Mehran University Research Journal of Engineering & Technology
Vol. 39, No. 1, 31-46, January 2020
p-ISSN: 0254-7821, e-ISSN: 2413-7219
DOI: 10.22581/muet1982.2001.04

A Hybrid Sine Cosine Algorithm with SQP for Solving Convex and Nonconvex Economic Dispatch Problem

MUHAMMAD IMRAN BABAR*, AFTAB AHMAD*, AND SAQIB FAYYAZ*

RECEIVED ON 29.04.2018, ACCEPTED ON 30.10.2018

ABSTRACT

ED (Economic Dispatch) is one of the major problems of power system operation. The aim of ED problem is the efficient utilization of resources to provide the demanded power while generating cost turns out to be minimum and no constraint is violated either equality or inequality. The ED optimization problem, is necessary because of limited resources, high fuel cost and ever growing demand of power. This paper presents solution to convex and nonconvex ED problems using a novel HSCA (Hybrid Sine Cosine Algorithm). The proposed HSCA technique enhances the exploration capabilities of SCA (Sine Cosine Algorithm) by equipping it with mutation and crossover operators from DE(Differential Evolution) algorithm. DE algorithm introduces diversity in the operation of SCA enabling it to avoid local minima and premature convergence. To ensure precise and accurate optimum tracking results are finally refined by SQP (Sequential Quadratic Programming) algorithm. The high feasibility and applicability of proposed technique has been tested and validated on 13, 15 and 40 IEEE Standard test systems considering transmission losses and prohibited operating zones in "MATLAB 2014a". Comparisons of results obtained from HSCA indicate significant improvement in convergence time and fuel cost as compared to the techniques reported in the literature.

Key Words: Differential Evolution, Economic Dispatch, Sine Cosine Algorithm, Population Based Algorithm, Economic Load Dispatch.

1. INTRODUCTION

There has seen soaring competition in the electricity market propelled by de-regularization of industry and the rampant electricity demand since last decade. In this scenario of ever increasing demand the electricity producers are left with the daunting task of meeting this demand at least cost to maximize profit. This herculean task of maximizing profits while meeting desired demand is termed as ED of the electric power systems. The main aim of ED problem is to assign power outputs to generation units, at a specified time interval, in an economic way, while taking into account different physical and operational constraints. Conventionally, fuel cost characteristics of thermal generators can be approximated by quadratic equations but the factual fuel cost characteristics of the fossil fuel-fired plants exhibit a large number of nonlinearities due to VPLE (Valve-PointLoading Effect) and POZs (Prohibited Operating Zones) [1]. The valve-point loading effect is

Authors E-Mail: (imran.babar@students.uettaxila.edu.pk, aftab.ahmad@uettaxila.edu.pk, saqib.fiaz@students.uettaxila.edu.pk)
* Department of Electrical Engineering, University of Engineering and Technology, Taxila, Pakistan.

due to multiple valve operations in thermal plants to change the fuel type according to the generation. And the valve operation makes the characteristic curve of the generating unit nonlinear and discontinuous. This effect is modeled [2] in the characteristic curve as cyclical sinusoidal function as shown in Fig. 1(a).

The discontinuity due to POZs in the fuel cost characteristics may be due to the resonant frequency created by the addition of all the frequencies of different parts of the machine, or due to the variation in shaft bearing affected by the valve operation or due to the faults in the auxiliary equipment of machine like boiler and feed pumps etc. Generally, the determination of prohibited zones is a difficult procedure accompanied by performance tests. In practical operation, the generation in these regions (POZs) is avoided as it would not be economical to use these zones of operation [3-4]. The objective function of cost which considers this constraint (POZs) is shown in Fig. 1(b).

To tackle with the ED problem various approaches have been proposed in literature so far. These proposed methods cab be classified as classical and non-classical. In classical methods, Base-Point and Participation Factors, λ-iteration method [5], linear programming, quadratic programming [6], branch and bound [7], gradient method [8] were included. These methods were able to compute the ED successfully but because of the discontinuities and nonlinearities introduced by valve-point loading and the POZs, the gradient-based methods were unsuccessful in achieving an optimum solution. The strength of classical methods was demonstrated for continuous and smooth objective functions but the difficulty faced in solution to discontinuous and non-convex problems established the need for further improvement. Many improvements in the classical methods were made in the last decade but these improvements required additional computations to address these complications.

On the other hand, Non-classical meta-heuristic techniques are auspicious alternative to deal with the complexities involved in ED problems. EP (Evolutionary Programming) [9-10], GA (Genetic Algorithm) [2], HNN (Hopfield Neural Network) [11], ITS (Improved Tabu Search) [1], SA (Simulated Annealing) [12-14], DE [15-17], Continuous Quick Group Search Optimizer [18], ACO (Ant Colony Optimization) [19], BBO (Biogeography-Based Optimization) [20], etc. have been developed and implemented on ED successfully.

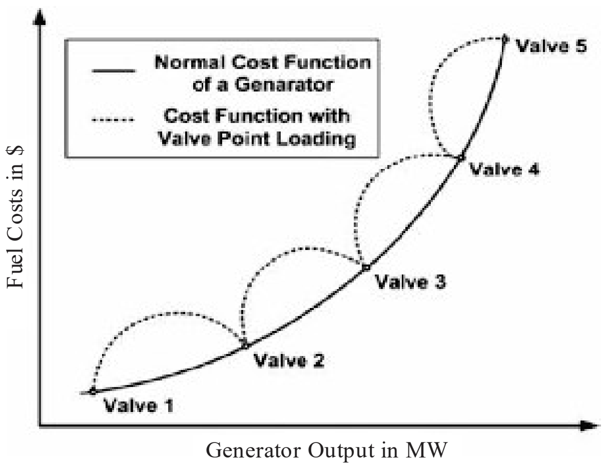

FIG. 1(a). FUEL COST CURVE REPRESENTING THE VALVE POINT LOADING EFFECT CAUSING THE FUNCTION TO BE NON-SMOOTH

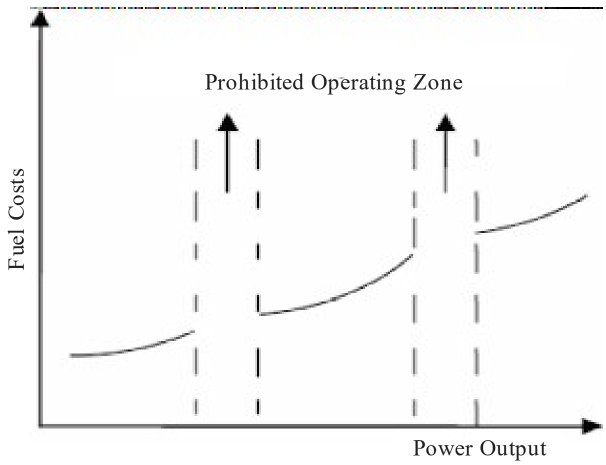

FIG. 1(b). FUEL COST CURVE REPRESENTING THE PROHIBITED OPERATING ZONES

AlthoughAI (Artificial Intelligence) techniques are not generally able to achieve the global solution still they can be used to get a feasible sub-optimal solution. Latest AI techniques used to solve the corresponding ED problem are SKH (Stud Krill Herd) [21], CPSO (Chaotic Particle Swarm Optimization) [22], CSA [23], IODPSO (Improved Orthogonal Design Particle Swarm Optimization) [24], MVMO (Mean Variance based Mapping Optimization) technique [25], LFA (Lightening Flash Algorithm) [26], GSO (Glowworm Swarm Optimization) [27], IFWA-CSO (Improved Fireworks Algorithm with Chaotic Sequence Operator) [28], ALO (Ant Lion Optimizer) [29], and CKH Algorithm [30]. The basic technique of SCA was proposed by Mirjalili [31].

All these techniques show remarkable results and convergence characteristics in their own rights but fail to perform optimally for all cases. Some drawbacks related to these evolutionary techniques are high computational time, curse of dimensionality, computational complexity, slow convergence rate and sensitivity to control parameters. This inability of algorithms to perform optimally for all cases is also summarized by No Free Lunch Theorem. To perform optimally for all cases we need either to modify our technique to suite the problem or find a new strategy to tackle the issue altogether. SCAs are no exception to this rule. To improve the capabilities of SCA several other techniques were considered such as PSO (Particle Swarm Optimization), MPC (Multi-Parent Crossover) and SEA (Simple Evolutionary Algorithm) but DE was eventually deemed suitable. DE was selected because of its mathematical ease of not having to compute derivative, less number of control parameters, robustness, same setting for almost all types of problems [32-33] and strong convergence characteristics equipped with diverse searching mechanism. Finally, to overcome the issue of precision in global optimum tracking the answer was refined by SQP resulting in a novel approach termed HSCA.

In this paper, the proposed novel meta-heuristic technique named "HSCA with SQP" has been employed to elucidate the ED problem.

2. PROBLEM FORMULATION

This section describes the formulation of ED problem.

2.1 Description of ED Problem

ED has been one of the most important power system operational planning problems. The limited energy resources and increasing cost of thermal power generation accompanied by ever-growing demand of power has necessitated the implementation of ED on the present power system. The main target of ED problem is to deal with assigning of optimized generation value from the available resources while considering the constraints associated with the system.

The target of ED is to minimize the cost which is mathematically denoted as:

$$FC = \sum_{i=1}^{n} F_i\left(P_i\right) \tag{1}$$

While, *FC* represent the total cost of fuel and the $F_i(P_i)$ represents the cost of ith the unit and "n" gives the total number of units. The expression for cost of fuel is represented as:

$$F_i\left(P_i\right) = a_i P_i^2 + b_i P_i + c_i \tag{2}$$

Where P_i gives the real power engendered from the ith unit and a_i is the fuel-cost coefficient for that specified unit i in [\$/MW^{2}h]. Similarly, b_i and c_i are also fuel cost coefficients in [\$/MWh] and [\$/h] respectively.

The Equation (2) is a reasonable approximation of thermal plants but in actual thermal generation there are multiple valves present to control the output power. As these valves are opened there is an abrupt increase in losses which creates a rippling effect in the characteristic curve making the fuel-cost plot non-smooth (Non-convex). This VPLEwhen taken into consideration makes the cost function non-smooth which can be expressed as a combination of quadratic and sine expression as:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| d_i \times \sin\left(e_i\left(P_i^{\min} + P_i\right)\right) \right| \quad (3)$$

While "i" represents the committed generating unit and "d" and "e" represent the valve point loading coefficients.

2.2 Constraints

ED problem is about the minimization of fuel cost using fuel cost function (either convex or nonconvex) subjected to different constraints as follows:

2.2.1 Power Balance Constraint

$$\sum_{i=1}^{m} P_i = P_D + P_{Loss} \quad (4)$$

Where the P_{Loss} represents the transmission loss and can be mathematically expressed by the use of B-coefficients as:

$$P_{Loss} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{i0} P_i + B_{00} \quad (5)$$

While, P_D denotes total load demand and B_{ij}, B_{i0}, and B_{00} are the B-coefficients.

2.2.2 Capacity Limit Constraint

The real power generated from each generation unit must not violate its max $\left(P_i^{\max}\right)$ and $\left(P_i^{\min}\right)$ limit.

Mathematically,

$$P_i^{\min} \le P \le P_i^{\max}, \ \mathrm{i} \in \mathrm{N} \quad (6)$$

2.2.3 Prohibited Operating Zones

There are some regions in the range of operation of generating unit in which the system may lose stability if operated in these specified regions due to synchronization of all the components of the generating unit. These regions are named as prohibited operating zones. And are therefore avoided in practical generations.

Mathematically these are represented as follows:

$$P_i \in \begin{cases} P_i^{\min} \le P_i \le P_{i,1}^{l} \\ P_{i,1}^{u} \le P_i \le P_{i,2}^{l} \\ \cdots\cdots\cdots \\ P_{i,n}^{u} \le P_i \le P_i^{\max} \end{cases} \quad (7)$$

Where the $P_{i,n}^{u}$ and $P_{i,n}^{l}$ represent the maximum and minimum limits of nth prohibited zone and "n" represent the number of prohibited zone. The POZs cause the function to be discontinuous.

3. PROPOSED HYBRID SINE COSINE ALGORITHM

Population-based algorithms reported in literature start to optimize the problem using a set of population generated randomly, each of these randomly populated solutions are then evaluated to compute the objective function and updated by a procedure specific to the respective technique which basically constitutes the core of an optimization algorithm. According to literature, the algorithms which are based on population are far more suitable for optimization problems as they start from a set of random solutions and naturally avoid being stuck into the local optimum as compared to individual based algorithms. These characteristics enable population-based algorithms to explore (global search) the search area freely and thoroughly while reducing the risk of being entrapped into the local optimum to a good extent. Similarly, SCA is a population-based algorithm and characteristic of sine and cosine function of being recurrent in cycle compels the solution to reposition itself around another solution. This pattern of search guarantees the exploitation (local search) of search area between two fitness values in SCA. And to exploit the search area, the range of cosine and sine functions can be increased as made known in Fig. 2.

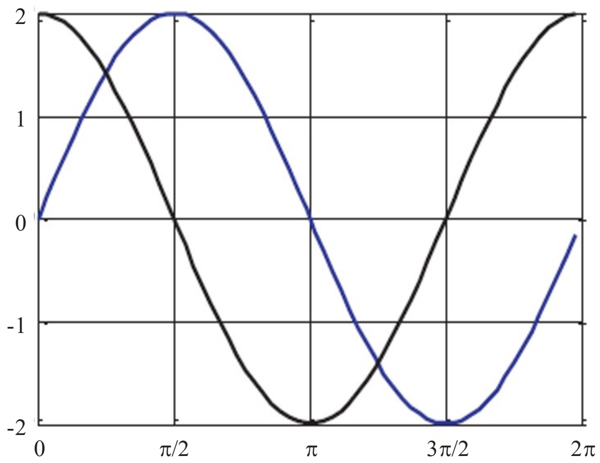

FIG. 2. SINE, COSINE IN RANGE OF [-2,2].

In more detail, the influence of CSA trigonometric functions in the specified range as in Fig. 2. i.e. [-2,2] is explained in Fig. 3. Fig. 3 clearly describes the effect of altering the range of cosine and sine that how this change necessitates an answer to update its next location inside or outside of the search space in between itself and next solution.

As we have discussed the performance measures of SCA, the technique has been hybridized with DE and SQP using the following steps to solve the concerned ED problem.

Step-1: Initialization: First, the population is initialized randomly in the lower and upper limit of generating units according to the following equation.

$$P = P^{min} + rand.(P^{max} - P^{min}) \quad (8)$$

Step-2: Evaluation of Fitness Function: The population is updated according to the CSA equations as stated below:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| d_i \times \sin\left(e_i\left(P_i^{\min} + P_i\right)\right) \right| \quad (9)$$

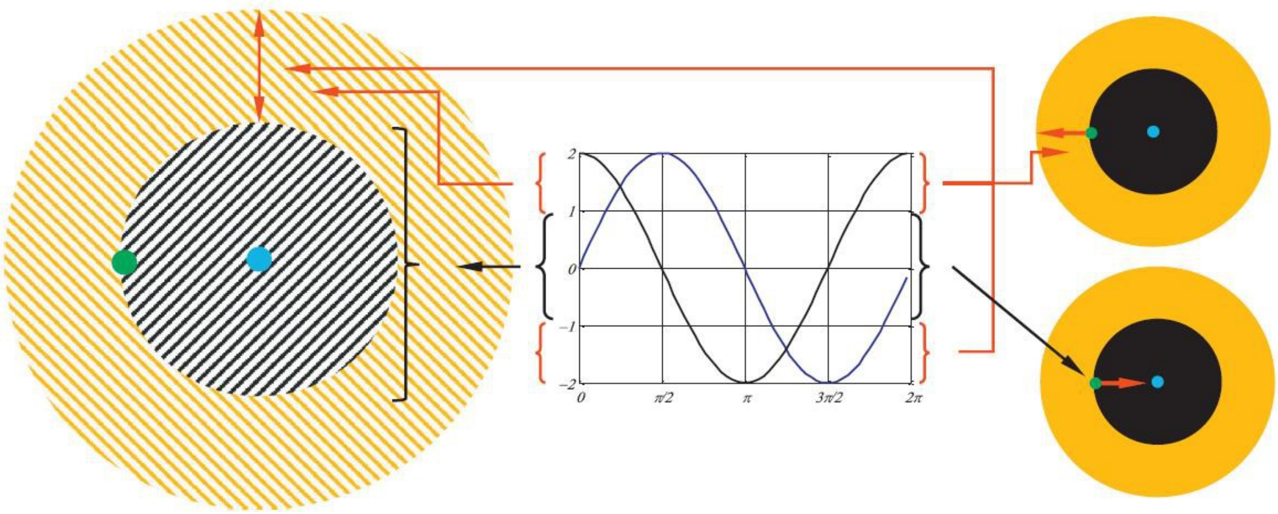

FIG. 3. SINE, COSINE IN THE RANGE IN [“2,2] REPRESENTING HOW A SOLUTION GOES INSIDE OR OUTSIDE THE SPACE CONFINED

Step-3: Update the Population According to SCA: The population is updated according to the CSA Equations (10-11) as stated below:

$$P_i^{t+1} = P + r_i \times \sin(r_2) \times \left| r_3 p_{best_i}^i - P_i^t \right|, \quad r_4 < 0.5 \tag{10}$$

$$P_i^{t+1} = P + r_i \times \cos(r_2) \times \left| r_3 p_{best_i}^i - P_i^t \right|, \quad r_4 \geq 0.5 \tag{11}$$

As Equations (10-11) show, there are four random parameters r_1, r_2, r_3, and r_4.

The first random parameter r_1 prescribes the direction of movement which could be outside the destination and solution or inside it. This random parameter adaptively changes the range of cosine and sine functions to balance between exploration and exploitation using the equation as:

$$r_1 = a - t\frac{a}{T} \tag{12}$$

Where "t" denotes the present iteration and "T" represents the max number of iteration and "a" is a constant. The second random parameter "r_2" emphasizes that how long next movement would be towards or outwards the destination point. This movement inside or outside the search space is obtained by defining the random parameter "r_2" in the range $[0, 2\pi]$. The third random parameter "r_3"is the random weight for the destination point distance stochastically. And the fourth random parameter "r_4"is the switch between the sine and cosine function to be used for updating the population.

Step-4: Application of Mutation and Crossover: By applying the crossover and mutation, the updated population is modified further to introduce diversity and avoid local optima stagnation.

Mutation: In the mutation operator, in the current population, a mutated vector is generated for each targeted vector except for the running index.

$$u_{i,p+1} = x_g + SF\,(x_{r1,g} - x_{r2,g}) \tag{13}$$

Where r_1 and r_2 are the randomly initialized integers dissimilar to each other and from the running index "i" too. And SF is the scaling factor which is a randomly engendered number between (0,1) but may not be homogeneously disseminated in the range of (0,1). Generally, the choice for the SF is between 0.4 and 1 but here in the proposed work, the dynamic behavior to the SF is applied by varying SF in a randomly generated number in the range of (0.5, 0) [34]. Here in this case due to the randomly scaled difference vector, there is a better chance of pointing the new mutated vector at the even better location until the true global optimum is achieved.

Crossover: After the application of mutation operator, the crossover operation is applied to upsurge the diversity of individuals. The previously generated vector is assorted with the vector produced after mutation to form a new trial vector $w_{ji,g+1}$.

$$W_{ji,g+1} = \begin{cases} y_{ji,g+1} & \text{if } rand_j(0,1) \leq C_R \forall j = m \\ z_{ji,g+1} & \text{Otherwise} \end{cases} \tag{14}$$

Where i=1…N_P and j=1 …Q;

And "m" is a random number elected between 1 and N_P which makes sure that the new trial vector takes the smallest parameter from the mutant vector. And C_R is the crossover parameter defined by the user and reins the diversity of the individuals and helps the solution to avoid from local minimum [34].

Step-5: Verification of Equality and Inequality Constraints: Check if the active power of any of the generating unit violates the limit or not. In case, power generation of any unit is less than the minimum limit then it is fixed at the minimum limit and if power generation of any unit exceeds the maximum limit then it is clamped at maximum limit. After the satisfaction of inequality constraint, the equality constraint is verified.

Step-6: Application of Sequential Quadratic Programming: After the completion of constraints handling, the SQP is applied to the best results obtained so far from the proposed algorithm.

Sequential Quadratic Programming: SQP is actually not a feasible point or heuristic method. But this turns out to be mathematical technique and it uses the feasible solution of a sub-problem to find a better solution to the major problem. Seemingly, SQP performs closely to the Newton and Quasi-Newton methods. The only thing which makes SQP different from Newton and Quasi-Newton is the handling of constraints [35].

In the SQP the QP is solved in each step to improve line search which can be mathematically defined as:

Minimize

$$\nabla F(P_k)^T + \frac{1}{2} d_k^T H_k d_k \tag{15}$$

Subject to

$$g_i(P_k) + [\nabla_g(P_k)] d_k = 0 \tag{16}$$

i = 1 ….. m

$$g_i(P_k) + [\nabla_g(P_k)] d_k \le 0 \tag{17}$$

i=m_e+1… m

Here, H_k is Hessian Matrix and d_k is direction search, P_k is the real power vector and$g_i(P_k)$ represents the equality and inequality constraints in current iteration which is represented by "k". And m_e is the equality constraint's quantity while "m" represents quantity of constraints.

$$L(P,\lambda) = F(P) + g(P)^T\lambda \tag{18}$$

Where λ represents the Lagrangian multiplier and H_k is formulated with the help of Quasi-Newton.

$$H_{K+1} = H_k + \frac{q_k q_k^T}{q_k^T S_k} - \frac{H_k^T S_k^T H_k}{S_k^T H_k S_k} \tag{19}$$

And,

$$S_k = P_{k+1} - P_k \tag{20}$$

$$q_k = \nabla L(P_{k+1}, \lambda_{k+1}) - \nabla L(P_k, \lambda_{k+1}) \tag{21}$$

In each iteration, the direction of sub-problem is achieved and the new solution is found from new iteration as follows:

$$P_{k+1} = P_k - \alpha_k d_k \tag{22}$$

For calculation of step length (α_k) the following formula is used as this step length is significant for the decrease in the Lagrangian merit function.

$$L_A(P, \lambda, \rho) = F(P) - \lambda^T g(P) + \frac{\rho}{2} g(P)^T g(P) \tag{23}$$

Step-7: Stopping Criteria: The same procedure from step-2 is repeated until the stopping criteria are achieved. The SCA stops further computations if there comes no noticeable improvement or a maximum number of iteration is completed. In this work, the stopping criteria are maximum number of iterations.

4. EXPERIMENTAL METHODS AND RESULTS

The proposed HSCA is implemented to three ED problems to verify its feasibility. These three ED problems refer to three types of test systems to validate the proposed technique. The test systems differ from each other with respect to the number of generating units, rippling effect which is generally termed as the VPLE, inclusion or exclusion of transmission losses and as well as POZs.

Test System-1: 13-unit nonconvex (with VPLE) test system without transmission losses.

Test System-2: 15-unit convex test system (without VPLE) considering transmission losses and POZs.

Test System-3: 40-unit nonconvex test system without transmission losses.

4.1 Test System-1

The load demand for 13-unit test system is 2520 MW. The input data consisting of load demand, cost coefficients and generator limits are taken from [5].

4.1.1 Parameters

The Table 1 shows the parameters of mutation, crossover, and others used to optimize the results of 13-unit test systems.

Table 2 shows the individual cost of each unit and total power corresponding to total fuel cost. Total power output comes to be 2520 MW and total fuel cost is 24164.1 US$/hr.

TABLE 1. LIST OF PARAMETERS TAKEN FOR TEST SYSTEM-I

Iteration	50	Search Agents	25
Trials	40	Mutation Scaling Factor	0.0101
Total Number of Computations	2000	Crossover Probability	0.2

TABLE 2. POWER OUTPUT OF INDIVIDUAL UNIT AND CORRESPONDING COST FOR TEST SYSTEM-I

Unit Number	P^{min} (MW)	P^{max} (MW)	Generation (MW)	Fuel Cost (US$/hr)
1	0	680	628.3184	5749.9
2	0	360	299.1988	2782.6
3	0	360	294.4871	2770.4
4	60	180	159.7327	1559
5	60	180	159.733	1559
6	60	180	159.7331	1559
7	60	180	159.7328	1559
8	60	180	159.7331	1559
9	60	180	159.7329	1559
10	40	120	77.39937	808.656
11	40	120	77.39962	808.658
12	55	120	92.39917	944.889
13	55	120	92.3999	944.884
Total			2520	24164.6

4.1.2 Results

In Table 3 there is the statistical comparison of the proposed algorithm with other techniques and clearly shows that SCA minimizes the fuel cost as compared to other techniques mentioned in Table 3.

Fig. 4 demonstrates the convergence curve of 13-unit test system solved using SCA and clearly describes that the system converges to optimum before stopping criteria.

In Fig. 5 the fuel cost of 13-unit test system is compared using a bar chart to simplify the analysis. Fig. 5 shows that lowest cost is obtained by using the proposed HSCA which in this case is 24164.06 US$//hr.

The results of 13 unit-test system show that the proposed technique owns significantly lesser fuel cost as compared to the former techniques conveyed in the literature. The proposed technique saves about 5 $/hr as compared to HGA (Hybrid Genetic Algorithm), DE and FAPSO-VDE (Fuzzy Adaptive Particle Swarm Optimization with Variable Differential Evolution).

TABLE 3. STATISTICAL COMPARISON OF 13 UNIT TEST SYSTEM

Methods	Total Generating Cost (US$/hr)		
	Minimum Cost	Maximum Cost	Average Cost
IPSO-TVAC [36]	24166.80	24167.37	24169.41
ICA-PSO [37]	24168.91	24175.34	24184.92
HGA [38]	24169.9177	NA (Not Available)	NA(Not Available)
DE [15]	24169.9177	NA(Not Available)	NA(Not Available)
FAPSO-VDE [39]	24169.9176	24169.9176	24169.9176
DE [40]	24165.6767	24169.5008	24172.0944
CRO [40]	24165.1664	24166.9355	24169.3642
CKH [30]	24164.1815	24166.11	24168.43
Proposed HSCA	24164.06	25015.26	24583.25

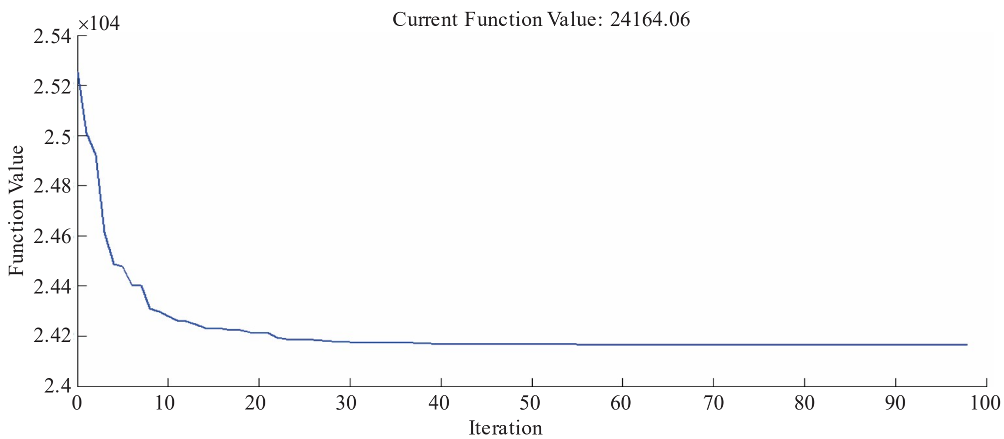

FIG.4. CONVERGENCE CURVE FOR TEST SYSTEM-1

4.2 Test System-2

The load demand for 15-unit test system is 2630 MW. The input data consisting of load demand, cost coefficients and generator limits are taken from [27]. The transmission losses are calculated using B-coefficients method.

4.2.1 Parameters

Table 4 shows the mutation, crossover and other parameters which are taken to optimize the results of 15-unit test system.

4.2.2 Results

Table 5 shows the individual cost of each unit and total power corresponding to total fuel cost. Total power output comes to be 2656.689 MW with transmission losses of 26.6956 MW and total fuel cost is 32548.03 US$/hr.

In Table 6 there is the statistical comparison of the proposed algorithm with other techniques and clearly shows that SCA minimizes the fuel cost as compared to other techniques mentioned in Table 6.

Fig. 6 shows the convergence curve of 15-unit test system solved using SCA and clearly describes that the system converges to optimum before stopping criteria.

In Fig. 7 cost of fuel for 15-unit system is compared using a bar chart to simplify the analysis. Fig. 7 shows that the lowest cost is acquired by using the proposed "HSCA with SQP" which in this case is 32548.03 US$//hr.

The results of 15-unit system show that the proposed technique owns significantly lesser fuel cost as compared to the other techniques conveyed in the literature. The proposed technique saves about 309and 156 US$/hr as compared to PSO and IPSO respectively.

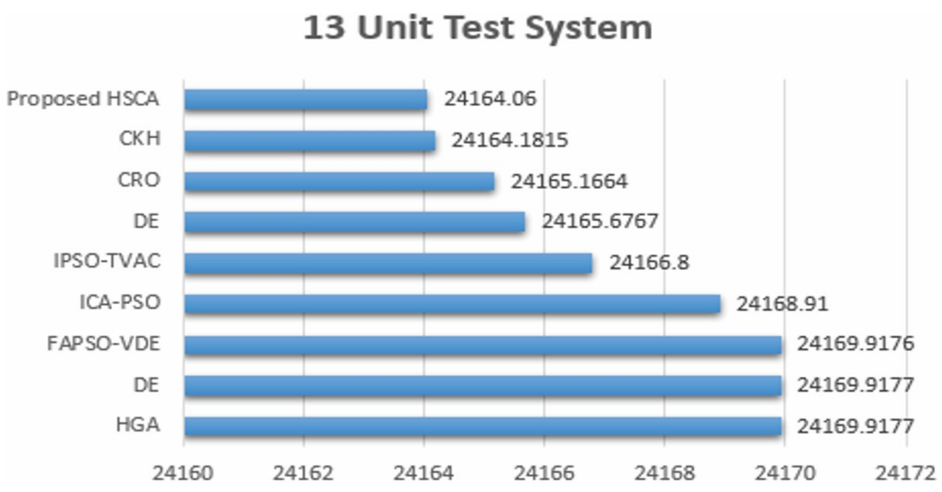

FIG. 5. COMPARISON OF FUEL COST FOR 13 UNIT TEST SYSTEM WITH THE DEMAND OF 2520 MW

TABLE 4. LIST OF PARAMETERS TAKEN FOR TEST SYSTEM-II

Iteration	50	Search Agents	25
Trials	40	Mutation Scaling Factor	0.000987
Total Numberof Computations	2000	Crossover Probability	0.2345

TABLE 5. POWER OUTPUT OF INDIVIDUAL UNIT AND CORRESPONDING COST FOR TEST SYSTEM-II

Unit Number	P^{min} (MW)	P^{max} (MW)	Generation (MW)	Fuel Cost (US$/hr)
1	150	455	455	5328.4
2	150	455	455	5252.9
3	20	130	130	1537
4	20	130	130	1537
5	150	470	228.3601	2846.6
6	135	460	460	5339.7
7	135	465	465	5183.7
8	60	300	60	900.2168
9	25	162	25	453.5044
10	25	160	36.7366	569.7055
11	20	80	76.5918	988.273
12	20	80	80	1057.3
13	25	85	25	552.7319
14	15	55	15	490.934
15	15	55	15	510.0006
Total			2656.689	32548.03
Transmission Losses			26.6956	

TABLE 6. STATISTICAL COMPARISON OF 15 UNIT TEST SYSTEM

Methods	Total Generating Cost (US$/hr)		
	Minimum Cost	Maximum Cost	Average Cost
IPSO [10]	32704.4514	32704.4514	32704.4514
PSO[41]	32858.00	33331	32039
KGMO[42]	32548.1736	32548.3755	32548.2163
Proposed HSCA	32548.03	32574.54	32555.1

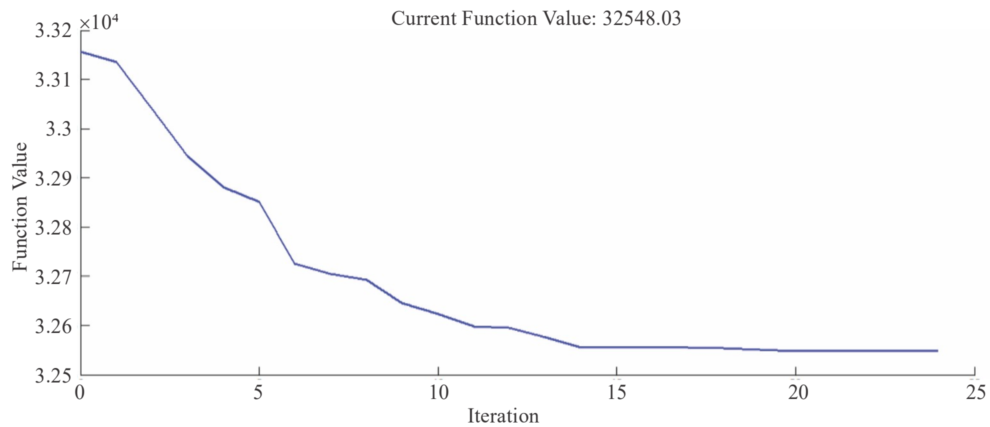

FIG. 6. CONVERGENCE CURVE FOR TEST SYSTEM-2

4.3 Test System-3

The load demand for 40-unit test system is 10500 MW. The input data consisting of load demand, cost coefficients and generator limits are taken from [43].

4.3.1 Parameters

The Table 7 shows the mutation, crossover and other parameters used to optimize the results of 40-unit test system.

4.3.2 Results

Table 8 shows the individual cost of each unit and total power corresponding to total fuel cost. Total power output comes to be 10500 MW and total fuel cost is 121983.5 $/hr.

And, in Table 9 there is the statistical comparison of the proposed algorithm with other techniques and clearly shows that SCA minimizes the fuel cost as compared to other techniques mentioned in Table 9.

Fig. 8 shows the convergence curve of 40-unit test system solved using SCA and clearly describes that the system converges to optimum before stopping criteria.

In Fig. 9 the fuel cost of 40-unit test system is compared using a bar chart to simplify the analysis. Fig. 9 shows that lowest cost is obtained by using the proposed HSCA which in this case is 121983.5 US$//hr.

The results of 40-unit system reveal that the offered technique owns significantly lesser fuel cost as compared to the other techniques conveyed in the literature. The proposed technique saves about 640, 269 and 138 US$/hr as compared to IFEP (Improved Fast Evolutionary Programming), MPSO (Modified Particle Swarm Optimization) and Efficient ESO (Evolutionary Strategy Optimization) respectively.

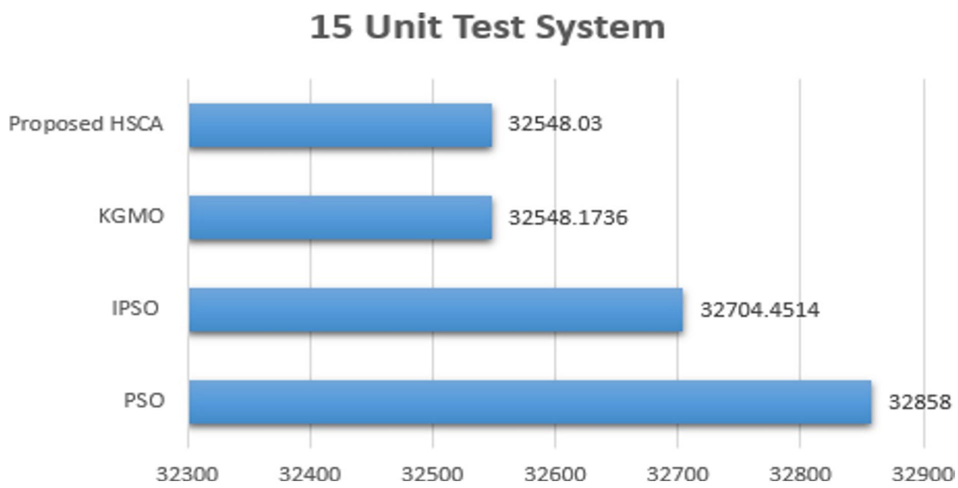

FIG. 7. COMPARISON OF FUEL COST FOR 15 UNIT TEST SYSTEM CONSIDERING LOSSES AND PROHIBITED OPERATING ZONE WITH THE DEMAND OF 2630 MW

TABLE 7. LIST OF PARAMETERS TAKEN FOR TEST SYSTEM-I

Iteration	50	Search Agents	25
Trials	40	Mutation Scaling Factor	0.0101
Total Number Computations	2000	Crossover Probability	0.2

TABLE 8. POWER OUTPUT OF INDIVIDUAL UNIT AND CORRESPONDING COST FOR TEST SYSTEM-III

Unit Number	P^{min} (MW)	P^{max} (MW)	Generation (MW)	Fuel Cost (US$/hr)
1	36	114	110.7996	925.0964
2	36	114	110.7998	925.0964
3	60	120	120	1544.7
4	80	190	179.7333	2143.6
5	47	97	87.7999	706.5002
6	68	140	140	1596.5
7	110	300	299.8777	3296.3
8	135	300	284.5997	2779.8
9	135	300	284.5995	2798.2
10	130	300	130	2502.1
11	94	375	243.5994	4083.2
12	94	375	168.7995	2977.5
13	125	500	214.7596	3792.1
14	125	500	214.7596	4005.7
15	125	500	394.2794	6436.6
16	125	500	304.5192	5171.2
17	220	500	489.2793	5296.7
18	220	550	550	6224.1
19	242	550	511.2793	5540.9
20	242	550	331.7598	3636.4
21	254	550	523.2793	5071.3
22	254	550	523.2792	5071.3
23	254	550	523.2793	5057.2
24	254	550	523.2794	5057.2
25	254	550	523.2793	5275.1
26	254	550	523.2794	5275.1
27	10	150	10	1140.5
28	10	150	10	1140.5
29	10	150	10	1140.5
30	47	97	87.8003	706.5062
31	60	190	190	1644
32	60	190	190	1644
33	60	190	190	1644
34	90	220	220	2228.4
35	90	220	220	2164.5
36	90	220	220	2164.5
37	25	110	110	1220.2
38	25	110	110	1220.2
39	25	110	110	1220.2
40	242	550	511.279	55409
Total			10500	121,983.5

TABLE 9. STATISTICAL COMPARISON OF 40 UNIT TEST SYSTEM

Methods	Total Generating Cost (US$/hr)		
	Minimum Cost	Maximum Cost	Average Cost
IPSO [10]	32704.4514	32704.4514	32704.4514
PSO[41]	32858.00	33331	32039
KGMO[42]	32548.1736	32548.3755	32548.2163
Proposed HSCA	32548.03	32574.54	32555.1

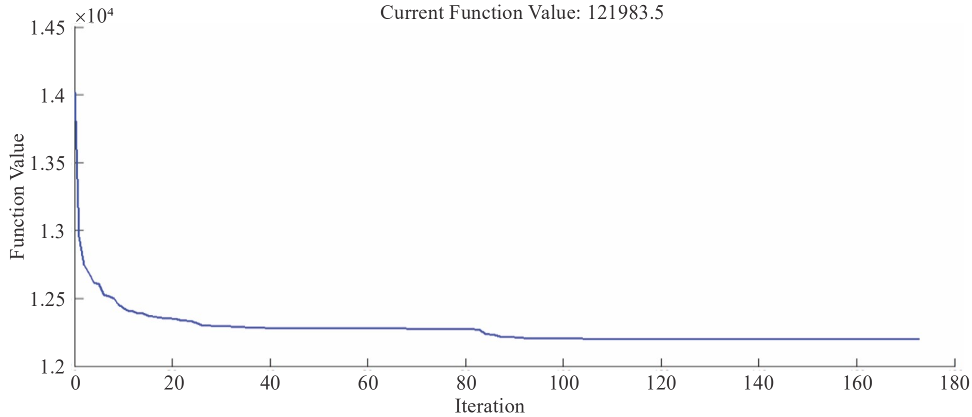

FIG. 8. CONVERGENCE CURVE OF TEST SYSTEM-3

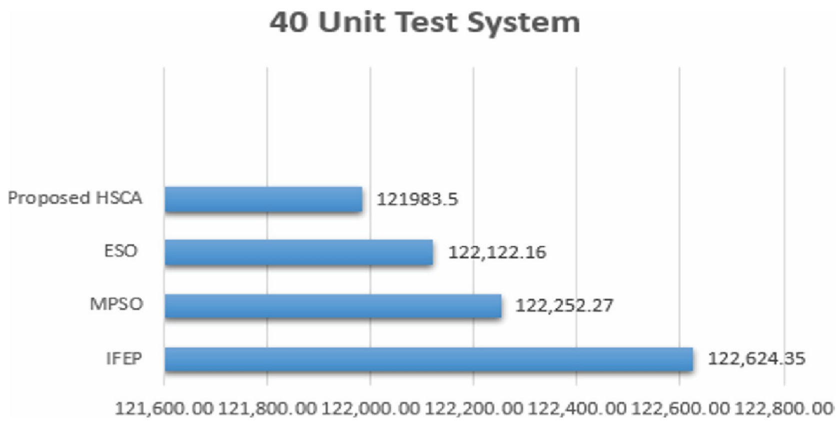

FIG. 9. COMPARISON OF FUEL COST FOR 40 UNIT TEST SYSTEM WITH THE DEMAND OF 10500 MW

5. CONCLUSION

The HSCA with SQP was successfully applied to various IEEE standard test systems while taking into account the equality and inequality constraints. And the results when compared with other techniques conveyed in literature clearly show that the proposed technique performs significantly better in terms of cost as well as fast convergence. Moreover, as the "HSCA with SQP" has performed very well on ED as compared to most of the methods, therefore, it can be applied to other problems of optimization related to power systems. And the hybridization of SCA with other evolutionary techniques may be a good area for the future research also.

ACKNOWLEDGEMENT

The first Authors would like to thank his supervisor for his continued guidance, supervision, friendliness and wise counsel throughout the research. Authors would like to thank University of Engineering & Technology, Taxila, Pakistan, and its staff for all the resources provided.

REFERENCES

[1] Lin, W.-M., Cheng, F.-S., and Tsay, M.-T., "An Improved Tabu Search for Cconomic Dispatch with Multiple Minima", IEEE Transactions on Power Systems, Volume 17, No. 1, pp. 108-112, 2002.

[2] Walters, D.C., and Sheble, G.B., "Genetic Algorithm Solution of Cconomic Dispatch with Valve Point Loading", IEEE Transactions on Power Systems, Volume 8, No. 3, pp. 1325-1332, 1993.

[3] Chen, P.-H., and Chang H.-C., "Large-Scale Economic Dispatch by Genetic Algorithm", IEEE Transactions on Power Systems, Volume10, No. 4, pp. 1919-1926, 1995.

[4] Pereira-Neto, A., Unsihuay, C., and Saavedra, O., "Efficient Evolutionary Strategy Optimisation Procedure to Solve the Nonconvex Economic Dispatch Problem with Generator Constraints", IEE Proceedings-Generation, Transmission and Distribution, Volume 152, No. 5, pp. 653-660, 2005.

[5] Wood, A.J., and Wollenberg, B.F., "Power Generation, Operation, and Control", John Wiley & Sons, 2012.

[6] Fan, J.-Y., and Zhang, L, "Real-Time Economic Dispatch with Line Flow and Emission Constraints Using Quadratic Programming", IEEE Transactions on Power Systems, Volume 13, No. 2, pp. 320-325, 1998.

[7] Ding, T., Bo , R., Li, F., and Sun, H., "A Bi-Level Branch and Bound Method for Economic Dispatch with Disjoint Prohibited Zones Considering Network Losses", IEEE Transactions on Power Systems, Volume 30, No. 6, pp. 2841-2855, 2015.

[8] Dodu, J., Martin, P., Merlin, A., and Pouget, J., "An Optimal Frmulation and Solution of Short-Range Operating Problems for a Power System with Flow Constraints", Proceedings of the IEEE, Volume 60, No. 1, pp. 54-63, 1972.

[9] Yang, H.-T., Yang, P.-C., and Huang, C.-L., "Evolutionary Programming Based Economic Dispatch for Units with Non-Smooth Fuel Cost Functions", IEEE Transactions on Power Systems, Volume 11, No. 1, pp. 112-118, 1996.

[10] Sinha, N., Chakrabarti, R., and Chattopadhyay, P., "Evolutionary Programming Techniques for Economic Load Dispatch", IEEE Transactions on Evolutionary Computation, Volume 7, No. 1, pp. 83-94, 2003.

[11] Su, C.-T., and Lin, C.-T., "New Approach with a Hopfield Modeling Framework to Economic Dispatch", IEEE Transactions on Power Systems, Volume 15, No. 2, pp. 541-545, 2000.

[12] Wong, K., and Fung, C., "Simulated Annealing Based Economic Dispatch Algorithm", IEE Proceedings on Generation, Transmission and Distribution, Volume 140, No. 6, pp. 509-515, 1993.

[13] Wong, K.P., and Wong, Y.W., "Genetic and Genetic/Simulated-Annealing Approaches to Economic Dispatch", IEE Proceedings on Generation, Transmission and Distribution, Volume 141, No. 5, pp. 507-513, 1994.

[14] Wong, K.P., and Wong, Y.W., "Thermal Generator Scheduling Using Hybrid Genetic/Simulated-Annealing Approach", IEE Proceedings on Generation, Transmission and Distribution, Volume 142, No. 4, pp. 372-380, 1995.

[15] Noman, N., and Iba, H., "Differential Evolution for Economic Load Dispatch Problems", Electric Power Systems Research, Volume78, No. 8, pp. 1322-1331, 2008.

[16] Santos-Coelho, L. dos, Bora, T.C., and Mariani, V.C., "Differential Evolution Based on Truncated Levy-Type Flights and Population Diversity Measure to Solve Economic Load Dispatch Problems", International Journal of Electrical Power & Energy Systems, Volume 57, pp. 178-188, 2014.

[17] Wang, S.-K., Chiou, J.-P., and Liu, C.-W., "Non-Smooth/Non-Convex Economic Dispatch by a Novel Hybrid Differential Evolution Algorithm", IET Generation, Transmission & Distribution, Volume 1, No. 5, pp. 793-803, 2007.

[18] Moradi-Dalvand, M., Mohammadi-Ivatloo, B., Najafi, A., and Rabiee, A., "Continuous Quick Group Search Optimizer for Solving Non-Convex Economic Dispatch Problems", Electric Power Systems Research, Volume 93, pp. 93-105, 2012.

[19] Hou, Y.-H., Wu, Y.-W., Lu, L.-J., and Xiong, X.-Y., "Generalized ant Colony Optimization for Economic Dispatch of Power Systems", Proceeedings of IEEE International Conference on Power System TechnologyVolume 1, pp. 225-229, 2002.

[20] Bhattacharya, A., and Chattopadhyay, P.K., "Biogeography-Based Optimization for Different Economic Load Dispatch Problems", IEEE Transactions on Power Systems, Volume25, No. 2, pp. 1064-1077, 2010.

[21] Bentouati, B., Chaib, L., Chettih, S., and Wang, G.-G., "An Efficient Stud Krill Herd Framework for Solving Non-Convex Economic Dispatch Problem", World Academy of Science, Engineering and Technology, International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering, Volume 11, No. 12, pp. 1095-1100, 2017.

[22] Rajapandiyan, A., and Alex, M., "Application of Chaotic Particle Swarm Optimization for Solving Economic Dispatch Problems with Non-convex Cost Function", Journal of Electrical and Power System Engineering, Volume 3, No. 1, pp. 1-14, 2017.

[23] Karthik, N., Parvathy, A., and Arul, R., "Non-Convex Economic Load Dispatch using Cuckoo Search Algorithm", Indonesian Journal of Electrical Engineering and Computer Science, Volume 5, No. 1, pp. 48-57, 2017.

[24] Qin, Q., Cheng, S., Chu, X., Lei, X., and Shi, Y., "Solving Non-Convex/Non-Smooth Economic Load Dispatch Problems via an Enhanced Particle Swarm Optimization", Applied Soft Computing, 2017.

[25] Khoa, T., Vasant, P., Singh, M.B., and Dieu, V., "Swarm Based Mean-Variance Mapping Optimization for Convex and Non-Convex Economic Dispatch Problems", Memetic Computing, Volume 9, No. 2, pp. 91-108, 2017.

[26] Kheshti, M., Kang, X., Bie, Z., Jiao, Z., and Wang, X., "An Effective Lightning Flash Algorithm Solution to Large Scale Non-Convex Cconomic Dispatch with Valve-Point and Multiple Fuel Options on Generation Units", Energy, Volume 129, pp. 1-15, 2017.

[27] Shahinzadeh, H., Moazzami, M., Fadaei, D., and Rafiee-Rad, S., "Glowworm Swarm Optimization Algorithm for Solving Non-Smooth and Non-Convex Economic Load Dispatch Problems", IEEE Iranian Joint Congress on Fuzzy and Intelligent Systems, pp. 103-109, 2017.

[28] Pandey, V.C., Jadoun, V.K., Gupta, N., Niazi, K., and Swarnkar, A., "Improved Fireworks Algorithm with Chaotic Sequence Operator for Large-Scale Non-Convex Economic Load Dispatch Problem", Arabian Journal for Science and Engineering, pp. 1-11, 2017.

[29] Kamboj, V. K.A., and Bath, S., "Solution of Non-Convex Economic Load Dispatch Problem for Small-Scale Power Systems Using ant Iion Optimizer", Neural Computing and Applications, Volume28, No. 8, pp. 2181-2192, 2017.

[30] Bentouati, B., Chettih, S., and Sehiemy, R.A.-A., "A Chaotic Krill Herd Algorithm for Optimal Solution of the Economic Dispatch Problem", International Journal of Engineering Research in Africa, Volume 31, pp. 155-168 2017.

[31] Mirjalili, S., "SCA: ASine Cosine Algorithm for Solving Optimization Problems", Knowledge-Based Systems, Volume 96, pp. 120-133, 2016.

[32] Xu, X. and Li, Y., "Comparison between Particle Swarm Optimization, Differential Evolution and Multi-Parents Crossover", IEEE International Conference on,Computational Intelligence and Security, pp. 124-127, 2007.

[33] Vesterstrom, J., and Thomsen, R., "A Comparative Study of Differential Evolution, Particle Swarm Optimization, and Evolutionary Algorithms on Numerical Benchmark Problems", IEEE Congress on Evolutionary Computation, Volume 2, pp. 1980-1987, 2004.

[34] Jasper, J., and Aruldoss, A.V.T., "Differential Evolution with Random Scale Factor for Cconomic Dispatch Considering Prohibited Operating Zones", Przegl¹d Elektrotechniczny, Volume 89, No. 5, pp. 187-191, 2013.

[35] Subathra, M., Selvan, S.E., Victoire, T.A.A., Christinal, A.H., and Amato, U., "A Hybrid with Cross-Entropy Method and Sequential Quadratic Programming to Solve Economic Load Dispatch Problem", IEEE Systems Journal, Volume 9, No. 3, pp. 1031-1044, 2015.

[36] Mohammadi-Ivatloo, B., Rabiee, A., Soroudi, A., and Ehsan, M., "Iteration PSO with Time Varying Acceleration Coefficients for Solving Non-Convex Economic Dispatch Problems", International Journal of Electrical Power &Energy Systems, Volume 42, No. 1, pp. 508-516, 2012.

[37] Vlachogiannis, J.G., and Lee, K.Y., "Economic Load Dispatch—A Comparative Study on Heuristic Optimization Techniques with an Improved Coordinated Aggregation-Based PSO", IEEE Transactions on Power Systems, Volume 24, No. 2, pp. 991-1001, 2009.

[38] He, D., Wang, F., and Mao, Z., "A Hybrid Genetic Algorithm Approach Based on Differential Evolution for Economic Dispatch with Valve-Point Effect", International Journal of Electrical Power &Energy Systems, Volume 30, No. 1, pp. 31-38, 2008.

[39] Niknam, T., Mojarrad, H.D., and Meymand, H.Z., "A Novel Hybrid Particle Swarm Optimization for Economic Dispatch with Valve-Point Loading Effects", Energy Conversion and Management, Volume 52, No. 4, pp. 1800-1809, 2011.

[40] Roy, P.K., Bhui, S., and Paul, C., "Solution of Economic Load Dispatch Using Hybrid Chemical Reaction Optimization Approach", Applied Soft Computing, Volume 24, pp. 109-125, 2014.

[41] Gaing, Z.-L., "Particle Swarm Optimization to Solving the Economic Dispatch Considering the Generator Constraints", IEEE Transactions on Power Systems, Volume 18, No. 3, pp. 1187-1195, 2003.

[42] Basu, M., "Kinetic Gas Molecule Optimization for Nonconvex Economic Dispatch Problem", International Journal of Electrical Power & Energy Systems, Volume 80, pp. 325-332, 2016.

[43] Park, J.-B., Lee, K.-S., Shin, J.-R., and Lee, K. Y., "A Particle Swarm Optimization for Economic Dispatch with no Smooth Cost Functions", IEEE Transactions on Power Systems, Volume 20, No. 1, pp. 34-42, 2005.