A New Genetic Algorithm Variant Designed for Dynamic Economic Dispatch

Harish Pulluri, Preeti, B.Vedik, and T. Anil Kumar

Abstract One of the key tasks of power production operations and control is dynamic economic dispatch (DED). It defines the optimum settings of generators for a given period with a projected load requirement. The aim is to run an electricity system cheaply as long as it operates within its safety limitations. Therefore, this article aims to propose a hybrid technique to solve DED. The basic genetic algorithm (GA) when used as a search level takes longer to get nearly optimal results. The proposed technique uses a three-parent crossover and diversity operator resulting in increasing the potential for both exploration and exploitation of the algorithm technique. Two test cases with quadratic cost function are employed to demonstrate the efficacy and validity of the proposed method. Experimental findings compared with many DED solution techniques, namely differential evolution (DE), hybrid DE, sequential quadratic programing, artificial bee colony, and other recently published results, and these results proved that proposed technique achieved superior solutions.

Keywords Dynamic economic dispatch · Three-parent crossover · Transmission loss · Diversity factor

1 Introduction

DED is an extension of the issue of static economic transmission (SED). SED scenario finds the cost-efficient production combination of generators to fulfil the anticipated demand for a single load at a particular time hour. Because of the high-power system

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load fluctuation, SED could not meet the operating restrictions of the generators. The primary aim of the DED is to reduce the overall cost of production while meeting the limitations of equality, inequality and dynamic restrictions. Moreover, owing to look ahead inability, the outcomes of SED will be suboptimal when evaluating a time horizon moment of a time instance [1]. The balance of load demand is the constraint on equality, and the restrictions on the forbidden area and limitations of capacity generation are the constraints of inequality. The solution of the DED issue is more complex by considering these dynamic restrictions. Much work has been expended in trying to successfully address the essential but complex DED issue, and a variety of solution approaches have been suggested. Until now, these techniques have been experimentally divided into two groups: classical and heuristic methods. Classical methods include Lagrangian method [2], quadratic programing [3] and dynamic programing [4], etc., and while they offer some benefits like great calculation efficiency and theoretically optimal [5], they have several drawbacks as well. As a substitute for traditional methods, heuristic techniques have received much attention and proven their efficacy as strong optimizers for the issue of DED in the past several decades, like evolutionary programing [6] particle swarm optimization (PSO) [7], differential evolution (DE) [8], artificial bee colony (ABC) [9], krill herd algorithm (KHA) [10] and artificial immune system (AIS) [11].

In 1960, John Holland invented the genetic algorithm (GA) [12]. To date GA has been used to resolve a number of real-world issues of optimization [13–15]. It may quickly reach the global minimum search area, and it takes more time to converge. A hybrid approach is one way of tackling this problem. Several GA variations were thus presented to avoid the disadvantage trap in local optima and reach global solution with in less time [16]. The major contributions in this paper are as follows:

(i) Consider DED problem instead of classical ED, since introduction of dynamic constraints makes the DED problem more complicated.
(ii) DED problem is solved using newly created a variant of GA with three-parent crossover. This method introduced a three-parent crossover and a typical mutation via a diversity operator, resulting in maintain efficient chromosomes.

The effectiveness of GA-TPC is shown with two distinct test systems. The remaining paper is arranged as follows, Sect. 2 provides a mathematical model of DED problem considering valve points, Sect. 3 offers about GA-TPC algorithm, Sect. 4 shows three different cases, and achieved results compare with the outcomes of the latest techniques and the final conclusion in Sect. 5.

2 Mathematical Model

DED is required to optimize the overall cost of all thermal generators exposed to different restrictions on a regular basis over a time horizon. The thermal cost characteristics, associated constraints and basic formulations are discussed more below [7].

2.1 Optimization of Total Cost (TC)

Usually, the DED problem's goal function may be approximated by a simple quadratic equation [7].

$$\min\ f = \sum_{t=1}^{T} \sum_{m=1}^{\text{NG}} a_m + b_m P_{\text{Gm},t} + C_m P_{\text{Gm},t}^2 \tag{1}$$

where f gives TC of all generators; $P_{\text{Gm},t}$ indicates active power of mth generator at tth hour.

2.2 Optimization of TC with Valve Points (TCV)

However, the production curve for multi-valve steam units differs considerably in comparison with the quadratic function of the active power output. The inclusion of a valve point effect on the fuel cost of the producing unit provides a better representation of the cost of fuel. As the valve point is completed with spiking, the fuel price function includes more nonlinear series. A non-convex function to assess the effect of the valve points is thus employed in the study given below [7].

$$\min\ f = \sum_{t=1}^{T} \sum_{m=1}^{\text{NG}} a_m + b_m P_{Gm,t} + C_m P_{Gm,t}^2 + \left| d_m \times \sin(e_m (P_{\text{Gm},t}^{\min} - P_{\text{Gm},t})) \right| \tag{2}$$

where $a_m, b_m, c_m, d_m \& e_m$ indicate cost coefficients of mth generator.

2.3 Constraints

The limitations in the current work are briefly described below [7].

Equality constraints: It is a real power balance constraint and is given below,

$$\sum_{n=1}^{\text{NG}} P_{Gnt} = P_D(t) + P_{\text{loss}}(t) \qquad t = 1, 2, \ldots T \tag{3}$$

where P_D reports load demand, and P_{loss} indicates transmission loss and is calculated as follows,

$$\sum_{k=1}^{NG}\sum_{m=1}^{NG} P_{kt}B_{km}P_{mt} + \sum_{k=1}^{NG} B_0 P_{kt} + B_{00} \qquad t = 1, 2, ...T \tag{4}$$

where B_{km}, $B_k \& B_{00}$ are called loss coefficients.

Inequality constraints: These are expressed among their low and high limits and are given below,

$$P_{Gn}^{\min} \le P_{Gnt} \le P_{Gn}^{\max} \quad n = 1, 2, \ldots, N_G \qquad t = 1, 2, \ldots, T \tag{5}$$

3 Proposed Genetic Algorithm with Three-Parent Crossover

Different GAs for many real-world numerical problems have been presented over several decades. However, the effectiveness of the various approaches is dependent only on features of the objective function. In certain instances, GA did not perform nor was compared with other algorithms [17, 18]. Therefore, GA performance is improved by adding three-parent crossover instead of a typical two-point crossover, and diversity operator is applied instead of a fairly regular mutation [17]. The current crossover uses three parents to produce three new children, helping explore and leverage the diversity operator.

Crossover is a GA operator of great importance. It is responsible for recombination structure and GA convergence speed. The conventional GA combines the chromosomes from the two chosen parents to produce a new chromosome which inherits information regions contained in parent chromosomes. The crossover suggested in the GA-MPC is based on an idea of heuristic crossover, and here, a child (c) is created from a set of two parents (a, b), like $c = a + rand(a - b)$, where 'rand' is a random number among 0,1. The GA-MPC nevertheless uses three rather than two parents.

The procedure for the proposed algorithm is explained below.

(i) **Selection**

Selection of the parents is a simple process by which parents are chosen based on fitness of the chromosomes. The likelihood of adding additional offspring to the following generation is that solutions with high fitness ratings. A basic selection of roulette wheels rule utilized in our approach [19].

(ii) **Proposed three-parent crossover**

Crossover procedure is very important in GA. To generate new offspring, the crossover must be able to use search space information. Offspring distribution should neither be disproportionately narrow or disproportionately large compared to that of their parents. It is possible that the offspring will lose diversity and converge early if their distribution is much smaller than that of their parents. The opposite may be true if the children are dispersed extensively, in which case they may be too varied and require an excessively long time to converge to optimality. There should be a balance between exploration and exploitation in the next generation. Based on the aforementioned idea, in the proposed work, three parent crossover based on random procedure is used rather than regular two parent crossover. The procedure is given below [17].

1. Select the parent individuals by using selection process.
2. If any two individuals are similar, then one is replaced with randomly from selection pool.
3. Arrange those three individuals according to best to worst fitness value.
4. A number 'Ɛ' is produced randomly;

   (a) New off springs are produced by using following equations

$$\begin{aligned} \mathrm{OF}_1 &= x_1 + \varepsilon(x_2 - x_3) \\ \mathrm{OF}_2 &= x_2 + \varepsilon(x_3 - x_1) \\ \mathrm{OF}_3 &= x_3 + \varepsilon(x_1 - x_2) \end{aligned} \tag{6}$$

where x_1, x_2 & x_3 are the selected parents by using selection process, and OF_1, OF_2 & OF_3 denote newly generated off springs.

(iii) **Diversity operator**

To improve the exploitation capability in the individuals, diversity operator introduced in [14] considered here.

The step-wise procedure of GA-TPC to solve ED is given below:

Step 1: Initialize GA-TPC variables, max generations ($\mathrm{G}_{\max}$).

Step 2: Each chromosome in GA-TPC is a solution to a DED issue. The *k*th chromosome in *m*th generation is expressed in below given form

$$X_k^m = \begin{bmatrix} P_{g1,1,k}^m & P_{g1,2,k}^m & \cdots & P_{g1,t,k}^g \\ P_{g2,1,k}^m & P_{g2,2,k}^m & \cdots & P_{g2,t,k}^m \\ \vdots & \vdots & \ddots & \vdots \\ P_{gNg,1,k}^m & P_{gNg,2,k}^m & \cdots & P_{gNg,t,k}^m \end{bmatrix} \begin{matrix} k = 1, 2 \ldots \mathrm{NP} \\ g = 1, 2 \ldots G_{\max} \end{matrix} \tag{7}$$

where t indicates number of intervals in the dispatch period.

Step 2: Evaluate fitness of every individual using Eq. 8.

$$|F| = f + w_P \left(|P_{G1} - P_{G1}^{\lim}|\right)^2 \tag{8}$$

where w_P indicates penalty value of slack bus real power.

Step 3: Apply the selection, proposed crossover, diversity operator, and create new generation.

Step 4: If any variable exceeds its existing limits, then it will be set to inline high or low value.

Step 5: Terminate the process, if utmost iterations are marked, and take the best result from previous iteration as best solution. Else, go to Step 2.

4 Simulation Results

Two different modules are investigated to assess the feasibility and efficacy of the GA-TPC technique suggested in the solution of the DED issue. The dispatch time is chosen as 24 h for one day. The number individuals and utmost iterations in all the cases are considered 40 and 300, respectively. The following are the two cases:

M1: a three-generator system without point loadings.

M2: a ten-generator system with valve point loadings.

4.1 M1: 3 Unit System

The proposed system consists of three generators and complete data for this system that includes cost characteristics of generators, generator limits, and load demand in each interval is referred from reference [20]. The optimal set of active powers obtained to this system with GA & GA-TPC are given in Table 1. These results are compared with CSA [20] and ISA [20], RGM [21] and ACO [21] and are given in Table 2. From this table, it is noticed that the suggested approach provides a superior way to discover solutions to such complex DED issues, with minimum, average and maximum costs. A minimum of 176,017.5363 ($/day) and a minimum of 176,059.3264 $/day achieved utilizing the formulations of proposed GA-TPC and original GA, showing the remarkable nature of the suggested method. In addition, the convergence characteristic of the method suggested is compared and shown in Fig. 1 with the original GA. This figure indicates that both convergence speed and optimum objective function of the proposed GA-TPC beats conventional GA. Here, 3-unit system size is very small, so the deviation of optimal cost from GA to GA-TPC is very small. Thus, the convergence curves are much closer to each other.

4.2 M2: 10 Unit System

GA-TPC performance is identified by considering 10 unit systems for solving DED problem with inclusion of valve points. This system is believed to have a complete date from [7]. Table 3 illustrates the findings achieved for the 10-unit system with

Table 1 Optimal solution of 3-unit system without VPL using GA & GA-TPC

	GA				GA-TPC			
t (h)	P_1 (MW)	P_2 (MW)	P_3 (MW)	Cost (S/h)	P_1 (MW)	P_2 (MW)	P_3 (MW)	Cost (S/h)
1	41.341	48.659	50	6150.808	37.909	42.5476	59.543	6148.4312
2	43.748	42.72	63.532	6377.581	40.711	45.7443	63.545	6376.6675
3	43.961	54.113	56.926	6493.501	43.022	47.1747	64.803	6491.4402
4	38.382	40	81.618	6614.415	43.423	49.8616	66.715	6606.4585
5	48.998	54.571	61.43	6723.759	43.688	52.0029	69.309	6722.0393
6	44.832	47.487	77.681	6839.822	45.969	52.9109	71.121	6837.9471
7	54.631	53.428	66.942	6955.989	48.22	53.6396	73.14	6954.2919
8	46.12	62.795	71.085	7073.065	49.569	55.1802	75.251	7071.0227
9	63.42	56.313	90.266	7781.993	59.315	63.64	87.045	7779.7419
10	67.692	68.29	94.018	8260.228	66.437	69.6138	93.95	8260.1533
11	69.608	74.686	95.705	8503.082	69.568	72.2599	98.172	8502.7299
12	79.374	72.439	98.187	8748.433	72.68	74.5422	102.78	8746.9002
13	71.719	74.971	93.309	8503.619	69.735	71.9122	98.353	8502.7284
14	66.244	65.051	88.705	8019.541	63.295	65.9794	90.725	8019.16
15	58.386	60.831	80.783	7542.076	56.408	60.8439	82.748	7541.9093
16	53.472	52.366	74.163	7071.661	50.478	55.3434	74.179	7071.0302
17	43.3	56.332	70.368	6838.516	47.312	52.192	70.496	6837.9732
18	48.842	56.649	79.508	7188.46	52.24	56.1071	76.652	7188.1803
19	45.17	59.664	95.166	7548.116	57.969	60.1938	81.837	7542.0067
20	72.003	64.392	103.6	8505.098	69.57	71.5997	98.83	8502.7353

(continued)

Table 1 (continued)

	GA				GA-TPC			
t (h)	P_1 (MW)	P_2 (MW)	P_3 (MW)	Cost (S/h)	P_1 (MW)	P_2 (MW)	P_3 (MW)	Cost (S/h)
21	67.307	65.251	92.442	8139.833	64.692	67.3155	92.992	8139.4628
22	54.213	55.534	80.253	7305.985	51.872	58.4052	79.723	7305.7212
23	48.387	49.286	62.327	6607.532	43.017	49.8323	67.151	6606.4604
24	45.796	49.204	50	6266.213	38.384	47.6841	58.932	6262.345
TC ($/h)				**176,059.3264**	**TC ($/h)**			**176,017.5363**

Table 2 Comparison of the statistical analysis for 3-unit system with the other methods

Method	Minimum cost ($/h)	Average cost ($/h)	Maximum cost ($/h)	ET (min)
RGM [21]	177,291	–	–	–
ACO [21]	176,212	–	–	–
CSA [20]	176,370	–	–	–
ISA [20]	176,320	–	–	–
GA	**176,059.3264**	**176,066.6535**	**176,095.8222**	**0.38**
GA-TPC	**176,017.5363**	**176,019.1552**	**176,028.3286**	**0.42**

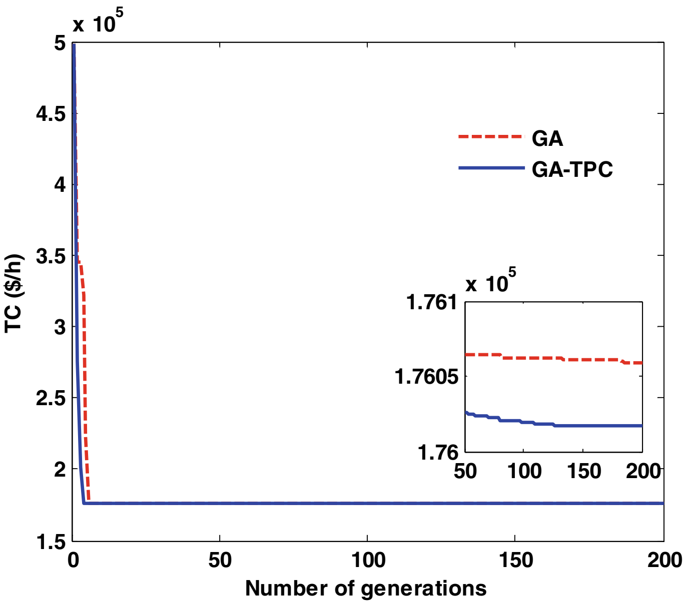

Fig. 1 Convergence curve of 3-unit system

valve point loading effect. These findings are compared to those of previously developed algorithms such as DE [8], hybrid EP-SQP [6], hybrid PSO-SQP [18], deterministically guided PSO (DGPSO) [7], hybrid DE (HDE) [7], improved DE (IDE) [7], ABC [6], modified DE (MDE) [7], AIS [12], AIS-SQP [12], chaotic DE (CDE) [7] and improved PSO (IPSO) [7]. This table shows a comprehensive comparison of solution quality, including lowest, average and maximum cost, as well as simulation time, and it is confirmed that the proposed method produces more optimum results outcomes that the methods described in the literature. Tables 4 and 5 shows the optimal set of active powers obtained to this system with GA-TPC and GA respectively. The suggested algorithm's convergence characteristic is shown in Fig. 2 and compared to the original GA. As can be seen from the graph, the suggested method beats the original GA in terms of convergence speed and optimality. The variation

Table 3 Comparison of the statistical analysis for 10-unit system with the other methods

Method	Minimum cost ($/h)	Average cost ($/h)	Maximum cost ($/h)	ET (min)
DE [8]	1,019,786	0	0	11.25
EP-SQP [6]	1,031,746	1,035,748	0	20.51
PSO-SQP [7]	1,027,334	1,028,546	1,033,986	16.37
DGPSO [7]	1,028,835	1,030,183	0	15.39
HDE [7]	1,031,077	0	0	0
IDE [7]	1,026,269	0	0	0
ABC [6]	1,021,576	1,022,686	1,024,316	2.6029
MDE [7]	1,031,612	1,033,630	0	12.5
AIS [12]	1,021,980	1,023,156	1,024,973	19.01
AIS-SQP [12]	1,029,900	0	0	0
CDE [7]	1,019,123	1,020,870	1,023,115	0.32
IPSO [7]	1,018,217	1,018,965	1,020,418	2.8
GA	**1,029,091.80**	**1,029,189.56**	**1,029,455.20**	**1.2**
GA-TPC	**1,015,473.71**	**1,015,536.60**	**1,015,823.71**	**1.1**

of TC with 20 trials is shown in Fig. 3 for 6-unit system, and it is observed that 17 trials were achieved optimal cost by the GA-TPC method over 20 trials and indicates the precision of the proposed method. Aforementioned simulation results depict that GA-TPC is successful in addressing small-scale test systems and using it to solve multi-objective DED for large and practical power systems would be an extension of the current study.

5 Conclusion

To address the dynamic economic dispatch issue of power systems with valve point loading effects, this article proposes a novel method termed genetic algorithm with three-parent crossover. Two different test scenarios are used to validate the technique. Comparing the suggested technique to other previously published approaches, including lowest, average and maximum costs as well as simulation time, provides a thorough understanding of the pros and cons of each. The findings of the study show that GA-TPC was able to find solutions that were more cost-effective. The comparison of suggested algorithm's convergence characteristics with conventional GA also confirms the speed and ability of the GA-TPC method to discover superior solutions. These facts suggest that the technique under consideration is capable of resolving DED problems.

Table 4 Optimal solution of 10-unit system using GA-TPC

t (h)	P_1(MW)	P_2(MW)	P_3(MW)	P_4(MW)	P_5(MW)	P_6(MW)	P_7(MW)	P_8(MW)	P_9(MW)	P_{10}(MW)	Cost ($/h)
1	226.62	135.00	73.00	60.00	167.33	122.45	129.59	47.00	20.00	55.00	28,359.6021
2	379.87	135.00	88.087	60.00	73.00	122.45	129.59	47.00	20.00	55.00	30,005.0057
3	455.69	222.26	73.00	60.00	73.00	122.45	129.59	47.00	20.00	55.00	33,095.292
4	303.25	309.53	286.17	60.00	73.00	122.45	129.59	47.00	20.00	55.00	36,169.1056
5	226.62	396.79	311.98	60.00	73.00	160.00	129.59	47.00	20.00	55.00	37,922.3118
6	379.87	396.79	306.73	60.00	73.00	160.00	129.59	47.00	20.00	55.00	41,117.5852
7	456.50	396.79	291.79	60.00	122.86	122.45	129.59	47.00	20.00	55.00	42,560.2457
8	379.87	396.79	305.13	60.00	222.59	160.00	129.59	47.00	20.00	55.00	44,339.2702
9	456.50	396.79	340.00	60.00	222.59	123.51	129.59	120.00	20.00	55.00	47,894.9451
10	456.50	396.79	307.81	241.25	222.59	122.45	129.59	120.00	20.00	55.00	51,346.7458
11	456.50	396.79	297.39	300.00	222.59	148.11	129.59	120.00	20.00	55.00	53,239.2323
12	456.50	460.00	298.94	300.00	222.59	160.00	129.59	85.31	52.05	55.00	55,271.1464
13	456.50	460.00	297.39	241.25	222.59	142.66	129.59	47.00	20.00	55.00	51,623.3424
14	379.87	309.53	300.40	300.00	222.59	160.00	129.59	47.00	20.00	55.00	48,140.8612
15	379.87	396.79	297.39	60.00	172.73	144.60	129.59	120.00	20.00	55.00	44,559.2939
16	303.25	309.53	284.57	60.00	222.59	122.45	129.59	47.00	20.00	55.00	39,418.2678
17	226.62	396.79	311.98	60.00	73.00	160.00	129.59	47.00	20.00	55.00	37,922.3118
18	456.50	309.53	305.06	60.00	122.86	122.45	129.59	47.00	20.00	55.00	40,981.7692
19	456.50	396.79	315.93	60.00	172.73	122.45	129.59	47.00	20.00	55.00	44,266.6374
20	456.50	460.00	317.61	241.25	222.59	122.45	129.59	47.00	20.00	55.00	51,600.466
21	456.50	396.79	340.00	60.00	222.59	126.144	129.59	85.31	52.05	55.00	47,921.2908

(continued)

Table 4 (continued)

t (h)	P_1(MW)	P_2(MW)	P_3(MW)	P_4(MW)	P_5(MW)	P_6(MW)	P_7(MW)	P_8(MW)	P_9(MW)	P_{10}(MW)	Cost ($/h)
22	456.50	135.00	304.00	60.00	222.59	160.00	129.59	85.31	20.00	55.00	41,303.7322
23	303.25	396.79	190.36	60.00	73.00	57.00	129.59	47.00	20.00	55.00	34,804.1756
24	456.50	135.00	85.46	60.00	73.00	122.45	129.59	47.00	20.00	55.00	31,611.0776
TC ($/h)											**1,015,473.713**

Table 5 Optimal solution of 10-unit system using the GA

t (h)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	P_7 (MW)	P_8 (MW)	P_9 (MW)	P_{10} (MW)	Cost ($/h)
1	295.18	135.00	73.00	60.00	116.58	104.23	130.00	47.00	20.00	55.00	28,835.4134
2	383.81	135.00	73.00	60.00	73.00	133.18	130.00	47.00	20.00	55.00	30,081.4690
3	234.70	135.00	311.54	60.00	73.00	118.74	130.00	120.00	20.00	55.00	33,514.2946
4	444.25	135.00	300.01	60.00	73.00	141.72	130.00	47.00	20.00	55.00	36,581.9959
5	452.82	399.24	73.00	60.00	123.12	125.20	124.58	47.00	20.00	55.00	38,159.0757
6	458.88	135.00	340.00	60.73	221.38	160.00	130.00	47.00	20.00	55.00	41,522.4435
7	450.83	391.59	289.50	60.00	84.679	144.79	130.00	47.00	48.58	55.00	43,423.0248
8	381.89	394.32	312.71	60.00	184.16	160.00	123.86	84.04	20.00	55.00	44,949.1070
9	455.97	460.00	316.42	165.23	112.55	160.00	130.00	48.81	20.00	55.00	48,765.2458
10	460.24	460.00	298.52	197.25	234.30	160.00	130.00	47.00	29.67	55.00	52,222.2846
11	378.76	460.00	314.69	300.00	243.00	124.53	130.00	120.00	20.00	55.00	53,935.9627
12	469.28	460.00	340.00	300.00	243.00	121.46	130.00	77.61	23.63	55.00	55,997.8655
13	391.29	419.50	340.00	300.00	243.00	126.19	130.00	47.00	20.00	55.00	52,381.0673
14	442.68	460.00	293.19	60.00	243.00	126.34	130.00	83.61	30.16	55.00	48,784.4983
15	456.99	460.00	340.00	60.00	73.00	134.01	130.00	47.00	20.00	55.00	44,967.6019
16	374.39	310.12	340.00	60.00	73.00	109.03	128.57	83.87	20.00	55.00	40,057.3805
17	464.17	135.00	292.44	60.00	157.71	120.45	128.21	47.00	20.00	55.00	38,271.5555
18	444.25	396.70	73.00	60.00	218.73	112.94	130.00	84.33	53.02	55.00	41,875.6074
19	379.08	384.23	340.00	60.00	243.00	126.28	121.39	47.00	20.00	55.00	45,209.9895
20	457.65	395.86	340.00	171.32	218.01	143.55	130.00	80.58	80.00	55.00	52,359.3581
21	467.50	309.39	318.71	170.77	211.23	160.00	130.00	81.38	20.00	55.00	48,655.8495

(continued)

Table 5 (continued)

t (h)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	P_7 (MW)	P_8 (MW)	P_9 (MW)	P_{10} (MW)	Cost ($/h)
22	454.19	306.56	276.10	60.00	119.13	160.00	130.00	47.00	20.00	55.00	41,456.3079
23	231.34	135.00	322.07	60.00	171.58	160.00	130.00	47.00	20.00	55.00	34,990.4801
24	226.30	135.00	157.17	60.00	235.83	114.92	130.00	49.75	20.00	55.00	32,093.9229
TC ($/h)											**1,029,091.801**

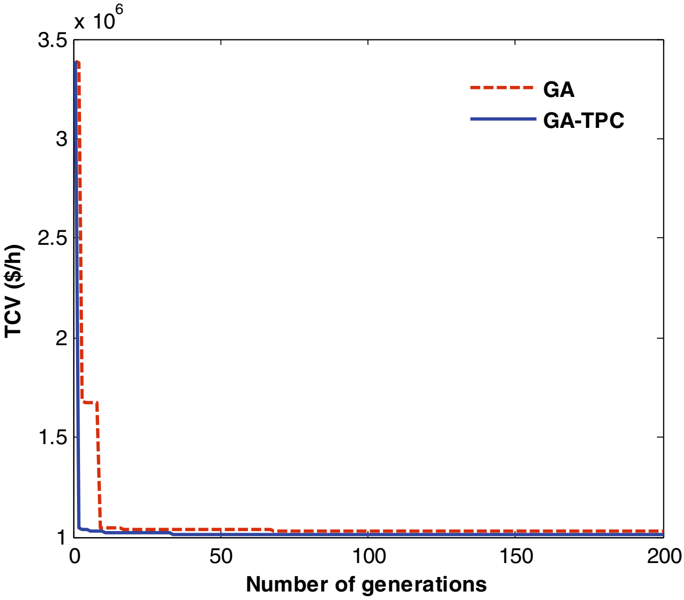

Fig. 2 Convergence characteristics of 10-unit system

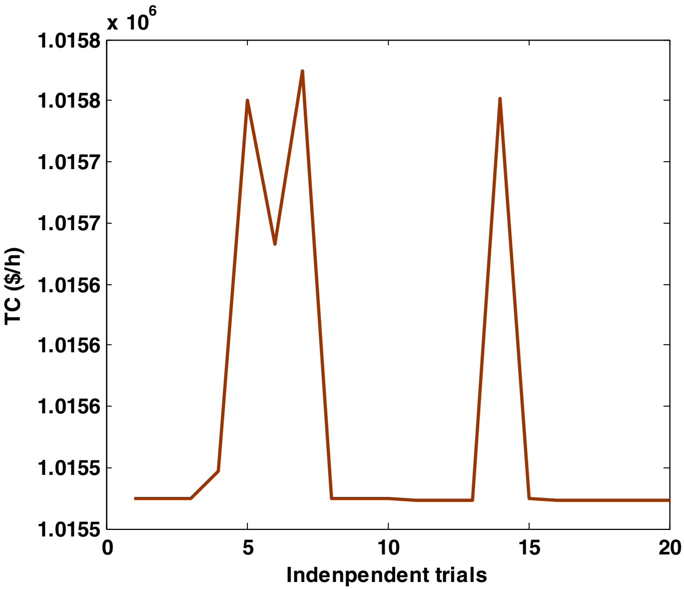

Fig. 3 Variation of TCV for 10-unit system with 20 trials

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