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Full Length Research Paper

Combined economic emission dispatch solution using genetic algorithm based on similarity crossover

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Combined economic emission dispatch (CEED) problem is to schedule the committed generating units outputs to meet the required load demand at minimum operating cost with minimum emission simultaneously. This multi-objective CEED problem is converted into a single objective function using a price penalty factor. In this paper, a novel Genetic Algorithm method based on similarity crossover for solving CEED problem in power systems is proposed. In the proposed method, children created by using similarity measurement between mother and father chromosomes relationship. The feasibility of the proposed approach is demonstrated for two different power systems, and it is compared in the recent literature. The study results show that the proposed approach is more efficient in finding higher quality solutions in CEED problems.

Key words: Genetic algorithm, similarity measurement, economic dispatch, emission dispatch.

INTRODUCTION

The main goal of electric vehicles at the lowest possible cost to consumers is to provide a reliable source. One should bear in mind that the power plant which is usually based on the lowest fuel costs and environmental pollution is not taken into consideration. But in recent years, electric industry and its contribution to environmental pollution, environmental protection and pollution caused by power plants to reduce or eliminate electric industry raises questions about it (Chaturvedi et al., 2008). Therefore, emissions from electric power distribution should be kept in mind. For that work, CEED which is a multi-objective problem has begun on the distribution of power.

Several researchers have considered emissions with fuel cost in the objective function. They converted the multi-objective CEED problem into a single objective function using a price penalty factor. In the traditional economic dispatch problem, the cost function for each generator has been approximately represented by a single quadratic function. Unfortunately, the characteristics of generating units are highly nonlinear inherently, because of the constraints power system and emission (Balamurugan and Subramanian, 2008).

A number of methods have been presented to solve CEED problems such as neural networks (King et al., 1995), Fuzzy logic (Song et al., 1997), evolutionary computation methods (Venkatesh et al., 2003), recursive method (Muralidharan et al., 2006), γ-iteration method, particle swarm optimization, differential evolution, simplified recursive method (Balamurugan and Subramanian, 2008) and genetic algorithms (Baskar et al., 2002; Song et al., 1995). Genetic algorithm is one of the modern heuristic algorithms, which can be used to solve nonlinear and non-continuous optimization problems. In genetic algorithms method, the genetic operators such as crossover and mutation have significant impact on its performance (Yalcinoz et al., 2001). Michalewicz described a crossover method which is called arithmetic in 1994. An arithmetic crossover operator linearly combines two parent chromosome vectors to produce two new children. The main drawback of this method is the use of random crossover constant. This coefficient can be obtained from the similarity of parents chromosomes.

Similarity is fundamentally important in almost every scientific field and makes a vital mission for all concepts of formation. There is mainly an important issue in this regard: How to measure the similarity between pairs of data points (Demirci, 2007). In this paper, a novel GA based on solving CEED problem is proposed. Firstly, children created by using similarity measurement between parents chromosomes relationship. The study results show that the proposed approach is more efficient in finding higher quality solutions in CEED problems.

Problem formulation

The list of symbols used in this section is as follows:

F_T = Total generation cost of the system.
FC = Total fuel cost of generators.
NC = Total emission of generators.
n = Number of generators connected in the network.
h_i = Price penalty factor of unit i.
P_i = Power generation of unit i.
$P_{i\min}$ = Minimum generation of unit i.
$P_{i\max}$ = Maximum generation of unit i.
P_{load} = Total load of the system.

The CEED problem is to find the optimal combination of power generation that minimizes the total fuel cost while satisfying the total demand and power system constraints. The CEED can be formulated as:

$$CEED = \begin{cases} problem & F_T = Min f(FC, EC) \\ subject\ to & P_{load} - \sum_{i=1}^{n} P_i = 0 \\ & P_{i\min} \le P_i \le P_{i\max} \end{cases} \quad (1)$$

The total fuel cost (FC) for power generation units should be as a quadratic polynomial:

$$FC = \sum_{i=1}^{n} \left(a_i P_i^2 + b_i P_i + c_i \right) \quad (2)$$

where a_i, b_i and c_i are the cost coefficients of the ith generating unit. Total emission of generation (EC) can be expressed as:

$$EC = \sum_{i=1}^{n} \left(d_i P_i^2 + e_i P_i + f_i \right) \quad (3)$$

where d_i, e_i and f_i are emission coefficients of the ith generating unit.

The bi-objective combined economic emission dispatch problem is converted into single optimization problem by introducing a price penalty factor h_i (Venkatesh et al., 2003) as follows:

$$Min F_T = \sum_{i=1}^{n} \left(\left(a_i P_i^2 + b_i P_i + c_i \right) + h_i \left(d_i P_i^2 + e_i P_i + f_i \right) \right) \quad (4)$$

The price penalty factor blends the emission with fuel cost and TC is the total operating cost in $/h and is the ratio between the maximum fuel cost and maximum emission of the corresponding generator (Balamurugan and Subramanian, 2008):

$$h_i = \frac{a_i P_{i\max}^2 + b_i P_{i\max} + c_i}{d_i P_{i\max}^2 + e_i P_{i\max} + f_i} \quad (5)$$

PROPOSED METHOD

Genetic algorithm is one of the modern heuristic and a search algorithms used in computing to find the exact or approximate solutions to optimization and search problems. The algorithm is initialized by randomly generating a solution set which is called generation. Each possible solution is numerically evaluated to determine its fitness function in a traditional search problem (Foy et al., 1992). An individual real code genetic algorithm involves some genetic operators such as; crossover and mutation. The crossover operator has significant impact on genetic algorithm performance. Michalewicz described a crossover method which is called arithmetic. This arithmetic crossover operator linearly combines two parent chromosome vectors to produce two new children according to the following equations:

Child 1 = a * father + (1- a) * mother
Child 2 = (1 – a) * father+ a * mother (6)

where ‘a’ is a random weighting factor, selected by user. In applications, there has always been a problem in selecting a perfect weighting factor. The similarities between the mother and father relationship to be obtained from the similarity ratio is used instead of the weight factor. Similarity is fundamentally important in almost every scientific field. Each element of the concept of similarity in pose performs a vital task. Similarity, as a distinguishing characteristic, is possible in any amount between two or more things. Also similarity is quite difficult to measure. If we can measure similarity or dissimilarity, then we can distinguish one’s object from another. Once we can group the objects, we can understand the characteristics of each group and also classify a new object into the group and predict the behavior of the new object. There are many types of similarity measure. A simplest similarity measure is the Generalized Context Model (GCM) (Nosofsky, 1986). GCM of categorization assumes that humans represent categories by storing every exemplar in memory, and category decisions are based on a similarity computation between a probe stimulus and stored exemplars (Demirci, 2007). The variables in parent’s chromosomes in a cluster are defined as follows:

$$m_k = \{x_i;\ i = 1\ to\ n\}$$

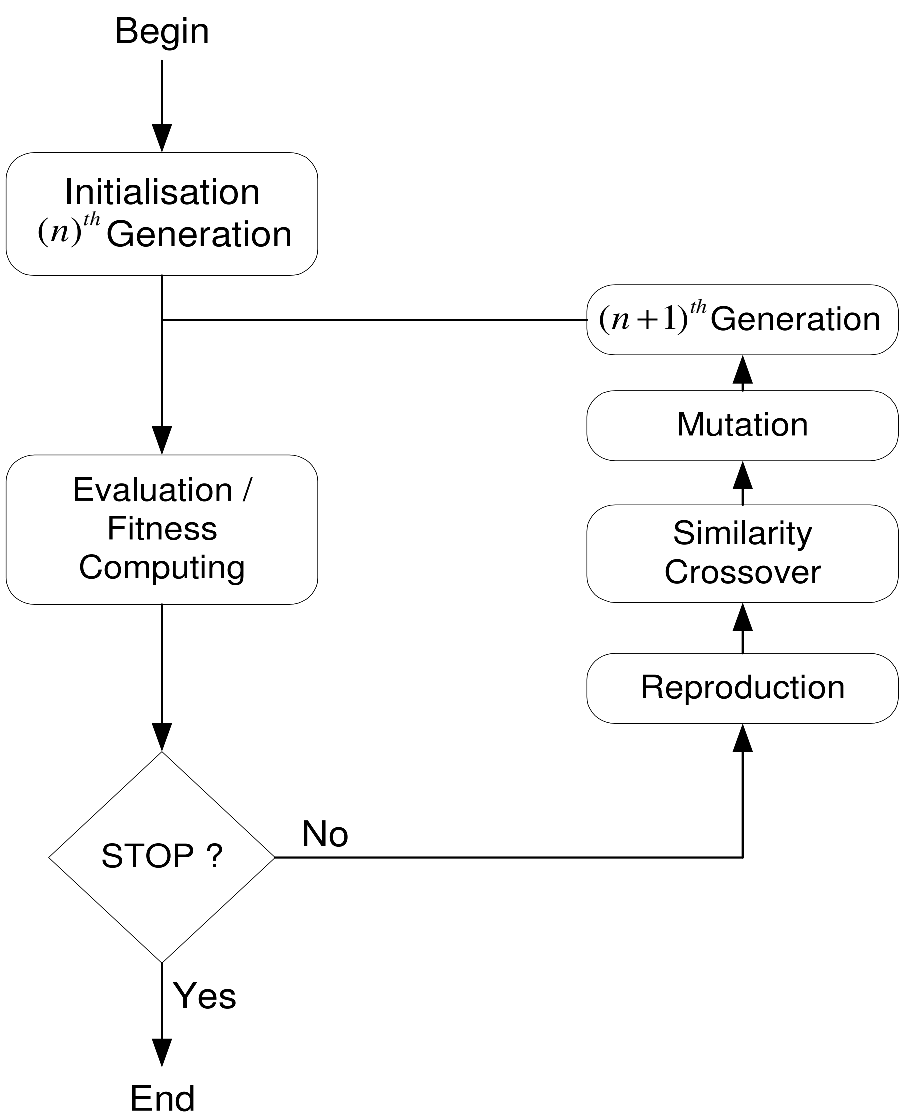

Figure 1. Flow diagram of genetic algorithm based on similarity crossover.

$$f_k = \{y_i;\ i = 1\ to\ n\} \quad (7)$$

where m_k is the mother and f_k is the father chromosomes. Unit load differences of mother and father chromosomes for ith generator could be stated as follows:

$$\Delta_i = (x_i - y_i) \qquad i = 1\ to\ n \quad (8)$$

The generator distance between any two unit loads is calculated by Euclidean norm as:

$$d_{f,m} = \frac{1}{\sqrt{n}} \cdot \left(\Delta_1^2 + \Delta_2^2 + ...\Delta_n^2\right)^{1/2} \quad (9)$$

In Generalized Context Model, the similarity of two unit loads could be calculated as: The $S_{f,m}$ value could be used instead of a coefficient in arithmetic crossover and varies between zero and one:

$$S_{f,m} = e^{\left(-d_{f,m}\right)} \quad (10)$$

Figure 1 illustrates a genetic algorithm for CEED problem.

RESULTS AND DISCUSSION

The proposed method has been applied to two power systems on six-generator system and eleven-generator power systems. The fuel cost, emission coefficients and generation limits of six-generator system are taken from Balamurugan and Subramanian (2008) and are given in

Table 1. Fuel cost, emission coefficients and generation limits of six-generator system.

Generator	ai ($/MW2h)	bi ($/MWh)	ci ($/h)	di (kg/MW2h)	ei (kg/MWh)	fi (kg/h)	Pimin (MW)	Pimax (MW)
1	0.1525	38.540	756.800	0.0042	0.3300	13.860	10	125
2	0.1060	46.160	451.325	0.0042	0.3300	13.860	10	150
3	0.0280	40.400	1050.000	0.0068	-0.5455	40.267	35	225
4	0.0355	38.310	1243.530	0.0068	-0.5455	40.267	35	210
5	0.0211	36.328	1658.570	0.0046	-0.5112	42.900	130	325
6	0.0180	38.270	1356.660	0.0046	-0.5112	42.900	125	315

Table 2. CEED solution of six-generator system.

	Load (MW)						
	500	600	700	800	900	1000	1100
Unit 1 (MV)	19.7943	31.5526	43.5288	55.6516	66.4835	78.3182	90.4300
Unit 2 (MV)	14.3378	28.6321	42.0893	55.5373	69.7397	83.8070	97.1218
Unit 3 (MV)	93.1141	108.2958	123.6530	138.7751	154.7004	170.1774	185.4560
Unit 4 (MV)	90.4993	103.6615	117.9493	131.8891	145.7569	159.5111	173.4595
Unit 5 (MV)	143.8381	166.7562	189.6947	212.1676	235.0348	258.0468	281.0503
Unit 6 (MV)	138.4166	161.1021	183.0852	205.9797	228.2848	250.1397	272.4835
Fuel cost ($/h)	27,089.45	31,626.79	36,310.80	41,144.47	46,124.54	51,262.31	56,542.01
Emission output (kg/h)	261.3307	338.4397	433.6409	546.7831	678.2906	827.2612	994.5205

Table 3. Fuel cost, emission coefficients and generation limits of eleven-generator system.

Generator	ai ($/MW2h)	bi ($/MWh)	ci ($/h)	di (kg/MW2h)	ei (kg/MWh)	fi (kg/h)	Pimin (MW)	Pimax (MW)
1	0.00762	192.699	387.85	0.00419	-0.67767	33.93	20	250
2	0.00838	211.969	441.62	0.00461	-0.69044	24.62	20	210
3	0.00523	219.196	422.57	0.00419	-0.67767	33.93	20	250
4	0.00140	201.983	552.50	0.00683	-0.54551	27.14	60	300
5	0.00154	222.181	557.75	0.00751	-0.40060	24.15	20	210
6	0.00177	191.528	562.18	0.00683	-0.54551	27.14	60	300
7	0.00195	210.681	568.39	0.00751	-0.40006	24.15	20	215
8	0.00106	199.138	682.93	0.00355	-0.51116	30.45	100	455
9	0.00117	199.802	741.22	0.00417	-0.56228	25.59	100	455
10	0.00089	212.352	617.83	0.00355	-0.41116	30.45	110	460
11	0.00098	210.487	674.61	0.00417	-0.56228	25.59	110	465

Table 1. Table 2 gives the best optimal power output of generators for CEED problem using proposed method with system demands rising from 500 - 1100 MW for six-generator system.

The fuel cost, emission coefficients and generation limits of eleven-generator system are taken from Balamurugan and Subramanian (2008) Palanichamy and Sundar Babu (2002) and are given in Table 3. Table 4 gives the best optimal power output of generators for CEED problem using proposed method with system demands rising from 1000 - 2500 MW for eleven-generator system.

Table 5 presents the results of γ-iteration method (γM), recursive method (RM), particle swarm optimization (PSO), differential evolution (DE), simplified recursive method (SRM) and proposed method; when the load demands are varies from 500 - 1100 MW for six-generator system. The PSO produced the highest cost and emission and the obtained operation cost and emission by the RM, γM are smaller than the DE, respectively. For all of load demands, the operation cost of the SRM is slightly higher than the operation cost and

Table 4. CEED solution of eleven-generator system.

	Load (MW)						
	1000	**1250**	**1500**	**1750**	**2000**	**2250**	**2500**
Unit 1 (MV)	86.2758	93.9275	106.5199	113.0308	120.1685	129.7723	138.8618
Unit 2 (MV)	76.9797	83.0732	87.1458	94.8869	100.1012	107.5366	112.1312
Unit 3 (MV)	85.4269	96.3218	105.3690	114.5494	128.5257	136.2962	146.7169
Unit 4 (MV)	74.1836	98.4780	128.3770	150.5204	172.0086	198.0657	222.1041
Unit 5 (MV)	48.4590	64.4172	84.3938	93.4159	107.6713	121.8092	137.1962
Unit 6 (MV)	82.0134	100.8380	123.9698	144.9676	170.3618	197.1859	217.3208
Unit 7 (MV)	55.1207	63.7686	76.6512	99.0107	110.7550	124.7361	140.4711
Unit 8 (MV)	132.0029	167.9642	216.2395	235.1620	275.4063	312.2044	348.9008
Unit 9 (MV)	118.3090	160.3899	189.7588	224.3173	260.2487	295.3866	326.5188
Unit 10 (MV)	122.2074	161.1275	193.6024	244.1815	284.1039	320.0318	363.5275
Unit 11 (MV)	119.0241	159.6940	187.9736	235.9614	270.6491	306.9751	346.2508
Fuel cost ($/h)	8,501.85	9,107.99	9,733.22	10,377.01	11,040.84	11,723.25	12,423.77
Emission output (kg/h)	205.1750	339.7063	539.4933	807.2136	1138.2789	1538.3191	2003.0304

Table 5. Comparison of fuel cost and emission for six-generator system (Balamurugan and Subramanian, 2008).

Fuel cost ($/h)							
Method	**Load (MW)**						
	500	**600**	**700**	**800**	**900**	**1000**	**1100**
γ-iteration	27,092.5	31,628.7	36,314.0	41,148.4	46,131.8	51,264.6	56,546.4
Recursive	27,092.5	31,628.6	36,313.9	41,148.3	46,131.8	51,264.5	56,546.2
PSO	27,097.5	31,634.9	36,314.2	41,160.3	46,160.6	51,269.6	56,556.7
DE	27,098.1	31,629.2	36,314.0	41,152.6	46,152.6	51,264.6	56,546.6
Simplified recursive	27,092.5	31,628.6	36,313.9	41,148.3	46,131.8	51,264.6	56,546.2
Proposed	27,089.45	31,626.79	36,310.80	41,144.47	46,124.54	51,262.31	56,542.01
Emission output (kg/h)							
γ-iteration	261.635	338.993	434.380	547.797	679.241	828.720	996.224
Recursive	261.634	338.992	434.380	547.796	679.241	828.715	996.218
PSO	262.225	339.820	434.605	547.844	679.724	828.863	996.672
DE	261.859	339.065	434.453	547.802	679.283	828.715	996.222
Simplified recursive	261.634	338.992	434.380	547.796	679.241	828.715	996.218
Proposed	261.3307	338.4397	433.6409	546.7831	678.2906	827.2612	994.5205

emission of the proposed method. For varying 500 - 1100 MW of load demands, the operation costs and emissions of the SRM were 3.05 - 0.3033, 1.81 - 0.5523, 3.1 - 0.7391, 3.83 - 1.0129, 7.26 - 0.9504, 2.29 - 1.4538 and 4.19 $/h - 1.6975 kg/h higher than the operation costs and emissions of the proposed method.

In order to demonstrate the efficiency and the robustness of the proposed genetic algorithm, an eleven generator system is considered. The results of the proposed and other five methods are shown in Table 6. For all of load demands, the operation cost of the SRM is again slightly higher than the operation cost and emission of the proposed method. For varying 1000 - 2500 MW of load demands, the operation costs and emissions of the SRM is 0.44 - 0.029, 0.39 - 0.164, 0.32 - 1.051, 0.76 - 0.006, 0.24 - 1.632, 0.22 - 0.281 and 1.17 $/h - 0.27 kg/h higher than the operation costs and emissions of the proposed method. It is obvious that the proposed method produced the better solution than the compared methods for six-generator and eleven-generator systems.

Conclusion

In this paper, a novel genetic algorithm based on similarity crossover has been presented. The proposed method has been tested on a six-generator and eleven-generator economic emission load dispatch problems.

Table 6. Comparison of fuel cost and emission for eleven-generator system (Balamurugan and Subramanian, 2008).

Fuel cost ($/h)							
Method	**Load (MW)**						
	1000	**1250**	**1500**	**1750**	**2000**	**2250**	**2500**
γ-iteration	8502.30	9108.38	9733.54	10,377.78	11,041.08	11,723.47	12,424.94
Recursive	8502.29	9108.38	9733.54	10,377.77	11,041.08	11,723.47	12,424.94
PSO	8508.24	9114.42	9737.33	10,380.82	11,041.09	11,725.68	12,428.63
DE	8505.81	9117.63	9736.22	10,377.86	11,041.08	11,723.54	12,425.06
Simplified recursive	8502.29	9108.38	9733.54	10,377.77	11,041.08	11,723.47	12,424.94
Proposed	8501.85	9107.99	9733.22	10,377.01	11,040.84	11,723.25	12,423.77
Emission output (kg/h)							
γ-iteration	205.205	339.870	540.545	807.220	1,139.912	1,538.600	2,003.301
Recursive	205.204	339.870	540.544	807.220	1,139.911	1,538.600	2,003.300
PSO	208.012	345.669	545.347	812.263	1,142.182	1,540.465	2,003.720
DE	205.206	339.935	544.298	807.236	1,139.911	1,538.659	2,003.350
Simplified recursive	205.204	339.870	540.544	807.220	1,139.911	1,538.600	2,003.300
Proposed	205.175	339.706	539.493	807.214	1,138.279	1,538.319	2,003.030

Test results have shown that the proposed genetic algorithm can provide better solutions than particle swarm optimization, differential evolution, γ-iteration, recursive, and simplified recursive methods. Due to these properties, the proposed method in future should be applied in complex unit commitment problems and dynamic CEED problems, in the search of better quality results.

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