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Article

Addressing Economic Dispatch Problem with Multiple Fuels Using Oscillatory Particle Swarm Optimization

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Abstract: Economic dispatch has a significant effect on optimal economical operation in the power systems in industrial revolution 4.0 in terms of considerable savings in revenue. Various non-linearity are added to make the fossil fuel-based power systems more practical. In order to achieve an accurate economical schedule, valve point loading effect, ramp rate constraints, and prohibited operating zones are being considered for realistic scenarios. In this paper, an improved, and modified version of conventional particle swarm optimization (PSO), called Oscillatory PSO (OPSO), is devised to provide a cheaper schedule with optimum cost. The conventional PSO is improved by deriving a mechanism enabling the particle towards the trajectories of oscillatory motion to acquire the entire search space. A set of differential equations is implemented to expose the condition for trajectory motion in oscillation. Using adaptive inertia weights, this OPSO method provides an optimized cost of generation as compared to the conventional particle swarm optimization and other new meta-heuristic approaches.

Keywords: Economic load dispatch; valve point loading; industry 4.0; prohibited operating zones; ramp rate limit; oscillatory particle swarm optimization

1 Introduction

Management of energy would-be highly effective and efficient by optimizing the generating cost of fossil fuel-based systems. Economic operation of the power system with effective and reliable generation is highly essential for Industry 4.0, as the electricity market is moving towards the deregulated market. The generation cost of thermal power plants mostly relies on fuel cost. Economic load dispatch is a process of economic scheduling of generating power from each generator to meet the demand and attain the optimum fuel cost by considering various constraints [1]. Economic Dispatch is an optimization problem-solving method where the entire requisite generation is being dispersed amongst the operated generating units, by reducing the consumed fuel cost, considering equality, inequality and operational constraints. ELD governs the output power of every generating division for the specific system under a specified load condition by minimizing the fuel cost to meet the load demand. ELD processes such a real-time management of energy in the current power system to control, assign, and distribute the total generation among the accessible units [2]. Generating units used different types of fuel for power generation. During the practical operation, the spinning reserve constraints make a significant impact on financial planning. Considering all the constraints, the economic dispatch problem behaves as a non-convex, complex, and non-smooth optimization problem.

In recent years, the generator processed for the generation of electricity is non-linear as compared to the customary generator. The non-linearity are by the concern of valve point loading, prohibited operating zones, and ramp rate limit. The practical economic dispatch (ED) also satisfies the problems due to non-linearity, non-convexity, and non-smooth operation of the generator. Previously for solving ELD problem, some classical and conventional methods such as lambda iteration [3], quadratic programming [4], gradient programming [5], and non-linear programming [6] others were applied. These classical methods face many challenges during the problem solving of ELD with non-linearity. To overcome the challenges, many meta-heuristic approaches, swarm evolutionary methods, and evolutionary computing methods were applied to the problem. These methods are Particle swarm optimization [7], Genetic Algorithm [8], Differential Evolution [9], Exchange Market Algorithm [10], Social Spider Algorithm [11], Biogeography based optimization [12], Tabu Search Method [13], Particle Diffusion [14], Artificial Bee Colony [15], Grey wolf optimization [16,17] and Spotted Hyena Optimization [18]. Some of the original methods get stock in the local optima and take more time for the searching process; therefore, to improve the quality of the solution, many hybrid techniques were proposed to overcome the difficulties. Recently some hybridized and modified version of existing techniques are applied to ELD problem such as Differential evolution-biogeography based optimization (DE-BBO) [19], Differential Evolution and harmony search (DHS) [20], Hybridization of Genetic Algorithm with Differential evolution (HDEGA) [21], Combination of Simulated Annealing and PSO (SAPSO) [22], Particle Swarm Optimization and Sequential Programming technique (PSO-SQP) [23], Hybrid Chemical Reaction optimization and Differential Evolution Algorithm (CRO-DE) [24], Multi-objective Spotted Hyena Optimizer and Emperor Penguin Optimizer (MOSHEPO) [25], Hybrid Firefly and Genetic algorithm [26], Adaptive real coded genetic algorithm (ARCGA) [27], Improved harmony search (IHS) [28], Modified differential evolution (MDE) [29], Species-based Quantum Particle Swarm Optimization (SQPSO) [30], Modified particle swarm optimization [31], Improved Differential Evolution [32], Modified Artificial Bee Colony algorithm [33], Modified Bacterial Foraging Algorithm (MBFA) [34], Improved Harmony Search with Wavelet Mutation (IHSWM) [35], DHIMAN Algorithm [36] . In addition, authors in [37] propose a Clustering-based Travel Planning System while a network route optimizations scheme is proposed in [38]. According to No Free Lunch theorem (NFL) [39], no optimization technique will be able to claim as the superior optimized solution for the concerned problem. The existence for improvement of cost for economic dispatch problem encourages to further improving the quality of solution regarding optimum cost and convergence property. Each applied technique to get the solution of the economic dispatch problem is having some advantages and disadvantages.

In this paper, an improved version of conventional Particle Swarm Optimization (PSO) is applied to overwhelm certain difficulties. Oscillatory PSO instincts the particle to acquire the total search space for finding optimum cost in ELD problem by balancing exploration and exploitation perfectly. An actual setting of parameter attains the optimum cost. The selections of cognitive and social learning factors are taken by confirming that the divergence does not occur before the optimum cost.

2 Problem Formulation

The formulated problem of ELD is the economic scheduling of electric power among the committed generating units to satisfy the load demand and satisfying various constraints. The major objective is to optimize the cost of fuel by generator scheduling [15].

2.1 Objectives for Economic Load Dispatch Problem

The characteristics of every generator are unique with respect to cost. The steam valve controls the operation of the turbine for the generation of power and is known as the valve point loading effect. This practical approach due to valve point loading characteristics curve of the generator becomes non-convex curve. The cost curve behaves as a piecewise linear increasing quadratic function as shown in Fig. 1. The fuel cost function is dependent on the real power generation from each unit and is shown in Eq. (1) [15].

$$\min\left(F_{cc}\right)=\sum_{genc=1} F\left(P_{genc}\right)=\sum_{genc=1} A_{genc}P^2_{gen_c}+B_{genc}P_{genc}+C_{genc}+\left|E_{genc}\times\sin\left(F_{genc}\left(P^{\min}_{genc}-P_{genc}\right)\right)\right| \tag{1}$$

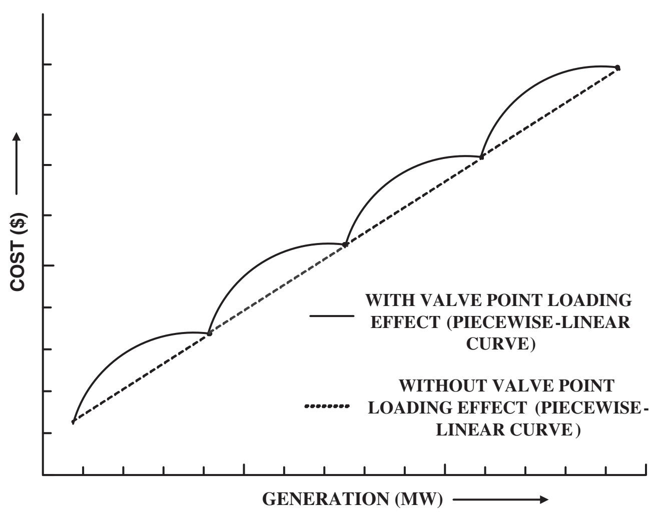

Figure 1: Cost characteristics of fossil fuel-based generator

Here F_{CC} is the fuel cost of all committed generator. $F(P_{genc})$ is the cost function of the generator. A_{genc}, B_{genc} and C_{genc} are the cost co-efficients and, E_{genc} and F_{genc} are the co-efficients due to the valve point loading effect. $\boldsymbol{P_{genc}}$ is the scheduled output power. The cost function for multiple fuel options is represented in Eq. (2) [40].

$$\sum_{genc=1} F\left(P_{gencj}\right) = \sum_{genc=1} \sum_{j} A_{gencj} P^2_{gen_{cj}} + B_{gencj} P_{gencj} + C_{gencj} + \left| E_{gencj} \times \sin\left(F_{gencj}\left(P^{\min}_{gencj} - P_{gencj}\right)\right)\right| \tag{2}$$

$\boldsymbol{A_{gencj}}$, $\boldsymbol{B_{gencj}}$, $\boldsymbol{C_{gencj}}$, $\boldsymbol{E_{gencj}}$ and $\boldsymbol{F_{gencj}}$ are the cost co-efficients for genc number of generating units and 'j' type of fuel.

2.2 *Constraints*

The economic scheduling of the generator should have to satisfy the practical operational constraints.

2.2.1 Power Balance Constraint

This is an equality constraint. In a given period, the total scheduled output power of committed generators should satisfy the load estimated following electricity demand and the transmission line losses in the power system [16].

$$\sum_{genc=1}^{N} P_{genc} - P_{de} - P_{Loss} = 0 \tag{3}$$

Here $\boldsymbol{P_{genc}}$ total scheduled power generation. $\boldsymbol{P_{de}}$ is forecasted load demand by the consumer. $\boldsymbol{P_{Loss}}$ is Transmission line loss. $\boldsymbol{P_{Loss}}$ is expressed in terms of B co-efficient by using Eq. (4) [16].

$$P_{Loss} = \sum_{genci=1}^{N} \sum_{gencj=1}^{N} P_{genci} B_{gencigencj} P_{gencj} + \sum_{genci=1}^{N} B_{genc0i} P_{genci} + B_{genc00} \tag{4}$$

2.2.2 Generating Capacity Constraint

Real power generates at the output of the generator should be within a prescribed limit higher and basic limit as shown in Eq. (5) [16].

$$P_{genc\min} < P_{genc} < P_{gencmax} \tag{5}$$

$\boldsymbol{P_{gencmain}}$ and $\boldsymbol{P_{gencmax}}$ are the minimum and higher bound for the generation of power.

2.2.3 Generator Ramp Rate Limit

The operational performance for generating units is reserved by ramp rate limits. These limits influencefunctional decisions. The present scheduling may interrupt the upcoming scheduling as a generation grows due to ramp rate bounds [19].

$$\max\left(P^{\min}_{gencj}, P^{0}_{gencj} - DR_j\right) \leq P_{gencj} \leq \min\left(P^{\max}_{gencj} + UR_j\right) \tag{6}$$

2.2.4 Prohibited Operating Zones

The generator performance is having some discontinuous portions due to some unsought and uncontrollable physical restrictions such asmechanical lossesorfailures. The generator discontinuities are shown in Fig. 2 and Eq. (7) [19].

$$P_{gencj}^{\min} \leq P_{gencj} \leq P^{l}{}_{gencj,1}$$
$$P_{gencj,J-1}^{U} \leq P_{gencj} \leq P^{l}{}_{gencj,j} \tag{7}$$
$$P_{gencj,n_i}^{U} \leq P_{gencj} \leq P_{gencj}^{\max}$$

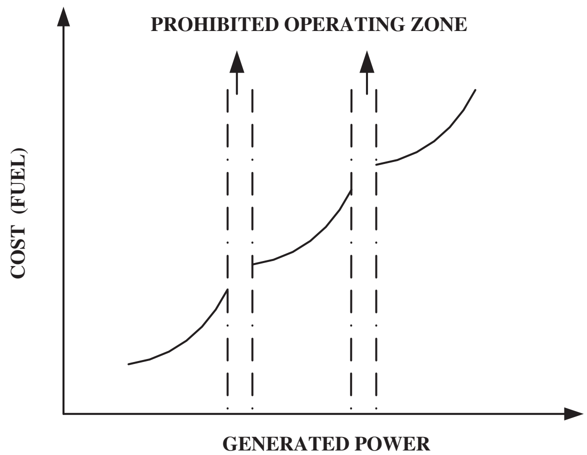

Figure 2: Generator characteristics with existing prohibited zones

3 Particle Swarm Optimization

The approached method is a swarm intelligence method based upon the process of collection of food by bird and fish. PSO works in the mechanism of birds to search for food randomly in a specified region. The key approach is to detect food with a reduced time [41]. This approach is based on the procedure to get the food and to observe the bird nearer to the food. The orthodox PSO learned from the condition and handled it to resolve the course to achieve an optimum value. Each bird is an alone solution in the total search space is known as a particle. All the particles are assessed by their corresponding fitness function, which is to be optimized. All the particles in the search space are having their velocities to search for the direction of food.

The initialization of PSO was done by using an arbitrary particle, which is the solution to find the optimal position by the process of updating during generations. During each reiteration course, the entire solutions particles are updated with two optimum values: (1) The finest value among the whole particles obtained by searching the food known as global best and, (2) the finest value monitored by the swarm itself during exploration in repetition process known as personal best. During the process of searching food, the velocity of the bird is to be maintained, by using the following formula by Eq. (8) [42].

$$V_k(i+1) = w_e \times V_k(i) + C_{e1} \times (p_e best_k - P_k(i)) + C_{e2} \times (g_e best_k - P_k(i)) \tag{8}$$

$$P_k(i+1) = P_k(i) + V_k(i+1) \tag{9}$$

In the above equation, $V_k(\boldsymbol{i+1})$ and $V_k(i)$ is the velocity component and $rand() \times (p_e best_k - P_k(i))$ is particle memory inspiration & $rand() \times (g_e best_k - P_k(i))$ is swarm inspiration. $\mathrm{V_k(i)}$ is the velocity of $\mathrm{k^{th}}$ particle at iteration (i) must lie in the range of velocity with upper and lower bounds.

$$\mathrm{V}_{\min} \leq \mathrm{V}_k(i) \leq \mathrm{V}_{\max} \tag{10}$$

$V_{\boldsymbol{max}}$ and $V_{\boldsymbol{min}}$ are the velocity indicesfor upper and lower boundaries of the particle to move in the search space to locate the food. If $V_{\boldsymbol{max}}$ is extremely high, the particles have a chance to past better solutions. If $V_{\boldsymbol{min}}$ is much small, then particles have a chance not to discover further than local optima. $C_{\boldsymbol{e1}}$ and $C_{\boldsymbol{e2}}$ are two constants to attract each solution towards the best among individual and whole particle locations.

The weight of inertia (w) follows the equation,

$$w_e = w_{e\max} - \left\{\frac{w_{e\max} - w_{e\min}}{iter_{\max}}\right\} \times iter \tag{11}$$

where $\mathrm{w_e}$, $\mathrm{w_{emax}}$, $\mathrm{w_{emin}}$ are the weight of inertia and (iter) is the iteration number.

4 Oscillatory Particle Swarm Optimizer

In this algorithm, the update equation of the conventional PSO isspecified as a differential equation of second order. The characteristics of convergence are resultant of social and cognitive learning rates. The particle transitional activities dependency on the inertia weight is discovered. Further, the induced oscillation feature and adaption of weight are derived.

4.1 Updating PSO as a Differential Equation of Second Order

In the conventional PSO, the velocity and position as per the above Eqs. (8) and (9) is processed. By reducing the iteration count, i + 1 to i the velocity particle is like $V_k(i) = P_k(i) - P_k(i-1)$.

The updated position is represented in the expansion form as in Eq. (12):

$$P_k(i+1) = P_k(i) + w_e(P_k(i) - P_k(i-1)) + C_{e1}(P_{ebestk} - P_k(i)) + C_{e2}(g_{ebestk} - P_k(i)) \tag{12}$$

$$= P_k(i)(1 + w_e - C_{e1} - C_{e2}) - w_e P_k(i-1) + C_{e1}P_{ebestk} + C_{e2}g_{ebestk} \tag{13}$$

Rearranging the above Eq. (13) can be rewritten as:

$$P_k(i+1) + P_{o1}P_k(i) + P_{o2}P_k(i-1) = R_k \tag{14}$$

Here the coefficients are $P_{o1} = C_{e1} + C_{e2} - w_e - 1$, $P_{o2} = w_e$, $R_k = C_{e1}P_{ebestk} + C_{e2}g_{ebestk}$.

4.2 Factors of Cognitive and Social Learning

From Eq. (14), the coefficients $P_{\boldsymbol{o1}}$ and $P_{\boldsymbol{o2}}$ determine the particle behavior. Assume the best position of a particle and global as $P_{\boldsymbol{ebestk}}$ and $g_{\boldsymbol{ebestk}}$ respectively remain constant, and both are equal for two successive iterations as shown in Eq. (15). One particle is having the personal best as the global best and the Eq. (15) can be rewritten as Eq. (16) as, $P_k{}^* = P_{ebestk}{}^* = g_{ebestk}{}^*$.

$$P_k{}^* + P_{k1}{}^* + P_{k2}{}^* = C_{e1}P_{ebestk}{}^* + C_{e2}g_{ebestk}{}^* \tag{15}$$

$$(1 + P_{o1} + P_{o2})P_k{}^* = C_{e1}P_k{}^* + C_{e2}P_k{}^* = (C_{e1} + C_{e2})P_k{}^* \tag{16}$$

$$1 + P_{o1} + P_{o2} = C_{e1} + C_{e2} \tag{17}$$

Letting $P_{o1} + P_{o2} = 0$ then, $C_{e1} + C_{e2} = 1$, their trajectories satisfy

$$P_k(i+1) + P_{o1}P_k + P_{o2}P_k(i-1) = C_{e1}P_{ebestk} + (1 - C_{e1})g_{ebestk} \tag{18}$$

Here the right-hand side shows the weighted sum of particle best and global best. Consider the complementary equation.

$$P_k(i+1) + P_{o1}P_k + P_{o2}P_k(i-1) = 0, \tag{19}$$

In the last iteration, the best particle value (P_{ebestk}) and best global value (g_{ebestk}) were considered as the optimal solution. The complexity of the applied algorithm was reduced by considering the social and cognitive leaning rates of personal and global best as $C_{e1} + C_{e2} = 1$

4.3 Weight of Inertia in OPSO

When the cognitive and social learning factor is $C_{e1} + C_{e2} = 1$, the coefficients become as per Eq. (20) and the complementary equation is Eq. (21). Here the inertia weight shows the convergence property of the particle trajectories while moving forward the iteration.

$$P_{o1} = C_{e1} + C_{e2} - w_e - 1 = -w_e \tag{20}$$

$$P_k(i+2) - w_e P_k(i+1) + w_e P_k(i) = 0 \tag{21}$$

For oscillating condition, considering the characteristics Eq. (21) with roots are shown in Eqs. (22) and (23) respectively.

$$\lambda_o^2 + P_{o1}\lambda_o + P_{o2} = 0 \tag{22}$$

$$\lambda_{o1,2} = \frac{-P_{o1} \pm \sqrt{P_{o1}^2 - 4P_{o2}}}{2} \tag{23}$$

Applying De Moivre's formula for the condition $P_{o1}^2 < 4P_{o2}$, the particle $\mathrm{P_k(i)}$ will be shown in Eq. (24).

$$P_k(i) = r^i\left[b_1 \cos i\theta + b_2 \sin i\theta\right] \tag{24}$$

Another phase angle ϕ is presented in Eq. (25).

$$\begin{aligned} \phi &= \tan^{-1}\left(\frac{b_1}{b_2}\right) \\ \cos\phi &= b_1/\sqrt{b_1^2 + b_2^2} \\ \sin\phi &= b_2/\sqrt{b_1^2 + b_2^2} \end{aligned} \tag{25}$$

The homogeneous equation solution will be shown in Eq. (26).

$$\begin{aligned} P_k(i) &= r^i\sqrt{b_1^2 + b_2^2}\left[\cos i\theta \cos\phi + \sin i\theta \sin\phi\right] \\ &= Br^i \cos(i\theta - \phi) \end{aligned} \tag{26}$$

where $B = \sqrt{b_1^2 + b_2^2}$ and the $\mathrm{P_k(i)}$ oscillates for the term $\cos(i\theta - \phi)$ in Eq. (26).

From Eq. (26), $\mathrm{P_k(i)}$ will converge for r < 1 and 'r' will be

$$r = \sqrt{\frac{{P_{o1}}^2}{4} + \frac{4{P_{o2}}^2 - {P_{o1}}^2}{4}} = \sqrt{P_{o2}} = \sqrt{w_e} \quad (27)$$

The oscillatory behavior of particle is governed by the amplitude an phase angle. The frequency of oscillation is determined by angles of the complex roots of the characteristics equation. And by substituting Po1 = −we and Po2 = we, the angle of the root is given byte Eq. (28).

$$\theta_{1,2} = \tan^{-1}\left(\frac{\pm\sqrt{4w_e - {w_e}^2}}{w_e}\right) \quad (28)$$

Determination of inertia weight can be done by applying normal distribution to the random inertia weights according to Eq. (29).

$$\widetilde{w}_e = N\left(w_e, \sigma\right), \quad \sigma = w_e \quad (29)$$

In this method the inertia weight is calculated by using the Eq. (30).

$$\begin{aligned} w_e\left(i\right) &= w_{ein} - w_{eend} \times \frac{i}{i_{\max}}, \\ w_k &= N\left(w_{ek}, w_{ek}\right) \end{aligned} \quad (30)$$

The detail pseudo of the applied algorithm for economic load dispatch is given in Algorithm 1.

Algorithm 1:

Step 1 Initialize the no. of Iterations i_{max}, Population, Particles, Velocity, Start and End inertia weight
Step 2 **Convential PSO**
For i = i_{max} do()
Find the fitness function (Cost) for each particle (Generator)
Identify the best fitness value (Cost) for each particle (P_{ebest}) and global best (g_{ebest})
Oscillatory PSO
Generate the social learning factor C_{e2}, and Cognitive learning factor $C_{e1} = 1 - C_{e2}$
Calculate the inertia weight using Eq. (29)
Update the Particle Velocity and Particle Position
endfor
Step 3 Best fitness value find (Optimum Generation Cost) due to the best particle is found

5 Results and Discussion

The proposed technique is applied to optimize the overall cost of four different test systems within the framework of different linear and non-linear technical constraints and multiple fuel systems. The four test systems considered in this study are: (1) A 6-unit system considering the transmission losses, (2) A 15-unit system considering the transmission losses (3) A large power system with 40 generating units considering valve-point loading and, (4) A ten-unit test system for different types of fuel. The simulation is performed on the MATLAB (version R2016b) platform. A total of 100 runs have been executed for generating an optimum solution to the discussed dispatch problem.

Case 1: Six generating Units test system

This case consists of six generating units to fulfill the load demand of 1263 MW. As transmission losses make a huge impact on the power system, transmission losses, prohibited operating zones, ramp rate limits, and valve point loading effect are considered. The system input data for all the constraints, cost co-efficient, and loss co-efficient are considered from [7]. The scheduled generation among all the six generating units within the capacity constraint with the optimum cost is presented in Tab. 1. The comparison of cost and scheduled generation with other techniques is also presented in Tab. 1. Fig. 4 shows the comparison graph of optimum cost with other techniques to validate the superiority of the applied technique. The optimum cost for this test system is found as 15,440.0982 $/h with a lesser transmission loss of 12.178 MW. The convergence graph is shown in Fig. 3. Prohibited operating zones, valve point loading, and ramp rate constraints are also considered for the complex problem. All the input data and co-efficient are referred to from [7] for this test system.

Table 1: Comparison table for scheduled generation and optimum cost for case 1 with losses

Method	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	Total generation (MW)	Total loss (MW)	Generation cost ($/h)
BSA [43]	447.4902	178.3308	263.4559	139.0602	165.4804	87.1409	1275.9583	12.9583	15449.8995
BFO [44]	449.4600	172.8800	263.4100	143.4900	164.9100	81.2520	1275.4020	12.4020	15,443.8497
CRO [45]	447.9314	173.5548	262.9452	138.8521	165.3046	86.8575	1275.4456	12.4456	15,443.080
HCRO-DE [24]	447.4021	173.2407	263.3812	138.9774	165.3897	87.0538	1275.4449	12.4449	15,443.0750
MIQCQP [46]	447.4000	173.2400	263.3800	138.9800	165.3900	87.0500	1275.4400	12.4400	15,443.0700
IABC-LS [47]	451.5204	172.1750	258.4186	140.6441	162.0797	90.3415	1275.1795	12.1795	15,441.1080
DHS [20]	447.5285	173.2791	263.4772	139.0291	165.4864	87.1587	1275.9590	12.9590	15,449.8996
SQ-PSO [30]	446.7273	173.4511	263.5318	138.9152	165.4092	87.2577	1275.2923	12.4422	15,441.0497
NPSO [48]	447.4734	173.1012	262.6804	139.4156	165.3002	87.9761	1275.9500	12.9571	15,450.0000
Θ–PSO [49]	445.5434	171.5376	263.0251	138.6269	165.6061	91.1055	1275.4446	12.4459	15,443.2717
MPSO-GA [50]	444.3230	173.1810	265.0000	140.3290	166.1200	86.4210	1275.3770	12.3700	15,442.4640
ICS [51]	447.6162	173.5795	262.7578	139.1206	165.6426	86.6658	1275.3800	12.3924	15,442.2652
APSO [52]	446.6690	173.1560	262.8260	143.4690	163.9140	85.3440	1275.3800	12.4220	15,443.5800
PSO	447.4970	173.3221	263.4745	139.0594	165.4761	87.1280	1276.0100	12.9583	15,450.0000
MPSO	446.4870	168.6610	265.0000	139.4930	164.0040	91.7470	1275.3900	12.3740	15,443.1000
OPSO	451.518	172.175	258.413	140.644	162.078	90.342	**1275.17**	**12.178**	**15,440.0982**

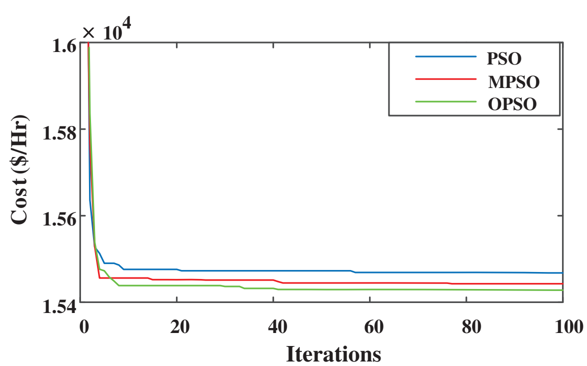

Figure 3: Convergence characteristics for case 1 with 1263 MW load demand

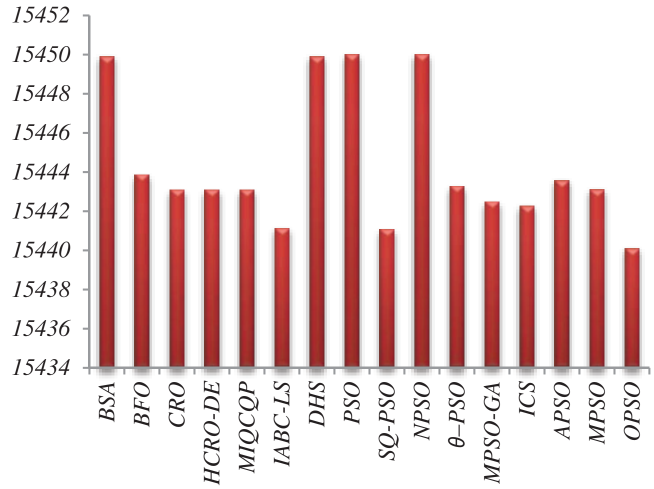

Figure 4: Comparison graph for six generating units with other applied techniques

Table 2: Comparison table for an optimum cost for 15 generating units with variation

Techniques	Best cost ($/h)	Average cost ($/h)	Worst cost ($/h)	Output power (MW)	CPU time (s)
ICS [51]	32,706.7358	32,714.4669	32,752.5183	2660.734	–
Θ-PSO [49]	32,706.5504	32,738.0235	32,707.6065	2660.8213	36.88
MIQCQP [46]	32,704.58	–	–	2660.66	4.65
MPSO-GA [50]	32,702	32,733.29	32,755.19	2660.034	
NRTO [53]	32,701.81	32.704.53	32,715.18	2660.42	29.38
RCCRO [54]	32,698.9950	32.698.995	32,698.995	2658.7040	4.0
MBBO [55]	32,692.3972	32,692.3973	32,692.3975	2659.5848	–
OLCSO [56]	32,692.3961	32,692.3981	32,692.4033	2659.5846	–
DEPSO [57]	32,588.81	32,588.99	32,591.49	2657.966	–
λ-Con [58]	32,568.06	–	–	2659.60	–
KGMO [59]	32,548.1736	32,548.2163	32,548.3755	2656.8983	7.24
PSO	32,705.3214	32,812.6654	32,922.3274	2660.479	10.25
MPSO	32,554.365	32,614.9854	32,662.3765	2658.586	7.41
OPSO	**32,548.021**	32,549.2541	32,549.9874	**2656.899**	4.12

Case 2: Fifteen generating units test system with transmission losses

Fifteen generating units are used for the generation of demand of 2630 with consideration of transmission losses, in the test generation for optimum cost from the applied technique with comparison to other techniques. Tab. 2 shows the evidence of the superiority of the applied technique for optimum cost with lesser variation during the iteration process as compared to MPSO-GA [50], NRTO [53], MsBBO [55], DEPSO [57], λ-Con [58], ICS [51] techniques. Fig. 5

represents the optimum cost comparison of the applied technique to the other techniques and Fig. 6 represents the convergence characteristics of the applied technique with the conventional PSO. Tab. 3 compares scheduled generation and optimum cost for case 2 with losses.

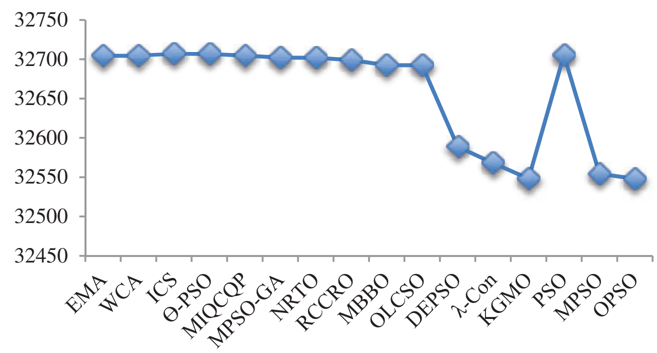

Figure 5: Comparison graph for fifteen generating units with other techniques

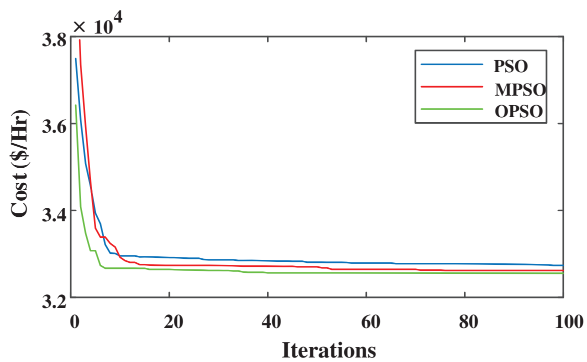

Figure 6: Convergence characteristics of case 2 for fifteen generating units

Table 3: Comparison table for scheduled generation and optimum cost for case 2 with losses

Method	DEPSO [57]	WCA [60]	DHS [20]	λ-Con [58]	EMA [10]	OLCSO [56]	MPSOGA [50]
P1 (MW)	455.000	455.000	455.0000	455.0000	455.0000	455.0000	455.0000
P2 (MW)	420.000	380.000	420.0000	455.0000	380.0000	380.0000	380.0000
P3 (MW)	130.000	130.000	130.0000	130.0000	130.0000	130.0000	130.0000
P4 (MW)	130.000	130.000	130.0000	130.0000	130.0000	130.0000	130.0000
P5 (MW)	270.000	170.000	270.0000	298.2294	170.000	170.000	169.9600
P6 (MW)	460.000	460.000	460.0000	460.0000	460.0000	460.0000	460.0000
P7 (MW)	430.000	430.000	430.0000	465.0000	430.0000	430.0000	430.0881
P8 (MW)	60.000	71.721	60.0000	60.0000	74.042	69.4738	60.1300
P9 (MW)	25.000	58.941	25.0000	25.0000	58.621	60.1108	72.6064
P10 (MW)	62.966	160.000	62.9762	25.0000	160.000	160.0000	157.0093
P11 (MW)	80.000	80.0000	80.0000	44.9350	80.0000	80.0000	80.0000
P12 (MW)	80.000	80.0000	80.0000	56.4370	80.0000	80.0000	79.2381

(Continued)

Table 3: Continued

Method	DEPSO [57]	WCA [60]	DHS [20]	λ-Con [58]	EMA [10]	OLCSO [56]	MPSOGA [50]
P13 (MW)	25.000	25.0000	25.0000	25.0000	25.0000	25.0000	26.0017
P14 (MW)	15.000	15.0000	15.0000	15.000	15.0000	15.0000	15.0000
P15 (MW)	15.000	15.0000	15.0000	15.000	15.0000	15.0000	15.0000
Total generation (MW)	2657.966	2660.66	2657.9762	2659.60	2660.66	2659.5846	2660.034
Total loss (MW)	27.976	30.66	27.9762	29.60	30.66	29.5846	29.4031
Cost ($/h)	32,588.81	32,704.449	32588.9182	32,568.06	32,704.450	32,692.3961	32,702
Method	**NRTO [53]**	**MIQCQP [46]**	**MsBBO [55]**	**Θ–PSO [49]**	**PSO**	**MPSO**	**OPSO**
P1 (MW)	455.0000	455.0000	455.0000	455.0000	455.0000	454.8914	454.8229
P2 (MW)	380.0000	380.0000	380.0000	380.0000	380.0000	454.8914	449.0101
P3 (MW)	129.9999	130.0000	130.0000	130.0000	129.9998	129.9997	129.4101
P4 (MW)	129.9999	130.0000	130.0000	130.0000	129.9998	129.9997	129.9999
P5 (MW)	170.0000	170.000	170.000	170.000	170.000	235.7547	239.7498
P6 (MW)	460.0000	460.0000	460.0000	460.0000	460.0000	459.9632	459.5598
P7 (MW)	430.0000	430.0000	430.0000	430.0000	430.0000	464.9668	464.9799
P8 (MW)	70.2250	72.13	69.4798	71.8045	70.3544	60.3255	61.2211
P9 (MW)	60.1965	58.54	60.1049	60.2379	60.1247	25.3741	25.5999
P10 (MW)	159.9999	160.00	160.0000	158.7524	159.9998	29.3001	28.1127
P11 (MW)	80.0000	80.0000	80.0000	80.0000	80.0000	77.7147	78.7451
P12 (MW)	80.0000	80.0000	80.0000	80.0000	80.0000	80.0201	80.3658
P13 (MW)	25.0000	25.0000	25.0000	25.0078	25.0000	25.3741	25.3214
P14 (MW)	15.0000	15.0000	15.0000	15.0147	15.0000	15.0010	15.0001
P15 (MW)	15.0000	15.0000	15.0000	15.0040	15.0000	15.0090	15.0001
Total generation (MW)	2660.4216	2660.66	2659.5848	2660.8213	2660.479	2658.586	**2656.899**
Total loss (MW)	30.4216	30.66	29.5848	30.8319	30.479	28.586	**26.899**
Cost ($/h)	32701.8145	32,704.45	32692.3972	32,706.5504	32,705.3214	32,554.365	**32,548.021**

Case 3: Test system 3 for forty generating units

This test system is considered for a large power system consisting of 40 generators. In this case, the effect of valve-point loading is considered as the non-linear constraint. The input data is referred from [61] for the co-efficient and various load demands. The scheduled generation among 40 units to meet the total demand of 10500 MW is illustrated in Tab. 4. Tab. 5 shows a comparison with other recent techniques for minimum cost. The deviation of the costs among different optimization techniques along with the proposed technique is presented in Tab. 5. The convergence graphs and cost comparison are shown in Figs. 7 and 8 respectively. It is analyzed from this case study that the applied OPSO algorithm provides better performance for minimizing the cost of the power supply, losses, and the convergence time as compared to the existing optimization techniques under the considered operating condition.

Table 4: Scheduled generation among 40 generators to satisfy the demand for optimum cost

UNIT	Output power (MW)	UNIT	Output power (MW)	UNIT	Output power (MW)	UNIT	Output power (MW)
P1 (MW)	110.7987	P11 (MW)	94.0000	P21 (MW)	523.2803	P31 (MW)	190.0000
P2 (MW)	110.7987	P12 (MW)	94.0000	P22 (MW)	523.2801	P32 (MW)	190.0000
P3 (MW)	97.4121	P13 (MW)	214.7602	P23 (MW)	523.2801	P33 (MW)	190.0000
P4 (MW)	179.7411	P14 (MW)	394.2833	P24 (MW)	523.2803	P34 (MW)	164.7875
P5 (MW)	87.8099	P15 (MW)	394.2833	P25 (MW)	523.2801	P35 (MW)	199.9988
P6 (MW)	140.0000	P16 (MW)	394.2833	P26 (MW)	523.2803	P36 (MW)	194.3198
P7 (MW)	259.6018	P17 (MW)	489.2801	P27 (MW)	10.0000	P37 (MW)	110.0000
P8 (MW)	284.6121	P18 (MW)	489.2801	P28 (MW)	10.0000	P38 (MW)	110.0000
P9 (MW)	284.6008	P19 (MW)	511.2811	P29 (MW)	10.0000	P39 (MW)	110.0000
P10 (MW)	130.0000	P20 (MW)	511.2811	P30 (MW)	87.8184	P40 (MW)	511.2866
						Total generation (MW)	10,500.00
						Cost ($/h)	1,21,410.3232

Table 5: Comparison of cost with deviation for 40 generators in test system 3

Techniques	Best cost ($/h)	Average cost ($/h)	Worst cost ($/h)	Output power (MW)	CPU time (s)
AA [62]	121,788.70	–	–	10500	–
CPSO–SQP [61]	121,458.54	122,028.16	–	10500	98.49
THS [63]	121,425.15	121,528.65	–	10500	–
Θ–PSO [49]	121,420.90	121,509.84	121,852.42	10500	
CRO [45]	121,416.69	121,418.03	121,422.92	10500	8.15
DFA [64]	121,414.64	121,415.78	121,422.12	10500	–
C-GRASP [65]	121,414.621	–	–	10500	–
NTHS [66]	121,412.74	121,549.95	–	10500	–
IABC [47]	121,412.73	–	121,471.61	10499.9999	8.76
DE [67]	121,412.68	121,439.89	121,479.63	10500	31.50
DEPSO [57]	121,412.56	121,419.31	121,468.25	10500	–
HCRO-DE [24]	121,412.55	121,413.11	121,415.66	10500	7.64
OIWO [68]	121,412.54	–	–	10500	–
MABC [33]	121,412.54	–	–	10500	–
ORCSA [69]	121,412.535	121,472.45	121,596.18	10500	3.02
MsBBO [55]	121,412.5344	121417.1877	121450.0026	10500	–
MINLP [70]	121,412.53	121,412.53	121,412.53	10500	39.33
PSO	121,426.21	121,433.14	121,438.85	10500	15.22
MPSO	121,412.33	121,415.65	121,416.73	10500	10.37
OPSO	121,410.32	121,410.55	121,410.86	10500	6.32

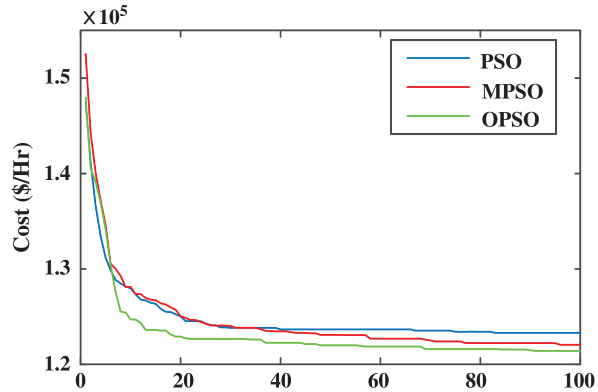

Figure 7: Convergence characteristics for test system 3 with 40 generators

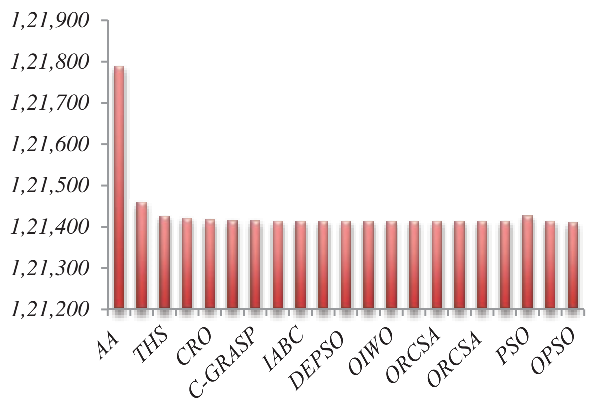

Figure 8: Comparison graph for forty generating units with other techniques

Table 6: Scheduled generation among 10 generators with multiple fuel types for minimum cost

Unit	Fuel type	Power output (MW)
P1 (MW)	2	218.722
P2 (MW)	1	211.361
P3 (MW)	1	281.682
P4 (MW)	3	239.379
P5 (MW)	1	279.198
P6 (MW)	3	239.362
P7 (MW)	1	287.796
P8 (MW)	3	239.703
P9 (MW)	3	426.803
P10 (MW)	1	275.994
	Total output power	2700 MW
	Generation cost ($/h)	623.542

Case 4: Test system 4 for ten generating units with multiple fuels as input

In this case, the performance is evaluated on a system with 10 generating units with multiple fuel options and valve point loading effects. The input data have been referred to from [71]. From the input data, it has been observed that the first generator is having options of two types of fuel and the other generating units have an option of three types of fuel. The total load demand is 2700 MW with no transmission losses. The optimum cost produced during the experiment is 623.542 $/h for OPSO. The comparison of cost with different techniques is represented in Tab. 7 and, it is found that the OPSO is optimizing the system cost for multiple fuel systems. Fig. 9 shows the convergence graph of OPSO and PSO with a faster convergence rate. The scheduled output with different fuels is depicted in Tab. 6.

Table 7: Comparison of cost with deviation for 10 generating units with different types of fuel

Techniques	Best cost ($/h)	Average cost ($/h)	Worst cost ($/h)
IGA-MU [71]	624.72	627.61	633.87
CGA-MU [71]	624.52	625.87	630.87
RCGA [72]	623.83	623.85	623.89
CBPSO-RVM [73]	623.96	624.08	624.29
ARCGA [74]	623.83	623.84	623.86
NPSO-LRS [48]	624.13	625.00	627.00
DEPSO [57]	623.83	623.90	624.08
PSO	625.21	626.32	627.74
MPSO	624.14	624.89	625.37
OPSO	623.542	623.65	623.33

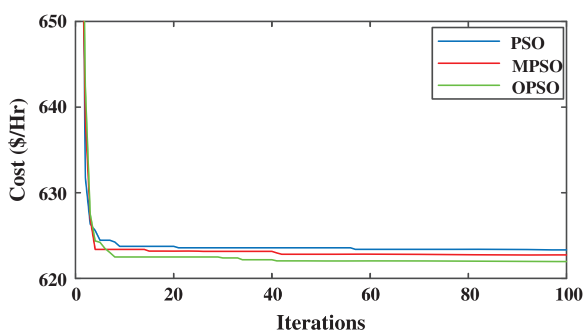

Figure 9: Comparison graph for ten generating units for case 4

Recent works presented in [75–78] depict interesting optimization works in different domains.

6 Conclusion

The increasing complexity of today's electrical networks in Industry 4.0 further adds to the severity of the issue which can be mitigated through robust economic load dispatch strategies. Application of Oscillatory Particle Swarm Optimization algorithm-a meta-heuristic algorithm, to solve complex ELD problems is presented in this paper. The performance of OPSO is evaluated for four different test systems with increasing complications considering various practical technical constraints such as valve-point loading effect, prohibited operating zones, ramp rates, and multiple fuel system. The effectiveness of different techniques for optimizing the cost and their convergence profiles and times have been studied for all these cases. A comparison is performed between the proposed and existing techniques based on the above-discussed problem. It is concluded from the work that the proposed OPSO algorithm provides better performance for minimizing the cost of the power supply, losses, and the convergence time as compared to the existing optimization techniques.

The applied technique can be further applied to an enhanced version of economic dispatch problems such as economic emission dispatch problem, dynamic dispatch problem, and economic dispatch incorporating renewable energy system.

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References

[1] A. J. Wood, B. F. Wollenberg and G. B. Sheblé, *Power Generation, Operation, and Control*. NJ, USA: John Wiley & Sons, 2013.

[2] J. S. Dhillon and D. P. Kothari, *Power System Optimization*. New Delhi, India: Preintce Hall of India Private Limited, 2010.

[3] B. H. Chowdhury and S. Rahman, "A review of recent advances in economic dispatch," *IEEE Transactions on Power Systems*, vol. 5, no. 4, pp. 1248–1259, 1990.

[4] G. F. Reid and L. Hasdorff, "Economic dispatch using quadratic programming," *IEEE Transactions on Power Apparatus and Systems*, vol. 6, pp. 2015–2023, 1973.

[5] G. B. Sheble, "Real-time economic dispatch and reserve allocate,ion using merit order loading and linear programming rules," *IEEE Transactions on Power Systems*, vol. 4, no. 4, pp. 1414–1420, 1989.

[6] D. Streiffert, "Multi-area economic dispatch with tie line constraints," *IEEE Transactions on Power Systems*, vol. 10, no. 4, pp. 1946–1951, 1995.

[7] Z. Gaing, "Particle swarm optimization to solving the economic dispatch considering the generator constraints," *IEEE Transactions on Power Systems*, vol. 18, no. 3, pp. 1187–1195, 2003.

[8] D. C. Walters and G. B. Sheble, "Genetic algorithm solution of economic dispatch with valve point loading," *IEEE Transactions on Power Systems*, vol. 8, no. 3, pp. 1325–1332, 1993.

[9] N. Noman and H. Iba, "Differential evolution for economic load dispatch problems," *Electric Power Systems Research*, vol. 78, no. 8, pp. 1322–1331, 2008.

[10] N. Ghorbani and E. Babaei, "Exchange market algorithm for economic load dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 75, pp. 19–27, 2016.

[11] J. Q. James and V. Li, "A social spider algorithm for solving the non-convex economic load dispatch problem," *Neurocomputing*, vol. 171, no. 2, pp. 955–965, 2016.

[12] A. Bhattacharya and P. Chattopadhyay, "Biogeography-based optimization for different economic load dispatch problems," *IEEE Transactions on Power Systems*, vol. 25, no. 2, pp. 1064–1077, 2009.

[13] W. Lin, F. Cheng and M. Tsay, "An improved tabu search for economic dispatch with multiple minima," *IEEE Transactions on Power Systems*, vol. 17, no. 1, pp. 108–112, 2002.

[14] L. Han, C. E. Romero and Z. Yao, "Economic dispatch optimization algorithm based on particle diffusion," *Energy Conversion and Management*, vol. 105, no. 6, pp. 1251–1260, 2015.

[15] S. Hemamalini and S. P. Simon, "Artificial bee colony algorithm for economic load dispatch problem with non-smooth cost functions," *Electric Power Components and Systems*, vol. 38, no. 7, pp. 786–803, 2010.

[16] M. Pradhan, P. Roy and T. Pal, "Grey wolf optimization applied to economic load dispatch problems," *International Journal of Electrical Power & Energy Systems*, vol. 83, pp. 325–334, 2016.

[17] V. Kamboj, S. K. Bath and J. S. Dhillon, "Solution of non-convex economic load dispatch problem using grey wolf optimizer," *Neural Computing and Applications*, vol. 27, no. 5, pp. 1301–1316, 2016.

[18] G. Dhiman, S. Guo and S. Kaur, "ED-SHO: A framework for solving nonlinear economic load power dispatch problem using spotted hyena optimizer," *Modern Physics Letters A*, vol. 33, no. 40, pp. 850239, 2018.

[19] A. Bhattacharya and P. Chattopadhyay, "Hybrid differential evolution with biogeography-based optimization for solution of economic load dispatch," *IEEE Transactions on Power Systems*, vol. 25, no. 4, pp. 1955–1964, 2010.

[20] L. Wang and L. Li, "An effective differential harmony search algorithm for the solving non-convex economic load dispatch problems," *International Journal of Electrical Power & Energy Systems*, vol. 44, no. 1, pp. 832–843, 2013.

[21] A. Trivedi, D. Srinivasan, S. Biswas and T. Reindl, "Hybridizing genetic algorithm with differential evolution for solving the unit commitment scheduling problem," *Swarm and Evolutionary Computation*, vol. 23, pp. 50–64, 2015.

[22] V. Karthikeyan, S. Senthilkumar and V. J. Vijayalakshmi, "A new approach to the solution of economic dispatch using particle swarm optimization with simulated annealing," arXiv preprint arXiv: 1307.3014, 2013.

[23] T. Victoire and A. E. Jeyakumar, "Hybrid PSO-SQP for economic dispatch with valve-point effect," *Electric Power Systems Research*, vol. 71, no. 1, pp. 51–59, 2004.

[24] P. Roy, S. Bhui and C. Paul, "Solution of economic load dispatch using hybrid chemical reaction optimization approach," *Applied Soft Computing*, vol. 24, pp. 109–125, 2014.

[25] G. Dhiman, "MOSHEPO: A hybrid multi-objective approach to solve economic load dispatch and micro grid problems," *Applied Intelligence*, vol. 50, no. 1, pp. 119–137, 2020.

[26] M. P. Varghese and A. Amudha, "Enhancing the efficiency of wind power using hybrid fire fly and genetic algorithm-economic load dispatch model," *Current Signal Transduction Therapy*, vol. 13, no. 1, pp. 3–10, 2018.

[27] P. Subbaraj, R. Rengaraj and S. Salivahanan, "Enhancement of self-adaptive real-coded genetic algorithm using Taguchi method for economic dispatch problem," *Applied Soft Computing*, vol. 11, no. 1, pp. 83–92, 2011.

[28] S. C. Dos, Leandro and V. C. Mariani, "An improved harmony search algorithm for power economic load dispatch," *Energy Conversion and Management*, vol. 50, no. 10, pp. 2522–2526, 2009.

[29] S. Sayah and K. Zehar, "Modified differential evolution algorithm for optimal power flow with non-smooth cost functions," *Energy Conversion and Management*, vol. 49, no. 11, pp. 3036–3042, 2008.

[30] V. Hosseinnezhad, M. Rafiee, M. Ahmadian and M. T. Ameli, "Species-based quantum particle swarm optimization for economic load dispatch," *International Journal of Electrical Power & Energy Systems*, vol. 63, pp. 311–322, 2014.

[31] S. S. Subramani and P. R. Rajeswari, "A modified particle swarm optimization for economic dispatch problems with non-smooth cost functions," *International Journal of Soft Computing*, vol. 3, no. 4, pp. 326–332, 2008.

[32] H. Liu, J. Qu and Y. Li, "The economic dispatch of wind integrated power system based on an improved differential evolution algorithm," *Recent Advances in Electrical & Electronic Engineering*, vol. 13, no. 3, pp. 384–395, 2020.

[33] D. C. Secui, "A new modified artificial bee colony algorithm for the economic dispatch problem," *Energy Conversion and Management*, vol. 89, no. 1, pp. 43–62, 2015.

[34] I. A. Farhat and M. E. El-Hawary, "Modified bacterial foraging algorithm for optimum economic dispatch," in *Proc. 2009 IEEE Electrical Power & Energy Conf.*, Montreal, QC, Canada, IEEE, pp. 1–6, 2009.

[35] V. R. Pandi, B. K. Panigrahi, A. Mohapatra and M. Mallick, "Economic load dispatch solution by improved harmony search with wavelet mutation," *International Journal of Computational Science and Engineering*, vol. 6, no. 1–2, pp. 122–131, 2011.

[36] G. Dhiman, P. Singh, H. Kaur and R. Maini, "DHIMAN: A novel algorithm for economic dispatch problem based on optimization met Hodus Ing Monte Carlo simulation and astrophysics concepts," *Modern Physics Letters A*, vol. 34, no. 4, pp. 1950032, 2019.

[37] L. Ravi, V. Subramaniyaswamy, V. Vijayakumar, R. H. Jhaveri and J. Shah, "Hybrid user clustering-based travel planning system for personalized point-of-interest recommendation," in *Proc. Int. Conf. on Mathematical Modeling, Computational Intelligence Techniques and Renewable Energy*, Ahmedabad, India, 2020.

[38] R. H. Jhaveri, R. Tan and S. V. Ramani, "Real-time QoS routing scheme in SDN-based robotic cyber-physical systems," in *Proc. 5th Int. Conf. on Mechatronics System and Robots*, Singapore, pp. 18–23, 2019.

[39] S. Kaboli and A. Alqallaf, "Solving non-convex economic load dispatch problem via artificial cooperative search algorithm," *Expert Systems with Applications*, vol. 128, pp. 14–27, 2019.

[40] D. N. Vo and W. Ongsakul, "Economic dispatch with multiple fuel types by enhanced augmented Lagrange Hopfield network," *Applied Energy*, vol. 91, no. 1, pp. 281–289, 2012.

[41] J. Kennedy and R. Eberhart, "PSO optimization," in *Proc. IEEE Int. Conf. Neural Networks*, Piscataway, NJ, IEEE Service Center, vol. 4, pp. 1941–1948, 1995.

[42] A. Mahor, V. Prasad and S. Rangnekar, "Economic dispatch using particle swarm optimization: A review," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 8, pp. 2134–2141, 2009.

[43] M. Mostafa, S. Kaboli, E. Taslimi-Renani and N. Rahim, "Backtracking search algorithm for solving economic dispatch problems with valve-point effects and multiple fuel options," *Energy*, vol. 116, no. 1, pp. 637–649, 2016.

[44] A. Rathinam and R. Phukan, "Solution to economic load dispatch problem based on firefly algorithm and its comparison with BFO, CBFO-S and CBFO-Hybrid," in *Proc. Int. Conf. on Swarm, Evolutionary, and Memetic Computing*, Berlin, Heidelberg, Springer, pp. 57–65, 2012.

[45] K. Bhattacharjee, A. Bhattacharya and S. Dey, "Chemical reaction optimisation for different economic dispatch problems," *IET Generation, Transmission & Distribution*, vol. 8, no. 3, pp. 530–541, 2013.

[46] T. Ding, R. Bo, F. Li and H. Sun, "A bi-level branch and bound method for economic dispatch with disjoint prohibited zones considering network losses," *IEEE Transactions on Power Systems*, vol. 30, no. 6, pp. 2841–2855, 2014.

[47] S. Özyön and D. Aydin, "Incremental artificial bee colony with local search to economic dispatch problem with ramp rate limits and prohibited operating zones," *Energy Conversion and Management*, vol. 65, pp. 397–407, 2013.

[48] A. Selvakumar and K. Thanushkodi, "A new particle swarm optimization solution to nonconvex economic dispatch problems," *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 42–51, 2007.

[49] V. Hosseinnezhad and E. Babaei, "Economic load dispatch using θ-PSO," *International Journal of Electrical Power & Energy Systems*, vol. 49, pp. 160–169, 2013.

[50] H. Barati and M. Sadeghi, "An efficient hybrid MPSO-GA algorithm for solving non-smooth/non-convex economic dispatch problem with practical constraints," *Ain Shams Engineering Journal*, vol. 9, no. 4, pp. 1279–1287, 2018.

[51] E. Afzalan and M. Joorabian, "An improved cuckoo search algorithm for power economic load dispatch," *International Transactions on Electrical Energy Systems*, vol. 25, no. 6, pp. 958–975, 2015.

[52] B. K. Panigrahi, V. R. Pandi and S. Das, "Adaptive particle swarm optimization approach for static and dynamic economic load dispatch," *Energy Conversion and Management*, vol. 49, no. 6, pp. 1407–1415, 2008.

[53] Y. Labbi, D. Attous, H. Gabbar, B. Mahdad and A. Zidan, "A new rooted tree optimization algorithm for economic dispatch with valve-point effect," *International Journal of Electrical Power & Energy Systems*, vol. 79, pp. 298–311, 2016.

[54] K. Bhattacharjee, A. Bhattacharya and S. Dey, "Oppositional real coded chemical reaction optimization for different economic dispatch problems," *International Journal of Electrical Power & Energy Systems*, vol. 55, pp. 378–391, 2014.

[55] G. Xiong, D. Shi and X. Duan, "Multi-strategy ensemble biogeography-based optimization for economic dispatch problems," *Applied Energy*, vol. 111, no. 2, pp. 801–811, 2013.

[56] G. Xiong and D. Shi, "Orthogonal learning competitive swarm optimizer for economic dispatch problems," *Applied Soft Computing*, vol. 66, pp. 134–148, 2018.

[57] S. Sayah and A. Hamouda, "A hybrid differential evolution algorithm based on particle swarm optimization for nonconvex economic dispatch problems," *Applied Soft Computing*, vol. 13, no. 4, pp. 1608–1619, 2013.

[58] G. Binetti, A. Davoudi, F. L. Lewis, D. Naso and B. Turchiano, "Distributed consensus-based economic dispatch with transmission losses," *IEEE Transactions on Power Systems*, vol. 29, no. 4, pp. 1711–1720, 2014.

[59] M. Basu, "Kinetic gas molecule optimization for nonconvex economic dispatch problem," *International Journal of Electrical Power & Energy Systems*, vol. 80, no. 3, pp. 325–332, 2016.

[60] M. A. Elhameed and A. A. El-Fergany, "Water cycle algorithm-based economic dispatcher for sequential and simultaneous objectives including practical constraints," *Applied Soft Computing*, vol. 58, pp. 145–154, 2017.

[61] J. Cai, Q. Li, L. Li, H. Peng and Y. Yang, "A hybrid CPSO-SQP method for economic dispatch considering the valve-point effects," *Energy Conversion and Management*, vol. 53, no. 1, pp. 175–181, 2012.

[62] G. Binetti, A. Davoudi, D. Naso, B. Turchiano and F. L. Lewis, "A distributed auction-based algorithm for the nonconvex economic dispatch problem," *IEEE Transactions on Industrial Informatics*, vol. 10, no. 2, pp. 1124–1132, 2013.

[63] M. A. Al-Betar, M. A. Awadallah, A. T. Khader and A. L. Bolaji, "Tournament-based harmony search algorithm for non-convex economic load dispatch problem," *Applied Soft Computing*, vol. 47, no. 1, pp. 449–459, 2016.

[64] G. Chen and X. Ding, "Optimal economic dispatch with valve loading effect using self-adaptive firefly algorithm," *Applied Intelligence*, vol. 42, no. 2, pp. 276–288, 2015.

[65] J. Neto, G. Reynoso-Meza, T. H. Ruppel, V. C. Mariani and L. S. Coelho, "Solving non-smooth economic dispatch by a new combination of continuous GRASP algorithm and differential evolution," *International Journal of Electrical Power & Energy Systems*, vol. 84, pp. 13–24, 2017.

[66] M. Azmi, M. A. Awadallah, A. T. Khader, A. L. Bolaji and A. Almomani, "Economic load dispatch problems with valve-point loading using natural updated harmony search," *Neural Computing and Applications*, vol. 29, no. 10, pp. 767–781, 2018.

[67] W. Elsayed and E. F. El-Saadany, "A fully decentralized approach for solving the economic dispatch problem," *IEEE Transactions on Power Systems*, vol. 30, no. 4, pp. 2179–2189, 2014.

[68] A. K. Barisal and R. C. Prusty, "Large scale economic dispatch of power systems using oppositional invasive weed optimization," *Applied Soft Computing*, vol. 29, pp. 122–137, 2015.

[69] T. T. Nguyen and D. N. Vo, "The application of one rank cuckoo search algorithm for solving economic load dispatch problems," *Applied Soft Computing*, vol. 37, pp. 763–773, 2015.

[70] A. Rabiee, B. Mohammadi-Ivatloo and M. Moradi-Dalvand, "Fast dynamic economic power dispatch problems solution via optimality condition decomposition," *IEEE Transactions on Power Systems*, vol. 29, no. 2, pp. 982–983, 2013.

[71] C. Chiang, "Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels," *IEEE Transactions on Power Systems*, vol. 20, no. 4, pp. 1690–1699, 2005.

[72] N. Amjady and H. Nasiri-Rad, "Economic dispatch using an efficient real-coded genetic algorithm," *IET Generation, Transmission & Distribution*, vol. 3, no. 3, pp. 266–278, 2009.

[73] H. Lu, P. Sriyanyong, Y. H. Song and T. Dillon, "Experimental study of a new hybrid PSO with mutation for economic dispatch with non-smooth cost function," *International Journal of Electrical Power & Energy Systems*, vol. 32, no. 9, pp. 921–935, 2010.
[74] N. Amjady and H. Nasiri-Rad, "Solution of nonconvex and nonsmooth economic dispatch by a new adaptive real coded genetic algorithm," *Expert Systems with Applications*, vol. 37, no. 7, pp. 5239–5245, 2010.
[75] S. P. RM, P. K. Maddikunta, M. Parimala, S. Koppu S, T. R. Gadekallu *et al.,* "An effective feature engineering for DNN using hybrid PCA-GWO for intrusion detection in IoMT architecture," *Computer Communications*, vol. 160, pp. 139–149, 2020.
[76] T. R.Gadekallu, D. S. Rajput, P. K. Reddy, K. Lakshmanna, S. Bhattacharya *et al.,* "A novel PCA-whale optimization-based deep neural network model for classification of tomato plant diseases using GPU," *Journal of Real-Time Image Processing*, 2020. https://doi.org/10.1007/s11554-020-00987-8.
[77] M. Alazab, S. Khan, S. S. R. Krishnan, Q. V. Pham, P. K. Reddy *et al.,* "A multidirectional LSTM model for predicting the stability of a smart grid," *IEEE Access*, vol. 8, pp. 85454–85463, 2020.
[78] T. Reddy, S. Bhattacharya, P. K. R. Maddikunta, S. Hakak, W. Z. Khanet *et al.,* "Antlion re-sampling based deep neural network model for classification of imbalanced multimodal stroke dataset," *Multimedia Tools and Applications*, 2020. https://doi.org/10.1007/s11042-020-09988-y.