Environmental Engineering and Management Journal July 2019, Vol.18, No. 7, 1599-1607
http://www.eemj.icpm.tuiasi.ro/; http://www.eemj.eu

"Gheorghe Asachi" Technical University of Iasi, Romania

A MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION ALGORITHM BASED ON HUMAN SOCIAL BEHAVIOR FOR ENVIRONMENTAL ECONOMICS DISPATCH PROBLEMS

Daqing Wu[1, 2, 3]*, Yanli Liu[1], KaigeZhou[4], Kang Li[5], Jiao Li[6]

[1]College of Economics and Management, Shanghai Ocean University, Shanghai 201306, China
[2]Computer Institute, University of South China, Hengyang 421001 China
[3]School of Economics & Management, TongJi University, Shanghai 20092, China
[4]Department of Economics and Management, Huaiyin Normal University, Huai'an 223001,China
[5]School of Business Administration, Shanghai Lixin University of Accounting and Finance, Shanghai 201620, China
[6]Microelectronics R&D Center, Shanghai University, Shanghai 200444, China

Abstract

Due to emissions from power station using fossil fuels, the decrease of existing pollution as well as of operational costs should be taken into consideration, when resolving environmental economic dispatch problems. In this research, we will evidence that nonlinear constraints of generating units, forbidden regions, and ramp-rate of generating units will reduce operational costs and environmental pollution, to achieve environmental economic dispatch effectiveness, by employing an improved multi-objective optimization algorithm based on human social behavior. With reward and penalty learning factors leading to excellent particles matting and optimization capability to achieve optimal solution, data transactions among particles have been conducted in the suggested approach. To get a more effective comparable result from the recommended algorithm, we conducted simulation experiments on IEEE 10-bus power systems in different load levels. Then we compared the outcomes with those other algorithms that were validated. The results show that the proposed algorithm can achieve diverse Pareto optimal solutions, fast convergence and high robustness, and unlikely to be trapped in local minima. It is revealed that the proposed technique is superior in terms of accuracy and speed in solving power system complex problems over the other methods.

Key words: economic dispatch, human social behaviour, multi-objective optimization problem, particle swarm optimization

Received: January, 2019; Revised final: May, 2019; Accepted: June, 2019; Published in final edited form: July, 2019

1. Introduction

With the growing awareness of environmental pollution, many scholars have shifted their attention towards the environment economic dispatch (EED), which considers the cost of power generation and the emission of polluting gases. The EED aims to achieve two conflicting goals at the same time, namely, the minimum fuel cost and the minimum air pollution. This calls for a feasible scheduling strategy capable of striking a balance between the two objectives. The existing EED models largely favors the minimum fuel cost under the constraints of power scheduling, failing to effectively solve the non-convex Pareto optimality problem.

To solve the problem, multi-objective optimization algorithms, which support parallel processing of two or more targets, have been applied to deal with the EED. Alrashidi and El-Hawary (2006) presented an epsilon (e)-dominance based multi-objective genetic algorithm for multi-objective EED optimization problem. Abido (2009) presented MOPSO algorithm to solve MOEED problem. Wang and Singh (2009) worked on MOEED problem by

* Author to whom all correspondence should be addressed: e-mail: dqwu@shou.edu.cn; Phone: +86-21-6190-0856

using a modified MOPSO algorithm for searching out a set of Pareto-optimal solutions. Airashidi and El-Hawary (2006) describes a multi-objective evolutionary programming method to solve the MOEED problem by converting it into single objective optimization problem using weighted sum method. Bhattacharya et al., (2011) successfully implemented the hybrid differential evolution DE/biogeography-based optimization (BBO) method to solve to solve MOEED problems of thermal generators of power systems. (Güvençet al., 2012) formulated gravitational search algorithm as a bi-objective optimization problem to find the optimal solution for MOEED problems. This technique provides a high-quality solution for MOEED problems.

Various new approaches have been reported in literature to handle the EED problem. A two-stage approach is proposed by combining multi-objective optimization (MOO) with integrated decision making (Yang et al., 2018). To solving the non-convex economic dispatch problem with valve point effects and emissions, Elsakaan et al. (2018) proposes a new Moth-Flame Optimization (EMFO) algorithm, this EMFO optimizes optimal generation schedule of generating units by minimizing two objectives which are fuel cost and emission while the system constraints are achieved. A multi-objective neural network was trained with differential evolution for dynamic economic emission dispatch (Mason et al., 2018; Wu et al., 2019; Zou et al., 2017). Qu et al., (2017) developed multi-objective differential evolution with ensemble of selection method to solve the standard IEEE 30 bus system. A Quantum-behaved bat algorithm was developed to handle the EED problems. This algorithm is a hybrid version of deterministic search, multi-agent system and bee decision-making process and it used a modified Nelder-Mead method to find the optimal solutions (Mahdi et al., 2018). Mostafa et al., (2018) handled the EED problems using a backtracking search algorithm. This algorithm used a strong mutation technique to increase the population diversity. In addition to the above-mentioned methods, there are also many novel methods proposed in the literature to handle the EED problems in the recent years (AghayKaboli et al., 2016, 2017; Asadi et al., 2012; Modiri-Delshad et al., 2016; Rafieerad et al., 2016, 2017; Sebtahmadi et al., 2017).

In the above studies, the EED problem is not transformed into single-objective problems. However, the multi-objective algorithms still face low accuracy and lack diverse Pareto optimal solutions, owing to the neglecting of particle spatial distribution and particle evolution. Thus, these algorithms are not suitable to be adopted for actual engineering. So, this paper proposes a multi-objective PSO algorithm based on human social behaviours (HBPSO). The particle speeds were updated based on the reward/penalty learning factor to prevent the Pareto solution set from falling into the local optimal trap. The proposed algorithm was compared with other algorithms through simulation experiments on six standard test functions and a power system EED model. The results show that the HBPSO can achieve diverse Pareto optimal solutions, fast convergence and high robustness.

2. Problem definition

The EED refers to the optimization of environmental and economic effects of the grid through load scheduling between various generators under multiple physical and operational constraints.

2.1. Objective functions

The general EED model aims to minimize the fuel cost and pollutant emission under the operation constraints of the power generating system and units (Bhattacharya, 2011; Hota et al., 2010). The mathematical expression of the model can be expressed as Eq. (1):

$$\min\left[\sum_{i=1}^{NG} F_i(p_{Gi}), \sum_{i=1}^{NG} E_i(P_{Gi})\right] \tag{1}$$

where: $F(P_{Gi})$ is the fuel cost function, $E(P_{Gi})$ is the pollutant emission function,N_G is the total number of generators in the system, I is the serial number of generators.

Objective 1: Fuel cost function (Eq. 2)

$$F_i(P_{Gi}) = \sum_{i=1}^{N}\left[a_i + b_i \cdot P_{Gi} + c_i \cdot P_{Gi}^2 + \left|d_i \cdot \sin(e_i \cdot (P_{Gi}^{\min} - P_{Gi}))\right|\right] \tag{2}$$

where: P_{Gi} is the active power of the ith generator; $a_i, b_i, c_i$are the system parameters.

Objective 2: Pollutant (NO_x ,SO_2) emission function (Eq. 3)

$$E_i(P_{Gi}) = \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 + \varepsilon_i \exp(\delta_i P_{Gi} \tag{3}$$

where:$\alpha_i, \beta_i, \xi_i, \gamma_i, \delta_i$ are system parameters.

2.2. Constraints

(1) Operating capacity constraint of generators

The generating power of each generator should fall between the maximum and minimum active power outputs (Eq. 4):

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \tag{4}$$

where: $P_{Gi}^{max}, P_{Gi}^{min}$ are the maximum and minimum active power outputs of the ith generator, respectively.

(2) Active power balance constraint

The total power generated by all generators should be equal to the sum of the total power demand and the network loss (Eq. 5):

$$p_{LOSS} + p_D - \sum_{i=1}^{NG} p_{Gi} = 0 \tag{5}$$

where: P_{LOSS} is the network loss, P_D is total power demand. According to the B coefficient method, the relationship between the network loss and the active power of each generator should satisfy (Eq. 6):

$$P_{LOSS} = \sum_{i=j}^{NG}\sum_{j=1}^{NG} P_{Gi}B_{ij}P_{Gj} \quad (6)$$

(3) Ramping rate constraints

During conjoint dispatching time periods, each generator must satisfy certain ramping rate limit and this constraint can be model as (Eq. 7):

$$\begin{cases} P_{Gi,t} - P_{Gi,t-1} - U_{Ri} \times \Delta i \le 0 \\ P_{Gi,t-1} - P_{Gi,t} - D_{Ri} \times \Delta i \le 0 \end{cases}, i = 1, 1co \quad (7)$$

where U_{Ri} and D_{Ri} are the up and down ramping rate limits for the ith thermal unit, respectively while ΔT is the dispatching time interval.

3. HSPSO approach

3.1. Mechanism analysis

In the PSO all particles learn from the individual and global best-known solutions, denoted as *Pbest* and *gbest*, respectively (Dengetal., 2017; Isah et al., 2017; Jiang et al., 2017; Quabab, 2012; Wu et al., 2018). This learning method only works under ideal social condition and faces difficulties in balancing exploration and exploitation. In fact, the people with bad behaviors will exert negative effects on those around them. The imitation of these behaviors is harmful while the resistance to these behaviors is beneficial. For particles in a swarm, only the local optimal and global optimal ones are immune to the neighborhood environment. All the other particles should develop an objective and rational view on the bad behaviors of their neighbors. In this case, it is meaningful to reward the particles playing positive roles and penalize those playing passive roles. This will promote the convergence to Pareto optimal solutions that obey uniform distribution and cover a wide area.

As shown in Fig. 1, a reward factor and a penalty factor were introduced to treat the new individuals in each iteration depending on their contribution to the Pareto solution set. If a new individual dominates the non-dominant solutions in the external Pareto solution set, the reward factor should be adopted to speed up the flight speed and enhance the exploration depth of the particle; otherwise, the penalty factor should be adopted to slow down the flight speed and constrain the exploration depth of that particle.

In this section, the original PSO is modified into the HBPSO in light of the human behaviour. Firstly, the author introduced a learning coefficient r2 and an influential particle N_{max}. The latter is a random number satisfying the standard normal distribution, i.e. $r_2 \in N(0, 1)$, while the latter can be defined as (Eq. 8):

$$N_{\max} = \arg\max\left\{f\left(pbest_1\right), f\left(pbest_1\right), bes\left(pbest_n\right)\right\} \quad (8)$$

where f(pbest) is the fitness of the corresponding particle? In every five iterations, the fitness values of the optimal individual particles were sorted, and the particle with the maximum fitness was considered asNmax. If *Nmax* dominates any solution in the external Pareto solution set, it was taken as the reward learning coefficient that enhances the flying speed of the particle.

3.2. HBPSO model

In the HBPSO, all particles learn from the particle with the individual best-known solution, the influential particle N_{max} and external Pareto solution set. Thus, the flight speed of each particle is dynamically adjusted according to the experience of itself, the swarm and the environment. Let n be the number of particles in a d-dimensional search space.

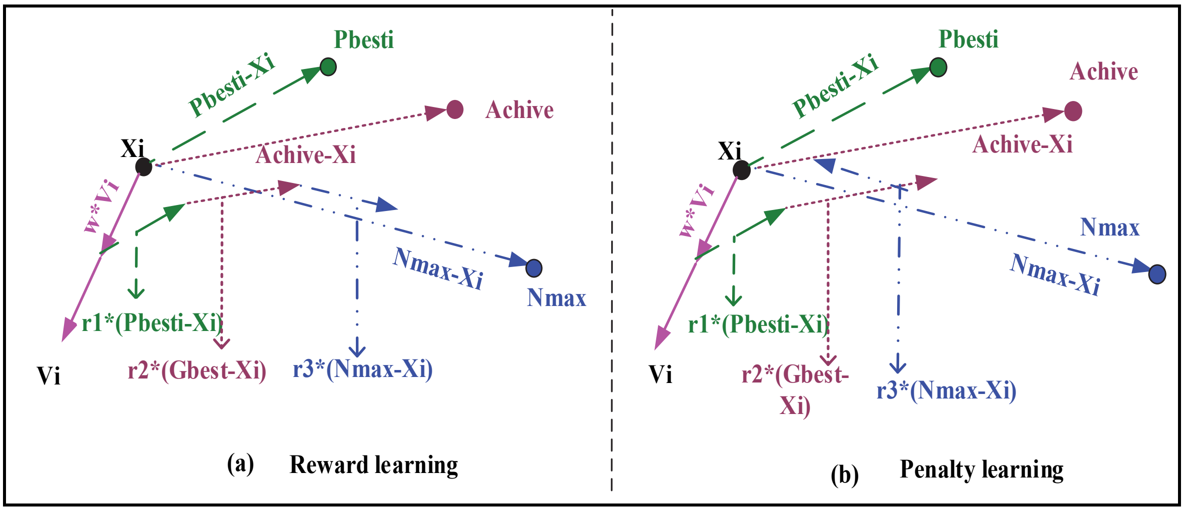

Fig. 1. Reward and penalty learning factors

Then, the n particles will look for the optimal solution through competition according to the HBPSO. The process is similar to the foraging process of ants. The particle speed and position can be updated as given by Eqs. (9-10).

$$v_i^d(t+1) = w \times v_i^d(t) + r_1^d \times \left(pbest_i^d(t) - x_i^d(t)\right) + r_2^d \times \times \left(Achieve_i^d(t) - x_i^d(t)\right) + r_3^d \times \left(N\max_i^d - x_i^d(t)\right) \tag{9}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t) \tag{10}$$

where: r_1, r_2, and r_3 are learning factors; w is *the* inertia coefficient; t is the number of iterations, $x_i(t)$ and $v_i(t)$ are the position and speed vectors of the i-th particle in the t-th iteration, respectively. $Pbest_i$ is the best-known individual solution, *chive* is the external Pareto solution set. Maxis the influential particle in the neighbourhood, I=1, 2,…, n, d=1, 2,…, D. Note that the learning factors are random numbers subjected to the U(0,1) distribution and$r_1+r_2+r_3=1$.

Obviously, the particle speed in the HBPSO is updated through four parts. In the first part, the particle tends to maintain the original speed. In the second part, the particle tends to approach its best-known solution. In the third part, the particle is affected by the neighbour particles. Inthe fourth part, the particle tends to approach the best-known solution of the swarm. The procedure of the HBPSO as follow:

Step 1: Initialize the maximum and minimum power outputs of each generator in the power generation system, the coefficients of fuel cost function and pollutant emission function, the B-coefficient of network loss and the total system load.

Step 2: Establish the mathematical model for the EED.

Step 3: Initialize the swarm, Initialize particle speed, particle position, the maximum number of iterations (*max_gen*) and other parameters; evaluate the fitness of each parameter and assign the individual and global best-known solutions (*pbest* and *gbest*); set up an orthogonal array; design the attractor for each particle.and determine the individual best-known solution (*pbest*), the global best-known solution (*gbest*), the influential particle (*Nmax*) and the external Pareto solution set (*Archi*) as well as the maximum number of iterations.

Step 4: Perform iterative update of the speed and position of each particle in the swarm by equations (7)-(10).

Steps 5: Compute the fitness of each new particle and judge whether it dominates the non-dominant solution in the external Pareto solution set. If yes, generate the reward learning factor and jump to step 7. Otherwise, increase the flag and jump to Step 6.

Step 6: Determine whether the flag is greater than the observed value. If yes, generate the penalty learning factor. Otherwise, jump to Step 7.

Step 7: Calculate the fitness function and update *best* and *gbest*.

Step 8: Update the external Pareto solution set. Store non-inferior solutions produced for each iteration in all swarms sharing the external Pareto solution set. If the number of such solutions surpasses the maximum capacity of the set, identify the representative individuals and preserve them in the set. Ensure that the set size is consistent with that of the swarm. Introduce the crowding distance algorithm (Deb, 2002) to maintain a uniform distribution of the solutions.

Step 9: Judge if the termination condition is satisfied when the iterative counter accumulates to one. If yes, jump to Step 11. Otherwise, jump to Step 5.

Step 10: Output the Pareto optimal front.

Step 11: Determine the final solution in the Pareto optimal solution set.

Step 12: Send the final solution to the automatic control device of the power plant to realize thecontrol of generator power.

4. Simulation experiment and results analysis

4.1. Function tests

The HBPSO algorithm was tested on six classical multi-objective test problems, including a two-objective optimization problem of SCH, a two-objective optimization problem of FON, a three-objective optimization problem of DTLZ (Debet al., 2000) and three two-objective optimization problems of ZDT series (Qiet al., 2013; Wuet al., 2017). The expressions of the six test functions are listed in Table 1 below.

Then, the test results of the HBPSO were compared with those of the NSGA-II (Debet al., 2000), the multi-objective artificial bee colony (MOABC) algorithm (Quabab, 2012) and multi-objective comprehensive learning particle swarm optimization (MOCLPSO) algorithm (Yue, 2017).

The algorithm performance was evaluated by a comprehensive index called the inverted generational distance (IGD) (Qi et al., 2013; Suganthan, 2012). Let p* be a set of uniform samples in the ideal Pareto front (PF) of the multi-objective optimization problem (MOP) and P be a set of ideal approximation solutions towards to PF. Then, the IGD index of the solution set P can be defined as (Eq. 11):

$$IGD(P^*, P) = \frac{\sum_{v\epsilon P^*} d(v,p)}{\left|p^*\right|} \tag{11}$$

where $d(v, P)$ is the Euclidean distance between v and its nearest neighbour in the population $|P^*|$ is the number of Pareto optimal solutions in the population p*. The IGD index can evaluate the overall convergence and diversity of the Pareto optimal solution set P generated by each multi-objective optimization algorithm. The value of the IGD index is negatively correlated with the algorithm performance.

Table 3 shows the evaluation IGD of four algorithms on different test functions. The data of mean value and variance obtained after 30 runs by each algorithm. The convergence and distribution of HBPSO are better than the other three algorithms. Fig.2 shows four algorithms on three test functions, At the Pareto front, it also shows the strong robustness of proposed algorithm. This is because a reward factor and a penalty factor were introduced to treat the new individuals in each iteration depending on their contribution to the Pareto front set.

A new individua1dominateed the non-dominant solutions in the external Pareto front set, the reward factor adopted to speed up the flight speed and enhance the exploration depth of the particle. The penalty adopted to slow down the fight speed and constrain the exploration depth of that particle. This mechanism promoted the convergence to pare to optimal solutions that obey uniform distribution and cover a wide area.

4.2 EED simulation experiment

The standard IEEE 30-node system was adopted as a test example. The system includes 10 generator nodes. The correlation coefficient between fuel cost and pollutant emission was extracted from Reference (Zhang and Li, 2007). The reference standard output was set to 2,000MV, the initial population size was set to 100, and the maximum number of iterations (the termination condition) was set to 2,000. The proposed algorithm was compared with NSGA-II, MOABCand MOCLPSO. The results are illustrated in Fig. 4 and Table 4. The best compromise solutions obtained by typical MOEAs on 6-generator 30-bus system considering loss and all constraints in Table 5.

In this experiment, the transmission network losses are neglected, and the results of the proposed algorithm was compared with other computational algorithms in this systems. As seen in Fig. 4 and Table 4, the HBPSO algorithm has high accuracy, and it reaches the least possible fuel cost and pollution on each load level compared to the other computational algorithms. In Table 5, it can be seen that the HBPSO struck a perfect balance between the pollutant emission and fuel cost of the EED. The solutions obtained by the HBPSO were both well distributed and sufficiently diverse. This algorithm is clearly more diverse and efficient than the other algorithms.

Table 1. Test function

function	***dimension***	***Objective function***
SCH	1	$f_1(x)=x^2, f_2(x)=(x-2)^2$
FON	3	$f_1(x)=1-\exp\left(-\sum_{i=1}^{3}\left(x_i-\frac{1}{\sqrt{3}}\right)^2\right), f_2(x)1-\exp\left(-\sum_{i=1}^{3}\left(x_i+\frac{1}{\sqrt{3}}\right)^2\right)$
ZDT1	30	$f_1(x)=x_1, f_2(x)=g(x)\left[1-\sqrt{\frac{x_1}{g(x)}}\right], g(x)=1+9\frac{\left(\sum_{i=2}^{n}x_i\right)}{(n-1)}$
ZDT2	30	$f_1(x)=x_1, f_2(x)=g(x)\left[1-\sqrt{\frac{x_1}{g(x)}}\right], g(x)=1+9\frac{\left(\sum_{i=2}^{n}x_i\right)}{(n-1)}$
ZDT3	30	$f_1(x)=x_1, f_2(x)=g(x)\left[1-\sqrt{\frac{x_1}{g(x)}}-\frac{x_1}{g(x)}\sin(10\pi x_1)\right], g(x)=1+9\frac{\left(\sum_{i=2}^{n}x_1\right)}{(n-1)}$
DTLZ2	$k+\lvert x_k\rvert-1$	$f_1(x)=\left(1+g(x_k)\right)\cos\left(x_1\pi/2\right)\cos\left(x_2\pi/2\right)\ldots\ldots\cos\left(x_{k-2}\pi/2\right)\cos\left(x_{k-1}\pi/2\right)$ $f_2(x)=\left(1+g(x_k)\right)\cos\left(x_1\pi/2\right)\cos\left(x_2\pi/2\right)\ldots\ldots\cos\left(x_{k-2}\pi/2\right)\sin\left(x_{k-1}\pi/2\right)$ $f_{M-1}(x)=\left(1+g(x_k)\right)\cos\left(x_1\pi/2\right)\sin\left(x_2\pi/2\right)$ $f_M(x)=\left(1+g(x_k)\right)\sin\left(x_1\pi/2\right)$ Where $g(x_k)=\sum_{x_j\in x_k}(x_i-0.5)^2$

Table 2. Parameter settings of four algorithms

Algorithms	***Reference***	***Parameters Settings***
HBPSO	Wu et al., 2018	N=100, w=0.729, max_iter=5000
NSGA-II	Debet al., 2000	N=100, Pc=0.9,Pm=1/D,η_c=20, η_m=20, max_iter=5000
MOABC	Quabab, 2012	N=100, Pm=0.4, max_iter=5000
MOCLPSO	(Yue, 2017	N=100, Pc=0.6, Pm=0.03, max_iter=5000

Table 3. Evaluation IGD of different algorithms

Problems		*HBPSO*	*MOABC*	*MOCLPSO*	*NSGA-II*
SCH	**Mean**	1.04E-004	1.17E-001	4.36E-004	1.81E-003
	Std	1.54E-005	6.45E-004	2.19E-004	3.32E-005
FON	**Mean**	1.86E-004	2.59E-003	3.26E-001	1.09E-003
	Std	4.64E-005	3.14E-004	4.196E-01	9.59E-003
ZDT1	**Mean**	1.09E-003	0.41	4.8E-003	5.00E-003
	Std	8.05E-005	2.60E-002	1.76E-004	2.33E-004
ZDT2	**Mean**	3.34E-002	0.43	0.38	0.19
	Std	1.02E-004	2.53E-001	0.30	0.28
ZDT3	**Mean**	3.67E-003	0.67	5.49E-003	1.54E-002
	Std	1.53E-003	8.23E-002	2.49E-004	2.71E002
DTLZ2	**Mean**	5.66E-005	6.64E-002	8.79E-003	5.81E-003
	Std	1.07E-004	9.05E-003	8.06E-004	4.7E-004

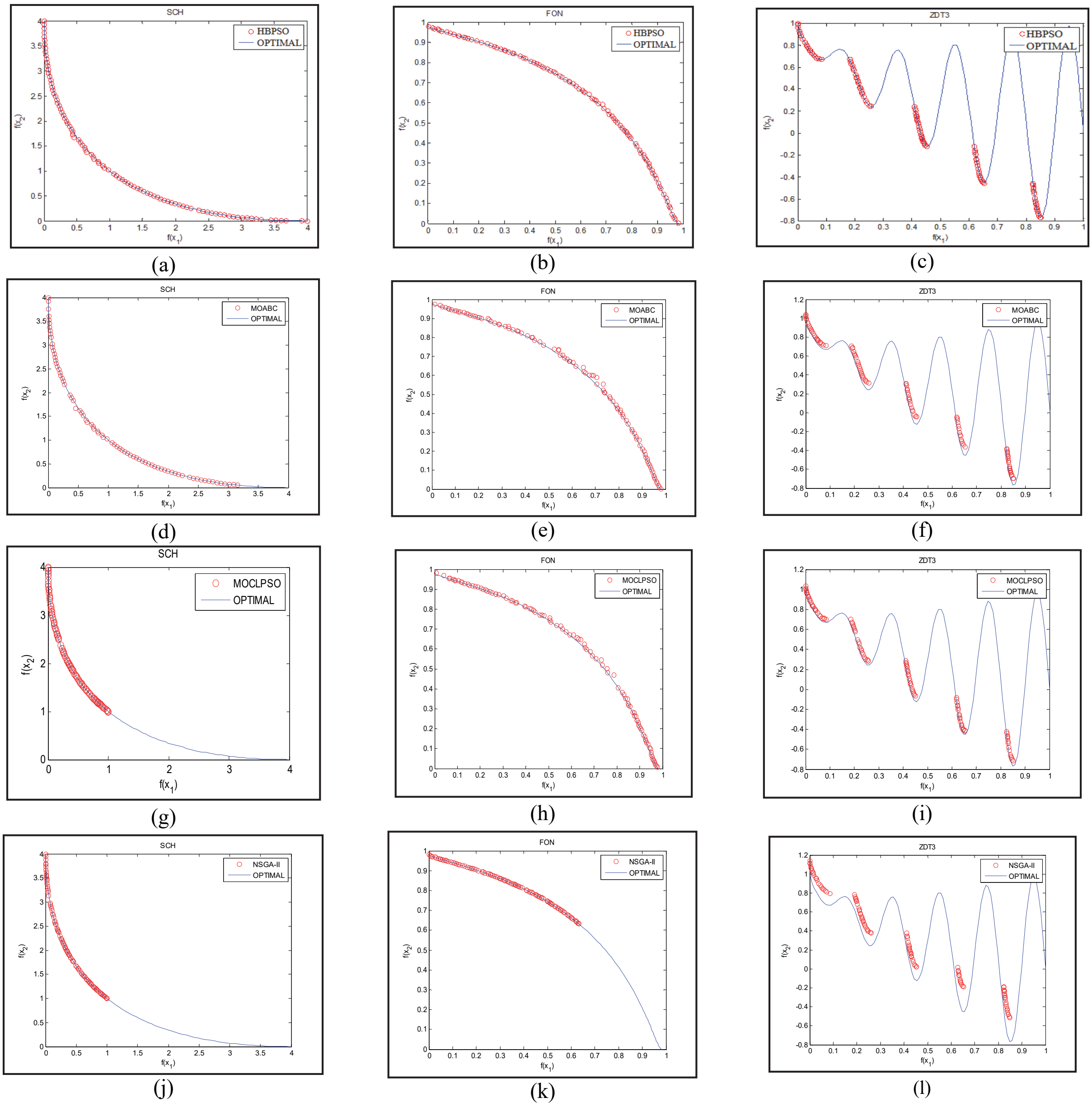

Fig. 2. Pareto optimal fronts of different algorithms: (a) represents the result of HBPSO on SCH function, (b) represents the result of HBPSO on FON function, (c) represents the result of HBPSO on on ZDT3 function, (d) represents the result of MOABC on SCH function, (e) represents the result of MOABC on FON function, (f) represents the result of MOABC on on ZDT3 function, (g) represents the result of MOCLPSO on SCH function, (h) represents the result of MOCLPSO on FON function, (i) represents the result of MOCLPSO on on ZDT3 function, (j) represents the result of NSGA-II on SCH function, (k) represents the result of NSGA-II on FON function, (l) represents the result of NSGA-II on on ZDT3 function

Table 4. Pareto solutions of different algorithms

	HBPSO	*MOABC*	*NSGAII*	*MOCLPSO*
P1(MW)	54.9086	54.9487	51.9515	54.9300
P2(MW)	80.0567	75.5821	67.2584	79.0035
P3(MW)	83.5594	78.4294	73.6879	84.6547
P4(MW)	84.6031	79.6876	91.3554	84.7854
P5(MW)	142.5852	135.8546	134.0522	135.5672
P6(MW)	168.5681	174.4635	174.9504	171.8543
P7(MW)	301.8570	282.5634	289.4350	293.6397
P8(MW)	318.8675	315.5758	314.0556	315.3474
P9(MW)	420.5487	447.5936	455.6978	432.7433
P10(MW)	436.8564	436.0013	431.8054	441.6435
Power losses(MV)	84.86	85.87	86.25	84.97
Fuel cost($)	112,009.87	113,339.76	112,996.57	112,998.46
Emission(lb)	4108.67	4099.86	4100.56	4195.57
Computing time(s)	3.34	4.84	5.98	6.03

Table 5. The best compromise solutions obtained by typical MOEAs on 6-generator 30-bus system considering loss and all constraints

	HBPSO	*MBFA* Hota et al., 2010	*MOACSA* Rao et al., 2013	*SMODE* Qu et al., 2016	*SLFA* Niknam et al., 2013
1	0.3133	0.2983	0.3004	0.3140	0.3230
2	0.3844	0.4332	0.3873	0.4169	0.4056
3	0.4399	0.7350	0.5659	0.5424	0.5669
4	0.4039	0.6899	0.6023	0.5856	0.5725
5	0.4581	0.1569	0.5481	0.5490	0.5305
6	0.4631	0.5503	0.4588	0.4552	0.4638
Cost	619.76	629.56	622.41	624.44	625.29
Emission	0.1874	0.2080	0.1976	0.1968	0.1966

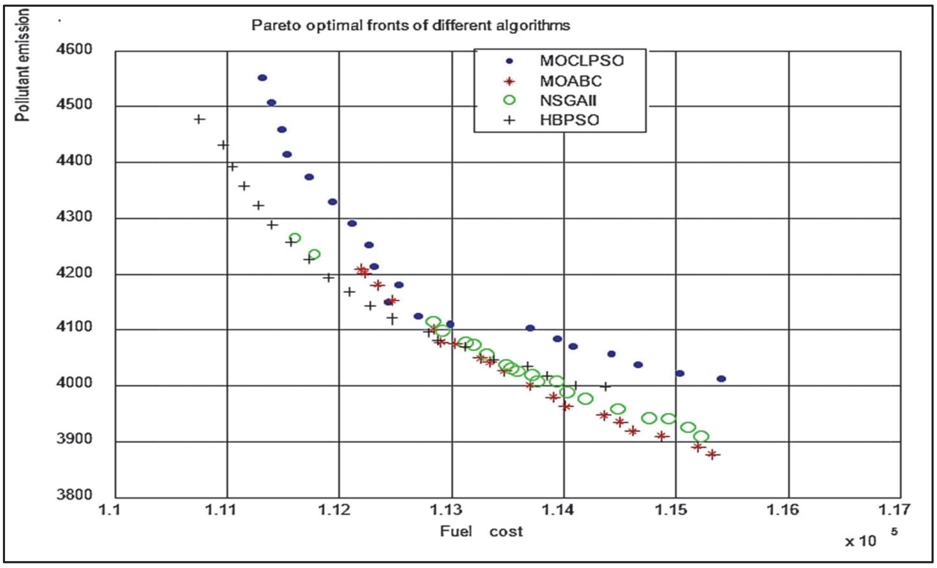

Fig. 3. Pareto optimal fronts of different algorithms

5. Conclusions

In this paper, a multi-objective PSO algorithm inspired by human social behavior was implemented to reduce operational costs and environmental pollution, which are typical two standard systems. As a matter of fact, to achieve an accurate prediction of production cost of power in power plants, one of the approach enables us to model objective functions appropriately and precisely. By comparing with a different variety of algorithms through load flow calculations for case system, the proposed multi-objective PSO algorithm inspired by human social behavior proved to be more effective.

Results of standard test function and economic dispatch shows evidence of better results and effectiveness of the proposed algorithm when handling much more complicated situations. In the presented objective function with goal of simultaneous decrease of transmission and system costs, particles tends to be more successful in finding optimal points near to global ones.

The proposed algorithm explored the solution space more thoroughly than the contrastive algorithms, and found an optimal set of solutions with good convergence, broadness and uniformity. As a result, the practice of the proposed algorithm in power systems is highly effective in obtaining more precise numbers of actual operational costs. To better solve the EED problem, the proposed algorithm will be implemented and analyzed on more standard and practical systems.

Acknowledgements
This research was funded by the China Ministry of Education, Humanities and Social Science, Research, Youth fund project (No.18YJCZH192), the Applied Undergraduate Pilot Project for Logistics Management of Shanghai Ocean University (No. B1-5002-18-0000), the project of Ministry of Education of Hunan province (No.2016NK2135), the open project program of artificial intelligence key laboratory of Sichuan province (No. 2015RYJ01), the China Statistical Science Research Project (No.2015LZ17), the social science project in Hunan province (No.16YBA316).

References

Abido M.A., (2003), Environmental/economic power dispatch using multi-objective evolutionary algorithms, *IEEE Transactions on Power Systems*, **18**, 1529-1537.

Abido M.A., (2009), Multi-objective particle swarm optimization for environmental/economic dispatch problem, *Electric Power Systems Research*, **79**, 1105-1113.

Aghay Kaboli S.Hr., Fallahpour A., Kazemi N., (2016), An expression-driven approach for long-term electric power consumption forecasting, *American Journal of Data Mining and Knowledge Discovery*, **1**,16-28.

Aghay Kaboli S.Hr., Selvaraj J., Rahim N.A., (2017), Rain-fall optimization algorithm: a population based algorithm for solving constrained optimization problems, *Journal of Computational Science*, **19**, 31-42.

Aghay Kaboli S.Hr., Fallahpour A., Kazemi N., Selvaraj J., Rahim N.A., (2018), Electric energy consumption forecasting via expression-driven approach,Clean Energy & Technology Conference, On line at: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8278568.

Asadi H., Aghay Kaboli S.Hr., Arash M., Maysam O., (2012), Fuzzy-control-based five-step Li-ion battery charger by using AC impedance technique, Fourth Int. Conf. on Machine Vision (ICMV 11): Machine Vision, Image Processing, and Pattern Analysis, vol. 8349, Singapore.

Bhattacharya A., Chattopadhyay P.K., (2011), Solving economic emission load dispatch problems using hybrid differential evolution, *Applied Soft Computing Journal*,**11**, 2526-2537.

Deb K., (2002), A fast and elitist multiobjective genetic algorithm: NSGA-II, *IEEE Transactions on Evolutionary Computation*, **4**, 182-197.

Deb K., Agrawal S., Pratap A., Meyarivan T., (2000), A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II, *Lecture Notes in Computer Science*,**1917**, 849-858.

Deng W., XuJ., Zhao H., (2019), An improved ant colony optimization algorithm based on hybrid strategies for scheduling problem, *IEEE ACCESS*, **7**, 20281-20292.

Deng W., Yao R., Zhao H., Yang X., Li G., (2017), A novel intelligent diagnosis method using optimal ls-svm with improved pso algorithm, *Soft Computing*, **2**, 1-18.

Elsakaan A.A., El-Sehiemy R.A., Kaddah S.S., Elsaid M.I., (2018), An enhanced moth-flame optimizer for solving non-smooth economic dispatch problems with emissions, *Energy*, **157**, 1063-1078.

Güvenç U., Sönmez Y., Duman S., Yörükeren N., (2012), Combined economic and emission dispatch solution using gravitational search algorithm, *Scientia Iranica*, **19**, 1754-1762.

Hota P.K., Barisal A.K., Chakrabarti R., (2010), Economic emission load dispatch through fuzzy based bacterial foraging algorithm, *International Journal of Electrical Power & Energy Systems*, **32**, 794-803.

Isah O.R., Usman A.D., Tekanyi A.M.S., (2017), A hybrid model of PSO algorithm and artificial neural network for automatic follicle classification, *International Journal Bioautomation*, **21**, 43-58.

Jiang C.H., Zhang C., Zhang Y.H., Xu H., (2017), An improved particle swarm optimization algorithm for parameter optimization of proportional–integral–derivative controller, *Traitement du Signal*, **34**, 93-110.

Mahdi F.P., Vasant P., Abdullah-Al-Wadud M., Kallimani V., Watada J., (2018), Quantum-behaved bat algorithm for many-objective combined economic emission dispatch problem using cubic criterion function, *Neural Computing & Applications*, **1**, 1-13.

Mason K., Duggan J., Howley E. (2018), A multi-objective neural network trained with differential evolution for dynamic economic emission dispatch, *International Journal of Electrical Power & Energy Systems*, **100**, 201-221.

Modiri-Delshad M., Kaboli S.H.A., Taslimi-Renani E., Rahim N.A., (2016), Backtracking search algorithm for solving economic dispatch problems with valve-point effects and multiple fuel options, *Energy*, **116**, 637-649.

Niknam T., Narimani M.R., Jabbari M., Malekpour A.R. (2011), A modified shuffle frog leaping algorithm for multi-objective optimal power flow, *Energy*, **36**, 6420-6432.

Qi Y.T., Liu F., Chang W.Y., Ma X.L., Jiao L.C., (2013), Memetic immune algorithm for multi-objective optimization, *Journal of Software*, **24**,1529-1544.

Qu B.Y., Liang J.J., Zhu Y.S., Suganthan P.N., (2017). Solving dynamic economic emission dispatch problem considering wind power by multi-objective differential evolution with ensemble of selection method, *Natural Computing*, **4**, 1-9.

Qu B.Y., Liang J.J., Zhu Y.S., Wang Z.Y., Suganthan P.N., (2016). Economic emission dispatch problems with stochastic wind power using summation based multi-objective evolutionary algorithm, *Information Sciences*, **351**, 48-66.

Quabab B.Y., (2012), Niching particle swarm optimization with local search for multi-modal optimization, *Information Sciences*, **197**, 131-143.

Rafieerad A.R., Bushroa A.R., Nasiri-Tabrizi B., Fallahpour A., Vadivelu J., Musa S.N., Kaboli S.H.A., (2016), GEP-based method to formulate adhesion strength and hardness of Nb PVD coated on Ti-6Al-7Nb aimed at developing mixed oxide nanotubular arrays, Journal of the Mechanical Behavior of Biomedical Materials, 61, 182-196.

Rafieerad A.R., Bushroa A.R., Nasiritabrizi B., (2017), Toward improved mechanical, tribological, corrosion and in-vitro bioactivity properties of mixed oxide nanotubes on Ti–6Al–7Nb implant using multi-objective PSO, *Journal of the Mechanical Behavior of Biomedical Materials*, **69**, 1-18.

Rao B.S., Vaisakh K. (2013). Multi-objective adaptive clonal selection algorithm for solving environmental/economic dispatch and OPF problems with load uncertainty, *International Journal of Electrical Power & Energy Systems*, **53**, 390-408.

Sebtahmadi S.S., Azad H.B., AghayKaboliS.Hr., Islam M.D., Mekhilef S., (2017), A pso-dq current control scheme for performance enhancement of z-source matrix converter to drive IM fed by abnormal voltage, *IEEE Transactions on Power Electronics*, **33**, 1666-1681.

Suganthan P.N., (2012), *Differential Evolution Algorithm: Recent Advances, Theory and Practice of Natural Computing,* Int. Conf. on Theory and Practice of Natural Computing TPNC 2012, Tarragona, Spain, October 2-4, 30-46.

Wang L., Singh C., (2009), Reserve-constrained multiarea environmental/economic dispatch based on particle swarm optimization with local search, *Engineering Applications of Artificial Intelligence*, **22**, 298-307.

Wu D., Zhao H., Yang X., Xiong J., Sun M., Li B., (2017), Study on an improved adaptive PSO algorithm for solving multi-objective gate assignment, *Applied Soft Computing*, **59**, 288-302.

Wu D.Q, Huo J.Z, Zhang G.F., (2018), Minimization of logistics cost and carbon emissions based on quantum particle swarm optimization, *Sustainability*, **12**, 1-15.

Yue C., Qu B., Jing L., (2017), A multi-objective particle swarm optimizer using ring topology for solving multimodal multi-objective problems, *IEEE Transactions on Evolutionary Computation*, **22**, 805-817.

Zhang Q., Li H., (2007), Moea/d: a multiobjective evolutionary algorithm based on decomposition, *IEEE Transactions on Evolutionary Computation*, **11**, 712-731.

Zou D., Li S., Li Z., Kong X. (2017). A new global particle swarm optimization for the economic emission dispatch with or without transmission losses, *Energy Conversion & Management*, **139**, 45-70.