Chapter 11

Krill Herd Algorithm-Based Approach for Combined Economic and Emission Dispatch Optimization

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Abstract

This paper addresses the multi-objective economic load dispatch (ELD) problem by simultaneously considering fuel cost and environmental emission functions. The Krill Herd Algorithm (KHA) is employed to obtain optimal solutions for this multi-objective optimization task. The effectiveness of the proposed approach is validated using a six-unit power system. The results demonstrate the algorithm's strong performance in terms of rapid convergence and solution quality.

Keywords: Economic Load Dispatch; Krill Herd Algorithm; Multi-objective Optimization; Emission Reduction;

1. Introduction

In recent times, the planning and operation of power systems have become increasingly challenging for power engineers due to system

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complexity and the growing demand for reliable and continuous electricity supply. A primary objective in power system operation is to deliver this service at the lowest possible cost while maintaining system reliability.

The application of soft computing techniques has significantly impacted the field of power systems, particularly in solving complex optimization problems, owing to their robustness, fast convergence, and reliability [1]. Among these challenges, the Economic Load Dispatch (ELD) problem stands out as a critical non-linear optimization task. It involves minimizing the total fuel cost of generation units over a specific time period, ensuring optimal power allocation while satisfying load demand and adhering to operational constraints, such as ramp rate limits and prohibited operating zones [2].

Several approaches have been proposed to address the ELD problem. S.K. Dash [3] introduced a method combining radial basis function neural networks with heuristic rule-based search and Hopfield neural networks to manage multiple fuel options. Dr. G. Srinivasan et al. [4] utilized a particle swarm optimization (PSO) technique incorporating chaotic sequences and crossover operations to enhance global search performance and prevent premature convergence. Radhakrishnan Anandhakumar et al. [5] proposed a non-iterative Direct Composite Cost Function method for economic dispatch with reduced computational time. Umamaheswari Krishnasamy et al. [6] presented a Refined Teaching–Learning-Based Optimization (RTLBO) algorithm for dynamic economic dispatch integrated with wind power and multiple fuel sources. Additionally, R. Balamurugan et al. [7] developed a self-adaptive mechanism to adjust control parameters during the optimization process for better handling of valve-point effects and multi-fuel options.

In this study, the Combined Economic and Emission Dispatch (CEED) problem is addressed using the Krill Herd Algorithm (KHA), a nature-inspired metaheuristic optimization technique. The algorithm's performance is evaluated using a standard test system. Furthermore, the self-tuning of KHA parameters is explored, as these parameters play a crucial role in directing the search process and significantly influence the convergence behavior and solution quality.

2. Problem Formulation

2.1. Mathematical Model of Objective Function and Constraints

In this paper two objective functions were considered. First objective is to minimize the total generation cost of generating power plant and the second objective is to minimize the environmental emission of the generating plants.

2.2. Objective I

Economic Generation Cost Function Generation quadratic fuel cost characteristic of generating power plant is formulated as follows:

$$F_T = \text{Min } f(FC) \quad (1)$$

$$f(FC) = \sum_{i=1}^{N} a_i P_i^2 + b_i P_i + c_i$$

2.3. *Objective* II

Emission Objective Function In this paper environmental emission was evaluated with consideration of NOx gas. A typical NOx emission at thermal power plants can be formulated as shown . Consider the

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following:

$$E_T \text{ Min} \sum_{i=1}^{N} f\big(E_i(P_i)\big) \tag{2}$$

$$E_i(P_i) = (\propto_i + \beta_i P_i + \gamma_i P_i^2) + \varepsilon_i \sin(\lambda_i P_i) \tag{3}$$

Now both objectives may be combined in a single objective as given in (4), (5), and (6). The generation cost of each generator was evaluated at its maximum output:

$$F_i(P_{i\,max}) = (a_i P_{i\,max}^2 + b_i P_{i\,max} + c_i) \tag{4}$$

NOx emission of each generator at its maximum output was evaluated:

$$E_i(P_{i\,max}) = (\alpha_i + \beta_i P_{i\,max} + \gamma_i P_{i\,max}^2) \tag{5}$$

By (4) and (5) get

$$\frac{F_i\,(P_{i\,max})}{E_i(P_{i\,max})} = k_i \tag{6}$$

So the final objective incorporated total generation cost and environmental emission generation which is given as

$$F_{final\_object} = F_T + k_i(E_T) \tag{7}$$

2.4. Power Balance Constraints

The total generated power should be equal to the sum of total load demand and line loss. It can be formulated as (8). Consider the following:

$$\sum_{i=1}^{n} P_i = P_D + P_L \tag{8}$$

$$P_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j \tag{9}$$

2.5. Generator Limits Constraint

Generating output of each generating unit should lie between the maximum and minimum limits as given in

$$P_i^{min} \leq P_i \leq P_i^{max} \tag{10}$$

2.6. Lagrangian Formulation for Krill Herd Movement Dynamics

Predation in nature reduces the number of individuals in a krill swarm, thereby decreasing the average krill density and increasing the swarm's distance from the food source. This natural phenomenon is conceptually aligned with the initialization phase of the Krill Herd (KH) algorithm. In the biological system, an individual krill's fitness is influenced by both its proximity to the food source and its position relative to the densest region of the swarm. In the KH algorithm, this fitness is represented by the objective function value, interpreted as an "imaginary distance." The position of each krill over time, on a two-dimensional surface, is dynamically updated based on three key behaviors:

- Movement induced by other krill individuals
- Foraging behavior
- Random diffusion

These three mechanisms collectively guide the swarm's search process toward optimal solutions.

It is known that an optimization algorithm should be capable of searching spaces of arbitrary dimensionality. Therefore, the following Lagrangian model is generalized to an n dimensional decision space:

$$\frac{dX_i}{dt} = N_i + F_i + D_i \tag{11}$$

where Ni is the motion induced by other krill individuals; Fi is the

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foraging motion, and Di is the physical diffusion of the ith krill individuals.

3. Motion induced by other krill individuals

According to theoretical arguments, the krill individuals try to maintain a high density and move due to their mutual effects. The direction of motion induced is estimated from the local swarm density (local effect), a target swarm density (target effect), and a repulsive swarm density (repulsive effect) . For a krill individual, this movement can be defined as:

$$N_i^{new} = N^{max}\alpha_i + \omega_n N_i^{old} \tag{12}$$

where,

$$\alpha_i = \alpha_i^{local} + \alpha_i^{target} \tag{13}$$

and Nmax is the maximum induced speed, xn is the inertia weight of the motion induced in the range [0, 1], N_i^{old} is the last motion induced, a local i is the local effect provided by the neighbors and a target i is the target direction effect provided by the best krill individual. According to the measured values of the maximum induced speed , it is taken 0.01 (ms). The effect of the neighbors can be assumed as an attractive/repulsive tendency between the individuals for a local search. In this study, the effect of the neighbors in a krill movement individual is determined as follows:

$$\alpha_i^{local} = \sum_{j=1}^{NN} \hat{K}_{i,j} \hat{X}_{i,j} \tag{14}$$

$$\hat{X}_{i,j} = \frac{X_j - X_i}{\|X_j - X_i\| + \xi} \tag{15}$$

$$\hat{K}_{i,j} = \frac{K_i - K_j}{K^{worst} - K^{best}} \tag{16}$$

where $K^{worst}$and $K^{best}$are the best and the worst fitness values of the krill individuals so far; Ki represents the fitness or the objective function value of the ith krill individual; Kj is the fitness of jth (j = 1,2,. . .,NN) neighbor; X represents the related positions; and NN is the number of the neighbors. For avoiding the singularities, a small positive number, e, is added to the denominator. The right sides of Eqs. contain some unit vectors and some normalized fitness values. The vectors show the induced directions by different neighbors and each value presents the effect of a neighbor. The neighbors' vector can be attractive or repulsive since the normalized value can be negative or positive. For choosing the neighbor, different strategies can be used. For instance, a neighborhood ratio can be simply defined to find the number of the closest krill individuals. Using the actual behavior of the krill individuals, a sensing distance (ds) should be determined around a krill individual (as shown in Fig. 1) and the neighbors should be found. The sensing distance for each krill individual can be determined using different heuristic methods. Here, it is determined using the following formula for each iteration:

$$d_{s,i} = \frac{1}{5N}\sum_{j=1}^{N}\left\|X_i - X_j\right\| \tag{17}$$

Where, ds,i is the sensing distance for the ith krill individual and N is the number of the krill individuals. The factor 5 in the denominator is empirically obtained. Using Eq. (17), if the distance of two krill individuals is less than the defined sensing distance, they are neighbors.

The known target vector of each krill individual is the lowest fitness of an individual krill. The effect of the individual krill with the best fitness on the ith individual krill is taken into account using Eq. (18).

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This level leads it to the global optima and is formulated as:

$$\alpha_i^{target} = C^{best}\hat{K}_{i,best}\hat{X}_{i,best} \tag{18}$$

where, C^{best} is the effective coefficient of the krill individual with the best fitness to the ith krill individual. This coefficient is defined since a target i leads the solution to the global optima and it should be more effective than other krill individuals such as neighbors. Here in, the value of C^{best} is defined as:

$$C^{best} = 2\left(\text{rand} + \frac{I}{I_{max}}\right) \tag{19}$$

where rand is a random values between 0 and 1 and it is for enhancing exploration, I is the actual iteration number and I_{max} is the maximum number of iterations.

3.1. Foraging motion

The foraging motion is formulated in terms of two main effective parameters. The first one is the food location and the second one is the previous experience about the food location. This motion can be expressed for the ith krill individual as follows:

$$F_i = V_f\beta_i + \omega_f F_i^{old} \tag{20}$$

where

$$\beta_i = \beta_i^{food} + \beta_i^{best} \tag{21}$$

and V_f is the foraging speed, ω_f is the inertia weight of the foraging motion in the range [0, 1], is the last foraging motion, $\beta_i^{food}$is the food attractive and β_i^{best} is the effect of the best fitness of the ith krill so far. According to the measured values of the foraging speed , it is taken 0.02 (ms-1). The food effect is defined in terms of its location. The center of food should be found at first and then try to formulate food attraction. This cannot be determined but can be estimated. In this study, the virtual center of food concentration is estimated according to the fitness distribution of the krill individuals, which is inspired from "center of mass". The center of food for each iteration is formulated as:

$$X^{food} = \frac{\sum_{i=1}^{N} \frac{1}{K_i} X_i}{\sum_{i=1}^{N} \frac{1}{K_i}} \tag{22}$$

Therefore, the food attraction for the ith krill individual can be determined as follows:

$$\beta_i^{food} = C^{food} \hat{K}_{i,food} \hat{X}_{i,food} \tag{23}$$

where C^{food} is the food coefficient. Because the effect of food in the krill herding decreases during the time, the food coefficient is determined as:

$$C^{food} = 2\left(1 - \frac{I}{I_{max}}\right) \tag{24}$$

The food attraction is defined to possibly attract the krill swarm to the global optima. Based on this definition, the krill individuals normally herd around the global optima after some iteration. This can be considered as an efficient global optimization strategy which helps improving the globality of the KH algorithm. The effect of the best fitness of the ith krill individual is also handled using the following equation:

$$\beta_i^{best} = C^{best} \hat{K}_{i,ibest} \hat{X}_{i,ibest} \tag{25}$$

where Kibest is the best previously visited position of the ith krill individual.

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3.2. Physical diffusion

The physical diffusion of the krill individuals is considered to be a random process. This motion can be express in terms of a maximum diffusion speed and a random directional vector. It can be formulated as follows:

$$D_i = D^{max}\delta \qquad (26)$$

$$D_i = D^{max}\left(1 - \frac{I}{I_{max}}\right)\delta \qquad (27)$$

3.3. Motion Process of the KH Algorithm

The physical diffusion performs a random search in the proposed method. Using different effective parameters of the motion during the time, the position vector of a krill individual during the interval t to t + Δt is given by the following equation:

$$X_i(t + \Delta t) = X_i(t) + \Delta t\frac{dX_i}{dt} \qquad (28)$$

It should be noted that Δt is one of the most important constants and should be carefully set according to the optimization problem. This is because this parameter works as a scale factor of the speed vector. Δt t completely depends on the search space and it seems it can be simply obtained from the following formula:

$$\Delta t = C_t\sum_{j=1}^{Nv}\left(UB_j - LB_j\right) \qquad (29)$$

where NV is the total number of variables, and LBj and UBj are lower and upper bounds of the jth variables (j = 1,2,. . .,NV), respectively. Therefore, the absolute of their subtraction shows the search space. It is empirically found that Ct is a constant number between [0, 2]. It is also obvious that low values of Ct let the krill individuals to search the space carefully.

3.4. Genetic operators

To improve the performance of the algorithm, genetic reproduction mechanisms are incorporated into the algorithm. The introduced adaptive genetic reproduction mechanisms are crossover and mutation which are inspired from the classical DE algorithm.

3.5. Crossover

The crossover operator is first used in GA as an effective strategy for global optimization. A vectorized version of the crossover is also used in DE which can be considered as a further development to GA. In this study, an adaptive vectorized crossover scheme is employed. The crossover is controlled by a crossover probability, Cr, and actual crossover can be performed in two ways: (1) binomial and (2) exponential. The binomial scheme performs crossover on each of the d components or variables/parameters. By generating a uniformly distributed random number between 0 and 1, the mth component of Xi ,Xi,m, is manipulated as:

$$\mathrm{X}_{\mathrm{i,m}} = \begin{cases} \mathrm{X}_{\mathrm{r,m}} & \mathrm{rand}_{\mathrm{i,m}} < \mathrm{C}_{\mathrm{r}} \\ \mathrm{X}_{\mathrm{i,m}} & \text{else} \end{cases} \tag{30}$$

$$\mathrm{C}_{\mathrm{r}} = 0.2\widehat{\mathrm{K}}_{\mathrm{i,best}} \tag{31}$$

3.6. Mutation

The mutation plays an important role in evolutionary algorithms such as ES and DE. The mutation is controlled by a mutation probability (Mu). The adaptive mutation scheme used herein is formulated as:

$$\mathrm{X}_{\mathrm{i,m}} = \begin{cases} \mathrm{X}_{\mathrm{gbes,m}} + \mu\left(\mathrm{X}_{\mathrm{p,m}} - \mathrm{X}_{\mathrm{q,m}}\right) & \mathrm{rand}_{\mathrm{i,m}} < Mu \\ \mathrm{X}_{\mathrm{i,m}} & \text{else} \end{cases} \tag{32}$$

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$$\mathrm{Mu} = {0.05}/{\widehat{\mathrm{K}}_{\mathrm{i,best}}} \tag{33}$$

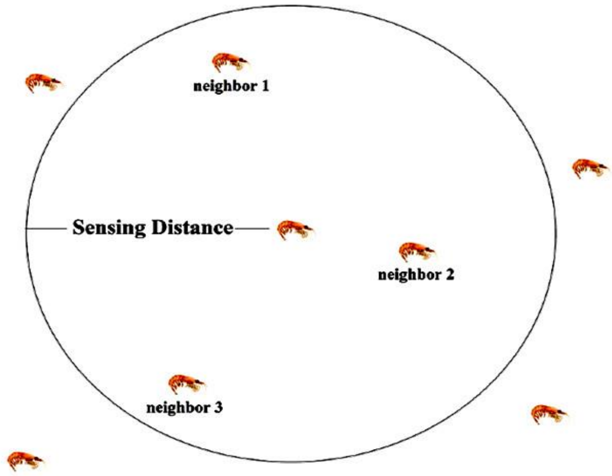

Figure. 1: Schematic representation of Sensing Distance around a krill individual

4. Methodology of the KH algorithm

Various krill-inspired algorithms can be developed by idealizing the motion characteristics of the krill individuals. Generally,the KH algorithm can be introduced by the following steps:

I. Data Structures: Define the simple bounds, determination of algorithm parameter(s) and etc.

II. Initialization: Randomly create the initial population in the search space.

III. Fitness evaluation: Evaluation of each krill individual according to its position.

IV. Motion calculation:

- Motion induced by the presence of other individuals,
- Foraging motion
- Physical diffusion

V. Implement the genetic operators

VI. Updating: updating the krill individual position in the search space.

VII. Repeating: go to step III until the stop criteria is reached.

VIII. End

5. Result

In this study, the Krill Herd Algorithm (KHA) is applied to solve the Combined Economic and Emission Dispatch (CEED) problem for the IEEE 30-bus test system with a total load demand of 283.4 MW. The simulation results, are given in table-1

Table1: Results of IEEE 30 bus systems for the load of 283.4MWwith line loss

Unit power output	CPSO [20]	WIPSO [20]	MRPSO [20]	Proposed KHA with minimum Emission	Proposed KHA with minimum Fuel cost
$P1$ (MW)	146.034	147.581	145.7801	146.564	146.0885
$P2$ (MW)	46.0732	46.889	43.0912	42.0854	46.836
$P5$ (MW)	34.0742	47.0705	43.07654	42.1506	34.084
$P8$ (MW)	26.0198	16.7863	24.0763	25.3844	25.0125
$P11$ (MW)	24.108	24.7219	23.1732	24.3856	24.8
$P13$ (MW)	26.0911	19.8925	23.0453	22.1458	25.248
Loss (MW)	19.0003	19.5407	18.8468	18.584	18.352
Fuel cost($/h)	2607622	2661327	2575426	2607638	2575419
Total power output	302.4	302.940	302.2468	302.7191	302.0092
Emission (Ton/h)	162228.5	167729	162153.6	162145.1	163338.9

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6. Conclusion

In this paper, the Krill Herd Algorithm (KHA) is applied to solve the combined economic and emission dispatch problem using a six-unit system as a test case. The results obtained are compared with those from other soft computing techniques. The comparison demonstrates that KHA delivers superior performance, exhibiting faster and more stable convergence behavior. Key advantages of the algorithm include high-quality solutions, consistent convergence characteristics, and strong computational efficiency. These findings suggest that KHA is a promising and effective approach for addressing complex optimization problems in power system operations.

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