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An Incorporated Algorithm for Power Economic Dispatch Considering of Units with Fuel Changes

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***Abstract*— This paper proposes an incorporated algorithm for solving the power economic dispatch problem (PEDP) of generating units with fuel changes. The particle swarm optimization (PSO) enhances the proposed method efficaciously find and accurately search. The multiple updating (MU) can help the incorporated algorithm prevent deforming the augmented Lagrange function and caused difficultly in searching an optimal solution. The incorporated approach (PSO-MU) combines the PSO and a MU that has benefits of adopting a widespread area of punishment parameters and a small-size population. The proposed PSO-MU has been demonstrated on a practical ten power generators system; each generating unit is composed of two or three fuel sources. The entire generating cost of PEDP got by the proposed algorithm has been competed with previous researches for validating its efficacy. Simulation results of three examples clearly show that the incorporated algorithm is an effective alternative for solving PEDP of generating units with fuel changes in the realistic operation of power system.**

***Index Terms*—Fuel changes, power economic dispatch, particle swarm optimization, multiple updating.**

I. INTRODUCTION

The power economic dispatch problem (PEDP) traditionally decides the best electricity generation for all power generators, which will reduce the entire cost while the system both of demand and constraints have been contented [1]~ [3]. The PEDP is always an integration problem due to its huge size, a nonlinear objective function, and a big amount of system constraints [4].

In practical operations of power system, some fired generators, which are provided with diverse fuels like natural gas, oil and coal. Functions of fuel price are always segmented as piecewise quadratic cost functions with multi-fuel sources. The power generating units having fuel changes is to reduce entire fired cost between available fired sources for each generator meeting loading and generation ranges. The PEDP is a nonconvex and complex optimal issue because it involves segmented values at each limit constituting numerous local optima. Consequently, traditional algorithms are usually hard to handle the PEDP of units with fuel changes. A conventional method [5] linearized segments of cost function to resolve the PEDP of generators having multiple fuel options. A numerical method (HM) [6] retained the supposition of piecewise quadratic price curves and solve the PEDP of units with fuel changes. Nevertheless, the computation of HM was still exponentially growing time complexities for bigger systems with nonconvex constraints. The Hopfield neural network (HNN) [7] was also ingenious to punishment factors correlative with system constraints. An evolutionary programming (EP) [8] for solving the PEDP with quadratic cost function arising due to different fuel options The enhanced Lagrangian neural network (ELANN) [9] had speedy computational efficacy because a momentum technique was used in learning procedure of ELANN. Nonetheless, approaches of HNN and ELANN needed a big iterative loop for convergence of the best answer, and they usually expressed oscillation in the transient procedure. The Adaptive Hopfield neural network (AHNN) [10], [11] always adjusts the gradient and biases of neurons within the convergent procedure to promote the computational property.

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Some deductive approaches have been utilized to resolve the PEDP of units having fuel changes, too. The genetic algorithm (GA) [12], [13], evolutionary programming (EP) [14], [15], differential evolution (DE) [16], particle swarm optimization (PSO) [17], a combination of the EP, tabu search and quadratic programming (ETQ) [18], the hybrid real coded genetic algorithm (HRCGA) [19], and the hybrid integer coded differential evolution-dynamic programming (HICDEDP) [20]. Nevertheless, methods mentioned above are usually tardy because of combining single techniques.

Various algorithms also have been presented to solve PEDP of units with multi-fuel options recently. Such as a synergic predator-prey optimization (SPPO) [21], an integrated of modified shuffled frog leaping algorithm (MSFLA), a global-best harmony search algorithm (GHS), and the SFLA-GHS [22], augmented Lagrange Hopfield network (ALHN) [23], ALHN initialized using quadratic programming (QP-ALHN) [24], improved particle swarm optimization (IPSO) [25], the enhanced augmented Lagrange Hopfield network (EALHN) [26], the composite cost function (CCF) [27], the chaotic improved honey bee mating optimization (CIHBMO) [28], and Pseudo-Gradient Based PSO [29].

The PSO exploited from Kennedy et al. [30], its developing was based on observations of animals' societal actions, such as bird flocking, fish schooling, and swarm concept. PSO has been diffusely used in power optimal problems. Even if this method can bring about high-quality answers with less calculation iterations and steady convergency contrast to other algorithms [31], it appears to be ingenious to tuning of certain weightings or factors. The PSO has shown its simplicity and facile realization in many previous reports [32]-[36].

II. SYSTEM FORMULATION

The objective function of PEDP is mainly to decide the best loading for all online dispatching generators, which reduces the entire fired price while approving of system constraints. It can be described below.

A. Fuel Cost

Generally, fuel cost function of every power generating unit is denoted by a sole quadratic cost function. Herein, because of generating unuts having multiple fuel changes, this cost function is piecewise and quadratic. Accordingly, the PEDP of generators having multiple fuel changes with piecewise quadratic price functions are expressed as [6]

$$\min\ f = \sum_{i=1}^{n} F_i(P_i) \tag{1}$$

$$F_i(P_i) = \begin{cases} a_{i,1} + b_{i,1}P_i + c_{i,1}P_i^2, & fuel\ 1,\quad \underline{P}_i \le P_i \le P_{i1} \\ a_{i,2} + b_{i,2}P_i + c_{i,2}P_i^2, & fuel\ 2,\quad P_{i1} \le P_i \le P_{i2} \\ \vdots & \qquad\qquad \vdots \\ a_{i,k} + b_{i,k}P_i + c_{i,k}P_i^2, & fuel\ k,\quad P_{ik-1} \le P_i \le \overline{P}_i \end{cases} \tag{2}$$

Where $F_i(P_i)$ stands fuel cost of generating unit i. P_i expresses power output of generating unit i. The $a_{i,k}$, $b_{i,k}$ and $c_{i,,k}$ respectively indicate cost coefficients of unit i for using fuel kind k, and n is entire amount of generating units.

B. System Balance Constraint

The entire generation must be match to the summation of system demand and transmission loss [21]

$$\sum_{i=1}^{n} P_i - P_d - P_L = 0 \tag{3}$$

Where P_d is the entire system demand and P_L is the transmission loss.

C. Capacity Limit Constraints

The power productivity of every generating unit i should be between its minimum $\underline{P}_i$ and maximum $\overline{P}_i$, and it can be expressed as [6]:

$$\underline{P}_i \le P_j \le \overline{P}_i \tag{4}$$

III. THE INCORPORATED ALGORITHM

A. PSO

The PSO [30], [31] is an iterative algorithm based on the searching action of swarm particles in a multidimensional search area. In PSO, the velocity and the position of each particle are updated. In the light of the fitness of the updated individuals, the personal best position of each particle and the global best position in all the particles are updated. Regarding the update of the velocities in the PSO, a particle is affect by its personal best position and the global best position. Thus, the PSO finds the global optimum by regulating the trajectory of each particle toward its personal best position and the global best position. In PSO with m individuals, each individual is treated as a volume-less particle in the n-dimensional space, with the position vector and velocity vector of particle i at the t^{th} generation expressed as $x_i(t) = [x_{i,1}(t), x_{i,2}(t), \ldots, x_{i,n}(t)]$ and $v_i(t) = [v_{i,1}(t), v_{i,2}(t), \ldots, v_{i,n}(t)]$. The particle shifts in accordance with the following equations [31]:

$$\begin{aligned} V_{i,j}(t+1) = w \cdot V_{i,j}(t) + c_1 \cdot r_{1,j}(t) \cdot \left[(Pbest_{i,j}(t) - x_{i,j}(t)\right] \\ + c_2 \cdot r_{2,j}(t) \cdot \left[(gbest_{i,j}(t) - x_{i,j}(t)\right] \end{aligned} \tag{5}$$

$$x_{i,j}(t+1) = x_{i,j}(t) + V_{i,j}(t+1) \tag{6}$$

Where $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$, where c_1 and c_2 are called acceleration coefficients, and w is the inertia weight. Vector $pbeset_{i,j(t)} = [pbest_{i,1}(t), pbest_{i,2}(t), \ldots, pbest_{i,n}(t)]$ is the best former position of particle i called personal best (*pbest*) position, and vector $gbest(t) = [gbest_{i,1}(t), gbesti,2(t), \ldots, gbest_{i,n}(t)]$ is the position of the best particle between all the particles in the population and called global best (*gbest*) position.

B. MU

Michalewicz et al. [37] surveyed and compared several constraint-handling techniques used in evolutionary algorithms. Among these techniques, the penalty function method is one of the most popularly used to handle constraints. In this method, the objective function includes a penalty function that is composed of the squared or absolute constraint violation terms. Powell [38] noted that classical optimization methods include a penalty function have certain weaknesses that become most serious when penalty parameters are large. More importantly, a large penalty parameter tends to be ill conditioned the penalty function so that obtaining a good solution is difficult. However, if the penalty parameter is too small, the constraint violation does not contribute a high cost to the penalty function. Accordingly, choosing appropriate penalty parameters is not trivial. Herein, the MU [38], [39] is introduced to handle this constrained optimization problem. Such a technique can overcome the ill conditioned property of the objective function. Considering the nonlinear problem with general constraints as follows:

$$\begin{aligned} & \min_x f(x) \\ subject\quad to\quad & h_k(x) = 0,\quad k = 1,\ldots,m_e \\ & g_k(x) \le 0,\quad k = 1,\ldots,m_i \end{aligned} \tag{7}$$

Where $h_k(x)$ and $g_k(x)$ stand for equality and inequality constraints respectively.

The augmented Lagrange function (*ALF*) [39], [40], [41] for constrained optimization problems is defined as:

$$\begin{aligned} L_a(x,\nu,\upsilon) = f(x) + \sum_{k=1}^{m_e} \alpha_k \left\{ [h_k(x) + \nu_k]^2 - \nu_k^2 \right\} \\ + \sum_{k=1}^{m_i} \beta_k \left\{ \langle g_k(x) + \upsilon_k \rangle_+^2 - \upsilon_k^2 \right\} \end{aligned} \tag{8}$$

Where α_k and β_k are the positive penalty parameters, and the corresponding Lagrange multipliers $\nu = (\nu_1, \ldots, \nu_{m_e})$ and $\upsilon = (\upsilon_1, \ldots, \upsilon_{m_i}) \ge 0$ are associated with equality and inequality constraints, respectively.

The contour of the *ALF* does not change shape between generations while constraints are linear. Therefore, the contour of the *ALF* is simply shifted or biased in relation to the original objective function, *f*(*x*). Consequently, small penalty parameters can be used in the MU. However, the shape of contour of L_a is changed by penalty parameters while the constraints are nonlinear, demonstrating that large penalty parameters still create computational difficulties. Adaptive penalty parameters of the MU are employed to alleviate the above difficulties. More details of the MU have shown in [42].

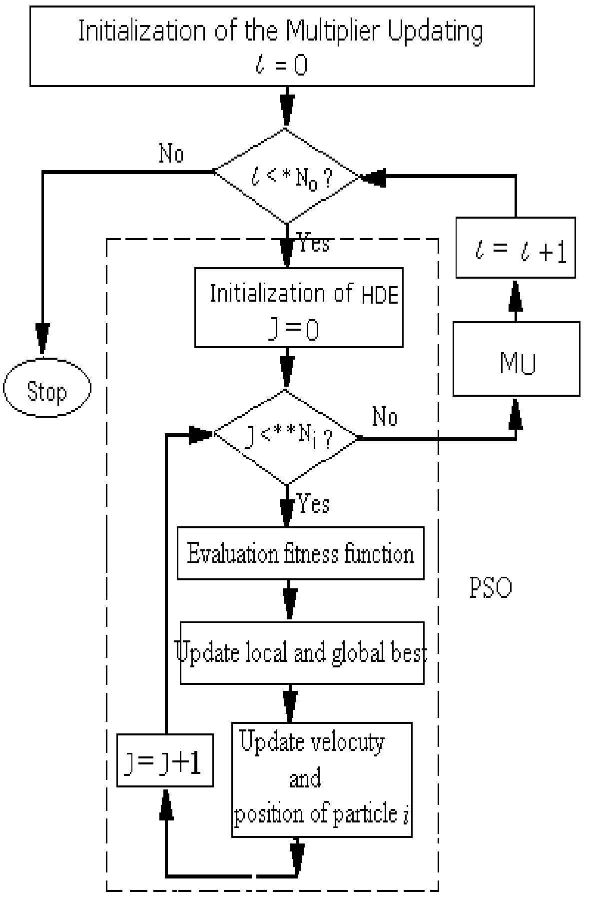

Fig.1 The flow chart of the PSO-MU

*N$_0$: maximum number of iterations of outer loop

**N$_i$: maximum number of iteartions of inner loop

C. The proposed PSO-MU

Figure 1 displays the flow chart of the incroporated algorithm, which has two iterative loops. The *ALF* is used to obtain a minimum value in the inner loop with the given penalty parameters and multipliers, which are then updated in the outer loop toward producing an upper limit of L_a. When both inner and outer iterations become sufficiently large, the *ALF* converges to a saddle-point of the dual problem [38]. Advantages of the proposed PSO-MU are that the PSO efficiently searches the optimal solution in the economic dispatch process and the MU effectively tackles system constraints.

IV. System Simulations

In this section, three cases are used to illustrate the effectiveness of the proposed algorithm with respect to the quality of the solution obtained for solving the PEDP considering of generators having multiple fuel changes. The proposed method has been tested on a realistic 10-unit power system, and each generating unit is composed of two or three fuel sources. The cost function using (2) considers multiple fuels. The cost coefficients along with the smallest and biggest generating capacity limits for every fuel option are the same as [6]. The MU was used in the incorporated algorithm (PSO-MU) to manage system constraints of the inequality and equality. The computational program was executed on a desktop computer (Intel(R) Core(TM) i7-3770 CPU @ 3.4 GHz with 8G Ram) coded in FORTRAN-90 program and run 100 independent trials for each test case. Setting parameters employed in these cases demonstrate as the following; the population dimension is fixed as 20. The iteration numbers of outer loop and inner loop are set to (outer, inner) as (10, 1000) for the proposed PSO-MU. The implementation of the proposed algorithm for the test system can be described as follows:

$$L_a(x,\nu,\upsilon) = f(x) + \{[h_1(x)+\nu_1]^2 - \nu_1^2\} + \sum_{k=1}^{20} \beta_k \{\langle g_k(x)+\upsilon_k \rangle_+^2 - \upsilon_k^2\} \quad (9)$$

The objective function:

$$\min_{x=(P_1,P_2,\cdots,P_{10})} f(x) = \sum_{i=1}^{10} F_i(P_i) \quad (10)$$

$$F_i(P_i) = \begin{cases} a_{i,1} + b_{i,1}P_i + c_{i,1}P_i^2, & fuel\ 1, \quad \underline{P}_i \le P_i \le P_{i1} \\ a_{i,2} + b_{i,2}P_i + c_{i,2}P_i^2, & fuel\ 2, \quad P_{i1} \le P_i \le P_{i2} \\ \vdots & \vdots \\ a_{i,k} + b_{i,k}P_i + c_{i,k}P_i^2, & fuel\ k, \quad P_{ik-1} \le P_i \le \overline{P}_i \end{cases} \quad (11)$$

$$subject\ to \quad \begin{aligned} h_1 &: \sum_{i=1}^{10} P_i - P_d = 0 \\ g_1 &: P_1 - P_1^{\max} \le 0 \\ &\vdots \\ g_{10} &: P_{10} - P_{10}^{\max} \le 0 \\ g_{11} &: P_1^{\min} - P_1 \le 0 \\ &\vdots \\ g_{20} &: P_{10}^{\min} - P_{10} \le 0 \end{aligned} \quad (12)$$

Table 1: Comparisons of the proposed PSO-MU with previous methods for case 1

Methods / Items	PGPSO [29]		QP-ALHN [24]		ALHN [23]		EALHN [26]		MSFLA [22]		GHS [22]		SFLA-GHS[22]		PSO-MU	
	FT	Gen	*FT*	Gen	*FT*	Gen	*FT*	Gen	*FT*	Gen	*FT*	Gen	*FT*	Gen	*FT*	Gen
1	2	216.2074	2	216.543	2	216.543	2	216.5441	2	216.5442	2	216.5436	2	216.5442	2	216.5440
2	1	210.8414	1	210.906	1	210.906	1	210.9057	1	210.9058	1	210.9035	1	210.9058	1	210.9052
3	1	278.5687	1	278.544	1	278.544	1	278.5441	1	278.5441	1	278.5415	1	278.5441	1	278.5442
4	3	238.9349	3	239.097	3	239.097	3	239.0967	3	239.0967	3	239.0998	3	239.0967	3	239.0967
5	1	275.7003	1	275.520	1	275.520	1	275.5195	1	275.5195	1	275.5219	1	275.5194	1	275.5197
6	3	239.0876	3	239.097	3	239.097	3	239.0967	3	239.0967	3	239.0948	3	239.0967	3	239.0966
7	1	286.0002	1	285.717	1	285.717	1	285.7170	1	285.7170	1	285.7165	1	285.7170	1	285.7173
8	3	239.1758	3	239.097	3	239.097	3	239.0967	3	239.0967	3	239.1000	3	239.0967	3	239.0967
9	1	343.3878	1	343.493	1	343.493	1	343.4932	1	343.4934	1	343.4896	1	343.4934	1	343.4934
10	1	272.0959	1	271.987	1	271.987	1	271.9863	1	271.9861	1	271.9889	1	271.9861	1	271.9863
TP (MW/h)	2600.0000		2600.001		2600.001		2600.0000		2600.0002		2600.0001		2600.0001		2600.0000	
TC ($/h)	574.3814		574.381		574.381		574.381		574.3808		574.3808		574.3808		574.380823	
SCV	0.0000		0.0001		0.001		0.0000		0.0002		0.0001		0.0001		0.0000	

Table 2: Comparisons of the proposed PSO-MU with previous methods for case 2

Methods / Items	MSFLA [22]		EALHN [26]		HICDEDP [20]		CCF [27]		GHS [22]		SFLA-GHS [22]		SPPO [21]		PSO-MU	
	FT	Gen	*FT*	Gen	*FT*	Gen	*FT*	Gen	*FT*	Gen	*FT*	Gen	*FT*	Gen	*FT*	Gen
1	2	226.5694	2	218.2502	2	218.2499	2	218.2499	2	218.2499	2	218.2499	2	218.3507	2	218.2499
2	1	215.3542	1	211.6627	1	211.6626	1	211.6626	1	211.6624	1	211.6626	1	211.5895	1	211.6626
3	1	291.3490	1	280.7230	1	280.7228	1	280.7228	1	280.7229	1	280.7228	1	280.7704	1	280.7228
4	3	242.2402	3	239.6316	3	239.6315	3	239.6315	3	239.6313	3	239.6315	3	239.6790	3	239.6315
5	1	293.0212	1	278.4975	1	278.4973	1	278.4973	1	278.4971	1	278.4973	1	278.4467	1	278.4973
6	3	242.2402	3	239.6316	3	239.6315	3	239.6315	3	239.6318	3	239.6315	3	239.5304	3	239.6315
7	1	302.5705	1	288.5847	1	288.5845	1	288.5845	1	288.5846	1	288.5845	1	288.5161	1	288.5845
8	3	242.2402	3	239.6316	3	239.6315	3	239.6315	3	239.6318	3	239.6315	3	239.6159	3	239.6316
9	3	355.4991	3	428.5203	3	428.5216	3	428.5216	3	428.5215	3	428.5216	3	428.6269	3	428.5216
10	1	288.9161	1	274.8671	1	274.8667	1	274.9967	1	274.8666	1	274.8667	1	274.8742	1	274.8667
TP (MW/h)	2700.0001		2700.0003		2699.9999		2700.1299		2699.9999		2699.9999		2699.9998		2700.0000	
TC ($/h)	626.2543		623.8093		623.8092		623.8092		623.8092		623.8092		623.80900		623.80915	
SCV	0.0001		0.0003		-0.0001		0.1299		-0.0001		-0.0001		-0.0002		0.0000	

The optimization of PEDP of generating units with multi-fuel types is formed by the objective function (1), the power balance constraint of (3) and the capacity limit constraints of (4). Thus, the optimal cost problem composes of one objective function with ten variable parameters and one equality equation for the power balance constraint. This minimum cost problem consists of one objective function with ten variable parameters, (P_1~ P_{10}), one equality constraint, (h_1), and twenty inequality constraints, (g_1~ g_{20}), for the PEDP of units with multi-fuel types. The sum of system constraint violations (*SCV*) is defined in (13) to inspect effect of the constraint feasibility at the final solution.

$$SCV = |h_1| + \sum_{k=1}^{20} \max\{\ g_k\ ,\quad 0.0\ \}(MW) \qquad (13)$$

A. Case 1

To address the realistic operation of power units with multi-fuel changes, the optimal economic dispatch is obtained only if each generator uses the most economic source to burn. The first case is a practical system from [6] comprising 10 generating units supplying to a load demand (P_d) of 2600MW/h neglecting power loss. For comparison, Table 1 lists eight optimal results of this practical test system for this case. Results obtained from an integrated of modified shuffled frog leaping algorithm (MSFLA), a global-best harmony search algorithm (GHS), and the SFLA-GHS [22], augmented Lagrange Hopfield network (ALHN) [23], ALHN initialized using quadratic programming (QP-ALHN) [24], the enhanced augmented Lagrange Hopfield network (EALHN) [26], Pseudo-Gradient Based PSO [29], and the proposed PSO-MU, are shown in this Table clearly. The Gen, *TP*, *TC*, and *FT* stand the units generation, total power, total cost, and the fuel types respectively.

The proposed PSO-MU exhibits not only better solution quality but also acquire an exact *TP* for load demand than the previous papers. Although results obtained from MSFLA [22], GHS [22], and SFLA-GHS [22] have the less cost than the proposed PSO-MU. However, such solutions are infeasible ones, because of insufficient or excess demand. The *SCV* indicates that these outputs are infeasible solutions. As seen from the optimal solution of the proposed PSO-MU with an exact total power (*TP*) listed in Table 1, the *TP* is 2600.0000 MW/h. In this Table, all methods have the same fuel type (*FT*) used for the dispatching generators of this case.

B. Case 2

The second case is also used to demonstrate that the proposed PSO-MU is an effective alternative for solving PEDP of generating units with fuel changes in the realistic operation of power system. The test system of this case 2 is employed the same practical ten-unit system [6] as case 1 in a load demand (P_d) of 2700MW/h neglecting power loss.

Seven optimal solutions of previous researches of the hybrid integer coded differential evolution-dynamic programming (HICDEDP) [20], a synergic predator-prey optimization (SPPO) [21], MSFLA [22], GHS [22], SFLA-GHS [22], EALHN [26], and a composite cost function (CCF) [27], have been presented in the Table 2 to compare the production cost for case 2.

By investigating results shown in Table 2, it is observed that the best total cost (*TC*) utilizing PSO-MU is 623.80915 $/h, which is less much than the best result previously reported in MSFLA [22] and is close to before studies of the HICDEDP [20], SPPO [21], GHS [22], SFLA-GHS [22], EALHN [26], and CCF [27]. Despite the fact that the SPPO [21] has the less cost than the proposed PSO-MU, the *SCV* of the SPPO [22] is -0.0002 and the result of the SPPO [22] is still an infeasible solution. Therefore, the result got from the proposed PSO-MU is an optimal and feasible solution.

Moreover, Table 3 shows comparisons of the *TP*, *TC* and average CPU time (*CPU_AV*) obtained from former studies and the proposed PSO-MU for this case. According to the *CPU_AV* of different methods listed in the Table 3, the proposed PSO-MU is faster than most of the compared algorithms, but slightly slower than EALHN [26]. Consequently, the PSO-MU is both providing the precise entire power and spending the less *CPU_AV* than most methods for the PEDP of units with multi-fuel sources.

Table 3: Comparisons of the *TC* and *CPU_AV* obtained from different approaches and the proposed PSO-MU for case 2.

Method	*TP* (MW/h)	*TC ($/h)*	*CPU_AV* (Sec)
HM [6]	2702.7	625.18	-
HNN [7]	2699.7	626.12	~ 60
ELANN [9]	2700	623.88	21.36
AHNN [10]	2700	626.24	~ 4
ARCGA [12]	2700	623.828	0.85
IEP [15]	2700	623.851	-
DE [16]	2700	623.809	0.083
MPSO [17]	2700	623.809	-
HRCGA [19]	2700	623.809	6.47
HICDEP [20]	2700	623.809	0.513
QP-ALHN [24]	2699.999	623.809	0.047
IPSO [25]	2700.0001	623.8089	0.922
EALHN [26]	2700.0003	623.8090	0.013
CIHMBO [28]	2700.0002	623.5960	2
PGPSO [29]	2700.0000	623.8095	0.233
CGA-MU [42]	2700.0000	623.8095	19.42
IGA-MU [42]	2700.0000	623.8093	5.27
PSO-MU	2700.0000	623.80915	0.015

C. Case 3

The identical ten units system [6] considering both power demand of 2700MW/h and transmission losses is applied in the last case. The data of power transmission losses are derived from the SPPO [21]. Table 4 provides compared results of the SPPO [21] and the proposed PSO-MU in terms of power generating cost. The proposed PSO-MU also yields better solution quality than the SPPO [21], Table 4 reveals that the proposed method not only has the lower total cost (*TC*) than the SPPO [21] method tested, but also generates the exact total power (*TP*) for the system constraints of (11), showing that the proposed approach is more effective than the SPPO [21] for the PEDP considering power transmission losses. Consequently, the comparisons in Tables 1 to 4, have clearly revealed that the proposed PSO-MU is more effective than previous methods in applying the practical PEDP with power units having fuel changes.

Table 4: Comparisons of the proposed PSO-MU with the SPPO [21] considering transmission losses for case 3

Methods / Items	SPPO [21]		PSO-MU	
	FT	**Gen**	***FT***	**Gen**
1	2	229.708	2	230.7420
2	1	222.829	1	218.9839
3	1	304.310	1	299.7028
4	3	240.348	3	244.4580
5	1	316.169	1	306.8470
6	3	246.015	3	244.9148
7	1	317.186	1	314.3372
8	3	236.998	3	243.9950
9	3	432.065	3	439.9140
10	1	295.962	1	297.9250
TP (MW/h)	2841.590		2841.8197	
P_L (MW/h)	141.593		141.8197	
TC ($/h)	700.296		699.3436	
SCV	-0.003		0.0000	

V. Conclusions

An incorporated algorithm (PSO-MU) for solving the PEDP of power generators with multiple fuel sources has been proposed herein. The PSO helps the proposed method efficiently search and refined exploit. The MU assists the presented algorithm both of preventing out of shape of the *ALF* and leading to difficulty of solution finding. The proposed approach combines the PSO with the MU that has benefits of taking a large area of penalty parameters and a small population. Three cases of a practical ten-unit system are employed to compare the proposed PSO-MU with previous methods. Simulation results demonstrate that the proposed algorithm is superior to previous approaches in solution quality for solving the PEDP of units with multi-fuel changes. Contributions of this paper are the PSO accurately finds the optimal solution in the economic dispatch process, and the MU validly handles in system constraints management of power system.

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