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A Novel Hybrid Algorithm for Nonconvex Economic Power Dispatch Problems

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Abstract: *In this study, a solution is proposed for economic dispatch problem with valve-point effect, which is one of the nonconvex optimization problems. These kinds of problems which require accurate and strong solution methods are described as real problems. For this reason the hybrid approach used for solution of this problem is formed as a combination of modified subgradient (MSG) and particle swarm optimization (PSO) algorithms. This hybrid approach has been applied to a system with 13 generators for two different load demand as being lossy and lossless. System transmission losses are calculated by using B-loss matrix. The resulting optimal solution values are compared with the solution values in the literature and the results are discussed.*
Keywords: *Modified subgradient algorithm (MSG), Particle swarm optimization algorithm (PSO), Economic power dispatch, Nonconvex cost function, Valve-point effect.*

I. Introduction

The optimal operating and planning of power generation systems have an important role in power production industry. The optimal operation of a classical power system is achieved by minimizing the cost of fuel consumed [1].

The electricity companies have tried to use fuel in a more efficient manner because of the fact that the cost of fuel used for generation of electricity is a significant burden over production costs. Thus, efficient operation of electricity generation system has become a problem to be solved throughout the history of electricity. In literature, these kinds of problems are described as economic dispatch problems. In economic dispatch problems, some simplifications and omissions may be applied on calculation of fuel costs to ease the optimization process. However, those simplifications and omissions should not be preferred, since they lead economic dispatch problems to differ from real problems [2,3]. For this reason, economic power dispatch problem with valve point effect, which is one of the real problems, is studied in this study.

Technically, economic dispatch problem in operation of electricity generation systems is described as the optimization of active power outputs of the generation units, so that the current load in the system can be compensated by these units under the limitations of the system. In general, convex and nonconvex optimization problems are used to categorize these economic dispatch problems. Partially linear and monotone increasing characteristics are used to define input and output characteristics of convex optimization problems, whereas non-smooth (discontinuous, non-differentiable and nonlinear) characteristics, as in the real problem case, are utilized in the definition of nonconvex optimization problems. Fast, accurate and robust solution methods are required for those nonconvex problems [4].

In economic power dispatch problems, both generating capacity of generation units and power balance between load, loss and generation are considered. However, ramp rate limits, valve point effects and multi fuel options are also included in practical economic dispatch problems. When these limitations are introduced into the economic dispatch problem, the problem transforms into a nonconvex optimization problem [3,4].

In the system, which is composed of thermal generation units with multi-valve steam turbines, a nonconvex function is used to express the fuel cost. This expression contains sinusoidal surges. Four categories can be used to group the most recent techniques, which are able to handle the limitations regarding the solution of the optimization problems. These categories can be summarized as follows; methods based on preservation of the solution's feasibility, methods based on punishment of fitness functions, methods based on a clear distinction between feasible and infeasible solutions, and hybrid methods [3].

In literature nonconvex valve-point effect economic power dispatch problems have been solved with many evolutionary programming algorithms (EA) [1], natural updated harmony search algorithm (NGHS, NPHS, NTHS, NRHS) [2], new hybrid search optimization algorithms (MSG-HS, GA-APO, NSOA) [3,4], rooted tree optimization algorithm (RTO) [5], backtracking search algorithm (BSA) [6], crisscross optimization algorithm (CSO) [7], symbiotic organisms search algorithm (SOS) [8,9], particle swarm optimization and improved particle swarm optimization algorithms (PSO, HMAPSO, QPSO) [10,11], modified group search optimizer method (MGSO) [12], self-adaptive firefly algorithm (DFA) [13], oppositional real coded chemical reaction optimization (ORCCRO) [14], incremental artificial bee colony algorithm (IABC, IABC-LS) [15], differential evolution and modified differential evolution algorithms (DE, SDE, CDE) [16,17], cultural self-organizing migrating strategy optimization method (CSOMA) [18], dynamic adaptive bacterial foraging algorithm (DBFA) [19] and mine blast algorithm (MBA) [20].

In this study, a novel hybrid approach is used for solution of nonconvex economic dispatch problem with valve point effect. This approach is based on a combination of a modified subgradient algorithm (MSG) and particle swarm optimization algorithm (PSO).

II. Formulation of the Nonconvex Economic Power Dispatch Problem

The solution of the economic power dispatch problem is found by the minimization of the total fuel cost (F_{TFC}) under system constraints. And, this is the purpose function of the optimization problem given in equation (1).

$$\min F_{TFC} = \min \sum_{n=1}^{N} F_n(P_{G,n}) \qquad (1)$$

The fuel cost function belonging to generation units has been shown in Figure 1. In the figure, the graphic shown with broken line is convex fuel cost function and as represented in equation (2) it is taken as two-degree function of active power generation for each unit [1].

$$F_n(P_{G,n}) = a_n P_{G,n}^2 + b_n P_{G,n} + c_n, \ (\$/h) \qquad (2)$$

In the equation, F_n *($P_{G,n}$)* shows the fuel cost function of *n.* generation unit, a_n, b_n and c_n respectively show the cost function coefficients of the generation unit, and $P_{G,n}$ shows the output power of n. generation unit.

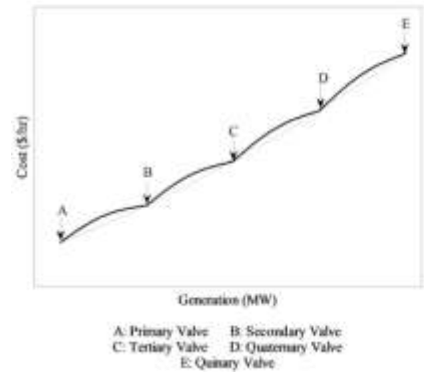

Figure 1. Input-output characteristics of the generation units

In fact, when the input-output curve of the generation units with multi-valve steam turbine is compared with the equality in equation (2), it is very different. The inclusion of the valve point effect as well to the fuel cost of the generation unit makes the presentation of the fuel cost more appropriate. As shown in figure 1, since valve point results in sinusoidal surges, the fuel cost function contains nonlinear higher sequences (series). Therefore, in the studies done to be able to consider the valve point effects instead of equation (2), the nonconvex fuel cost function in the following equation has been used [1].

$$F_n(P_{G,n}) = a_n P_{G,n}^2 + b_n P_{G,n} + c_n + \left| e_n . \sin\left[f_n (P_{G,n}^{\min} - P_{G,n}) \right] \right|, \ (\$/h) \qquad (3)$$

In the equation, e_n and f_n are the fuel cost function coefficients of *n.* generation unit showing valve point effect. In equation (2) and (3) the unit of $P_{G,n}$ is taken as MW.

Active power equality constraint in the lossy system, power balance constraint (Φ) is shown in the equation (4) [3].

$$\Phi = \sum_{n=1}^{N} P_{G,n} - P_{load} - P_{loss} = 0 \qquad (4)$$

The generating capacity constraints are given as below.

$$P_{G,n}^{\min} \le P_{G,n} \le P_{G,n}^{\max}, \quad (n \in N) \qquad (5)$$

Power losses, which occur in dispatch lines of the system, are calculated through B loss matrix by using the following equation [1,3].

$$P_{loss} = \sum_{n=1}^{N} \sum_{j=1}^{N} P_{G,n} B_{nj} P_{G,j} + \sum_{n=1}^{N} B_{0n} P_{G,n} + B_{00} \qquad (6)$$

III. A Novel Hybrid Algorithm (MSGPSO)

The MSG and the PSO algorithms, which form the structure of the hybrid approach used for solution of the problem, are described in this section. The MSG algorithm makes up the main structure of the hybrid approach. The MSG algorithm adds the constraints of the system into the sharp augmented langrangian function and turns the optimization problem into an unconstrained one. This unconstrained optimization problem is solved through the PSO algorithm. The results are observed by the MSG algorithm and it is checked whether the stopping condition is fulfilled or not.

III.I The Modified Subgradient Method (MSG)

The most important characteristics of the MSG algorithm, which was developed by Gasimov, are as follows. The MSG algorithm assures the zero duality gap for a wide range of nonconvex optimization problems, creates a continuously increasing series of duality values, which is an unknown characteristic in the classic subgradient method, and assures convergence. Basic disadvantages for the MSG algorithm are typical for most subgradient algorithms. This algorithm uses the unconstrained global minimum of the augmented Lagrange function and it is necessary to know the approximate upper bound of the initial problem so as to update step size parameters for each iteration. In the event that an unconstrained minimization algorithm fails to find the global minimum of the sub problems and that the augmented Lagrangian local minimum value is higher than the combined optimum primal-dual value, the algorithm can only stop by reaching the local minimum [3,21]. To illustrate how MSG algorithm proceeds, let a nonlinear problem (*NP*) be defined as;

$$\text{Min} \quad f_0(x)$$

$$\textit{subject to} \begin{cases} f(x)=0 \\ x\in S \end{cases} \tag{7}$$

where S is a subset of a metric space X, and $f_0 : X \to R$ and $f : X \to R^m$ are given functions.

Sharp augmented lagrangian (L_{SA}) is defined in equation (8).

$$L_{SA}(x,u,c) := f_0(x) + v\|f(x)\| - < u, f(x) > \tag{8}$$

And the dual function associated with the problem (*NP*) is designated as follows;

$$H(u,v) := \min_{x\in S} L_{SA}(x,u,v) \tag{9}$$

The dual problem (NP^*) is given in equation (10).

$$NP^* = \max_{(u,v)\in R^m \to R} H(u,v) \tag{10}$$

Using the above definitions, the MSG algorithm is outlined as follows [3,21].

- **Step 1.** Choose (u_1, v_1) with $v_1 \geq 0$. Set $k = 1$.
- **Step 2.** Given (u_k, v_k). Solve the following subproblem:

$$H_k = H(u_k, v_k) = \min_{x\in S}\left[f_0(x) + v_k \|f(x)\| - \langle u_k, f(x)\rangle \right] \tag{11}$$

Let x_k be a solution. If $f(x) = 0$ then STOP; (u_k, v_k) is a solution of (NP^*) and x_k is a solution of *(NP)*.

- **Step 3.** Set

$$\begin{aligned} u_{k+1} &:= u_k - s_k f(x_k) \\ v_{k+1} &:= v_k + (s_k + \varepsilon_k)\|f(x_k)\| \end{aligned} \tag{12}$$

where $s_k, \varepsilon_k > 0$ are step size parameters defined as;

$$\begin{aligned} s_k &= \frac{\delta\left|\bar{H} - H_k\right|}{5\|f_k\|^2}, (0 < \delta < 2) \\ \varepsilon_k &= (0.1 \sim 1.0) s_k \end{aligned} \tag{13}$$

Set $k = k + 1$ and repeat Step 2.

Given a dual iterate (u_k, v_k), we introduce the following notation for brevity;

$$\begin{aligned} u_{k+1} &:= \arg\min_{x\in S} L_{SA}(x, u_k, v_k) \\ f_k &:= f(x_k) \\ H_k &:= H(u_k, v_k) \\ \bar{H} &:= H(\bar{u}, \bar{v}) \end{aligned} \tag{14}$$

where H_k is the global minimum value of augmented Lagrangian calculated at *k*-th iteration of the MSG algorithm, and $\bar{H}$ is the common optimal primal dual value for the problem (*NP*) [21].

III.II Particle Swarm Optimization Algorithm (PSO)

PSO has been introduced by Kennedy and Eberhart in 1995. The method has been improved by observing the social behavior of bird flocks and fish schools. The method has been developed to enable its use in the global optimal solutions of more complex engineering problems. A flock or school in the algorithm is composed of many particles, and each particle represents a potential solution [22].

Although PSO seems to be a simple and effective optimization tool as it can catch global optimum values very fast without distracted by local optimum values, and can be encoded easily, it also has some weak points. For example; it depends on initial conditions, and some time is needed for more effective combination of different parameters for consistency.

Particles are initially created randomly to spread out in the feasible space. Particles which have its self-positions and flight velocities keep these values unvaried for each iteration throughout the process. Equations are updated to state the location of each particle for the next iteration. Particles progress towards the optimal solution at each iteration.

Each particle initially is spotted randomly in PSO algorithm. Novel velocity of each particle is defined by equation (15) and new position is defined by equation (16) [22].

$$v_i(k+1) = wf.v_i(k) + c_1.r_1(k).\left[Xlbest_i(k) - x_i(k)\right] + c_2 r_2(k)\left[Xgbest(k) - x_i(k)\right] \quad (15)$$

$$x_i(k+1) = x_i(k) + v_i(k+1)\,,\ v_i(0)=0 \quad (16)$$

In equations, k represents iteration number, M particle numbers in each iteration (swarm population), $x_i(k)$, $i \in (1,\ldots,M)$ location of *i*-th particle in *k*-th iteration, $v_i(k)$, $i \in (1,\ldots,M)$ velocity of *i*-th particle in *k*-th iteration, positive numbers c_1 and c_2 represents learning factors (cognitive and social acceleration constants), $r_1(k), r_2(k) \sim U(0,1)$ random number regularly distributed between *0* and *1*, and w represents inertia weight factor. The best location memory of each particle in the population is recorded in $Xlbest_i(k)$ variable. Also, the location of the particles in the swarm which is the closest to the optimum is saved in $Xgbest(k)$.

Linearly decreased inertia weight factor, w, is a variable which adjusts prior velocity value, and computed by the equation (17) [22].

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \quad (17)$$

where $w_{\min}$ and $w_{\max}$ indicate the initial and final inertia weight factors respectively, $iter$ is current iteration number, and $iter_{\max}$ is the maximum iteration number in the equation.

IV. Application of the Novel Hybrid Algorithm

In order to solution of the problem, equation (18) is acquired if $f_0(x) = F_{TFC} = \sum_{n=1}^{N} F_n(P_{G,n})$ is added for the objective function and $f(x) = \Phi$ is added for the equality constraint as described by the sharp augmented Lagrange [3].

$$L_{SA} = F_{TFC} + v\|\Phi\| - \langle u, \Phi \rangle = \sum_{n=1}^{N} F_n(P_{G,n}) + v\|\Phi\| - \langle u, \Phi \rangle \quad (18)$$

Φ indicates the equality constraint in the equation (2). Flowchart of the novel hybrid approach (MSGPSO) is given in Figure 2.

Values of the parameters (δ, ε_k, TOL_Φ, $\bar{H}$, *u* and *v*) of the MSG algorithm and the data in relation to the problem (load demand, cost coefficients of the generation units) are inserted. Then, the PSO parameters (k, M, N, $w_{\max}$, $w_{\min}$, c_1 and c_2) are inserted and the iteration is reset.

Swarm members (which are particles) are initially generated randomly. $P_{G,n}$, $n \in N_G$ values for M particle are appointed randomly by the equation below [3].

$$P_{G,n} = P_{G,n}^{\min} + U(0,1) \times (P_{G,n}^{\max} - P_{G,n}^{\min}) \quad (19)$$

$U(0,1)$ is a regularly disbanded random number between zero and one in the equation. Sharp augmented Lagrange, L_{SA}, is computed by equation (18) using solution values presented by the particle, and process sustains. In this application, objective function in equation (18) is described as consistency function. The particle which is generated with that process embodies a solution, and so joins the swarm. That process sustains until M number of particles (swarm population) has been generated.

Particles with the best consistency value in $Xgbest(k)$ are selected in each iteration. The solution with the optimum function value is selected as the best solution at the end of iteration process.

The maximum number of iterations is determined as stopping criteria. It is checked if the iteration is completed. If not completed, the process is continued. L_{SA} is computed at the completion of the iteration, and checked if it is $\Phi \leq TOL_{\Phi}$ or not. If $\Phi > TOL_{\Phi}$, *u* and *v* values are updated as shown in Figure 2, and the process proceeds. If $\Phi \leq TOL_{\Phi}$ is satisfied, *k*, *u*, *v*, *s* and $P_{G,n}$, $(n \in N)$ values are registered, and the process is stopped.

The software, which is developed in the style of the novel hybrid approach, is written in MATLAB R2015a and run in a computer with Intel Core i7-2760QM 2.40GHz processor and 8 GB RAM memory.

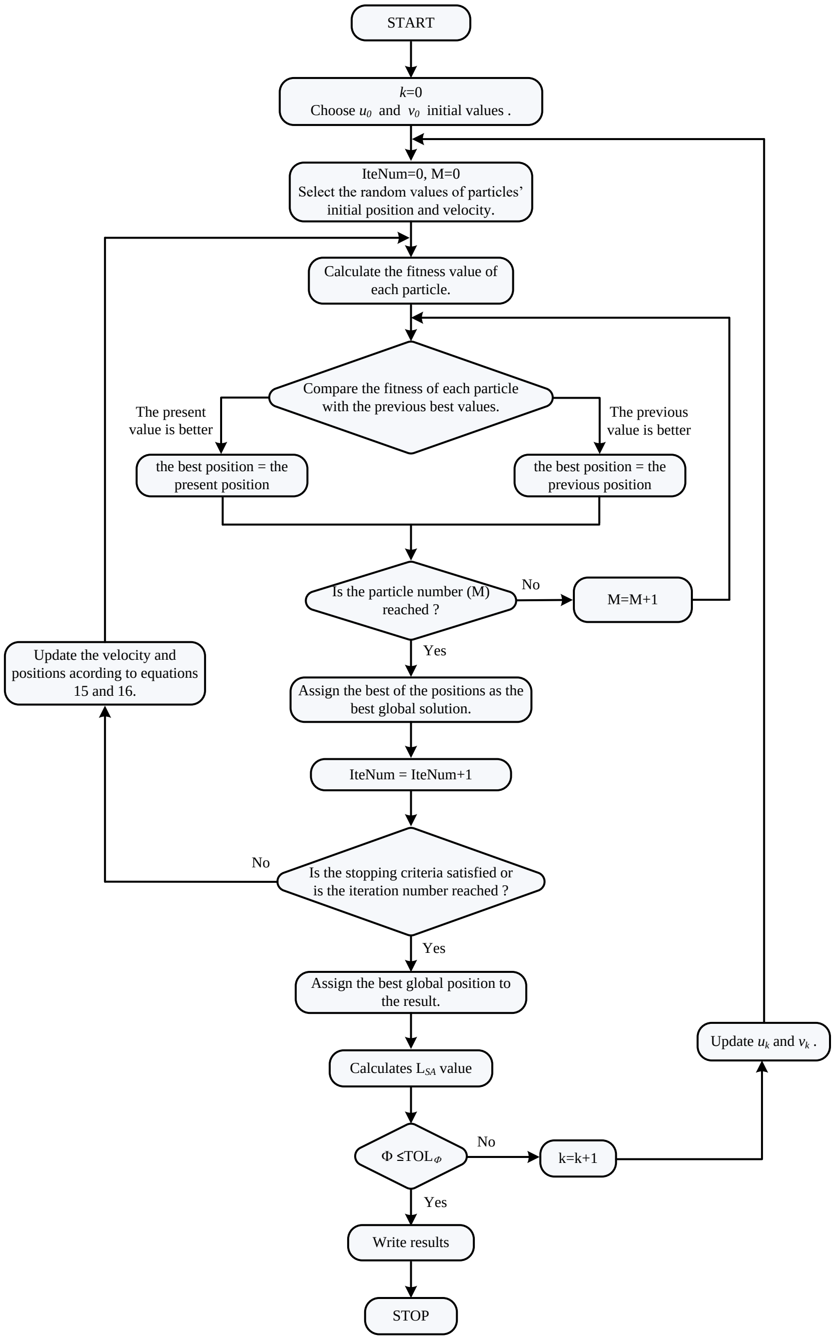

Figure 2. Flowchart of the novel hybrid approach (MSGPSO)

V. Solution of the Sample Problems

This approach (MSGPSO) is applied in the test system with 13 generators for a load demand of *1800 MW* and *2520 MW*. The fuel cost function coefficients and active power generation limits with regard to this test system is obtained from the literature [1,16] and given in Table 1 while B loss matrix values used for calculation of losses in the transmission lines are given in Table 2.

Table 1. Fuel cost coefficients and active power generation limits of the generation units [1]

	Bus No	a_n	b_n	c_n	e_n	f_n	P_{min} *(MW)*	P_{max} *(MW)*
13 generator system	1	0.00028	8.10	550	300	0.035	0	680
	2	0.00056	8.10	309	200	0.042	0	360
	3	0.00056	8.10	307	200	0.042	0	360
	4	0.00324	7.74	240	150	0.063	60	180
	5	0.00324	7.74	240	150	0.063	60	180
	6	0.00324	7.74	240	150	0.063	60	180
	7	0.00324	7.74	240	150	0.063	60	180
	8	0.00324	7.74	240	150	0.063	60	180
	9	0.00324	7.74	240	150	0.063	60	180
	10	0.00284	8.60	126	100	0.084	40	120
	11	0.00284	8.60	126	100	0.084	40	120
	12	0.00284	8.60	126	100	0.084	55	120
	13	0.00284	8.60	126	100	0.084	55	120

In this study, while $\bar{H}$ is selected as an appropriate solution value for example test system, the values of $\delta = 2.0$, $\varepsilon_k = 0.5 s_k$, $TOL_{\Phi} = 1\times10^{-6} MW$ are used in test system for the MSG algorithm. Besides, parameters of the PSO algorithm are selected as $M = 50$, $N = 13$, $w_{\max} = 0.5$, $w_{\min} = 0.1$, $c_1 = c_2 = 2.0$ and $k = 250$.

Table 2. Transmission loss coefficients for example test system. [16]

	B-Coefficients
13 generator system	$[B]=\begin{bmatrix} 0.0014 & 0.0012 & 0.0007 & -0.0001 & -0.0003 & -0.0001 & -0.0001 & -0.0001 & -0.0003 & -0.0005 & -0.0003 & -0.0002 & 0.0004 \\ 0.0012 & 0.0015 & 0.0013 & 0.0000 & -0.0005 & -0.0002 & 0.0000 & 0.0001 & -0.0002 & -0.0004 & -0.0004 & 0.0000 & 0.0004 \\ 0.0007 & 0.0013 & 0.0076 & -0.0001 & -0.0013 & -0.0009 & -0.0001 & 0.0000 & -0.0008 & -0.0012 & -0.0017 & 0.0000 & -0.0026 \\ -0.0001 & 0.0000 & -0.0001 & 0.0034 & -0.0007 & -0.0004 & 0.0011 & 0.0050 & 0.0029 & 0.0032 & -0.0011 & 0.0000 & 0.0001 \\ -0.0003 & -0.0005 & -0.0013 & -0.0007 & 0.0090 & 0.0014 & -0.0003 & -0.0012 & -0.0010 & -0.0013 & 0.0007 & -0.0002 & -0.0002 \\ -0.0001 & -0.0002 & -0.0009 & -0.0004 & 0.0014 & 0.0016 & 0.0000 & -0.0006 & -0.0005 & -0.0008 & 0.0011 & -0.0001 & -0.0002 \\ -0.0001 & 0.0000 & -0.0001 & 0.0011 & -0.0003 & 0.0000 & 0.0015 & 0.0017 & 0.0015 & 0.0009 & -0.0005 & 0.0007 & 0.0000 \\ -0.0001 & 0.0001 & 0.0000 & 0.0050 & -0.0012 & -0.0006 & 0.0017 & 0.0168 & 0.0082 & 0.0079 & -0.0023 & -0.0036 & 0.0001 \\ -0.0003 & -0.0002 & -0.0008 & 0.0029 & -0.0010 & -0.0005 & 0.0015 & 0.0082 & 0.0129 & 0.0116 & -0.0021 & -0.0025 & 0.0007 \\ -0.0005 & -0.0004 & -0.0012 & 0.0032 & -0.0013 & -0.0008 & 0.0009 & 0.0079 & 0.0116 & 0.0200 & -0.0027 & -0.0034 & 0.0009 \\ -0.0003 & -0.0004 & -0.0017 & -0.0011 & 0.0007 & 0.0011 & -0.0005 & -0.0023 & -0.0021 & -0.0027 & 0.0140 & 0.0001 & 0.0004 \\ -0.0002 & 0.0000 & 0.0000 & 0.0000 & -0.0002 & -0.0001 & 0.0007 & -0.0036 & -0.0025 & -0.0034 & 0.0001 & 0.0054 & -0.0001 \\ 0.0004 & 0.0004 & -0.0026 & 0.0001 & -0.0002 & -0.0002 & 0.0000 & 0.0001 & 0.0007 & 0.0009 & 0.0004 & -0.0001 & 0.0103 \end{bmatrix}$ $[B_0]=[-0.0001\ \ -0.0002\ \ 0.0028\ \ -0.0001\ \ 0.0001\ \ -0.0003\ \ -0.0002\ \ -0.0002\ \ 0.0006\ \ 0.0039\ \ 0.0017\ \ 0.0000\ \ -0.0032]$ $B_{00} = 0.0055$

In this study, the test system with 13 generators in literature has been solved with the proposed new hybrid method for 1800 MW and 2520 MW load demands as with loss and without loss in transmission line. The obtained optimum results have been given in Table 3.

Table 3. The results obtained from the proposed solution algorithm (13-Generators Test System)

		P_{load}=1800 *MW*		P_{load}=2520 *MW*	
		without loss	with loss	without loss	with loss
$P_{G,n}$ *(pu)*	$P_{G,1}$	6.283172	4.487989	6,283185	6,283185
	$P_{G,2}$	2.229398	2.991684	2,991947	2,991721
	$P_{G,3}$	1.495543	2.243455	2,991962	2,991903
	$P_{G,4}$	1.097145	1.098566	1,597331	1,597308
	$P_{G,5}$	0.600001	1.581268	1,597109	1,597326
	$P_{G,6}$	1.098319	1.098560	1,597320	1,597317
	$P_{G,7}$	1.099415	1.098635	1,597306	1,596777
	$P_{G,8}$	1.098479	0.600000	1,597331	1,596814
	$P_{G,9}$	1.098521	1.098434	1,596516	1,597330
	$P_{G,10}$	0.400000	0.400000	0,773623	0,773979
	$P_{G,11}$	0.400000	0.400000	0,738183	1,147620
	$P_{G,12}$	0.550003	0.550000	0,922291	0,913198
	$P_{G,13}$	0.550005	0.550000	0,915897	0,923740
$\sum P_{G,n}$ *(pu)*		18.000001	18.198591	25.200001	25.608218
F_{TFC} *($/h)*		17965.408	18135.504	24170.928	24515.584
P_{loss} *(pu)*		-	0.198591	-	0.408219
Time (s)		0.3610	1.104	0.378	1.501

The comparison of the optimum fuel cost values obtained by MSGPSO with the other methods in literature has been given in Table 4. As is seen in the table, the sample test system has been solved in literature generally by ignoring transmission line losses. In this study, the solution of the sample system with loss has been done in order to make contribution to the literature as a main source for the latter studies.

Table 4. Comparison of the results obtained through different methods in the literature (13 Generator Test System)

Solution Methods	P_{load}=1800 *MW*		P_{load}=2520 *MW*	
	without loss	with loss	without loss	with loss
	F_{TFC} *($/h)*		F_{TFC} *($/h)*	
CEP [1]	18048.21	-	-	-
FEP [1]	18018.00	-	-	-
MFEP [1]	18028.09	-	-	-
IFEP [1]	17994.07	-	-	-
EP-SQP [5]	17991.03	-	24266.44	-
PSO-SQP [5]	17969.93	-	24261.05	-
RTO [5]	17969.8024	-	24167.7042	-
SOS [9]	-	-	24169.918	-
HMAPSO [10]	17969.31	-	-	-
SPSO [11]	17988.15	-	-	-
QPSO [11]	17969.01	-	-	-
ICA-PSO [14]	-	-	-	24540.06
STHDE [14]	-	-	-	24560.08
BBO [14]	-	-	-	24515.21
ORCCRO [14]	-	-	-	24513.91
SDE [16]	-	18134.49	-	24514.88
MSGPSO	**17965.408**	**18135.504**	**24170.928**	**24515.584**

It can be said that the obtained results are close to or even better than some of the results in literature given in Table 4. The graphics obtained in the solution of the test system done by ignoring transmission line losses, have been given in Figure 3 and Figure 4 for 1800 MW load demand and in Figure 5 and Figure 6 for 2520 MW load demand.

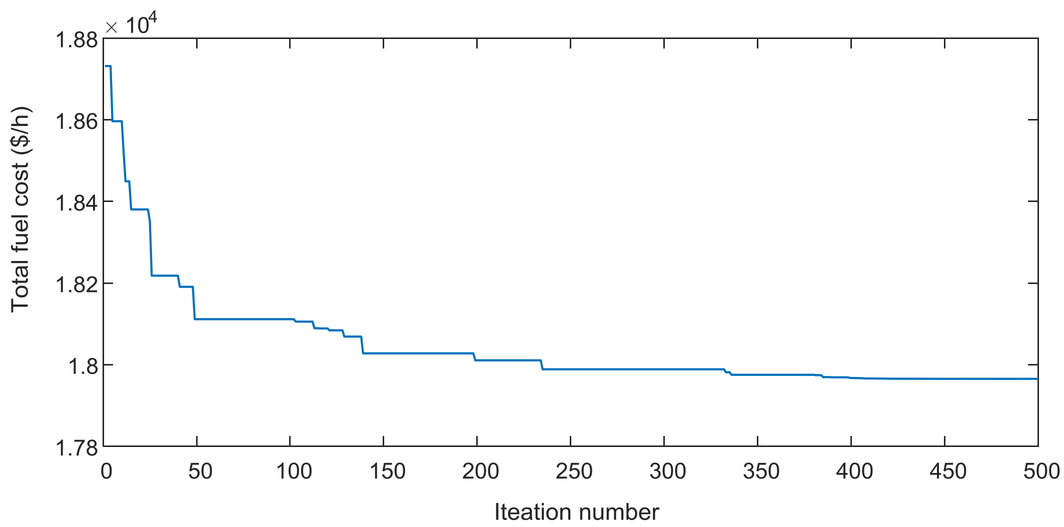

Figure 3. The variation of the total fuel cost versus iteration number (1800 MW – without loss)

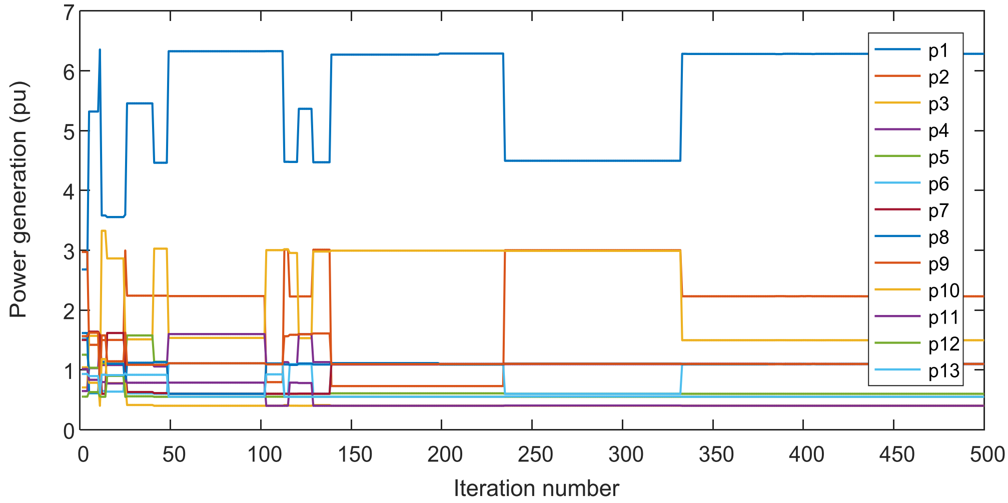

Figure 4. The variation of the power generation versus iteration number (1800 MW – without loss)

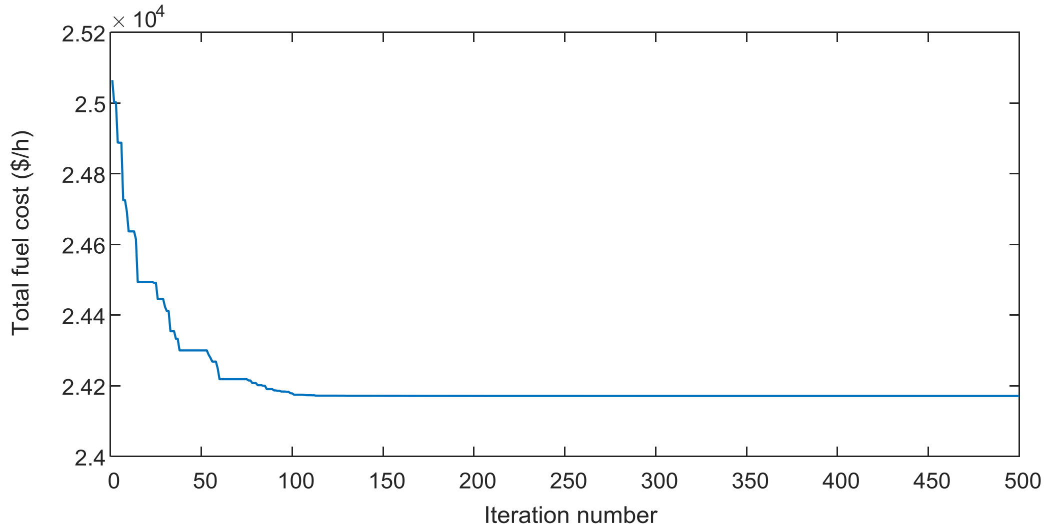

Figure 5. The variation of the total fuel cost versus iteration number (2520 MW – without loss)

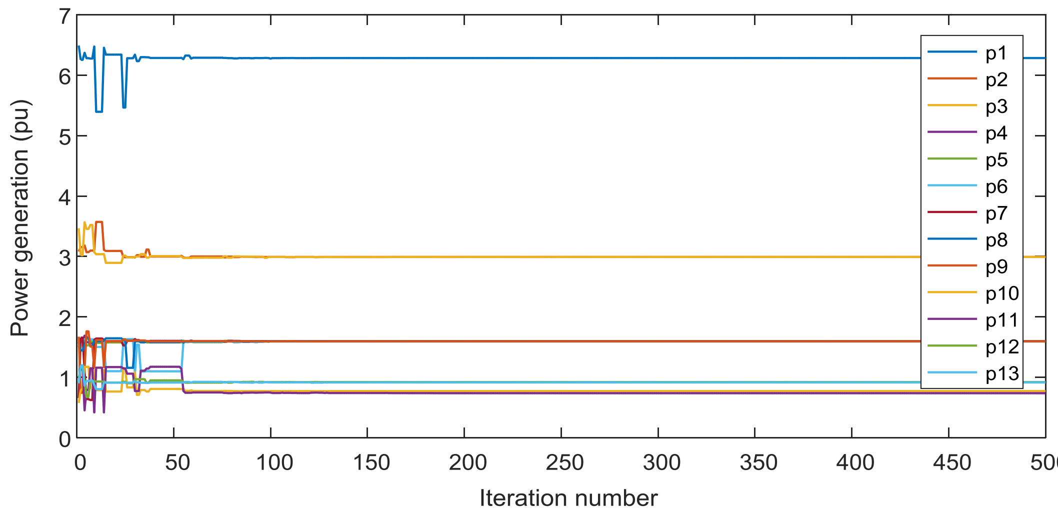

Figure 6. The variation of the power generation versus iteration number (2520 MW – without loss)

In Figure 3 and Figure 4, it is observed that the optimal solution is approximately achieved by the algorithm following the 380th iteration. It is observed that the change in the fuel cost and power generations remain the same following the 340th iteration.

In Figure 5 and Figure 6, it is observed that the optimal solution is approximately achieved by the algorithm following the 100th iteration. It is observed that the change in the fuel cost and power generations remain the same following the 60th iteration.

VI. Conclusion

The purpose of this study is to develop a new hybrid algorithm for the solution of the valve point effect nonconvex economic power dispatch problem whose solution by mathematical methods is difficult. Therefore, a new hybrid algorithm has been developed by using PSO algorithm, which is used successfully in literature for the solution of different problems, together with MSG method. MSG algorithm transforms constrained optimization problems into unconstrained problems by providing both equality constraints and inequality constraints. As for PSO, it is an algorithm which can catch global optimum in a very fast way without being distracted by local optimums. The advantages of the developed hybrid approach have appeared as the sum of the advantages of both algorithms which form the new hybrid algorithm. Hence, the optimum solutions of the problems have been obtained in a short time. This developed algorithm has been applied to the test system with 13 generators for different load demands. It has been seen that the results obtained by the solution of the test system converge to the results given in literature or they are better than some of them.

As a result, it has been shown that the hybrid approach (MSGPSO) can be applied to the solution of the valve point effect nonconvex economic power dispatch problem. As far as is known, MSGPSO algorithm has been used for the first time for the solution of this kind of problems. The developed approach is considered to be applied to different kinds of engineering problems in the latter studies.

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