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Economic Power Dispatch Considering Multi-Fuel Source and Prohibited Operating Zones using Ant Lion Optimizer

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ABSTRACT:

The electrical power generation from fossil fuel releases several contaminants into the air and this become excrescent if the generating unit is fed by Multiple Fuel Sources (MFS).The ever more stringent environmental regulations have forced the utilities to produce electricity at the cheapest price with the minimum level of pollutants. The restriction in generator operations increases the complexity in plant operations. The cost effective responsive operations in MFS environment can be recognized as a multi-objective constrained optimization problem. The Ant Lion Optimizer (ALO) has been chosen as an optimization tool and its application for solving the MFS dispatch problems. The intended algorithm is implemented on the standard test systems considering the prevailing operational constraints such as valve-point loadings and prohibited operating zones.

Keywords: Ant Lion Optimizer, Economic Dispatch, Multiple Fuel Sources, Prohibited Operating Zone

MULTI-FUEL POWER GENERATION DISPATCH (MFPGD)

In practical conditions of power system operations, different Fuel Sources (FS) like coal, natural gas and oil supply certain generating units. The cost function for each fuel type is derived and is segmented as Piecewise Quadratic Cost Function (PQCF) for a generating unit fed by Multiple Fuel Sources (MFS). These generating units face with the dilemma of finding out the most economical fuel to fire. Further, the operational complexity is increased while considering the valve-point discontinuities and prohibited operating zones.

The solution approaches addressing this problem can be categorized into mathematical and heuristic methods.

The classical optimization methods, including Hierarchical Method (HM) and artificial neural network models such as Hopfield Neural Network (HNN) and Adaptive HNN (AHNN) models have been reported to address the economic operation of MFS (Shoults & Mead, 1984; Lin & Viviani, 1984; Park et al., 1993; Lee et al., 1998). The main drawback of these methods is the exponentially growing time for large scale systems with non-convex constraints.

The meta-heuristic search techniques such as Genetic Algorithm (GA) (Baskar et al., 2003), Evolutionary Programming (EP) (Jayabarathi et al., 2005), Particle Swarm Optimization (PSO) (Park et al., 2005), Artificial Immune System (AIS) (Panigrahi et al., 2007), Differential Evolution (DE) (Noman & Iba, 2008), Artificial Bee Colony Algorithm (ABC) (Hemamalini & Simon, 2010) and Biogeography Based Optimization (BBO) (Bhattacharya & Chattopadhyay,

2011) have been reported for solving ED with PQCF. The modified versions of heuristic search techniques such as hybrid Real Coded GA (RCGA), fast EP, improved fast EP, Improved GA – Multiplier Updating (IGA-MU), New PSO-Local Random Search (NPSO-LRS), penalty parameter less PSO/DE and New Adaptive PSO (NAPSO) have been reported to solve multi-fuel power dispatch problem (Baskar et al., 2003, Jayabarathi et al., 2005; Park et al., 2005; Chiang, 2005; Selvakumar & Thanushkodi, 2007; Manoharan et al., 2008; Niknam et al., 2011). The improved version of PSO has been reported to solve the ED problem considering the valve-point effects (Polprasert et al., 2013). Further, improved versions of HNN and mathematical methods such as Augmented Lagrange HNN (ALHNN), Enhanced ALHNN (EALHNN), Quadratic Programming – Augmented Lagrange Hopfield Network (QP-ALHN), Hopfield Lagrange Network (HLN), Auction based Algorithm (AA) and Dimensional Steepest Decline (DSD) have also been reported to determine cost effective dispatch schedules (Vo & Ongsakul, 2012; Dieu et al., 2013; Dieu & Schenger, 2013; Thang, 2013; Binetti et al., 2014; Zhan et al., 2015). The Teaching Learning Based Optimization (TLBO) algorithm and Chaotic Global Best ABC (CGBABC) algorithm have been applied for the economic solution considering tie line flows and MFS (Basu, 2014; Secui, 2015).

Recently, the population based soft computing techniques like Kinetic Gas Molecule Optimization (KGMO) (Basu, 2016), Crisscross Optimization (CCO) (Meng & Yin, 2016), Grey Wolf Optimization (GWO) (Pradhan et al., 2016), Backtracking Search Algorithm (BSA) (Modiri-Delshad et al., 2016),Predator-Prey Optimization (PPO) (Singh et al., 2016), Synergic PPO (SPPO) (Singh et al., 2016), Lightning Flash Algorithm (LFA) (Kheshti et al., 2017) have been reported for cost effective multi-fuel power dispatch schedules. Further, the modified versions of meta-heuristic algorithms such as DE-PSO (Parouha & Das, 2016), Colonical Competitive DE (CCDE) (Ghasemi et al., 2016), Opposition based Greedy Heuristic Search (OGHS) (Singh & Dhillon, 2016), Surrogate Worth Trade-off Method (SWTM) (Singh et al., 2017), Pseudo-inspired Choatic Bat Algorithm (PCBA) (Shukla & Singh, 2017), Ant Lion Optimizer (ALO) (Balachandar et al., 2017; Balachandar 2017), Double Weighted PSO (DWPSO) (Kheshti et al., 2018) and Adaptive Predator – Prey Optimization (APPO) (Singh et al., 2018) have been reported for the economical real power scheduling considering multiple energy sources. An improved version of TLBO and group leader optimization technique have also been reported for the ED solutions (Banerjee et al., 2016; Roy et al., 2017).

The mathematical approaches suffer from the drawback of trapping in local solutions and their applications are limited to small-scale linear MFS problems. Withal, the meta-heuristic methods also accept a few drawbacks like algorithmic parameter settings, premature phenomena, trapping into infeasible solution and are computationally expensive. Hence, it is of great significance to improve the existing optimization techniques or exploring new optimization techniques to solve MFS problem.

MULTI FUEL POWER GENERATION DISPATCH (MFPGD)

Profuse solution methods have been addressed the multi-fuel power dispatch problems aiming the minimum cost as the operational objective. Since, the clean air amendment forces the electric power utilities to maintain the pollutant level within the predefined limits, a multi-objective problem formulation has been desirable that optimizes the total fuel cost and emission in a single framework. The economic-environmental compromising operation is less concentrated in the area of multi-fuel power generation dispatch. The environmental issues must be integrated into the operational model to get it desirable for practical power system conditions.Thang (2013) has reported a model considering environmental issues with MFS. Dieu et al, 2013 has incorporated the Prohibited Operating Zone (POZ) as an operational constraint in the MFS environment.

MATHEMATICAL MODEL OF MFPGD

The mathematical model for performing cost operation of thermal power plants is given in this section. In this formulation, the decision variables are real power outputs of online generators.

Minimization of Total Fuel Cost

The total fuel cost of thermal power plant (FC) is the sum of fuel costs of online generating units and is expressed as,

$$FC = Min \sum_{i=1}^{N} F_i\,(P_i) \;\; \$/h \tag{1}$$

The fuel cost of a generating unit '*i*' considering valve-point loadings and MFS (*j*) is expressed as,

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2 + \left|e_{i1} \times \sin(f_{i1} \times (P_{i1}{}^{\min} - P_i))\right| & fuel\,1, P_i^{\min} \le P_i \le P_{i1} \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2 + \left|e_{i2} \times \sin(f_{i2} \times (P_{i2}{}^{\min} - P_i))\right| & fuel\,2, P_{i1} \le P_i \le P_{i2} \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ a_{ij} + b_{ij}P_i + c_{ij}P_i^2 + \left|e_{ij} \times \sin(f_{ij} \times (P_{ij}{}^{\min} - P_i))\right| & fuel\,j, P_{ij-1} \le P_i \le P_i^{\max} \end{cases} \tag{2}$$

Constraints

The system and operational constraints are as follows:

Power Balance

The total generation by all the generators must be equal to the total power demand (P_d) and transmission line loss (P_L).

$$\sum_{i=1}^{N} P_i = P_d + P_L \tag{3}$$

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i\, B_{ij} P_j \tag{4}$$

Generation Limits

The real power generation of each generator is to be controlled inside its upper (P_i^{max}) and lower (P_i^{min}) operating limits.

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1, 2, \ldots N \tag{5}$$

Prohibited Operating Zones

The restricted operating regions of generating units decomposes the entire feasible operating regions into a number of feasible sub-regions and the operating point of a generator should lie in any one of the sub-regions as follows:

$$\begin{gathered} P_i^{min} \leq P_i \leq P_{i,1}^l \\ P_{i,j-1}^u \leq P_i \leq P_{i,j}^l, \quad j = 2,3,\ldots,n_i \\ P_{i,n_i}^u \leq P_i \leq P_i^{max} \end{gathered} \tag{6}$$

ANT LION OPTIMIZER

The ant lions are a class of net winged insects in nature. The lifecycle of ant lions comprises the stages as: larvae and adult. A larva is the longest period in their lifecycle and ant lions mostly hunt during this period. An ant lion larva digs a cone shaped pit in sand by moving along a circular path, then the larvae hides underneath the bottom of the cone and waits for the prey to be trapped in the pit. Once the ant lion realizes a prey in the trap, it tries to catch intelligently by throw sands towards the edge of the pit to slide the prey into the bottom of the pit. After consuming the prey, the ant lions throw leftovers outside the pit and amend the pit for next hunt.

The ALO mimics the interactions between the ant lions and ants in the trap. The ants are allowed to move over the search space and ant lions hunt those using traps to become fitter. These activities are mathematically modelled and are detailed in the literature (Mirjalili, 2015). The main steps involved in the ALO are random walk of ants, trapping in ant lion's pits, building traps, entrapment of ants in preys, catching in prey and rebuilding of traps.

Random walks of ants

To model the interactions between ant lions and ants in the trap, ants are necessitated to move over the search space and ant lions are consented to hunt them and become fitter using traps. A random walk is chosen for modelling ants' movement, since during the search for food the ants move stochastically in nature. Therefore, to facilitate the random walks inside the search space they are normalized using Equation (7).

$$X_i^k = \frac{(X_i^k - r_i)(m_i - q_{i,k})}{(m_{i,k} - r_i)} + q_i \tag{7}$$

Trapping in ant lion's pits

The assumption considered in ALO is that "The random walks of ants are affected by ant lion's traps" (Mirjalili, 2015). The above assumption is mathematically modelled as:

$$q_{i,k} = AL_{j,k} + q_k \; ; m_{i,k} = AL_{j,k} + m_k \tag{8}$$

Building trap

In this phase, a roulette wheel operator is used to select the ant lions based on their fitness during optimization. This mechanism offers high possibilities to the fitter ant lions for grasping ants.

Exploration of search space

To prevent the trapped ants from escaping the radius of ants' random walks hyper sphere is reduced adaptively. To mathematically model the above behaviour, the following equations, which shrink the radius of updating ant's positions and mimic the sliding process of ant inside the pits, are used.

$$q_k = {q_k}/{R}; m_k = {m_k}/{R} \tag{9}$$

Where, R = 10S ($k/itermax$) and S = 2 if k> 0.1$itermax$; = 3 if k> 0.5 $itermax$; = 4 if$k$> 0.75 $itermax$; = 5 if$k$> 0.9 $itermax$; = 6 if$k$> 0.95 $itermax$. The accuracy level of exploitation depends on the constant S.

Catching prey and re-building the pit

The final stage of hunting behaviour is when an ant reaches the bottom of the pit and is caught in the ant lion's jaw. After this stage, the ant lion pulls the ant inside the sand and consumes its body. This behaviour is modelled using the following equation:

$$AL_{j,k} = A_{i,k} \quad if\, f(A_{i,k}) > f(AL_{j,k}) \tag{10}$$

Elitism

It is assumed that every ant randomly walks around a selected ant lion from the roulette wheel and the elite simultaneously as follows:

$$A_{i,k} = {R_{A,k} + R_{B,k}}/{2} \tag{11}$$

Implementation for MFPGD

The algorithmic steps for solving multiple fuel power dispatch are as follows.

Step 1: Read the system data and initialize the algorithmic parameters such as search agents (Ps), maximum number of iterations ($iter_{max}$), number of variables (Nd) and its limits.

Step 2: The decision variables such as real power outputs of generating units are randomly generated within the lower and upper bounds to initialize the first population of ant and ant lions using Equations (12) and (13).

$$P_i^j = P_j^{\min} + rand * (P_j^{\max} - P_j^{\min}) \; i = 1,2,.....Ps; \; j = 1,2,..Nd \tag{12}$$

$$P^{AL}{}_i^j = P_j^{\min} + rand * (P_j^{\max} - P_j^{\min}) \; i = 1,2,.....Ps; \; j = 1,2,..Nd \tag{13}$$

The population matrix of ants and ant lions are formed as matrices as in Equations (14) and (15) respectively.

$$Pop^{A} = \begin{bmatrix} P_1^1 & P_1^2 & \cdots\cdots & P_1^{Nd-1} & P_1^{Nd} \\ P_2^1 & P_2^2 & \cdots\cdots & P_2^{Nd-1} & P_2^{Nd} \\ \cdots & \cdots & \cdots\cdots & \cdots & \cdots \\ P_{PS-1}^1 & P_{PS-1}^2 & \cdots\cdots & P_{PS-1}^{Nd-1} & P_{PS-1}^{Nd} \\ P_{PS}^1 & P_{PS}^2 & \cdots\cdots & P_{PS}^{Nd-1} & P_{PS}^{Nd} \end{bmatrix} \begin{matrix} \rightarrow & f_1(FC),\, f_1(EC) \\ \rightarrow & f_2(FC),\, f_2(EC) \\ \rightarrow & \cdots\cdots \\ \rightarrow & f_{PS-1}(FC),\, f_{PS-1}(EC) \\ \rightarrow & f_{PS}(FC),\, f_{PS}(EC) \end{matrix} \tag{14}$$

$$Pop^{AL} = \begin{bmatrix} P^{AL1}_{\ \ 1} & P^{AL2}_{\ \ 1} & \cdots\cdots & P^{AL\,Nd-1}_{\ \ 1} & P^{AL\,Nd}_{\ \ 1} \\ P^{AL1}_{\ \ 2} & P^{AL2}_{\ \ 2} & \cdots\cdots & P^{AL\,Nd-1}_{\ \ 2} & P^{AL\,Nd}_{\ \ 2} \\ \cdots & \cdots & \cdots\cdots & \cdots & \cdots \\ P^{AL1}_{\ \ PS-1} & P^{AL2}_{\ \ PS-1} & \cdots\cdots & P^{AL\,Nd-1}_{\ \ PS-1} & P^{AL\,Nd-1}_{\ \ PS-1} \\ P^{AL1}_{\ \ PS} & P^{AL2}_{\ \ PS} & \cdots\cdots & P^{AL\,Nd-1}_{\ \ PS} & P^{AL\,Nd-1}_{\ \ PS} \end{bmatrix} \begin{matrix} \rightarrow & f_1(FC^{AL}, EC^{AL}) \\ \rightarrow & f_2(FC^{AL}, EC^{AL}) \\ \rightarrow & \cdots\cdots \\ \rightarrow & f_{PS-1}(FC^{AL}, EC^{AL}) \\ \rightarrow & f_{PS}(FC^{AL}, EC^{AL}) \end{matrix} \tag{15}$$

Step 3: Compute the objective function (EC) using Equation (1).

Step 4: The ant lion having the best fitness is assumed as elite.

Step 5: Iteration = Iteration +1.

Step 6: Apply Roulette wheel selection to select an ant lion for each ant and perform the following steps for each ant.

Step 7: Update the minimum and maximum bounds of all variables using Equation (8).

Step 8: Create a random walk and normalize it using Equation (7).

Step 9: Update the positions of ants using Equation (10).

Step 10: Compute the objective value after update the position of ants.

Step 11: Replace an ant lion with its corresponding ant if becomes fitter.

Step 12: Update elite if an ant lion becomes fitter than elite using Equation (11).

Step 13: Check for maximum iterations reached. Otherwise, go to Step 5.

Step 14:Print the best feasible solution**.**

TEST CASE STUDIES AND DISCUSSIONS

The optimization procedure is coded in MATLAB 7 and is executed in the personal computer with the hardware configuration of Intel Core i3 2.4 GHz processor and 4 GB RAM.

The standard ten-unit system is used for demonstration. Lin & Viviani, 1984 have proposed first this test system that has 3 subsystems and 10 generating units and the system particulars are available in the literature (Lin & Viviani, 1984; Chiang, 2005). The generating units are fueled with two or three fuels and the piecewise quadratic cost functions represents different fuel types. The total system demand is gradually varied in steps of 100 MW from 2400 MW to 2700 MW neglecting transmission loss.

Cost Effective (CE) Schedules

The intended algorithm is applied for the following scenarios:

- **Scenario 1:** CE operation considering PQCF
- **Scenario 2:** CE operation considering PQCF and valve-point loadings and
- **Scenario 3:** CE operation considering POZ.

Scenario 1:

The ALO is implemented on the standard 10-unit system neglecting valve-point loadings. The intended algorithm is executed and the obtained best feasible solution including fuel type, the best dispatches of generators and total costs for different load demands are presented in Table 1. The ALO has converged to the total fuel costs of \$481.7223, \$526. 2386, \$574.3808 and \$623.8085 for load demands of 2400 MW, 2500 MW, 2600 MW and 2700 MW respectively. In order to validate the obtained numerical results, the total fuel costs are compared with the earlier reports and the comparison is presented in Table 2. It is worthy to note that the ALO provides an improved CE dispatch schedule for all load demands. As erroneous test data is followed in the reports using ABC (Hemamalini & Simon, 2010) and OGHS (Singh & Dhillon, 2016), they cannot be taken for direct comparison.

Table 1. Best CE dispatches neglecting for 10-unit system by ALO

Unit No.	P_d = 2400 MW		P_d = 2500 MW		P_d = 2600 MW		P_d = 2700 MW	
	FS	**P_i (MW)**	**FS**	**P_i (MW)**	**FS**	**P_i (MW)**	**FS**	**P_i (MW)**
P_1	1	189.7403	2	206.5191	2	216.54	2	218.2511
P_2	1	202.3426	1	206.4573	1	210.91	1	211.6626
P_3	1	253.895	1	265.7392	1	278.5	1	280.7217
P_4	3	233.0455	3	235.9532	3	239.1	3	239.6315
P_5	1	241.8293	1	258.017	1	275.5	1	278.4963
P_6	3	233.0457	3	235.953	3	239.1	3	239.6315
P_7	1	253.275	1	268.8636	1	285.7	1	288.5845
P_8	3	233.0456	3	235.9532	3	239.1	3	239.6315
P_9	1	320.383	1	331.4878	1	343.55	3	428.5212
P_{10}	1	239.3973	1	255.0563	1	272	1	274.8669
FC (\$/h)	**481.7223**		**526.2386**		**574.3808**		**623.8085**	

Scenario 2:

Further, the valve-point effects along with the quadratic fuel cost functions are considered. The obtained best feasible dispatches for different load demands using ALO are presented in Table 3. For the sake of comparison, the total fuel cost for load demand of 2700 MW is compared against the published reports and is presented in Table 4. The reports by using ABC (Hemamalini & Simon, 2010), BBO (Bhattacharya & Chattopadhyay, 2011), NAPSO (Niknam et al., 2011), DPD (Parouha & Das, 2016), KGMO (Basu, 2016), CSO (Meng et al., 2016), OGHS (Singh & Dhillon, 2016) and GWO (Pradhan et al., 2016) cannot be taken for direct comparison due to erroneous test data has been adopted. It is also seen from Table 4 that the ALO affords the exact dispatch schedule that leads to a nominal savings in the fuel cost.

Table 2. Fuel cost comparison for Scenario 1

Methods	P_d **= 2400 MW**	P_d **= 2500 MW**	P_d **= 2600 MW**	P_d **= 2700 MW**
HM	488.50	526.70	574.03	625.18
HNN	487.87	526.13	574.26	626.12
AHNN	481.72	526.23	574.37	626.24
GA	481.723	526.239	574.396	623.809
Hybrid RCGA	481.722	526.238	574.380	623.809
Improved Fast EP	NR	526.246	NR	NR
Fast EP	NR	526.262	NR	NR
Classical EP	NR	526.246	NR	NR
Modified PSO	481.723	526.239	574.381	623.809
IGA-MU	NR	NR	NR	623.8093
AIS	481.723	526.240	574.381	623.809
DE	481.723	526.239	574.381	623.809
ABC	470.9506*	516.2793*	588.5632*	607.7481*
EALHNN	481.723	526.239	574.381	623.809
ALHNN	481.723	526.239	574.381	623.809
HLN	481.7226	526.2388	574.7413	623.8092
EP	NR	NR	NR	626.26
OGHS	NR	NR	NR	623.8082*
QP-ALHN	481.723	526.239	574.381	623.809
SPPO	NR	NR	NR	623.809
APPO	NR	NR	NR	623.809
ALO	481.7223	526.2386	574.3829	623.8085

*-Not feasible NR- Not Reported

Scenario 3:

The POZ has been considered as an additional operational constraint in the optimization frame that increases complexity of the dispatch problem under study. The generating units 3, 5,7 and 10 having restricted operations and prohibited operating regions are detailed in the literature (Dieu & Schenger, 2013). The ALO is implemented and the best economic dispatch schedules for various load demands are detailed in Table 5. The attained numerical results are compared with the recent reports such as QP-ALHN (Dieu & Schenger, 2013), PSO (Dieu & Schenger, 2013), DE (Dieu & Schenger, 2013), PPO (Singh et al., 2018), SPPO (Singh et al., 2018), APPO (Singh et al., 2018) and the comparison is also presented in Table 6. It is also observed that the intended algorithm attains the competitive results.

Table 3. Best CE dispatches considering valve-point loadings for 10-unit system by ALO

Unit No.	P_d **= 2400 MW**		P_d **= 2500 MW**		P_d **= 2600 MW**		P_d **= 2700 MW**	
	FS	P_i **(MW)**	**FS**	P_i **(MW)**	**FS**	P_i **(MW)**	**FS**	P_i **(MW)**
P_1	1	189.283	2	206.283	2	218	2	218.593

P_2	1	200.21	1	206	1	210	1	211.216
P_3	1	254.4623	1	266.2502	1	278.1012	1	280.656
P_4	3	234.0337	3	235.6046	3	237	3	239.3707
P_5	1	241.3677	1	258.3708	1	275	1	279.934
P_6	3	233.0557	3	235.3683	3	239.912	3	239.3707
P_7	1	253.6068	1	268.6968	1	286	1	287.7275
P_8	3	233.4948	3	235.9671	3	239	3	239.5051
P_9	1	320.6885	1	331.6617	1	343	3	427.7583
P_{10}	1	239.7971	1	255.7971	1	274	1	275.865
FC ($/h)	**482.4127**		**526.8142**		**575.0544**		**623.8278**	

Table 4. Fuel cost comparison for Scenario 2

Methods	**P_d = 2400 MW**	**P_d = 2500 MW**	**P_d = 2600 MW**	**P_d = 2700 MW**
IGA-MU	NR	NR	NR	624.5178
NPSO	NR	NR	NR	624.1624
NPSO-LRS	NR	NR	NR	624.1273
PSO-LRS	NR	NR	NR	624.2297
RGA	482.5114	527.0189	575.1610	624.5081
DE	482.5275	527.0360	575.1753	624.5146
PSO	482.5088	527.0185	575.1606	624.5074
RCGA	NR	NR	NR	623.8281
ABC	NR	NR	NR	609.2250*
BBO	NR	NR	NR	605.6387*
NAPSO	NR	NR	NR	623.6217*
AA	NR	NR	NR	623.9524
DSD	NR	NR	NR	623.8325
DE-PSO-DE	NR	NR	NR	623.8265*
KGMO	NR	NR	NR	608.1096*
CCO	NR	NR	NR	623.8237*
OGHS	NR	NR	NR	623.8240*
GWO	NR	NR	NR	605.6818*
BSA	NR	NR	NR	623.9016
CCDE	NR	NR	NR	623.8288
SPPO	NR	NR	NR	623.8279
APPO	NR	NR	NR	623.827
ALO	482.4127	526.8142	575.0544	623.8278

*-Not feasible NR- Not Reported

Table 5. Best CE dispatches considering POZ for 10-unit system by ALO

Unit No.	P_d = 2400 MW		P_d = 2500 MW		P_d = 2600 MW		P_d = 2700 MW	
	FS	P_i (MW)	FS	P_i (MW)	FS	P_i (MW)	FS	P_i (MW)
P_1	1	189.5489	2	206.4992	2	219.2200	2	221.0370
P_2	1	202.2591	1	206.4769	1	212.0940	1	212.8995
P_3	1	253.5949	1	265.6989	1	281.9526	1	284.2837
P_4	3	232.9593	3	235.9534	3	239.8460	3	240.5154
P_5	1	241.4902	1	258.1081	1	260.0000	1	260.000
P_6	3	232.9991	3	235.9529	3	239.9558	3	240.4955
P_7	1	255.0000	1	268.8637	1	290.2970	1	293.2792
P_8	3	232.9796	3	235.9329	3	239.9362	3	240.4953
P_9	1	320.0990	1	331.5075	1	346.6984	3	436.9954
P_{10}	1	239.0699	1	255.0065	1	270.000	1	269.999
FC ($/h)	**481.7102**		**526.1924**		**574.6999**		**624.310**	

Table 6. Fuel cost comparison for Scenario 3

Methods	Load Demand (MW)			
	2400	2500	2600	2700
DE	482.0683	526.4616	575.1903	624.6675
PSO	482.0510	526.4546	574.9327	624.4452
QP-ALHN	481.7266	526.2388	574.7291	624.3212
PPO	---	---	---	624.403
SPPO	---	---	---	624.321
APPO	---	---	---	624.321
ALO	**481.7102**	**526.1924**	**574.6999**	**624.310**

PERFORMANCE EVALUATION AND DISCUSSIONS

Convergence and Robustness Tests

The convergence behaviors of the ALO for all the test systems are illustrated in Figure 3. The ALO method can reach to the optimum solution more quickly than the other methods reported in literature. The ALO is thus demonstrated to have a better convergence property. Over 200 iterations with several initial random solutions, the ALO has confirmed it as a trustworthy solution procedure by generating the global best solution.

Like other evolutionary algorithms, ALO uses the stochastic techniques, thus randomness is an intrinsic feature of these techniques. Several runs with different initial ant lions have been conducted to test the performance and consistency of ALO. The spread of best fuel costs for 50 runs are calculated and graphically displayed in Figures 4 and 5 to illustrate the robustness of the ALO.

Figure 3. Convergence characteristics of ALO (a) neglecting valve-point and (b) considering valve-point

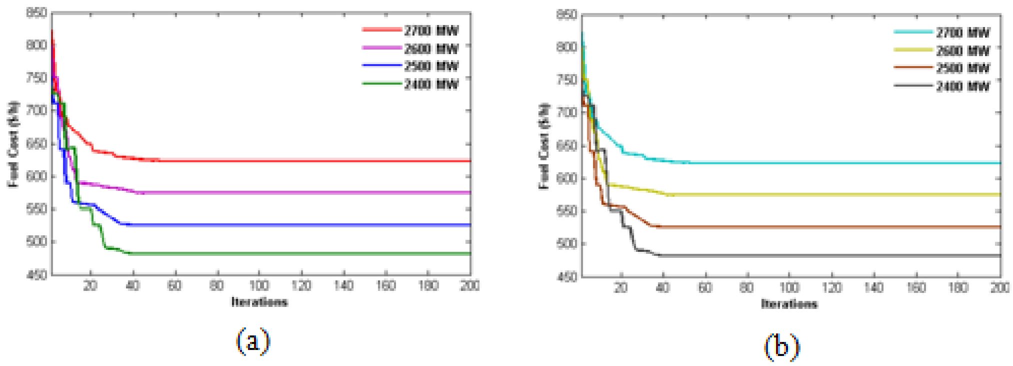
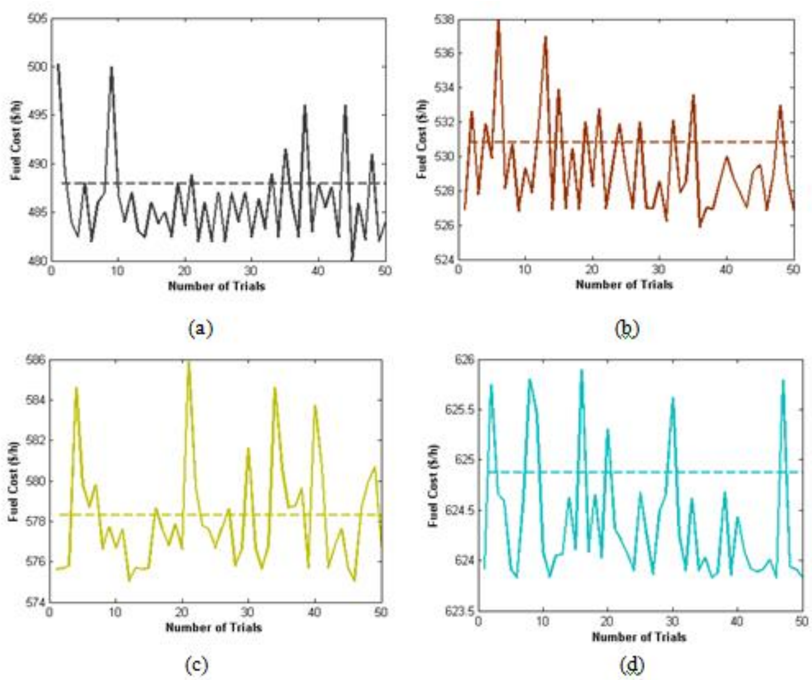


Figure 4. Robustness characteristics of ALO for scenario 2



Success Rate

The success rate is defined as the ratio of total number of experiments performed to the number of successes that converge to the best solution that is expressed in terms of percentage. The success rate of the intended algorithm for all case studies is above 80% that confirms the algorithm has satisfactory success rate.

CONCLUSIONS

The thermal power utilities are facing challenges in cost effective and minimum pollutant emission operations. As these two operational objectives are conflicting in nature, handling of these objectives has become crucial. The utilities require a realistic operational model that comprises of cost effective and environmental concern operational objectives and operational constraints such as generation limits, valve -point loadings, prohibited operation regions and tie line power limits. This chapter outlines the mathematical formulation as follows: economic operation with various operational constraints, combined economic and emission operation and economic operation considering tie-line flow limits.

Among the solution procedures, meta-heuristic algorithms are highly preferable as they are efficient in exploring the search space; handling multiple objectives simultaneously; easy constraint handling mechanisms; and can be implemented for system of any size. ALO is a modern bio-inspired algorithm and is implemented on standard 10-unit system for various kinds of operations. The ALO solves in an exact way, for the different ranges of power demand, the underlying combinatorial problem of determining the fuel that must be used by each power station. The effectiveness of the proposed approach is verified by numerical simulation of different test systems ranging from 10 to 100 units. The results have shown very satisfactory performance when compared to the other algorithms reported in the literature.

The thermal power plants experiencing enormous competitive pressure due to the stringent implementation of energy-saving scheduling approaches. Large-scale thermal power units must adopt effective strategies to reduce energy consumption, reduce emissions and improve the utilization hours in order to create more benefits and survive and develop in the fierce competition. The ALO based ED operation optimizes the units' operation levels and reduce emissions in an effective way to reduce power generation cost and enhance competitiveness. Future work will extend the problem formulation to address the integration of renewable energy sources and energy storage devices that increases the further complexity in the solution procedure.

In a nut-shell, this chapter details the mathematical formulation of multi-fuel power dispatch problems in multi-objective framework and application of ALO for solving various kinds of MFPGD problems.

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