International Journal of Multidisciplinary Research and Modern Education (IJMRME)
Impact Factor: 6.725, ISSN (Online): 2454 - 6119
(www.rdmodernresearch.org) Volume 3, Issue 1, 2017

SOLVING COMBINED ECONOMIC AND EMISSION DISPATCH USING KRILL HERD ALGORITHM

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Cite This Article: Dr. A. Subramanian, A. Sindhu & S. Vijayaraj, "Solving Combined Economic and Emission Dispatch Using Krill Herd Algorithm", International Journal of Multidisciplinary Research and Modern Education, Volume 3, Issue 1, Page Number 496-501, 2017.

Abstract:

In this paper, fuel cost and the environmental emission functions are considered and formulated as a multi-objective economic load dispatch problem. For obtaining the solution of multi-objective economic load dispatch Krill Herd Algorithm was used. Potency of the algorithm is tested on six unit system. The promising results show the quick convergence and effectiveness of the Krill Herd Algorithm.

Key Words: Economic Load Dispatch & Krill Herd Algorithm

Introduction:

Nowadays, the planning and operating power system is a challenging task for power engineers because of its complexity and to satisfy the demand for electric energy of the area served by the system with Continuity of service and reliability. An elite objective here is to perform the service at the lowest possible cost. The role of soft computing techniques has influenced a lot in the field of power system especially in solving optimization problems because of their reliability, speed of convergence and robustness [1]. The ELD problem, one of the different non-linear programming commitment in power system, is about minimizing the fuel cost of generating units for a specific period of operation so as to accomplish optimal generation dispatch among operating units and to satisfy the system load demand and generator operation constraints with ramp rate limits and prohibited operating zones [2]. S. K. Dash [3] was presented a new method to solve the problem of optimal generation dispatch with multiple fuel options using a Radial basis function neural network along with a heuristic rule based search algorithm and a Hopfield neural network. Dr .G. Srinivasan, et al. [4] solved economic load dispatch problem with Valve point effects and multi Fuels using particle swarm algorithm with chaotic sequences and the crossover operation to improve the global searching capability by preventing premature convergence through increased diversity of the population. Radhakrishnan Anandhakumar, et al. [5] was proposed a non-iterative direct Composite Cost Function method, to solve economic dispatches of the online units with less Computation time. Umamaheswari Krishnasamy,et al. [6] presented a Refined Teaching-Learning Based Optimization Algorithm for Dynamic Economic Dispatch of Integrated Multiple Fuel integrated with Wind Power Plants. R. Balamurugan, et al. [7] proposed a self-adaptive mechanism is used to change these control parameters during the evolution process. These control parameters are applied at the individual levels in the population to solve economic dispatch with valve point and multi fuel options. In this paper, Combined Economic and Emission Load Dispatch has been solved by using the Krill Herd Algorithm (KHA). The KHA algorithm approach has been verified by applying it to test system. The performance of the proposed KHA algorithm is analysed and its parameters was self tuned. Because this parameter plays a major role in controlling the searching process of algorithm.

1. Problem Formulation:

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.

Objective 1:

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

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

Objective 2:

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 following:

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

$$E_i(P_i) = \left(\propto_i + \beta_i P_i + \gamma_i P_i^2\right) + \varepsilon_i \sin(\lambda_i P_i) \quad (3)$$

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:

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

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

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

By (4) and (5) get

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

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

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

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:

$$\sum_{i=1}^{n} P_i = P_D + P_L \quad (8)$$

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

Generator Limits Constraint:

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

$$P_i^{min} \leq P_i \leq P_i^{max} \quad (10)$$

2. Lagrangian Model of the Krill Herding:

Predation removes individuals, leads to reduction of the average krill density, and distances the krill swarm from the food location. This process is assumed to be the initialization phase in the KH algorithm. In the natural system, the fitness of each individual is supposed to be a combination of the distance from the food and from the highest density of the krill swarm. Therefore, the fitness (imaginary distances) is the value of the objective function. The time-dependent position of an individual krill in 2D surface is governed by the following three main actions:

- ✓ Movement induced by other krill individuals;
- ✓ Foraging activity; and
- ✓ Random diffusion

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:

$$\frac{dX_i}{dt} = N_i + F_i + D_i \quad (11)$$

Where N_i is the motion induced by other krill individuals; F_i is the foraging motion, and D_i is the physical diffusion of the i_{th} krill individuals.

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:

$$N_i^{new} = N^{max} \alpha_i + \omega_n N_i^{old} \quad (12)$$

Where,

$$\alpha_i = \alpha_i^{local} + \alpha_i^{target} \quad (13)$$

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:

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

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

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

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:

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

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 i_{th} individual krill is taken into account using Eq. (18). This level leads it to the global optima and is formulated as:

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

Where, C^{best} is the effective coefficient of the krill individual with the best fitness to the i_{th} 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:

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

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.

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 i_{th} 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, β_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 i_{th} krill individual can be determined as follows:

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

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 i_{th} krill individual is also handled using the following equation:

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

Where K_{ibest} is the best previously visited position of the i_{th} krill individual.

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:

$$D_i = D^{max}\,\delta \tag{26}$$

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

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:

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

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:

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

Where NV is the total number of variables, and LB_j and UB_j are lower and upper bounds of the j_{th} variables (j = 1,2,. . .,NV), respectively. Therefore, the absolute of their subtraction shows the search space. It is empirically found that C_t is a constant number between [0, 2]. It is also obvious that low values of C_t let the krill individuals to search the space carefully.

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.

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 m_{th} component of X_i ,$X_{i,m}$, is manipulated as:

$$X_{i,m} = \begin{cases} X_{r,m} & rand_{i,m} < C_r \\ X_{i,m} & else \end{cases} \tag{30}$$

$$C_r = 0.2\hat{K}_{i,best} \tag{31}$$

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:

$$X_{i,m} = \begin{cases} X_{gbes,m} + \mu(X_{p,m} - X_{q,m}) & rand_{i,m} < Mu \\ X_{i,m} & else \end{cases} \tag{32}$$

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

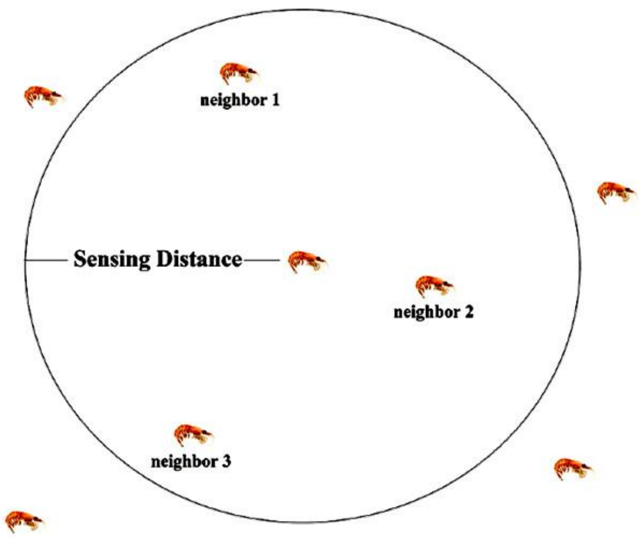

Figure 1: Schematic representation of Sensing Distance around a krill individual

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:

- ✓ Data Structures: Define the simple bounds, determination of algorithm parameter(s) and etc.
- ✓ Initialization: Randomly create the initial population in the search space.

- ✓ Fitness evaluation: Evaluation of each krill individual according to its position.
- ✓ Motion calculation:
  - Motion induced by the presence of other individuals,
  - Foraging motion
  - Physical diffusion
- ✓ Implement the genetic operators
- ✓ Updating: updating the krill individual position in the search space.
- ✓ Repeating: go to step III until the stop criteria is reached.
- ✓ End

3. Result:

In this case KHA is employed to solve the Combined Economic and Emission Dispatch of IEEE 30bus system with demand 283.4MW. The simulation results and the converge of the cost function is shown in Fig-2 for 500 iterations.

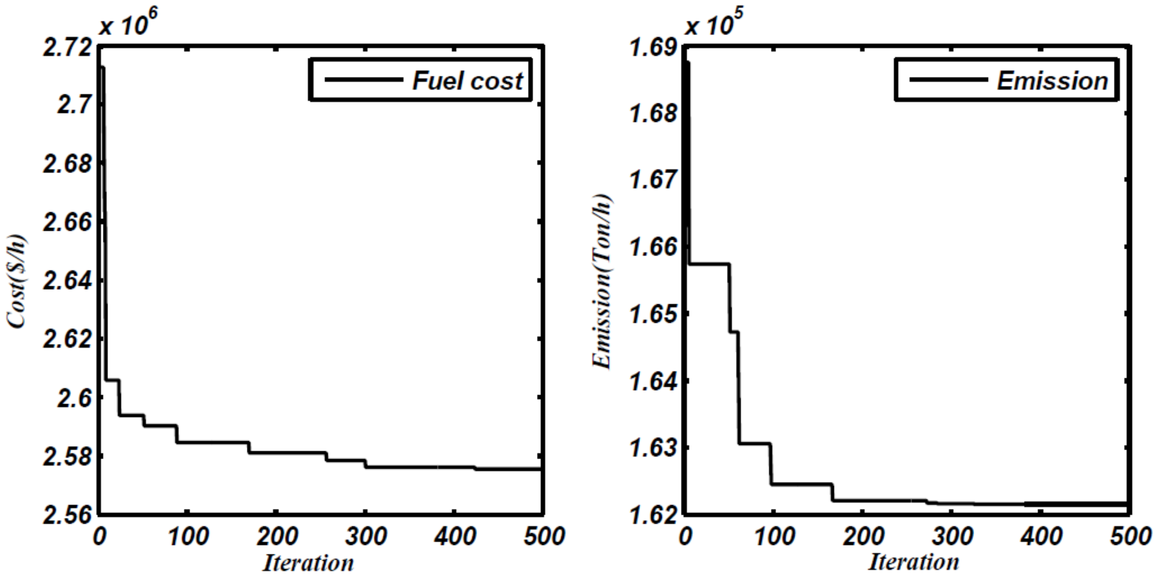

Figure 2: Convergence characteristics of Fuel cost and Emission.

Table 1: 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
***P*1 (MW)**	146.034	147.581	145.7801	146.567	146.0885
***P*2 (MW)**	46.0732	46.889	43.0912	42.0854	46.836
***P*5 (MW)**	34.0742	47.0705	43.07654	42.1508	34.0742
***P*8 (MW)**	26.0198	16.7863	24.0763	25.3845	25.0125
***P*11 (MW)**	24.108	24.7219	23.1732	24.3856	24.85
***P*13 (MW)**	26.0911	19.8925	23.0453	22.1458	25.148
Loss (MW)	19.0003	19.5407	18.8468	18.584	18.332
Fuelcost($/h)	2607622	2661327	2575426	2607639	2575421
Total Power Output	302.4	302.9407	302.2468	302.7191	302.0092
Emission (Ton/h)	162228.5	167729.1	162153.6	162150.1	163338.5

4. Conclusion:

In this paper, KHA is applied to economic emission load dispatch problems with six unit system as a test case. The results obtained by this method are compared with other soft computing techniques. The comparison shows that KHA performs better and got good convergence characteristics. The KHA has superior features, including quality of solution, stable convergence characteristics and good computational efficiency. Therefore, this results shows that KHA is a promising technique for solving complicated problems in power system.

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