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Exchange Market Algorithm for Solving Economic Load Dispatch Problem with Valve Point Effects

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Abstract: Economic load dispatch (ELD) is one of the primary issues of optimization in the planning and operation of power systems. Its goal is to allocate power supply among generators in the most economical manner while meeting all physical and operational limitationsIn this document, a fresh heuristic algorithm, Exchange market algorithm (EMA) is implemented to solve the issue of non-convex financial load dispatch (NCELD). EMA mimics share market behavior in a standard and oscillating market scenario. The EMA is used to discover solutions for convex and non-convex ELD issues (with valve-point impact) with limitations such as generator capability, transmission loss, ramp rate limits, and forbidden working areas. To check the effectiveness of EMA, it is introduced on two test schemes, 13 and 15 generating units with non-convex and non-smooth cost functions. In addition, numerical outcomes are assessed using GA and PSO methods.

Keywords: Economic load dispatch, exchange market algorithm, power systems, smooth function, valve-point loading.

NOMENCLATURE

F_i	total fuel cost of the generators
a_i, b_i, c_i	cost coefficients of generator i.
e_i, f_i	emission cost coefficients
P_D	power demand
P_L	transmission losses
B_{ij}	line loss coefficients
$P_{i,min}, P_{i,max}$	minimum and maximum generation of unit i.
P_i, P_i^0	current and previous power output of i^{th} unit respectively
UR_i, DR_i	up and down ramp limits of i^{th} unit respectively
k	index of prohibited zone
nz	number of prohibited zones of unit i
$P_{i,k}^L, P_{i,k}^U$	lower and upper limits of kth prohibited zone of generator i
n_i	n^{th} person of the first group
n_j	n^{th} person of the second group
r	random number within [0, 1]
$pop_j^{group(2)}$	j^{th} member of the second group
$pop_{1,i}^{group(1)}$	members of the first group
$pop_{2,i}^{group(1)}$	members of the second groupr_1 and r_2 random numbers
n_k	n^{th} member of the third group
$pop_k^{group(3)}$	k^{th} member of the third group and
S_k	share variation of the kth member of the third group
Δn_{t1}	share value added randomly to some shares
n_{t1}	total shares of member t
S_{ty}	shares of the t^{th} member
δ	information of exchange market
η_1	risk level for each member of the second group
t_{pop}	number of the t^{th} member in exchange market
n_{pop}	number of the last member in exchange market
μ	constant coefficient for each member
g_1	common market risk amount
$Iter_{max}$	maximum iteration number
$g_{1,max}$, $g_{2,max}$	maximum and minimum values of risk in market respectively
Δn_{t3}	share value added randomly to some shares
r_s	random number between -0.5 and 0.5
g_2	market variable risk in third group

1. INTRODUCTION

ELD is one of the most significant problems to solve for the smooth and economic operation of a power scheme. It is a method of exchanging the complete load on a power scheme between different generating plants to obtain the biggest operating economy. Conventional techniques such as linear programming algorithms[1], quadratic programming algorithms[2], non-linear programming algorithms[3], dynamic programming algorithms[4,5], Lagrangian relaxation algorithms[6,7] etc. have been implemented to ELD issues. The classical calculus-based methods can not perform satisfactorily to solve ELD issues due to highly non-linear characteristics of the issue and a big amount of limitations. Recent meta-heuristic algorithms for example, particle swarm optimization (PSO) [8-12], adaptive PSO [13], chaotic PSO [14], differential evolution (DE) [15], evolutionary programming (EP) [16], genetic algorithm (GA) [17,18], real coded GA [19], bacterial foraging optimization (BFO) [20], biogeography based optimization (BBO) [21], gravitational search algorithm (GSA) [22], pattern search method (PSM) [23], Clonal search algorithm [24] and artificial bee colony (ABC) [25, 26] are promising alternatives to solving complicated ELD issues. An opposition-based learning idea is implemented to enhance GSA's performance [27]. Liao provided GA algorithm based on nicheimmune isolation to solve dynamic ELD (DELD) problem [28]. Modified chaotic DE (MCDE) is suggested to fix the DELD issue of a large-scale integrated power system [29]. Chaotic map update mechanism and metropolis rule are used in the MCDE to improve normal DE features. Modified shuffled frog jumping algorithm is implemented to solve the ELD problem [30]. Iteration-based PSO alogorithm is implemented to solve the ELD issue. [31]. Modified PSO that combines the merits of PSO and BF is provided to solve the restricted dynamic ELD problem [32]. In the BF-PSO-DE algorithm, BFO, PSO and DE algorithms are hybridized to solve static and dynamic ELD issues of multiple test systems [33].

Ghorbani and Babaei first created the Exchange market algorithm (EMA) [34]. It is mimicked by the stock market in which shareholders purchase and sell all kinds of stocks under balanced and oscillating market circumstances. This algorithm utilizes two search operators and two absorbents. These operators enable EMA to solve the issues of exploration and exploitation.

In this article, EMA was submitted to tackle the NCELD issue. Transmission losses, ramp rate restrictions and forbidden generator working areas were regarded in this algorithm. 13-units and15-units are used to study and show the efficacy of the suggested algorithm. The findings of the numerical studies along with comparisons of GA and PSO techniques show the effectiveness of the suggested algorithm to fix the NCELD issue.

2. ELD FORMULATION

The goal of the ELD issue is to discover an ideal power generation timetable while minimizing fuel costs and also meeting the operating limitations of multiple power systems.

2.1 Objective Function

The problem of ELD is formulated as follows:

$$Minimize\ F = \sum_{i=1}^{ng} F_i(P_i) \qquad (1)$$

The total generator fuel cost is defined by:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + C_i$$

The fuel cost function of the ith thermal generating unit is expressed as the sum of a quadratic and a sinusoidal function in the following form, taking into consideration the valve-point effects:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + C_i + \left| e_i \times \sin(f_i \times (P_{i,min} - P_i)) \right|$$

2.2 System Constraints

2.2.1 Power balance constraints

The generators' complete power output should be equal to the sum of energy requirements and complete transmission losses and is provided by:

$$\sum_{i=1}^{ng} P_i = P_D + P_L$$

The transmission losses are expressed as

$$P_L = \sum_{i=1}^{ng} \sum_{j=1}^{ng} P_i B_{ij} P_j + \sum_{i=1}^{ng} B_{0i} P_i + B_{00}$$

2.2.2 Generator capacity constraints

Each unit's output power requires to be limited with inequality limitations between their limits.This constraint is given by

$$P_{i,min} \le P_i \le P_{i,max}$$

2.2.3 Ramp rate constraints

The real working range of all generating units is restricted by the ramp rate constraint and is provided as follows:

$$P_i - P_i^0 \le UR_i$$

$$P_i^0 - P_i \le DR_i$$

2.2.4 Prohibited operating zone

Prohibited operating zones constraint is given by,

$$P_{i,min} \le P_i \le P_1$$

$$P_{i,k-1}^U \le P_i \le P_{i,k}^L \quad k = 2, \ldots nz$$

$$P_{i,nz}^U \le P_i \le P_{i,max}$$

3. OVERVIEW OF EXCHANGE MARKET ALGORITHM

EMA, first implemented by Ghorbani and Babaei [34], is a flexible, robust population-based stochastic optimization algorithm with intrinsic parallelism. It is motivated by human behavior of stock market in which shareholders trade shares under balanced and oscillated market situations. This algorithm uses two searcher and absorbent operators in normal and oscillation modes respectively. In EMA, optimum solution is considered to be one that a shareholder population is searching for. Each person in this population is called a shareholder. The individuals of searcher group and absorbent group are responsible for improving the exploration and exploitation abilities of the algorithm.

3.1 Exchange Market in Normal Mode

In the ordinary situation of the exchange market, the shareholders attempt to maximize their profit using the expertise of the elite shareholders. Each shareholder is ranked according to the fitness function in the population.

3.1.1 Shareholders with High Ranks

These shareholders do not alter their stocks without performing out any danger and trade to preserve their ranks. This group of shareholders composes up 10-30 percent of the population.

3.1.2 Shareholders with Average Ranks

This group of shareholders arranges 20–50 percent of the population. Members of this group take advantage of the experiences of elite stockbrokers and take the least possible risk in changing their shares.

$$pop_j^{group\,(2)} = r \times pop_{1,i}^{group\,(1)} + (1-r) \times pop_{2,i}^{group\,(1)} \tag{2}$$

$i = 1,2,3,\ldots n_i$ and $j = 1,2,3,\ldots. n_j$

3.1.3 Shareholders with Weak Ranks

This group of shareholders arranges 20-50% of the population. With their share values, the members of this group exploit the differences in the share values of elite and medium shareholders. The population of this group is given in the following equation.

$$S_k = 2 \times r_1 \times \left(pop_{i,1}^{group\,(1)} - pop_k^{group\,(3)}\right) + 2 \times r_2 \times \left(pop_{i,1}^{group\,(1)} - pop_k^{group\,(3)}\right) \tag{3}$$

$$pop_k^{group\,(3)\,new} = r \times pop_k^{group\,(3)} + 0.8 \times S_k$$

$$k = 1,2,3,\ldots n_k$$

3.2 Exchange Market in Oscillaion Mode

In this mode, shareholders perform intelligent hazards among other employees according to their own rank to achieve the highest possible profit. The shareholders can be split into three distinct organizations depending on their performance.

3.2.1 Shareholders with High Ranks

This group arranges 10-30 percent of the market population known as elite members not contributing to the market exchange.

3.2.2 Shareholders with Medium Ranks

The second group's market share is altered in such a manner that the group's total share values are constant. The shared values of people can be updated as

$$\Delta n_{t1} = n_{t1} - \delta + (2 \times r \times \mu \times \eta_1) \tag{4}$$

$$\mu = \frac{t_{pop}}{n_{pop}}$$

$$n_{t1} = \sum_{y=1}^{n} (S_{ty}) \quad y = 1,2,3,\ldots, n$$

$$\eta_1 = \eta_{t1} \times g_1$$

$$g_1^k = g_{1,\max} - \frac{g_{1,\max} - g_{1,\min}}{Iter_{\max}} \times k$$

To preserve the shares, remain constant, each shareholder randomly sells some of the shares equivalent to the shares bought. Hence, each shareholder reduces the share value which is given as follows.

$$\Delta n_{t,2} = n_{t,2} - \delta$$

Where $n_{t\,2}$ is the t^{th} member's complete share valuation after employing differences in the share.

3.2.3 Shareholders with Weak Ranks

The shareholders can either purchase or sell the shares. Hence, the total share value is variable. The shared values of people can be updated as

$$\Delta n_{t,3} = 4 \times r_s \times \mu \times \eta_2 \quad (5)$$

$$r_s = 0.5 - \text{rand}$$

$$\eta_1 = \eta_{t1} \times g_1$$

$$g_1^k = g_{1,\max} - \frac{g_{1,\max} - g_{1,\min}}{Iter_{\max}} \times k$$

4. IMPLEMENTATION OF EMA TO NCELD PROBLEM

The EMA comprehensive implementation is defined as follows.

Step 1 Input data for market operation

The total shareholders in the market (m), shares (n), lower and upper limits of each shares (design variables), maximum iteration number, risk factors (g1 and g2) and EMA constants are initialized.

Step 2 Initialization of shareholders

Since the choice variables for ELD issues are unit producing values, they are used to form shareholders' shares. The i^{th} shareholder for n generating units is represented as

$$x_i = \left[x_{i1,}\ x_{i2,} \ldots, x_{im}\right]$$

Every share of the shareholder matrix is initialized using a uniform probability distribution function within the range (0 – 1) and located between the design variables' maximum and minimum limits.

The shareholder can be represented below:

$$x_{ij} = x_{j\min} + \text{rand} \times \left(x_{j\max} - x_{j\min}\right)$$

Step 3 Evaluation of shareholders' cost

The cost of shareholders is evaluated using Eq. (1).

Step 4 Ranking and allocation of shareholders

The shareholders are sorted in increasing order and divided into three distinct groups. The 30%, 40% and 30% of population are allocated for elite, medium and weak shareholders respectively.

Step 5 Updating the shares of medium and weak shareholders in normal market condition

The share values of medium and weak ranking shareholders are updated using Eqs. (2) and (3) respectively.

Step 6 Reevaluation, ranking and allocation of shareholders

The medium and weak shareholders' costs are reevaluated using Eq. (1). The shareholders will subsequently be repositioned and divided into three different groups.

Step 7 Updating the shares of medium and weak shareholders in oscillated market condition

The share values of medium and weak ranking shareholders in oscillated market situation are updated using Eqs. (4) and (5) respectively.

Step 8 Stopping Criteria

If the maximum generation number is reached, then the EMA is terminated and the optimal generations schedule is obtained. Otherwise, the procedure is repeated from Step 3.

5. RESULTS AND DISCUSSIONS

In order to assess the efficacy of the suggested EMA-based NCELD issues, two distinct schemes were implemented: a 15-unit system with equality and inequality limitations, forbidden working areas, ramp rate limits and network transmission losses ; and a 13-unit system with equality and inequality limitations and a valve-point impact. In order to compare the solving quality and convergence characteristics, 50 independent tests were performed for each of the test systems. MATLAB 7.1 executes the EMA.

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Table 1. System data for 15-units

Unit(i)	Pi^{min}	Pi^{max}	a_i	b_i	c_i	P^{UR}	P^{DR}	Pi^{prev}	POZs
1	150	455	671	10.1	0.000299	80	120	400	
2	150	455	574	10.2	0.000183	80	120	300	[185,225],[305,335],[420,450]
3	20	130	374	8.80	0.001126	130	130	105	
4	20	130	374	8.80	0.001126	130	130	100	
5	150	470	461	10.4	0.000205	80	120	90	[180,200],[305,335],[390,420]
6	135	460	630	10.1	0.000301	80	120	400	[230,255],[365,395],[430,455]
7	135	465	548	9.80	0.000364	80	120	350	
8	60	300	227	11.2	0.000338	65	100	95	
9	25	162	173	11.2	0.000807	60	100	105	
10	25	160	175	10.7	0.001203	60	100	110	
11	20	80	186	10.2	0.003586	80	80	60	
12	20	80	230	9.90	0.005513	80	80	40	[30,40],[55,65]
13	25	85	225	13.1	0.000371	80	80	30	
14	15	55	309	12.1	0.001929	55	55	20	
15	15	55	323	12.4	0.004447	55	55	20	

Table 2. Best solution for 15-unit system

Unit (MW)	GA	PSO	EMA
P_1	415.31	439.12	455
P_2	359.72	407.97	380
P_3	104.42	119.63	130
P_4	74.98	129.99	130
P_5	380.28	151.07	170
P_6	426.79	459.99	459.54
P_7	341.32	425.56	430
P_8	124.79	98.56	76.8065
P_9	133.14	113.49	50.647
P_{10}	89.26	101.11	159.926
P_{11}	60.06	33.91	79.96
P_{12}	50.0	79.96	80
P_{13}	38.77	25.0	25.32
P_{14}	41.94	41.41	17.64
P_{15}	22.64	35.61	15.324
P_L	38.2782	32.4306	30.672
Minimum cost ($/hr)	33113	32858	32706.562

Table 3. Results obtained by various methods for 15-unit system

Compared items	GA	PSO	EMA
Max. cost	33337	33331	32986
Min. cost	33113	32858	32706.562
Mean cost	33228	33039	32760
CPU time (sec)	49.31	26.59	18.63

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Table 4. System data for 13-units

Unit(i)	Pi^{min}	Pi^{max}	a_i	b_i	c_i	e_i	f_i
1	0	680	550	8.1	0.00028	300	0.035
2	0	360	309	8.1	0.00056	200	0.042
3	0	360	307	8.1	0.00056	200	0.042
4	60	180	240	7.74	0.00324	150	0.063
5	60	180	240	7.74	0.00324	150	0.063
6	60	180	240	7.74	0.00324	150	0.063
7	60	180	240	7.74	0.00324	150	0.063
8	60	180	240	7.74	0.00324	150	0.063
9	60	180	240	7.74	0.00324	150	0.063
10	40	120	126	8.6	0.00284	100	0.084
11	40	120	126	8.6	0.00284	100	0.084
12	55	120	126	8.6	0.00284	100	0.084
13	55	120	126	8.6	0.00284	100	0.084

Table 5. Best solution for 13-unit system

Unit (MW)	PSO	EMA
P_1	538.561	628.3185
P_2	299.355	149.5836
P_3	75.037	222.7934
P_4	159.734	109.8666
P_5	60.078	109.8665
P_6	109.864	109.8664
P_7	109.913	109.8664
P_8	109.87	109.8666
P_9	60.069	60.00
P_{10}	40.035	40.00
P_{11}	77.561	40.00
P_{12}	55.042	55.00
P_{13}	55	55.00
Minimum cost ($/hr)	18014.16	17963.784

Table 6. Results obtained by PSO and EMA methods for 13-unit system

Compared items	PSO	EMA
Max. cost	18249.89	18204.7452
Min. cost	18014.16	17963.784
Mean cost	18104.65	17965.48
CPU time (sec)	-	7.5

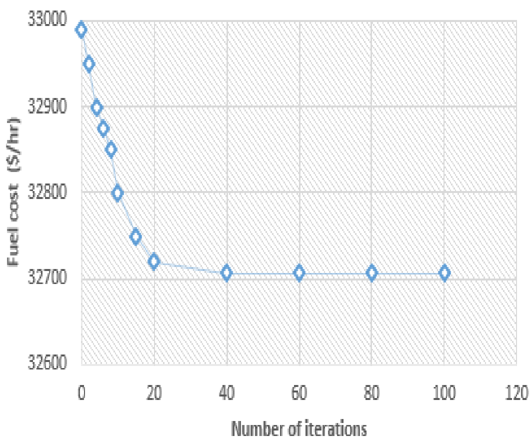

Figure 1. Convergence Characteristic of EMA for 15-unit system

5.1 Test system 1

In this case study, heuristic algorithm is introduced on a bigger test scheme composed of the 15 generating units. Transmission losses and forbidden operating zone are regarded. The complete load demand of the scheme is regarded to be 2630 MW. Table 1 provides the generator coefficients, capacity limits ramp rate limits and forbidden areas. Table 2 evaluates the optimum generation timetable, cost and energy loss discovered by the EMA strategy with GA and PSO methods. In addition, the statistical results of 50 independent trials for the 15-unit system are are tabulated in Table 3. The comparative results evidently show that the EMAapproach is proficient of producing higher quality solutionthan the other evolutionary approaches. Figure 1 shows the convergence characteristic of EMA. From

Figure it is evident that EMA converges faster. It is observedfrom Tables 2 and 3 that the cost obtained from EMA is the lowestamong the GA and PSO approaches.

5.2 Test system 2

This case study scheme consists of 13 generating units with non-smooth cost function (with valve-point loading). Input information for this test scheme are provided in Table 4. The complete system load demand is 1800 MW.
The results obtained using the proposed EMA approach are compared with those PSOs in Table 5. Table 6 shows the maximum, minimum and mean cost and calculation time reached by the heuristic algorithms. As stated in Tables 5 and 6, in terms of solution quality and computational efficiency, the proposed EMA approach performs better than the PSO approach.

6. CONCLUSION

In this article, a new heuristic algorithm based on an exchange market algorithm (EMA) is introduced to solve the NCELD problem. The EMA algorithm was tested against GA and PSO approaches on two test systems (13 and 15 units) with convex and non-convex cost functions. The proposed EMA based NCELD method provides better dispatch results within a shorter computational time than the other approaches. In this study, it is shown that the EMA approach could be easily applied to the solution of nonconvex economic dispatch problem.

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