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Dynamic Dispatch of Wind Integrated Thermal Power System considering Multi-fuel Sources

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ABSTRACT
The economic operation of power system has become crucial while considering the multi-fuel power generation sources. This process can be achieved by identifying the most economical fuel to meet out the power demand. Research endeavors clearly indicate that the Multi-Fuel Economic Dispatch (MFED) has been dealt only for the static load demands. As the solution space of MFED is more non-linear an efficient optimization tool is required to determine the optimal operating point of generating units. The contributions of this work can be summarized as: the MFED has been addressed in the dynamic environment and the modern meta-heuristic algorithm namely Ant Lion Algorithm (ALA) has been used as the prime optimization tool for the first time. Further, the current trend in power system operations has also been considered by integrating the wind power generation with MFED problem. The standard 10 unit system and a practical seven unit system have been used to validate the applicability of the ALA. Moreover, the comparison and performance analysis confirm that the current proposal is found better in terms of solution quality.

Keywords- Dynamic economic dispatch, Multi-fuel sources, wind power, Ant lion optimization

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I. INTRODUCTION

In practical power system operations, certain generating units are supplied with different fuel sources like coal, natural gas and oil. The cost function for each fuel type is derived and is segmented as piecewise quadratic cost function for a generating unit fed with Multiple Fuel Sources (MFS). These generating units face with the dilemma of determining the most economical fuel to burn. So far, the Multi Fuel Economic Dispatch (MFED) problem has been concentrated only for static load demands but it is worthy to extend the MFED problem by incorporating time varying load demands. As the load demands are dynamic in nature the MFED problem is formulated as the Dynamic MFED (DMFED) problem which aims to meet the power demand at each interval economically.

1.1 Existing solution methods

The MFED problem contains the discontinuity values at each boundary forming multiple local minima; hence it can be formulated as a non-convex and complicated optimisation problem. The solution approaches addressing the multi-fuel power dispatch problem can be categorised into mathematical and heuristic methods. As the classical mathematical methods cannot solve the MFED problem easily, the piecewise quadratic function is approximated as piecewise linear function and is solved by the traditional methods. Lin and Viviani, 1984 have reported a Hierarchical based numerical Method (HM) to approach the problem. The main drawback of these methods is the exponential growing time for large scale systems with non-convex constraints.

The heuristic search techniques such as Artificial Bee Colony Algorithm (ABC) (Hemamalini and Sishaj P. Simon, 2010) and Biogeography Based Optimisation (BBO) (Aniruddha Bhattacharya and Pranab Kumar Chattopadhyay, 2010) have been reported for solving ED with piecewise cost functions.

An distributed approach introduced by Giulio Binetti et al., in 2014 namely Auction based Algorithm (AA) and Dimensional Steepest Decline (DSD) (Junpeng Zhan et al., 2015) method have been reported for solving economic operation considering valve point effects. Recently, Grey Wolf Optimization (GWO) (Pradhan, 2016), Kinetic Gas Molecule Optimization (KGMO) (Basu, 2016) and Opposition-based Greedy Heuristic Search (OGHS) (Singh and Dhillon, 2016) have been applied for the feasible solution.

1.2 Highlights and Contribution

From the literature survey, it is clear that the researchers have concentrated the economic operation of multi-fuel sources considering a static load demand. In the continuous operational perspective, the variations of load demands must be considered for practical implications that necessitate extending the MFED in dynamic environment. This motivates to concentrate on DMFED problems as it depicts the practical power system operational conditions.

Identifying the most economic fuel in the dynamic environment has become more crucial, hence an efficient optimization tool is required. The reported heuristic methods have few drawbacks like algorithmic parameter settings, premature phenomena, trapping into infeasible solution and computationally expensive. Hence, it is of great significance to improve the existing optimisation techniques or to explore new optimisation techniques. Recently, inspiring the hunting mechanism of ant lions in nature, a nature inspired optimisation algorithm, the so called Ant Lion Algorithm (ALA), has been proposed by Syed Mirjalili, 2015. This algorithm has few parameters and easy to implement, which makes it superior than earlier ones. Moreover, the ALA has superior features than other heuristic techniques in terms of improved exploration, local optima avoidance, exploitation and convergence characteristics.

The main contribution and highlights of this article are: the proposed work aims to handle the MFED problem in dynamic environment, wind power generation is integrated with DMFED problem and the modern meta-heuristic technique, ALA is applied for the first time to solve the DMFED problems.

II. DYNAMIC MULTI-FUEL POWER GENERATION DISPATCH MODEL

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

2.1 Multi-fuel Power Dispatch Model

The objective function FGi, total cost of committed generators over NT number of intervals in the scheduling horizon considering the valve-point effect can be expressed as,

$$FC = Min\ (\sum_{t=1}^{NT}\sum_{i=1}^{NG} F_{Gi}(P_{i,t}))\ (\$) \qquad (1)$$

Where,

$$F_{Gi}(P_{i,t}) = a_{im}P_{i,t}^{\ 2} + b_{im}P_{i,t} + C_{im} + \left|e_{im} * sin(f_{im} * (P_{im}^{min} - P_{i,t}))\right| \quad m = 1,2,.....NF \qquad (2)$$

System and Operational Constraints

Power Balance

The total generation by all the generators must be equal to the total power demand and wind power at all interval ($P_{d,t}$).

$$\sum_{i=1}^{NG} P_{i,t} = P_{d,t} + W_{d,t}, \quad t = 1,2,.......NT \qquad (3)$$

Generation Limits

The real power generation of each generator is to be controlled inside its lower (Pi,tmin) and upper (Pi,tmax) operating limits, so that,

$$P_{i,t}^{\ min} \leq P_i \leq P_{i,t}^{\ max}, \quad i \varepsilon NG, t \varepsilon NT \quad (4)$$

III. ANT LION ALGORITHM

The ant lions are a class of net-winged insects in nature. The lifecycle of ant lions include: larvae and adult. A larva is the longest period in their lifecycle and ant lions mostly hunt during this period. An ant lion larvae 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 realises a prey in the trap, it tries to catch it by intelligently throw sands towards the edge of the pit to slide the prey into the bottom of the pit. After consuming the prey, ant lions throw leftovers outside the pit and amend the pit for next hunt.

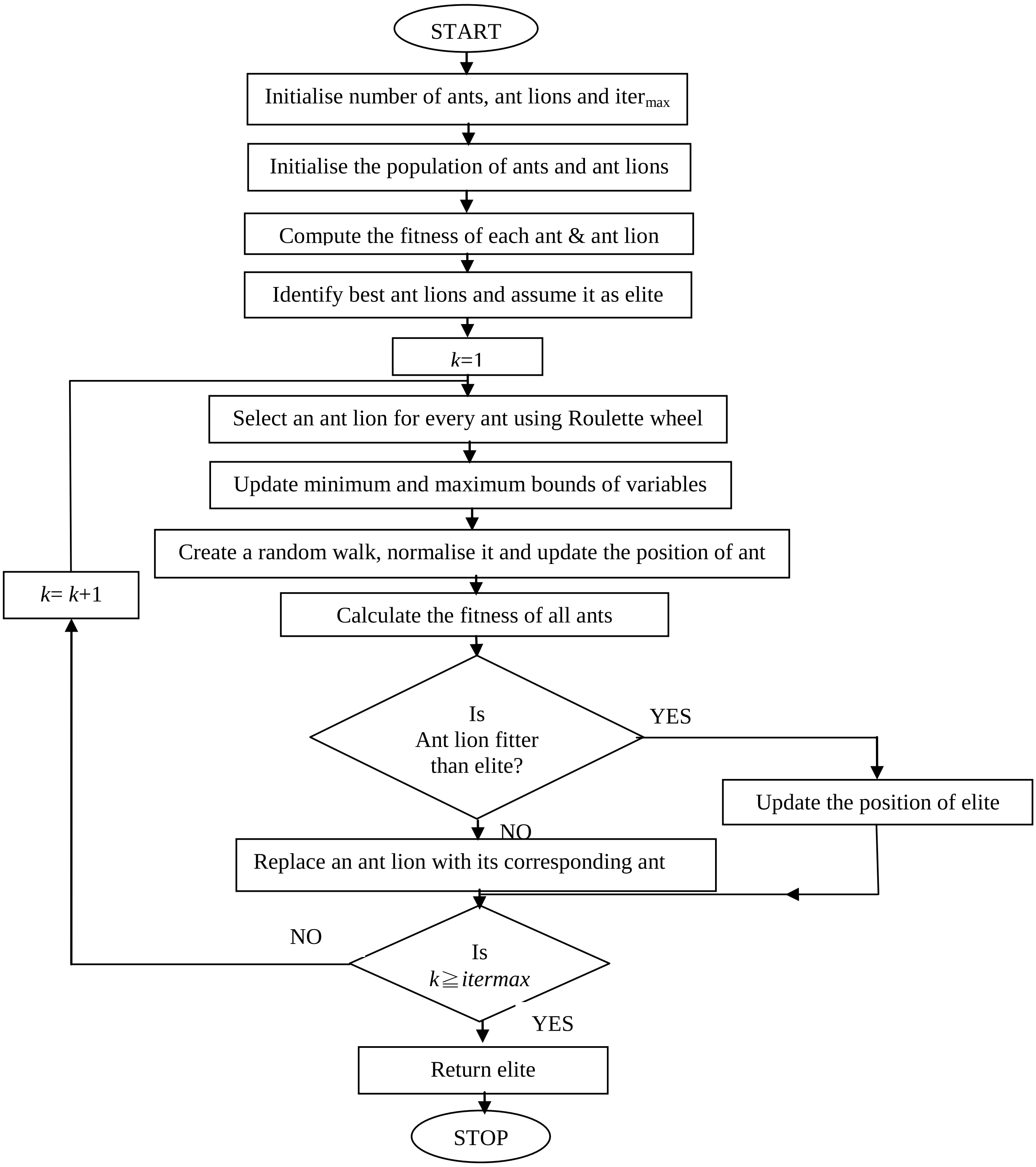


Fig.1. Computational Flow of ALA

The Ant Lion Algorithm (ALA) 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 Syed Mirjalili, 2015.

The main steps involved in the ALA are

i) random walk of aunts,
ii) building traps,
iii) entrapment of ants in preys,
iv) catching in preys and rebuilding of traps.
The computational flow of ALA is presented in Fig.1.

3.1 Implementation of ALA for Multi Fuel Source Power Dispatch

The algorithmic steps of ALA are described below.
Step 1: Read the system data and initialize the algorithmic parameters such as search agents (Pop), maximum number of iterations, number of variables and bounds of the variables.
Step 2: Initialize population size and find the optimal fuel type for each generating unit.
Step 3: Compute the objective function subject to system and operational constraints.
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.
Step 8: Create a random walk and normalise it.
Step 9: Update the positions of ants.
Step 10: Repeat objective computation strategy.
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.
Step 13: Check for maximum iterations reached. Otherwise, go to Step 5.
Step 14: Print the best feasible solution.

IV. TEST CASE STUDIES AND DISCUSSIONS

The ALA is chosen as the main optimisation tool to address the multi-fuel power generation dispatch problem and the implementation steps are detailed in the previous section. The optimisation 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 following cases have been performed to validate the potential of the method.
Case 1: Static MFED
Case 2: DMFED and
Case 3: DMFED considering wind power generation

4.1 Static MFED

The applicability of ALA is tested with the standard 10-unit system considering valve point loadings. This system has three subsystems and 10 generating units are considered as the benchmark test system for economic operation with MFS studies. The test system particulars are available in Lin and Viviani, 1984. Moreover, the valve point loadings are detailed in Chiang, 2005. The generating units are fuelled with two or three fuels. Each generator has two or three fuel options and the piecewise quadratic cost functions represent different fuel types. The generating unit 9 is a special case where fuel 2 is not always economical to burn but it may be substituted immediately in the solution algorithm if fuel 1 or 3 is exhausted or not available. The total system demand is gradually varied in steps of 100 MW from 2400 MW to 2700 MW neglecting transmission loss.

Table - I: Best Feasible Dispatches for 10-Unit System by ALA

Unit	**Power Demand in MW**			
	2400	**2500**	**2600**	**2700**
	Pi (MW)	**Pi (MW)**	**Pi (MW)**	**Pi (MW)**
P1	189.283	206.283	218	218.593
P2	200.21	206	210	211.216
P3	254.4623	266.2502	278.1012	280.656
P4	234.0337	235.6046	237	239.3707
P5	241.3677	258.3708	275	279.934
P6	233.0557	235.3683	239.912	239.3707
P7	253.6068	268.6968	286	287.7275
P8	233.4948	235.9671	239	239.5051
P9	320.6885	331.6617	343	427.7583
P10	239.7971	255.7971	274	275.865
FC ($/h)	482.4127	526.8142	575.0544	623.8278
	Fuel 1	Fuel 2	Fuel 3	

The intended algorithm is executed and the obtained best 3feasible solution including fuel type, the best dispatch of generators and total cost for different load demands are presented in Table I. The total fuel costs attained by the ALA are to be $482.4127, $526.8142, $575.0544 and $623.8278 for 2400 MW, 2500 MW, 2600 MW and 2700 MW respectively. For the sake of comparison, the total fuel cost for load demand of 2700 MW is used and the comparison against the published reports is presented in Table II. The reports using ABC, BBO and NAPSO cannot be taken for direct comparison as the results contain errors due to erroneous test data. Table II also indicates that the ALA is in close agreement with the earlier reports and it affords the exact dispatch schedule that leads to a nominal savings in the fuel cost.

Table - II: Comparison of Total Fuel Costs ($/h) Obtained by ALA and other reports for 10-Unit System

Methods	Pd = 2400 MW	Pd = 2500 MW	Pd = 2600 MW	Pd = 2700 MW
CGA-MU	NA	NA	NA	624.7193
NPSO	NA	NA	NA	624.1624
NPSO-LRS	NA	NA	NA	624.1273
PSO-LRS	NA	NA	NA	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	NA	NA	NA	623.8281
ABC	NA	NA	NA	609.2250*
BBO	NA	NA	NA	605.6387*
NAPSO	NA	NA	NA	623.6217*
AA	NA	NA	NA	623.9524
DSD	NA	NA	NA	623.8325
GWO	NA	NA	NA	605.6818*
KGMO	NA	NA	NA	608.1096*
OGHS	NA	NA	NA	623.8240*
ALA	482.4127	526.8142	575.0544	623.8278

*-Not feasible NA- Not Applicable

Table -III: Dynamic Dispatch (MW) for 7-Unit System MFED obtained using ALA

H	P1	P2	P3	P4	P5	P6	P7	Pd
1	116.833	304.5894	229.7135	257.5584	188.6588	202.4929	267.1561	1567
2	151.2383	281.4531	188.245	199.7651	176.1212	231.0015	339.1747	1567
3	151.1684	259.6263	257.6244	220.6987	175.5284	315.3536	130	1510
4	116.7321	317.9511	217.3119	190	199.2117	248.0759	220.7173	1510
5	230	244.7914	150.5106	216.8764	154.8224	499	131	1627
6	184.0855	395.7835	220.3412	213.9238	265	499.9	249.9685	2029
7	201.3183	261.1081	265	336.835	255.1555	499.9	367.6811	2187
8	230	373.1492	265	336.9761	228.9749	499.9	400	2334
9	230	392.1693	265	336.0022	264.9277	499.9	400	2388
10	150.5124	479.479	264.6691	214.4559	265	499.9	399.9837	2274
11	209.696	300.1109	218.197	285.7669	265	499.9	327.3273	2106
12	217.9537	405.3075	251.1675	303.9588	241.304	315.9603	314.3478	2050
13	153.7724	243.6508	178.2608	300.0919	220.1964	377.0635	399.9639	1873
14	200.385	200	219.7856	244.6923	129.0288	290.9644	215.1435	1500
15	119.3823	214.5266	162.087	190.605	147.8255	263.1378	342.4395	1440
16	114.3268	311.9591	265	274.936	136.6872	211.1021	286.9893	1601
17	215.696	258.413	214.2197	300.5017	118.1434	252.0297	400	1759
18	136.2907	245.2361	235.1789	312.3827	155.2928	499.9	217.717	1802
19	74.26351	456.9019	174.9437	250.9926	265	499.9	400	2122
20	229.4377	216.5956	264.8491	324.9053	235.3774	499.9	268.9312	2040
21	219.4983	200	197.5916	337	202.7343	499.9	271.2731	1928
22	162.2092	336.3705	227.0615	306.8591	233.4106	233.0045	368.0819	1867
23	153.7018	271.4331	177.339	250.1784	157.0966	323.0472	393.2041	1726
24	230	224.6383	161.2801	284.4032	175.0268	272.1535	305.5013	1653
Total fuel cost = $10954.98								
Fuel 1			Fuel 2			Fuel 3		

Table -IV: Dynamic Dispatch (MW) for 7-Unit System with MFED obtained by ALA with Wind

H	P1	P2	P3	P4	P5	P6	P7	Wd	Pd
1	193.474	200	147.1641	236.976	150.205	206.688	302.5592	129.9336	1567
2	137.1525	206.1745	171.5802	194.534	165.045	276.550	285.4134	130.5483	1567
3	198.4091	200	99.19009	247.356	150.740	247.610	237.0005	129.6927	1510
4	195.4897	200	137.8176	190.148	100.110	268.660	287.4344	130.3383	1510
5	125.4638	223.6891	265	255.350	93.4289	351.147	182.3946	130.5251	1627
6	159.2405	361.4286	265	295.969	257.754	221.764	337.282	130.5604	2029
7	152.3	281.5806	188.8638	321.114	228.106	482.578	400	132.4563	2187
8	230	424.0375	261.3532	226.738	214.738	437.053	399.9043	140.1752	2334
9	229.9887	255.474	262.6908	337	264.761	499.99	395.7522	142.3433	2388
10	229.8989	314.7281	232.3159	336.425	244.538	371.689	400	144.4042	2274
11	136.3361	269.5651	264.7597	304.623	237.747	363.136	383.5845	146.2464	2106
12	138.7172	247.9571	247.8355	304.179	164.069	414.356	385.9414	146.9441	2050
13	181.6524	331.5918	145.074	316.504	226.187	245.849	279.6975	146.443	1873
14	186.0488	200	99	211.755	205.500	260.689	190.0023	147.0039	1500
15	121.5415	200.7195	125.7907	275.331	150.155	225.693	196.6354	144.1318	1440
16	190.8466	268.3112	108.5047	228.186	229.612	200	233.9093	141.6287	1601
17	114.9856	315.7868	171.8617	303.426	238.569	265.355	214.5457	134.4697	1759
18	154.896	321.5952	153.3486	223.757	163.482	355.148	295.3023	134.4699	1802
19	230	284.7891	202.7337	313.330	230.963	373.370	354.4656	132.3468	2122
20	154.7068	254.7512	206.0686	219.498	265	432.379	375.3808	132.2144	2040
21	167.3345	250.8979	255.4291	302.973	222.095	216.341	381.3696	131.5594	1928
22	154.1905	295.2549	204.845	233.023	209.69	318.214	321.593	130.1897	1867
23	117.5906	200	163.0937	282.961	207.729	308.717	315.5919	130.3156	1726
24	162.0939	200	139.7391	296.442	212.533	247.095	264.9119	130.1835	1653
Total fuel cost = $9211.49									
Fuel 1			Fuel 2			Fuel 3			

4.2 Dynamic MFED

In order to view the practical power system operations dynamic environment is considered. Dynamic MFED is an extension of static MFED problem which schedules the online generator outputs with the predicted load demands over a certain interval of time so as to operate an electric power system most economically. A practical 7 unit system with multi-fuel options has been chosen to investigate the suitability of the ALA for solving DMFED problems. Input data of 7 unit system including cost coefficients and load demands over the planning horizon of 24 hours are extracted from Umamaheswari Krishnasamy and Devarajan Nanjundappan, 2014 and the objective function given by (1) subject to constraints given by (3) and (4) are considered in this case.

The ALA is applied to determine the best feasible solution and the obtained hourly generation schedules corresponding to the minimum cost are presented in Table III. The total generation cost obtained by the ALA for a 24 hour scheduling horizon is $10954.98.

4.3 DMFED considering Wind Power Generation

Further, the wind power generation is integrated with the DMFED problem. The practical system as detailed in previous case has been used for demonstration and the wind power particulars are taken from Umamaheswari krishnamoorthy and Devarajan Nanjundappan, 2014. The ALA is applied for the best cost schedule and is detailed in Table IV. The algorithm is attained the minimum cost of $9211.49.

Table IV shows the hourly dispatch schedules that satisfy the power demands. When wind prediction is taken into consideration, the best cost achieved by ALA is less as against the costs obtained by TLBO ($9736.1471) and TLBO-SQP ($9538.1851) approaches. It is clear from the results compiled in Tables 4 and 5, that for this practical system, the solution is feasible and all the ALA variants converged in the vicinity of the best solution with full constraint satisfaction.

4.4 Performance Evaluation

4.4.1 Selection of Algorithmic Parameters

For the successful implementation of ALA, number of search agents should be selected properly to provide a compromise between a wider exploration of the search space and increased computational time. Owing to the stochastic nature of the heuristic algorithms, many trials with different initialisations have to be conducted to judge their performance. Accordingly, many trials with different search agents have been conducted to determine the performance of ALA.

The convergence behaviour of operating cost obtained for search agents 10, 30, 50 and 100 are provided in Fig. 2. It can be inferred from Fig. 2, that when the Pop is increased beyond 30, the values of operating cost remains the same, but the computational time gets increased. Therefore, after a careful experimentation, the number of search agents has finally been settled to 30.

Table - V: Comparison of Cost Comparison for 7-Unit System DMFED for Various Methods

Method	Maximum Cost($)	Minimum Cost ($)	Average Cost ($)	Average Time (mins)
TLBO	9952.2471	9736.1471	9754.2321	4.21
TLBO-SQP	9588.2141	9538.1851	9551.3271	2.53
ALA	9258.12	9211.49	9221.667	1.01

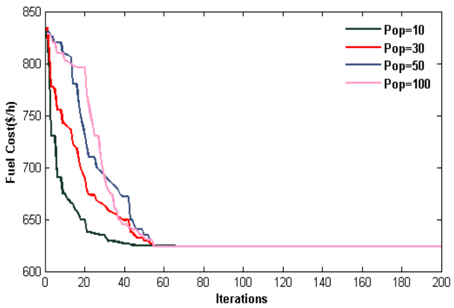


Fig.2. Convergence Characteristics of ALA for Different Population Sizes of 10-Unit System for Pd = 2700 MW

4.4.2 Convergence Test

To verify the feasibility and effectiveness of ALA, the fuel cost variation during the evolutionary process for 200 iterations is observed for the considered test systems and the convergence characteristic is demonstrated in Fig. 3.

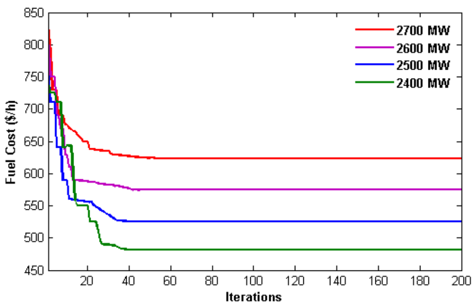


Fig.3. Convergence Characteristics of ALA for 10- Unit System

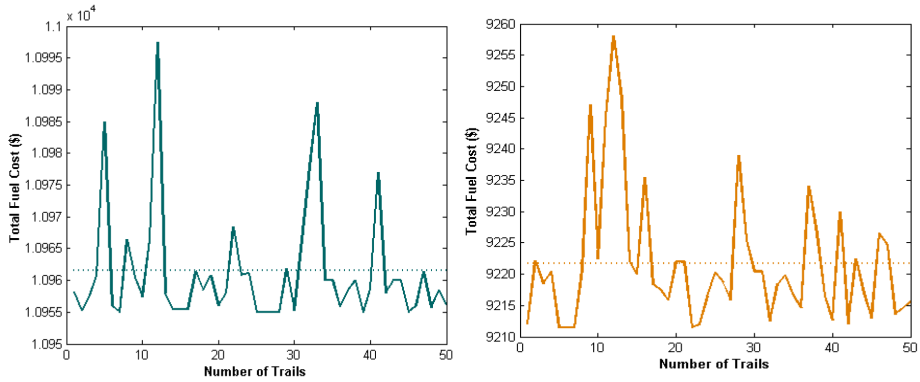
It is obvious from Fig. 3 that the ALA method has the ability to reach the optimal solution very quickly with less number of iterations itself. Thus, the proposed ALA based method has better convergence property.

4.4.3 Robustness Test

To inspect the quality of the obtained solutions, the variations of the objective function value for 50 runs of the algorithm are investigated and the generated solutions for each trial show small range of variations for the cost objective. The spread of best fuel costs for 50 runs are graphically displayed in Fig. 4.It is obvious from Fig. 4, that the values of mean and minimum are closer in economic operation. This description clears that the ALA provides great searching ability and higher solution quality.

4.4.4 Success Rate

To further show the proficiency of the intended algorithm, the success rate which is defined as the ratio of total number of trials performed to the number of successful that converge to the best solution that is expressed in terms of percentage is evaluated. For all the case studies, the percentage of success rate is above 80 that confirm the ability of ALA to produce global best solutions.



(a) (b)

Fig.4. Robustness Characteristics (a) DMFED and (b) DMFED Considering wind

V. CONCLUSIONS

In this paper, the most realistic operational model including valve point effects, dynamic issues and MFS is proposed. Further the wind power generation is integrated to MFS problem. These makes operational constraints increase further the complexity in the non-linear solution space. The modern swarm intelligence algorithm known as ALA is applied for solving the best feasible solution. Various kinds of power system operational problems considering MFS including valve point and dynamic power dispatch involving wind predictions are demonstrated on the standard test systems such as standard 10-unit system and a practical 7-unit system. The obtained numerical results for all test cases are compared with the earlier reports. The comparison clearly indicates that new best feasible dispatches have been attained for the problem under study. The salient features of ALA for solving cost effective problems are: it can consistently find good dispatch schedule within a reasonable execution time; simple, easy implementation and has the ability to handle the operational constraints. The proposed operational model brings together the major operational issues. The developed model is useful to enhance the effective usage of fuels which is desirable in the present operational scenario. In future, the ALA would be likely to be applied for solving optimal operation of hybrid power system which has multiple renewable energy sources.

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