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An Improved Strength Pareto Evolutionary Algorithm 2 with application to the optimization of distributed generations

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ABSTRACT

This paper presents an Improved Strength Pareto Evolutionary Algorithm 2 (ISPEA2), which introduces a penalty factor in objective function constraints, uses adaptive crossover and a mutation operator in the evolutionary process, and combines simulated annealing iterative process over SPEA2. The testing result of ISPEA2 by authoritative testing functions meets the requirement of Petro-optimum fronts. The case study result shows that the proposed algorithm provides a rapid convergence in obtaining Pareto-optimal solutions during the calculation process of evolution. Based on the fuzzy set theory, ISPEA2 is able to solve the multi-objective problems in the IEEE 33-bus system, and its validity and practicality are demonstrated by the utilization on DG's economic dispatch and optimal operation in the field of power industry.

1. Introduction

With the increasing demand of clean and renewable energy, the issue of distribution generation (DG) draws more and more attention all over the world. The injection of DG provides voltage support to the bulk power system, which result to the reliability improvement and loss reduction of the grid. Compared to the traditional fuel energy, the DG is regarded as a kind of economical and reliable energy resources, and its connection to the distribution power system contributes to higher-quality electricity. From the perspective of mathematical optimization, DG's injection is a complex multi-objective optimization problem, which brings a challenge in the optimization analysis of distribution power system. The objectives include optimal energy consumption, the minimum power consumer's electricity purchasing cost and the minimum power loss based on the constraints of power grid's safety and DGs' power output. In the literature research of optimization methods, the simulated annealing technique has been applied to optimize the proposed multi-objective model of DG planning [1]. The multi-objective Tabu search is utilized to optimize DG allocation problem [2]. Fuzzy optimization is also used to solve multi-objective optimization of DG allocation in [3].

The multi-objective evolutionary algorithms (MOEAs) can find the optimal solution set by means of coordinating the relationship of the objectives in an objective function. About the Pareto-optimal solution searching algorithm, related works have been done in particle swarm optimization [4], multi-object genetic algorithm [5], SPEA [6], etc. SPEA (Strength Pareto Evolutionary Algorithm) becomes a popular evolutionary algorithm for MOEA in the last few years. And it is a very important algorithm in MOEA's development [6]. SPEA2, proposed by Zitzler, is the improved version of SPEA, which can obtain orderly-distributed Pareto solution by truncation and controlling the archive set. SPEA2 [7], regarded as a successful multi-objective evolutionary algorithm, possesses few configuration parameters, rapid converging speed, good robustness

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and orderly-distributed solution sets. It has been applied to multiple domains of multi-objective planning in both industrial and academic fields. Zhe Wei, Yixiong Feng and Jianrong Tan, etc. used SPEA2+ in the quality performance conceptual design domain. Through the Pareto optimal set based on the fuzzy set theory, effective references can be got [8]. However, SPEA2 has a disadvantage of localized solution sets. At the same time, SPEA2's application to DG's coordination and optimization is seldom explored in a distribution network.

The ISPEA2 proposed in this paper is equipped with Boltzmann Acceptance Rule [9] in Simulated Annealing Algorithm [10], its crossover and mutation operator [11] is processed by means of adaptive adjustment [12]. The Pareto-optimal solution is obtained from the Pareto-optimal solution set based on the fuzzy set theory [13]. The authoritative testing function (Binh) [14] for multi-objective problems with constraints is applied to ISPEA2, and ISPEA2 is used to solve DG's coordination and optimization in distribution networks, with objectives of DG's optimal injection, reduction of system loss and minimum bill saving for users. The constraint of DG's permitted injection and forecasting output, is used as a penalty function in the optimization problem to promote the elimination of poor individual and ensure the population's optimum. The IEEE 33 power distribution system [15] is selected as the test case. The experiments show that the proposed ISPEA2 can get optimal solutions. The other parts are organized as follows. In Section 2, the improved SPEA2 is explained in detail. The coordination optimization model of distributed generations is discussed in Section 3. In Section 4, the application case and comparison experiments have been done. The conclusion is given in Section 5.

2. Process of ISPEA2 algorithm

2.1. Process of SPEA2

The calculation process of SPEA2 is described as follows:

Initial setting: population size N, archive size $\overline{N}$, maximum generations' number T.

Step 1: set $t = 0$, generate an initial set P_0 randomly, and an empty archive set P'_0.

Step 2: calculate the individuals' fitness value in both internal and external sets.

Step 3: duplicate the non-dominators in both internal and archive sets to a new archive set P'_{t+1}, if the size of P'_{t+1} exceeds $\bar{N}$, reduce P'_{t+1} by means of the truncation operator; otherwise, fill P'_{t+1} with dominated individuals in P_t and P'_t;

Step 4: if the loop number $t \geq T$, terminate the computation to obtain the Pareto-optimal and output, otherwise proceed to Step 5;

Step 5: copy the P'_{t+1} to create a new P_{t+1}, whose individuals are calculated by the pre-set crossover and mutation probability, and let $t = t + 1$, go back to Step 2.

In the SPEA2 process, the individual's fitness $F(i)$ will be obtained from the sum of the primitive fitness value $R(i)$ and the density $D(i)$ as follows:

$$F(i) = R(i) + D(i) \tag{1}$$

where $R(i) = \sum_{x^j \in P_t + A_t, x^i \succ x^j} S(j)$ ($\succ$ means a dominate relation, $x^i \succ x^j$ means x^i dominates x^j, x^i is non-dominated, x^j is dominated). The raw fitness $R(i)$ of an individual i is the sum of its all dominators' strength value $S(i)$, when $R(i) = 0$ corresponds to a non-dominated individual; the strength value $S(i) = \left|\left\{j | x^j \subset P_t + A_t, x^i \succ x^j\right\}\right|$ represents the number of its dominators, the raw fitness assignment process provides non-dominated sorting; the individual's density to distinguish the individuals with the same raw fitness values is estimated by the K-Nearest Neighbor (KNN) method as $D(i) = \frac{1}{\sigma_i^k + 2}$, σ_i^k represents the objective-space distance between individual i and the k-th nearest neighbor and $k = \sqrt{N + \overline{N}}$.

The external archive maintenance [16] process is described as follows:

(1) Copy all the non-inferior solutions in both P_t and P'_t to P'_{t+1}, if the solution size is $\bar{N}$, then proceed;

(2) If the solution size is less than $\bar{N}$, then add the best dominated solutions in size of $\bar{N} - \left|P'_{t+1}\right|$ in both P_t and P'_t to P'_{t+1};

(3) Otherwise, remove the solutions until $\bar{N} = \left|P'_{t+1}\right|$ by the truncating principles of

$$i \leq_d j \Leftrightarrow \forall 0 < k < \left|P'_{t+1}\right| : \sigma_i^k = \sigma_j^k$$
$$\exists 0 < k < \left|P'_{t+1}\right| : \left[\left(\forall 0 < l < k : \sigma_i^l = \sigma_j^l\right) \wedge \sigma_i^k < \sigma_j^k\right].$$

2.2. Process of ISPEA2

The main improvements of ISPEA2 in comparison to SPEA2 can be described as follows: the penalty function is established to constraint the solution of objective function; the adaptive operation is adopted to the crossover mutation in the evolution process which improves the probability of global-optimal; the Boltzmann Accepting Strategy in the simulated annealing algorithm is added to the iterative process so that the algorithm is able to seek the optimal solution globally and converge to the optimal solution rapidly. The flow chart of ISPEA2 is illustrated in Fig. 1, and the dotted modules are the improvements over SPEA2:

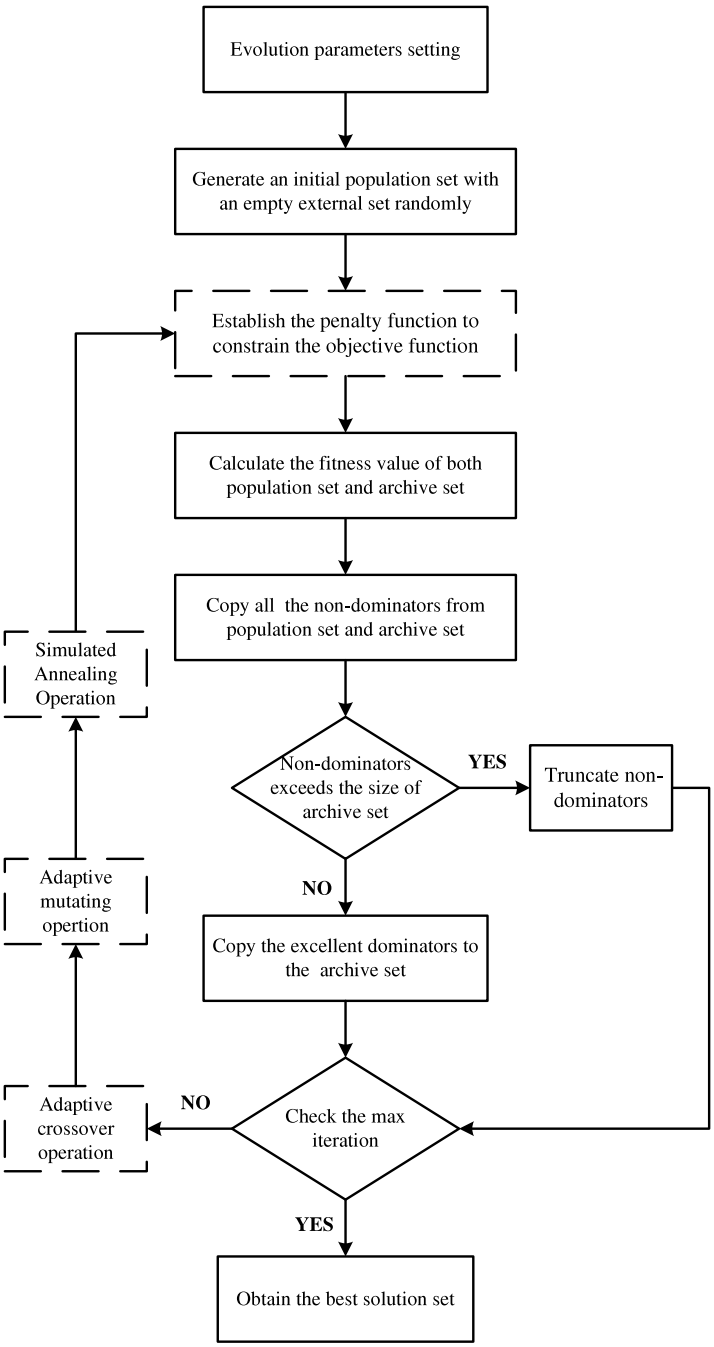

Fig. 1. Flow chart of ISPEA2.

Constrained Optimization problems (Cops) are usually applied to the industry, which is solved by penalty function. How to determine the penalty factor is the core part. The methodology is to evaluate the feasible solution according to the value of objective function, and evaluate the infeasible solution according to the constraint. The non-linear programming problem can be described as

$$\begin{aligned} &\text{Minimize } [f_1(x), f_2(x), \ldots, f_k(x)] \\ &\text{Subject to } \quad g_i(x) \le 0, \quad i = 1, \ldots, n; \\ &\qquad\qquad\quad h_i(x) = 0, \quad i = 1, \ldots, p \end{aligned} \tag{2}$$

where x is a vector of $[x_1, x_2, \ldots, x_r]^T$, n is the number of inequation constraints, p is the equation constraints, k is the number of objectives.

The penalty function applied to the objective function from each generation is established as follows:

$$G_i(x) = \begin{cases} \max(0, g_j(x)), & j = i \\ \left|h_j(x)\right|, & j = i \end{cases} \tag{3}$$

where $G_i(x)$ represents for the distance between the individual x and the i-th constraint condition.

$$G(x) = \sum_{i=1}^{n+p} G_i(x) \tag{4}$$

where $G(x)$ represents for the total penalty function.

The selection of crossover probability P_c and mutation probability P_m dominates the solution process of ISPEA2. The P_c and P_m determines the generation speed and the probability of new individual respectively. If P_c exceeds the threshold, the generation speed of new population will be more quick, which means stronger capability of exploring new space; if P_c is extremely small, the searching process will be quite slow. If P_m is over-sized, the searching process will be more random. In contrast, the new individuals are difficult to generate with small value of P_m. The adaptive value of P_c and P_m are obtained from the following evaluation algorithm:

$$P_c = \begin{cases} \dfrac{k_1\left(f_{\max} - f'\right)}{f_{\max} - f_{\text{avg}}}, & f \geq f_{\text{avg}} \\ k_2, \quad f < f_{\text{avg}} \end{cases} \tag{5}$$

$$P_m = \begin{cases} \dfrac{k_3\left(f_{\max} - f\right)}{f_{\max} - f_{\text{avg}}}, & f \geq f_{\text{avg}} \\ k_4, \quad f < f_{\text{avg}} \end{cases} \tag{6}$$

where f_{avg} is the average fitness value, $f_{\max}$ is the biggest fitness value, f' is the bigger fitness value between the crossover sides, f is the mutating individual's fitness value and $0 < k_1, k_2, k_3, k_4 < 1$.

From Eqs. (5) and (6), the crossover and mutation rate will be decreased while the fitness value is increased, and reach to zero at a maximum fitness value. As the better individuals remain stable during the initial stages of the evolution process, this adjustment will largely increase the localization of Pareto-optimal. To avoid this problem, the improved adaptive operator applied to the calculation process is described as follows:

$$P_c = \begin{cases} \dfrac{P_{c1}\left(f_{\text{avg}} - f'\right) + P_{c2}\left(f' - f_{\min}\right)}{f_{\text{avg}} - f_{\min}}, & f' < f_{\text{avg}} \\ \dfrac{P_{c2}\left(f_{\max} - f'\right) + P_{c3}\left(f' - f_{\text{avg}}\right)}{f_{\max} - f_{\text{avg}}}, & f' \geq f_{\text{avg}} \end{cases} \tag{7}$$

$$P_m = \begin{cases} \dfrac{P_{m1}\left(f_{\text{avg}} - f\right) + P_{m2}\left(f - f_{\min}\right)}{f_{\text{avg}} - f_{\min}}, & f < f_{\text{avg}} \\ \dfrac{P_{m2}\left(f_{\max} - f\right) + P_{m3}\left(f - f_{\text{avg}}\right)}{f_{\max} - f_{\text{avg}}}, & f \geq f_{\text{avg}} \end{cases} \tag{8}$$

where constants $P_{c1}, P_{c2}, P_{c3}, P_{m1}, P_{m2}, P_{m3} \in [0, 1]$ and $P_{c1} > P_{c2} > P_{c3}, P_{m1} > P_{m2} > P_{m3}$. In this paper, P_c and P_m are defined as $P_{c1} = 0.4, P_{c2} = 0.3, P_{c3} = 0.2; P_{m1} = 0.2, P_{m2} = 0.1, P_{m3} = 0.05$.

The principle of the simulated annealing algorithm is to simulate the freezing/crystallization process of liquids or the cooling/annealing process of metals. In the process of seeking an optimal solution, except accepting the optimal solution, SA can also accept secondary solutions by Metropoli Rule, and the probability of accepting bad solutions will be gradually decreased to zero. Therefore, SA will converge to the global-optimal rather than local-optimal. In this paper, Boltzmann Accepting Strategy is implemented to SPEA2 with the main idea of SA to determine whether accepting the new solution x', the accept probability is calculated as follows:

$$A = \min\left\{1, \exp\left(-\Delta E\left(x, x'\right)\right)/T_K\right\} \tag{9}$$

where $\Delta E = E\left(x'\right) - E(x)$, T_K is the current temperature, $E(x)$ is the energy function of x. In SA's iterative process, the temperature change is obtained from the function as follows:

$$T\,(k+1) = \lambda \times Tk \quad (k \to k+1, \lambda \to 1)$$

where k is the temperature cooling times.

2.3. Benchmark on ISPEA2

The benchmark function proposed by Binh, is widely admitted in solving the multi-objective optimization problem with constraints. In this paper, the benchmark function is applied to both SPEA and ISPEA, the comparison results shows ISPEA2's ability of convergence and distribution of Pareto-optimal. The test function is established as follows:

$$\begin{array}{ll} \text{Objective function} & F = (f_1(x,y), f_2(x,y)) \\ \text{where} & f_1(x,y) = 4x^2 + 4y^2 \\ & f_2(x,y) = (x-5)^2 + (y-5)^2 \\ \text{Subject to} & -5 \le x \le 15 \\ & -5 \le y \le 15 \\ & (x-5)^2 + y^2 - 25 \le 0 \\ & -(x-8)^2 - (y+3)^2 + 7.7 \le 0. \end{array}$$

Parameters:
Initial population: 80, offspring individuals: 40, parent individuals: 40.
Generations of evolution: 80.
Probability of crossover: $P_{c1} = 0.7$, $P_{c2} = 0.8$, $P_{c3} = 0.9$, with single-point crossover.
Probability of mutation: $P_{m1} = 0.05$, $P_{m2} = 0.1$, $P_{m3} = 0.15$, with single-point mutation.
Annealing temperature: $T = 200$, $\lambda = 0.95$.
Archive size: 40.

The testing result of SPEA2 and ISPEA2 are shown in Fig. 2. The X-axis represents the main function f_1 while Y-axis represents the main function f_2:

From the comparison of the results, it is obvious that the optimal distribution of ISPEA2 has a great similarity with SPEA2's. Besides, the computing time is reduced considerably from 2.89 to 1.91 s. The decrease in globalized optimal and computing time verifies the efficiency of ISPEA2.

2.4. Pareto-optima selection by fuzzy set theory

In this paper, fuzzy set theory is used to select the optimal solution set among the obtained multi-objective solution sets. The selection process is shown as follows:

First, define a member function τ_i as the weight of target i in a solution:

$$\tau_i = \frac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}}, \quad F_i^{\min} \le F_i \le F_i^{\max} \tag{10}$$

where $F_i^{\max}$ is the maximum of i-th objective, $F_i^{\min}$ is the minimum of i-th objective, F_i is the solution of i-th objective.

The dominate function τ_k for each non-dominant solution k in Pareto solution set is as follows:

$$\tau_k = \sum_{i=1}^{N_0} \tau_k^i \Big/ \sum_{j=1}^{u} \sum_{i=1}^{N_0} \tau_j^i \tag{11}$$

where u is the number of the *Pareto* solution set, N_0 is the number of the optimization objectives.

Since the value of τ_k determines the capability of the solution, the solution with maximum τ_k will be Pareto-optimal. Moreover, the priority sequence of the feasible can be obtained by the value of τ_k, in descending order.

3. Optimization model of DGs in power systems

3.1. Objective functions

Three objectives are considered in the optimization model, which includes the coal cost and the penalty on pollutant emission, bill saving for users when the DG is injected to the distribution network and the system loss.

$F_1(x)$ is the objective function of coal cost and the penalty on pollutant emission, which reflects the impact of energy utilization on environment, is calculated as follows:

$$F_1(x) = \sum_{t=1}^{T} [C_R + C_W] \tag{12}$$

where C_R is the energy consumption cost, C_W is the penalty on pollutant emission.

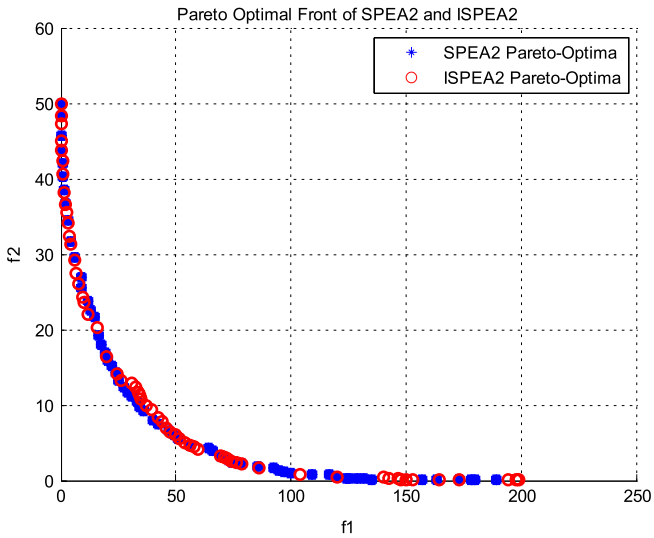

Fig. 2. The Pareto optimal front of ISPEA2 obtained from the test function.

$F_2(x)$ is the bill saving for electricity users as the DG is injected to the distribution network. The saved electric quantity, which should have been purchased from power supply enterprise, is the total power output of DGs. By means of DGs' output and Time-Of-Use rate, the electricity purchasing expenses of consumers could be minimized.

$$F_2(x) = \sum_{t=T_1}^{T_2} C_{d1} P_{\mathrm{DG}t} + \sum_{t=0}^{T_1} C_{d2} P_{\mathrm{DG}t} + \sum_{t=T_2}^{24} C_{d2} P_{\mathrm{DG}t} \tag{13}$$

where C_{d1} is the peak price from T_1 to T_2, C_{d2} is the off-peak price, $P_{\mathrm{DG}t}$ is DG's total power output at moment t.

$F_3(x)$ is the energy loss of the power system after DG's injection into the distribution network and is defined as follows:

$$F_3(x) = P_{\mathrm{loss}} = \sum_{i=0}^{m} \left(\frac{P[i]^2 + Q[i]^2}{U[i]^2} \right) R[i] \tag{14}$$

where $P[i]$ is the active power loss, $Q[i]$ is the reactive power loss, $U[i]$ is the voltage at load node i after DGs' injection, n is the number of injected DGs, m is the number of nodes in the distribution network.

In the optimization model, the coal cost and the penalty on the pollutant emission function $F_1(x)$ and the system loss function $F_3(x)$ should be minimized while the bill saving function $F_2(x)$ should be maximized.

3.2. Constraints

Three constraint conditions are considered in the optimization model, which includes constraints of power flow balancing, node-voltage and DGs' capacity.

The constraint of power flow balancing is described in the following equation:

$$\begin{aligned} P_i - e_i \sum_{j \subset i} (G_{ij} e_j - B_{ij} f_j) - f_i \sum_{j \subset i} (G_{ij} f_j + B_{ij} e_j) = 0 \\ Q_i - f_i \sum_{j \in i} (G_{ij} e_j - B_{ij} f_j) + e_i \sum_{j \in i} (G_{ij} f_j + B_{ij} e_j) = 0 \end{aligned} \tag{15}$$

where G_{ij} is the branch admittance matrix, B_{ij} is the branch conductance matrix.

The constraint of node-voltage is described in the following equation:

$$U_i^{\min} \le U_i \le U_i^{\max}, \quad i \in \Phi \tag{16}$$

where $U_i^{\min}$ is the minimum of U_i, $U_i^{\max}$ is the maximum of U_i, Φ is the *Z-node* set in distribution network.

The connection of DGs will have influence on the power flow in distribution network. To ensure the reliability of the power system, the capacity of DGs should be limited in terms of constraints. In this paper, the maximum injected capacity of DGs is limited to the 25% of the maximum total load in distribution network, which is described as follows:

$$\sum_{i=1}^{n} P_{\mathrm{DG}i} \le 0.25 S^{\max}, \quad (i \in \Phi_S) \tag{17}$$

where $P_{\mathrm{DG}t}$ is DG's access capacity at node i, $S^{\max}$ is the maximum load capacity of distribution network.

Table 1
The pollutant emission rate of DGs (g/kW h).

Pollutant emission	Coal generation	Diesel engine	PV panel	Wind turbine
NO_x	6.46	4.3314	0	0
CO_2	1070	232.0373	0	0
CO	1.55	2.3204	0	0
SO_2	9.93	0.4641	0	0

Table 2
The penalty standard on pollutant emission ($/kg).

SO_2	NO_x	CO_2	CO
0.75	1.00	0.002875	0.125

Table 3
The forecasting power output of solar and wind generation in 24 h.

Time (h)	Solar power output (kW)	Wind power output (kW)
1	0	0
2	0	0
3	0	0
4	0	11.19
5	0	11.19
6	0	17.08
7	0	0
8	60.87	20.16
9	242.05	178.16
10	382.07	435.81
11	488.58	530.2
12	532.85	596.14
13	529.43	566.71
14	466	454.72
15	349.17	271.4
16	198.98	204.18
17	41.01	19.16
18	0	0
19	0	0
20	0	0
21	0	0
22	0	0
23	0	0
24	0	0

3.3. Energy utilization cost and penalty on pollutant emission

(1) Energy utilization cost.

The cost of fossil-fuel consumed by micro-turbines and fuel-cells is calculated as follows:

$$C_R = \sum_{i=1}^{n} f\left(P_i^t\right) C_i \tag{18}$$

where C_i is fuel price at power unit i, $f\left(P_i^t\right)$ is the required fuel quantity for power unit i at the moment t.

(2) Penalty on pollutant emission.

As the global environmental pollution is growing, the power generation cost which represents economic benefits, and pollutant emission cost which has significant influence on environment, are two conflicting goals, they present a restrictive and coordinative relationship. Environmental cost mainly refers fines caused by pollutant emission [17]. Tables 1 and 2 give the pollutant emission data of various DGs and the fine standard of electric power industry's pollution respectively [18].

According to DGs' output, one is able to obtain the pollutant emission quantity. Then, based on the penalty standard, the environmental penalty on pollutant emission is calculated as follows:

$$C_W = \sum_{j=1}^{P} Y_j D_j \tag{19}$$

where Y_j is pollutant j's emission quantity, D_j is the fine standard of pollutant j.

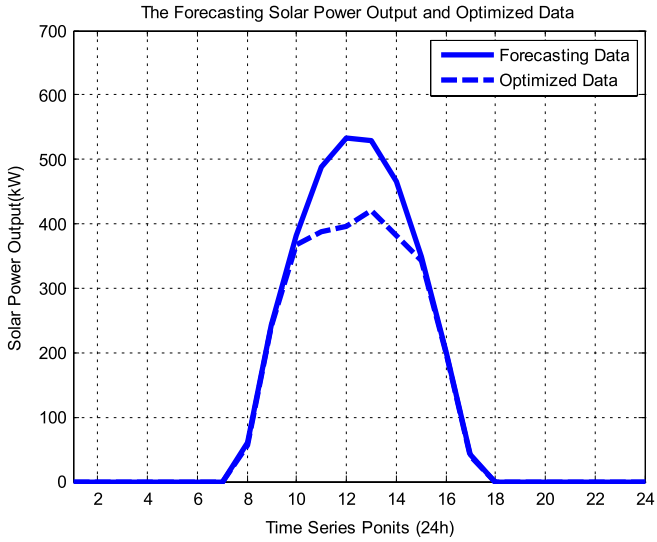

Fig. 3. The forecasting and optimized solar power output.

Table 4
Optimized power output of DGs and system loss after DGs' injection in 24 h.

Time (h)	Optimized power output of DG (kW)				System loss (kW)
	Bus 7	Bus 17	Bus 21	Bus 32	
	PV Panel	Diesel turbine	Diesel turbine	Wind turbine	
1	0	394.09	399.31	0	140.73
2	0	394.09	399.31	0	140.73
3	0	394.09	399.31	0	140.73
4	0	398.52	387.07	10.73	139.35
5	0	398.52	387.07	10.73	139.35
6	0	395.94	397.54	16.78	138.49
7	0	397.17	399.12	0	140.49
8	55.87	381.34	350.78	20	135.87
9	240.13	177.91	319.38	175.12	122.21
10	366.7	92.94	9.87	435.28	108.96
11	387.78	52.93	8.76	422.78	109.82
12	396.13	59.5	13.46	436.6	107.31
13	420.19	0.09	0.86	423.74	117.09
14	381.93	11.88	19.41	435.27	113.49
15	342.34	176.93	111.44	270.19	111.02
16	197.73	394.23	130.69	204.07	110
17	39.43	394.6	394.6	18.86	135.61
18	0	397.17	397.17	0	140.49
19	0	397.17	397.17	0	140.49
20	0	397.17	397.17	0	140.49
21	0	397.17	397.17	0	140.49
22	0	397.17	397.17	0	140.49
23	0	394.09	394.09	0	140.73
24	0	394.09	394.09	0	140.73

4. Case study

The IEEE 33-Bus system is used to verify the proposed algorithm in the paper. PV panel, gas turbine, diesel turbine and wind turbine from user-side are injected into bus 7, bus 17, bus 21, bus 32 respectively. The forecasting power output of solar and wind generation in 24 h are shown in Table 3.

Based on the forecasting power output data in Table 3, by means of the optimization model developed in Section 3, the optimized output of four DGs in 24 h and the power system loss after DGs' injection are as shown in Table 4.

4.1. Solar and wind power output

According to the computed result, the forecasting and optimized solar power output is shown in Fig. 3. And the forecasting and optimized wind power output is shown in Fig. 4. From Figs. 3 and 4, when the solar and wind power output are in low-

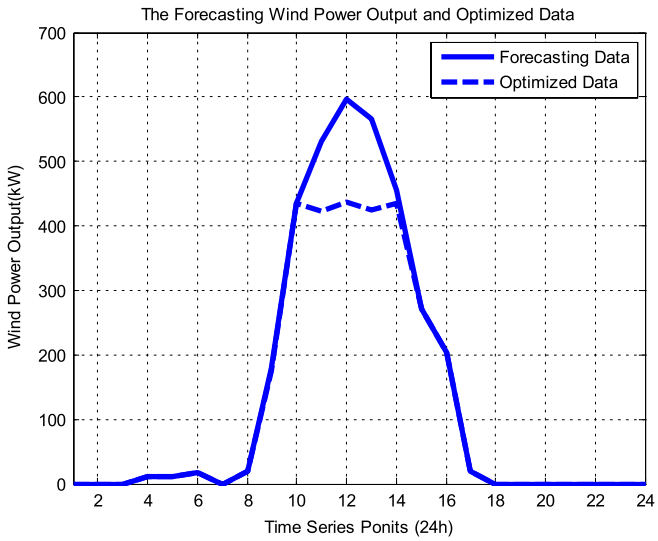

Fig. 4. The forecasting and optimized wind power output.

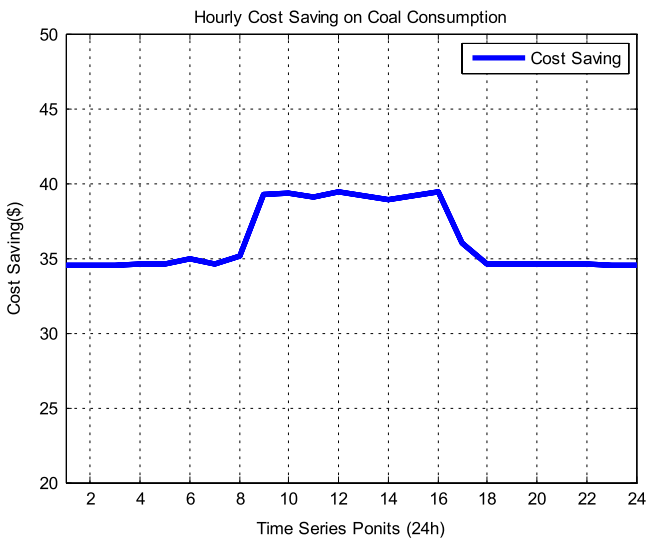

Fig. 5. Hourly cost saving on coal consumption.

level, the diesel power output will be increased. When the PV output and wind power output increase to the peak, it will stop increasing and stay at the peak power output, then the diesel power output will be decreased gradually.

4.2. Cost saving on coal consumption

Assuming the coal consumption from power plant is 0.35 kg/kW h and the highest coal price is 0.124 $/kg, the cost saving on coal consumption is illustrated in Fig. 5, which shows that the more the solar and wind power output, the more cost saving on coal consumption.

4.3. Penalty reduction on pollutant emission

The pollutant emission penalty reduction curve is obtained based on the data from Tables 1 and 2 and the hourly penalty reduction on pollutant emission figure is shown in Fig. 6. As there is no pollutant emission of pollutant solar and wind power generation, when the output of new energy power supply increases, the environment cost will decrease.

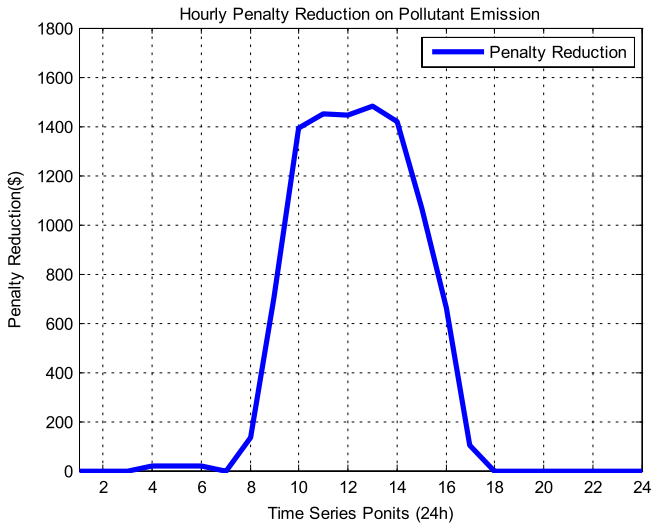

Fig. 6. Hourly penalty reduction on pollutant emission.

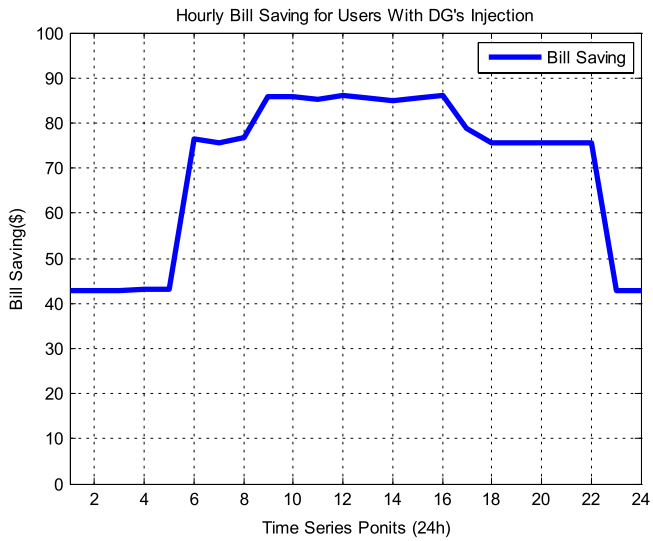

Fig. 7. Hourly bill saving for users with DG's injection.

4.4. Bill saving for electricity users

Assuming that the TOU price is 0.095 $/kW h for peak time from 6:00 am to 22:00 pm, and 0.054 $/kW h in the other period, the bill saving for electricity users per hour is shown in Fig. 7. Since the price is in high level from 6:00 am to 18:00 pm, the bill saving increases with the increase of PV output and wind power output.

4.5. The power system loss after DGs' injection

Suppose that the hourly load in a day remains the same, the power loss before and after DGs' connection are shown in Fig. 8. Obviously, the power loss is reduced efficiently after DGs' injection. As the DGs' power output is increasing, the system load is balanced efficiently.

5. Conclusion

This paper presented an Improved Strength Pareto Evolutionary Algorithm 2 (ISPEA2), which increases the ability of global optimization with the introduction of a simulated annealing iterative process, to solve the multi-objective optimization problem. The proposed ISPEA2 provides a rapid convergence in searching Pareto-optimal solutions by means

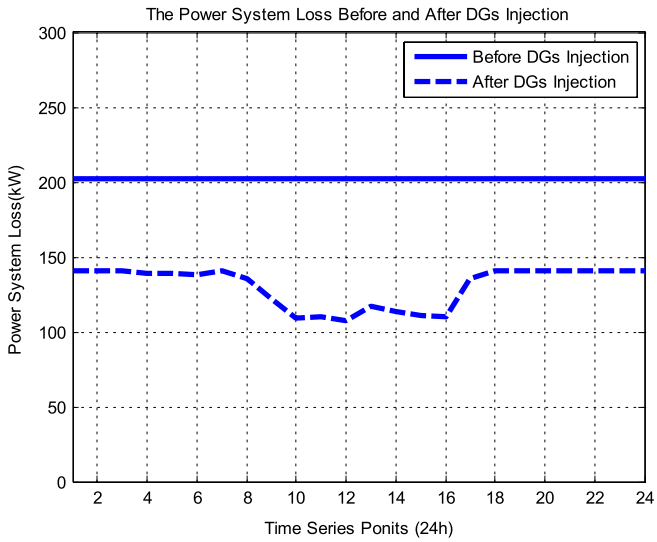

Fig. 8. The power system loss before and after DG's injection.

of the adaptive crossover and mutation operators. The testing result of ISPEA2 by authoritative testing function shows that it can converge to Pareto-optimal and can distribute uniformly. Compared with SPEA2, the computing time is significantly decreased and the computing speed is 1.34 times faster.

The proposed ISPEA2 is utilized to an optimization model of DG's injection in the IEEE 33-bus system with the objective of maximizing the utilization of the DG while minimizing the system loss and environmental pollution. The result from the case study shows that the system loss is greatly reduced by 65%, so that users can save $1671 per day on their electricity bills totally, and power plant can save $870 and $9906 on coal cost and penalty of pollutant emission per day respectively. It also indicates that the optimization model with ISPEA2 is applicable to the practical multi-objective optimization problems in power industry, considering the requirements from utilities, consumers and the environment.

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