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Search and Rescue Optimization for Combined Economic Load and Emission Dispatch

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ABSTRACT

The goal of combined economic and emission dispatch (CEED) in the power system is to solve the economics management of generators in order to achieve both minimum fuel prices and pollution levels while meeting load demands and operating limits. The Search and Rescue (SAR) optimization methodology is developed in this study to address the CEED problem, and the results gained are compared with the Evolutionary Programming and Flower Pollination Algorithm methods. Those analyses are able to evaluate the effectiveness as well as the rate of convergence of the methods under consideration. In general, the CEED problem is initially considered a bi-objective problem that has been turned into a single objective function by the use of the price penalty element in its solution. Both solutions were tested on an IEEE 10-Generator 39-Bus System, which has a valve point impact with transmission loss. MATLAB is additionally utilized to run modeling for the evaluated system, with each system subjected to three separate load demands. The results reveal that the SAR technique performs better because it generates resilient and effective solutions to the CEED problem with the lowest fuel price, greenhouse gas emissions, CEED price, and power loss.

Keywords: combined economic and emission dispatch; valve point effect; search and rescue algorithm; flower pollination algorithm; evolutionary programming

INTRODUCTION

The generation of energy, such as electricity, is critical to the growth and sustainability of contemporary civilization. Electricity is unquestionably a crucial aspect of contemporary society, and it plays a significant part in both economic development and living quality. Fuel prices have risen as a result of the paucity of fuels used to generate energy, as well as the expanding population number. As a result, the power generation industry is concerned with running their power company economically with lower operational prices while meeting their customers' load demand. Economic load dispatch (ELD) was recently implemented to attain this situation.

ELD is generally intended the most appropriate source of electricity from every generator in the system whereas operational limitations and electrical demands are met. In addition, in order for ELD to become an actual worry in implementation, the valve point impact must be addressed Hoorebeeck et. al. 2020). As a result, the ELD problem is an essential tool for attaining optimum operation and efficient generation management in electrical networks. However, because of the government's stringent constraints and laws aimed at protecting the environment, it is recommended that electric companies and energy providers focus on the environmental implications of power generation. As a result, the combined economic and emission dispatch (CEED) has been implemented to reduce both running fuel prices and greenhouse (GHG) emissions at the same time.

Such a financial and environmental dispatch challenge could be addressed with technology that is capable of meeting operational restrictions. As a result, numerous types of optimization methods, namely traditional optimization techniques and current optimization techniques, have been introduced. Traditional approaches often begin with an arbitrarily chosen initial solution and progress to an ideal solution with each succeeding iteration. The majority of them will have a low degree of convergence and a lengthy execution duration. The Newton approach and the Lambda Iteration method are two well-known traditional techniques. Modern optimization techniques, on the other hand, usually incorporate heuristic algorithms, and metaheuristic algorithms. Evolutionary Programming (EP) (Kamari et al. 2020) and Flower Pollination Algorithm (FPA) (Ramli et al. 2021) are examples of popular metaheuristic algorithms.

The Search and Rescue (SAR) optimization approach will be suggested to tackle the CEED problem. According to (Shabani et al. 2019), the word ‘search’ refers to a methodical operation to locate persons in difficulty using accessible resources, whereas ‘rescue’ refers to an operation that saves people and brings them to a place of safety. Despite the fact that human strategies for searching changed over thousands of years, there is no algorithm that uses human-like characteristics to solve optimization problems. In addition to SAR, this study looks into two more classic metaheuristic algorithms: FPA and EP. SAR, FPA, and EP will be compared to assess their efficacy and effectiveness.

In this work, all methods will be simulated in Matlab using two test systems, an IEEE 3-Generator 9-Bus system and an IEEE 10-Generator 39-Bus system, each with three different load needs. Differing generators will have differing fuel prices due to their position in respect to the load. Higher generating prices will follow, particularly for those who provide output that is not at the ideal level for load demand. As a result, the focus of this research is on offering the lowest fuel prices while minimizing the greenhouse gas emissions of power systems for the purpose to find the efficiency and convergence features in most effective power management across SAR, FPA, and EP.

CEED PROBLEM FORMULATION

The two objective functions have to satisfy equality and the inequality limitation. The quantity of electricity produced must meet the particular power requirement while maintaining according to the generating constraints for every generator. As a result, the CEED problem structure is illustrated as follows.

FUEL PRICES

The fuel prices in terms of output power, $F(P_i)$ can be expressed as below.

$$F(P_i) = x_i + y_i P_i + z_i {P_i}^2 \tag{1}$$

Here, P_i is the real output power for the generating unit i. Whereas x_i, y_i and z_i are the prices coefficients for P_i. When the valve point effect is considered, the price function based on the ripple curve (valve point effect) becomes more accurate and is reformed by integrating with sinusoidal functions, as illustrated below.

$$F_v(P_i) = \sum_{i=1}^{N} \left\{ \begin{matrix} x_i + y_i P_i + z_i {P_i}^2 \\ + \left| u_i \sin\left(v_i \left(P_i^{min} - P_i \right) \right) \right| \end{matrix} \right\} \tag{2}$$

Here, F_v is the total fuel price of the system based on the valve point effect. N is the number of generators. Whereas x_i, y_i, z_i, u_i and v_i are the price coefficients of P_i.

GHG EMISSIONS

GHGs are released into the atmosphere when the generators run on fuel from fossil sources. As illustrated below, the total GHG emission, E, is linked to the total of exponential and quadratic formulae.

$$E(P_i) = \sum_{i=1}^{N} \left\{ \begin{matrix} \alpha_i + \beta_i P_i + \gamma_i {P_i}^2 \\ + |\eta_i \exp(P_i \delta_i)| \end{matrix} \right\} \tag{3}$$

Here, $\alpha_i, \beta_i, \gamma_i, \eta_i$ and δ_i are the emission coefficients for P_i.

POWER LOSSES

The sum of the transmission loss from every generator comprised is given below using Kron’s formula.

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{j=1}^{N} B_{0j} P_j + B_{00} \tag{4}$$

Here, P_L is the oberall power loss in the transmission network. While B_{00}, B_{0i} and B_{ij} are the B-loss coefficients for the generating plants.

CONSTRAINTS

There are a pair of sorts of limitations: equality constraints and inequality constraints. To satisfy the equality constraint, the entire quantity of power produced, P_T, must be equivalent to the power demand, P_D, and the power loss, P_L, as shown as follows.

$$P_T = \sum_{i=1}^{N} P_i = P_L + P_D \tag{5}$$

Different operating limitations for distinctive generators can be evaluated for the inequality constraint, as indicated below.

$$P_i^{min} \leq P_i \leq P_i^{max}, i \in N \tag{6}$$

Here, P_i^{min} and P_i^{max} are the lowest and highest power boundaries for generator i.

OVERALL PRICE OF CEED

CEED can be created by combining two goals: fuel prices and GHG emissions. The total price of CEED, F_{CEED}, is displayed below:

$$F_{CEED} = F_{vpe}(P_i) + h * E(P_i) \tag{7}$$

$$h = \frac{\left\{\begin{matrix} x_i + y_i P_i^{max} + z_i (P_i^{max})^2 \\ + \left|u_i \sin\left(v_i\left(P_i^{min} - P_i\right)\right)\right| \end{matrix}\right\}}{\left\{\begin{matrix} \alpha_i + \beta_i P_i^{max} + \gamma_i (P_i^{max})^2 \\ +\eta_i \exp(P_i^{max} \delta_i) \end{matrix}\right\}} \tag{8}$$

In this case, h is the ratio of the maximum fuel price to the maximum GHG emission.

SEARCH AND RESCUE ALGORITHM

The Search and Rescue (SAR) optimization strategy is a novel metaheuristic method for identifying individuals who have gone lost or are in distress. During the procedure, humans can find clues and locate individuals who are missing. Human searches are classified into two types: social searches and individual searches. SAR, in summary, its seven requirements. The improved clues will be recorded in the irst component's location matrix *X*, while the old clues will be saved in the memory matrix *M*. As shown below, the clue matrix *C* will include both matrices.

$$C = \begin{bmatrix} X \\ M \end{bmatrix} \tag{9}$$

The social phase that follows will look for random regions that have a higher chance of harboring a hint. In any case, the search will be focused on the present place of the clue. The equations below describe the social phase.

If $r2 < SE \ or \ j = j_r$

$$X_i = \begin{cases} C_{k,j} + r1 \times (X_{i,j} - C_{k,j}) & \text{If } f(C_k) > f(X_i) \\ X_{i,j} + r1 \times (X_{i,j} - C_{k,j}) & \text{otherwise} \end{cases} \tag{10}$$

If $r2 \geq SE$ and $j \neq j_r$

$$X'_{i,j} = X_{i,j} \tag{11}$$

In (10) and (11), SE is the parameter of the social effect, j_r is the randomly determined value of *J*. $X'_{i,j}$ and $X_{i,j}$ represent the new and current spots of dimension *j* for person i respectively. $C_{k,j}$ is the dimension *j* spot for the obtained hint *k*. $r1$ and $r2$ accordingly mark the distributed random number [-1,1] and [0,1]. $f(C_k)$ and $f(X_i)$ are accordingly represent the C_k and X_i objective functions.

In the third part (the individual phase), in search processes will be oversee within the present location despite the dimension. Individuals will also correlate and integrate diverse social clues. The associated equation is as follows:

$$X'_i = X_i + r3 \times (C_k - C_m) \ , \ i \neq k \neq m \tag{12}$$

Here, X'_i symbolizes the new location for human i. $r3$ represents a uniformly distributed value [0,1]. *k* and *m*, are random numbers [1, *N*].

If the result is beyond its solution space, the fourth component executes boundary control as an alternate method, and the equation is displayed below.

$$X'_{i,j} = \begin{cases} \left(X_{i,j} + X_j^{max}\right)/2 & \text{if } X'_{i,j} > X_j^{max} \\ \left(X_{i,j} + X_j^{min}\right)/2 & \text{if } X'_{i,j} < X_j^{max} \end{cases} \tag{13}$$

In this scenario, X_j^{max} and X_j^{min} are the highest and lowest constraints for the dimension j, varying [1, D].

The matrices M and X in the fifth component will have to be modified after each occurrence. If $f(X_i')$ exceeds $f(X_i)$, X_i is saved in matrix M. The corresponding equations are as follows:

$$M_n = \begin{cases} X_i & \text{if } f(X_i') > f(X_i) \\ M_n & \text{otherwise} \end{cases} \tag{14}$$

$$X_i = \begin{cases} X_i' & \text{if } f(X_i') > f(X_i) \\ X_i & \text{otherwise} \end{cases} \tag{15}$$

M_n represents the location of n in a memory matrix, and X_i represents the location array for human i. While $f(X_i')$ represents the new location function, $f(X_i)$ represents the current location function.

The sixth element involves failed search number USN, and maximum failed search number MU. If the USN is unsuccessful to uncover a better clue, it may get one point; otherwise, it will remain at 0. When USN_i is greater than MU, it is set to 0.

$$USN_i = \begin{cases} USN_i + 1 & if\ f(X_i') < f(X_i) \\ 0 & otherwise \end{cases} \tag{16}$$

$$X_{i,j} = X_j^{min} + r4 \times \left(X_j^{max} - X_j^{min}\right) \tag{17}$$

Two control parameters will be introduced in the seventh component: social effect SE, and MU. When the value of SE increases, so does the convergence rate, which is between [0, 1]. It corresponds directly to the dimension in the context of MU, and the equation is as follows.

$$MU = 70 \times D \tag{18}$$

The SAR framework depicted in Figure 1 is constructed on the seven already mentioned components.

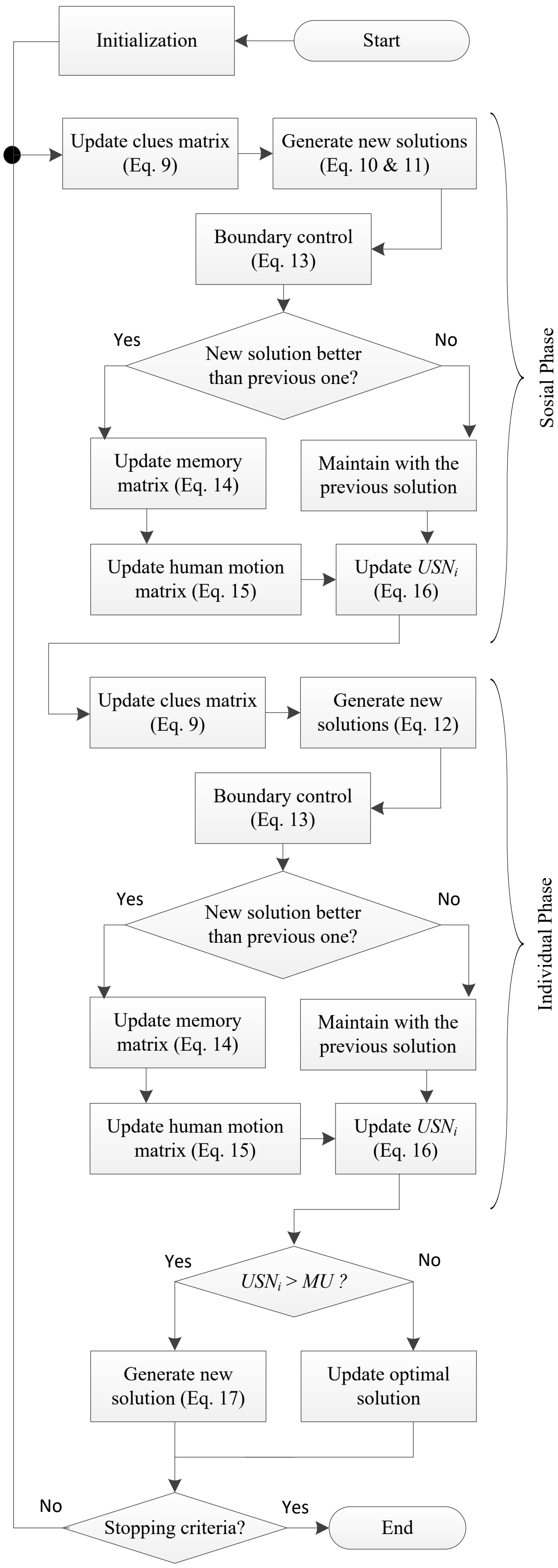

FIGURE 1. The Framework of SAR

FLOWER POLLINATION ALGORITHM

Flower Pollination Algorithm (FPA) is a metaheuristic method created in 2012 by Xin-She Yang. It is inspired by the act of mating a plant known as pollination, which has two types: self-pollination and cross-pollination. In general, there are four rules in the formation of FPA. According to Rule 1, by following Levy flights, cross-pollination and biotic pollination are deemed global pollination. According to Rule 2, self-pollination and abiotic pollination are both categorised as local pollination. According to Rule 3, the constant of a flower is equal to the chance of its reproduction and proportionate to the similarities of the two flowers implicated. According to Rule 4, a switch probability p is utilised to manage both global and local pollination.

Based on the stated rules, some equations were developed. Equation (19) refers to the combination between global pollination and flower constant. Whereas (20) refers to the combination of local pollination and flower constant.

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(g_* - x_i^t) \tag{19}$$

$$x_i^{t+1} = x_i^t + \varepsilon\left(x_j^t - x_k^t\right) \tag{20}$$

Here, x_i^t is the pollinator i or the solution vector of x_i on iteration t. g_* is the best solution. $L(\lambda)$ is the step size of Levy-Flight. x_j^t and x_k^t are the pollinators from different flowers but similar species. Levy-flight can be accounted for the movement of insects over longer distance with different steps. A related equation is shown below. $\Gamma(\lambda)$ refers to the gamma function for the step $s > 0$. Detail explanation about FPA can be found in (Ramli et. al. 2021).

$$L \approx \frac{\lambda\Gamma(\lambda)}{\pi s^{\lambda+1}} sin\left(\frac{\pi\lambda}{2}\right), s \gg s_0 > 0 \tag{21}$$

EVOLUTIONARY PROGRAMMING

D. Fogel proposed Evolutionary Programming (EP) in 1962. EP is predicated on the biological evolution process of developing the greatest breeds. The best breed search model in this technique can be used to find solutions to complex engineering problems. The unique process of the EP algorithm is the process of mutation and competition between old and new breeds. The overall process of the EP algorithm is given in (Kamari et. al. 2020).

OPTIMAL ECONOMIC DISPATCH ALGORITHM

SAR, FPA, and EP optimisation techniques will be computed in MATLAB utilising an IEEE 10-Generator 39-Bus test system in this study. Table 1 tabulates the price coefficients (x_i, y_i, z_i, u_i and v_i) and the generation operating components (P_i^{min} and P_i^{max}) for the evaluated system. Meanwhile, the emission coefficients (α_i, β_i, γ_i, η_i and δ_i) for the evaluated system are tabulated in Table 2.

A total of 500 iterations value and 20 population size are employed in this simulation. Furthermore, in general, optimisation methods have unique variables that regulate the efficiency and effectiveness of solving the optimisation issue by modifying the values. In FPA, as stated in (Ramli et. al. 2021),

TABLE 1. The Test System Price Coefficients and Generation Operating Components

Unit	P_1	P_2	P_3	P_4	P_5
x_i (\$/h)	1000.403	950.606	900.705	800.705	756.799
y_i (\$/MWh)	40.5407	39.5804	36.5104	39.5104	38.5390
z_i (\$/(MW)^{2}h)	0.12951	0.10908	0.12511	0.12111	0.15247
u_i (\$/h)	33	25	32	30	30
v_i (rad/MW)	0.0174	0.0178	0.0162	0.0168	0.0148
P_i^{min} (MW)	10	20	47	20	50
P_i^{max} (MW)	55	80	120	130	160
Unit	P_6	P_7	P_8	P_9	P_{10}
x_i (\$/h)	451.325	1243.531	1049.998	1658.569	1356.659
y_i (\$/MWh)	46.1592	38.3055	40.3965	36.3278	38.2704

continue ...

... cont.

z_i ($/(MW)²h)	0.10587	0.03546	0.02803	0.02111	0.01799
u_i ($/h)	20	20	30	60	40
v_i (rad/MW)	0.0163	0.0152	0.0128	0.0136	0.0141
P_i^{min} (MW)	70	60	70	135	150
P_i^{max} (MW)	240	300	340	470	470

the variables λ and p were adjusted to 1.5 and 0.8, respectively, to produce the optimum answers. As described in (Shabani et. a. 2019) and (Kamari et. al. 2020), the parameter β in EP and the parameter SE in SAR are both set to 0.05.

Power loss is taken into account when B-coefficients are considered. Equation (22) depicts the transmission loss of the test system.

$$B_{ij,B} = \frac{\begin{bmatrix} 4.9 & 1.4 & 1.5 & 1.5 & 1.6 & 1.7 & 1.7 & 1.8 & 1.9 & 2.0 \\ 1.4 & 4.5 & 1.6 & 1.6 & 1.7 & 1.5 & 1.5 & 1.6 & 1.8 & 1.8 \\ 1.5 & 1.6 & 3.9 & 1.0 & 1.2 & 1.2 & 1.4 & 1.4 & 1.6 & 1.6 \\ 1.5 & 1.6 & 1.0 & 4.0 & 1.4 & 1.0 & 1.1 & 1.2 & 1.4 & 1.5 \\ 1.6 & 1.7 & 1.2 & 1.4 & 3.5 & 1.1 & 1.3 & 1.3 & 1.5 & 1.6 \\ 1.7 & 1.5 & 1.2 & 1.0 & 1.1 & 3.6 & 1.2 & 1.2 & 1.4 & 1.5 \\ 1.7 & 1.5 & 1.4 & 1.1 & 1.3 & 1.2 & 3.8 & 1.6 & 1.6 & 1.8 \\ 1.8 & 1.6 & 1.4 & 1.2 & 1.3 & 1.2 & 1.6 & 4.0 & 1.5 & 1.6 \\ 1.9 & 1.8 & 1.6 & 1.4 & 1.5 & 1.4 & 1.6 & 1.5 & 4.2 & 1.9 \\ 2.0 & 1.8 & 1.6 & 1.5 & 1.6 & 1.5 & 1.8 & 1.6 & 1.9 & 4.4 \end{bmatrix}}{10^5} \tag{22}$$

TABLE 2. The Emission Coefficients for The Test System

Unit	P_1	P_2	P_3	P_4	P_5
α_i (Kg/h)	360.0012	350.0056	330.0056	330.0056	13.8593
β_i (Kg/MWh)	-3.9864	-3.9524	-3.9023	-3.9023	0.3277
γ_i (Kg/(MW)²h)	0.04702	0.04652	0.04652	0.04652	0.00420
η_i (Kg/h)	0.25475	0.25475	0.25163	0.25163	0.24970
δ_i (1/MW)	0.01234	0.01234	0.01215	0.01215	0.01200
Unit	P_6	P_7	P_8	P_9	P_{10}
α_i (Kg/h)	13.8593	40.2669	40.2669	42.8955	42.8955
β_i (Kg/MWh)	0.3277	-0.5455	-0.5455	-0.5112	-0.5112
γ_i (Kg/(MW)²h)	0.00420	0.00680	0.00680	0.00460	0.00460
η_i (Kg/h)	0.24970	0.24800	0.24990	0.25470	0.25470
δ_i (1/MW)	0.01200	0.01290	0.01203	0.01234	0.01234

RESULTS AND DISCUSSION

SAR, FPA, and EP results and findings are evaluated using 5 objective values: power produced P_{all}, power loss P_L, fuel price F_{all}, CEED price, F_{CEED}, and GHG emission E_{all}. This study will also acquire and compare convergence trajectories. The IEEE 10-Generator 39-Bus system is made up of ten generator units. Table 3 shows the optimisation results for the test system with power demand P_D of 1000 MW utilising SAR, FPA, and EP.

TABLE 3. Test on the Evaluated System with a P_D of 1000 MW

Outputs	SAR	FPA	EP
P_{all} (MW)	1,005.1332	1,009.0138	1014.2216
P_L (MW)	5.1332	9.0138	14.2216
F_{all} (\$/h)	55,219.8834	55,338.4803	55,591.4838
E_{all} (kg/h)	1,641.0548	1,643.4027	1,650.9509
F_{CEED} (\$/h)	90,203.8949	90,225.1381	90,499.2119

Based on the results tabulated in Table 3, SAR still maintains its best performance behaviour compared to FPA and EP. The overall CEED price, F_{CEED} that obtained by SAR is 90,203.8949 \$/h, which is cheaper than FPA and EP, which are 90,225.1381 \$/h and 90,499.2119 \$/h, respectively. For P_{all}, F_{all} and E_{all} point of view, the results obviously show that FPA and EP give higher prices and GHG emission compared to SAR. SAR, on the other hand, produces a power loss, P_L, that is 0.51% of P_D, which is slightly lower than FPA (0.90%) and EP (1.42%).

Tables 4 and 5 illustrate the optimisation results utilising all three strategies on the evaluated system with P_D of 1500 MW and 2000 MW, respectively.

TABLE 4. Test on the Evaluated System with a P_D of 1500 MW

Outputs	SAR	FPA	EP
P_{all} (MW)	1,510.0504	1,521.0058	1535.9736
P_L (MW)	10.0504	21.0058	35.9736
F_{all} (\$/h)	82,418.7832	82,696.2859	83,424.1728
E_{all} (kg/h)	2,556.9246	2,640.2669	2,672.3450
F_{CEED} (\$/h)	141,677.4646	142,416.8538	143,985.1360

From the results tabulated in Table 8 and Table 9, SAR still remains the forefront to produce lower CEED price, generation price, GHG emission and power loss, in comparison to EP and FPA. Again, SAR is believed to be more cost-effective and efficient in producing optimal solutions in a 10-generator system than FPA and EP.

TABLE 5. Test on the Evaluated System with a P_D of 2000 MW

Outputs	SAR	FPA	EP
P_{all} (MW)	2,010.0014	2,017.2834	2,018.8974
P_L (MW)	10.0014	17.2834	18.8974
F_{all} (\$/h)	110,347.0541	110,655.8859	110,812.4584
E_{all} (kg/h)	3,866.6101	3,926.9780	3,932.8379
F_{CEED} (\$/h)	208,043.8108	208,930.9766	209,249.7959

CONVERGENCE CURVE

FPA, SAR and EP are further evaluated in terms of convergence. The convergence curve (F_{CEED} against the quantity of iterations) of every three approaches for the evaluated system at P_D of 2000 MW is displayed in Fig. 2.

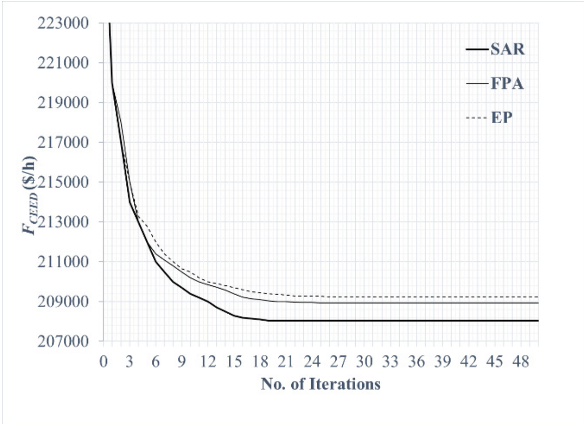

FIGURE 2. Convergence Curve (Test System at P_D of 2000 MW)

According to Fig. 2, all three approaches begin to converge at 19 iterations after steadily declining. These findings imply that SAR, EP and FPA possess about the identical beginning decreasing pace. Equivalent results have been reported for the SAR, EP and FPA convergence curves in evaluated system at P_D of 1000 MW and 1500 MW.

CONCLUSIONS

This work compares three methods for optimization, SAR, FPA, and EP, to provide an economic management technique for solving the CEED problem. There is one recommended test system, which is an IEEE 10-Generator 39-Bus with a valve point effect and transmission loss. This system was used in MATLAB simulations with three distinct power demands, P_D. According to the simulation outcomes, SAR outperforms FPA and EP in terms of efficiency and effectiveness while staying unaffected by varying power demands. SAR is thought to be more cost-effective since it may reduce generation costs, GHG emissions, and overall CEED costs with greater efficiency. Furthermore, the power loss, P_L, resulted from SAR is believed to be in a narrower range when weighed against the other approaches. The convergence curves demonstrate that all three techniques have nearly identical convergence pace. On summary, SAR is the best appropriate economic management algorithm for the CEED issue in the power system when weighed against EP and FPA.

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DECLARATION OF COMPETING INTEREST

None

REFERENCES

Ai B., Li B. and Gao S. 2019. An intelligent decision algorithm for the generation of maritime search and rescue emergency response plans. *IEEE Access* 7:155835–155850.

Alhelou H. H., Golshan M. E. H. and Fini M. H. 2018. Wind driven optimization algorithm application to load frequency control in interconnected power systems considering GRC and GDB nonlinearities. *Electric Power Components and Systems* 46(11-12):1223–1238.

Alshammari M. E., Ramli M. A. M. and Mehedi I. M. 2021. A new chaotic artificial bee colony for the risk-constrained economic emission dispatch problem incorporating wind power. *Energies* 14(13):4014.

Basset M. A. and Shawky L. A. 2018. Flower pollination algorithm: a comprehensive review. *Artificial Intelligence Review* 52:2533–2557.

Chen S. D. and Chen J. F. 2003. A direct newton–raphson economic emission dispatch. *International Journal of Electrical Power & Energy Systems* 25(5):411–417.

Darvish Falehi A. 2020. Optimal harmonic mitigation strategy based on multiobjective whale optimization algorithm for asymmetrical half-cascaded multilevel inverter. *Electrical Engineering* 102:1639–1650.

Hoorebeeck L. V., Absil P. A. and Papavasiliou A. 2020. Global solution of economic dispatch with valve point effects and transmission constraints. *Electric Power Systems Research* 189:106786.

Jiang S., Zhang C. and Wu W. 2019. Combined economic and emission dispatch problem of wind-thermal power system using gravitational particle swarm optimization algorithm. *Mathematical Problems in Engineering* 2019:5679361.

Kamari N. A. M., Musirin I. and Ibrahim A. A. 2020. Swarm intelligence approach for angle stability improvement of PSS and SVC-based SMIB. *Journal of Electrical Engineering and Technology* 15(3):1001–1014.

Kour V. and Singh L. 2017. Comparitive analysis of lambda iteration method and particle swarm optimization for economic emission dispatch problem. *International Journal of Engineering Research & Technology* 5(5):1–5.

Mohamad Zamani M. K., Musirin I., Omar M. S., Ghani N.A.M. and Kamari N.A.M. 2018. Gravitational search algorithm based technique for voltage stability improvement. *Indonesian Journal of Electrical Engineering and Computer Science* 9(1):123–130.

Mousavi Y., Alfi A. and Kucukdemiral I. B. 2020. Enhanced fractional chaotic whale optimization algorithm for parameter identification of isolated wind-diesel power systems. *IEEE Access* 8:140862–140875.

Ramakurthi V. B., Manupati V. K. and Machado J. 2021. A hybrid multi-objective evolutionary algorithm-based semantic foundation for sustainable distributed manufacturing systems. *Applied Sciences* 11(14):6314.

Ramli N. F., Kamari N. A. M. and Halim S. A. 2022. A non-convex economic dispatch problem with point-valve effect using a wind-driven optimisation approach. *Journal of Electrical Engineering and Technology* 17:85–95.

Ramli N. F., Kamari N. A. M., Halim S. A., Ibrahim A. A. and Musirin I. 2021. Pelaksanaan algoritma pendebungaan bunga untuk menyelesaikan masalah penghantaran ekonomi dalam sistem kuasa. *Jurnal Kejuruteraan* 33(4):1053–1060.

Rana N., Latiff M. S. A. and Abdulhamid S. M. 2020. Whale optimization algorithm: a systematic review of contemporary applications, modifications and developments. *Neural Computing and Applications* 32:16245–16277.

Roy P. K., Ghoshal S. P. and Thakur S. S. 2010. Combined economic and emission dispatch problems using biogeography-based optimization. *Electrical Engineering* 92:173–184.

Shabani A., Asgarian B. and Gharebaghi S. A. 2019. A new optimization algorithm based on search and rescue operations. *Mathematical Problems in Engineering* 2019:2482543.

Tahir M. W., Abbas G., Ilyas M. A., Ullah N. and Muyeen N. M. 2020. Economic emission and energy scheduling for renewable rich network using bio-inspired optimization. *IEEE Access* 10:79713-79729.

Takeang C. and Aurasopon A. 2019. Multiple of hybrid lambda iteration and simulated annealing algorithm to solve economic dispatch problem with ramp rate limit and prohibited operating zones. *Journal of Electrical Engineering and Technology* 14:111–120.