Multi-Area Dynamic Economic Dispatch Problem with Multiple Fuels Using Improved Fireworks Algorithm

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***Abstract*—This paper presents an Improved Fireworks Algorithm (IFWA) to solve Multi Area Dynamic Economic Dispatch (MADED) problem with the consideration of multiple fuels and other practical constraints. The objective of MADED problem is to determine the optimal value of power generation and interchange of power through tie-lines interconnecting areas in such a way that total fuel cost of thermal generating units of all the areas is minimized with predicted load demands over a certain period of time while satisfying several operational constraints. This paper attempts to overcome the drawbacks of some existing FWA methods and presents an Improved Fireworks Algorithm (IFWA) method by suggesting Limiting Mapping Operator (LMO), and Adaptive Dimension Selection Operator (ADSO). The effectiveness of the proposed method has been tested on three areas, 10 generators test system. The application results show that IFWA is very promising to solve MADED problem.**

***Index Terms*—multi-area economic dispatch, fuel cost minimization, tie-line capacity, fireworks algorithm**

I. Introduction

Modern power systems are large, with multiple control areas interconnected through tie-lines. Each control area has its own load and generation. The power generation utilities can stagger their generations to optimize the cost of unit energy generation from fossil fuel plants. This can be accomplished through Multi-Area Economic Dispatch (MAED). The aim of MAED is to determine the optimal power generation schedule and interexchange of power in such a way that minimizes the overall fuel cost of all thermal generating units while satisfying several operational and network constraints. However, the system security imposes restriction on the inter-area power transactions through tie-lines. In fact, the complexity of MAED problem arises due to the stringent area power balance constraints, tie-line constraints and other operational constraints [1].

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Some early efforts to attempt MAED problem can be briefly stated as: Jayabarathi *et al.* [2] solved multi-area economic dispatch problems with tie-line constraints using evolutionary programming. Chen and Chen [3] presented direct search method for solving economic dispatch problem considering transmission capacity constraints. Manoharan *et al.* [4] proposed covariance matrix adapted evolutionary strategy for MAED problems, where a Karush Kuhun Tucker (KKT) optimality criterion is applied to guarantee the optimal convergence. Wang and Singh [5] used Particle Swarm Optimization (PSO) for this problem, where tie-line transfer capacities and area spinning reserve sharing are incorporated to ensure security and improve reliability, respectively. Zhu [6] presents a new nonlinear optimization neural network approach to study the problem of security-constrained interconnected MAED. Manisha *et al.* [1] formulated MAED problem with various constraints and also compares the solution quality of Differential Evolution (DE) variants with an improved PSO strategy. Basu [7] applied Teaching-Learning-Based Optimization algorithm (TLBO) to solve MAED problem with a variety of system constraints. The author claims that TLBO is capable to generate better quality solution than other established meta-heuristic techniques.

In general, MADED is an optimization operation in the power system to obtain the optimal scheduling of online generators and interchange power between areas to satisfy the predicted load demand. It is an extended version of conventional MAED problem with incorporation of ramp rate limits of generation units. This incurs due to the physical limitation of the generator, which results in change in generation limits of the generator in each time period. Basu [8] presented quasi-oppositional group search optimization for solving multi-area dynamic economic dispatch problem with multiple fuels and valve-point loading. In this paper, the results obtained by proposed QOGSO approach are compared with different techniques and found that the proposed QOGSO based approach is able to provide better solution.

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In the recent years several meta-heuristic techniques have been developed to overcome the difficulty of classical optimization method owing to their shape of the objective function and their ability to obtain global or near global solution even for very hard combinatorial optimization problems. Fireworks Algorithm (FWA) [9] is one of the recently established powerful meta-heuristic techniques inspired by the explosion of fireworks. It mimics firework's explosion process to perform the local and global search simultaneously. This unique feature imitates an adaptive strategy for exploration and exploitation of the search space. The algorithm works surprisingly well on benchmark functions which have their optimum at the origin of the search space, but its performance severely affected when being applied to functions with optimum resides away from the origin [10]. These limitations overcome in the Enhance Fireworks Algorithm (EFWA) [10]. Thereafter several other improved variants have been reported [11]-[13] by experimenting on the selection method and operators of the algorithm.

The conventional FWA therefore suffers badly when dealing with dispatch problems where the global optima exist very far away from the origin. Therefore, this paper attempts to overcome the drawbacks of some existing FWA methods and presents an improved Fireworks Algorithm (IFWA) method by suggesting Limiting Mapping Operator (LMO), and Adaptive Dimension Selection Operator (ADSO). The effectiveness of the proposed method has been tested on three areas, 10 generators test system to solve MADED problem by considering various operational constraints like valve-point loading effect, power balance, ramp rate limits, power loss and tie line capacity constraints etc. The application results are presented and compared with other established methods.

II. Problem Formulation

In practical power system operation conditions, many thermal generating units being supplied with Multiple Fuels (MF) sources such as coal, natural gas and oil require that their fuel cost functions may be segmented as piecewise quadratic cost functions for different fuel types [14]. In reality, the objective function of the practical MADED problem has non-differentiable points according to valve point loadings and multiple fuels. Therefore, the objective function should be composed of a set of non-smooth functions to obtain an accurate and practical MADED solution. The cost function of the jth generator in area i with N fuel type at time t is framed by combining both valve point loadings and multi-fuel options, which can be realistically represented as shown in the equation (1) as to minimize.

$$F(P_{ijt}) = \sum_{i=1}^{M}\sum_{j=1}^{N_i}\sum_{t=1}^{T}(a_{ijtm} + b_{ijtm}P_{ijt} + c_{ijtm}P_{ijt}^2) + |\, e_{ijtm}\sin(f_{ijtm}(P_{ijtm}^{\min} - P_{ijt}))\,| \quad (1)$$

where a_{ijtm}, b_{ijtm}, c_{ijtm}, are the cost coefficients, and e_{ijtm} and f_{ijtm} are the valve point effect coefficients of the jth generator in area i at the tth schedule interval for fuel type m, P_{ijt} is the real power output of the jth generator in area i at the tth schedule interval, M is the number of areas, N_i is the number of generating units in the system in area i, T is the tth schedule interval and m is the fuel type, where m= 1; 2; ... ; N_F.

Subject to the following constraints:

A. Power Balance Constraints

In area i, the total power generation of all generators must be equal to the area power demand PDit with the consideration of imported and exported power and can be stated as:

$$\sum_{j=1}^{N_i} P_{ijt} = P_{Dit} + \sum_{k,k\neq i} P_{Tikt}; \quad i \in M, \quad t \in T \qquad (2)$$

where $P_{\mathrm{D}i}$ is the power demand of area i; $P_{\mathrm{T}ikt}$ is the tie line real power transfer from area i to area k at the tth schedule interval. P_{Tikt} is positive when power flows from area i to area k and is negative when power flows from area k to area i.

B. Generator Constraints

For stable operation, power output of each generator is restricted within its minimum and maximum limits for fuel type m. The generator power limits are expressed as:

$$P_{ijtm}^{\min} \le P_{ijtm} \le P_{ijtm}^{\max} \qquad (3)$$

C. Tie-Line Capacity Constraints

The transfer of real tie-line power $P_{\mathrm{T}ijt}$ from area i to area k at the tth schedule interval should not exceed the tie-line limit for security consideration

$$-P_{Tij}^{\max} \le P_{Tijt} \le P_{Tij}^{\max} \qquad (4)$$

D. Ramp Rate Limits

In practical MADED problems, ramp rate limits restrict the operating range of all the online units for adjusting the generation operation between two operating periods. Thus, generation schedule of thermal generators may increase or decrease with respect to their ramp rate limits. The inequality constraints due to ramp rate limits for unit generation changes can be expressed as:

$$\max(P_{ijt}^{\min}, P_{ijt}^{0} - DR_{ij}) \le P_{ijt} \le \min(P_{ijt}^{\max}, P_{ijt}^{0} + UR_{ij}) \quad (5)$$

If generation increases, $P_{ijt} - P_{ijt}^{0} \le UR_{ij}$ (6)

If generation decreases, $P_{ijt}^{0} - P_{ijt} \le DR_{ij}$ (7)

where P^{0}_{ijt} is the previous output power. UR_{ij} is the up ramp limit of the jth generator (MW/time-period) in area i; and DR_{ij} is the down ramp limit of the jth generator (MW/time-period) in area i.

III. Proposed FWA

A. Overview of Fireworks Algorithm

Fireworks Algorithm (FWA) initializes with a predefined number of randomly generated fireworks (tentative solutions) in the problem search space. The algorithm is governed by the explosion amplitude and number of sparks for each firework, which are evaluated by their functional value. Fireworks exploded and crafts different types of sparks within their potential space. The predefined better fit fireworks are selected among all original fireworks and their sparks and the current best firework is preserved. In due course of time, the fitness of best firework improves. The algorithm terminates after definite iterations, the best firework so obtained is assumed as the solution. As, the firework explosion is characterized by good and bad explosion. Good explosion (firework) generates more sparks in close vicinity of the firework. On the other hand, the bad explosion (firework) generates less sparks with larger search radius. Therefore, in order to mimics these features of firework, the number of sparks s_i and their explosion amplitudes A_i are governed by the following model:

$$s_i = m.\frac{y_{\max} - f(x_i) + \xi}{\sum_{i=1}^{n}(y_{\max} - f(x_i)) + \xi} \; ; \quad i \in \{1,2,.....,n\} \tag{8}$$

$$A_i = \hat{A}.\frac{f(x_i) - y_{\min} + \xi}{\sum_{i=1}^{n}(f(x_i) - y_{\min}) + \xi} \; ; \; i \in \{1,2,.....,n\} \tag{9}$$

where $y_{\max}$ and $y_{\min}$ are max ($f(x_i)$) and min ($f(x_i)$) values of the objective function respectively. m and $\hat{A}$ are the limiting values of total sparks and the explosion amplitude, respectively. ξ is a very small real number to counter zero-division error. To avoid the overwhelming effects of maximum sparks for good firework, the boundary conditions for s_i are defined as below

$$s_i = \begin{cases} round(\alpha.m) & ; s_i < (\alpha.m) \\ round(\beta.m) & ; s_i > (\beta.m), \alpha < \beta < 1 \\ round(s_i) & ; else \end{cases} \tag{10}$$

where, α and β are algorithm specific values and round command is used to set the value to the nearest integer. There are many ways to generate explosion sparks around the firework which may be referred from [9]. In order to maintain adequate diversity, probabilistic distance based selection approach is employed. For more details, the reader may refer [9].

B. Proposed Improved Fireworks Algorithm

In FWA, the sparks of the given firework are generated by randomly selecting the number of dimensions, quite irrespective of the fitness of fireworks. This may cause over diversity in population and thus results in slow convergence. Furthermore, its distance based selection operator increases CPU time on account of large number of distance calculation among the individuals [10]. Another limitation of FWA is that it causes insignificant explosion amplitude prevents the explosion for best firework. This deteriorates its local search potential especially at the anaphase of the algorithm. Finally, the mapping and Gaussian mutation operators of FWA have inherent tendency to map/create tentative solutions towards the origin of the search space [10]. The conventional FWA therefore suffers badly when dealing with this type problem where the global optima exist very far away from the origin. Therefore, IFWA is proposed by suggesting Limiting Mapping Operator (LMO) and Adaptive Dimension Selection Operator (ADSO) as described below.

1) Limiting Mapping Operator (LMO)

The function of the mapping operator is to keep the fireworks within the problem search space whenever they tend to fall out of it during the evolutionary process. This could be achieved in a random fashion as in EFWA of [10]. But, it hampers all previous efforts of the algorithm in selecting this value for the dimension. Therefore, LMO is proposed where the dimensions violating the boundary limits are intended to set at the boundary limits as defined below.

$$x_{i,j} = \begin{cases} x_j^{\min} & ; x_{i,j} < x_j^{\min} \\ x_j^{\max} & ; x_{i,j} > x_j^{\max} \end{cases} \tag{11}$$

where $x_{i,j}$ is jth dimension of ith individual. $x_j^{\max}$ and $x_j^{\min}$ are upper and lower limits of the problem.

2) Adaptive Dimension Selection Operator (ADSO)

In FWA, both explosion and specific sparks are created through randomly selecting dimensions. This causes better fit fireworks may undergo wild variations whereas less fit fireworks may faces less variations among their dimensions. It may lead to over diversity in population so retards the pace of algorithm, whatsoever, the convergence of the algorithm suffers badly. Therefore, fitness based operator ADSO is proposed which select the number of dimensions of the given firework by its fitness value i.e., higher the fitness, more will be the selected dimensions and vice-versa. The mathematical modeling proposed for ADSO is derived from the amplitude explosion of FWA as given below.

$$D_i = 1 + \hat{D}.\frac{f(x_i) - y_{\min} + \xi}{\sum_{i=1}^{n}(f(x_i) - y_{\min}) + \xi} \; ; \; i \in \{1,2,.....,n\} \tag{12}$$

where $y_{\min}$ is the min ($f(x_i)$) value of the objective function. $\hat{D}$ is algorithm parameter to control the dimension number. Care has been taken while generating sparks of fireworks so it could generates sparks by selecting at least one dimension.

IV. Simulation Results and Discussion

The proposed algorithm is tested on three areas, 10 generators system with non-convexity in fuel cost function due to valve-point loading effects, multi-fuel sources having three fuel options, the transmission losses and other related constraints [8]. The ten generators are divided into three areas. Area 1 consists of the first four units; area 2 includes the next three units and area 3 includes the last three units. The load demand for area 1 is assumed as 50%, area 2 is 25%, and area 3 is 25% of the total predicted load demand for 24 hours. The tie-line limit from area 1 to area 2, from area 1 to area 3 and from area 2 to area 3 or vice versa is taken as 100 MW as in [8]. The population size for this system is set as 10 and the maximum iterations are considered as 500. The proposed algorithm has been developed using MATLAB and the simulations have been carried on a personal computer of Intel i5, 3.2 GHz, and 4 GB RAM.

TABLE I. COMPARISON RESULTS

Method	Best fuel cost ($)	Average fuel cost ($)	Worst fuel Cost ($)	COV
PSO [8]	13134.05	13151.32	13170.27	-
DE [8]	13042.28	13050.04	13062.47	-
BBO [8]	13081.08	13092.74	13106.53	-
GSA [8]	13121.05	13134.32	13149.53	-
GSO [8]	13013.66	13021.20	13031.93	-
QOGSO [8]	12976.90	12983.56	12992.38	-
FWA	12815.35	13446.23	14566.21	4.529
Proposed FWA	12708.26	12948.47	13107.96	0.701

The comparison results obtained after 50 independent trials of FWA, and proposed FWA are presented and compared with other established methods in Table I. It can be observed from the table that FWA, and proposed FWA, both have obtained the minimum value of best fuel cost as compared with the latest techniques available in literature. But, the proposed FWA method is capable to provide the least value of best and average fuel cost as compared with PSO [8], DE [8], BBO [8], GSA [8], GSO [8], QOGSO [8] and FWA. The existing FWA algorithm may also be qualitatively compared with proposed variants of FWA on the basis coefficient of variation (COV) of their respective sampled solutions. The table reveals that the suggested modification is contributing towards improvement in proposed FWA and it performs significantly better than existing FWA and other latest techniques to solve MADED problem. The optimal generating schedule and related power loss of MADED problem obtained by proposed FWA can be referred from Table A1 and A2 of the Appendix. The negative sign of tie-line power indicates that it is actually flowing in opposite direction.

A comparison of the set of convergence characteristics for best fuel cost between the FWA and proposed FWA is shown in Fig. 1. It can be observed from figure that by suggesting Limiting Mapping Operator (LMO) and Adaptive Dimension Selection Operator (ADSO) in the conventional FWA, the convergence characteristics are progressively improved by avoiding more and more local trappings.

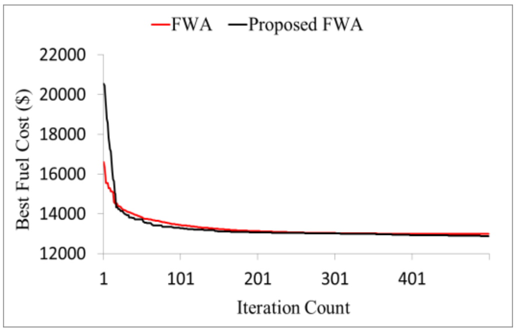

Figure 1. Convergence characteristic of best fuel cost.

V. CONCLUSION

The Multi-Area Dynamic Economic Dispatch (MADED) is a highly complex combinatorial constrained optimization problem with continuous decision variables. The FWA based methods have proven potential to solve such hard combinatorial problem, but they usually get trapped into local minima while dealing with high dimensional MADED problems. The conventional FWA therefore suffers when dealing with this type of problems where the global optima exist very far away from the origin. This paper attempts to overcome the drawbacks of the existing FWA methods and presents an improved FWA (IFWA) method by suggesting Limiting Mapping Operator (LMO) and Adaptive Dimension Selection Operator (ADSO). The applicability of the proposed method has been investigated to solve complex MADED with a variety of operational constraints. The application results show that the proposed method is efficient and is not trapped in local minima. The application results are also compared with existing established methods. The comparison and application results show that the proposed method is capable of producing better quality solution than the other established techniques.

APPENDIX

TABLE A1. OPTIMAL GENERATING SCHEDULE OF MULTI AREA DYNAMIC MULTI-AREA DYNAMIC ECONOMIC DISPATCH FOR 10-UNITS OBTAINED BY PROPOSED FWA

Hour	$P_{1,1}$	$P_{1,2}$	$P_{1,3}$	$P_{1,4}$	$P_{2,1}$	$P_{2,2}$	$P_{2,3}$	$P_{3,1}$	$P_{3,2}$	$P_{3,3}$	$T_{1,2}$	$T_{1,3}$	$T_{2,3}$
1	158.99	157.13	210.03	172.21	154.11	137.12	131.54	86.53	370.12	115.85	-51.52	-94.37	-51.52
2	166.90	157.18	191.46	161.77	150.70	137.13	145.51	98.17	370.58	156.67	-91.76	-95.93	-91.76
3	186.75	167.76	232.93	171.67	168.88	137.64	162.03	105.42	370.41	172.73	-88.02	-88.03	-88.02
4	205.36	192.98	229.10	187.11	209.12	137.92	153.16	161.17	370.32	153.82	-99.84	-82.89	-99.84
5	209.12	180.85	239.63	234.27	225.75	137.49	170.08	217.07	370.26	145.86	-99.11	-99.35	-99.11
6	218.49	188.66	281.33	241.38	203.90	137.54	217.82	171.13	380.18	195.57	-94.58	-90.51	-94.58
7	220.96	223.58	292.62	238.83	223.48	137.71	226.75	223.11	371.03	190.80	-99.42	-96.33	-99.42
8	227.21	211.36	388.64	233.32	249.46	137.92	222.50	186.85	390.05	189.30	-61.68	-93.79	-61.68
9	216.87	215.93	390.05	242.60	192.57	217.47	221.46	226.06	372.95	232.90	-99.97	-97.33	-99.97
10	247.65	229.83	391.48	245.69	194.96	232.11	230.38	235.21	373.13	252.26	-99.96	-99.92	-99.95
11	250.00	230.00	430.58	254.55	241.44	235.48	206.38	230.10	397.46	258.62	-99.99	-100.00	-99.99
12	249.94	229.99	461.77	250.52	237.40	228.09	230.40	237.09	423.84	237.26	-99.94	-99.26	-99.94
13	247.08	229.99	418.83	247.71	221.45	227.02	221.66	228.09	376.52	264.52	-99.71	-96.23	-99.71
14	237.34	215.58	392.54	236.82	177.08	215.31	238.94	224.85	370.65	219.26	-93.53	-87.07	-93.53
15	181.00	223.17	429.76	239.78	252.87	137.91	235.60	182.48	370.09	251.56	-97.51	-78.90	-97.51
16	211.04	205.78	414.49	232.52	227.66	137.98	251.91	226.06	270.10	290.58	-69.28	-99.18	-69.28

17	223.75	215.77	389.56	253.34	195.89	137.74	250.48	183.95	212.96	272.18	-75.87	-9.11	-75.87
18	249.66	229.94	408.68	255.50	225.36	137.75	280.80	244.34	212.89	327.58	-99.49	-41.02	-99.49
19	248.67	229.27	445.40	252.94	221.18	217.58	236.74	242.07	212.95	400.22	-99.38	-75.53	-99.38
20	249.39	229.75	451.64	258.05	264.16	137.90	285.15	250.79	212.98	405.87	-99.94	-80.27	-99.93
21	242.41	226.48	396.88	243.94	222.66	137.92	272.95	229.97	212.90	345.91	-99.71	-54.10	-99.71
22	229.40	210.68	388.28	240.04	190.90	137.79	250.51	187.99	212.92	267.46	-62.84	-26.32	-62.84
23	209.23	166.52	388.04	175.51	193.82	137.46	193.60	226.47	212.98	195.28	-70.50	-39.91	-70.50
24	179.77	172.60	288.22	221.90	176.45	135.64	163.95	160.37	212.65	192.11	-96.38	7.45	-96.38

TABLE A2. OPTIMAL LOSS OF MULTI-AREA DYNAMIC ECONOMIC DISPATCH FOR 10-UNITS OBTAINED BY PROPOSED FWA

Hour	1	2	3	4	5	6	7	8	9	10	11	12
PL_1	5.24	4.99	6.16	7.28	7.84	8.95	10.25	12.5	12.75	13.53	15.13	16.43
PL_2	3.27	3.34	4.05	5.2	6.07	6.25	7.19	8.13	6.5	6.95	8.3	8.39
PL_3	7.11	7.73	8.01	7.59	7.48	8.79	8.45	8.99	9.61	10.22	11.19	11.49
Hour	13	14	15	16	17	18	19	20	21	22	23	24
PL_1	14.55	12.89	14.62	13.28	12.91	14.29	15.69	16.05	13.53	12.57	10.71	7.92
PL_2	7.63	6.33	8.63	8.06	6.86	8.91	7.76	10.7	8.54	6.7	5.37	4.29
PL_3	10.69	9.16	9.97	8.77	6.85	9.3	12.58	12.93	9.96	6.71	4.81	4.44

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