Hybrid krill herd optimizer for thermal power scheduling problem

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Abstract
A hybridized meta-heuristic technique is applied to solve Economic-Environmental Power Dispatch (EEPD) problem. Krill Herd Algorithm (KHA) is a meta-heuristic technique of swarm intelligence based on populations of krill individuals and its motion for searching food. To improve the convergence characteristics of KHA, it is combined with a confined selective operator, termed as the Hybrid Krill Herd Optimizer (HKHO). In this technique, the krill’s position is upgraded with confined krill individuals instead of the arbitrarily chosen individuals as processed in basic KHA. This proposed HKHO technique prevents entrapping of best possible solution in confined optima which means, it avoids the premature convergence of optimal solutions. A non-interactive multi-objective optimization technique is applied whereby the price penalty factor is applied to get scalar objective optimization in case of EEPD problem. The HKHO is implemented in small and medium standard test systems to show the applicability to solve EEPD problem. The developed optimizer is applied to validate the results on two power systems consisted of 6- and 40-thermal units. It gives 2.27% savings in fuel cost and 13.3% reduction in emission of pollutants for 6-thermal units’ power systems with respects to the results undertaken for comparison. Whereas, 40-units’ power system, depicts the conflicting nature of the objectives, when the fuel cost is decreased by 0.16% and emission of pollutants decreases by 0.04%. In both the cases, the achieved results are comparable to already published work in terms of fuel cost and emission of pollutants as shown in tables of comparative analysis of achieved results. The examination of the results shows the satisfactory improvement in best possible solution.

Keywords
Confined selective operator, Economic dispatch, Emission dispatch, Hybrid krill herd optimizer, Price penalty factor.

1. Introduction
The active world is changing each and every day with the advancement of technology and its growing use in daily life, which in turns increases the use of electricity. To fulfil this increase in electricity demand, the electric power system is becoming more complex. The effective functioning of electric power system includes the satisfaction of its consumers with continuous and qualitative service of power supply. In today’s world, the most important task is to use the available resources for thermal power generation at lowest price with intermittent power supply [1].

In the problem of Economic Load Dispatch (ELD), the output of dedicated thermal unit is allocated for minimum fuel cost while satisfying the generation constraints of the electric power system network. Also, the operational planning is required to run the power systems economically, with minimum pollution, maintaining security and reliability of the power system.

A number of investigations have been described in the literature to solve Economic-Environmental Power Dispatch (EEPD) problem. Initially, direct approaches, conventional methods and then linear programming, evolutionary programming, bio or nature inspired methods have been reported in the literature and are applied till date [2].
The study of economic-environmental dispatch draws the attention of researchers for reducing the pollutants to protect the environment. According to the international energy agency in 2011, 45% of energy related carbon dioxide emission was coal based and it reaches to 31.6 Giga tons due to the combustion of coal. In the same year, China contributed the highest increase in emission by 720 million tons [3]. In view of the increasing concern with the environmental considerations, operating at minimum cost is not merely an indicator for scheduling of electric power. Now days, due to increase in environmental concern, there is a need of modification in the existing optimization methods and exploration of new methods according to environmental protection act [4]. Both economic and emission dispatch is equally significant issues in the power industry as the emission of pollutants can harm the health of all the living beings. These pollutants are NO\textsubscript{x}, SO\textsubscript{x} and CO\textsubscript{x}, which are being released into the atmosphere due to combustion of fuel used in thermal power plants. The conflicting and non-commeasurable nature of fuel cost and pollutant’s emission are considered as the objectives of EEPD. The objectives are to optimize the power generated by thermal power generating units through minimizing the fuel cost and pollutant emission, simultaneously [5]. Therefore, to fulfil the future power demand of different consumers, more specific research is needed for best technical, economic and environmental conditions. The utilities would like to supply power to its customers with minimum environmental emission as well as fuel cost simultaneously [6].

The objectives of this paper are as follows:
1. To provide the study of literature review and analysis of the work related to economic-environmental power dispatch problem.
2. To propose the methodology and its systematic implementation with the help of flow chart.
3. To analyze the results obtained by the proposed optimizer and comparison of results with other optimization methods.

The motivation of this paper is as follows
- To consider the economic as well as environmental aspects for power generation scheduling.
- To explore the new technique and its modification along with its impact on the performance and applicability.

The contribution of this paper is as follows:
- To analyze the proposed optimizer in terms of its performance characteristics.
- Parametric analysis of approach with its results and limitations.

This paper consists of six sections. Section 1 presents the introduction. In section 2 literature review is discussed. In section 3, methodology is presented. In section 4, results are discussed. Discussion and analysis are covered in section 5. Finally, conclusions and future scope are presented in section 6.

2. Literature review
The operation of power generators should run at minimum operating fuel cost and environmental effect due to pollutants while fulfilling the generator constraints and power demand. The economic-environmental power scheduling problems have been solved using gravitational search algorithm [7]. Environmental and economic power scheduling problem has been solved using an improved multi-objective interactive honey bee mating optimization while satisfying the operational constraints [8]. The multi-objective optimization problem has been solved by flower pollination, chaotic improved harmony search and whale optimization algorithms [9–11]. Also, sensitivity measure has been incorporated as a dispersion index, which needs to be minimized and best weight pattern approach has been implemented while solving a multi-objective thermal power scheduling problem [12, 13]. The multi-objective electric scheduling problem has been solved using an emended salp swarm algorithm with the exterior penalty to handle the physical and operating constraints [14].

The combination of manta ray foraging optimization and gradient-based optimizer has been applied to multi-objective optimization problem [15]. Various economic emission dispatch problems have been solved with hybrid technique of teaching learning and Particle Swarm Optimization (PSO) [16]. An opposition-based harmony search has been implemented to deal with non-linear environmental and economic dispatch problem [17]. A hybrid optimization approach hybridizes differential evolution and harmony search algorithms to solve multi-objective scheduling problems with non-smooth curves [18].

A combination of PSO and the simplex search method has been implemented to solve economic-emission dispatch problems. PSO finds a global search in the exploration area, whereas simplex
search method searches in the confined search area [19]. A technique based on piecewise-linear programming has been developed to solve economic dispatch problem with non-convex characteristics [20]. The overall cost of flexible sources has been minimized using a combination of distributed, robust optimization technique and self-adaptive line search method [21]. Bacterial foraging optimization has been proposed to solve economic-emission dispatch, which is based on natural choice of most favorable bacterium having a foraging strategy in the fitness function [22].

The ELD problem has been solved using conglomerated ion-motion and crisscross search optimizer [23]. A hybrid technique with firefly algorithm and self-regulated PSO has been implemented to solve the heat and ELD problem with transmission losses, valve point loading effect and Prohibited Operating Zones (POZ) [24]. An algorithm which is hybridized form of modified genetic algorithm and improved PSO has been implemented to environmental-economic dispatch problem [25].

Kho-Kho optimization technique has been proposed which is inspired by the strategies used by the players in the game. The algorithm has been applied to benchmark functions and active time combined heat and economic emission dispatch problem [26]. Quantum PSO based on differential evolution has been used to solve environmental, economic dispatch problem [27]. A new α-constrained simplex method has been implemented on a multi-objective hydrothermal considering wind and solar power scheduling [28]. A hybridized technique of PSO and the simplex search method has been used to solve economic power dispatch of thermal generating units considering valve point loading, ramp-rate and POZ. A hybrid evolutionary algorithm which is a combination of shuffle frog technique and PSO has been implemented to economic power dispatch problem considering physical and operational constraints [30]. A multi-objective hybrid bat method based on the combination of modified crowding distance sorting and non-dominated sorting method has been used to solve the combined economic and emission dispatch problem with different restrictions [31]. A combination of genetic algorithm and whale optimization algorithm has been implemented to economic-emission power dispatch to eliminate the conflict between economic and emission constraints and to revise the trade-off relationship among operating cost and emissions [32]. A new multi-factorial immune algorithm along with an information transfer technique has been implemented to solve multiple objective optimization problems [33].

Multi-objective grey prediction evolution algorithm has adopted two learning processes to update the uniformity and diversity of the optimal solutions of economic and environmental dispatch [34]. The proposed algorithm is a combination of squirrel search algorithm and Pareto dominance theory, which has been applied to minimize total fuel cost and emission of pollutants [5]. An algorithm inspired by kernel tricks has been proposed and implemented to solve the multi-objective optimization problem along with weighted sum and Newton method [35]. The chaotic artificial ecosystem based algorithm was used to find the optimal solution which ensures the minimum fuel cost and pollutant’s emission in the atmosphere [36]. A meta-heuristic algorithm, which is a combination of Newton method, gradient search rule and a local operator, has been applied to solve combined economic-emission dispatch problem [37]. A recurrent neural network has been proposed to minimize fuel cost and emission of pollutants with the effect of valve point loading effects and wind turbines [38]. A polar bear optimization and variants of the chaotic population have been proposed to solve combined economy and emission dispatch problem [39].

The purpose of an optimization procedure while solving a specific set of optimization problems may not ensure optimal solutions in another set of optimization problems. The optimization techniques can be integrated to exchange the good qualities of each other. All the above-mentioned optimization techniques are implemented on different ELD and EEPD problems and have the potential to find global solutions while considering the operating constraints. As mentioned in no lunch theorem [40], not any single optimization technique, individually or in the hybrid form is applicable to each and every optimization problem for obtaining the best global optimal solution with the same efficiency and characteristics. So, it is an essential requirement to explore new techniques and implement them for finding the global solutions for various EEPD problems. Mostly, the optimization lacks a balance between the exploration and exploitation, fast convergence, trapping into local solution and robustness of the global solution. It is worth to investigate for a better meta-heuristic search technique that has good balance between exploitation
The objective of this paper is to apply the proposed optimizer to solve economic–environmental power dispatch problem. The Hybrid Krill Herd Optimizer (HKHO) is a combination of basic Krill Herd Algorithm (KHA) and confined selective operator. This hybrid technique enhances the robustness of optimal solution and convergence characteristics. The non-interactive approach is implemented whereby the price penalty factor is applied to unify the economic and environmental objectives of power dispatch problem into the scalar objective of dispatch problem. The HKHO is implemented on six and forty thermal power generating units’ power system network neglecting transmission losses. Cost coefficients, active power constraints, emission of the pollutant’s coefficients for each unit are undertaken. The thermal power generation schedule is also achieved. The results obtained by proposed optimizer are compared with the results obtained by already published techniques in terms of fuel cost and gaseous pollutant’s emission to prove the competency of proposed optimizer.

3. Methodology

3.1 Economic-environmental power dispatch (EEPD) problem

The economic-environmental power dispatch problem is structured mathematically in order to minimize conflicting objectives, i.e. operating fuel cost and pollutant’s emission functions simultaneously, while satisfying the system constraints. The operating fuel cost has to consider valve point loading effect due to the presence of multiple valves in thermal generating unit which causes a variation in the quadratic operating fuel cost function. The sine wave ripples are augmented in quadratic fuel cost function. The EEPD problem is formulated as under:

Minimization of operating fuel cost as shown in Equation 1.

\[
F(P_i) = \sum_{i=1}^{NG} [\alpha_{2i}P_i^2 + \beta_{2i}P_i + \gamma_{2i} + \delta_{2i}e^{\lambda_{2i}P_i}] \quad ($/h)
\]

(1)

Minimize pollutant’s emission as shown in Equation 2.

\[
E(P_i) = \sum_{i=1}^{NG} [\alpha_{2i}P_i^2 + \beta_{2i}P_i + \gamma_{2i} + \delta_{2i}e^{\lambda_{2i}P_i}] \quad (kg/h)
\]

(2)

Subject to the equality constraint or energy balance equation is given as Equation 3.

\[
\sum_{i=1}^{NG} P_i = P_D + B_{00} + \sum_{i=1}^{NG} B_{0i}P_i + \sum_{i=1}^{NG} \left( \sum_{j=1}^{NG} B_{ij}P_j \right)
\]

(3)

The inequality constraint of active power is represented as Equation 4.

\[
p_i^{min} \leq P_i \leq P_i^{max} \quad (i = 1, 2, ..., NG)
\]

(4)

where \(F(P)\) ($/h) is total operating cost function, \(NG\) is number of thermal powers generating units, \(P_i\) is real thermal power output. The fuel cost coefficients are symbolized by \(\alpha_{1i} ($/MW^2h), \beta_{1i} ($/MWh), \gamma_{1i} ($/h), \delta_{1i} ($/h)\) and \(\lambda_{1i} (rad/MW)\) are stated for \(i^{th}\) thermal power generating unit. The emission coefficients are symbolized by \(\alpha_{2i} (kg/MW^2h), \beta_{2i} (kg/MWh), \gamma_{2i} (kg/h), \delta_{2i} (kg/h),\) and \(\lambda_{2i} (MW^{-1})\) are stated for \(i^{th}\) thermal power generating unit. \(P_i^{min}\) (MW) and \(P_i^{max}\) (MW) are the lower and upper limits of active power generation of \(i^{th}\) unit, respectively. \(P_D\) (MW) is power demand. \(B_{00}\) (MW), \(B_{0i}\) and \(B_{ij}\) (MW^{-1}) are the loss coefficients obtained from load flow analysis [6].

The EEPD problem is to achieve global best power generation schedule with defined power balance equation and real power limits such that the total power generation cost as well as emission can be minimized. In this optimization problem, both operating cost function and pollutant’s emission are transformed into singular objective using price penalty factor, where price penalty factor can be calculated by taking ratio among minimum or maximum of total operating cost and minimum or maximum emissions of specific generators [19]. EEPD problem is shown in Equation 5.

\[
F_T = F(P_i) + hE(P_i)
\]

(5)

Subject to the system constraints which are given by Equation 3 and Equation 4. Where \(h ($/kg)\) is the price penalty factor.
The price penalty factor is stated as the ratio of operating fuel cost to emission of pollutants evaluated at either minimum or maximum generations [19]. The price penalty factor, $HF_1$ is defined as the ratio of operating fuel cost to emission of pollutants whereas both objectives are evaluated at minimum generation limit. The price penalty factor, $HF_2$ is defined as the ratio of operating fuel cost to emission of pollutants while both are evaluated at maximum generation limits. The average of two penalty factors is selected and is given as Equation 6.

$$h = \frac{HF_1 + HF_2}{2} \quad (6)$$

Where price penalty function, $HF_1 = F(P_{\text{min}})/E(P_{\text{min}})$ Price penalty function, $HF_2 = F(P_{\text{max}})/E(P_{\text{max}})$ with $P_{\text{min}} = [P_{1\text{min}}, P_{2\text{min}}, \ldots, P_{N\text{G} \text{min}}]$ and $P_{\text{max}} = [P_{1\text{max}}, P_{2\text{max}}, \ldots, P_{N\text{G} \text{max}}]$. This penalty is being used in Equation 5 for decision making while calculating the fitness of the functions.

### 3.2 Hybrid krill herd optimizer (HKHO)

KHA is a swarm intelligence technique based on population of krill individuals and their herding behavior. Each krill moves in a particular direction to look ahead for food. The motion of krill herd is in multi-dimensional search space for searching food and the position of each krill is updated by three movements. First movement of krill is due to presence and displacement of other krill. Second movement is foraging which is associated with search for food. This shift in krill individual’s position is acquired due to current food location and the prior spot of food. The third movement causes shift in position due to random flow of krill individual with respect to time. The combination of all the three displacement forms a vector which shows the activities of krill individual in searching area to find the food.

To improve the convergence characteristics of KHA, it is hybridized with a new confined selective operator, which is termed as hybrid krill herd optimizer. In addition to this, a constraint handling technique has been implemented so that the achieved optimal solutions should be feasible solution of power generation. The exclusive advantage of HKHO is the requirement of minimum number of parameters for fine tuning; therefore, it is effortless to implement the optimizer to solve optimization problems to discover the most favourable solutions with better convergence characteristics. Also, this optimizer uses stochastic random search rather than gradient search and parallel computation to find the optimal solutions with the non-requirement of any derivative information.

In next paragraphs, these three processes are shown mathematically and upgradation of the time dependent positions of krill individual are also explained [41]. The mathematical modeling to solve economic environmental power dispatch problem using HKHO is given as:

**Initialization of krill individuals**: Randomly, initialize active power of all thermal power generating units which should remain within their active power generation limits (Equation 7).

$$P_{ki} = P_{i\text{min}} + R(0.1)(P_{\text{max}} - P_{\text{min}}) \quad (i = 1, 2, \ldots, N\text{G}; k = 1, 2, \ldots, NK) \quad (7)$$

where real power vector is represented as, $P_{ki} = [P_{k1}, P_{k2}, \ldots, P_{kN\text{G}}]^T$. Equation (4) representing the power generation limits must be fulfilled. Start with another set of solutions, in case the assumed solution is not feasible. Apply constraint handling procedure to get the feasible solution.

**Fitness evaluation**: Equation 5 calculates the fitness of each krill of present set of individuals, giving feasible solution.

**Induction Motion**: To realize the presence of other krill around affects the motion of krill individual. The induced shift of $k$th krill due to other krill is expressed as

$$\left| \sum_{j=1}^{N\text{S}} \frac{F_k - F_j}{|F_k - F_j|} \times \frac{P_k - P_j}{|P_k - P_j|} + \varepsilon \right| + 2 \left[ R[0,1] + \frac{m}{\sum_{k=1}^{m} F_k} \right] F_k^{\text{best}} P_k^{\text{best}}$$

For $k$th krill, the maximum induced motion is given by $N_k^{\text{max}} \cdot N_k^{\text{m}}$ and $N_k^{\text{m}-1}$ are the respective induced motions at the $m$th and $(m-1)$th movement. $F_k^{\text{best}}$ is the best value of fitness function and $P_k^{\text{best}}$ is the corresponding position of the $k$th krill. $\sum_{k=1}^{m} F_k$ represents maximum iterations, Inertia weight is given by $\alpha_n$. $F_k^w$ is worst position of krill individual. $F_k$ is the best position of krill. $F_k$ and $F_j$ are the fitness values of $k$th and $j$th individual, respectively.
Ns is the number of neighboring krill. Current iteration is m.

Foraging Motion: In foraging motion factors are allied with the existing and last site of food. This situation is formulated as in Equation 9.

\[
FG^m_k = V_f \left[ 2 \left( 1 - \frac{m}{IT_{max}} \right) \frac{1}{\sum_{j=1}^{N_F} F_j} \sum_{j=1}^{N_F} \frac{P_j}{F_j} + F_{k\text{best}}^m \right] + \omega_f FG^{m-1}_k \quad (k = 1, 2, \ldots, NK)
\]  

(9)

The \(V_f\) is foraging rate to discover food, \(\omega_f\) indicates weight of inertia. \(FG^m_k\) and \(FG^{m-1}_k\) are foraging motions of the \(k\)th krill at the \(m\)th and \((m-1)\)th movements, respectively. This foraging motion is calculated on the basis of individual’s motion and previous food location.

Random diffusion: This motion serves to improve the variety in krill members. The random diffusion process is given in Equation 10.

\[
\Delta P_k = \mu \Delta P_{max} \quad (k = 1, 2, \ldots, NK)
\]  

(10)

Where \(\mu \in [-1, 1]\) is normalized directional vector. The maximum speed of diffusion is \(\Delta P_{max}\). Equations (8, 9, and 10) find out the induced motion, foraging motion and random diffusion. Equation 11 upgrades the location of individual krill.

\[
P^m_{k+1} = P^m_k + (N^m_F + FG^m_k + D_k) \sum_{i=1}^{NG} (P^\text{max}_i - P^\text{min}_i) \quad (k = 1, 2, \ldots, NK)
\]  

(11)

Where \(P^m_{k+1}\) is updated position of \(k\)th krill and \(P^m_k\) is old krill position. The position constant factor is \(C_t\).

Mutation and Crossover: Equations 12, 13 and 14 adjust the location of each krill employing the mutation and crossover operators.

\[
P_{ki} = \begin{cases} 
P^\text{rand}_i & \text{if} \quad \text{rand} \leq C_R \\
\text{Random} & \text{if} \quad \text{rand} \geq C_R 
\end{cases} \quad (i = 1, 2, \ldots, NG; \ k = 1, 2, \ldots, NK; \ j \neq k)
\]  

(12)

Where crossover probability is \(C_R\). \(j\) is random integer \([1, NK]\).

The position of every krill is upgraded by mutant operator. The rate of mutation is \(M_R\). Two vectors \(P_{mi}\) and \(P_{ni}\) are selected randomly. Optimal solution is \(P^\text{best,mi}\) and the mutant solution is \(P^\text{mutant,mi}\).

\[
P^\text{mutant,mi} = P^\text{best,mi} + F_{k\text{rand}} (P_{mi} - P_{ni}) \quad (i = 1, 2, \ldots, NG; k = 1, 2, \ldots, NK; m \neq n \neq k)
\]  

(13)

\(P^\text{mod}_{ki}\) is the modified value of krill’s position that depends on mutation rate and is chosen from \(P^\text{mutant,mi}\) and \(P_{ki}\) [41].

\[
p^\text{mod}_{ki} = \begin{cases} 
P^\text{mutant}_{ki} & \text{; rand} \leq M_R \quad (k = 1, 2, \ldots, NK, i = 1, 2, \ldots, NG) \\
\text{Random} & \text{; rand} > M_R
\end{cases}
\]  

(14)

Equation 15 upgrades the position of krill individual employing a preferred krill to enhance the quality of global solution. The position of krill individual is updated with a selected individual position \(P^\text{selected}_{i}\) to find the new updated position \(P^\text{new}_i\) [42].

\[
P^\text{new}_i = P^\text{old}_i + \text{Rand}(-1, 1)(P^\text{selected}_i - P^\text{old}_i) \quad (i = 1, 2, \ldots, NG)
\]  

(15)

And, old position of the respective krill individual is denoted by \(P^\text{old}_i\).

Stopping criterion: When, the iteration counter, \(m\) reaches to its maximum, \(IT_{max}\) set value, the program stops.

3.3 Constraints handling strategy

The procedure of handling the system constraints in economic-environmental power dispatch problem is given below. To find the feasible solution, the difference in power requirement and actual power generation in the system can be given as shown in Equation 16.

\[
\Delta P_D = P_D - B_{00} + \sum_{i=1}^{NG} B_{0i}P_i + \sum_{i=1}^{NG} P_i (\sum_{j=1}^{NG} B_{ij}P_j) - \sum_{i=1}^{NG} P_i
\]  

(16)

If the condition \(|\Delta P_D| = 0\), the constraint is satisfied, that means, the total generation of power by all the thermal generating units meets the power demand. So, there is no need to mend the solution. If the condition \(|\Delta P_D| \neq 0\) and the constraint is not satisfied, then there is need to mend the generation so that power balance constraint given by Equation 16 is fulfilled. When \(\Delta P_D > 0\), there is a need to raise the power generation and when \(\Delta P_D < 0\), there is a need to cut the power generation. This management of constraint is framed as.

\[
P^\text{new}_i = \begin{cases} 
P_i + \min \left( \frac{\Delta P_D}{\sum_{i=1}^{NG} P_i} P_i \right) & (\Delta P_D > 0) \\
\text{Random} & (\Delta P_D < 0)
\end{cases} \quad (i = 1, 2, \ldots, NG)
\]  

(17)
Where, $P_i$ is power generation, $P_i^{\text{min}}$, $P_i^{\text{max}}$ are minimum and maximum limits of power generation, $\Delta P_d$ is given by Equation (16), $z_i$ is random number within range [0, 1]. This systemized mathematical formulation yields power generation proportional to power requirement by consumers. The stopping criteria is to set a very small constant value and the cycle is repeated until $\Delta P_d$ becomes smaller than small constant value.

Inequality constraint given by Equation (4) is adjusted by replacement method. It means the generation is set the corresponding limits on violation of the limit.

### 3.4 Flow chart of hybrid krill herd optimizer (HKHO)

*Figure 1* shows the flow chart of KHA with constraint handling strategy.
3.5 Parameters selection
The developed program is executed for 25 independent runs and each run is executed for 200 iterations. The parameters for KHA are given as, $N^\text{max} = 0.01$ in induced motion. In foraging motion the value of $V_f$ is 0.02 and maximum diffused speed is $D^\text{max} \in [0.02, 0.005]$. Number of krill is taken as 100. The position constant factor, $C_t \in [0, 2]$ is calculated for the up-gradation of position of krill individual, using the following formula (Equation 18).

$$C_t = \frac{C_{tmax} - C_{tmin}}{m_{(current \ iteration)}}$$

(18)

The inertia weights in case of induced motion $\omega_n$ and foraging motion $\omega_f$ are calculated using chaotic sequences. These chaotic sequences are very sensitive to initial conditions and parameters. These sequences are combined with heuristic algorithm to avoid the trapping into confined optimum solution. The expression for logistic map is:

$$X^{t+1} = 4X^t (1 - X^t); \quad X \in [0, 0.25, 0.5, 0.75, 1]$$

The value of chaotic variable is distributed between $(0, 1)$ and initially $X^0$ is set to 0.2027.

While applying the differential operators, a mutant vector is generated using best, worst and mean population vector with random numbers generated by chaotic variables and crossover probability $C_R$ is taken as $C_R = 0.01 + 0.15 R_f$ where $R_f$ is calculated as chaotic variable. Though applying confined selective operator, a constant value of mutation rate, $M_R$ is considered as 150.

4. Test systems and results
To validate the feasibility of proposed HKHO, two standard test systems consisting of six and forty thermal generating units are undertaken [43].

4.1 Test system 1
This electric power test system consists of six thermal power generators. Table 1 shows the active power limits and cost coefficients and Table 2 shows the pollutant emission coefficients of each unit. The power demand $P_D$ is considered as 1200 MW.

| Unit | $P^\text{min}_i$ (MW) | $P^\text{max}_i$ (MW) | $\alpha_{\text{af}}$ ($$/\text{MW}^2\text{h}$$) | $\beta_{\text{af}}$ ($$/\text{MW}\text{h}$$) | $Y_{\text{af}}$ ($$/\text{h}$$) |
|------|-----------------|-----------------|----------------|----------------|----------------|
| 1    | 10              | 125             | 756.800        | 38.5390        | 0.15247        |
| 2    | 10              | 150             | 451.325        | 46.1591        | 0.10587        |
| 3    | 35              | 210             | 1243.5311      | 38.3055        | 0.03546        |
| 4    | 35              | 225             | 1049.9977      | 40.3965        | 0.02803        |
| 5    | 125             | 315             | 1356.6592      | 38.2704        | 0.01799        |
| 6    | 130             | 325             | 1658.5696      | 36.3278        | 0.02111        |

| Unit | $\alpha_{\text{af}}$ ($$/\text{kg}/\text{MW}^2\text{h}$$) | $\beta_{\text{af}}$ ($$/\text{kg}/\text{MW}\text{h}$$) | $Y_{\text{af}}$ ($$/\text{kg}/\text{MW}$$) |
|------|-----------------|-----------------|----------------|
| 1    | 13.8593         | 0.32767         | 0.00419        |
| 2    | 13.8593         | 0.32767         | 0.00419        |
| 3    | 40.2669         | -0.54551        | 0.00683        |
| 4    | 40.2669         | -0.54551        | 0.00683        |
| 5    | 42.8955         | -0.51116        | 0.00461        |
| 6    | 42.8955         | -0.51116        | 0.00461        |

The program for proposed HKHO is executed for 25 runs and implemented to solve EEPD problem. The obtained schedule of active power generation, $P_i(l = 1, 2, \ldots, NG)$ is shown in Table 3. The operating fuel cost and pollutant’s emission values are compared with the results obtained by other three methods viz. Multi-objective Differential Evolution (MODE), Teaching Learning Based Optimization (TLBO); Quasi-opposition Teaching Learning based optimization (QOTLBO) [43]. Table 3 depicts the comparison of results, which reveals that fuel cost is 63478 ($$/\text{h}$$) and emission of pollutants is 1133 ($$/\text{h}$$) obtained by proposed HKHO, which is less than the value of fuel cost and emission of pollutant by MODE, QOTLBO and TLBO.

| Unit | $P_i(l = 1, 2, \ldots, NG)$ | $\alpha_{\text{af}}$ ($$/\text{kg}/\text{MW}^2\text{h}$$) | $\beta_{\text{af}}$ ($$/\text{kg}/\text{MW}\text{h}$$) | $Y_{\text{af}}$ ($$/\text{kg}/\text{MW}$$) |
|------|-----------------|----------------|----------------|----------------|
| 1    | 13.8593         | 0.32767 | 0.00419        |
| 2    | 13.8593         | 0.32767 | 0.00419        |
| 3    | 40.2669         | -0.54551 | 0.00683        |
| 4    | 40.2669         | -0.54551 | 0.00683        |
| 5    | 42.8955         | -0.51116 | 0.00461        |
| 6    | 42.8955         | -0.51116 | 0.00461        |

Table 4 shows the satisfaction of active power generation constraint, as the active power generation by all the six thermal power generating units lies in their respective power generation limits. First and
second units are generating power equal to their maximum limits and the remaining four generators are generating power quite close to the maximum power generation limits. This constraint is taken care of, by the application of constraint handling technique as mentioned in section 5.

The energy balance equation or equality constraint is satisfied by calculating the difference between power demand and actual power generation. The calculated difference is denoted by DPD and is equal to 0.988255E-04 in the case of minimum value of combined economic and emission objective function. Table 5 depicts the comparison of achieved results in terms of minimum operating fuel cost and minimum pollutant’s emission as compared to other methods.

Table 3 Comparison of operating fuel cost and pollutant emission

| Unit, i | Power generation, $P_i$ (MW) by applied methods |
|--------|-----------------------------------------------|
|        | MODE [43] | QOTLBO [43] | TLBO [43] | Proposed HKHO |
| 1      | 108.6284  | 107.3101    | 107.8651  | 125.000      |
| 2      | 115.9456  | 121.4970    | 121.5676  | 150.000      |
| 3      | 206.7969  | 206.5010    | 206.1771  | 186.002      |
| 4      | 210.0000  | 206.5826    | 205.1879  | 186.649      |
| 5      | 301.8884  | 304.9838    | 306.5555  | 276.016      |
| 6      | 308.4127  | 304.6036    | 304.1423  | 276.333      |
|        | Fuel cost ($/h) | 64843 | 64912 | 64922 | 63478 |
|        | Emission (kg/h) | 1286 | 1281 | 1281 | 1133 |

Table 4 Active power generation schedule and constraints for six thermal power generating units

| Unit, i | $P_{\text{min}}$ (MW) | $P_i$ (MW) | $P_{\text{max}}$ (MW) |
|--------|-----------------------|------------|----------------------|
| 1      | 10                    | 125.000    | 125                  |
| 2      | 10                    | 150.000    | 150                  |
| 3      | 35                    | 186.002    | 210                  |
| 4      | 35                    | 186.649    | 225                  |
| 5      | 125                   | 276.016    | 315                  |
| 6      | 130                   | 276.333    | 325                  |
| Total  |                      | 1200.0     |                      |

Table 5 Comparative analysis of achieved results

| Method     | Fuel cost ($/h) | Emission (kg/h) |
|------------|-----------------|-----------------|
| PDE [43]   | 64920           | 1281            |
| NSGA-II [43] | 64962      | 1285            |
| SPEA-2 [43] | 64884       | 1285            |
| Proposed HKHO | 63478     | 1133            |

The fuel cost obtained by Pareto Differential Evolution (PDE) is 64920 ($/h), Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is 64962 ($/h) and Strength Pareto Evolutionary Algorithm 2 (SPEA-2) is 64884 ($/h) [43].

All the mentioned values of fuel cost are higher than the fuel cost obtained by proposed optimizer which is 63478 ($/h). The emission obtained by PDE is 1281 (kg/h), NSGA-II is 1285 (kg/h) and SPEA-2 is 1285 (kg/h), where emission obtained by proposed optimizer is 1133 kg/h and is less than the values of other techniques as mentioned above. It gives 2.27% saving in fuel cost and 13.3% reduction of emission of pollutants.

To check the randomness of results obtained, t-test is performed. The probability values are less than their respective critical values as shown in Table 6.

Table 6 T-test performance for six thermal generating units

| T-test measures       | One-tail P (T<\text{t}) | One-tail t-Critical | Two-tails P (T<\text{t}) | Two-tails t-Critical |
|-----------------------|-------------------------|---------------------|--------------------------|---------------------|
| One-tail P (T<\text{t}) | 1.77402E-08             | 1.710882067         | 3.54804E-08              | 2.063898547         |
| One-tail t-Critical    |                         |                     |                          |                     |
| Two-tails P (T<\text{t})|                         |                     |                          |                     |
| Two-tails t-Critical   |                         |                     |                          |                     |
The probability value is $1.77402 \times 10^{-8}$ (one tail) is less than $1.710882067$ (critical) and $3.54804 \times 10^{-8}$ (two tails) is less than $2.063898547$ (critical).

The statistical measures give the mean and maximum values of fuel cost as $63478.0$ ($$/h$) and $63478.1$ ($$/h$) and the calculated standard deviation is $0.37031 \times 10^{-1}$ and minimum Number of Function Evaluation (NFE) is $2594650$.

*Figure 2 and Figure 3* represent the variation in operating fuel cost and emission of pollutant with respect to number of runs for test system 1 depicting robustness of the solution, respectively.

**4.2 Test system 2**

A standard electric power test system of forty thermal power generating units having non-convex characteristics is considered to validate the proposed optimizer. The valve point loading effect is undertaken by adding valve point loading coefficients in the system. The data for cost coefficients and emission coefficients are taken from reference [7]. The power demand $P_d$ is taken as $10,500$ MW and the program is executed for $25$ runs. The obtained schedule of active power generation, $P_t(i=1, 2, ..., NG)$ is depicted in *Table 7*. The operating fuel cost and pollutant’s emission is compared with three methods viz. TLBO, QOTLBO and DE [43]. *Table 7* depicts the comparison of results, which reveals that the results achieved by proposed optimizer in terms of minimum operating fuel cost and minimum pollutant’s emission are compared with other methods. The fuel cost obtained by TLBO is $129955$ ($$/h$), QOTLBO is $129952$ ($$/h$) and DE is $129961$ ($$/h$) [43]. All the values of fuel cost mentioned in above methods are higher than the fuel cost obtained by proposed optimizer which is $129744$ ($$/h$). The emission obtained by TLBO is $176682.5$ (kg/h), QOTLBO is $176683.5$ (kg/h) and DE is $176683.5$ (kg/h) [43] whereas emission obtained by proposed optimizer is $176753.2$ (kg/h), which is less than the emission obtained by above mentioned techniques. This system depicts the conflicting nature of the objectives. The operating cost is decreased by $0.16\%$ and emission of pollutants decreases by $0.04\%$.

*Table 8* represents the satisfaction of active power.
generation constraints and total demand. Out of 40 units, eight units are generating power exactly equal to maximum active power generation of that particular unit. Whereas, the four units are close to their respective minimum active power generation limit. Most of the remaining twenty-eight units are generating power which is close to their respective maximum power generation limits.

### Table 7 Comparison of fuel cost and pollutant’s emission

| Unit, i | Power generation, $P_i$(MW) by applied methods | QOTLBO [43] | TLBO [43] | DE [43] | Proposed HKHO |
|---------|------------------------------------------------|-------------|-----------|---------|--------------|
| 1       |                                                | 113.9986    | 110.8684  | 114.000 | 114.000      |
| 2       |                                                | 113.9992    | 114.000   | 114.000 | 114.000      |
| 3       |                                                | 119.9998    | 120.000   | 120.000 | 120.000      |
| 4       |                                                | 169.3712    | 169.2755  | 169.2933| 171.3607     |
| 5       |                                                | 97.0000     | 97.0000   | 97.000  | 97.000       |
| 6       |                                                | 124.2561    | 124.2907  | 124.2828| 125.1440     |
| 7       |                                                | 297.9140    | 297.9220  | 297.8554| 298.2422     |
| 8       |                                                | 297.2581    | 297.2571  | 297.1332| 297.4635     |
| 9       |                                                | 130.0000    | 130.2007  | 130.000 | 130.0016     |
| 10      |                                                | 298.4145    | 298.3876  | 298.5980| 300.2156     |
| 11      |                                                | 298.0278    | 298.2678  | 297.7226| 299.7909     |
| 12      |                                                | 433.5600    | 433.5655  | 433.7471| 433.5298     |
| 13      |                                                | 421.7308    | 421.3705  | 421.9529| 420.4447     |
| 14      |                                                | 422.7808    | 422.5429  | 439.2250| 439.0639     |
| 15      |                                                | 439.4144    | 439.5159  | 439.2581| 441.2540     |
| 16      |                                                | 439.4038    | 439.4102  | 439.4908| 439.0905     |
| 17      |                                                | 439.4128    | 439.2949  | 439.6189| 439.0933     |
| 18      |                                                | 439.4082    | 439.7375  | 439.2250| 439.0459     |
| 19      |                                                | 439.4460    | 439.5429  | 439.6821| 439.0639     |
| 20      |                                                | 439.7680    | 439.2180  | 439.8757| 439.4262     |
| 21      |                                                | 439.7708    | 439.9235  | 439.8937| 439.3920     |
| 22      |                                                | 440.1155    | 440.3795  | 440.4401| 439.7114     |
| 23      |                                                | 440.1110    | 439.9939  | 439.8408| 439.6782     |
| 24      |                                                | 28.9934     | 28.9930   | 28.7758 | 26.5264      |
| 25      |                                                | 28.9931     | 29.0119   | 29.0747 | 26.4921      |
| 26      |                                                | 28.9943     | 29.0599   | 28.9047 | 26.5136      |
| 27      |                                                | 97.0000     | 97.0000   | 97.000  | 97.0000      |
| 28      |                                                | 172.3331    | 172.3063  | 172.4036| 172.9287     |
| 29      |                                                | 172.3324    | 172.3457  | 172.3956| 172.9538     |
| 30      |                                                | 172.3304    | 172.4643  | 172.3144| 172.9204     |
| 31      |                                                | 199.9996    | 200.000   | 200.000 | 200.000      |
| 32      |                                                | 199.9989    | 200.000   | 200.000 | 200.000      |
| 33      |                                                | 100.8369    | 100.9472  | 100.8765| 101.4023     |
| 34      |                                                | 100.8385    | 100.8250  | 100.000 | 101.4522     |
| 35      |                                                | 100.8378    | 100.8901  | 100.7789| 101.3943     |
| 36      |                                                | 439.4138    | 439.3752  | 439.1894| 439.1041     |

**Fuel cost ($/h)**

129955
129952
129961
129744

**Emission (kg/h)**

176682.5
176683.5
176683.5
176753.2

$\sum P_i$ (MW)

10500
10496.93
10499.1
10500
Table 8: Active power generation schedule and constraints for forty thermal power generating units

| Unit, i | \( P_{i}^{\text{min}} \) (MW) | \( P_i \) (MW) | \( P_i^{\text{max}} \) (MW) |
|--------|-----------------|-----------------|-----------------|
| 1      | 36              | 114.000         | 114             |
| 2      | 36              | 114.000         | 114             |
| 3      | 60              | 120.000         | 120             |
| 4      | 80              | 171.3607        | 190             |
| 5      | 47              | 97.000          | 97              |
| 6      | 68              | 125.1440        | 140             |
| 7      | 110             | 299.9987        | 300             |
| 8      | 135             | 298.2422        | 300             |
| 9      | 135             | 297.4635        | 300             |
| 10     | 130             | 300.2156        | 375             |
| 11     | 94              | 300.2156        | 375             |
| 12     | 94              | 299.7909        | 375             |
| 13     | 125             | 433.5298        | 500             |
| 14     | 125             | 420.4447        | 500             |
| 15     | 125             | 421.4961        | 500             |
| 16     | 125             | 421.6273        | 500             |
| 17     | 220             | 441.2540        | 500             |
| 18     | 220             | 441.2413        | 500             |
| 19     | 242             | 439.0905        | 500             |
| 20     | 242             | 439.0933        | 500             |
| 21     | 254             | 439.0459        | 550             |
| 22     | 254             | 439.0639        | 550             |
| 23     | 254             | 439.4262        | 550             |
| 24     | 254             | 439.3920        | 550             |
| 25     | 254             | 439.7114        | 550             |
| 26     | 254             | 439.6782        | 550             |
| 27     | 10              | 26.5264         | 150             |
| 28     | 10              | 26.4921         | 150             |
| 29     | 10              | 26.5136         | 150             |
| 30     | 47              | 97.0000         | 97              |
| 31     | 60              | 172.9287        | 190             |
| 32     | 60              | 172.9538        | 190             |
| 33     | 60              | 172.9204        | 190             |
| 34     | 90              | 200.000         | 200             |
| 35     | 90              | 200.000         | 200             |
| 36     | 90              | 200.000         | 200             |
| 37     | 90              | 200.000         | 200             |
| 38     | 25              | 101.4023        | 110             |
| 39     | 25              | 101.4522        | 110             |
| 40     | 242             | 439.1041        | 550             |
| Total  |                 | 10500.00        |                 |

The energy balance equation or equality constraint is satisfied by calculating difference between power demand and actual power generation. The calculated difference is denoted by DPD and is equal to 0.144716965E-03 in the case of minimum value of EE PD objective function. To check the randomness of results obtained, t-test is performed. The probability values are less than their respective critical values as given in Table 9.

Table 9: T-test performance for forty thermal generating units

| T-test measures | Value          |
|----------------|----------------|
| One-tail P (T<\(t\)) | 2.19967E-08 |
| One-tail t-Critical     | 1.713871517  |
| Two-tails P (T<\(t\))  | 4.39934E-08  |
| Two-tails t-Critical    | 2.068657599  |

The probability value is 2.19967E-08 (one tail) is less than 1.713871517 (critical) and 4.39934E-08 (two tails) is less than 2.068657599 (critical).
The statistical measures give the mean and maximum values of fuel cost as 129746 ($/h) and 129748 ($/h). The calculated standard deviation is 1.394 and minimum number of function evaluation is 2521300. Figure 4 and Figure 5 represent the variation in operating fuel cost and emission of pollutant with respect to number of runs for test system 2 depicting robustness of the solution, respectively.

![Fuel cost variation for test system 2](image1)

**Figure 4** Fuel cost variation for test system 2

![Emission variation for test system 2](image2)

**Figure 5** Emission variation for test system 2

5. **Discussions**

The outcome of the proposed HKHO is discussed in the ensuing sub-sections when implemented to solve economic environmental load dispatch problems.

5.1 **General discussion of results**

The proposed optimizer is implemented on two systems: one is small test system with six thermal power generating units while the second one is a medium power system with forty thermal power generating units. The results obtained with first test system depicts that defined equality and inequality constraints in subsection 3.1 are fulfilled. Inequality constraint is considered for each power generating unit and its fulfilment is depicted in Table 4. In case of each run, DPD is also calculated to confirm the fulfilment of equality constraints. In test system 2, valve point loading effect is also taken as one of the constraints. So, while executing the program, all the calculations are performed considering valve point loading effect as given in Equation (1). Along with this constraint, the fulfillment of inequality constraint is depicted in Table 8 and the value of DPD is also given along with other numerical values to prove the fulfilment of equality constraints.

The graphs showing the variation of operating fuel cost and pollutant emission with respect to the number of runs give an idea about the value of fuel cost and emission at one particular run. T-test is performed to check the randomness of the results obtained if all the results in 25 runs are considered as
it helps to prove the validity of obtained results.

The fuel cost and pollutant emission are the objectives to be minimized, simultaneously. It is satisfied with the execution of programs on standard test system 1 which gives 2.27% savings in fuel cost and 13.3% reduction of emissions of pollutants and in test system 2, the operating cost is decreased by 0.16% and emission of pollutants decreased by 0.04%. The proposed optimizer maintains a balance between exploration and exploitation which can avoid the trapping into local region and leads to better convergence properties. The constraint handling strategy is providing support to get the feasible solutions.

The t-test performance reveals the robustness of the global solution. The fine tuning of few parameters plays an important role for easy implementation.

Hence, through comparative analysis, it is clear that the proposed optimizer is more effective than the existing methods with respect to the performance characteristics. Complete list of abbreviations is shown in Appendix I.

5.2 Limitations
The increase in the number of constraints in economic, environmental power dispatch problem increases the complexity of the program. In more practical optimization problem, all the physical constraint viz, valve point loading effect, ramp rate limits, prohibited operating zones and minimization of transmission losses are being considered. Because of a number of parameters involved, there is possibility that with the consideration of all the physical constraints in the system, there could be a need to change the parameters depending upon the results, so it will further increase the complexity of the program.

6. Conclusions and future scope
In this research work, HKHO is developed which enhances the convergence properties of basic KHA by hybridizing with a new confined selective operator. The HKHO solves economic-environmental thermal power load dispatch problem ignoring transmission losses. The comparative analysis of achieved results with recently published techniques is presented. The statistical measures in terms of minimum, maximum values of fuel cost and standard deviation are calculated to show the strength of the optimizer. T-test is also performed to check the randomness of fuel cost values obtained in 25 runs.

The investigation of the achieved results reveals that the proposed optimizer successfully finds the optimal active thermal power generation schedule while fulfilling the system constraints. It also provides better convergence characteristics. The proposed optimizer can be implemented for a power system with a number of objectives. Reactive power can be taken into consideration in addition to active power. The dynamic load and multiple fuel options can be considered in further research.

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Conflicts of interest
The authors have no conflicts of interest to declare.

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### Appendix I

| S. No. | Abbreviation | Description |
|-------|--------------|-------------|
| 1     | $b_{ij}$, $b_{i0}$ and $b_{ij}$ | Transmission Coefficients |
| 2     | $c_k$        | Crossover Probability |
| 3     | $c_k$        | Position Constant Factor |
| 4     | $d_k$        | Random Diffusion |
| 5     | $d_{max}$    | Maximum Speed of Diffusion |
| 6     | EEPD         | Economic-Environmental Power Dispatch |
| 7     | ELD          | Economic Load Dispatch |
| 8     | $f_k^a$ and $f_k^b$ | Worst and Best Position of kth Krill |
| 9     | $f_k$ and $f_j$ | Fitness Values of kth and jth Krill |
| 10    | $f_k^{best}$ | Best Value of Fitness Function |
| 11    | $FG_k^m$ and $FG_k^{m-1}$ | Foraging Motions of the kth krill at mth and (m-1)th Movements |
| 12    | h            | Price Penalty Function |
| 13    | HKKO         | Hybrid Krill Herd Optimizer |
| 14    | $IT_{max}$   | Maximum Iterations |
| 15    | KHA          | Krill Herd Algorithm |
| 16    | $M_k$        | Mutation Rate |
| 17    | MODE         | Multi-objective Differential Evolution |
| 18    | m            | Current Iteration |
| 19    | $n_{FE}$     | Number of Function Evaluation |
| 20    | NK           | Number of Krill |
| 21    | NG           | Number of Thermal Power Generating Units |
| 22    | $n_{max}$    | Non-dominated Sorting Genetic Algorithm-II |
| 23    | $N_k^{max}$  | Maximum Induced Motion |
| 24    | $N_k^m$      | Induced Motion at mth Movement |
| 25    | $N_k^{m-1}$  | Induced Motion at (m-1)th |


| No. | Symbol | Definition |
|-----|--------|------------|
| 26  | Ns     | Number of Neighboring Krill |
| 27  | P_k   | Pareto Differential Evolution |
| 28  | PSO   | Particle Swarm Optimization |
| 29  | POZ   | Prohibited Operating Zones |
| 30  | P^m_k | Old Krill Position |
| 31  | P^m+1_k | Updated Position of kth Krill |
| 32  | P^selected_k | Selected Krill Position |
| 33  | P_D   | Power Demand |
| 34  | ΔP_D  | Change in Power Demand |
| 35  | P^min_i | Lower Limit of Active Power Generation of ith Unit |
| 36  | P^max_i | Upper Limit of Active Power Generation of ith Unit |
| 37  | P_i   | Active Power Generation of ith Unit |
| 38  | P_{k^*} | Real Power Vector |
| 39  | P_{k^*}^{best} | Position of kth Krill |
| 40  | P_{k^*}^{modified} | Modified Value of Krill’s Position |
| 41  | QOTLBO | Quasi-opposition Teaching Learning based optimization |
| 42  | S-PARETO | Strength Pareto Evolutionary Algorithm 2 |
| 43  | TLBO   | Teaching Learning Based Optimization |
| 44  | V_f   | Foraging Rate To Discover Food |
| 45  | α_f   | Foraging inertia weight |
| 46  | ω_D   | Induced Inertia Weight |
| 47  | γ_{1i}, δ_{1i}, δ_{2i} and λ_{1i} | Fuel Cost Coefficients |
| 48  | γ_{2i}, δ_{3i}, δ_{4i}, and λ_{2i} | Emission Coefficients |