAr)	$Q_{i,min}$ (MVAr)	$V_{i,max}$ (p.u.)	$V_{i,min}$ (p.u.)	$P_{i,max}$ (MW)	$P_{i,min}$ (MW)
G_{30}	9999	-9999	1.06	0.94	350	0
G_{31}	9999	-9999	1.06	0.94	1145.55	0
G_{32}	9999	-9999	1.06	0.94	750	0
G_{33}	9999	-9999	1.06	0.94	732	0
G_{34}	9999	-9999	1.06	0.94	608	0
G_{35}	9999	-9999	1.06	0.94	750	0
G_{36}	9999	-9999	1.06	0.94	660	0
G_{37}	9999	-9999	1.06	0.94	640	0
G_{38}	9999	-9999	1.06	0.94	930	0
G_{39}	9999	-9999	1.06	0.94	1100	0

To demonstrate the superiority of the proposed approach for DOPF problems, simulation results have been compared with the EP method. Owing to the randomness in intelligent algorithms, two algorithms are executed 20 times when applied to the test system.

For DOPF problem including VSWGs, Tab. VII and Tab. VIII list the best control variables found by IEP and EP algorithm for the modified IEEE 30-bus system respectively. In Tab. VII, it is clearly shown that, by using IEP, the total production cost savings of 28.3677$/h is obtained compared with EP algorithm. Hence, it is justified that IEP approach gives the exact minimum dispatch solution. From Tab. XI, the best, worst and average cost values are 9080.5735$/h, 9200.4325$/h, 9132.5035$/h and 9108.9412$/h, 9250.1672$/h, 9188.56373$/h respectively with IEP and EP after 20 independent trials. From the results, the superiority of IEP strategies over EP can be noticed. The difference between the best and worst solutions are 119.859$/h with IEP. At the same time, the difference between the best and worst solutions is 141.226 $/h with EP. Moreover, the best and worst solutions obtained by IEP are very close to the average value, which proves that IEP is more robust and consistent. In conclusion, it is clearly shown that IEP is the most accurate and gives the exact minimum dispatch solution.

In order to verify algorithm effectiveness in more complex power system, IEEE 39-bus system is used test system. Tab. IX and Tab. X list the best control variables found by IEP and EP algorithm respectively. In Tab. IX, it is clearly shown that, by using IEP, the total production cost savings of 815.457$/h is obtained compared with EP algorithm. Hence, The same results are obtained. From Tab. XIII, the best, worst and average cost values are 460571.8601$/h, 461226.8524$/h, 460886.3652$/h and 461387.3171$/h, 462537.4354$/h, 461952.4763$/h respectively with IEP and EP after 20 independent trials. The difference between the best and worst solutions are 654.9923$/h with IEP. At the same time, the difference between the best and worst solutions is 1150.1183 $/h with EP.

TABLE VII
BEST SOLUTION OBTAINED USING IEP METHOD IN THE MODIFIED IEEE 30-BUS SYSTEM

Stage	1	2	3	4	5	6	7	8	9
P_{G1}(MW)	32.1628	26.881	30.61201	34.51722	29.78709	31.29296	31.07789	32.61336	16.72349
P_{G2}(MW)	57.00394	61.08434	55.17584	45.11469	52.62017	45.44802	44.2772	43.06717	57.77425
P_{G22}(MW)	23.05492	28.29231	24.03166	30.68287	29.96296	37.48977	29.89494	32.55328	22.52746
P_{G27}(MW)	25.79418	26.01045	30.52419	29.68614	28.98494	30.16027	26.72748	25.80592	20.62617
P_{G23}(MW)	21.3959	18.5878	15.68668	16.15716	9.585935	6.024802	13.87003	15.62889	18.70101
P_{G13}(MW)	32.11083	25.97463	26.30325	21.53214	22.25072	18.29059	18.17907	9.930773	18.55814

Total production cost: 9080.5735 $/h

TABLE VIII
BEST SOLUTION OBTAINED USING EP METHOD IN THE MODIFIED IEEE 30-BUS SYSTEM

Stage	1	2	3	4	5	6	7	8	9
P_{G1}(MW)	36.65525	43.1043	30.6769	17.91149	32.04969	15.60642	16.76836	13.58982	7.69469
P_{G2}(MW)	59.36403	58.5255	54.9398	51.61109	56.61143	47.39638	53.91842	60.12006	55.17884
P_{G22}(MW)	21.47479	18.14985	27.65491	30.40768	23.19058	29.44758	29.83708	36.22827	30.44646
P_{G27}(MW)	24.23683	19.73205	20.8879	31.6879	28.29225	31.76615	23.96418	21.04326	26.11672
P_{G23}(MW)	23.43493	17.99541	19.81188	18.72996	15.15849	17.75405	21.13465	10.16315	18.56167
P_{G13}(MW)	26.531	29.76962	28.29633	27.1601	18.00986	26.39931	18.31043	18.31929	16.81538

Total production cost: 9108.9412 $/h

TABLE IX
BEST SOLUTION OBTAINED USING IEP METHOD IN THE IEEE 39-BUS SYSTEM

Stage	1	2	3	4	5	6	7	8	9	10	11	12
P_{G30}(MW)	297.845	306.2852	302.6746	299.8669	274.7264	335.2846	301.1622	294.8944	308.8122	316.6097	302.4517	276.8535
P_{G31}(MW)	550.5877	600.1873	671.5014	605.8921	606.2954	538.8119	564.3921	584.1886	608.1819	607.222	600.5313	586.509
P_{G32}(MW)	626.5221	640.2318	569.7617	622.8446	616.9007	560.5899	594.6618	569.9685	600.4495	646.3009	639.911	624.6706
P_{G33}(MW)	634.3726	610.493	620.8039	614.5901	634.593	653.5109	654.2763	639.7166	623.09	573.336	598.1811	590.8908
P_{G34}(MW)	511.1227	476.2915	443.175	493.175	477.3373	510.5703	460.5703	472.3293	483.933	465.6822	487.3279	491.51
P_{G35}(MW)	610.7836	594.3052	627.8122	590.7639	587.3861	623.3719	618.3914	591.8316	585.7375	566.0117	556.7142	590.8262
P_{G36}MW)	568.042	555.3821	549.7241	570.1911	550.7421	579.9209	586.7932	616.7932	586.7932	587.416	567.623	579.9771
P_{G37}(MW)	527.2084	544.5856	545.6563	542.6359	555.7967	540.9971	550.4644	548.0077	553.644	562.9881	562.9605	539.0908
P_{G38}(MW)	849.1404	850.5165	832.8275	820.6171	850.6171	826.3819	827.0456	840.5518	829.1908	843.1028	819.0072	849.0072
P_{G39}(MW)	1008.702	1001.955	1011.994	1012.711	1002.851	988.7539	999.6285	999.6381	1012.127	1013.031	1042.002	1043.645

Total production cost : 460571.8601 \$/h

TABLE X

BEST SOLUTION OBTAINED USING EP METHOD IN THE IEEE 39-BUS SYSTEM

Stage	1	2	3	4	5	6	7	8	9	10	11	12
P_{G30}(MW)	282.7469	238.4208	282.6066	338.1247	341.7531	333.3748	327.2719	306.0325	319.6207	322.2673	342.0072	305.8343
P_{G31}(MW)	594.6711	538.4092	504.6806	435.1558	475.9911	527.6847	564.3274	544.4797	607.5929	661.6504	646.2157	598.6778
P_{G32}(MW)	660.1812	689.5568	631.677	657.2323	622.9245	609.8651	565.3495	554.2467	531.8468	509.444	493.9961	502.6156
P_{G33}(MW)	633.0862	647.1537	657.152	695.4439	656.121	613.5017	634.5771	624.303	650.9625	654.4778	639.7837	643.3003
P_{G34}(MW)	497.4557	495.9905	523.4377	506.0668	491.8216	456.7792	470.8762	449.5858	423.7924	451.8563	445.8726	460.6822
P_{G35}(MW)	605.0152	616.4778	602.7038	583.1142	612.878	641.2923	592.1213	642.1213	650.9918	608.5196	650.9933	665.4863
P_{G36}MW)	544.6999	547.3016	570.5253	579.3933	565.1149	593.0327	567.4237	569.0068	574.9087	564.7232	548.5948	554.9131
P_{G37}(MW)	546.2254	571.3317	582.452	561.9026	563.9268	545.5942	575.5942	574.6134	573.9448	547.9221	550.402	529.3439
P_{G38}(MW)	817.0216	835.4741	852.515	841.1737	846.6516	871.43	864.4906	894.4906	880.61	898.6867	872.7176	902.7176
P_{G39}(MW)	1001.559	1002.257	974.3036	980.9517	982.4731	966.97	996.97	1002.012	981.4998	965.9979	989.3619	1013.062

Total production cost: 461387.3171 \$/h

The average execution time taken to complete the fixed number of iterations (T_{fix}) and the average execution time taken to converge into the lower solution range (T_{low}) for 20 trials are shown in Tab. XII for the modified IEEE 30-bus system and Tab. XIV for IEEE 39-bus system respectively.

For the modified IEEE 30-bus system, EP takes an average execution time of 1800.23 sec. to complete 150 iterations. EP converges faster than IEP by reason of the small sub-memeplex generation number of IEP. In comparison to EP, IEP has additional components, i.e., the LS procedure. This extra burdens increase the execution time of IEP. IEP takes 1898.34 sec. more than EP to complete 150 iterations. Nevertheless, IEP takes only 1020.33 sec. to converge into the lower solution range (9080–9098\$/h) , EP are not able to converge into the lower solution range.

For IEEE 39-bus system, EP takes an average execution time of 4247.25 sec. to complete 150 iterations. EP converges faster than IEP by reason of the small sub-memeplex generation number of IEP. In comparison to EP, IEP has additional components, i.e., the LS procedure. This extra burdens increase the execution time of IEP. IEP takes 4347.92 sec. more than EP to complete 150 iterations. Nevertheless, IEP takes only 2243.82 sec. to converge into the lower solution range (460571–460671\$/h) , EP are not able to converge into the lower solution range.

TABLE XI
COMPARISON OF BEST, WORST AND AVERAGE COST VALUES IN THE MODIFIED IEEE 30-BUS SYSTEM

Algorithms	Best (\$/h)	Worst (\$/h)	Average (\$/h)
IEP	9080.5735	9200.4325	9132.5035
EP	9108.9412	9250.1672	9188.5637

TABLE XII
AVERAGE EXECUTION TIME COMPARISON IN THE MODIFIED IEEE 30-BUS SYSTEM

Methods	Average execution time (sec.)	
	T_{fix}	T_{low}
EP	1800.23	——
IEP	1898.34	1020.33

TABLE XIII
COMPARISON OF BEST, WORST AND AVERAGE COST VALUES IN THE IEEE 39-BUS SYSTEM

Algorithms	Best (\$/h)	Worst (\$/h)	Average (\$/h)
IEP	460571.860	461226.8524	460886.365
EP	461387.317	462537.4354	461952.4763

TABLE XIV
AVERAGE EXECUTION TIME COMPARISON IN THE IEEE 39-BUS SYSTEM

Methods	Average execution time (sec.)	
	T_{fix}	T_{low}
EP	4247.25	——
IEP	4347.92	2243.82

V. CONCLUSION

Considering the valve-point effect and ramp rate limits of conventional generators including VSWGs, DOPF model, which takes the all conventional units cost minimum as the objective function and takes the whole time and the inherent relations of different stages into account in wind power integrated system, is established. The PV-bus model of VSWGs bus is adopted in power flow calculation in this paper. A novel IEP is proposed for solving the established DOPF model and the detailed methods of the algorithm are given. The modified IEEE 30-bus system is used to illustrate the effectiveness of the proposed method compared with those obtained from EP algorithm. In order to verify algorithm effectiveness in more complex power system, IEEE 39-bus system is used test system. It is shown that the proposed method is capable of yielding higher-quality solutions.

ACKNOWLEDGMENTS

The authors would like to thank anonymous reviewers. This work is supported by the Science Research Program of Education Bureau of Hubei Province under Grant No. D20092906.

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