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Economic load dispatch using krill herd algorithm

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ABSTRACT

Economic load dispatch (ELD) is an important topic in the operation of power plants which can help to build up effective generating management plans. The practical ELD problem has non-smooth cost function with nonlinear constraints which make it difficult to be effectively solved. This paper presents, a new and efficient krill herd algorithm (KHA) to solve both convex and non-convex ELD problems of thermal power units considering valve point loading, multiple fuel operation, transmission losses and constraints such as ramp rate limits and prohibited operating zones. To enhance the overall performance and effectiveness of the proposed algorithm, the crossover and mutation operation of differential evolution (DE) are integrated with the proposed method. The different versions of KHA are successfully applied to small, medium, and large-scale power systems for solving six different ELD problems. The simulation results obtained by the proposed algorithms are compared with the results obtained using other recently develop methods available in the literature. From numerical results, it is found that the proposed KHA with crossover and mutation operators approach is able to provide better solution than other reported techniques in terms of fuel cost. Furthermore, this algorithm is better in terms of robustness than most of the existing algorithms used in this study.

1. Introduction

During the last decade, the electrical power market became more and more liberal and highly competitive. The main goal is to generate of a given amount of electricity at the lowest possible cost. This need proper planning, operation and control of such large complicated systems. ELD is one of the most important problems to be solved for smooth and economic operation of a power system. A good load dispatch reduces the production cost, increases the system reliability and maximizes the energy capability of thermal units. ELD is a process for sharing the total load on a power system among various generating plants to achieve greatest economy of operation. The ELD, a nonlinear optimization problem is basically solved to generate optimal amount of generating power from the fossil fuel based generating units in the system by minimizing the fuel cost and satisfying all system constraints of power system. The careful and intelligent scheduling of the generating units can not only reduce the operating cost significantly but also assure higher reliability and security of power system. Thus, for last few decades, ELD has become an essential optimization area for economic operation and control of modern power system.

Previously, a number of derivative-based approaches such as gradient method [1], lambda iteration method (LIM) [2,3], linear programming (LP) [4], quadratic programming (QP) [5], Lagrangian multiplier method [6], classical technique based on co-ordination equations [7] were applied to solve ELD problems. However, in large practical thermal generation plants with large size turbines, the input–output characteristics of generators are highly nonlinear and discontinuous due to the presence of valve point loading effect. Because of highly nonlinear characteristics of the problem with many local optimum solutions and a large number of constraints, the classical calculus-based methods cannot perform satisfactorily for solving ELD problems. Recently, Yang et al. [8] presented a mathematical programming based method named quadratically constrained programming (QCP) to solve non-smooth and non-convex ELD problem.

Some traditional algorithms such as dynamic programming (DP) [9] impose no restrictions on the nature of the cost curves and therefore it can solve ELD problems with inherently nonlinear and discontinuous cost curves. However, DP method may cause the dimensions of the problem to become extremely large, thus requiring enormous computational efforts. Hopfield neural networks based method is another alternative to solve nonlinear ELD problems. An augmented Lagrange Hopfield network (ALHN) [10] for solving ELD problem was proposed by Dieu et al. Furthermore, Dieu et al. [11] introduced a hybrid method based on quadratic

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programming (QP) and augmented Lagrange Hopfield network (ALHN) for solving ELD problem with piecewise quadratic cost functions and prohibited zones. However, these methods suffer from excessive numerical iterations, resulting in huge computations.

Thus, developing a reliable, fast and efficient algorithm is still an active area for research in power systems. Various investigations on ELD have been explored till date, as better solutions would result in significant economical benefits. Modern meta-heuristic algorithms such as particle swarm optimization (PSO) [12–16], adaptive PSO [17], chaotic PSO [18], self-organizing hierarchical PSO [13], differential evolution (DE) [19], evolutionary programming (EP) [20], genetic algorithm (GA) [21,22], real coded GA (RCGA) [23], bacterial foraging optimization (BFO) [24], biogeography based optimization (BBO) [25], gravitational search algorithm (GSA) [26], pattern search method (PSM) [27], and clonal search algorithm [28] are promising alternative for solution of complex ELD problems. In addition to the above mentioned methods, few other methods have recently applied in ELD problems. Basu developed artificial bee colony (ABC) [29] optimization technique to solve multi-area economic dispatch (MAED) problem considering tie line constraints and nonlinearities like multiple fuels, valve-point loading and prohibited operating zones. The effectiveness of the proposed method was illustrated by applying it in three different test systems and its results were compared with the results of DE, EP and RCGA. Kumar et al. [30] proposed a multi-objective directed bee colony optimization algorithm (MODBC) is comprehensively developed and successfully applied for solving a multi-objective problem of optimizing the conflicting economic dispatch and emission cost with satisfying both equality and inequality constraints. Cai et al. [31] developed a fuzzy adaptive chaotic ant swarm optimization (FCASO) algorithm for solving the ELD problems of thermal generators in power systems. A multi-objective mesh adaptive direct search (MOMADS) algorithm [32] was employed by Mohamed et al. for minimizing the cost and emissions simultaneously of a micro-grid.

Recently, modifications of conventional population based methods are made for getting better quality solutions of ELD problem. Barisal implemented an improved PSO (IPSO) [33] to solve non-smooth ELD problem. In this proposed IPSO method, the dynamic search space squeezing strategy is incorporated in conventional PSO to improve the convergence speed and to efficiently handle inequality constraints, of ELD problem. Hosseinnezhad and Babaei implemented θ-PSO [34] method on 6, 13, 15 and 40 generating units test systems to solve ELD problems considering various non-linear constraints like ramp rate limits, valve point loadings, prohibited operating zone and proposed method was compared with few modified versions of PSO and other optimization techniques. Aydın and Ozyon applied incremental artificial bee colony (IABC) and incremental ABC with local search (IABC_LS) algorithms [35] to solve ELD problem of 3, 5, 6 and 40 generating unit systems. Shaw et al. [36] applied oppositional based learning (OBL) concept to accelerate the performance of the GSA. Chatterjee et al. [37] proposed opposition-based harmony search algorithm (OHSA) to employ opposition-based learning for harmony memory initialization and also for the generation jumping. Liao presented isolation Niche immune based GA algorithm [38] for solving dynamic ELD (DELD) problem. Peng et al. proposed bi-population chaotic differential evolution (BPCDE) algorithm [39] to solve DELD problem of a power system integrated with large scale wind farms. In the proposed algorithm, chaotic map update mechanism and metropolis rule are used to improve the performance of standard differential evolution algorithm.

Various researchers were looking for better alternatives, and therefore, hybrid methods combining different conventional techniques were identified. Recently, different hybridization techniques such as GA-SQP [40], PSO-SQP [41,42], hybrid EP-PSO-SQP [43], hybrid DE (HDE) [44,45], hybrid DE-PSO [46], hybrid shuffled differential evolution (SDE) [47], hybrid differential harmony search [48] are proposed for getting better quality solutions of ELD problems. Recently, Roy et al. proposed modified shuffled frog leaping algorithm (MSFLA) [49] with genetic algorithm (GA) for the ELD problem. To test the effectiveness, the proposed method was implemented on IEEE standard 30-bus [30], 13 [20] and 40 [20] thermal units systems. Mohammadi-Ivatloo et al. [50] presented a novel heuristic algorithm for solving ELD problems, by employing iteration based PSO with time varying acceleration coefficients (IPSO-TVAC) method. Saber [51] presented a novel modified PSO (MPSO), which includes advantages of bacterial foraging (BF) and PSO for constrained DELD problem. Vaisakh et al. implemented bacterial foraging PSO-DE (BPSO-DE) algorithm [52] by integrating BFO, PSO and DE for solving static and dynamic ELD problems of various test systems.

Krill herd algorithm (KHA) is a recently developed powerful evolutionary algorithm proposed by Gandomi and Alavi [53] to solve non-convex optimization problem. The proposed KHA method is based on the herding behavior of krill individuals. Each krill individuals modify its position using three process namely, (1) movement induced by other individuals (2) foraging motion, and (3) random physical diffusion. The foraging motion and the motion induced by other individuals contain global and local strategies, respectively which make KHA a powerful technique. However, sometime, conventional KHA is unable to generate global optimal solutions on some high-dimensional nonlinear optimization problems. To improve the performance of the KHA, adaptive crossover and mutation mechanisms are incorporated into the algorithm. The crossover operator helps to avoid premature convergence in the early run phase, and refine the final solutions in the later. Due to these excellent properties of this new algorithm and as it does not have any tendency to stick in local optimum points in the nonlinear optimization problem, the present authors applied this newly developed algorithm, to solve non-convex complex ELD problems. The different version of KHA techniques are applied on six different test cases (6-unit, 10-unit, 15-unit, 40-unit without transmission loss, 40-unit with transmission loss and 80 unit systems) with varying degree of complexity for verifying its performance with other established methods such as simulated annealing (SA), GA, PSO, DE, self-organizing hierarchical PSO (SOH-PSO), GAAPI, new PSO (NPSO), fuzzy adaptive PSO (FAPSO), passive congregation based PSO (PC_PSO), tabu search (TS), multiple TS (MTS), NPSO with local random search (NPSO-LRS), teaching learning based optimization (TLBO), and quasi-oppositional TLBO (QOTLBO).

The rest of this paper is organized as follows: Section 2 presents the problem formulation. The key points of the proposed KHA technique are described in Section 3. In Section 4, the proposed method applied to ELD problem is illustrated. Six cases based on five different power systems are studied and the simulation results are discussed in Section 5. The conclusion is summarized in Section 6.

2. Problem formulation

2.1. Objective function

The ELD problem is addressed as to simultaneously minimize the power production cost and meet the load demand of a power system while satisfying the equality and inequality constraints. Main production cost of thermal generator is fuel cost. Therefore, the objective function of ELD problem may be expressed as under:

$$F_t = \sum_{i=1}^{m} F_i(P_i) \tag{1}$$

where F_t is the total fuel cost; $F_i(P_i)$ is the cost of the ith thermal generator and m is the number of committed generators to the operating system.

Usually, fuel cost of a thermal unit is expressed as a quadratic polynomial of its output (P_i) as below.

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

where a_i, b_i, c_i are the cost coefficients of the ith generator; P_i is the power output of the ith generator.

However, it is more practical to consider the effect of valve-point loading for thermal power plants. These effects, which occur as each steam admission valve in a turbine, produce a rippling effect on the unit's cost curve. Considering the valve-point effects, the fuel cost function of the ith thermal generating unit is expressed as the sum of a quadratic and a sinusoidal function in the following form:

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

where d_i, e_i are the fuel cost coefficients of the ith unit reflecting the effect of valve point loading; $P_i^{\min}$ is the minimum active power of the ith generating unit.

Moreover, there are many practical thermal generating units that can be supplied fuel by multiple fuel sources. Therefore, it is more practical and appropriate to represent the unit's fuel cost as a piecewise function, reflecting the effects of fuel type changes. To obtain an accurate and practical ELD solution, valve-point effects and multi-fuel options should be included in the cost function which may mathematically expressed as follows:

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1} P_i + c_{i1} P_i^2 + \left| d_{i1} \sin\left(e_{i1} \left(P_i^{\min} - P_i \right) \right) \right| & \text{if } P_i^{\min} \leqslant P_i \leqslant P_{i1} \\ a_{i2} + b_{i2} P_i + c_{i2} P_i^2 + \left| d_{i2} \sin(e_{i2} (P_{i1} - P_i)) \right| & \text{if } P_{i1} \leqslant P_i \leqslant P_{i2} \\ a_{ik} + b_{ik} P_i + c_{ik} P_i^2 + \left| d_{ik} \sin(e_{ik} (P_{ik} - P_i)) \right| & \text{if } P_{ik} \leqslant P_i \leq P_i^{\max} \end{cases} \tag{4}$$

2.2. Constraints

The ELD problem is subjected to the following equality and inequality constraints.

2.2.1. Real power balance constraint

The sum of the generated powers of all units must be equal to sum of the power demanded by the load and the total transmission loss.

$$\sum_{i=1}^{m} P_i - P_d - P_{loss} = 0 \tag{5}$$

where P_d is the total load demand; P_{loss} is the transmission loss of the system and it is calculated using power flows coefficients by the following formula:

$$P_{loss} = \sum_{i=1}^{m} \sum_{j=1}^{m} P_i B_{ij} P_j + \sum_{i=1}^{m} B_{0i} + B_{00} \tag{6}$$

where B_{00}, B_{i0}, B_{ij} are loss coefficients which can be assumed to be constant under normal operating condition.

2.2.2. Generator capacity constraints

The power generated by each generator must be within its lower and upper operating limits. It may mathematically formulated by

$$P_i^{\min} \leq P_i \leq P_i^{\max} \quad i = 1, 2, \ldots, m \tag{7}$$

where $P_i^{\min}, P_i^{\max}$ are the minimum and maximum active power, respectively, of the ith generating unit.

2.2.3. Prohibited operating zone

Due to vibration in its shaft bearing, practical generating units might have prohibited operating zone in the input–output curve of generator and each unit must avoid operation in prohibited zones. The operating zone of the ith unit may be described as follows:

$$\begin{aligned} & P_i^{\min} \leq P_i \leq P_{i,1} \\ & P_{i,j-1} \leq P_i \leq P_{i,j}, \quad j = 2, 3, \ldots, n_i \\ & P_{i,n_i} \leq P_i \leq P_i^{\max} \end{aligned} \tag{8}$$

where n_i represents the number of prohibited operating zones of the ith unit; $P_{i,j-1}$, $P_{i,j}$ are the generation limits of the jth prohibited zone of the ith unit.

3. Krill herd algorithm (KHA)

KHA is a recently developed heuristic algorithm based on the herding behavior of krill individuals. It has been first proposed by Gandomi and Alavi [53]. It is a population based method consisting of a large number of krill in which each krill moves through a multi-dimensional search space to look for food. In this optimization algorithm, the positions of krill individuals are considered as different design variables and the distance of the food from the krill individual is analogous to the fitness value of the objective function. In KHA, the individual krill alters its position and moves to the better positions. The movement of each individual is influenced by the three process namely (i) induction process, (ii) foraging activity and (iii) random diffusion. These operators are briefly explain and mathematically expressed as follows:

3.1. Induction

In this process, the velocity of each krill is influenced by the movement of other krill individuals of the multi-dimensional search space and its velocity is dynamically adjusted by the local, target and repulsive vector. The velocity of the ith krill at the mth movements may be formulated as follows [53]:

$$V_i^m = \alpha_i V_i^{\max} + \omega_n V_i^{m-1} \tag{9}$$

$$\alpha_i = \sum_{j=1}^{N_S} \left[\frac{f_i - f_j}{f_w - f_b} \times \frac{Z_i - Z_j}{|Z_i - Z_j| + rand(0,1)} \right] + 2\left[rand(0,1) + \frac{i}{i_{\max}} \right] f_i^{best} X_i^{best} \tag{10}$$

where $V_i^{\max}$ is the maximum induced motion; V_i^m, V_i^{m-1} are the induced motion of the ith krill at the mth and ($m-1$)th movement; ω_n is the inertia weight of the motion induced; f_w and f_b are the worst and the best position respectively, among all krill individuals, of the population; f_i, f_j are the fitness value of the ith and jth individuals, respectively; N_S is the number of krill individuals surrounding the particular krill; $i, i_{\max}$ are the current iteration and the maximum iteration number.

A sensing distance (SD_i) parameter is used to identify the neighboring members of each krill individual. If the distance between the two individual krill is less than the sensing distance, that particular krill is considered as neighbor of the other krill. The sensing distance may be represented by [53]:

$$SD_i = \frac{1}{5n_p}\sum_{k=1}^{n_p}|Z_i - Z_k| \tag{11}$$

where n_p is the population size; Z_i, Z_k are the position of the ith and kth krill, respectively.

3.2. Foraging action

Each individual krill updates its foraging velocity according to its own current and previous food location. The foraging velocity of the ith krill at the mth movement may be expressed by [53]

$$V_{f_i}^m = 0.02\left[2\left(1 - \frac{i}{i_{\max}}\right)f_i\frac{\sum_{k=1}^{N_S}\frac{Z_k}{f_k}}{\sum_{k=1}^{N_S}\frac{1}{f_j}} + f_i^{best}X_i^{best}\right] + \omega_x V_{f_i}^{m-1} \tag{12}$$

where ω_x is the inertia weight of the foraging motion; $V_{f_i}^{m-1}, V_{f_i}^m$ are the foraging motion of the ith krill at the $(m-1)$th and m movement.

3.3. Random diffusion

In KHA algorithm, in order to enhance the population diversity, random diffusion process is incorporated in krill individuals. This process maintains or increases the diversity of the individuals during the whole optimization process. The diffusion speed of krill individuals may be expressed as follows [53]

$$V_{D_i}^m = \mu V_D^{\max} \tag{13}$$

where $V_D^{\max}$ is the maximum diffusion speed; μ is a directional vector uniformly distributed between (−1, 1).

3.4. Position update

In KHA, the krill individuals fly around in the multidimensional space and each krill adjusts its position based on induction motion, foraging motion and diffusion motion. In this way, KHA combines local search with global search for balancing the exploration and exploitation. The updated position of the ith krill may be expressed as [53]:

$$Z_i^{m+1} = Z_i^m + \left(V_i^m + V_{f_i}^m + V_{D_i}^m\right)P_t\sum_{j=1}^{N_d}(u_j - l_j) \tag{14}$$

where N_d is the number of control variables; u_j, l_j are the maximum and minimum limits of the jth control variable; P_t is the position constant factor.

In order to speed up the convergence property and to find better results, the crossover and mutation operations of DE are combined with the proposed algorithm to utilize the exploration ability of DE. These two operators are briefly described below:

3.4.1. Crossover

Depending upon the crossover probability, each krill individual interacts with others to update its position. The jth components of the ith krill may be updated by

$$Z_{i,j} = \begin{cases} Z_{k,j} \text{ if } rand \le C_{R_i} \\ Z_{i,j} \text{ if } rand > C_{R_i} \end{cases} \quad \text{where } k = 1,2,\ldots,n_p; k \ne i \tag{15}$$

where C_{R_i} is the crossover probability and is given by [53]

$$C_{R_i} = 0.2 f_i^{best}$$

3.4.2. Mutation

In this process, a scalar number F_R scales the difference of two randomly selected vectors $Z_{m,j}$ and $Z_{n,j}$ and the scaled difference is added to the best vector $z_{best,j}$ whence the mutant vectors $z_{i,j}^m$ is obtained.

$$Z_{i,j} = Z_{best,j} + F_R(Z_{m,j} - Z_{n,j}) \tag{16}$$

Using mutation probability (M_R) the modified value, $Z_{i,j}^{\text{mod}}$ is selected from $Z_{i,j}^m$ and $Z_{i,j}$ and it may mathematically expressed as:

$$Z_{i,j}^{\text{mod}} = \begin{cases} Z_{i,j}^m \text{ if } rand \le M_R \\ Z_{i,j} \text{ if } rand > M_R \end{cases} \tag{17}$$

4. KHA applied to ELD

In this article, the proposed KHA algorithm is developed and successfully implemented to solve different types of ELD problems. The different steps of KHA algorithm for solving ELD problems are described below

- **Step 1:** Active power generation of all generating units except the last unit is initialized randomly within their effective real power operating limits i.e. each element must satisfy generator capacity constraint of (7). The active power generation of the last unit is evaluated using (5) and check whether it satisfies the inequality constraint (7) or not. If it does not satisfy the inequality constraints; the corresponding solution set is reinitialize. Several initial solutions set depending upon the population size are generated. The feasible solution set (control variables) represents the position of different krill individual. Depending upon the population size (n_p), initial krill position matrix P is created which is given by

$$P = \begin{bmatrix} P_{g_1}^1, P_{g2}^1, \ldots, P_{gi}^1 \ldots, P_{gn}^1 \\ P_{g_1}^2, P_{g2}^2, \ldots, P_{gi}^2 \ldots, P_{gn}^2 \\ P_{g_1}^i, P_{g2}^i, \ldots, P_{gi}^i \ldots, P_{gn}^i \\ \cdots \quad \cdots \quad \cdots \\ P_{g1}^{n_p}, P_{g2}^{n_p}, \ldots, P_{gi}^{n_p} \ldots, P_{gn}^{n_p} \end{bmatrix} \tag{18}$$

- **Step 2:** Evaluate fitness of each individual of current population using (1).
- **Step 3:** Evaluate induced motion, foraging motion and diffusion motion using (9), (12) and (13).
- **Step 4:** Modify the position of each krill individual using (14).
- **Step 5:** Applying crossover and mutation of DE to modify the position of each individual krill using (15) and (16). The position of each krill individual represents a potential solution comprises of active power generation of ELD problem.
- **Step 6:** Check whether the active power of all generating units except last unit violate the operating limits or not. If any power generation is less than the minimum level it is made equal to minimum value and if it is greater than the maximum level it is made equal to maximum level. Afterward, the power generation of the last unit is evaluated using (5) and check whether it satisfies the inequality constraints or not. The infeasible solutions are replaced by the best feasible solutions.
- **Step 7:** Go to Step 2 until stopping criteria is met. The KHA is stopped running when there is no significant improvement in the solution or the maximum number of iterations (generations) is reached. In this study, the stopping criterion is the maximum number of iterations for which most of the krill individuals are idle.

5. Simulation results and discussion

In this study, four different KHA techniques namely, KHA without any genetic operators (KHA-I); KHA with crossover operator

Table 1
Optimal generation and cost obtained by KHA-IV for test system 1 (6-unit with loss and with POZ).

Unit	Pgmin	Pgmax	POZ	Generation	Unit	Pgmin	Pgmax	POZ	Generation
1	100	500	[210,240]; [350,380]	447.4150	4	50	150	[80,90]; [110,120]	138.9646
2	50	200	[90,110]; [140,160]	173.2917	5	50	200	[90,110]; [140,150]	165.3759
3	80	300	[150,170]; [210,240]	263.3559	6	50	120	[75,85]; [100,105]	87.0417
Cost ($/h)					15443.0752				
Transmission loss (MW)					12.4449				

Table 2
Statistical results of various algorithms for test system 1 (6-unit system).

Algorithms	Best fuel cost ($/day)	Average fuel cost ($/day)	Worst fuel cost ($/day)
GA binary [55]	15451.66	15469.21	15519.87
GA [56]	15459.00	15469.00	15524.00
NPSO-LRS [14]	15450.0	15454.00	15455.00
SOH-PSO [13]	15446.02	15497.35	15609.64
GAAPI [55]	15449.78	15449.81	15449.85
NPSO [54]	15443.765664	15443.765671	15443.765683
FAPSO [54]	15445.244	15448.052	15451.63
PSO [54]	15,450	–	15,492
DE [56]	15449.766	15449.777	15449.874
SPSO [13]	15466.63	–	–
PC_PSO [13]	15453.09	–	–
TS [57]	15454.89	15472.56	15498.05
MTS [57]	15450.06	15451.17	15453.64
SA [57]	15461.1	15488.98	15545.5
KHA-I	15450.7492	15452.8219	15455.4561
KHA-II	15448.2117	15450.8322	15453.4289
KHA-III	15445.3560	15447.2175	15449.6078
KHA-IV	15443.0752	15443.1863	15443.3265

(KHA-II); KHA with mutation operator (KHA-III); and KHA with crossover and mutation operators (KHA-IV) approaches are carried out on six different case studies namely, 6-unit, 10-unit, 15-unit, 40-unit without transmission loss, 40-unit with transmission loss and 80 unit systems of ELD problems. To investigate the effectiveness of the proposed approach, the results obtained from different KHA methods are compared with other results reported in the recent literature. The programming of proposed ELD based KHA methods are developed in MATLAB 7.1 and run on PC with 2.5 GHz core duo processor of 2 GB RAM. For implementing the various KHA techniques in ELD problems, population size of 50 and the maximum number of generation (iterations) of 100 is taken in this simulation study for all the test systems. To verify the robustness of the different methods, 50 independent runs are made in each case study involving 50 different initial trial solutions.

The KHA input parameters used in [53] are adopted for this simulation study and these parameters are as follows: the maximum induced speed, $V_i^{\max} = 0.01$; the maximum diffusion speed $V_D^{\max} = 0.05$; the position constant factor, $P_t = 0.2$; the inertia weights, ω_n, ω_x are initially taken as 0.9 to emphasize exploration capability of the search process and these values are linearly decreased to 0.1 at the end to exploit the search space.

5.1. Test system 1

Initially, the proposed KHA techniques are applied on a small test system consisting of 6 generating units with a load demand of 1263 MW. The transmission loss and prohibited operating zones are taken into account for this test system. The total system data of this test case are available in [50,51]. Table 1 provides the optimal generation schedule and total generation cost obtained by the proposed KHA-IV method. It is found from Table 1 that the proposed method minimizes the fuel cost without violating any system operating constraints. In addition, the statistical results of the minimum, maximum and average fuel cost obtained by the different kind of KHA algorithms are compared with the reported results of GA binary [55], GA [56], self-organizing hierarchical PSO (SOH-PSO) [13], GAAPI [55], new PSO (NPSO) [54], fuzzy adaptive PSO (FAPSO) [54], PSO [54], DE [56], SPSO [13], passive congregation based PSO (PC_PSO) [13], tabu search (TS) [57], multiple TS (MTS) [57], NPSO with local random search (NPSO-LRS) [14] and simulated annealing (SA) [57]. From Table 2, it is clearly visible that the proposed KHA-IV method outperforms all other methods in terms of achieving the best, average and worst fuel cost.

5.2. Test system 2

A system consisting of ten generators with valve point loading, multiple fuels cost functions without transmission loss is used to demonstrate how good the proposed approach works for this type of nonlinear and non-convex ELD problem. The load of this system is taken as 2700 MW. The system input data including fuel cost for this test system are adopted from [58]. The best fuel cost, fuel type and generation value of each unit obtained in 50 trials for KHA-IV technique is tabulated in Table 3. It can be inferred from the results that the solution obtained by the proposed method does not violate any system constraints. Moreover, for this 10-unit system, the best, worst and mean cost obtained in 50 different independent trials are compared with those obtained other optimization methods available in the literatures and are summarized in Table 4. The results listed in Table 4 show that the KHA-IV method is better than KHA-I, KHA-II, KHA-III, new adaptive PSO (NAPSO) [54], FAPSO [54], improved GA with multiplier updating (IGA-MU) [59], PSO with local random search (PSO-LRS) [59], NPSO [59], NPSO-LRS [59], TSA [60], distributed PSO and tabu search

Table 3
Optimal generation and cost obtained by KHA-IV for test system 2 (10-unit without loss and with multiple fuel).

Unit	Pgmin	Pgmax	Fuel type	Generation	Unit	Pgmin	Pgmax	Fuel type	Generation
1	100	250	2	212.3865	6	85	265	3	237.6310
2	50	230	3	208.7381	7	200	500	1	280.7793
3	200	500	2	332.5949	8	99	265	3	239.1042
4	99	265	3	236.4131	9	130	440	3	414.9190
5	190	490	1	270.0975	10	200	490	1	267.3368
Cost ($/h)					605.7582				

Table 4
Statistical results of various algorithms for test system 2 (10-unit without loss and with multiple fuel).

Algorithms	Best fuel cost ($/h)	Average fuel cost ($/h)	Worst fuel cost ($/h)
NAPSO [54]	623.62170	623.6335	623.67543
FAPSO [54]	624.2189	624.2782	624.2951
IGA-MU [59]	624.5178	627.6087	630.8705
PSO-LRS [59]	624.2297	625.7887	628.3214
NPSO [59]	624.1624	625.2180	627.4237
NPSO-LRS [59]	624.1273	624.9985	626.9981
DSPSO-TSA [60]	623.8375	623.8625	623.9001
PSO [60]	624.3045	624.5054	625.9252
GA [60]	624.5050	624.7419	624.8169
TSA [60]	624.3078	635.0623	624.8285
ARCGA [59]	623.8281	623.8431	623.8550
KHA-I	611.3276	613.0895	614.8293
KHA-II	609.0768	610.3271	611.2105
KHA-III	607.5437	608.1164.	608.5431
KHA-IV	605.7582	605.8043	605.9426

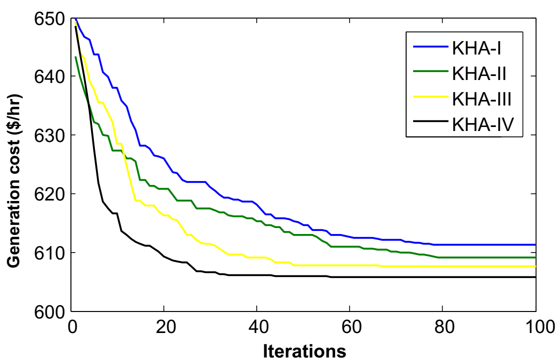

Fig. 1. Cost convergence characteristics of KHA-I, KHA-II, KHA-III and KHA-IV algorithms for 10-unit system.

algorithm (DSPSO-TSA) [60], PSO [60], GA [60] and adaptive real coded GA (ARCGA) [59]. Fig. 1 shows the convergence characteristics of cost yielded by the different KHA techniques.

5.3. Test system 3

In this case study, the same algorithm is applied on a larger test system consisting of the 15 generating units. The transmission losses and prohibited operating zone are taken into consideration for this test system. The total load demand of the system is 2630 MW. The generating units 2, 5, 6, and 12 have prohibited operating zones and these data are taken from [54]. The rest of the system data are taken from [61]. The optimal cost, power loss and optimal generation scheduling obtained by the proposed KHA-IV method are presented in Table 5 which shows that the simulation results satisfy all the operational constraints. Furthermore, the statistical results of 50 independent trials for the 15 unit system are tabulated in Table 6 and these results are compared with the results of NAPSO [54], FAPSO [54], PSO [54], GA [56], ESO [56], DE [56], SPSO [13], PC-PSO [13], SOH-PSO [13], MTS [62], SA [62], society-civilization algorithm (SCA) [62], APSO [17], civilized swarm optimization (CSO) [62] and GAAPI [55] reported in the literature. The comparative results clearly shows that the proposed KHA-IV method is capable of producing a higher quality solution than the other evolutionary methods considering all three statistical cost measurements (maximum, mean and minimum).

Table 6
Statistical results of various algorithms for test system 3 (15-unit with loss and with POZ).

Algorithms	Best fuel cost ($/h)	Average fuel cost ($/h)	Worst fuel cost ($/h)
NAPSO [54]	32548.585876	32548.5869	32548.5904
FAPSO [54]	32659.794	32663.19	32676.07
PSO [54]	32,858	32,989	33,031
GA [56]	33063.54	33,228	33,337
ESO [56]	32640.86	32,620	32,710
DE [56]	32588.865	32609.851	32641.419
SPSO [13]	32798.69	–	–
PC-PSO [13]	32775.36	–	–
SOH-PSO [13]	32751.39	32,878	32,945
MTS [62]	32716.87	32767.4	32796.13
SA [62]	32786.4	32869.51	33028.95
SCA [62]	32867.025	33138.3020	33381.0607
APSO [17]	32742.77	2976.6812	–
CSO [62]	32588.9189	32679.8775	32796.7792
GAAPI [55]	32732.95	–	–
KHA-I	32586.7458	32592.0364	32598.0145
KHA-II	32569.8042	32571.4457	32573.6286
KHA-III	32564.3892	32566.5782	32567.3250
KHA-IV	32547.3700	32548.1348	32548.9326

5.4. Test system 4

5.4.1. Without transmission loss

To demonstrate the efficiency of the proposed method, simulation studies are carried out on 40-unit system with considering valve point effects and prohibited operating zones. The generating units 10–14 have the constraints of prohibited operating zones. The transmission loss is not considered for this simulation study. The load demand of this system is 10,500 MW. The system data of fuel cost and power generation limits are taken from [20] whereas the prohibited operating zone data are adopted from

Table 5
Optimal generation and cost obtained by KHA-IV for test system 3 (15-unit with loss and with POZ).

Unit	Pgmin	Pgmax	POZ	Generation	Unit	Pgmin	Pgmax	POZ	Generation
1	150	455	–	455.0000	9	25	162	–	25.0000
2	150	455	[185,225]; [305,335]; [420,450]	455.0000	10	25	160	–	31.2698
3	20	130	–	130.0000	11	20	80	–	76.7013
4	20	130	–	130.0000	12	20	80	[30,40]; [55,65]; [55,65]	80.0000
5	150	470	[180,200]; [305,335]; [390,420]	233.8017	13	25	85	–	25.0000
6	135	460	[230,255]; [365,395]; [430,455]	460.0000	14	15	55	–	15.0000
7	135	465	–	465.0000	15	15	55	–	15.0000
8	60	300	–	60.0000					
Cost ($/h)					32547.3700				
Transmission loss (MW)					26.7673				

Table 7
Optimal generation and cost obtained by KHA-IV for test system 4 (40-unit without loss and with POZ).

Unit	Pgmin	Pgmax	POZ	Generation	Unit	Pgmin	Pgmax	POZ	Generation
1	36	114	–	110.7998	21	254	550	–	523.2792
2	36	114	–	110.8004	22	254	550	–	523.2794
3	60	120	–	97.4002	23	254	550	–	523.2793
4	80	190	–	179.7342	24	254	550	–	523.2794
5	47	97	–	87.7995	25	254	550	–	523.2797
6	68	140	–	140.0000	26	254	550	–	523.2795
7	11	300	–	259.6001	27	10	150	–	10.0000
8	13	300	–	284.5992	28	10	150	–	10.0000
9	13	300	–	284.6002	29	10	150	–	10.0000
10	13	300	[130,150]; [200,230]; [270,290]	130.0000	30	47	97	–	87.7999
11	94	375	[100,140]; [230,280]; [300,350]	94.0000	31	60	190	–	190.0000
12	94	375	[100,140]; [230,280]; [300,350]	94.0000	32	60	190	–	190.0000
13	12	500	[150,200]; [250,300]; [400,450]	214.7598	33	60	190	–	190.0000
14	12	500	[200,250]; [300,350]; [450,490]	394.2790	34	90	200	–	164.7998
15	12	500	–	394.2789	35	90	200	–	194.3953
16	12	500	–	394.2796	36	90	200	–	200.0000
17	22	500	–	489.2801	37	25	110	–	110.0000
18	22	500	–	489.2794	38	25	110	–	110.0000
19	24	550	–	511.2794	39	25	110	–	110.0000
20	242	550	–	511.2796	40	242	550	–	511.2791
Cost ($/h)					121412.5991				

Table 8
Statistical results of various algorithms for test system 4 (40-unit without loss and with POZ).

Algorithms	Best fuel cost ($/h)	Average fuel cost ($/h)	Worst fuel cost ($/h)
NAPSO (POZ1) [54]	121412.6102	121412.7373	121412.9109
FAPSO (POZ1) [54]	121719.73	121783.093	121842.52
PSO (POZ1) [54]	123861.45	124162.4819	124663.047
NAPSO (POZ2) [54]	121491.0662	121491.2756	121491.5261
FAPSO (POZ2) [54]	122261.3706	122471.0751	122597.5196
PSO (POZ2) [54]	124875.8523	125162.7011	125368.9204
KHA-I	121460.4156	121468.9822	121477.4582
KHA-II	121448.3643	121453.6799	121461.3895
KHA-III	121423.4557	121428.2263	121433.5631
KHA-IV	121412.5991	121413.1454	121415.0042

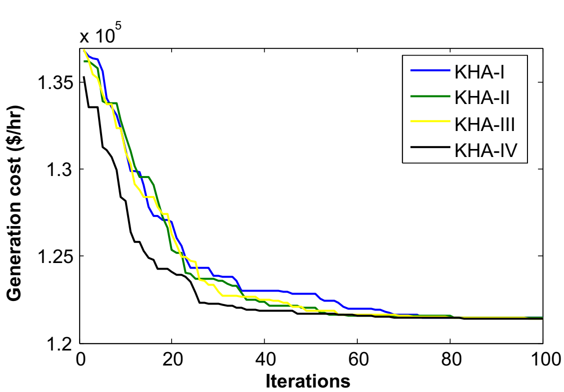

Fig. 2. Cost convergence characteristics of KHA-I, KHA-II, KHA-III and KHA-IV algorithms for 40-unit system without loss.

[54]. The best generation cost and optimal active power of the all 40 generating units obtained by the proposed KHA-IV method are illustrated in Table 7. In order to check the robustness of the proposed KHA methods, their statistical results are compared with those obtained by NAPSO (POZ1) [54], FAPSO (POZ1) [54], PSO (POZ1) [54], NAPSO (POZ2) [54], FAPSO (POZ2) [54] and PSO (POZ2) [54]. These statistical results are listed in Table 8. It can be observed that the minimum, maximum and average cost obtained from the proposed KHA-IV method is better than the KHA-I, KHA-II, KHA-III and other techniques reported in the literature. The convergence characteristics of the objective function are plotted in Fig. 2 for different KHA algorithms.

Table 9
Optimal generation and cost obtained by KHA-IV for test system 5 (40-unit with loss).

Unit	Pgmin	Pgmax	Generation	Unit	Pgmin	Pgmax	Generation
1	36	114	114.0000	21	254	550	524.4678
2	36	114	114.0000	22	254	550	535.5799
3	60	120	120.0000	23	254	550	523.3795
4	80	190	190.0000	24	254	550	523.15527
5	47	97	88.5944	25	254	550	524.1916
6	68	140	105.5166	26	254	550	523.5453
7	110	300	300.0000	27	10	150	10.1245
8	135	300	300.0000	28	10	150	10.1815
9	135	300	300.0000	29	10	150	10.0229
10	130	300	280.6777	30	47	97	87.8154
11	94	375	243.5399	31	60	190	190.0000
12	94	375	168.8017	32	60	190	190.0000
13	125	500	484.1198	33	60	190	190.0000
14	125	500	484.1662	34	90	200	200.0000
15	125	500	485.2375	35	90	200	164.9199
16	125	500	485.0698	36	90	200	164.9787
17	220	500	489.4539	37	25	110	110.0000
18	220	500	489.3035	38	25	110	110.0000
19	242	550	510.7127	39	25	110	110.0000
20	242	550	511.3040	40	242	550	512.06775
Cost ($/h)				136670.3701			
Transmission loss (MW)				978.9251			

5.4.2. With transmission loss

The implementations of the proposed KHA algorithms of this example are identical to the previous example. Only the transmission losses of 40 units are taken into account to convert it a more realistic practical system. The B-coefficient data of this system are adopted from [55]. The optimal power output of all 40 units obtained by the proposed KHA-IV method is illustrated in Table 9. In order to inspect the quality of the obtained solutions, the result

Table 10
Statistical results of various algorithms for test system 5 (40-unit with loss).

Algorithms	Best fuel cost ($/h)	Average fuel cost ($/h)	Worst fuel cost ($/h)
QOTLBO [63]	137329.86	–	–
TLBO [63]	137814.17	–	–
GAAPI [55]	139864.96	–	–
SDE [47]	138157.46	–	–
KHA-I	136702.5833	136715.0864	136723.8428
KHA-II	136692.6544	136704.6738	136713.1147
KHA-III	136683.6542	136690.7652	136698.5031
KHA-IV	136670.3701	136671.2293	136671.8648

Table 12
Statistical results of various algorithms for test system 6 (80-unit without loss and with POZ).

Algorithms	Best fuel cost ($/h)	Average fuel cost ($/h)	Worst fuel cost ($/h)
NPSO [54]	242844.1172	–	–
FAPSO [54]	244273.5429	–	–
PSO [54]	249248.3751	–	–
KHA-I	242857.3982	242863.2659	242868.0074
KHA-II	242844.5620	242851.1472	242858.9565
KHA-III	242836.7114	242844.5534	242853.6792
KHA-IV	242825.2089	242826.9347	242828.1350

obtained by the different KHA algorithms are compared with teaching learning based optimization (TLBO) [63], quasi-oppositional TLBO (QOTLBO) [63], GAAPI [55] and Shuffled DE (SDE) [44] and Table 10 represents the comparative results of the aforementioned methods. From the presented results it can be found that best fuel cost obtained by KHA-IV is better than that obtained by others methods.

5.5. Test case 5

In order to further investigate the superiority and robustness, the proposed KHA methods are finally applied on a large system consisting of 80 generating units. This case has a larger and more complex solution space than all the previous cases, and so the difference between different ELD solution methods can be better revealed in this case. This large-scale system is created by expanding the 40 generating unit system. The system load demand is taken as 21,000 MW. The transmission loss is not considered in this simulation study. The cost coefficients, generation limits, and valve point coefficients are derived from [20] with modifications to consider prohibited operating zones of units 10–14 and 50–54. The prohibited operating zone data are taken from [54]. Table 11 shows the generation schedule of 80 generating units and fuel cost for this test system obtained by the proposed KHA-IV method. The simulation results suggest that KHA-IV method generates feasible solutions without violating any operational constraint. To validate

Table 11
Optimal generation and cost obtained by KHA-IV for test system 4 (80-unit without loss and with POZ).

Unit	Pgmin	Pgmax	POZ	Generation	Unit	Pgmin	Pgmax	POZ	Generation
1	36	114	–	110.8012	41	36	114	–	110.7994
2	36	114	–	110.7994	42	36	114	–	110.8003
3	60	120	–	97.4002	43	60	120	–	97.3995
4	80	190	–	179.7329	44	80	190	–	179.7331
5	47	97	–	87.8001	45	47	97	–	87.7992
6	68	140	–	140.0000	46	68	140	–	140.0000
7	110	300	–	259.995	47	110	300	–	259.6002
8	135	300	–	284.996	48	135	300	–	284.5991
9	135	300	–	284.5998	49	135	300	–	284.6005
10	130	300	[130,150]; [200,230]; [270,290]	130.0000	50	130	300	[130,150]; [200,230]; [270,290]	130.0000
11	94	375	[100,140]; [230,280]; [300,350]	94.0000	51	94	375	[100,140]; [230,280]; [300,350]	94.0000
12	94	375	[100,140]; [230,280]; [300,350]	94.0000	52	94	375	[100,140]; [230,280]; [300,350]	94.0000
13	125	500	[150,200]; [250,300]; [400,450]	214.7599	53	125	500	[150,200]; [250,300]; [400,450]	214.7598
14	125	500	[200,250]; [300,350]; [450,490]	394.2792	54	125	500	[200,250]; [300,350]; [450,490]	394.2789
15	125	500	–	394.2795	55	125	500	–	394.2797
16	125	500	–	394.2793	56	125	500	–	394.2802
17	220	500	–	489.2793	57	220	500	–	489.2789
18	220	500	–	489.2794	58	220	500	–	489.2797
19	242	550	–	511.2793	59	242	550	–	511.2788
20	242	550	–	511.2794	60	242	550	–	511.2803
21	254	550	–	523.2795	61	254	550	–	523.2794
22	254	550	–	523.2794	62	254	550	–	523.2794
23	254	550	–	523.2794	63	254	550	–	523.2799
24	254	550	–	523.2796	64	254	550	–	523.2789
25	254	550	–	523.2793	65	254	550	–	523.2794
26	254	550	–	523.2794	66	254	550	–	523.2794
27	10	150	–	10.0000	67	10	150	–	10.0000
28	10	150	–	10.0000	68	10	150	–	10.0000
29	10	150	–	10.0000	69	10	150	–	10.0000
30	47	97	–	87.8002	70	47	97	–	87.7999
31	60	190	–	190.0000	71	60	190	–	190.0000
32	60	190	–	190.0000	72	60	190	–	190.0000
33	60	190	–	190.0000	73	60	190	–	190.0000
34	90	200	–	164.8004	74	90	200	–	164.7992
35	90	200	–	194.3976	75	90	200	–	194.3954
36	90	200	–	200.0000	76	90	200	–	200.0000
37	25	110	–	110.0000	77	25	110	–	110.0000
38	25	110	–	110.0000	78	25	110	–	110.0000
39	25	110	–	110.0000	79	25	110	–	110.0000
40	242	550	–	511.2792	80	242	550	–	511.2794
Cost ($/h)					242825.2089				

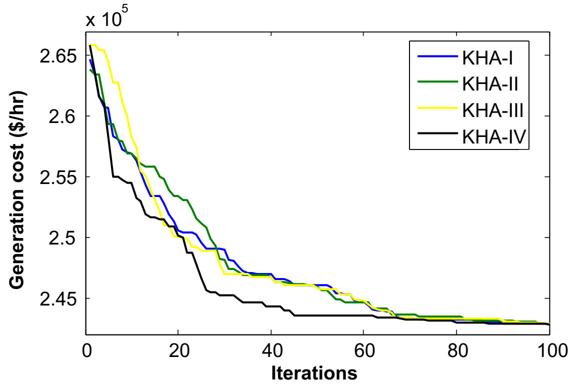

Fig. 3. Cost convergence characteristics of KHA-I, KHA-II, KHA-III and KHA-IV algorithms for 80-unit system.

the superiority, a comparison is made among the best solution obtained from the different KHA methods and the solutions obtained by the PSO [54], NPSO [54] and FAPSO [54]. The results of this comparison are shown in Table 12. The comparison shows that KHA-IV provides the minimum cost among all the algorithms, which demonstrate that the proposed method outperforms the other techniques in terms of optimal solutions. The convergence profiles of fuel cost obtained by the proposed KHA-I, KHA-II, KHA-III and KHA-IV techniques are shown in Fig. 3. It is also noticed from this figure that the convergence profile of KHA-IV based fuel cost objectives is promising ones.

5.6. Robustness test

In order to check the robustness of the different KHA techniques for solving the ELD problems, 50 different trials with different initial populations are made on all the test systems. Tables 2, 4, 6, 8, 10 and 12 presents the statistical results obtained by the different algorithms for various ELD problems. From these tables, it is clear that the difference amongst the minimum, maximum and mean objective values obtained by KHA-IV are very insignificant. It clearly suggests that the proposed KHA-IV method produces similar results in most of the trials. Thus proofs the robustness of KHA-IV to solve ELD problems.

6. Conclusion

In this article, a new stochastic search technique named KHA is proposed to solve the different types of non-convex ELD problems. Moreover, to enhance the convergence behavior of the proposed technique, the mutation and crossover operation of DE is incorporated in its evolution. Six different types of non-smooth and non-convex ELD problems with the nonlinearities of valve-point loading, prohibited operating zones, ramp rate constraints and multiple fuels options are used to evaluate the performance of the different KHA algorithms. To test the superiority, the proposed KHA-I, KHA-II, KHA-III and KHA-IV solution methods are compared with some of the most recently published techniques available in the literature. Moreover, to better illustrate the robustness of the proposed KHA based methods, the statistical analysis are carried out on all the test systems. The simulation results show that the proposed KHA-IV method outperforms KHA-I, KHA-II, KHA-III and other reported methods in terms of solution quality, computational efficiency, robustness and stability. This clearly suggests that the proposed KHA-IV method is promising and encouraging for further research in this direction.

In future studies, the proposed KHA method can also be applied in other power system optimization problems such as dynamic ELD (DELD), optimal power flow (OPF), hydrothermal scheduling and unit commitment, considering their complexities as combinatorial optimization problems. Moreover, an important future development of the proposed method is to integrate opposition based learning (OBL) with KHA to improve the computational efficiency of the proposed algorithm when the number of variables is increased.

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