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Economic Load Dispatch Problem Based on Search and Rescue Optimization Algorithm

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ABSTRACT The Search and Rescue optimization algorithm (SAR) is a recent metaheuristic inspired by the exploration's behaviour for humans throughout search and rescue processes. The SAR is applied to solve the Combined Emission and Economic Dispatch (CEED) and Economic Load Dispatch (ELD). The comparative performance of SAR against several metaheuristic methods was performed to assess its reliability. These algorithms include the Earthworm optimization algorithm (EWA), Grey wolf optimizer (GWO), Tunicate Swarm Algorithm (TSA) and Elephant Herding Optimization (EHO) for the same two networks study. Also, the proposed SAR method is compared with other literature algorithms such as Sine Cosine algorithm, Monarch butterfly optimization, Artificial Bee Colony, Chimp Optimization Algorithm, Moth search algorithm. The cases applied in this work are seven cases: three cases of 6-unit for ELD issue, three cases of 6-unit for CEED issue and 10-unit for ELD problem. The evaluation of counterparts is performed for 30 different runs based on measuring the Friedman rank test and robustness curves. Furthermore, the standard deviation, maximum objective function, minimum, mean and values over 30 different runs are applied for a statistical analysis of all used techniques. The obtained results proved the superiority of the SAR in determining the fitness function of ELD and CEED is minimizing the cost of fuel for ELD and emission and fuel costs for CEED.

INDEX TERMS Search and rescue algorithm, economic load dispatch, optimization.

I. INTRODUCTION

Economic load dispatch (ELD) is one of the important optimization problems for smooth and hassle-free operation of power system. The net demand of power is increasing at an alarming rate. Subsequently, the fuel price for power generation is also increasing. Thus, this calls for the necessity to reduce the operational cost thereby achieving reliable operation of the power system. The main aim of the ELD problem is to reduce the operating cost of the system by optimizing the energy capability of thermal units and enhance the reliable operation of the system. In recent years, it is observed that the trend is to consider both cost and emission while considering planning and operation of power system thereby giving rise to Combined Economic-Emission Dispatch (CEED) problem. Thus, ELD and CEED are complex problems of power system optimization having nonlinear objective function, equality as well as inequality constraints. The efficacy of the conventional algorithms is limited in solving the ELD problem because of the nonlinear nature of the problem. Researchers have proposed distinct metaheuristic techniques for solving that problem. The merits of metaheuristic algorithms have provided confirming alternative methods for solving complex optimization issues [1]–[5]. In [6], authors have proposed an enhanced version of Grey Wolf Optimization (GWO) mimicking the hunting process of grey wolf for solving the ELD problem. The algorithm was validated on standard test functions and ELD for 38 unit, 40 unit, 80 unit, 110 unit, 140 unit test system. The performance of GWO was compared with other

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metaheuristics such as Differential Evolution (DE), Improved DE (IDE), Particle Swarm Optimization (PSO) etc. and the superior behaviour of GWO was noticed.

In [7], authors have used a novel Crow Search Algorithm (CSA) mimicking the food searching process of crows for solving nonconvex ELD with cost as objective function. In [8], Class Topper Optimization (CTO) and Advanced CTO (ACTO) were to solve ELD as well as CEED. It was observed that CTO performed better than other metaheuristics such as TLBO, DE, GA, PSO etc. In [9], the authors have addressed the problem of ELD in the context of a micro grid. Further, they have hybridized Spotted Hyena and Emperor Penguin Optimizer for solving multi-objective CEED with cost as well as emission as objective functions. Simulation results validated the supremacy of the aforementioned algorithm over NSGA II and MOPSO. In [10], authors solved nonconvex ELD problem by artificial cooperative algorithm. Valve point effect and a novel constraint handling strategy were further introduced in ref [10]. In [11], proposed a novel parallel hurricane optimization algorithm (PHOA) for solving ELD and CEED. The speciality of PHOA is that it has several sub-populations that can move independently in the search space. The algorithm was validated on IEEE 30 and IEEE 57 bus test system.

In [12], authors have introduced a phasor PSO (PPSO) for solving nonconvex ELD problem. PPSO is nothing but a trigonometric model of PSO with faster convergence rate and more efficiency. In [13], authors proposed Gradient Based Optimization (GBO) to solve ELD as well as CEED. In [14], the dynamic ELD problem have been modelled considering the integration of renewable sources and solved the problem by an enhanced version of firework algorithm. In [15], authors contributed to the state-of-the-art with a novel algorithm that considers hybridization of artificial algae algorithm and simplex method for solving ELD. In [16], authors have introduced an optimized version of DE incorporating multiple mutation strategies for solving ELD. In [17], authors have proposed an enhanced version of Jaya algorithm incorporating multiple population and Levy flight for solving ELD and CEED. In [18], authors validated the performance of Turbulent Flow of Water Optimization (TFWO) algorithm on ELD and CEED and concluded that the algorithm is as competitive as other state of art metaheuristics. In [19], the authors proposed a Chameleon Swarm Algorithm (CSA) mimicking the behaviour of chameleons for solving ELD and CEED.

In [20] a novel hybrid algorithm based on Coulomb's law Franklin's law was put forward for solving different variants of ELD. In [21], authors have hybridized Sine Cosine Algorithm (SCA) with β hill climbing algorithm to enhance the exploitation capacity of SCA for solving ELD of large-scale networks. In [22], also hybrid GWO applied for ELD with effect of valve load. In [23], also hybrid SSA applied for ELD problem. In [24], authors have proposed a narrowing down area-based approach for solving ELD. In [25], authors have used a data mining-based approach for solving multi-objective ELD. In [26], authors have used nonconvex ELD problem by Slime Mould Algorithm (SMA). In [27], authors have proposed an adaptive version of Class Topper Optimization (CTO) along with the incorporation of chaos theory for solving ELD, EED, and CEED. In [28], authors have proposed an Arithmetic Optimization algorithm based on elementary function disturbance for solving ELD problem. In [29], enhanced WOA applied for ELD. In [30], an improved competitive swarm algorithm is applied for ELD.

As stated by No Free Lunch (NFL) theorem [31]–[35] metaheuristics differ in performance as well as behavior while solving different class of problems. So, the Search and Rescue optimization algorithm (SAR) [36] is such a novel meta-heuristic method to solve the ELD problem. SAR algorithm is easy to implement because of its basic concept, simple formula, and small number of parameters. In [36], the SAR showed greater performance compared to several algorithms. Particularly, SAR has been validated over 18 benchmark constraint functions presented in CEC 2010, 13 benchmark constraint functions, and 7 constrained engineering design problems, which are considered challenging optimization problems. However, all meta-heuristic algorithms should strike a balance between exploration and exploitation; other solutions can be stuck in optimal solutions or fail to converge [41]. Indeed, depending on the optimization problem, SAR may suffer from slow convergence speed, fall into to a local minimum, performance depends on algorithm parameters, and difficulty to balance between exploration and exploitation phases.

The main items of contribution in this work are as follow:

- Discuss two network cases such as Combined Emission-Economic Dispatch (CEED) and Economic Load Dispatch (ELD).
- Search and Rescue Algorithm (SAR) is used as a new metaheuristic method for the seven cases study.
- The proposed SAR method is compared with Earthworm optimization algorithm (EWA), Grey wolf optimizer (GWO), Tunicate Swarm Algorithm (TSA) and Elephant Herding Optimization (EHO) for the same seven networks study.
- The fitness function of ELD and CEED minimize the fuel cost for ELD and emission and fuel costs for CEED.
- The evaluation of all algorithms is performed for 30 different runs based on measuring the Friedman rank test and robustness curves.
- The standard deviation, maximum objective function, minimum, mean and values over 30 different runs are applied for the statistical analysis of all employed techniques.
- The evaluation of SAR and all techniques performance is accomplished according to the power mismatch between the generated power from units in the system and the summation of the load demand and losses of transmission.

The paper is prepared as follow: the problems of ELD and CEED are discussed in section two. The SAR algorithm is analyzed in section three. The experimental analysis of results is extracted in section four and also in this section analysis of Friedman rank test is performed. The conclusion of work and future work is discussed in section five.

II. ECONOMIC LOAD DISPATCH PROBLEM

Multiple problems can be found in power system operation including economic load dispatch, ELD. Reducing the costs of fuel consumption is the principle issue to improve the ELD problem for maximizing the benefit economic for power system. The principle variable for ELD problem represents the allocating vector from every unit that sets the best production in every unit of the system. ELD with losses and CEED are discussed as follows.

A. ELD

The ELD mathematical model with losses can be identified as follows. In order to operate n generators, the cost for fuel consumption will be identified as follows:

$$Min\left(F\right) = F_1\left(P_1\right) + \ldots F_n\left(P_n\right) \quad (1)$$

where F represents the cost for total fuel, F_1 denotes the cost for fuel in 1st generator whereas F_n indicates the cost for fuel in *nth* generator. A function of fuel consumption cost will be further obtained in quadratic form using:

$$Min\left(F\right) = \sum_{k=1}^{n} F_i\left(P_i\right) = \sum_{k=1}^{n} a_k P_k^2 + b_k P_k + c_k \quad (2)$$

where c, b *and* a represent the weight constants for the fuel cost. Also, the generator constraints from each unit can be given using Eqs. (3 and 5).

$$\sum_{k=1}^{n} P_k - P_D - P_L = 0 \quad (3)$$

where P_D denotes total network demand whereas P_L indicates network transmission losses which can be taken as follows:

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j \quad (4)$$

where B_{ij} indicates loss factor, P_i represents the generated power at the *ith* generator, whereas P_j denotes the generated power at the *jth* generator.

$$P_k^{min} \leq P_k \leq P_k^{max} \quad (5)$$

B. CEED

Development of the ELD problem can be performed by considering the reduction of emission along with the production cost, which is referred as CEED. This problem sheds light on minimizing gases from the power plants. The emission factor can be mathematically specified by:

$$Min\left(E\right) = \sum_{k=1}^{n} E_i\left(P_i\right) = \sum_{k=1}^{n} \alpha_k P_k^2 + \beta_k P_k + \gamma_k \quad (6)$$

The fitness function for CEED problem is:

$$objective\,function = Min\left(\sum_{k=1}^{n} E_i\left(P_i\right) + h_e \sum_{k=1}^{n} F_i\left(P_i\right)\right) \quad (7)$$

where h_e denotes the penalty factor for price as given in Eq. (8):

$$h_e = \frac{F_i\left(P_{imax}\right)}{E_i\left(P_{imax}\right)} \quad (8)$$

The generator constraints in each unit are taken by Eqs. (3 and 5).

III. SEARCH AND RESCUE ALGORITHMIC METHOD

This section presents the mathematical model of SAR algorithm to solve the "minimization problem". In which, the humans' position confronts to the solution for the optimization problem whereas the clue significance reached in this position denotes the fitness for that solution. An optimal solution indicates a clue with high significance and vice versa [36].

A. CLUES

Throughout the course of search operation, the group members bring clues information together. To find additional significant clues, the group members leave some clues, but the information got from them is used to optimize the searching process. The matrix M is a memory matrix that stores the positions of left clues, whereas the matrix X is a position matrix which stores the humans' positions. The dimensions of the two matrices are equal. They are Y × Z matrices where Y represents the dimension for the problem and Z denotes the group members number. The matrix C indicates the clues matrix which includes the positions for found clues and comprises two matrices, X and M. The new solutions from individual and social phases are all created based upon the clue's matrix and the matrices, C, M, and X are updated in all phases of human searches.

$$C = \begin{bmatrix} X \\ M \end{bmatrix} = \begin{bmatrix} X_{11} & \cdots & X_{1Z} \\ \vdots & \ddots & \vdots \\ X_{Y1} & \cdots & X_{YZ} \\ M_{11} & \cdots & M_{1Z} \\ \vdots & \ddots & \vdots \\ M_{Y1} & \cdots & M_{YZ} \end{bmatrix} \quad (9)$$

where X and M represent humans' positions and memory matrices, respectively whereas X_{Y1} denotes the position for the 1st dimension of the Y^{th} human. Furthermore, M_{1Z} indicates the position for the Z^{th} dimension of the 1st memory.

B. SOCIAL PHASE

Considering random clue among the found clues, the search direction is obtained by Eq. (10). In which, SD_i, X_i, and C_k, represent the search direction from the i^{th} human, the position from the i^{th} human, and the position from the i^{th} clue, respectively. Additionally, k represents random integer number in the 1 and 2N range. For $i = k$, C_i equals to X_i. Therefore, taking into consideration that $k \neq i$, k is chosen.

$$SZ_i = (X_i - C_k), \quad k \neq i \tag{10}$$

Usually, the group members attempt to avoid the search for location several times. Therefore, the search has to be implemented in a way that the movement for the group members towards each other is restricted. Accordingly, all the dimensions of X_i has not be modified by the movement in a direction of Eq. (10). A binomial crossover operator is employed to implement this constraint. If the significance of considered clue is greater than that from the clue of the current position, the area around the direction of SZ_i and around the clue position is searched; otherwise, the searching around current position will be continued along with SZ_i direction. Thus, Eq. (11) is implemented in the social phase:

$$\acute{X}_{ij} = \begin{cases} \begin{cases} C_{kj} + r1 \times (X_{ij} - C_{kj}) & if\ f(C_k) > f(X_i) \\ X_{ij} + r1 \times (X_{ij} - C_{kj}) & otherwise \end{cases} \\ \qquad if\ r2 < SE \\ X_{ij} \qquad otherwise \end{cases} \tag{11}$$

where $\acute{X}_{ij}$ indicates the new position for the j^{th} dimension from the i^{th} human, C_{kj} represents the position for the j^{th} dimension from the k^{th} clue. The values of objective function from the solution X_i and C_k are indicated by $f(X_i)$ and $f(C_k)$, respectively. r1 denotes a random number within a uniform distribution of the range $[-1, 1]$ whereas r2 represents a random number uniformly distributed within the [0, 1] range. j_{rand} indicates an integer number randomly ranged in 1 and Z which confirms that one dimension from $\acute{X}_{ij}$ is at least different from $\acute{X}_{ij}$, whereas SE represents an algorithm parameter within the range 0 and 1. In this context, the new position from the i^{th} human over all the dimensions can be taken by Eq. (11).

C. INDIVIDUAL PHASE

Human searches around its current position in this individual phase and different clues are connected as employed through the social phase. Every new position from the i_{th} human can be taken by Eq. (12).

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

where the integer numbers k and m are randomly ranged in 1 and 2N. For preventing movement along the other clues, the choice of k and m is done in a manner that $i \neq k \neq m$. Furthermore, r3 represents a random number within a uniform distribution of the range 0 and 1.

D. BOUNDARY CONTROL

In this regard, the solutions taken by the individual and social phases must be located within the solution space, but if they locate out of solution space, they have to be modified. Accordingly, the new position from the i^{th} human can be modified by Eq. (13).

$$\acute{X}_{ij} = \begin{cases} \left(X_{ij} + X_j^{max}\right)/2 & if\ \acute{X}_{ij} > X_j^{max} \\ \left(X_{ij} + X_j^{min}\right)/2 & if\ \acute{X}_{ij} > X_j^{min}, \end{cases} \quad j = 1, \ldots, Z \tag{13}$$

where X_j^{min} and X_j^{max} represent the values of the minimum and maximum threshold, respectively, from the j^{th} dimension.

E. UPDATING INFORMATION AND POSITIONS

The group members, through each iteration, will search based on these two phases. Furthermore, after every phase, if the objective function value in a position $\acute{X}_i(f\left(\acute{X}_i\right)$ exceeds the previous value, $(f(X_i)$, a random position in a memory matrix M will be used to store the previous position, X_i, as in Eq. (14) and such position will be considered as new position by using Eq. (15). Otherwise, such position will be left and also the memory will not be updated.

$$M_n = \begin{cases} X_i & if\ f\left(\acute{X}_i\right) > f(X_i) \\ M_n & otherwise \end{cases} \tag{14}$$

$$X_i = \begin{cases} \acute{X}_i & if\ f\left(\acute{X}_i\right) > f(X_i) \\ X_i & otherwise \end{cases} \tag{15}$$

where M_n denotes the position from the n^{th} kept clue within the memory matrix, n represents an integer number randomly ranges in 1 and N. This kind of memory updating can increase the diversity for the algorithm and its capability to find the global optimum.

F. ABANDONING CLUES

The time is necessary factor in the search and rescue processes as the lost people can be injured. In addition, the delay of the teams responsible for the search and rescue might cause their deaths. So, these processes have to be performed in such a manner that the greatest space is searched through the least time. Thus, if the group member could not find many significant clues after some searches surrounding his/her current position, it is expected that s/he will leave the current position and go to new position. Accordingly, this behavior can be modeled firstly by setting unsuccessful search number, USN, to 0 for every group member. If a human reaches many significant clues through the first or even second phase in the search process, the USN will be set to 0 in case of such human, otherwise, 1 point will be added to theUSN as in Eq. (16).

$$USN_i = \begin{cases} USN_i + 1 & if\ f\left(\acute{X}_i\right) > f(X_i) \\ 0 & otherwise \end{cases} \tag{16}$$

where USN_i denotes number of times through which the i^{th} human was not able to reach many significant clues. If the USN from a human exceeds MU, s/he will go to another different position within the search space. For solving the problems of constrained optimization, for any solution, if it is observed that USN > MU, current solution will be swapped with random solution within the search space as in Eq. (17). Furthermore, for any solution, if it is observed that USN > MU, the solution within the memory matrix of a minimum degree in the constraint violation will be chosen and current solution will be substituted with that solution whereas current solution will take its place within the memory matrix.

$$X_{ij} = X_j^{min} + r_4 \times \left(X_j^{max} - X_j^{min}\right), \quad j = 1, \ldots, Z \quad (17)$$

where r_4 denotes random number uniformly distributed in the range of 0 and 1, which is different in each dimension.

G. THE TECHNIQUE OF CONSTRAINT-HANDLING

Many constraint-handling methods are used, e.g., the penalty functions approach, stochastic ranking, and the ε-constrained method. For instance, the penalty functions approach is popular in solving the problems of constrained optimization, but they are proven to be sensitive for penalty factors. In the ε-constrained method, for the minimization problem, the solution will be optimal than another solution when the subsequent conditions are met:

$$X_1 \text{ is better than } X_2 : \begin{cases} f(X_1) > f(X_2) & \text{if } G(X_1) \leq \varepsilon \text{ and } G(X_2) \leq \varepsilon \\ f(X_1) > f(X_2) & \text{if } G(X_1) = G(X_2) \\ G(X_1) > G(X_2) & \text{otherwise} \end{cases} \quad (18)$$

where ε parameter is employed to control the feasible space size. It is computed by Eq. (19):

$$\varepsilon(t) = \begin{cases} G_\theta \left(1 - \frac{t}{T_c}\right)^{cp} & \text{if } t \leq T_c \\ 0 & \text{otherwise} \end{cases} \quad (19)$$

where t denotes current iteration number. G_0 represents the θ^{th} lowest constraint violation within the initial population. The parameter T_c indicates truncate ε value while the parameter cp controls the speed for reducing feasible space. In the problems of constraint optimization, comparisons of SAR algorithm are performed according to the ε-constrained approach. Thus, Eqs. (11, 14, 15, and 16) will be modified as in the following:

$$\acute{X}_{ij} = \begin{cases} \begin{cases} C_{kj} + r1 \times (X_{ij} - C_{kj}) & \text{if } C_k \text{ is better than } X_i \\ & \text{if } r2 < SEorj = j_{rand}, \\ & j = 1, \ldots, Z \\ X_{ij} + r1 \times (X_{ij} - C_{kj}) & \text{otherwise} \end{cases} \\ X_{ij} \quad\quad \text{otherwise} \end{cases} \quad (20)$$

TABLE 1. Parameters of each algorithm used in this work.

Algorithms	Parameter values
General setting	No. of Iteration = 1000
	Decision variables = 6 Population' size = 30
SAR	SE=0.05
TSA	$P_{min} = 1$ and $P_{max} = 4$ (default)
EWA	$\propto = 0.98$, $\beta_o = 0.1$ and $\gamma = 0.9$
EHO	$\alpha = 0.5$ and $\beta = 0.1$
GWO	A which linearly decreases from 2 to 0

$$M_n = \begin{cases} \acute{X}_i & \text{if } \acute{X}_i \text{ is better than } X_i \\ M_n & \text{otherwise} \end{cases} \quad (21)$$

$$X_i = \begin{cases} \acute{X}_i & \text{if } \acute{X}_i \text{ is better than } X_i \\ X_i & \text{otherwise} \end{cases} \quad (22)$$

$$USN_i = \begin{cases} 0 & \text{if } f\left(\acute{X}_i\right) > f(X_i) \\ USN_i + 1 & \text{otherwise} \end{cases} \quad (23)$$

H. RESTART STRATEGY

The problems of constraint optimization may have complicated constraints. Such constraints are multimodal where optimization and nonlinear algorithms may converge in infeasible regions. So, a restart strategy was suggested to avoid that point. In the infeasible regions, a method is firstly required to recognize if the population converged in local optima. Accordingly, the whole population is infeasible. Furthermore, similarities between them are excessive, e.g., if standard deviation of the constraint violations degree or the objective function values were very small. If the α predefined value is greater than standard deviation of the constraint violations degree and the population was infeasible, the algorithm employs the restart strategy while the matrices of memory and human are randomly regenerated.

According on the previous steps, the flowchart of SAR algorithm is presented in Figure 1 to solve the problem of minimization constrained.

IV. RESULTS OF NUMERICAL ANALYSIS

The performance of SAR algorithm for two cases of ELD is discussed. The proposed SAR method is compared with Earthworm optimization algorithm (EWA) [37], Grey Wolf Optimizer (GWO) [38], Tunicate Swarm Algorithm (TSA) [39] and Elephant Herding Optimization (EHO) [40] for the same two networks study. The first network is ELD problem for 6 generators unit network at three levels of load demand as follow: 1200, 1000, and 700 MW. The second network is CEED problem for 6 generators unit network at three levels of load demand as follow: 700, 1000, and 1200 MW. The overall setting for all algorithms is illustrated in Table 1.

A. RESULTS OF ELD PROBLEM

Case study of 6 generators at three levels of load is applied to solve ELD issue. Several techniques are used in this

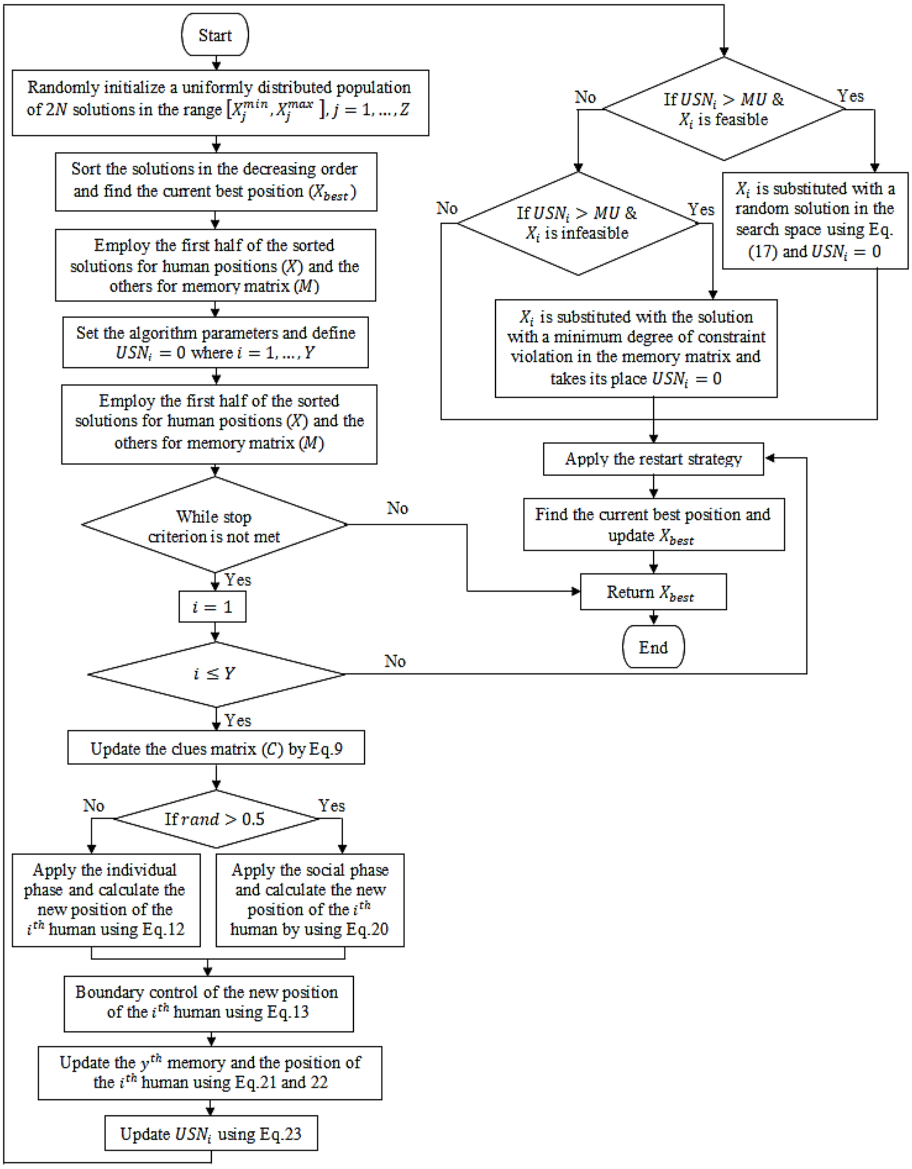

FIGURE 1. Flowchart of SAR algorithm.

TABLE 2. Parameters of each algorithm used in this work.

Demand (MW)	Algorithm	SD	max	mean	min
700	SAR	55606.53334	245848.9878	30565.16566	8543.678882
	TSA	11464055.69	43445577.33	13242490.67	275801.5266
	EWA	66375860.4	244645523.2	42827773.86	29445.71163
	EHO	208559054.2	904072137.8	225933121.5	744637.0511
	GWO	4862857.508	18492971.2	6216649.832	77581.5973
1000	SAR	23970.02948	94453.21286	27278.65799	12216.18978
	TSA	25787851.34	100550789.9	23876720.91	513017.4415
	EWA	52844654.12	268561019.9	31634359.22	103024.2258
	EHO	30299165.71	116819671.4	33060167.78	2775506.229
	GWO	9639762.69	43875780.32	8542630.726	37315.95616
1200	SAR	64312.93448	359469.1506	35847.5843	14893.32371
	TSA	15447223.38	59693585.68	22343301.98	356166.7317
	EWA	176794336.4	842861368.6	105046777.6	32251.07236
	EHO	4045382835	20600426781	3301712150	11512349.61
	GWO	10206452.1	39006032.81	12261554.6	38161.43314

TABLE 3. Minimum fuel consumption costs of case 1 in ($ per hour).

Algorithm	700 MW	1000 MW	1200 MW
SAR	8536.578073	12213.08975	14893.32321
TSA	8755.288223	12352.53542	14890.39485
EWA	9290.599374	13655.88847	16384.85345
EHO	9225.735035	13535.68419	16640.70332
GWO	9101.367455	12296.40155	15000.56429

TABLE 4. The value of power generated (MW) from each generator for case 1 with load level of 700 MW.

SAR	TSA	EWA	EHO	GWO
280.891608	141.3053858	53.00082661	81.02099422	104.1852297
114.107787	200	64	93.84736919	195.5282081
70.73084215	171.9075607	72.0024561	97.27104527	102.9844775
108.4858022	51.70787633	101	101.0689918	147.3228766
75.23183439	98.14614977	145.0079506	166.1349969	57.04849501
61.97800695	50	249.9985388	173.626733	106.7050996

TABLE 5. The value of power generated (MW) from each generator for case 1 with load level of 1000 MW.

SAR	TSA	EWA	EHO	GWO
413.5381133	500	51.07116947	100.7205506	495.8829288
97.11432466	190.2175803	80.0754891	115.2499079	116.7271178
160.819485	94.11613766	114.9287934	141.1628118	132.6834266
119.0534279	73.19660117	137.1398829	167.2109452	150
126.8011693	111.8730319	232.4202156	167.3316043	74.73016267
106.53652	52.3490818	376	333.1243936	51.59571718

TABLE 6. The value of power generated (MW) from each generator for case 1 with load level of 1200 MW.

SAR	TSA	EWA	EHO	GWO
509.4656347	500	82.01817953	112.0761519	500
163.2981256	163.2411789	133.8684334	128.3963197	102.7634159
251.7499969	300	134	144.0680366	295.1236759
144.4995777	111.8069123	162.7599846	180.6707543	149.8323055
155.0685298	107.0600108	230	267.3987062	66.35670923
9.57459306	51.4005784	448.3121752	403.0754487	120

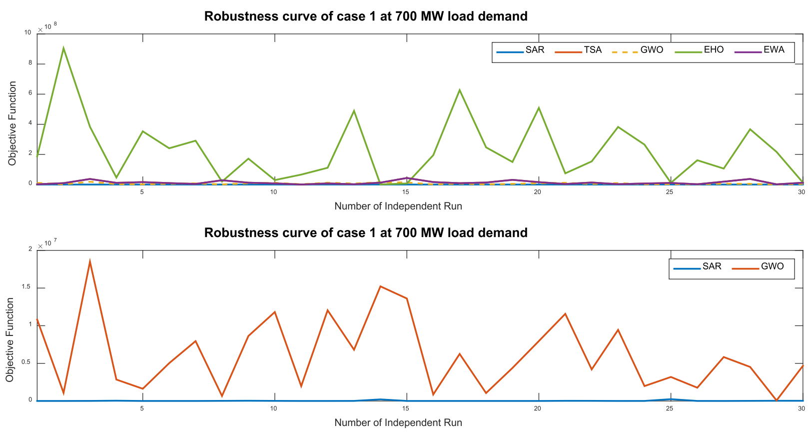

FIGURE 2. Robustness characteristics for case 1 with load level of 700 MW.

application such as SAR, EWA, GWO, TSA and EHO algorithm. The results of 30 independent runs are extracted for all competitor algorithms. The comparison between these methods is performed based on statistical data of 30 runs. The minimum objective function, mean, maximum value and standard deviation are the main items in statistical recorded data at each level of load demand as in table 2. Referring to the data recorded in this table; the best fitness function is achieved by the SAR algorithm and also the best standard deviation is achieved by the proposed SAR technique. Hence,

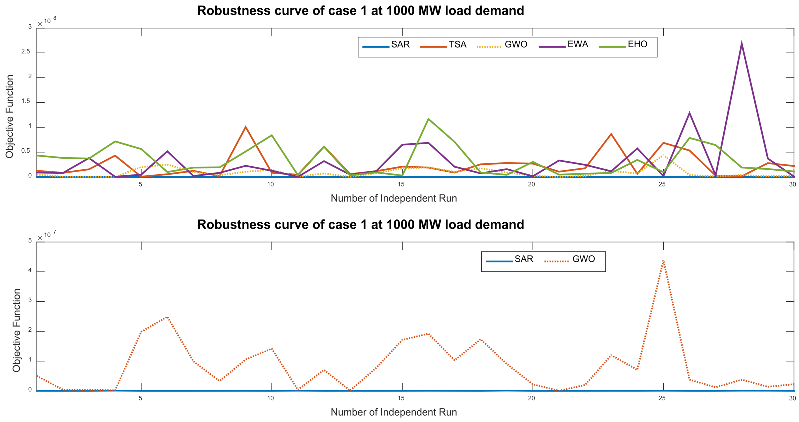

FIGURE 3. Robustness characteristics for case 1 with load level of 1000 MW.

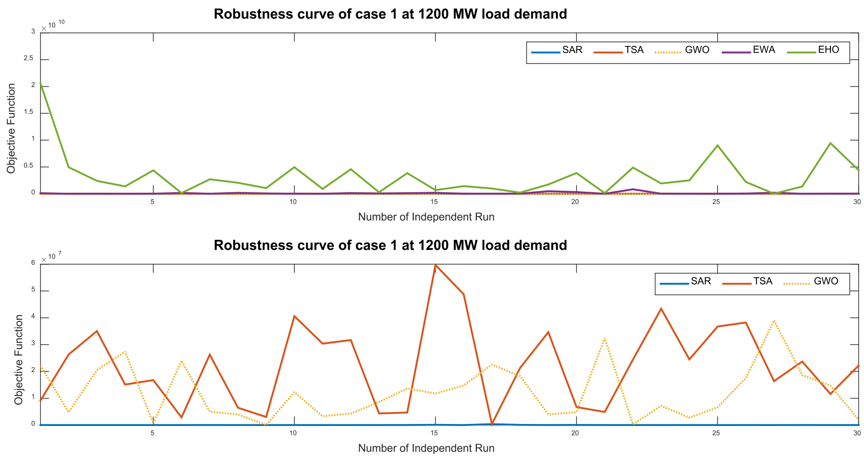

FIGURE 4. Robustness characteristics for case 1 with load level of 1200 MW.

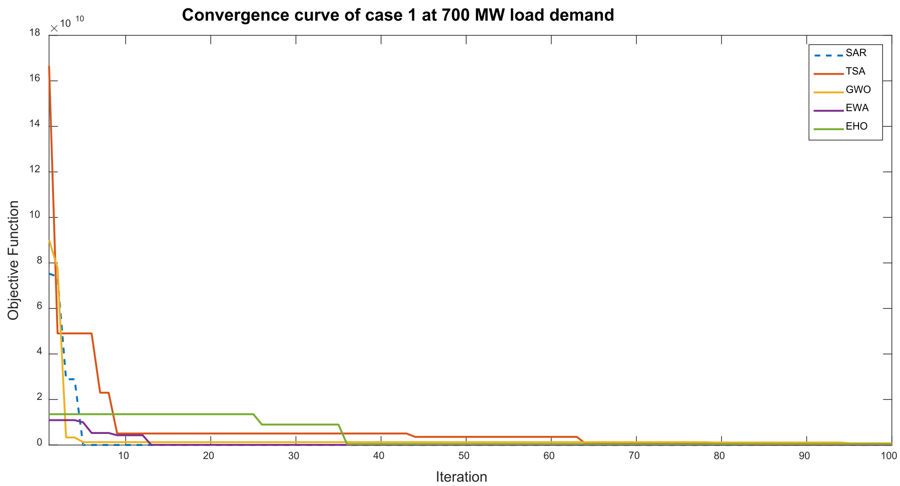

FIGURE 5. Convergence characteristics for case 1 at load level of 700 MW.

the results estimated by SAR method is high accuracy and more reliable than all algorithms used in this study. The minimum cost of fuel consumption for all demand levels used in this case is illustrated in table 3. The value of power generated from each generator is extracted as in table 4 for 700 MW load level. The value of power generated from each generator is extracted as in table 5 for 1000 MW load level. The value of power generated from each generator is extracted as in table 6 for 1200 MW load level. The data recorded in tables 4,5 and 6 are based on the minimum

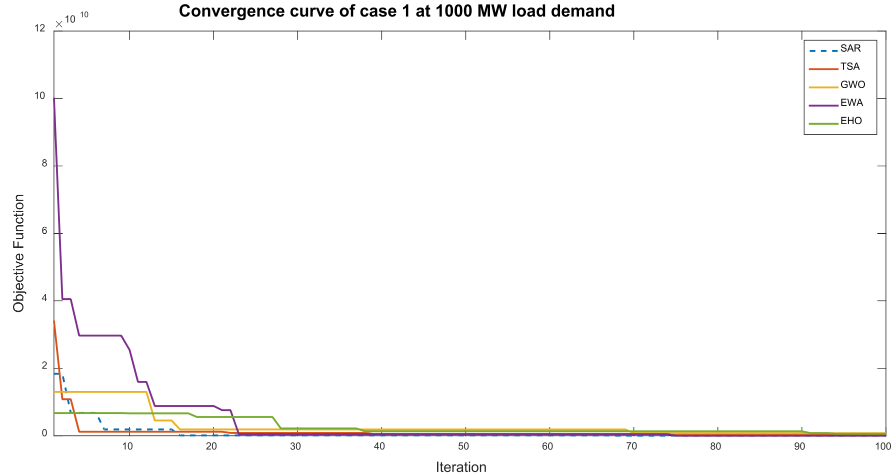

FIGURE 6. Convergence characteristics for case 1 at load level of 1000 MW.

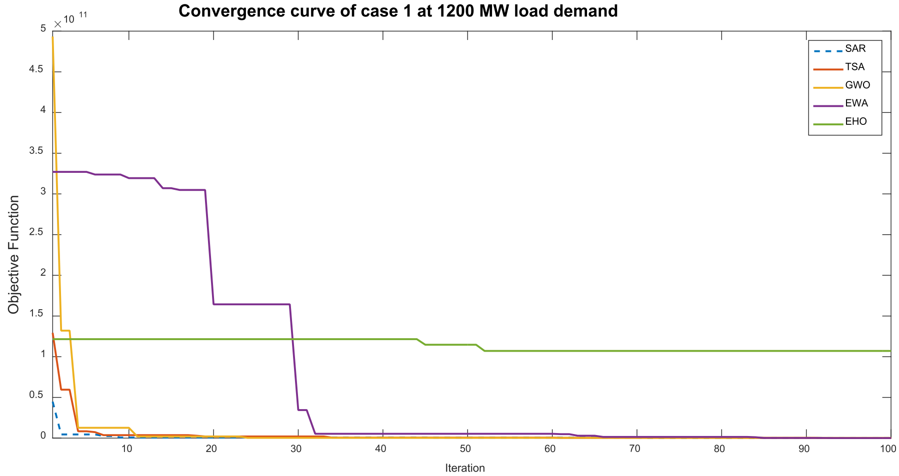

FIGURE 7. Convergence characteristics for case 1 at load level of 1200 MW.

TABLE 7. Statistical recorded data for case 2.

Demand (MW)	Algorithm	SD	max	mean	min
700	SAR	13798.84441	33793.36677	181820.674	36732.29057
	TSA	10731747.71	42219737.54	12658164.49	221163.2708
	EWA	69645534.63	336969212.3	36483350.16	22325.7472
	EHO	11691360.09	204720511	499872502.1	123308166.4
	GWO	5228740.372	20163441.61	5809853.255	234235.4394
1000	SAR	21895.63163	36041.37006	121474.9088	25110.04976
	TSA	26782647.95	104560461.7	20200913.27	579498.6101
	EWA	19449264.29	81905471.65	10667872.53	57007.61007
	EHO	250535.9703	45753050.04	167977714.5	43157836.88
	GWO	7944972.278	30373317.01	10386716.64	177824.4601
1200	SAR	29074.45844	73166.83013	307958.234	69644.96909
	TSA	22767833.1	90336653.91	21145788.47	568641.7148
	EWA	260964544.3	1325436141	129645632.7	556671.3405
	EHO	121679044.4	1882764224	6464536933	1693829131
	GWO	10261965.16	42728669.23	10790450.61	585360.9853

value of fitness function for all algorithms used in this work. The extracted results from all algorithms are compared along 30 runs for all load levels. Based on this data the robustness and convergence characteristics is performed for the best function for all methods in each runs as in figure 2, 3 and 4 as a robustness curves and figures 5, 6 and 7 as a convergence curve for 700 MW load level, 1000 MW load level and 1200 MW load level respectively. Based on the

TABLE 8. Minimum fuel consumption and emission costs of case 2 in ($ per hour).

Algorithm	700 MW		1000 MW		1200 MW	
	fuel	Emission	Fuel	Emission	Fuel	emission
SAR	8407.547001	7352.212268	12208.75425	10792.67902	14890.23056	17948.23832
TSA	8835.650248	9346.501116	12156.78351	9211.30619	14914.53759	15639.3182
EWA	9173.696676	8246.294368	13887.70944	34026.14467	16369.97692	31664.73178
EHO	9419.025517	10407.54045	13674.81196	26247.35079	17137.2867	45432.61852
GWO	8940.890004	5980.92318	12271.31808	10602.56874	14924.13695	16278.87748

TABLE 9. The value of power generated (MW) from each generator for case 2 at load level of 700 MW.

SAR	TSA	EWA	EHO	GWO
284.8221789	119.368407	82.20884693	69.29405881	114.0732492
70.45889296	60.40130478	113.2219045	69.47692619	170.8635487
198.7523186	239.4461211	114.6965031	73.64088866	123.94231
13.53594835	119.813426	120.3089002	148.2614539	51.44745787
75.73512417	125.5566485	143.1039495	172.6286723	143.356137
68.53194184	50	144	180.1536913	110.2491001

TABLE 10. The value of power generated (MW) from each generator for case 2 at load level of 1000 MW.

SAR	TSA	EWA	EHO	GWO
426.4675747	403.712259	78.00038339	55.57666967	500
62.75087073	180.7595382	118.0006019	100.0605225	90.14848327
191.4591783	173.4459086	134.9847813	170.6210971	155.4753064
107.3590047	93.78730482	139.9980982	191.0562113	121.8662569
156.5711735	109.1817177	160.0015571	200	75.46002613
79.64642096	62.11170465	392.995093	307.9115306	78.74612226

TABLE 11. The value of power generated (MW) from each generator for case 2 at load level of 1200 MW.

SAR	TSA	EWA	EHO	GWO
442.7253595	490.7396876	109.965428	92.5222746	500
157.8807508	200	149.9764533	95.35419047	200
309.004929	259.9323433	174.9302042	112.6943089	281.8347626
89.2616598	58.57800604	180.9736908	189.5123302	69.1395628
129.2369223	112.2794992	275.8988491	292.5175716	90.87214432
107.2606882	112.2166867	345.9167858	451.8652694	91.43231402

TABLE 12. Minimum fuel consumption costs of 10 units system in ($ per hour).

Algorithm	Cost
SAR	85233843.42
GWO	93742096.92

TABLE 13. The value of power generated (MW) from each generator for 10 units system.

SAR	TSA
52.06098202	152.7192224
101.3550603	140.9270131
234.8732339	73
130.2124381	97.09493826
104.9570837	190.0149111
121.0660646	132.7303314
107.7862989	82.80092477
44.4449512	50.89074604
80.39470552	74.56561181
72.02988988	54.21931187

characteristics of robustness and convergence figures, the optimum global solution is achieved by the SAR algorithm.

B. RESULTS OF CEED PROBLEM

Case study of 6 generators at three levels of load is applied to solve ELD issue. Several techniques are used in this application such as SAR, EWA, GWO, TSA and EHO algorithm. The results of 30 independent runs are extracted for all competitor algorithms. The comparison between these methods is performed based on statistical data of 30 runs. The minimum objective function, mean, maximum value and standard deviation are the main items in statistical recorded data at each level of load demand as in table 7. Referring to the data recorded in this table; the best fitness function is achieved by the SAR algorithm and also the best standard deviation is achieved by the proposed SAR technique. Hence, the results estimated by SAR method is high accuracy and more reliable than all algorithms used in this study. The minimum cost of fuel consumption for all demand levels used in this case is illustrated in table 8. The value of power generated from each generator is extracted as in table 9 for 700 MW load level. The value of power generated from each generator is extracted as in table 10 for 1000 MW load level. The value of power generated from each generator is

TABLE 14. The power mismatch value (MW) for all cases.

Cases	Method	1200 MW	1000 MW	700 MW
Case 1	SAR	3.62377E-13	3.10756E-10	7.10189E-10
	TSA	3.41276E-05	5.00665E-05	2.67046E-05
	EWA	59.28668221	44.66443804	31.65464393
	EHO	15.88113591	9.506222837	2.725491776
	GWO	2.31609E-06	2.50196E-06	6.84802E-06
	SCA	0.00154	0.000182	0.00076719
	ABC	0.000464669	0.000172518	8.85E-05
	MBO	13.5932468	20.33553784	2.338728225
	ChOA	1.28E-05	0.000476787	0.000284475
	MSA	22.86726197	16.26317	8.164408631
Case 2	SAR	8.14784E-08	2.17426E-12	6.20304E-12
	TSA	5.40222E-05	5.57843E-05	2.06158E-05
	EWA	11.53407616	12.63020626	2.495708213
	EHO	21.08914786	9.735103699	3.177958676
	GWO	5.56911E-05	1.55565E-05	2.19E-05
	SCA	0.00153618	0.001259941	0.000128581
	ABC	0.000402522	3.74E-05	0.000176679
	MBO	19.58822153	18.75789013	2.224948582
	ChOA	6.47E-05	0.000476787	0.000284475
	MSA	23.26274643	12.18295414	7.228241532

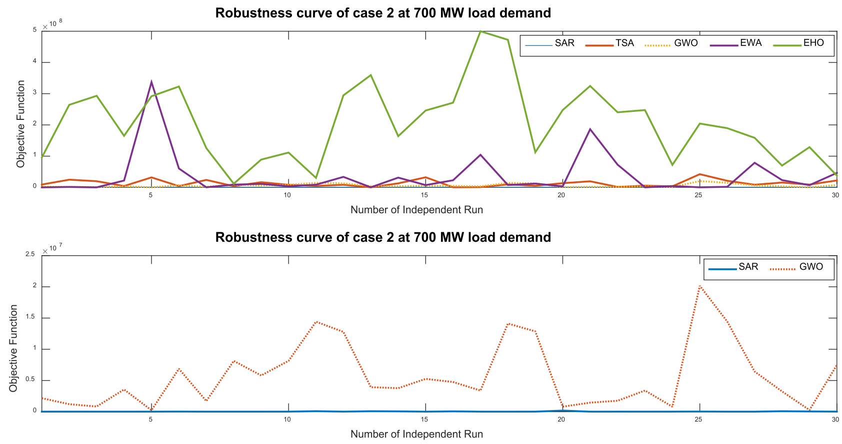

FIGURE 8. Robustness characteristics for case 2 at load level of 700 MW.

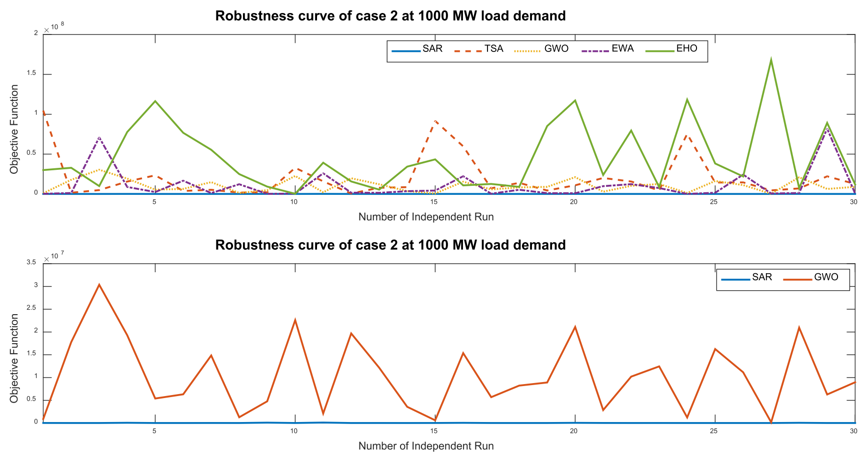

FIGURE 9. Robustness characteristics for case 2 at load level of 1000 MW.

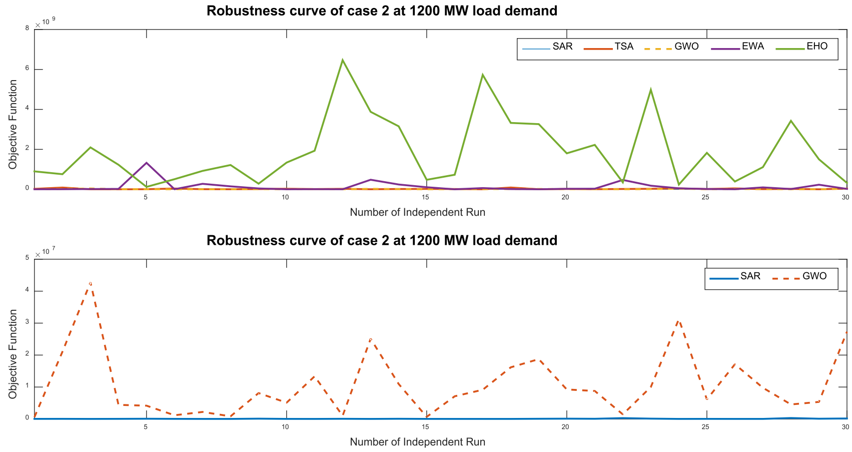

FIGURE 10. Robustness characteristics for case 2 at load level of 1200 MW.

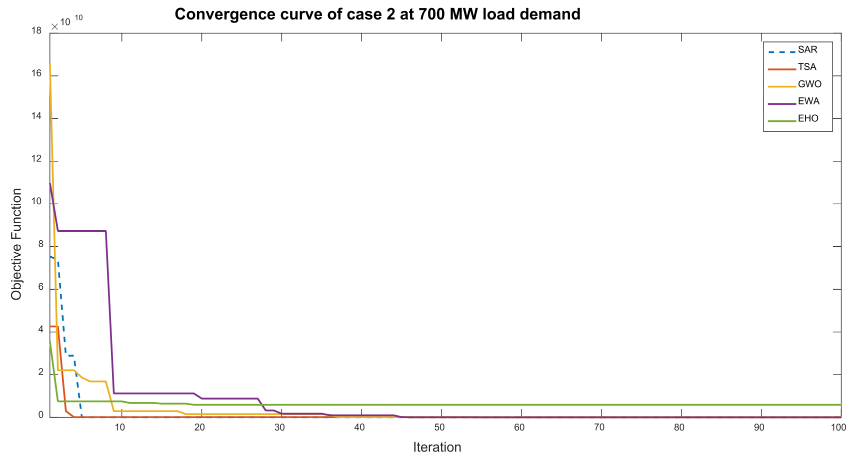

FIGURE 11. Convergence characteristics for case 2 at load level of 700 MW.

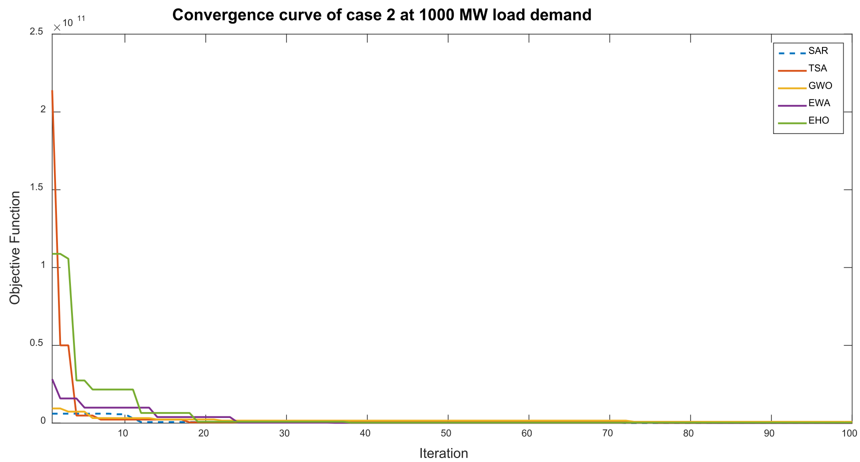

FIGURE 12. Convergence characteristics for case 2 at load level of 1000 MW.

extracted as in table 11 for 1200 MW load level. The data recorded in tables 9,10 and 11 are based on the minimum value of fitness function for all algorithms used in this work. The extracted results from all algorithms are compared along 30 runs for all load levels. Based on this data the robustness and convergence characteristics is performed for the best function for all methods in each runs as in figure 8, 9 and 10 as a robustness curves and figures 11, 12 and 13 as a convergence for 700 MW load level, 1000 MW load level and 1200 MW load level respectively. Based on the characteristics

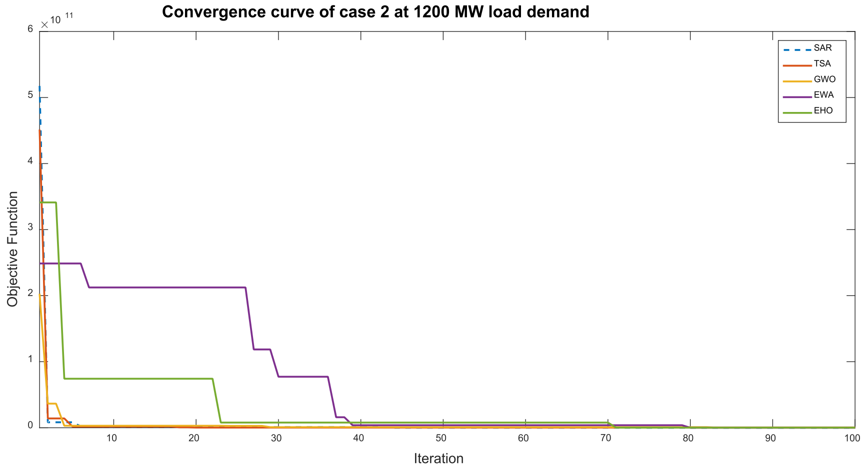

FIGURE 13. Convergence characteristics for case 2 at load level of 1200 MW.

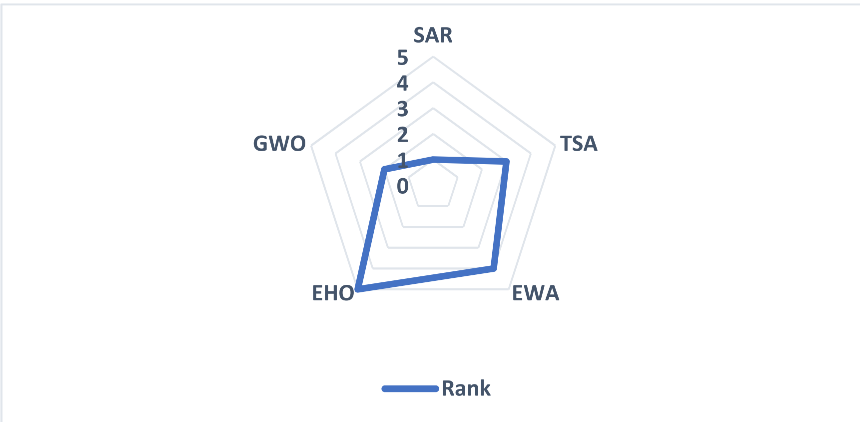

FIGURE 14. Friedman rank test result for case 1.

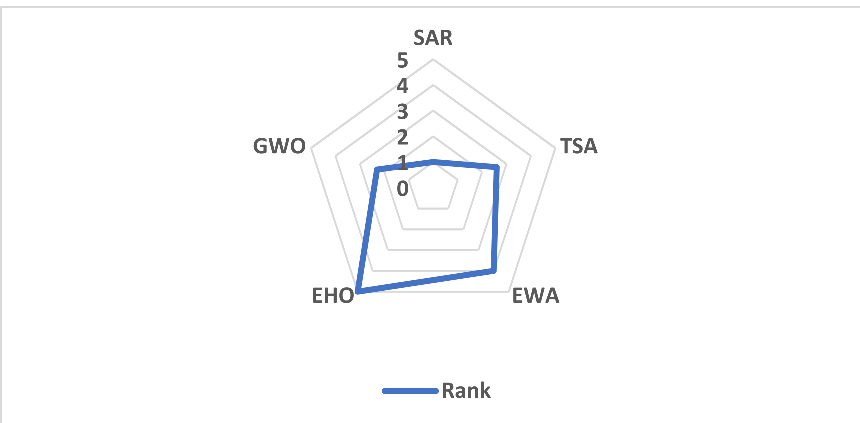

FIGURE 15. Friedman rank test result for case 2.

of robustness figures, the optimum global solution is achieved by the SAR algorithm.

C. FRIEDMAN RANK TEST

The Friedman Test represents a statistical test utilized to decide whether three or more measurements to one group of subjects were different in a significant manner from each other based on skewed variable. This variable ought to be continuous and show similar spread over the groups. The best performing algorithm i.e., shows least significant difference will be the one with the lowest rank. The Friedman rank test is performed, and the results are shown in Fig. 14 and Fig. 15 for case 1 and case 2 respectively. It is observed that SAR obtains the best rank for both the cases followed by GWO.

D. DISCUSSION

Case study of 10 generators is applied to solve ELD issue to achieve the performance quality of the SAR method compared with GWO method. The minimum cost of fuel consumption in this case is illustrated in table 12. The value of power generated from each generator is extracted as in table 13.

The ELD problems have a main item is called power mismatch value. The absolute error between the generated power from units in the system and the summation of the load demand and losses of transmission. The algorithm with high performance for the extracted parameters must achieve the nearest value of this factor to zero. Table 14 summarizes the factor value for the two cases based on the estimated variables from each algorithm. Also, the proposed SAR method is compared with other literature algorithms such as sine cosine algorithm, Artificial Bee Colony, Monarch butterfly optimization, Chimp Optimization Algorithm, Moth search algorithm as explain in table 14. According to this data the SAR method achieve the best power mismatch value for the six cases. The 10-unit network achieve 0.0000157367539692643 power mismatch value for SAR algorithm and 0.000127766302846055 for GWO algorithm. Based on these results, the SAR method achieved the best power mismatch factor foe the seven-network used in this work compared to the GWO, EHO, SCA, ABC, EWA, MSA, MBO, TSA and ChOA algorithms.

V. CONCLUSION AND FUTURE WORK

The Search and Rescue optimization algorithm (SAR) is a novel metaheuristic algorithm mimics the explorations behavior for humans throughout search and rescue processes. SAR is proposed to solve eighteen constraint functions from the benchmark of CEC 2010, which involves: thirteen benchmark constraint functions and seven design problems of constrained engineering. In this paper, SAR is applied to solve two power system operation including the Combined Emission and Economic Dispatch (CEED) and Economic Load Dispatch (ELD). To be specific, the role of SAR is to minimize the fuel consumption cost which represents the principle issue concerning ELD problem optimization for maximizing the power system's economic benefit. The main variable for the ELD problem represents the allocating vector at each unit which sets the best production from each unit of the system. To prove the performance of SAR, a series of experiments were conducted, and the results were compared to several metaheuristics methods, including: the Earthworm optimization algorithm (EWA), Grey wolf optimizer (GWO), Tunicate Swarm Algorithm (TSA) and Elephant Herding Optimization (EHO) of 30 different runs is applied as a statistical analysis for all used methods. Eventually, the results confirmed the efficiency of the SAR in minimizing the cost of fuel for ELD and emission and fuel costs for CEED compared with the counterparts. The SAR method achieved the best factor of power mismatch in solving ELD and CEED for the seven cases compared to the GWO, EHO, SCA, ABC, EWA, MSA, MBO, TSA and ChOA techniques. As future perspectives, the SAR algorithm can be adapted for solving other real-world and large-scale optimization problems of the power system operations.

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