International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:11, No:6, 2017

An Improved Particle Swarm Optimization Technique for Combined Economic and Environmental Power Dispatch Including Valve Point Loading Effects

Badr M. Alshammari, T. Guesmi

Abstract**—**In recent years, the combined economic and emission power dispatch is one of the main problems of electrical power system. It aims to schedule the power generation of generators in order to minimize cost production and emission of harmful gases caused by fossil-fueled thermal units such as CO, CO_2, NO_x, and SO_2. To solve this complicated multi-objective problem, an improved version of the particle swarm optimization technique that includes non-dominated sorting concept has been proposed. Valve point loading effects and system losses have been considered. The three-unit and ten-unit benchmark systems have been used to show the effectiveness of the suggested optimization technique for solving this kind of nonconvex problem. The simulation results have been compared with those obtained using genetic algorithm based method. Comparison results show that the proposed approach can provide a higher quality solution with better performance.

Keywords**—**Power dispatch, valve point loading effects, multiobjective optimization, Pareto solutions.

I. Introduction

THE economic environmental dispatch (EED) problem has received in the two past decades much attention. It aims to provide the optimum generation schedule for minimum production cost and minimum emission of harmful gases caused by fossil-fueled thermal units [1]–[3]. Within this context, several research works have been proposed to solve this problem. Various studies have considered the traditional EED problem where the production cost function of each thermal unit is approximated by a quadratic function [4]-[6]. Unfortunately, practical EED problem incorporates the valve-point loading effects (VPLE) in the production cost. These additional constraints make the problem with high nonlinear functions. Thus, traditional optimization techniques, such as Newton methods [5], lambda iteration, and linear programming [6] cannot provide the best solution. In recent years, numerous intelligent optimization techniques, such as genetic algorithms (GA), particle swarm optimization (PSO), bacterial foraging, artificial bee colony (ABC), and simulated annealing have been used to solve this non-convex EED problem [7], [8].

In recent years, PSO algorithms have attracted much attention for solving EED problem [9], [10]. This heuristic technique was introduced by Kennedy and Eberhart [11]. It emulates the social behavior of organisms such as flocking of birds and schooling of fish. However, conventional PSO was criticized for its premature convergence, while the problem has multiple minima and with nonconvex objective functions. Thus, several works have suggested modifications in the classic PSO algorithm. Reference [10] presents a review of PSO application in economic dispatch problems. Unfortunately, these modified PSO approaches have been tested only for single objective problems. Therefore, if it is a multi-objective optimization problem (MOP), all objectives are weighted as per the importance and added together to form a single objective function. Thus, there is a loss of diversity in Pareto optimal solutions. To overcome these problems, this study presents a PSO-based technique called non-dominated sorting PSO (NSPSO) algorithm for solving the nonconvex EED problem. This technique incorporates the non-dominated sorting mechanism used in the NSGAII approach [12], into the original PSO algorithm.

A fuzzy set theory [2] is used to extract the best compromise solution, from the Pareto-optimal solutions, for the decision makers. The proposed approach was tested on the tree-unit and the ten-unit systems. Total production cost in $/h and total emission in ton/h have been minimized simultaneously subject to several operating conditions such as generation limits, VPLE and real power balance constraints. In addition, power losses calculated using the B-loss formula have been considered in the problem formulation.

Simulation results show that this new algorithm proved a very competitive performance in finding much better spread of solutions and better convergence near the true Pareto-optimal solutions compared to the NSGAII method.

II. Problem Formulation

The EED problem is formulated as MOP. Two objective functions are considered in this study to simultaneously minimize the total fuel cost and total emission of the thermal units under several operating conditions.

A. Objective Functions

Considering a power system with N generators, its total fuel cost function C_T in ($/h) with VPLE and emission in (ton/h) is respectively given by the following equations [13].

$$C_T = \sum_{i=1}^{N}\left[a_i + b_i P_i + c_i \left(P_i\right)^2 + \left| d_i \sin\left\{ e_i \left(P_i^{\min} - P_i \right) \right\} \right| \right] \quad (1)$$

Badr M. Alshammari and T. Guesmi are with the Electrical Engineering Department, College of Engineering, University of Hail, Saudi Arabia (e-mail: badr_ms@hotmail.com, t.guesmi@uoh.edu.sa).

$$E_T = \sum_{i=1}^{N}\left[10^{-2}\left(\alpha_i + \beta_i P_i + \gamma_i\left(P_i\right)^2\right) + \eta_i \exp\left(\lambda_i P_i\right)\right] \quad (2)$$

where a_i, b_i, c_i, d_i, and e_i are the cost coefficients of the i^{th} unit, while α_i , β_i , γ_i , η_i and λ_i are the emission coefficients of the i^{th} unit. Pi is the generation the i^{th} unit.

B. Problem Constraints

Total cost and emission functions will be minimized subject to the following constraints.

- Generation limits

$$P_i^{\min} \le P_i \le P_i^{\max},\ i = 1,...,N \quad (3)$$

where $P_i^{\min}$ and $P_i^{\max}$ are the lower and upper power generation limits of the i^{th} unit.

- Power balance constraints

For a given total demand power P_D, the generation schedule should verify the following equality.

$$\sum_{i=1}^{N} P_i - P_D - P_L = 0 \quad (4)$$

where PL is the total losses in MW.

The total transmission losses can be calculated using the following equation [13].

$$P_L^t = \sum_{j=1}^{N} P_i B_{ij} P_i + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \quad (5)$$

where B_{ij} , B_{oi} , B_{oo} are the loss parameters also called *B* coefficients.

III. Proposed Algorithm

PSO is firstly presented by Kennedy and Eberhart. It emulates the social behavior of organisms such as flocking of birds and schooling of fish.

In a physical-dimensional search space with the dimension *n*, the i^{th} particle at iteration k is presented by its position $X_i^k = \left(X_{i1}^k, \ldots, X_{in}^k\right)$ and velocity $V_i^k = \left(V_{i1}^k, \ldots, V_{in}^k\right)$. The updated velocity and position of this particle at the next generation $\left(k+1\right)$ can be governed, respectively, by the following equations

$$V_i^{k+1} = wV_i^k + c_1 r_1\left(pbest_i^k - X_i^k\right) + c_2 r_2\left(gbest^k - X_i^k\right) \quad (6)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (7)$$

where w is the inertia weight factor, c_1 andc_2 are the acceleration constants. The coefficients w, c_1, and c_2 can be determined according to [11]. r_1 andr_2 are two random numbers between 0 and 1. $pbest_i^k$ and $gbest^k$ are the best position of the i^{th} particle achieved based on its own experience and the best position among all the particles in the swarm at the k^{th} iteration, respectively.

Several research works have been proposed to adopt the PSO algorithm for MOP, such as in [14].

In this study, a PSO-based MOP algorithm symbolized by NSPSO is presented for solving the EED problem. The proposed NSPSO algorithm is based on the non-dominated sorting concept presented by [12].

The non-dominated sorting concept, has been developed in this paper and used for solving the EED problem. At each iteration k, this elitist approach extends the basic form of PSO by combining the *pbest* of *N* particles P^k and the *N* particles offspring Q^k. The combined population $R^k = P^k \mathrm{U} Q^k$ of size 2*N* will be sorted into different non-domination levels F_j [13]. Therefore, we can write.

$$R^k = \bigcup_{j=1}^{r} F_j \quad (8)$$

where r is the number of fronts.

Once the non-dominated sorting is completed, a crowding distance, as given in [13], is assigned to each solution of the combined population R^k to provide an estimate of the density of solutions surrounding that solution in the same front F_j. Thus, every solution in R^k has two indices, non-domination level and crowding distance. Then, particles of the next population P^{k+1} will be the first N individuals of the subsequent non-dominated fronts in the order of their levels, i.e. members of F1 have priority to will be in P^{k+1}, followed by members from F2, and so on until the number of these individuals is greater than or equal to N. Let us consider that Fj is the last non-dominated set. Then, individuals of Fj will be selected to fill P^{k+1} according to their crowding distance in the descending order. The global best position is selected randomly from the 5% of the top crowded solutions of F_1.

IV. Simulation Results

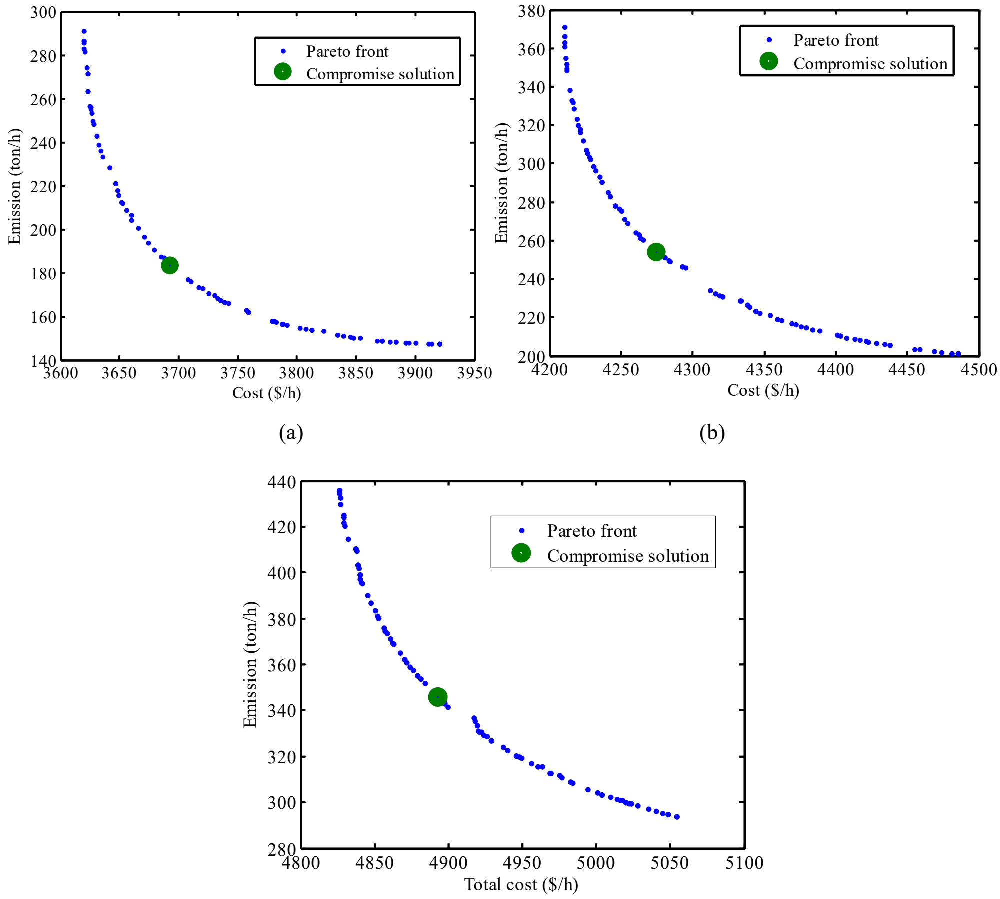
Two test systems with different complexities have been used to demonstrate the effectiveness of the proposed NSPSO technique. The compromise solutions were extracted from the Pareto front using the fuzzy based membership function value assignment method [2].

A. Case 1: Three-Unit System

In this case, the three-unit system is used to prove the feasibility of the proposed technique. The unit data taken from [15] are shown in Table I. The B-loss matrix is given below.

$$B = \begin{bmatrix} 0.000136 & 0.0000175 & 0.000184 \\ 0.0000175 & 0.000154 & 0.000283 \\ 0.000184 & 0.000283 & 0.00165 \end{bmatrix}$$

The Pareto set and the compromise solution obtained using the NSPSO algorithm for three load levels are given in Fig. 1. Optimum solutions are illustrated in Table II. It is clear that total cost and emission are monotonically increasing functions with respect to the total demand power



(a) (b) (c)

Fig. 1 Pareto front for the three-unit system: (a) for $P_D = 300$ MW (b) for $P_D = 350$ MW (c) for $P_D = 400$ MW

TABLE I
GENERATOR DATA FOR THE THREE-UNIT SYSTEM

Unit	P_{min}	P_{max}	a	B	C
1	50	250	328.13	8.663	0.00525
2	5	150	136.91	10.04	0.00609
3	15	100	59.16	9.76	0.00592

B. Case 2: Ten-Unit System

For this test system, the VPLE is considered for all units. The B-loss matrix is given below. The generator data taken from [16] are illustrated in Table III.

$$B = 10^{-4}\begin{bmatrix} 0.49 & 0.14 & 0.15 & 0.15 & 0.16 & 0.17 & 0.17 & 0.18 & 0.19 & 0.20 \\ 0.14 & 0.45 & 0.16 & 0.16 & 0.17 & 0.15 & 0.15 & 0.16 & 0.18 & 0.18 \\ 0.15 & 0.16 & 0.39 & 0.10 & 0.12 & 0.12 & 0.14 & 0.14 & 0.16 & 0.16 \\ 0.15 & 0.16 & 0.10 & 0.40 & 0.14 & 0.10 & 0.11 & 0.12 & 0.14 & 0.15 \\ 0.16 & 0.17 & 0.12 & 0.14 & 0.35 & 0.11 & 0.13 & 0.13 & 0.15 & 0.16 \\ 0.17 & 0.15 & 0.12 & 0.10 & 0.11 & 0.36 & 0.12 & 0.12 & 0.14 & 0.15 \\ 0.17 & 0.15 & 0.14 & 0.11 & 0.13 & 0.12 & 0.38 & 0.16 & 0.16 & 0.18 \\ 0.18 & 0.16 & 0.14 & 0.12 & 0.13 & 0.12 & 0.16 & 0.40 & 0.15 & 0.16 \\ 0.19 & 0.18 & 0.16 & 0.14 & 0.15 & 0.14 & 0.16 & 0.15 & 0.42 & 0.19 \\ 0.20 & 0.18 & 0.16 & 0.15 & 0.16 & 0.15 & 0.18 & 0.16 & 0.19 & 0.44 \end{bmatrix}$$

The Pareto solution set and the compromise solution obtained using the NSPSO for total demand power of 1500 MW, are given in Fig. 2.

To demonstrate the effectiveness of the proposed approach, a comparison with GA based method called NSGAII is investigated. Table IV shows that the NSPSO outperforms NSGAII in providing the best results for both minimum cost and minimum emission.

TABLE II
OPTIMUM SOLUTIONS FOR CASE 1

	P_D (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	Losses (MW)	C_T ($/h)	E_T (ton/h)
Best cost	300	207.6346	87.2951	15.0000	9.9297	3619.8606	291.0804
	350	235.8080	112.2470	15.0000	13.0549	4.2103545	371.2281
	400	249.9331	150.0000	16.7696	16.7028	4825.6814	436.0657
Best emission	300	96.3336	135.9757	100.0000	32.3092	3920.4545	147.5014
	350	136.7485	150.0000	100.0000	36.7484	4485.2530	201.1073
	400	191.4945	150.0000	100.0000	41.4945	5053.8599	293.9778
Compromise solution	300	142.6288	127.7517	44.3052	14.6857	3692.6519	183.4570
	350	178.4722	143.5784	46.8624	18.9131	4274.9795	253.9790
	400	218.4445	150.0000	57.6805	26.1250	4.8927865	345.6210

TABLE III
UNIT DATA FOR THE TEN-UNIT SYSTEM

Unit	P_{min}	P_{max}	a	b	c	d	e	α	β	γ	η	λ
1	150	470	786.7988	38.5397	0.1524	450	0.041	103.3908	−2.4444	0.0312	0.5035	0.0207
2	135	470	451.3251	46.1591	0.1058	600	0.036	103.3908	−2.4444	0.0312	0.5035	0.0207
3	73	340	1049.9977	40.3965	0.0280	320	0.028	300.3910	−4.0695	0.0509	0.4968	0.0202
4	60	300	1243.5311	38.3055	0.0354	260	0.052	300.3910	−4.0695	0.0509	0.4968	0.0202
5	73	243	1658.5696	36.3278	0.0211	280	0.063	320.0006	−3.8132	0.0344	0.4972	0.0200
6	57	160	1356.6592	38.2704	0.0179	310	0.048	320.0006	−3.8132	0.0344	0.4972	0.0200
7	20	130	1450.7045	36.5104	0.0121	300	0.086	330.0056	−3.9023	0.0465	0.5163	0.0214
8	47	120	1450.7045	36.5104	0.0121	340	0.082	330.0056	−3.9023	0.0465	0.5163	0.0214
9	20	80	1455.6056	39.5804	0.1090	270	0.098	350.0056	−3.9524	0.0465	0.5475	0.0234
10	10	55	1469.4026	40.5407	0.1295	380	0.094	360.0012	−3.9864	0.0470	0.5475	0.0234

TABLE IV
OPTIMUM SOLUTION FOR CASE 2 (P_D = 1500 MW)

	Best cost		Best emission		Best compromise	
	NSPSO	NSGAII	NSPSO	NSGAII	NSPSO	NSGAII
P_1	151.0699	150.3148	222.1862	212.3576	158.4670	153.8185
P_2	135.0000	135.0000	218.8816	225.0995	216.5657	210.2501
P_3	256.2241	186.2797	160.4036	160.4766	195.4399	184.5587
P_4	240.2177	300.0000	165.2440	171.8264	184.9382	234.6255
P_5	225.3609	240.4124	231.0923	228.9496	241.8616	224.9765
P_6	160.0000	156.6727	160.0000	159.4759	160.0000	159.4020
P_7	129.3573	129.3020	129.3139	129.8012	130.0000	130.0000
P_8	119.1260	120.0000	119.8741	120.0000	119.5020	119.1583
P_9	78.6276	78.8148	80.0000	79.0047	79.5426	79.0766
P_{10}	45.4832	43.8151	55.0000	54.9215	54.8865	45.1678
Cost ($/h)	**85466.98**	**85486.91**	91736.17	91530.43	88627.74	87893.51
Emission (ton/h)	9425.09	9793.64	**7959.50**	**7977.11**	8224.15	8597.81
Losses (MW)	40.4666	40.6115	41.9957	41.9131	41.2035	41.0339

V. CONCLUSION

In this study, a new PSO-based optimization technique symbolized by NSPSO is proposed for solving the non-convex economic-environmental dispatch (EED). The EED problem has been formulated as an MOP. Several operating constraints have been considered such as generation limits, valve point loading effects and real power balance constraints. The proposed NSPSO technique incorporates the non-dominated sorting mechanism to adopt the original PSO algorithm for MOP. The effectiveness of the proposed optimization technique is tested on the three-unit and ten-unit systems. Simulations results have demonstrated that NSPSO can provide acceptable optimum solutions for the EED problem with different complexities.

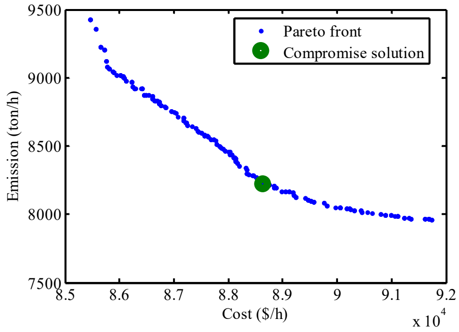


Fig. 2 Pareto front for the ten-unit system (1500 MW)

ACKNOWLEDGMENT

This research work was supported by University of Hail, Saudi Arabia.

REFERENCES

[1] K. S. Damodaran, and T. K. Sunil Kumar, "Optimal Environmental Economic Dispatch Using a Classical Technique," International review of automatic control (IREACO), vol. 7, no. 3, pp. 300 – 306, 2014.
[2] M. A. Abido, "Multiobjective evolutionary algorithms for electric power dispatch problem," IEEE Transactions on Evolutionary Computation, vol. 10, no. 3, pp. 315 – 329, 2006.
[3] S. Sivasubramani, and K. S. Swarup, "Environmental/economic dispatch using multi-objective harmony search algorithm, Electric Power Systems Research," vol. 81, no. 9, pp. 1778 – 1785, 2011.
[4] G. Irisarri, L. M. Kimball, K. A. Clements, A. Bagchi, and P. W. Davis, "Economic dispatch with network and ramping constraints via interior point methods," IEEE Transactions on Power Systems, vol. 13, no. 1, pp. 236 – 242, 1998.
[5] C. E. Lin, S. T. Chen, and C. L. Huang, "A Direct Newton-Raphson Economic Dispatch," IEEE Transactions on Power Systems, vol. 7, no. 3, pp. 1149-1154, 1992.
[6] C. W. Gar, J. G. Aganagic, T. M. B. Jose, and S. Reeves, "Experience with mixed integer linear programming based approach on short term hydrothermal scheduling," IEEE Transaction on Power Systems, vol. 16, no. 4, pp. 743-749, 2001.
[7] Z. Yang, K. Li, Q. Niu, Y. Xue, and A. Foley, "A self-learning TLBO based dynamic economic/environmental dispatch considering multiple plug-in electric vehicle loads," Journal of Modern Power Systems and Clean Energy, vol. 2, no. 4, pp. 298-307, 2014.
[8] P. Jain, K. K. Swarnkar, S. Wadhwani, and A. K. Wadhwani, "Prohibited Operating Zones Constraint with Economic Load Dispatch using Genetic Algorithm," International Journal of Engineering and Innovative Technology, vol. 1, no. 3, pp. 179-183, 2012.
[9] B. Zhao, and Y. J. Cao, "Multiple objective particle swarm optimization technique for economic load dispatch," Journal of Zhejiang University Science, vol. 6A, no. 5, pp. 420 – 427, 2005.
[10] A. Mahor, V. Prasadb, and S. Rangnekar, "Economic dispatch using particle swarm optimization:A review," Renewable and Sustainable Energy Reviews, vol. 13, pp. 2134 – 2141, 2009.
[11] J. Kennedy, and R. Eberhart, "Particle swarm optimization," Proc. IEEE Int Conference on Neural Networks, pp. 1942 – 1948, 1995.
[12] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," IEEE Transactions on Evolutionary Computation, vol. 6 no.2, pp. 182 – 197, 2002.
[13] M. Basu, "Dynamic economic emission dispatch using nondominated sorting genetic algorithm-II," Electric Power and Energy Systems, vol. 30, pp. 140 – 149, 2008.
[14] M. Reyes-Sierra, and C. A. C. Coello, "Multiobjective particle swarm optimizers: a survey of the state-of-the-art," International Journal of Computational intelligence Research, vol. 2, no. 3, pp. 287 – 308, 2006.
[15] Y. A. Gherbi, H. Bouzeboudja, and F. Z. Gherbi, "The combined economic environmental dispatch using new hybrid metaheuristic," Energy, vol. 115, pp. 468-477, 2016.
[16] N. Pandit, A. Tripathi, S. Tapaswi, and M. Pandit, "An improved bacterial foraging algorithm for combined static/dynamic," Applied Soft Computing, vol. 12, pp. 3500–3513, 2012.