Multi-Area Economic Dispatch With Multi-Fuel Option Using Krill Herd Algorithm

[1]Dr.S.Vijayaraj, [2]P.Dayanithi, [3]P.P.Arjun, [4]N.Varaprasad, [5]Parthasarathy. K and [6]R.Chandrasekaran

[1]Assistant Professor, Department of Electrical and Electronics Engineering, Vels Institute of Science, Technology & Advanced Studies, Chennai
[2,3,4]U.G Scholar, Department of Electrical and Electronics Engineering, Vels Institute of Science, Technology & Advanced Studies, Chennai
[5,6]Research Scholar, Department of Electrical and Electronics Engineering, Vels Institute of Science, Technology & Advanced Studies, Chennai
Corresponding Author: [1]vijayaraj.se@velsuniv.ac.in

Article History: Received: 11 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 23 May 2021

ABSTRACT

This paper presents the application of the Krill Herd Algorithm to solve the Multi-Area Economic Load Dispatch Problem (MAED) by considering tie line constraint, valve point loading effect, and Multi-fuel option. The algorithm effectiveness is tested on a two-area system with six generating units. It is compared with Particle Swarm Optimization (PSO) algorithm and Genetic Algorithm (GA).

1. INTRODUCTION

One of the most common important optimization problems in the industrial operation of power systems is the economic dispatch [1] problem. The main goal of the ED issue is to find an excellent schedule of online generating units that will satisfy power demand at the lowest possible operating cost under different systems and operating constraints. In a typical power system, generators are divided into multiple generation areas and linked by tie-lines. Economic dispatch has been expanded to include multi-area economic dispatch (MAED). MAED determines the degree of generation and power exchange between areas so that overall fuel costs in all areas are reduced while power balance constraints, generating limits constraints, and tie-line constraints are met.

For solving the economic dispatch issue, Shoults et al. [2] included power transfer limits between areas for solving the economic dispatch issue. This paper presents a comprehensive formulation of multi-area generation scheduling as well as a multi-area study concept. Romano et al. [3] Constrained economic dispatch of multi-area systems were solved using the Danzig-Wolfe decomposition principle, which divides the problem into many sub-problems reduces its complexity.

A.L.Desell et al. [4] used linear programming to analyze transmission constrained generation operational costs in an extensive electrical network's power system planning. Ouyang and Shahidehpour [5] proposed a heuristic multi-area unit commitment with economic dispatch incorporating easy and efficient tie-line constraint testing. Expert systems used by Wang etal. [6] to propose a decomposition method for multi-area generation scheduling with non-linear tie-line constraints. For solving the multi-area economic dispatch with transmission constraints, Dan Streiffert et al. [7] proposed an Incremental Network Flow Programming algorithm.

Jayabarathi et al. [8] used evolutionary programming to solve multi-area economic dispatch problems with tie-line constraints. On multi-area economic dispatch problems, Manoharan et al. [9] investigated the efficiency and efficacy of various evolutionary algorithms, i.e., Real-coded Genetic Algorithm, Particle Swarm Optimization, Differential Evolution, and Covariance Matrix Adapted Evolution Strategy.

Prasanna et al. [10] used a Fuzzy logic technique combined with Evolutionary Programming and Tabu-Search algorithms to solve the Security Constrained Economic Dispatch in an integrated power system. For solving MAED problems, Manisha Sharma et al. [11] compared the search capability and convergence behaviour of algorithms like Classical differential evolution (DE) and its various strategies, Classical particle swarm optimization (PSO), and an improved PSO with a parameter automation strategy with time-varying acceleration coefficients (PSO-TVAC). S. Manoharan et al. [12] proposed an Evolutionary Programming with the Levenberg-Marquardt Optimization technique to solve the multi-area economic dispatch problems with multiple fuel options.

M. Zarei et al. [13] proposed a suitable direct search method (DSM) for solving the two-area economic dispatch of generating units with equality and inequality constraints and various types of complex fuel cost functions. Arthur K. Kordon [14] guides how to deal with a wide range of technological and nontechnical problems, as well as for popular real-world applications.

The dynamic behaviour of swarms and their success under various optimization problems is explained by James Kennedy and Russell C. Eberhart [15].Sumathi and Surekha [16] illustrate how to apply the optimization problem in the Matlab programming environment.

Andries P. Engelbrecht [17] provides a brief overview of evolutionary algorithms and swarm intelligence-based algorithms, as well as their parameter effects on applications.BijayaKetanPanigrahi and YuhuiShi [18] presents swarm intelligence applications on various realistic real-world problems.

The KH algorithm is based on a simulation of individual krill herding behavior. The objective function for krill movement is determined by the minimum distances between each krill and the herd's highest density.[19]

The Krill Herd Algorithm was used to solve Multi-area economic dispatch in this article. The application of the KHA approach to a test method was tested. The proposed KH algorithm's efficiency was evaluated and its parameters were self-tuned since this parameter is so important in controlling the algorithm's searching operation.

2. PROBLEM FORMULATION

The critical goal of MAED in the electrical power system is to reduce the total production cost of delivering loads to all areas as much as possible while meeting power balance constraints, generating limits constraints, and tie-line capability constraints.

2.1. Multi-area economic dispatch with quadratic cost function prohibited operating zones and transmission losses.

The objective of the MAED problem is: -

$$F_t = \sum_{i=1}^{N}\sum_{j=1}^{M_i} F_{ij}(P_{ij}) = \sum_{i=1}^{N}\sum_{j=1}^{M_i} a_{ij} + b_{ij}P_{ij} + c_{ij}P_{ij}^2 \qquad (1)$$

where $F_{ij}(P_{ij})$ is the cost function of jth generator in area i and is usually expressed as a quadratic polynomial; a_{ij}, b_{ij} and c_{ij} are the fuel cost coefficients of j_{th} generator in area i; N is the number of areas, M_i is the number of committed generators in area i; P_{ij} is the real power output of j_{th} generator in area i. The MAED problem minimizes F_t subject to the following constraints.

2.2 Active power balance constraint

$$\sum_{j=1}^{M_i-1} P_{ij} = P_{Di} + P_{Li} + \sum_{k,k\neq i} T_{ik} \; i \in N \qquad (2)$$

where, P_{Di} real power demand of area i; T_{ik} is the tie line real power transfer from area i to area k. T_{ik} is positive when power flows from area i to area k and when power flows from area k to area i, T_{ik} is negative.

2.3. Tie line capacity constraints

The tie line real power transfer T_{ik} from area i to area k should not exceed the tie line transfer capacity for security consideration.

$$-T_{ik}^{max} \leq T_{ik} \leq T_{ik}^{max} \qquad (3)$$

Where $-T_{ik}^{max}$ the power flow is limit from area i to area k and T_{ik}^{max} is the power flow limit from area k to area i.

2.4. Real power generation capacity constraints

The real power generated by each generator should be within its lower limit $P_{ij}^{min}P_{ij}^{min}$ and upper limit $P_{ij}^{max}P_{ij}^{max}$, so that

$$P_{ij}^{min} \leq P_{ij} \leq P_{ij}^{max} \quad i \in N \quad j \in M_j \tag{4}$$

2.5. Multi-area economic dispatch with valve point loading multiple fuel sources

$$F_{ij}(P_{ij}) = a_{ijm} + b_{ijm}P_{ij} + c_{ijm}P_{ij}^2 + \left|d_{ijm} \times \sin\left\{e_{ijm} \times \left(P_{ijm}^{min} - P_{ij}\right)\right\}\right| \tag{5}$$

Where $P_{ij}^{min} \leq P_{ij} \leq P_{ij}^{max}$ $P_{ijm}^{min} \leq P_{ij} \leq P_{ijm}^{max}$ for fuel type m and m = 1, 2……N_F

The objective function F_t is given by

$$F_t = \sum_{i=1}^{N}\sum_{j=1}^{M_i} F_{ij}(P_{ij}) \tag{6}$$

3.Lagrangian model of the krill herding

Predation eliminates individuals, lowers the average krill density, and pushes the krill swarm away from the food source. The initialization step of the KH algorithm is assumed to be this operation. The health of each organism in the natural system is supposed to be a combination of the distance from the food and the krill swarm's highest density. As a result, the objective function's value is fitness (imaginary distances). The three key acts that control the time-dependent location of an individual krill in a 2D surface are [19]:

i. Movement induced by other krill individuals;

ii. Foraging activity; and

iii. Random diffusion

An optimization algorithm is considered to be capable of searching spaces of any dimensionality. As a result, we can generalise the following Lagrangian model to an n-dimensional decision space:

$$\frac{dX_i}{dt} = N_i + F_i + D_i \tag{7}$$

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

3.1 Motion induced by other krill individuals

Individual krills, according to theoretical arguments, attempt to maintain a high density and shift due to mutual effects. The local swarm density (local effect), a target swarm density (target effect), and a repulsive swarm density (repulsive effect) are used to calculate the induced motion direction. This movement can be described as follows for a krill [19]:

$$N_i^{new} = N^{max}\alpha_i + \omega_n N_i^{old} \tag{8}$$

where,

$$\alpha_i = \alpha_i^{local} + \alpha_i^{target} \tag{9}$$

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 induced last motion, a local i is the local effect provided by the neighbours and a target i is the direction of target effect provided by the best krill individual.

It is taken 0.01 based on the calculated values of the maximum induced speed (ms). For a local search, the effect of neighbours can be interpreted as an attractive/repulsive tendency between individuals. The effect of neighbours in a krill movement individual is calculated as follows in this study:

$$\alpha_i^{local} = \sum_{j=1}^{NN} \hat{K}_{i,j}\,\hat{X}_{i,j} \tag{10}$$

$$\hat{X}_{i,j} = \frac{X_j - X_i}{\|X_j - X_i\| + \xi} \tag{11}$$

$$\hat{K}_{i,j} = \frac{K_i - K_j}{K^{worst} - K^{best}} \tag{12}$$

where $K^{worst}$and $K^{best}$are the best and the worst fitness values of the krill individuals so far; K_i represents the fitness or the objective function value of the i_{th} krill individual; K_j is the fitness of j_{th} (j = 1,2, . . ., NN) neighbour; X represents the related positions; and NN is the number of the neighbours.

A small positive integer, e, is added to the denominator to prevent singularities. Some unit vectors and normalised fitness values can be found on the right sides of Eqs. The vectors depict the induced directions by various neighbours, and each value represents a neighbour's influence. Since the normalised value can be negative or positive, the neighbours' vector can be attractive or repulsive.

Different methods can be used to choose a neighbour. A neighbourhood ratio, for example, can be easily described to determine the number of closest krill individuals. A sensing distance (ds) around a krill individual (as shown in Fig. 1) should be calculated using the actual activity of the krill individuals, and the neighbours should be identified.

Different heuristic methods may be used to evaluate the sensing distance for each krill individual. For each iteration, it is calculated using the formula below.

$$d_{s,i} = \frac{1}{5N} \sum_{j=1}^{N} \|X_i - X_j\| \tag{13}$$

The sensing distance for the i_{th} krill individual is ds,i, and the number of krill individuals is N. The factor 5 in the denominator was calculated by trial and error. Using the Eq. (13), two krill individuals are neighbours if their distance is less than the given sensing distance.

The lowest fitness of an individual krill is the established target vector of that krill. Eq.(18) analyses the impact of the individual krill with the best fitness on the i_{th} individual krill . This level leads to the global optimum and is defined as follows:

$$\alpha_i^{target} = C^{best}\hat{K}_{i,best}\hat{X}_{i,best} \tag{14}$$

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 neighbours. Here in, the value ofC^{best} is defined as:

$$C^{best} = 2\left(rand + \frac{I}{I_{max}}\right) \tag{15}$$

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

3.2 Foraging motion

Two key effective parameters are used to describe the foraging motion. The first is the food location, and the second is previous experience about the food location. This motion can be expressed as follows for the i_{th} krill individual:

$$F_i = V_f \beta_i + \omega_f F_i^{old} \quad (16)$$

where

$$\beta_i = \beta_i^{food} + \beta_i^{best} \quad (17)$$

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.

It is taken 0.02 according to the calculated values of foraging speed (ms-1). The food effect is determined by the location of the food. First, find the food's centre, and then try to formulate a food attraction. This is not something that can be calculated, but it can be estimated.

The virtual centre of food concentration is calculated in this study using the fitness distribution of krill individuals, which is based on the concept of ‘‘centre of mass." For each iteration, the food centre is written as follows:

$$X^{food} = \frac{\sum_{i=1}^{N} \frac{1}{K_i} X_i}{\sum_{i=1}^{N} \frac{1}{K_i}} \quad (18)$$

Therefore, the food attraction for the i_{th} krill individual can be determined as follows:

$$\beta_i^{food} = C^{food} \hat{K}_{i,food} \hat{X}_{i,food} \quad (19)$$

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:

$$C^{food} = 2\left(1 - \frac{I}{I_{max}}\right) \quad (20)$$

The krill swarm may be attracted to the global optima by the food attraction. After some iteration, the krill individuals usually herd around the global optima, according to this description. This can be thought of as an effective global optimization technique that aids in the improvement of the KH algorithm's globality. The impact of the i_{th} krill individual's best fitness is also considered using the following equation:

$$\beta_i^{best} = C^{best} \hat{K}_{i,ibest} \hat{X}_{i,ibest} \quad (21)$$

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

3.3 Physical diffusion

Physical diffusion of individual krills is thought to be a random process. A maximum diffusion speed and a random directional vector can be used to describe this motion. It can be mentioned in the following way:

$$D_i = D^{max} \delta \quad (22)$$

$$D_i = D^{max} \left(1 - \frac{I}{I_{max}}\right) \delta \quad (23)$$

3.4 Motion Process of the KH Algorithm

$$X_i(t + \Delta t) = X_i(t) + \Delta t \frac{dX_i}{dt} \quad (24)$$

It should be noted that t is a critical constant that should be carefully set according to the optimization problem. This is due to the fact that this parameter acts as a speed vector scale factor Δt . t is entirely dependent on the search space, and it appears that it can be calculated using the following formula:

$$\Delta t = C_t \sum_{j=1}^{Nv} (UB_j - LB_j) \tag{25}$$

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.

3.5 Genetic operators

Genetic reproduction mechanisms have been introduced into the algorithm to enhance its accuracy. Crossover and mutation, which are inspired by the classic DE algorithm, are the adaptive genetic reproduction mechanisms that have been implemented.

3.6 Crossover

GA is the first to use the crossover operator as a global optimization technique. DE, which can be considered a development of GA, also uses a vectorized variant of the crossover. An adaptive vectorized crossover scheme is used in this analysis.

$$X_{i,m} = \begin{cases} X_{r,m} & rand_{i,m} < C_r \\ X_{i,m} & \text{else} \end{cases} \tag{26}$$

$$C_r = 0.2\hat{K}_{i,best} \tag{27}$$

3.7 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 [19]:

$$X_{i,m} = \begin{cases} X_{gbes,m} + \mu(X_{p,m} - X_{q,m}) & rand_{i,m} < Mu \\ X_{i,m} & \text{else} \end{cases} \tag{28}$$

$$Mu = \frac{0.05}{\hat{K}_{i,best}} \tag{29}$$

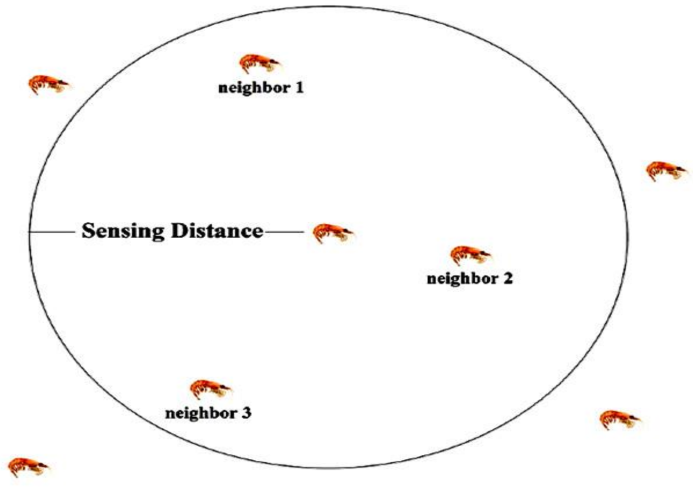

Figure 1: Schematic representation of Sensing Distance around a krill individual

3.8 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[19]:

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

4.Test System

The test system consists two areas, each area comprising three generating plants, as shown in Fig.2. The total demand for two area system is 1700 MW, which is shared by both areas equally. The tie-line power flow limit between area 1 and 2 is ±100 MW.

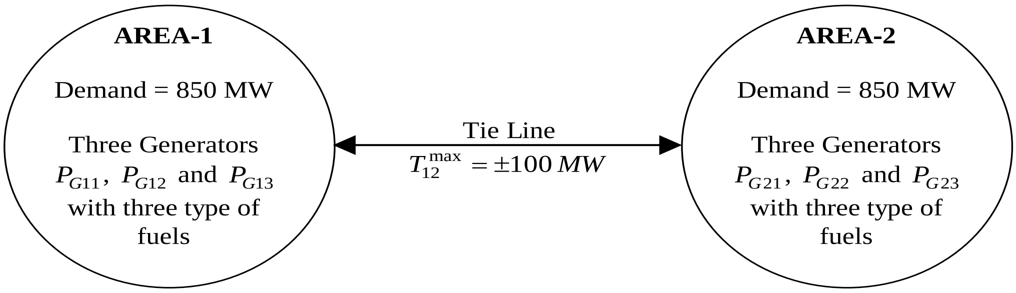

Figure. 2 Six Units MAED Problem

The results comprising the economic generations, fuel type, tie-line power flow, and the net fuel cost of the proposed method for two area MAED with multi fuel options are presented in Table 1. The table also contains the results of the GA and PSO based methods for illustrating the performances of the proposed method. The comparison of the net fuel cost clearly indicates that the proposed method offers the lowest fuel cost of 465.7311 \$/h, which is much lower than the existing methods. The generation cost at each generating plant of the proposed method for six units MAED with multi fuel option is graphically plotted in Figure 2. The resulting tie-line power flow is found to be well within its maximum limit of 100 MW.

Table 1 Comparison of Results of 6 units MAED

Methods	KHA		GA		PSO	
	PG	Fuel	PG	Fuel	PG	Fuel
P_{G11}	201.1675	2	203.5735	2	203.4239	2
P_{G12}	173.4756	1	169.8593	1	171.4688	1
P_{G13}	405.0896	2	406.5171	2	404.9915	2
P_{G21}	239.4282	3	238.074	3	238.8424	3
P_{G22}	443.6639	3	443.987	3	443.3071	3
P_{G23}	237.1752	3	237.9891	3	237.9663	3
T_{12}	70.2673	---	70.0501	---	70.1158	---
NET (Secs)	12.14	---	48.34	---	22.45	---
F_t (\$/h)	465.7311	---	466.8872	---	466.4494	---

5.COMPUTATIONAL EFFICIENCY AND ROBUSTNESS `

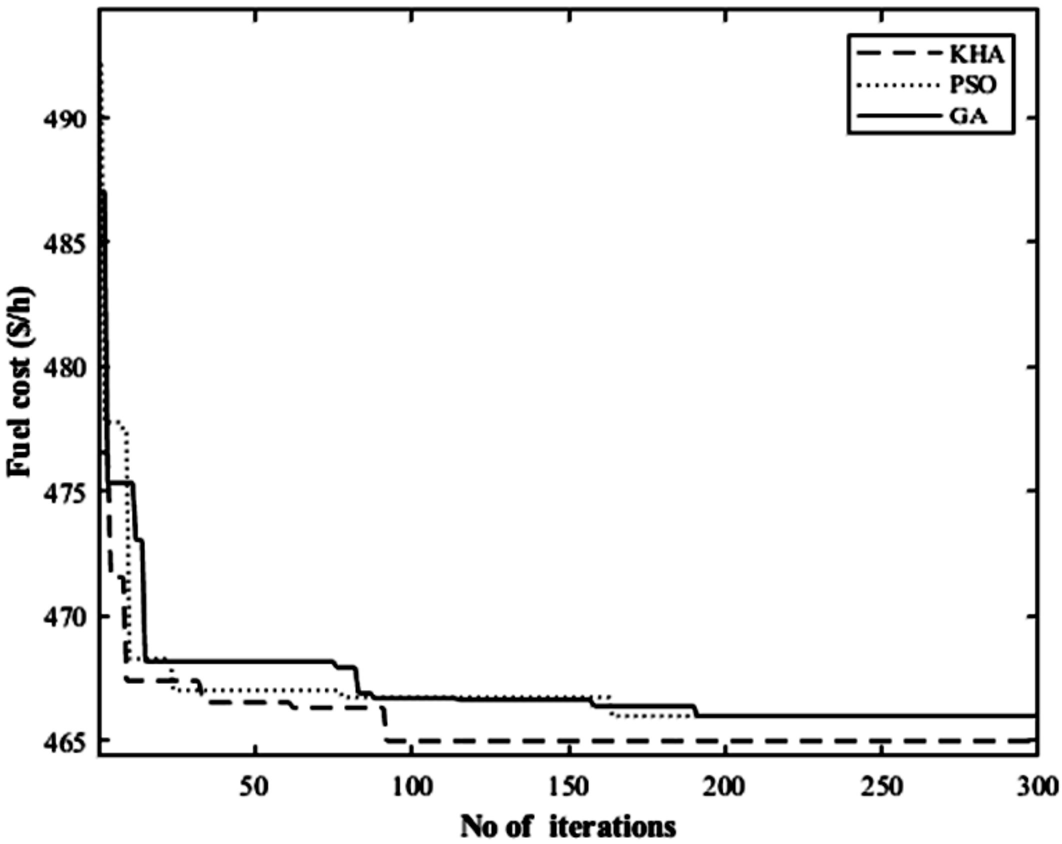

Figure 3 Convergence characteristics for six units MAED

The convergence characteristic that represents the variation of fuel cost against the number of iterations of the proposed method for six units MAED is shown in Figure 3. This figure also includes the convergence of GA and PSO-based methods. Although the maximum number of iterations for convergence check has been set as 1000 and 500 for KHA, GA, and PSO, respectively, the x-axis of the figure has been limited to 300 iterations, as they almost settled to the final solution in less than 300 iterations. It can be observed from the figure that the KHA quickly converges to the final solution in less than 100 iterations, but the GA and PSO-based methods require around 190 and 160 iterations to reach the global best solution. It is evident that the KHA can converge to the global best solution at a lower number of iterations than those of the existing GA and PSO-based methods.

The normalized execution time (NET) of the proposed method is compared with those of the existing GA and PSO approaches for six units MAED problem in Table 1. It can be observed from this table that the proposed method is relatively faster than the other two approaches. The relatively lower execution time of the proposed method affirms its computational efficiency.

6.CONCLUSION

In this paper, KHA is applied to Multi-area economic load dispatch problem with multi fuel options. The results obtained by this method are compared with GA and PSO. The comparison reveals that KHA outperforms the mentioned techniques above. For large systems, the KHA has superior features such as solution consistency, stable convergence characteristics, and good computational performance. As a consequence of these results, KHA appears to be a promising strategy for resolving complex power system problems.

REFERENCES

[1] Chowdhury BH, Rahman S. A review of recent advances in economic dispatch. IEEE Trans Power System 1990;5(4):1248–59.

[2] Shoults RR, Chang SK, Helmick S, Grady WM. A practical approach to unit commitment, economic dispatch, and savings allocation for multiple-area pool operations with import/export constraints. IEEE Trans Power Apparatus System1980;99(2):625–35.

[3] Romano R, Quintana VH, Lopez R, Valadez V. Constrained economic dispatch of multi-area systems using the Dantzig–Wolfe decomposition principle. IEEE Trans Power Apparat Syst 1981;100(4):2127–37.

[4] Desell AL, McClelland EC, Tammar K, Van Horne PR. Transmission constrained production cost analysis in power system planning. IEEE Trans Power Apparat Syst 1984;103(8):2192–8.

[5] Ouyang Z, Shahidehpour SM. Heuristic multi-area unit commitment with economic dispatch. IEE Proc-C 1991;138(3):242–52.

[6] Wang C, Shahidehpour SM. A decomposition approach to non-linear multi-area generation scheduling with tie-line constraints using expert systems. IEEE Trans Power Syst 1992;7(4):1409–18.

[7] Streiffert D.Multi-area economic dispatch with tie-line constraints.IEEE Trans Power Syst 1995;10(4):1946–51.

[8] Jayabarathi T, Sadasivam G, Ramachandran V. Evolutionary programming based multi-area economic dispatch with tie-line constraints. Electr Mach Power Syst 2000; 28:1165–76.

[9] Manoharan PS, Kannan PS, Baskar S, Willjuice Iruthayarajan M. Evolutionary algorithm solution and KKT based optimality verification to multi-area economic dispatch. Int J Electr Power Energy Syst 2009;31(7–8):365–73.

[10] Prasanna. T.S, and Somasundaram.P. multi-area security constrained economic dispatch by fuzzy- stochastic algorithms. journal of theoretical and applied information technology. .2005 – 2009.

[11] Sharma Manisha, Pandit Manjaree, Srivastava Laxmi. Reserve constrained multi-area economic dispatch employing differential evolution with time-varying mutation. Int J Electr Power Energy Syst 2011;33(3):753–66.

[12] Manoharan.P. S., Kannan p. S., Ramanathan. V. A Novel EP Approach for Multi-area Economic Dispatch with Multiple Fuel Options Turk J Elec Eng & Comp Sci, Vol.17, No.1, 2009, doi:10.3906/elk-0705-10.

[13] Zarei. M, Roozegar.A, Kazemzadeh.R., and Kauffmann J.M. Two Area Power Systems Economic Dispatch Problem Solving Considering Transmission Capacity Constraints. World Academy of Science, Engineering and Technology International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering Vol:1, No:9, 2007.

[14] Arthur K. Kordon. Applying Computational Intelligence. springer 2010.

[15] James Kennedy and Russell C. Eberhart. Swarm intelligence. Academic Press 2001.

[16] S. sumathi and surekha p. Computational Intelligence Paradigms Theory and Applications using MATLAB.CRC press 2010.

[17] Andries P. Engelbrecht. Computational Intelligence An Introduction. John Wiley & Sons 2002.

[18] Bijaya Ketan Panigrahi,Yuhui Shi, and Meng-Hiot Lim.Handbook of Swarm Intelligence Concepts, Principles and Applications. Springer 2011.

[19] Amir Hossein Gandomi, Amir Hossein Alavi. Krill herd: A new bio-inspired optimization algorithm. Communications in Nonlinear Science and Numerical Simulation 17 (2012) 4831–4845.

[20] Walter DC, Sheble GB. Genetic algorithm solution of economic dispatch with valve point loading. IEEE Trans Power Syst 1993; 8:1325–32.

[21] Chiang C-L. Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels. IEEE Trans Power Syst 2005;20(4):1690–9.

[22] Basu.M.Artificial bee colony optimization for multi-area economic dispatch. Electrical power and energy systems 49(2013)181-187.

[23] Gaing Z-L. Particle swarm optimization to solving the economic dispatch considering the generator constraints. IEEE Trans Power Syst 2003;18(3):1187–95.

[24] Sinha N, Chakrabarti R, Chattopadhyay PK. Evolutionary programming techniques for economic load dispatch. IEEE Trans Evol Comput 2003;7(1):83–94.

[25] S.Vijayaraj and Dr.R.K.Santhi Multi-Area Economic Dispatch Using Flower Pollination Algorithm. International Conference on Electrical, Electronics, and Optimization Techniques - 2016, pp4355-4360.

[26] S. Vijayaraj, Economic Dispatch with Valve Point Effect Using Flower pollination algorithm, Journal of Applied Science and Computations, 2018, pp.1289 – 1294.

[27] Parthasarathy K, Dr. S.Vijayaraj, An Overview of Battery Charging Methods, Charge Controllers, and Design of MPPT Controller based on Adruino Nano for Solar Renewable Storage Energy System, International Journal of Engineering Research & Technology Vol. 9 Issue 11, November-2020 pp 430 - 439.

[28] Parthasarathy K and Dr.S.Vijayaraj, A Method to Compensate Reactive Power in Double Fed Induction Generator based Windmill using STATCOM. International Conference on Computing Methodologies and Communication - 2021, pp 579-585.