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EFFECT OF POPULATION SIZE ON THE PERFORMANCE OF GENETIC ALGORITHM FOR SOLVING ECONOMIC LOAD DISPATCH PROBLEMS

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ABSTRACT
In the power industry, Economic Load Dispatch (ELD) operates the running generators at economical cost of operation under certain operational constraints for a specific load. The combinations of best generations are evaluated for economical operations of the plant. In this context, Genetic Algorithm (GA) is widely used to determine the optimal combination of the generators output in order to minimize plant cost. In this work, ELD of 3 generator system and 6 generator system have been determined using GA. Additionally, the effect of population size on the performance of GA for solving ELD has also been analyzed. For this, five populations (50, 100, 200, 500 and 1000) have been used in GA simulation for both the systems. Various operational cost (average, best, worst, and standard deviation), average power losses, average iteration, average computational time and number of trial runs hitting best operational cost in 20 trial runs have been analyzed for each population size. The study found that the population size, 1000 gives optimum results in terms of minimum operational cost, consistent result, précised result and takes less iterations to give result for both the system.
Keywords: Economic Load Dispatch (ELD), Genetic Algorithm (GA); Population size, Fuel cost.

I. Introduction
The world's energy demand is growing day-by-day. Due to which, the complexity of existing power system (PS) is expanding in terms of planning and operation. Economic load dispatch (ELD) deals with such problems of complex PS in context of supplying required load demand at economical fuel cost by distributing load among participating generating units under certain constraints [1].
Generally, the fitness function of ELD involves quadratic cost function of each generating units and the loss function of the system [2]. Various methods are adopted for analysing the ELD problems [3], [4]. These methods are classified into two broad categories, first is traditional techniques like Gradient methods, Newton's methods, Lagrangian method, Lembda method and Dynamic programing. The second method is the metaheiristics techniques such as linear programming, Genetic algorithm (GA), Particle swarm optimization (PSO), Ant colony optimization, Bee colony optimization, chemical reaction optimization etc. [5]-[7]. Among various metaheiristics methods GA and PSO are the most popular evolutionary technique for solving ELD problems [8], [9].
GA simulate the evolution process by applying genetic operator to the population. These operators include selection, crossover, and mutation [8]-[15]. GA has three main advantages over other optimization techniques. First, it encodes the control variables in the string. Secondly, it uses several search point. Finally, there is no need to know anything about the fitness function beforehand while using GAs. [8].
Various parameters that affect the performance and behaviour of GA are population sizes, selection methods, crossover rate, mutation rate etc. Choosing appropriate values for these parameters and understanding their effects on the optimization process is crucial for the success of GA in solving complex optimization problems [9]. Among these control parameters, the population size is a crucial parameter in GA as it directly impacts the diversity, exploration, and convergence characteristics of

the algorithm [10]. A larger population size typically leads to greater diversity within the population. With more individuals, there is a higher chance of covering a broader range of the solution space. This increased diversity helps prevent premature convergence by ensuring that a wide variety of potential solutions is explored. Moreover, larger population favours exploration as it allows for more individuals to be simultaneously evaluated and promotes the discovery of new regions of the solution space. However, larger populations tend to slow down the convergence process because more individuals need to be evaluated and selected at each generation [10]-[15]. Therefore, selecting an appropriate population size requires careful consideration of the specific problem domain, computational resources, and desired balance between exploration and exploitation.
In the present study, ELD problems of 3 generators and 6 generators systems have been analysed using GA. Additionally, the effect of population size has also been analysed. The rest of the sections of the work has been organised as follows: Section II deals the formulation of the fitness function of the ELD. Section III describes the basics of GA. In Section IV, simulation results and analysis of the results have been presented. In Section V, conclusions and future directions of the study have been described.

II. Fitness function

The ELD is optimization problems that aims to optimize a particular power system objective taking into account its physical limitations. ELD controls the power flow of the generating units, vary within the certain limits and fulfils the load demand with less fuel cost. It distributes the load among the generating unit which is parallel to the system in such a manner as to reduce the total cost of supplying. It also fulfils the minute to the minute requirement of the system [16], [17].
The production cost of each generating unit is generally expressed in terms of the quadratic equation of output power of generating units. The total production cost of the plant is given by the sum of production cost of each individual units of the plant. Mathematically it can be represented as,

$$F_i(P_i) = a_iP_i^2 + b_iP_i + c_i \tag{1}$$

Where $F_i(P_i)$ is the generating unit's operational cost, P_i is the generating unit's output power and (a_i,b_i,c_i) are the generating unit's cost coefficient of ith unit of the plant.
Therefore total fuel/production cost (FT) of the plant having n units will be,

$$F_T = \sum_{i=1}^{n} F_i(P_i) = \sum_{i=1}^{n} (a_iP_i^2 + b_iP_i + c_i) \tag{2}$$

The equality constraint has been introduced for power mismatch i.e. the sum of load demand and losses must be equal to power generated by the plant. Mathematically the power balance equation is given by,

$$P_D + P_L - \sum_{i=1}^{n} P_i = 0 \tag{3}$$

Where P_D and P_L are the load demand and losses of the plant respectively.
The losses of the plant can be calculated from generating unit's outputs and loss coefficients as,

$$P_L=\sum_{i=1}^{n} (\sum_{j=1}^{n} (P_i B_{ij}P_j)) + \sum_{i=1}^{n} (B_{i0}P_i) + B_{00} \tag{4}$$

Where B_{ij} is the ijth element of the loss coefficient square matrix, B_{i0} is the ith element of the loss coefficient vector, and B_{00} is the loss coefficient constant.
The inequality constraint has been also introduced for each generating units of the plant i.e. the output power of each generating unit must be laid between its minimum and maximum generation limit [16] and it is represented mathematically as,

$$P_i^{min} < P_i < P_i^{max} \tag{5}$$

Where P_i^{min} and P_i^{max} are the minimum and maximum generation limit of ith unit of the plant respectively.

The objective/fitness function (F) of ELD is defined as the sum of fuel/production cost given in equation 2 and penalized equality constraint given in equation 3. The ELD problem states as follows, Minimize the fuel cost,

$$F = \sum_{i=1}^{n} (a_iP_i^2 + b_iP_i + c_i) + K*(P_D + P_L - \sum_{i=1}^{n} P_i) \qquad (6)$$

Subjected to inequality constraints given in equation 5.
Where K is the penalty coefficient for the plant due to not fulfilling the load demands to consumer and chosen carefully for a feasible solution.

III. Basics of genetic algorithms

Genetic algorithms (GAs) are a type of optimization algorithm inspired by the principles of natural selection and genetics. They are used to find solutions to optimization and search problems by mimicking the process of natural evolution [8]-[15]. Genetic algorithm process involve following process:

1. Generate Initial Population: Start by creating a population of potential solutions to the optimization problem. This population usually consists of randomly generated individuals, each representing a potential solution. The size of the population is a parameter that needs to be defined based on the problem's complexity and other factors.
2. Fitness Function Evaluation: Evaluate the fitness of each individual in the population. The fitness function quantifies how well an individual solves the optimization problem. It provides a measure of the individual's quality or suitability for the given task. The fitness function is problem-specific and needs to be defined based on the problem's objectives and constraints.
3. Selecting Parents: Choose individuals from the current population to serve as parents for the next generation. The probability of selection is typically proportional to an individual's fitness; individuals with higher fitness values have a greater chance of being selected. Various selection techniques can be employed, including roulette wheel selection, tournament selection, or rank-based selection.
4. Generating Offspring: Perform crossover or recombination to create offspring from the selected parent individuals. Crossover involves exchanging genetic material between two parents to produce one or more offspring. The crossover point and method depend on the representation of individuals (binary, real-valued, etc.). Common crossover techniques include one-point crossover, two-point crossover, and uniform crossover.
5. Introducing Variation: Apply mutation to introduce random changes in the offspring's genetic material. Mutation helps maintain genetic diversity within the population and prevents premature convergence to suboptimal solutions. Mutation operators randomly alter certain genes or parameters in individual solutions. The mutation rate determines the probability of mutation occurring in each gene or parameter.
6. Fitness Evaluation: Evaluate the fitness of the newly generated offspring using the fitness function. This step is crucial to assess the quality of the offspring solutions and compare them with the parent solutions.
7. Selecting Survivors: Determine how the new offspring population will replace the old parent population. There are different replacement strategies, including generational replacement and steady-state replacement. In generational replacement, the entire parent population is replaced by the offspring population. In steady-state replacement, only a subset of the parent population is replaced by the offspring.
8. Check Termination: Determine whether the termination criteria are met to stop the algorithm. Termination criteria can include reaching a maximum number of generations, finding a satisfactory solution, or stagnation in the population's fitness improvement. If the termination criteria are not met, the algorithm repeats steps 3-7 to create a new generation of solutions.

Once the termination criteria are met, the algorithm returns the best solution found throughout the evolutionary process. This solution represents the optimal or near-optimal solution to the optimization problem based on the defined fitness function. By iteratively evolving populations of solutions through selection, crossover, and mutation, genetic algorithms efficiently search for optimal or near-optimal solutions to a wide range of optimization problems.

IV. Computatioal results and discussions

In this work, ELD problems of two test system have been analysed using GA and the effect of population size on the performance of GA has also been discussed. Test system 1 comprises of 3 generators while Test system 2 comprises of 6 generators. The load demand of Test system 1 is 150 MW whereas for Test system 2 is 700 MW. The cost and loss coefficients data for Test system 1 [17] and Test system 2 have been presented in Table 1 and 2 respectively. For analysing the effect of population size, five population sizes (50, 100, 200, 500 and 1000) have been considered in the GA for both systems. 20 trial runs have been performed using MATLAB simulations [18] for each population and for both systems.

Table 1: Cost coefficients of the systems

		a ($/MW^2)	b ($/MW)	c ($)	P_{min} (MW)	P_{max} (MW)
Test System 1	G1	0.008	7	200	10	85
	G2	0.009	6.3	180	10	80
	G3	0.007	6.8	140	10	70
Test System 2	G1	0.007	7	240	100	500
	G2	0.0095	10	200	50	200
	G3	0.009	8.5	220	80	300
	G4	0.009	11	200	50	150
	G5	0.008	10.5	220	50	200
	G6	0.0075	12	120	50	120

Table 2: Loss coefficients of the systems

Test System 1	$B = \begin{bmatrix} 0.0218 & 0.0093 & 0.0028 \\ 0.0093 & 0.0228 & 0.0017 \\ 0.0028 & 0.0017 & 0.0179 \end{bmatrix}$ $B_0 = [0.0003 \quad 0.0031 \quad 0.0015]$ $B_{00} = 0.00030523$
Test System 2	$B = 10^{-4} \times \begin{bmatrix} 0.14 & 0.17 & 0.15 & 0.19 & 0.26 & 0.22 \\ 0.17 & 0.6 & 0.13 & 0.16 & 0.15 & 0.2 \\ 0.15 & 0.13 & 0.65 & 0.17 & 0.24 & 0.19 \\ 0.19 & 0.16 & 0.17 & 0.71 & 0.3 & 0.25 \\ 0.26 & 0.15 & 0.24 & 0.3 & 0.69 & 0.32 \\ 0.22 & 0.2 & 0.19 & 0.25 & 0.32 & 0.85 \end{bmatrix}$

The best result of 20 trial runs for different population have been presented in Table 3 for Test system 1 and Table 5 for Test system 2. Further, the fuel cost (best, average, worst and standard deviation), average power losses, average iteration performed, average computational time and number of trial runs attaining best result in 20 trial runes have been summarised for different population sizes have been displayed in Table 4 for Test system 1 and Table 6 for Test system 2. The convergence characteristics of GA for different populations and for both system have been shown in Fig. 1.

The best fuel cost of 1599.98 $/hr for Test system 1 has been obtained when population size is 1000 (also same for population size 500) with individual generators (G1, G2, and G3) output as 33.52 MW, 63.55 MW, and 55.59 MW respectively in 52 iteration (minimum among all population sizes). However, best fuel cost is 1599.99 $/hr for other population sizes i.e.50, 100, and 200 (see Table III).

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Similar observation can be seen for Test system 2 in which the best fuel cost is 8353.22 $/hr when population size is 1000 with individual generators (G1, G2, G3, G4, G5 and G6) output as 325.49 MW, 75.55 MW, 160.19 MW, 50.21 MW, 51.51 MW, and 50.31 MW respectively in 76 iteration (minimum among all population sizes).

From Table 4, it has been seen that for test 1 in 20 trial runs, the best cost is 1599.99 $/hr, the average fuel cost is 1600.39 $/hr, and the worst fuel cost is 1602.99 $/hr for a population size of 50. The calculated standard deviation is 0.73 $/hr. However, the average power loss is 2.67 MW, the average iteration performed is 104, and the average computational time is 4.76 seconds. Moreover, the minimum best cost is 1599.98 $/hr (for population size 500 and 1000), the minimum average cost is 1599.99 $/hr (for population size 1000), minimum worst cost is 1600.05 $/hr (for population size 500), minimum standard deviation cost is 0.02 $/hr (for population size 500), minimum average power loss is 2.66 MW (for population size 100), least average iteration performed is 52 (for population size 1000), least average computational time is 4.76 sec (for population size 50), and the highest number of trial runs attaining best result is 7 (for population size 1000). Similarly, for Test system 2 as shown in Table 6, the minimum best cost is 8353.22 $/hr (for population size 1000), the minimum average cost is 8354.79 $/hr (for population size 1000), minimum worst cost is 8358.74 $/hr (for population size 1000), minimum standard deviation cost is 1.47 $/hr (for population size 1000), minimum average power loss is 10.75 MW (for population size 500), least average iteration performed is 121 (for population size 1000), and least average computational time is 7.25 sec (for population size 50). Hence, overall it can be seen that the population size of 1000 can be regarded as the one having the best fuel cost because it provides best, consistent and precise result too as iteration performed is also very less.

Table 3: Best results for test system 1 in 20 trial runs

Population Size	Fuel Cost (in $/hr.)	Power Generation (in MW)			Power losses (in MW)	Iteration Performed	Computational Time (in second)
		G1	G2	G3			
50	1599.99	32.64	64.52	55.52	2.67	145	5.75
100	1599.99	33.27	63.85	55.55	2.66	54	3.81
200	1599.99	32.89	61.66	58.08	2.63	55	5.21
500	1599.98	33.58	63.92	55.17	2.67	60	10.65
1000	1599.98	33.52	63.55	55.59	2.66	52	17.61

Table 4: Summarized results for test system 1 in 20 trial runs

Population Size	Fuel Cost (in $/hr.)				Average Power losses (in MW)	Average Iteration Performed	Average Computational Time (in second)	Number of trial runs attaining best result
	Best	Average	Worst	Std Dev				
50	1599.99	1600.39	1602.99	0.73	2.67	104	4.76	1
100	1599.99	1600.20	1601.30	0.35	2.66	68	4.90	1
200	1599.99	1600.03	1600.23	0.07	2.67	72	7.26	6
500	1599.98	1600.00	1600.05	0.02	2.67	59	11.18	2
1000	1599.98	1599.99	1600.11	0.03	2.67	52	17.64	7

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Table 5: Best results for test system 2 in 20 trial runs

Population Size	Fuel Cost (in $/hr.)	Power Generation (in MW)						Power losses (in MW)	Iteration Performed	Computational Time (in second)
		G1	G2	G3	G4	G5	G6			
50	8359.29	335.65	59.91	159.07	51.89	52.85	51.33	10.70	270	10.90
100	8355.69	327.13	70.36	156.66	51.52	53.29	52.39	10.74	280	19.28
200	8353.67	322.04	75.75	161.09	50.12	51.19	50.57	10.77	205	31.32
500	8353.41	323.77	76.01	155.93	50.46	51.22	50.50	10.69	160	22.98
1000	8353.22	325.49	75.55	160.19	50.21	51.51	50.31	10.71	76	22.72

Table 6: Summarized results for test system 2 in 20 trial runs

Population Size	Fuel Cost (in $/hr.)				Average Power losses (in MW)	Average Iteration Performed	Average Computational Time (in second)	Number of trial runs attaining best result
	Best	Average	Worst	Std Dev				
50	8359.29	8440.87	8687.41	86.31	11.19	156	7.25	1
100	8355.69	8392.17	8601.61	54.78	10.98	153	9.89	1
200	8353.67	8373.54	8578.39	48.43	10.82	146	14.15	1
500	8353.41	8355.54	8362.59	2.63	10.75	145	22.73	1
1000	8353.22	8354.79	8358.74	1.47	10.76	121	38.56	1

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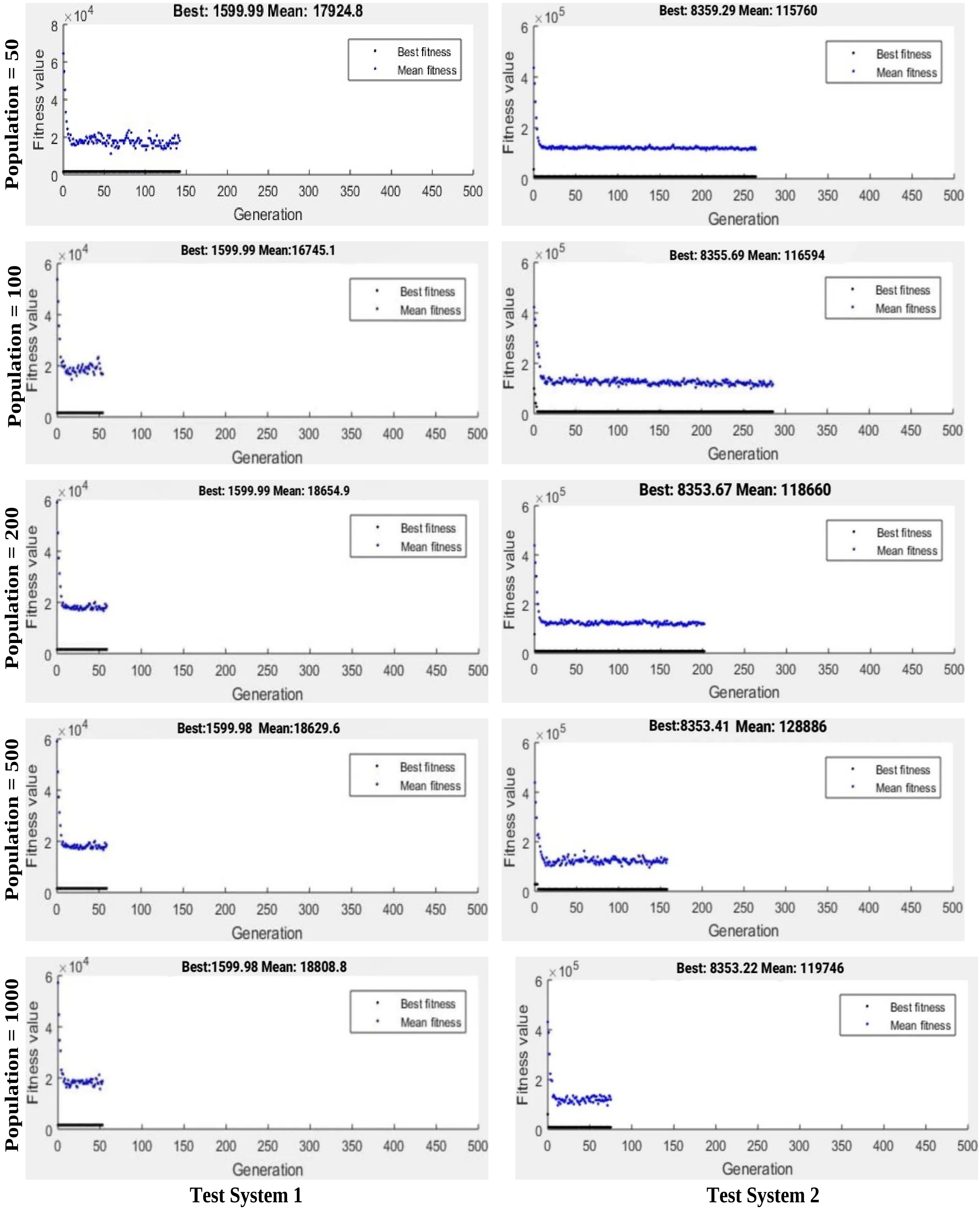

Figure 1: Convergence characteristics of GA for different populations

Table 7: Best population size on different basis

System	Best Result	Consistent Result	Précised Result	Less Iteration	Recommendations
Test System 1	500, 1000	500, 1000	200, 1000	500, 1000	1000
Test System 2	500, 1000	500, 1000	------	500, 1000	1000

In Table 7, two best population sizes of the GA for both Test system have been selected on different basis. The population size 500 and 1000 has been qualified on the basis of obtaining best results (having minimum best cost), consistent results (having minimum standard deviation cost), least iterations. However, population size 200 and 1000 for Test system 1 gives précised results (having highest number of trial runs attaining best results). Based on obtained results, population size of 1000 can be recommended for enhancing the performance of GA in context of obtaining best results, consistent results, and précised results in least iterations.

V. Conclusion

ELD are key optimization problem of the power industry and can be efficiently solved by GA technique. The population size in the GA has remarkable control on the performance of the technique. In this work, ELD of two systems have been solved by GA and the effect of population size on the performance of the GA has also analysed. Out of five considered population (50, 100, 200, 500, and 1000), the population of 1000 in the string provides efficient results in terms of optimal result, consistent result, précised and less iteration. Additionally, it can be also concluded that the higher the population in the GA algorithm gives better result in relatively less iteration. However, higher population increases the computation effort/time.

The effect of various parameters like crossover rate, mutation rate etc. on the GA performance can also be analyses in the future scope of the study. Moreover, the fitness function of the ELD can include some physical aspects such as valve point effects, emission costs etc. The renewable generators can also be considered for ELD operations.

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