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Economic Load Dispatch Using PSO and TLBO Algorithm

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Abstract – *Economic Load Dispatch (ELD) is a key optimization problem used in power systems to schedule the generation such that network constraints drawn from transmission capability, generation strengths and load demands among other aspects are met efficiently and production costs incurred are minimal. As has been mentioned before, data on generator input-output curves are non-linear and non-convex; therefore, ELD is not easy for traditional optimization. For these challenges, the present work proposes advanced techniques among which are Dynamic Programming (DP), Teaching-Learning Based Optimization (TLBO), and Particle Swarm Optimization (PSO). In this research, MATLAB environment was used to perform a number of evaluations to determine the performance of these algorithms. The results also state the potential of these approaches for practical power system dispatch by demonstrating their applicability of providing approximated optimal solutions for complex* ELD.

Keywords- *Teaching learning-based optimization, Particle swarm optimization, Economic load dispatch, and Network constraints*

INTRODUCTION

As a critical optimization problem in power system operations the optimal dispatch of economic load came out as an important subject in order to minimize total generation costs while fulfilling the load demands and under constraints. Based on advanced optimization techniques such as Particle Swarm Optimization (PSO) and Teaching-Learning-Based Optimization (TLBO),

ELD issues were solved efficiently. As Hybrid and adaptive controller design has been incorporated lately the use of PSO & TLBO for ELD has been brought into use. For that reason, it is worth to notice the hybrid PSO-TLBO models enhancing the convergence velocity and solution richness and reducing the chances for premature convergence. Besides, they also offer enhanced scalability with large- scale networks which are cases where so many generators are in place.

The authors of article [1] made a comprehensive analysis of the application of PSO algorithms for dealing with different kinds of ELD problems in the field of power system engineering. PSO a well-known technique to solve the economic operation constraints of highly restricted power systems which are usually operating at minimum operating costs required to meet the load demands. Based on the classroom teaching and learning methodology, the technique of TLBO is then applied and is tested with other optimization algorithms on several power systems. The results show that TLBO can easily solve the environmental problems because it has no complex algorithm, either directly when sampled from the ELD using standard industry tools like Power World or indirectly.

Authors in [2] applied bio-inspired algorithms, PSO and TLBO to the ELD problem. In order to compare the necessities of fuel, four networks were employed and the model put into test takes 3, 6, 15, & 20 generator units with different loads. In the case of the lambda iteration method, the usage of both PSO and TLBO results were compared. More specifically, the problems have been solved with and without the consideration of line losses for Various load demands. Despite, both methods were carefully analyzed, and the whole optimization process was performed based on the calculation of the total fuel cost as the fitness function.

In [5], authors were the work which, the researchers attempted to view the Pollution of Particle Reference Optimization (PSO) algorithm and its supply sustainable water resources engineering which include; water reservoir operation, runoff modelling and water quality. They compared 22 PSO and other PSO variants to the mathematical processes of the genetic algorithms and support vector machine. The three superiority characteristics of the PSO types mentioned in the review included the capability to provide better optimum solutions in terms of faster convergence time to arrive at the optimum solutions, the quality of the optimum solution and the variability factors. The authors of article [6] describe- a new solution to the problem referred to as improvement of the original Fractional Particle Swarm Optimization Gravitational Search Algorithm (FPSOGSA) to the optimal reactive power dispatch (RPD) of the power systems. The styling of the FPSOGSA is done on the basis of the summation of the first power of the fractional element in the damping coefficient of the eigen value matrix and applied for the optimization of the power systems.

In Article [7], a technique called Teaching-Learning-Based Optimization (TLBO) is introduced with an intention to dissolve to an advanced version known as Teaching-Learning Studying Based Optimizer (TLSBO) that can facilitate the energy management in AC-HVDC power grids. The experiment reveals that compare to TLBO and all other methods, TLSBO has achieved more optimum measures as well as, faster rate of convergence, not only this, more importantly, on IEEE 30-bus, 57-bus, 118-bus systems have obtained better and far more efficient result and most importantly, it is more robust. Article [8] is a source that discuss about the teaching learning-based optimization TLBO algorithm to solve the ELD problem in today's generation power plants.

Authors of [9] This is research aimed at power systems economic dispatch to minimize costs and to operate at a higher efficiency level while taking into account such issues as the aging infrastructure and pollutants. He approaches this difficult problem by using Particle Swarm Optimization (PSO) on IEEE 14-bus and 30-bus test systems and then compares the results to a Genetic Algorithm (GA). Article in [10] the main focus is on the enhanced social network search (ESNS) method for solving the Economic Load Dispatch (ELD) problem, which as a matter of fact is intended to minimize the power system running cost. The ESNS algorithm brightens the search extension of the present social network search (SNS) approach plus eludes local optima. When applied on benchmarking systems, it breaks many conjectures, nonlinear, and nonconvex problems, has been commonly applied in the power systems industry. The review organized the studies into five significant categories: single-objective economic load dispatch, dynamic economic load dispatch, economic load dispatch that employs non-conventional energy sources, multi-objective energy and economic dispatch, economic load dispatch in microgrids.

PROBLEM FORMULATION

The basic objective of the ELD problem is to select the most desirable power generation which would cause minimum total fuel cost and at the same time fulfill the system load demand which is necessary for the system. The problem is established as:

Fuel Cost Function

The fuel cost for each generator is modeled as a quadratic function of its output power:

$$Ci\,(Pg) = aiP2\mathrm{gi} + biPgi + c$$

Emission Function

The emissions from each generator are modeled as a quadratic function of its output power:

$$Ei\,(Pgi) = \alpha i + \beta iPgi + \gamma iP2gi$$

$\alpha i, \beta i, \gamma i$ are the emission coefficients for the i- th generator

Power Loss Model

The system power losses are calculated:

$$Ploss = \lambda.\,(\sum P)\,2$$

Power Balance

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The total power generated should meet the load demand as:

$$P_{demand} = \sum P + P_{loss}$$

Constraints

Each generator has a minimum and maximum power output:

$$P_{min} \leq P_{gi} \leq P_{max}$$

Optimization Goal

The goal is to minimize the total fuel cost while considering the power balance and emission constraints:

$$Minimize\ Z = \sum_{i=1}^{n} C_i(P_{gi})$$

Total System Cost and Emission

$$Total\ Cost = \sum_{i=1}^{n} C_i\ (P_{gi})$$

$$Total\ Emission = \sum_{i=1}^{n} E_i\ (P_{gi})$$

PSO Formulation

When it comes to Particle Swarm Optimization (PSO), actually the method is based on the population of so-called particles (candidates for solution). Every particle moves in response to its personal experience of the local environment as well as best-known position of the group. The problem formulation for PSO generally includes the following:

$$P^{k+1} = P^k + v^{k+1}$$

$$v^{k+1} = w.\ v^k + c1\ .\ r1\ .\ 7(Pi,\ best - P^k) + c2.\ r2\ .\ (Pbest - P^k)$$

TLBO Formulation

Teaching-Learning-Based Optimization (TLBO) is another metaheuristic algorithm similarly like the GTLS proposed on the notion of the teaching-learning process in classroom. In TLBO, solutions are treated in a way that the best solution amongst all is treated as the 'teacher'. The algorithm advances the solution by corresponding with the teacher and other students to get better positions on the solution space

$$X^{k+1} = X^k \quad + \ \alpha.(X^k \quad - \ X^k)$$

$$X^{k+1} = X^k + \beta.(X^k - X^k)$$

It is evident that PSO and TLBO are efficient algorithms of optimization designed for non-linear and constrained problems, including Economic Load Dispatch. Whereas, PSO gives significance to the social behavior by including the dynamic velocity updates, the TLBO on the other hand relies on deterministic teaching learning mechanism for enhancing the population. The selection of these methods depends with certain problem related criteria such as computational complexity and the rate of convergence.

METHODOLOGY

Being one of the most essential optimization problems in power systems, the ELD aims at minimizing the overall fuel costs in addition to meeting the load demand needs of the entities as well as the constraints of the generator technologies and the systems themselves. There exist numerous meta-heuristic techniques for solving ELD of which Particle Swarm Optimization (PSO) and Teaching– Learning –Optimization (TLBO) are common methods owing to the fact that they are effective in handling non- linear non-convex multimode problems. In PSO, each solution is represented by a particle to search for the solution space in the form of swarm. With their cognition component, these particles search the areas affected by experience and with the social component – the experience of the entire swarm. Both velocity and position of particle are updated to reach the global optima solution in MAS. Due to inherent ness of PSO, it can be made an alternative of preference.

A. Teaching-Learning-Based Optimization (TLBO) algorithm

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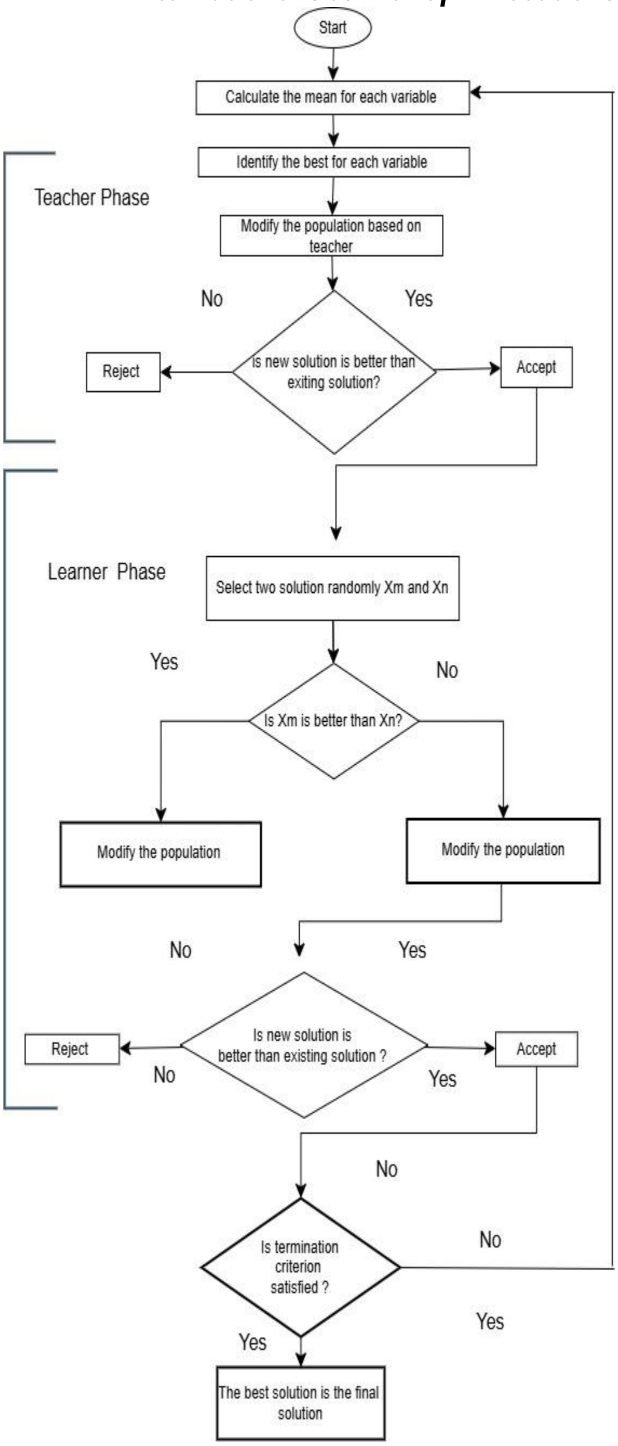

Fig.1 – TLBO Algorithm

In PSO each particle is a candidate solution and searches the solution space in the population of particles. Explorations of these particles happen in the search space which include the particles' cognitive knowledge and the knowledge of the swarm. This is done in each iteration, until they find the global optimum solution of a given function for velocity and position of each particle. Therefore, PSO which is easy to handle and able to solve complex problem formulation of ELD is the most preferable method, but excessive tweaking of the factors and parameters such as inertia weight and learning factors must be done judiciously to maintain a synthesis

B. Particle Swarm Optimization (PSO)

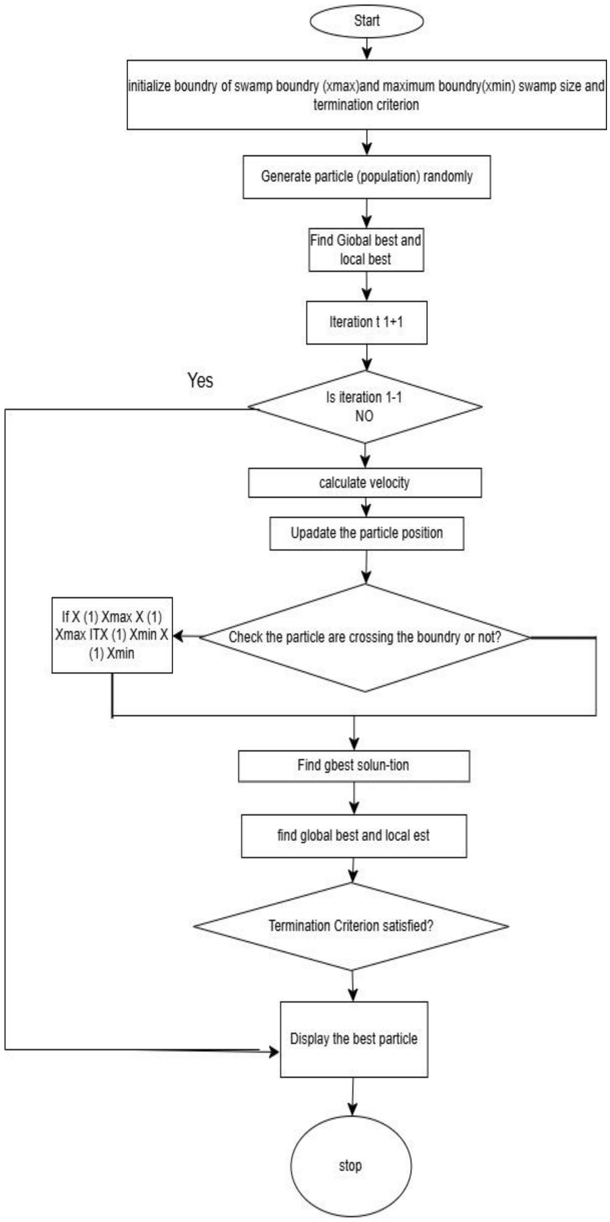

Fig.2 – PSO Algorithm

The above two methods also have their strengths and weaknesses; PSO is a stochastic method and therefore best suited for large search space, TLBO on the other hand is a deterministic method and often has best convergence and consistency. Adapting or transformation of these methods has also been studied to utilize these manners to select the most effective means in solving difficult ELD issues.

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RESULT & DISCUSSION

Case 1: 6 Generator system

Table 1: Generating Cost Function

Generator No.	a	b	c	$P_g$max (MW)	$P_g$min (MW)	α	β	γ	ξ	λ
1	10	200	100	150	5	4.091	-5.543	6.490	2.0e-4	2.857
2	10	150	120	150	5	2.543	-6.047	5.638	5.0e-4	3.333
3	20	180	40	150	5	4.258	-5.094	4.586	1.0e-6	8.000
4	10	100	60	150	5	5.326	-3.550	3.380	2.0e-3	2.000
5	20	180	40	150	5	4.258	-5.094	4.586	1.0e-6	8.000
6	10	150	100	150	5	6.131	-5.555	5.151	1.0e-5	6.667

The comparison of fuel costs for a 6-generator system using the Base Case Method, Particle Swarm Optimization, and Teaching- Learning-Based Optimization reveals significant differences in performance

Table 2: Result of Fuel cost for 6 generator system

Generating Unit	Base Case method	PSO	TLBO
Generator 1	24,908,300	10005.09	10014.32
Generator 2	17,947,640	7920.43	7932.09
Generator 3	23,636,922	12469.27	12485.87
Generator 4	13,143,808	7060.23	7101.30
Generator 5	29,056,640	9158.69	9165.09
Generator 6	17,541,102	7495.86	7505.86

The Base Case Method, while a traditional and reliable approach for economic dispatch, produces the highest fuel costs across all generators due to its inability to handle complex, non-linear optimization problem efficiently.

In contrast, PSO and TLBO achieve significantly lower fuel costs, with TLBO slightly outperforming PSO in most cases. For instance, Generator 1 shows a fuel cost of Rs. 10005.09 with PSO and 10014.32 with TLBO, both significantly lower than the Base Case Method cost of 24,908,300. Similar trends are observed across the other generators, where TLBO consistently achieves more efficient results.

This comparison underscores the advantages of metaheuristic methods like PSO and TLBO over traditional approaches. TLBO's two-phase teaching and learning mechanism appears particularly effective in finding optimal solutions, making it a more robust method for fuel cost optimization in power generation systems

	PSO	TLBO
Fuel Cost (Rs)	54,130.95	51,253.21
Emission (ton)	0.2248	0.1955
System loss (MW)	2.8758	1.7154

The comparison between Particle Swarm Optimization and Teaching-Learning-Based Optimization methods reveals that TLBO outperforms PSO in minimizing fuel costs, emissions, and system losses in power generation. TLBO achieves a significantly lower

fuel cost of ₹51,253.21 compared to ₹54,130.95 with PSO, indicating greater efficiency. Additionally, TLBO reduces emissions to 0.1955 tons, which is more environmentally friendly than the 0.2248 tons produced by PSO. Furthermore, system losses are notably lower with TLBO at 1.7154 MW, compared to 2.8758 MW for PSO, reflecting better resource utilization and operational efficiency. These results demonstrate that TLBO is a more effective optimization method for

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economic and environmental performance in power system

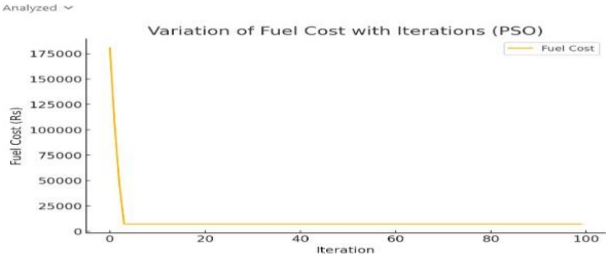

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Fig.3 – Graph showing the variation of power losses with iteration using PSO

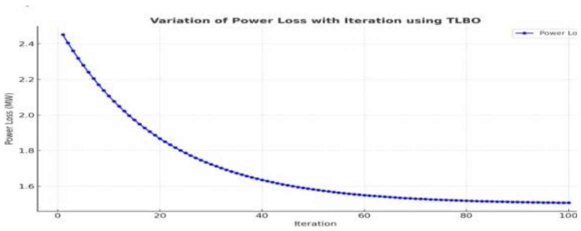

Fig.4 – Group showing the variation of power losses with iteration using TLBO

Case 2: 40 bus generator unit

Table 3 - Fuel Cost Comparison for PSO and TLBO

Generating Unit	Base Case	Using PSO	Using TLBO
Generator 1	66210678.44	145814543.7	129369107.67
Generator 2	66210677.44	134670453.6	117185179.22
Generator 3	116164503.9	114336461.5	86581795.31
Generator 4	103492745.8	97319144.37	82569589.21
Generator 5	82600877.94	84246824.66	65778389.56
Generator 6	104817961.9	68620716.20	51167477.32
Generator 7	122128715.4	61473489.60	42516881.12
Generator 8	99632376.26	56925964.96	32616102.24
Generator 9	90945657.26	53793877.21	27404588.80
Generator 10	71220802.05	49602291.20	23769361.85
Generator 11	75864177.79	48341547.17	21615473.25
Generator 12	74723829.95	47909146.23	21299738.46
Generator 13	64197236.13	47888394.54	19945251.56
Generator 14	51380353.73	47861691.68	18688033.07
Generator 15	51637064.55	47837220.13	17449016.63
Generator 16	51637063.55	47783051.01	17180670.36
Generator 17	75116214.38	47717639.27	16937333.96
Generator 18	75009845.99	47618779.46	16916550.34
Generator 19	75117371.86	47618779.46	16904458.32
Generator 20	75118530.42	47618779.46	16904458.32
Generator 21	68516550.70	47358776.31	16904458.32
Generator 22	68516549.70	47358776.31	16904458.32
Generator 23	68182629.49	47358776.31	16904458.32
Generator 24	68182628.49	47358776.31	16904458.32
Generator 25	67923134.98	47358776.31	16904458.32
Generator 26	67923133.98	47358776.31	16904458.32
Generator 27	60619665.84	47358776.31	16904458.32
Generator 28	60619663.84	47358776.31	16904458.32
Generator 29	82600852.94	47358776.3	16904458.32
Generator 30	104995520.9	47358776.3	16904458.32
Generator 31	104995519.9	47358776.3	16904458.32
Generator 32	104995518.9	47358776.3	16904458.32
Generator 33	70194278.93	47358776.3	16904458.32
Generator 34	72828871.43	47358776.3	16904458.32
Generator 35	72828870.43	47358776.3	16904458.32
Generator 36	116698820.6	47358776.3	16904458.32
Generator 37	116698819.6	47358776.3	16904458.32
Generator 38	116698818.6	47358776.3	16904458.32
Generator 39	75117350.86	47358776.3	16904458.32
Generator 40	75117350.86	47358776.3	16904458.32

Based on the data (as provided in Appendix), TLBO demonstrates superior performance over PSO in terms of fuel cost minimization. TLBO consistently achieves lower fuel costs across generating units compared to PSO, indicating its higher efficiency.

This is particularly evident in both the 6-generator system and the 40-generator system, where TLBO outperforms PSO by reducing overall operational costs.

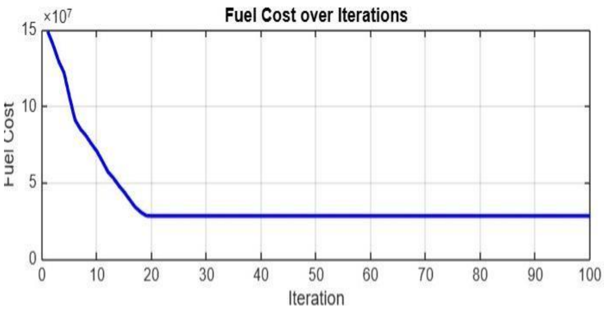

Fig.5 – Graph showing the variation of fuel cost with iteration using PSO

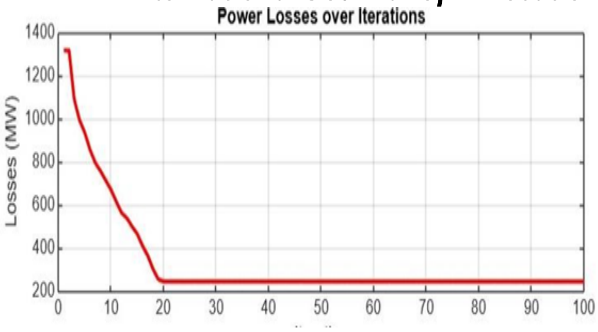

Fig.6 – Graph showing the variation of power losses with iteration using PSO

REFERENCES

[1] *Said, Mokhtar, Essam H. Houssein, Sanchari Deb, Rania M. Ghoniem, and Abeer Galal Elsayed. "Economic load dispatch problem based on search and rescue optimization algorithm." IEEE Access 10 (2022): 47109-47123.*

[2] *Abdi, Hamdi, Ehsan Dehnavi, and Farid Mohammadi. "Dynamic economic dispatch problem integrated with demand response (DEDDR) considering non-linear responsive load models." IEEE Transactions on Smart Grid 7, no. 6 (2015): 2586-2595.*

[3] *Chinnadurrai, C. L., and T. Aruldoss Albert Victoire. "Dynamic economic emission dispatch considering wind uncertainty using non- dominated sorting crisscross optimization." Ieee Access 8 (2020): 94678-*

[4] *94696.Khan, Noor Habib, Yong Wang, De Tian, Muhammad Asif Zahoor Raja, Raheela Jamal, and Yasir Muhammad. "Design of fractional particle swarm optimization gravitational search algorithm for optimal reactive power dispatch problems." IEEE Access 8 (2020): 146785-146806.*

[5] *Sakthivel, V. P., Hui Hwang Goh, Subramanian Srikrishna, P. D. Sathya, and Sharul Kamal Abdul Rahim. "Multi-objective squirrel search algorithm for multi-area economic environmental dispatch with multiple fuels and valve point effects." IEEE Access 9 (2020): 3988-4007.*

[6] *Saddique, Muhammad Shahzar, Salman Habib, Shaikh Saaqib Haroon, Abdul Rauf Bhatti, Salman Amin, and Emad M. Ahmed. "Optimal solution of reactive power dispatch in transmission system to minimize power losses using sine-cosine algorithm." IEEE Access 10 (2022): 20223-20239.*

[7] *Meraihi, Yassine, Asma Benmessaoud Gabis, Seyedali Mirjalili, and Amar Ramdane-Cherif. "Grasshopper optimization algorithm: theory, variants, and applications." Ieee Access 9 (2021): 50001-50024.*

[8] *Shaheen, Abdullah M., Ahmed Rabie Ginidi, Ragab A. El-Sehiemy, and Sherif SM Ghoneim. "Economic power and heat dispatch in cogeneration energy systems using manta ray foraging optimizer." IEEE Access 8 (2020): 208281-208295.*

[9] *Rugema, Francois Xavier, Gangui Yan, Sylvere Mugemanyi, Qi Jia, Shanfeng Zhang, and Christophe Bananeza. "A cauchy-Gaussian quantum-behaved bat algorithm applied to solve the economic load dispatch problem." IEEE Access 9 (2020): 3207-3228.*

[10] *Farh, Hassan MH, Abdullah M. Al-Shaalan, Ali Mohamed Eltamaly, and Abdulrahman A. Al-Shamma'A. "A novel crow search algorithm auto-drive PSO for optimal allocation and sizing of renewable distributed generation." IEEE Access 8 (2020): 27807-27820.*

[11] *Ebeed, Mohamed, Abdelfatah Ali, Mohamed I. Mosaad, and Salah Kamel. "An improved lightning attachment procedure optimizer for optimal reactive power dispatch with uncertainty in renewable energy resources." IEEE Access 8 (2020): 168721-168731.*

[12] *Liaquat, Sheroze, Muhammad Salman Fakhar, Syed Abdul Rahman Kashif, Akhtar Rasool, Omer Saleem, and Sanjeevikumar Padmanaban. "Performance analysis of APSO and firefly algorithm for short term optimal scheduling of multi-generation hybrid energy system." IEEE Access 8 (2020): 177549-177569.*

[13] *Deb, Sanchari, Kari Tammi, Xiao-Zhi Gao, Karuna Kalita, and Pinakeswar Mahanta. "A hybrid multi-objective chicken swarm optimization and teaching learning-based algorithm for charging station placement problem." IEEE Access 8 (2020): 92573-92590.*

[14] *Ellahi, Manzoor, Ghulam Abbas, Gandeva Bayu Satrya, M. Rehan Usman, and Jason Gu. "A modified hybrid particle swarm optimization with bat algorithm parameter inspired acceleration coefficients for solving eco-friendly and economic dispatch problems." IEEE Access 9 (2021): 82169-82187.*

[15] *Ginidi, Ahmed R., Abdallah M. Elsayed, Abdullah M. Shaheen, Ehab E. Elattar, and Ragab A. El-Sehiemy. "A novel heap-based optimizer for scheduling of large-scale combined heat and power economic dispatch." IEEE Access 9 (2021): 83695-83708.*

[16] *Yu, Jiang-tao, Chang-Hwan Kim, Abdul Wadood, Tahir Khurshaid, and Sang-Bong Rhee. "Jaya algorithm with self-adaptive multi-population and Lévy flights for solving economic load dispatch problems." IEEE Access 7 (2019): 21372-21384*