PERFORMANCE COMPARISION OF GENETIC ALGORITHM AND PARTICLE SWARM OPTIMIZATION FOR SOLVING ECONOMIC LOAD DISPATCH PROBLEMS

Dr. Nimish Kumar, Assistant Professor, Dept. of EEE, Bakhtiyarpur College of Engineering, Bakhtiyarpur, Bihar, India.
Sonal Kumari, Niharika Rani, Unnati Kiran, Preyashi Kumari, UG Student, Dept. of EEE, Bakhtiyarpur College of Engineering, Bakhtiyarpur, Bihar, India.
Mr. Santosh Kumar, Assistant Professor, Dept. of ME, Government Engineering College, Buxar, Bihar, India.
Mr. Sudarshan, Assistant Professor, Dept. of ME, Bakhtiyarpur College of Engineering, Bakhtiyarpur, Bihar, India.

ABSTRACT
Economic Load Dispatch (ELD) in the power sector runs generators at a low cost of operation for a certain load while adhering to certain operational restrictions. The optimal generational combinations are assessed for the plant's cost-effective operations. Genetic Algorithm (GA) and Particle Swarm Optimization are most commonly employed optimization technique to identify the best generator output combination that minimizes plant costs. In this study, ELD operation of 3 generator system has been analyzed using both GA and PSO. Furthermore, an analysis has been conducted about the impact of population size on the efficacy of GA and PSO in addressing ELD. Fuel costs, power losses, and computational time in 10 trial runs have been analyzed for five population size (10, 20, 30, 50 and 100). The study found that PSO gives optimum results in less time and GA provides consistent results for each population.

Keywords: Economic Load Dispatch (ELD), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Operational cost.

Introduction
Economic load dispatch (ELD) deals with problems of complex power system in context of supplying required load demand at economical fuel cost by distributing load among participating generating units under certain constraints. Proper planning of connected unit outputs can contribute to considerable saving in the plant operating cost [1].
During past years variety of techniques are adopted for the analysis of ELD problems [2, 3]. Particle swarm optimization (PSO) and genetic algorithm (GA) are the two most popular techniques used for ELD problems. PSO is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality [4]. It solves a problem by having a population of candidate solutions, generally called particles, and moving these particles around in the search space according to simple mathematical formulae over the particle’s position and velocity [5-7]. However, GA is based on the ideas of natural selection and genetics. It is intelligent exploitation of random searches provided with historical data to direct the search into the region of better performance in solution space [8, 9].
Both the techniques have some advantages and disadvantages. GA tends to be more effective in problems with a large solution space and discrete variables, while PSO works better in problems with a continuous solution space and a smooth fitness landscape. Additionally, GA requires a larger population size and more computational resources compared to PSO. Additionally, various control parameters influence the performance of these techniques. The population size is a crucial parameter in both PSO and GA as it directly impacts the diversity, exploration, and convergence characteristics of the algorithm. Therefore, selecting an appropriate population size requires for desired balance between exploration and exploitation

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 8, No.2, August : 2024

In the present study, ELD problems of 3 generators system have been analysed using both PSO and GA. Moreover, the performance of both the techniques has been discussed. Additionally, the effect of population size has also been analyzed. The rest of the sections of the work have been organized as follows: Section II describes the formulation of the fitness function of the ELD. Section III deals the basics of PSO and 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.

Fitness function

In ELD, the main objective is to determine the power generation of each unit of the plant so that the production/fuel cost is minimum and also fulfilling the required power demand of load under given equality and inequality constraint [10].

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,

$$F_i(P_i) = a_iP_i^2 + b_iP_i + c_i \qquad (1)$$

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 (F_T) of the plant having n units will be,

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

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,

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

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,

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

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 [10] and it is represented mathematically as,

$$P_i^{min} < P_i < P_i^{max} \qquad (5)$$

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.

Particle swarm optimization and genetic algorithm

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique inspired by the social behavior of organisms such as bird flocking and fish schooling. It was originally proposed by Kennedy and Eberhart in 1995 and has since become a popular method for solving various optimization problems [5].

Steps for solving optimization problems using PSO:

1. Initialization: PSO starts with a population of randomly initialized particles in the search space. Each particle represents a potential solution to the optimization problem.
2. Fitness Evaluation: The fitness (quality) of each particle is evaluated based on the objective function of the problem being optimized. This function guides the particles towards optimal solutions.
3. Velocity Update: Each particle adjusts its velocity based on its own best-known position (personal best) and the swarm's best-known position (global best). This adjustment is influenced by two main factors:

- Cognitive Component: Encourages a particle to move towards its personal best position.
- Social Component: Directs a particle towards the global best position found by any particle.

4. Position Update: After updating velocities, particles adjust their positions accordingly. This movement allows particles to explore the search space dynamically.
5. Iteration: Steps 3 and 4 are repeated iteratively until a termination condition is met, such as a maximum number of iterations or the achievement of a satisfactory solution.

Genetic Algorithms (GAs) are heuristic optimization techniques that emulate biological evolution. They harness the principles of natural selection and genetics to solve complex combinatorial optimization problems [8]. The core idea is to model potential solutions to a problem as chromosomes, composed of genes that represent decision variables or components of the solution. These chromosomes form an initial population, where each is evaluated based on a fitness function that quantifies its quality relative to the problem's objectives.

Steps for solving optimization problems using GA:

1. Initialization: Start with an initial population of randomly generated chromosomes.
2. Evaluation: Evaluate the fitness of each chromosome using the fitness function.
3. Selection: Choose chromosomes from the current population based on their fitness.
4. Crossover: Apply crossover to selected chromosomes to produce offspring.
5. Mutation: Introduce random changes (mutation) in offspring chromosomes.
6. Replacement: Replace the current population with the new generation of offspring.
7. Termination: Repeat the process for a fixed number of generations or until a termination condition is met (e.g., achieving a satisfactory fitness level).

Computational results and discussions

In this paper, ELD problem of 3 generator test system has been solved using GA and PSO and the performance of PSO and GA has been analysed based on population size. The demand of load for this test system is 150 MW. The table for cost and loss coefficient of the system is presented in table 1 [11]. For performance comparison of PSO and GA, five population sizes i.e. 10, 20, 30 50 and 100 has been considered. Ten trial runs have been performed using MATLAB programming for each population [12, 13]. The best results of each population for GA in 10 trial runs have been presented in table 2. Similarly, the best results for each population for PSO in 10 trial runs have been displayed in table 4. Moreover, the fuel cost on different basis (i.e. best, average and worst) for different mentioned populations for 10 trial runs for GA is specified in table 3. Similarly, the fuel cost on different basis (i.e., best, average and worst) for different specified populations for 10 trial runs for PSO is presented on table 5. The most optimum fuel cost which is best fuel cost of 1599.99 \$/hr for 3 generator test system for GA has been attained when population size is 30 with individual contributed generators (G1, G2 and G3) output as 33.52 MW, 63.62 MW and 55.52 MW respectively. The total computational time required to obtain this fuel cost is 7.16 seconds and the total power loss for the fuel cost of 1599.99 \$/hr is 2.66 MW. Besides, the fuel cost for other population sizes i.e., 10, 20, 50 and 100 has been exhibited on the table 2.

Similarly, the best fuel cost for 3 generators test system using PSO is 1599.05 \$/hr which has been attained when population size is 20. For this fuel cost the output from contributed generators are 42.22 MW, 62.96 MW and 47.25 MW respectively. The total computational time required for obtaining this fuel cost by using PSO is 0.92 seconds and the total power loss is 2.40 MW respectively. The furthermore details about different population sizes (i.e., 10, 30, 50 and 100) is presented on table 4 i.e., best results for each population of PSO in 10 trial runs. Table 3 present the summarized results for each population of GA in 10 trial runs. From table 3, it has winded up that the best fuel cost is 1600.02 \$/hr , the average fuel cost is 1601.96 \$/hr and the worst fuel cost is 1604.51\$/hr for the population size of 10. The evaluated standard deviation 1.82 \$/hr . Furthermore, the average power losses during this population size 2.73MW and the average computational time is 2.48 seconds. Additionally, the analyzed least best fuel cost is 1599.99\$/hr which is obtained when population size is 30 and this is the minimum from all the fuel cost which has been procured. Similarly, the minimum average fuel cost is 1600.4\$/hr (obtained from the population size of 100) and the minimum worst fuel cost is 1600.43\$/hr (obtained from the population size 100), the minimum calculated standard deviation is 0.15 (for the population size of 100), the minimum average power losses is 2.64MW (obtained from the population size of 30 and the minimum computational time i.e., 2.48 seconds is got from the population size of 10.

Moreover, table 5 present summarized result for each population of PSO in 10 trial runs. From table 5, the optimum results obtained for the population size of 10 are obtained as the best fuel cost is 1597.73 \$/hr , the average fuel cost is 1613.48 \$/hr and the worst fuel cost is 1632.13\$/hr. Additionally, for the population size of 10 the calculated standard deviation is 12.69, the average power losses is 2.61 MW and the average computational time is 0.93 seconds. Further, the analyzed the least best fuel cost is 1597.73\$/hr which is obtained when population size is 100 and this is the minimum from all the fuel cost which has been procured. Similarly, the minimum average fuel cost is 1598.44\$/hr (obtained from the population size of 100) and the minimum worst fuel cost is 1600.21\$/hr (obtained from the population size 100), the minimum calculated standard deviation is 0.83 (for the population size of 100), the m1inimum average power losses is 2.19MW (obtained from the population size of 30 and the minimum computational time i.e., 0.93 seconds is got from the population size of 10. So, on the sum up it has been analyzed that for the population size of 100 provided us with the best, average and worst fuel cost with all the other data included such as standard deviation, average power losses and average computational time. Into the interior of the problem of 3 generator test system which has been evaluated using optimization technique which are GA and PSO, table 6 (i.e., best population sizes on different basis) provide us the additional data which include best result, consistent result and computational effort. In case of GA, best result is obtained when the population sizes are 30 and 100 and the consistent result is obtained when population sizes are 50 and 100. The computational effort is considered to be efficient when the population sizes are 10 and 20. Generally, the computational effort is regarded to be as minimum as possible. Now, when PSO is taken in consideration best result is obtained when population sizes are 50 and 100. Similarly, the consistent result is obtained when population sizes are 50 and 100. Along with the computational effort calculated is considered to be best when population sizes are 10 and 30.

Table 1: Cost and loss coefficients of the system

<table>
<tr><th rowspan="2"></th><th colspan="3">Cost Coefficients</th><th rowspan="2">Pmin (MW)</th><th rowspan="2">P_{max} (MW)</th><th>Loss Coefficients</th></tr>
<tr><th>a ($/MW^2)</th><th>b ($/MW)</th><th>c ($)</th><td rowspan="3">$B = \begin{bmatrix} 0.0218 & 0.0093 & 0.0028 \\ 0.0093 & 0.0228 & 0.0017 \\ 0.0028 & 0.0017 & 0.0179 \end{bmatrix}$
$B_0 = \begin{bmatrix} 0.0003 & 0.0031 & 0.0015 \end{bmatrix}$</td></tr>
<tr><td>G1</td><td>0.008</td><td>7</td><td>200</td><td>10</td><td>85</td></tr>
<tr><td>G2</td><td>0.009</td><td>6.3</td><td>180</td><td>10</td><td>80</td></tr>
</table>

G3	0.007	6.8	140	10	70	$B_{00} = 0.00030523$

Table 2: Best results for each population of GA in 10 trial runs

Population Size	**Fuel Cost (in \$/hr.)**	**Power Generation (in MW)**			**Power losses (in MW)**	**Computational Time (in second)**
		G1	**G2**	**G3**		
10	1600.02	32.64	64.52	55.52	2.68	2.75
20	1600.01	33.79	64.99	53.91	2.68	2.24
30	1599.99	33.52	63.62	55.52	2.66	7.16
50	1600.11	31.93	62.55	58.16	2.64	6.95
100	1600.00	33.14	65.26	54.28	2.69	6.34

Table 3: Summarized results for each population of GA in 10 trial runs

Population Size	**Fuel Cost (in \$/hr.)**				**Average Power losses (in MW)**	**Average Computational Time (in second)**
	Best	**Average**	**Worst**	**Std Dev**		
10	1600.02	1601.96	1604.51	1.82	2.73	2.48
20	1600.01	1601.72	1603.99	1.50	2.71	2.59
30	1599.99	1600.77	1603.05	0.92	2.64	5.24
50	1600.11	1600.98	1602.40	0.70	2.67	5.31
100	1600.00	1600.14	1600.43	0.15	2.67	5.97

Table 4: Best results for each population of PSO in 10 trial runs

Population Size	**Fuel Cost (in \$/hr.)**	**Power Generation (in MW)**			**Power losses (in MW)**	**Computational Time (in second)**
		G1	**G2**	**G3**		
10	1599.26	42.77	63.28	46.39	2.41	1.01
20	1599.05	42.22	62.96	47.25	2.40	0.92
30	1598.13	27.30	67.12	57.96	2.35	0.93
50	1597.76	34.06	63.02	55.10	2.33	0.96
100	1597.73	32.66	65.31	54.41	2.35	0.95

Table 5: Summarized results for each population of PSO in 10 trial runs

Population Size	**Fuel Cost (in \$/hr.)**				**Average Power losses (in MW)**	**Average Computational Time (in second)**
	Best	**Average**	**Worst**	**Std Dev**		
10	1599.26	1613.48	1632.13	12.69	2.61	0.93
20	1599.05	1608.76	1624.90	8.79	2.46	0.94
30	1598.13	1601.32	1611.97	4.33	2.19	0.93
50	1597.76	1600.11	1608.20	3.23	2.36	0.94
100	1597.73	1598.44	1600.21	0.83	2.35	0.96

Table 6: Best population size on different basis

Optimization Techniques	**Best Result**	**Consistent Result**	**Computational Effort**	**Recommendations**
GA	30, 100	50, 100	10, 20	100
PSO	50, 100	50, 100	10, 30	100

Table 7: Best optimization technique on different basis

Population Size	Best Result	Consistent Result	Computational Effort	Recommendations
10, 20, 30, 50, and 100	PSO	GA	PSO	PSO

Table 7 provides the best optimization technique on different basis. Best fuel cost of 1597.73 $/hr has been obtained in case PSO for population size 100. Moreover, less standard deviation cost of 0.15 $/hr has been found in case of GA for population size 100. Additionally, least average computational time of 0.93 second has been observed in case PSO for population size 10 and 30. Therefore, PSO gives best results in less computational effort.

Conclusions and future scopes

The Economic Load Dispatch (ELD) Problem aims to allocate generation levels to various thermal units to meet a specific load demand at the minimum operational cost while satisfying system constraints. Traditional optimization method often struggle with the non-linear and non–convex nature of the ELD problem, leading to the exploration of advanced techniques such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). This paper explores the application of GA and PSO for solving the ELD problem, comparing their effectiveness and efficiency. In this study, ELD of 3 generators system have been determined using GA and PSO with five population sizes (10, 20, 50, 100 and 200). The effect of population size on the performance of GA and PSO for solving ELD problem has also been determined. The study found that PSO gives optimum results in less time and GA provides consistent results for each population.

In the future, the study's scope may also include an analysis of the impact of several factors on the GA performance (such as crossover rate and mutation rate) and PSO performance (such as inertia weight, acceleration coefficients). Additionally, the ELD's fitness function may incorporate some physical elements like emission costs and valve point impacts. For ELD operations, the renewable generators can also be taken into account..

References

[1] Kumar, N; Kumari, S; Rani, N; Kiran, U; Kumari, P; Kumar, S. Effect of population size on the performance of genetic algorithm for solving economic load dispatch problems. Industrial Engineering Journal 2024, 53(6), 108-116.
[2] Sahay, K.B; Kumar, N. ELD Operation of 26 Bus System using Global Optimization Techniques. Journal of Green Engineering 2020, 10, 11, 12687-12698.
[3] Sahay, K.B; Kumar, N; Triapthi, M.M. Implementation of Different Optimization Techniques to Solve ELD Problem. Proc. IEEE Int. Conf. Power India, 1-6, Dec., 2014.
[4] Papazoglou, G; Biskas, P. Review and Comparison of Genetic Algorithm and Particle Swarm Optimization in the Optimal Power Flow Problem. Energies 2023, 16, 1152.
[5] Kumar, N; Nangia, U; Sahay, K.B. Economic load dispatch using improved particle swarm optimization algorithms. Proc. IEEE Int. Conf. Power India, 1-6, Dec. 2014.
[6] Kumar, N; Pal, N; Kumar, P; Kumari, A. Impact of different inertia weight functions on particle swarm optimization algorithm to resolve economic load dispatch problems. Proc. IEEE 4th Int. Con. on Recent Advances in Information Technology, 1-5, 2018.
[7] Kumar, N; Saha, P.K; Pal, N; Kumari. N. Effect of Modulation Index of Nonlinearly Decreasing Inertia Weight on the Performance of PSO Algorithm for Solving ELD Problems. Advances in Smart Grid Automation and Industry 4.0: Select Proceedings of ICETSGAI4.0, 767-775, 2021.
[8] Cheng, D. et al. Optimal Economic Dispatch Strategy of a Hybrid Energy Storage Microgrid Based on Genetic Algorithm. 2023 IEEE 18th Conference on Industrial Electronics and Applications (ICIEA), Ningbo, China, 2023, 1776-1779.

[9] Yu, C; Chen, C; He, L; Tan, Z; Zhong, B. Economic Optimal Scheduling of Microgrid Based on Improved Genetic Algorithm. 2023 42nd Chinese Control Conference (CCC), Tianjin, China, 2023, 7182-7187.
[10] C. L. Wadhwa, Electrical Power Systems, Fourth Edition, New Age International, 2009.
[11] H. Saadat, Power System Analysis, Example 7.8, WCB/McGraw-Hill, 1999.
[12] RMS Danaraj (2024). Genetic Algorithm Solution to Economic Dispatch (https://www.mathworks.com/matlabcentral/fileexchange/20825-genetic-algorithm-solution-to-economic-dispatch), MATLAB Central File Exchange. Retrieved July 10, 2024.
[13] RMS Danaraj (2024). PSO solution to economic dispatch (https://www.mathworks.com/matlabcentral/fileexchange/20984-pso-solution-to-economic-dispatch), MATLAB Central File Exchange. Retrieved July 10, 2024.Ray, P.P. Internet of Things for smart agriculture: Technologies practices and future direction. J. Ambient. Intell. Smart Environ. 2017, 9, 395–420.