South Asian Journal of Engineering and Technology Research Article

Open Access Full Text Article 121(2022) 35-43 DOI: 10.26524/sajet.2022.12.28

Search and rescue optimization algorithm for combined economic and emission load dispatch

A Prakash [a], K Vamsi [b], D Anjaneyulu [c], A Manikanta [d], M Ravikumar [e], B Preethi [f]
[a] **Associate Professor, Department of EEE, QISCET, Ongole, AP, India**
[b,c,d,e,f] **UG Scholar, Department of EEE, QISCET, Ongole, AP, India**

Corresponding author.
Correspondence:A Prakash
E-mail:prksh830@gmail.com

Article info
Received 21th March 2022
Received in revised form 23 April 2022 Accepted 16 May 2022

Keywords
Load Dispatch, Emission, Search and Rescue, Metaheuristic, Constrained Optimization

Abstract
Economic-emission load dispatch minimizes fuel cost factors and gas emissions to provide optimal performance in generation units in a power plant, ensuring demand supply. The first variable is definitive to maintain business continuity, and the second to assure compliance with environmental legislation and no environmental harm. This work investigates the application of a new computational optimization technique known as the Search and Rescue Optimization Algorithm (SAR), which improves searching capability by employing specified parameters. This algorithm has three effective parameters and works with all generators to minimize the cost and emission while satisfying the defined demand. Simulations were run on multiple IEEE test systems with varying demand values. The obtained findings were compared to each other as well as to the results of other procedures mentioned in the literature. The acquired results appear to be superior to those achieved by other metaheuristics algorithms.

1. Introduction

The economic load dispatch (ELD) activity is a task within the various optimization problems in power generating systems. ELD is one of the main tasks in the power system operation and control, where many constraints have to be satisfied in producing the required power with reduced losses. A major constraint nowadays is the environment, which is directly related to gas emissions in electricity generation systems via thermal power plants, which emit significant amounts of pollutants such as oxides of sulphur (SOx), oxides of nitrogen (NOx), carbon monoxide (CO), carbon dioxide (CO2), and small amounts of toxic metals into the atmosphere. Several solutions for reducing air pollution have been presented. These include installing post-combustion cleaning equipment, converting to low-emission fuels, replacing old fuel burners with cleaner ones, and dispatching with emissions in mind. The first three choices necessitate the installation of new equipment and/or the modification of existing ones, which necessitates a significant financial investment and so can be regarded as long-term options. As a result, the latter choice is preferable.

The two objectives, namely cost and emission, are inherently antagonistic, and they must be evaluated concurrently in order to achieve overall optimal dispatch. Economic environmental dispatch (EED) is used to schedule committed generator outputs with expected load demand in order to minimise both cost and emission while meeting operating limitations. It is a multi-objective optimization problem with conflicting objectives due to the conflict between emission minimization and lowest generation cost. Without establishing any weather model, a day–night weather-based technique is proposed for minimizing the total generation cost subject to environmental restrictions. To satisfy the hourly emission requirements, a well-established renewable energy source, wind energy, and large-scale energy storage devices are introduced [1]. A Recursive dynamic programming for emission constrained economic dispatch (ECED) has been formulated and the multi-objective issue has been addressed analytically without the usual Lambda iteration method [2]. In order to tackle the

CEED problem, a basic dynamic programming (DP) method is described [3]. The introduction of dynamic crowding distance (DCD) and controlled elitism into the original NSGA-II algorithm is suggested as a solution to the economic and emission dispatch problems (CE). Gamma, delta, minimum spacing, and Inverted Generational Distance (IGD) were utilised to verify the results [4]. To solve CEED difficulties, the Gravitational Search Algorithm (GSA) has been proposed. Four separate test scenarios were used to evaluate the proposed technique, two of which included valve point effects while the other two did not [5]. A new dynamic ELD approach is designed to suit the general requirements for real-time application in a future power system, when load following capability is severely limited. Fast and stable computation times make this method ideal in terms of speed and efficiency for high-speed online applications [6]. Solving the CEED valve point loading problem with NSGA and MNSGA, two non-dominant sorting genetic algorithms, are employed in [7]. MNSGA is an enhanced version of NSGA. An IEEE 57-bus system and an IEEE 118-bus system are used to evaluate the efficacy of NSGA-II and MNSGA-II. There is a sophisticated optimal solution search technique known as the Bat Algorithm that can deal with complex restrictions, has a high success rate, and can be controlled easily [8]. The cost of generating electricity is also reduced if emissions from thermal plants are kept to a minimum. The Power Search Algorithm was developed and applied to reduce fuel costs, pollutants, and power loss. When compared to other optimization algorithms, the global optimum solution is obtained in substantially less time [9]. The problem of economic load dispatch (ELD) is addressed utilising the β-hill climbing optimizer, a recently discovered local search-based approach. The β-hill climbing algorithm is a revolutionary local search algorithm that escapes the trap of local optima by employing an intelligent stochastic operator known as the β-operator [10]. To address the EED problem, an ensemble multi-objective differential evolution (EMODE) is proposed. First, the problem's equality requirements have been turned into inequality constraints. Following that, two mutation techniques, DE/rand/1 and DE/current-to-rand/1, were used to improve the traditional DE [11]. A novel hybrid optimization approach, gravitational particle swarm optimization algorithm (GPSOA), based on particle swarm optimization (PSO) and gravitational search algorithm (GSA), is introduced to tackle the combined economic and emission dispatch (CEED) problem for the wind-thermal power system [12]. The suggested method employs an intriguing hybrid strategy that perfectly merges PSO collective behaviours with GSA Newtonian gravitation principles. For tackling single-objective continuous optimization problems, the search and rescue optimization algorithm (SAR) is proposed [13]. SAR is inspired by human explorations during search and rescue operations. To mimic the VPL effects, a new heuristic technique, Coulomb's and Franklin's laws-based optimization (CFLBO), is presented to solve the nonconvex economic and emission dispatch problem while taking non-smooth and nonconvex cost characteristics into account [14]. The CFLBO technique is based on Coulomb's and Franklin's theories, and it includes stages of attraction/repulsion, probabilistic ionisation, and contact. To solve the CEED problem, multi-objective crisscross optimization is proposed, which employs a rapid non-dominated sorting principle to achieve the optimal Pareto set of solutions [15]. Because of the problem's high dimensionality, the proposed non-dominated sorting ensures variety, elitism, and numerous complexities. From the above studies, it is inferred that many of the researchers formulated effective algorithms with dominant characteristics when compared to each other. Still, parameter tuning plays a major role in the developing challenging solutions. A new algorithm referred as Search and Rescue (SAR) Optimization [16] is developed and implemented for solving constrained optimization problems. Various benchmark systems are evaluated and the results are published. In this article, SAR is applied to CEED problem and the evaluation is carried out on an IEEE standard test system. The obtained results are compared with the state-of-the-art techniques.

2. Problem Formulation

Economic load dispatch is an important part of power system operational planning that has an impact on the overall economics of the power system. There is a computational programme that relocates the system's available generation in order to satisfy demand while keeping system security limits in mind. In the framework of the economy, the generating cost should be kept to a minimum while taking into account the various limitations connected with the dispatching unit. Reducing the fuel cost and emission are the two different objectives to be considered. As one has the conflict over the other, the single objective functions are converted into multi-objective and this is done by using the penalty factor (hi).

A. Maintaining the Integrity of the Specifications Fuel Cost Minimization

The first objective, F1 is the fuel cost function of the thermal generating units with the presence of multiple valves. So, the reframed objective function is given as follows:

$$F_1(P) = \sum_{t=1}^{T} \sum_{i=1}^{N}. a_i(P_{it})^2 + b_i(P_{it}) + c_i + \left|e_i \sin\left(f_i\left(P_{i,min} - P_{it}\right)\right)\right| \quad (1)$$

B. Emission Rate Minimization

The second objective, F2 is the emission rate of a generating unit depends on the power output of the unit. It is expressed as combination of polynomial and exponential function. The emission of SO2 and NOx in the atmosphere for a total T dispatch period is represented by

$$F_2(P) = \sum_{t=1}^{T} \sum_{i=1}^{N}. \propto_i (P_{it})^2 + \beta_i(P_{it}) + \gamma_i + \eta_i \exp(\delta_i P_{it}) \quad (2)$$

C. Constraints

1. Equality constraint

$$\sum_{i=1}^{N} P_{t,i} + w_t = P_{D,t} + P_{L,t} \quad (3)$$

Total actual power generation must balance expected power demand and transmission line real power losses. The loss mentioned in equation 3 has to be calculated by using the formula

$$P_{Lt} = \sum_{i=1}^{N} \sum_{j=1}^{N} P_{it} B_{ij} P_{jt} + \sum_{i=1}^{N} B_{io} P_{it} + B_{oo} \quad (4)$$

2. Inequality constraint

$$P_i^{min} \le P_i \le P_i^{max}, \text{ i}\epsilon\text{N} \quad (5)$$

Where P_i^{min} & P_i^{max} are the minimum and maximum power input of the generating units.

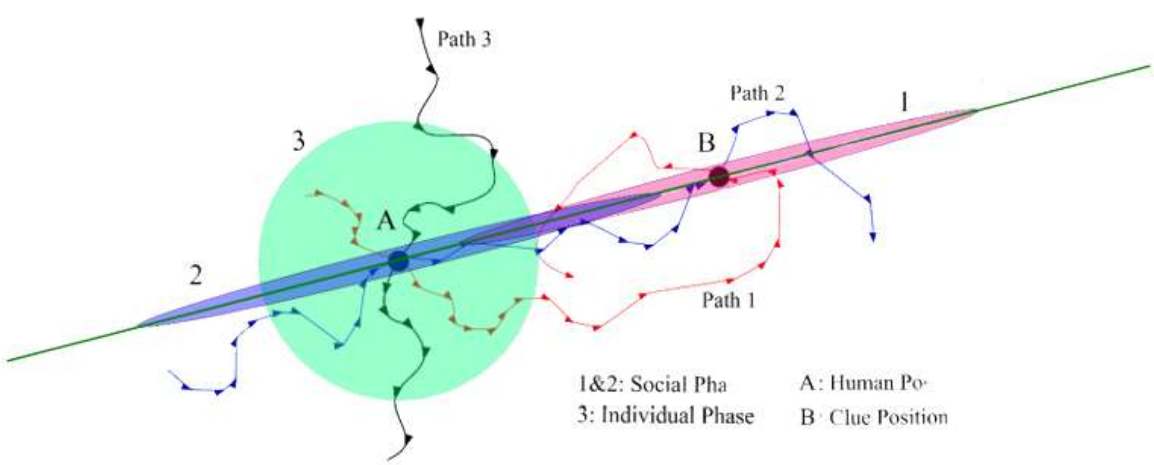

Fig. 1 Representation of SAR algorithm

3. Search and Rescue Optimization Algorithm

Humans, like all living animals, hunt for various objectives in groups. Searching can be done for a number of reasons, such as hunting, discovering food supplies, or finding lost persons. Search and rescue activities are one sort of group search. Based on search and rescue activities, the authors suggested search and rescue optimization algorithm (SAR), which is metaheuristic in nature. These activities are occasionally carried out in order to locate individual people who have gone missing. The technique for discovering lost persons is outlined here, taking into account the key ideas of this operation. Based on their training, adherents of the exploration group will identify clues and signs of missing persons. The training assists people (search group members) in evaluating clues. They may also use a compass and a global positioning system (GPS) to locate themselves. Communication equipment is used to disseminate the gathered information among humans. During the search, information about clues is obtained. Humans save few clues when better clues are identified in other places, but the search operations may be enhanced with the knowledge obtained from the abandoned and the clues can be divided into two sections, viz., hold clue, where the human searches around the clue place; and the other is the abandoned clue in which the human who discovered the clue would have abandoned it in order to hunt better clues, but it is still available to other humans.

In the proposed algorithm, human locations are equivalent to the solutions that are obtained, and number of clues in these locations denotes their respective objective function. The scientific model of SAR is discussed below. Figure 2 represents the flowchart of the proposed algorithm.

i) Algorithm of proposed SAR

S1: Start the program
S2: Initialize the algorithm parameters
S3: Initialize the random values, create matrix using
human positions with the help of best solution
S4: Create memory matrix using the other solutions
and determine optimal solution
S5: Check whether the criterion satisfied
If Yes, Goto S8
If No, Goto S6
S6: Enter social phase, individual phase and
abandon clues for finding optimal solution
S7: Update the Optimal solution
S8: Terminate the program

The locations of clues (hold, abandoned) are saved in matrices 'X' which refers to position of humans and 'M' which represents the memory. Here, the corresponding values are represented by the matrix 'N x D', where 'D' is the problem dimension and 'N' is the number of persons. By using equation 6, this information generates a clues matrix (matrix C).

$$C=\begin{bmatrix} X \\ M \end{bmatrix}=\begin{bmatrix} X_{11} \dots\dots X_{1D} \\ \vdots \\ X_{N1} \dots\dots X_{ND} \\ M_{11} \dots\dots M_{1D} \\ \vdots \\ M_{N1} \dots\dots M_{ND} \end{bmatrix} \tag{6}$$

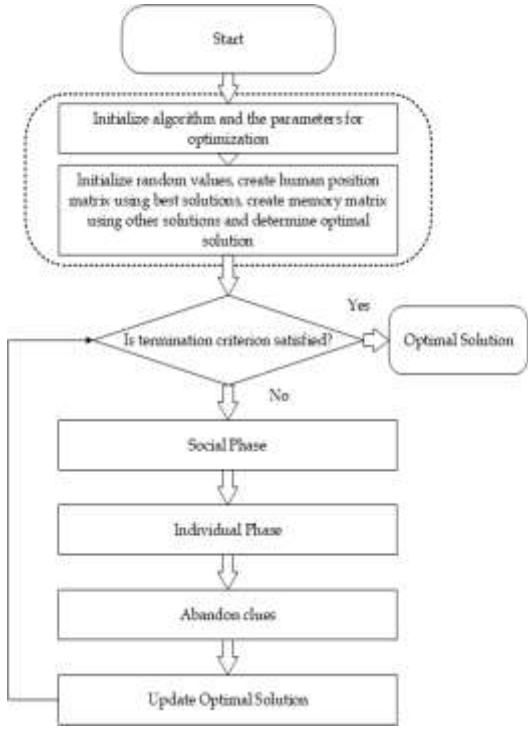

Fig. 2 Flowchart of the proposed SAR

ii) Social Phase

During this step, based on the information obtained, the humans will conduct further search. They link the discovered clues and seek in those directions. To simulate this phase, each individual is assigned a clue taken from matrix 'C'. The search direction is then determined by the equation 7.

$$SD_i = (X_i - C_k), k \neq i \qquad (7)$$

Where X_i, C_k, and 〖SD〗_i are the position of the ith human, the position of the kth clue, and the search direction for the ith human, respectively. k is a arbitrary integer value between 1 and 2N. For i=k, Ci will be equal to Xi. So, k is chosen in such a way that k≠i. Additionally, searching for better clues enhances the likelihood of discovering the missing individual. As a result, the search is focused on the position with the most useful clues. In other words, if the position of the ith person has stronger clues than the position of the kth clue, (for maximizing problems: the value of the objective function for solution Xi is larger than that of Ck. Xi is chosen to conduct the search, and vice versa.

iii) Individual Phase

During the individual phase, humans seek regardless of the location and number of clues discovered by others. They look for alternatives to their existing positions. This phase employs the concept of linking several clues. The new position of the ith human is calculated as following equation:

$$Xi' = X_i + r3 \times (C_k - C_m), i \neq k \neq m \qquad (8)$$

Where k and m are random integer numbers ranging between 1 and 2N that i ≠ k ≠ m. r3 is a random number with a uniform distribution ranging between 0 and 1. The matrix C is updated in each human search phase.

iv) Boundary Control

The solutions developed during the social and individual stages should be situated in the solution space, and if they are outside of the permissible solution space, they should be adjusted. The new position of the ith human is modified by equation 9.

v) Update Information and Positions

If the new solution Xi' generated in the social or individual phases is superior to the previous one (for maximization problems: the value of the objective function for solution Xi is greater than that of Xi', the previous position (Xi) will be stored in a random position of the memory matrix (M), and this position will be accepted as a new position). Otherwise, the memory is not changed and this place is destroyed. This step can be defined as defined in equation 10.

$$M_n = \begin{cases} X_i & if\ f(X_i') > f(X_i) \\ M_n & otherwise \end{cases} \tag{10}$$

$$X_i = \begin{cases} X_i' & if\ f(X_i') > f(X_i) \\ X_i & otherwise \end{cases}$$

Where M_n is the position of the n[th] stored clue in the memory matrix. 'n' is a random integer number in the range [1, N].

vi) Abandon Clues

People who have gone missing may have been injured. As a result, the searching zone must be searched as quickly as possible, and humans must cease unsuccessfully seeking around hints after some effort. The number of failed searches performed by each individual is recorded in order to mimic this behavior. For each individual, the Unsuccessful Search Number (USN) is initially set to zero. Also, anytime a human finds better clues, it is set to 0 for that human; otherwise, it increases by 1 point.

$$USN_i = \begin{cases} USN_i + 1 & if\ f(X_i') < f(X_i) \\ 0 & otherwise \end{cases} \tag{11}$$

When a solution cannot be improved after a certain number of searches (Maximum Unsuccessful Search Number (MU)), it is abandoned. Then, a new solution replaces it using equation 12.

$$X_{i,j} = X_j^{min} + r4\ x\ \left(X_j^{max} - X_j^{min}\right), j = 1, \dots \dots, D \tag{12}$$

Where X_(i,j) is the position of the jth dimension for the ith human, and r4 is a random value for the jth dimension created using a uniform distribution ranging from 0 to 1. The MU parameter specifies the number of failed searches that can be performed before leaving a hint. MU is closely related to the problem's dimension. As the search space expands, so does the maximum number of failed searches.

4. Information related to IEEE Test Data System

The input data required for analysis has been chosen from [17]. It is a ten generator IEEE standard test data system with a power demand of 2000 MW, including transmission losses and valve point loading effects. The two objective functions are converted in to single objective function using the penalty factor (hi), which is calculated by using the formula

$$h_i = \frac{a_i P_{imax}^2 + b_i P_{imax} + c_i}{d_i P_{imax}^2 + e_i P_{imax} + f_i} \tag{13}$$

Using the above formula, the penalty factor is calculated as 52.03.

5. Results and discussion

The proposed optimization algorithm is framed and executed in MATLAB and all runs were performed on a 64-bit computer with an Intel i7 (3.4 GHz) processor and 32GB of RAM. For solving the truss examples, the population size of SAR was considered as follows: 10, 15, 20 and 25. Also, SE and MU (two control parameters of SAR) were respectively set to 0.05 and 600 respectively. For the chosen population size, the results are obtained and are tabulated in the table 1.

Table 1 Results obtained by SAR for various populations

Social Effect Parameter (SE) = 0.05				
Maximum Unsearchable Number = 600				
	Population Sze			
Units	**10**	**15**	**20**	**25**
P1	54.9982	54.9987	54.9999	55.0000
P2	79.9569	79.6994	79.7013	79.0210
P3	81.0601	81.6927	81.2621	81.3939
P4	82.1756	80.9810	80.5141	81.6391
P5	159.7812	160.0000	159.9682	159.6737
P6	239.9998	239.9926	239.9840	239.8820
P7	288.7712	290.2887	290.6413	293.3031
P8	294.6056	296.0983	298.6009	297.2767
P9	402.1384	400.2934	399.1590	394.9559
P10	398.5733	397.9951	397.1967	399.8661
P_d	**2000**	**2000**	**2000**	**2000**
P_g	**2082.06**	**2082.04**	**2082.02**	**2082.01**
Loss	**82.06**	**82.04**	**82.02**	**82.01**
FC	**$1.1613*10^5$**	**$1.1614*10^5$**	**$1.1615*10^5$**	**$1.1614*10^5$**
E	**$3.9346*10^3$**	**$3.9339*10^3$**	**$3.9339*10^3$**	**$3.9347*10^3$**
Time	**2.2**	**2.5**	**2.6**	**2.5**

Table 2 Comparison of SAR with other reported techniques

	SAR [Proposed]	**GQPSO [17]**	**SAIWPSO [17]**	**NGPSO [17]**
FC	$1.1613*10^5$	$1.1850*10^5$	$1.1617*10^5$	$1.1617*10^5$
E	$3.9346*10^3$	$4.5151*10^3$	$3.9394*10^3$	$3.9394*10^3$
Time	2.2	3.2	2.8	2.6

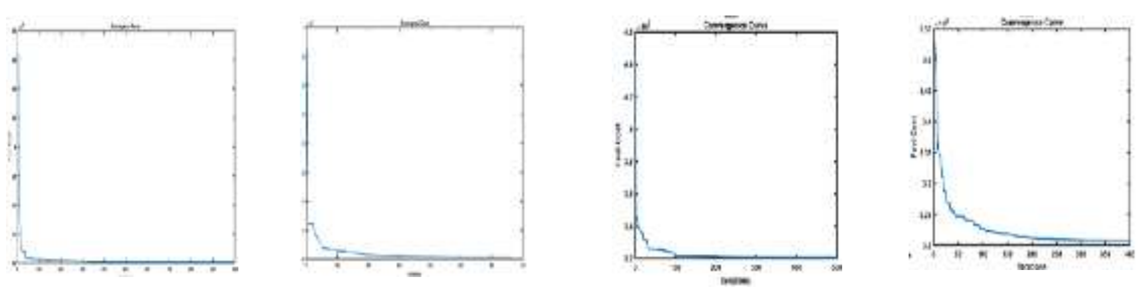

Fig. 3 Converge curves for various power demands

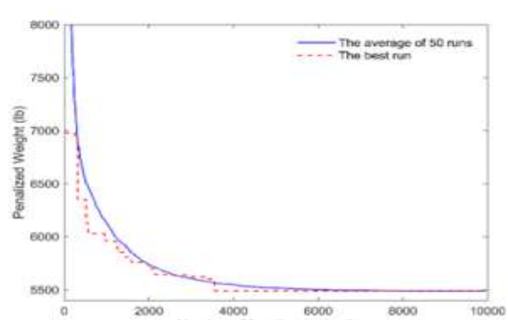

Fig. 4 Convergence curve of SAR for 50 trials

6. Conclusion

In this research, multi-objective SAR is offered as a solution to the economic environmental dispatch problem. The problem has been presented as a multi-objective optimization problem with competing objectives for fuel cost and emission reduction. The suggested approach's results have been compared to those achieved using GQPSO, SAIWPSO, and NGPSO. The comparison demonstrates that the proposed approach provides a cost-effective solution in terms of fuel, emissions, and computational time. The suggested multi-objective SAR is straightforward, robust, and effective. It has no restrictions on the number of objectives and may be expanded to accommodate new objectives.

References

1. C. Palanichamy and N. Sundar Babu, "Day-night weather-based economic power dispatch," IEEE Trans. Power Syst., vol. 17, no. 2, pp. 469–475, 2002, doi: 10.1109/TPWRS.2002.1007920.
2. S. Muralidharan, K. Srikrishna, and S. Subramanian, "Emission constrained economic dispatch - A new recursive approach," Electr. Power Components Syst., vol. 34, no. 3, pp. 343–353, 2006, doi: 10.1080/15325000500241225.
3. R. Balamurugan and S. Subramanian, "A simplified recursive approach to combined economic emission dispatch," Electr. Power Components Syst., vol. 36, no. 1, pp. 17–27, 2008, doi: 10.1080/15325000701473742.
4. S. Dhanalakshmi, S. Kannan, K. Mahadevan, and S. Baskar, "Application of modified NSGA-II algorithm to Combined Economic and Emission Dispatch problem," Int. J. Electr. Power Energy Syst., vol. 33, no. 4, pp. 992–1002, 2011, doi: 10.1016/j.ijepes.2011.01.014.
5. U. Güvenç, Y. Sönmez, S. Duman, and N. Yörükeren, "Combined economic and emission dispatch solution using gravitational search algorithm," Sci. Iran., vol. 19, no. 6, pp. 1754–1762, 2012, doi: 10.1016/j.scient.2012.02.030.
6. N. Yorino, H. M. Hafiz, Y. Sasaki, and Y. Zoka, "High-speed real-time dynamic economic load dispatch," IEEE Trans. Power Syst., vol. 27, no. 2, pp. 621–630, 2012, doi: 10.1109/TPWRS.2011.2169285.
7. M. Rajkumar, K. Mahadevan, S. Kannan, and S. Baskar, "Combined economic and emission dispatch with valve-point loading of thermal generators using modified NSGA-II," J. Electr. Eng. Technol., vol. 8, no. 3, pp. 490–498, 2013, doi: 10.5370/JEET.2013.8.3.490.
8. T. T. Nguyen and S. D. Ho, "Bat Algorithm for Economic Emission Load Dispatch Problem," Int. J. Adv. Sci. Technol., vol. 86, pp. 51–60, 2016, doi: 10.14257/ijast.2016.86.05.
9. P. Arumugam and R. Coimbatore Subramanian, "Power search algorithm (PSA) for combined economic-emission dispatch problems considering valve point effects in economic load dispatch," Turkish J. Electr. Eng. Comput. Sci., vol. 25, no. 6, pp. 4647–4656, 2017, doi: 10.3906/elk-1705-42.
10. M. A. Al-Betar, M. A. Awadallah, I. Abu Doush, E. Alsukhni, and H. ALkhraisat, "A Non-convex Economic Dispatch Problem with Valve Loading Effect Using a New Modified β -Hill Climbing Local Search Algorithm," Arab. J. Sci. Eng., vol. 43, no. 12, pp. 7439–7456, 2018, doi: 10.1007/s13369-018-3098-1.
11. X. Yu, X. Yu, Y. Lu, and J. Sheng, "Economic and emission dispatch using ensemble multi-objective differential evolution algorithm," Sustain., vol. 10, no. 2, pp. 1–17, 2018, doi: 10.3390/su10020418.
12. S. Jiang, C. Zhang, W. Wu, and S. Chen, "Combined Economic and Emission Dispatch Problem of Wind-Thermal Power System Using Gravitational Particle Swarm Optimization Algorithm," Math. Probl. Eng., vol. 2019, 2019, doi: 10.1155/2019/5679361.
13. A. Shabani, B. Asgarian, S. A. Gharebaghi, M. A. Salido, and A. Giret, "A New Optimization Algorithm Based on Search and Rescue Operations," Math. Probl. Eng., vol. 2019, 2019, doi: 10.1155/2019/2482543.
14. M. Suman and V. P. Sakthivel, "Coulomb's and Franklin's laws based optimization for nonconvex economic and emission dispatch problems," Int. Energy J., vol. 20, no. 2, pp. 225–238, 2020.
15. C. Chinnadurrai and T. A. A. Victoire, "Dynamic economic emission dispatch considering wind uncertainty using non-dominated sorting crisscross optimization," IEEE Access, vol. 8, no. Nsga Ii, pp. 94678–94696, 2020, doi: 10.1109/ACCESS.2020.2995213.
16. A. Shabani, B. Asgarian, M. Salido, and S. Asil Gharebaghi, "Search and rescue optimization algorithm: A new optimization method for solving constrained engineering optimization

problems," Expert Syst. Appl., vol. 161, p. 113698, 2020, doi: 10.1016/j.eswa.2020.113698.

17. D. Zou, S. Li, Z. Li, and X. Kong, "A new global particle swarm optimization for the economic emission dispatch with or without transmission losses," Energy Convers. Manag., vol. 139, pp. 45–70, 2017, doi: 10.1016/j.enconman.2017.02.035.
18. Jeyaselvi, M., M. Sathya, S. Suchitra, S. Jafar Ali Ibrahim, and N. S. Kalyan Chakravarthy. "SVM-Based Cloning and Jamming Attack Detection in IoT Sensor Networks." Advances in Information Communication Technology and Computing, pp. 461-471. Springer, Singapore, 2022.