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An Efficient Stud Krill Herd Framework for Solving Non-Convex Economic Dispatch Problem

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***Abstract*—**The problem of economic dispatch (ED) is the basic problem of power framework, its main goal is to find the most favorable generation dispatch to generate each unit, reduce the whole power generation cost, and meet all system limitations. A heuristic algorithm, recently developed called Stud Krill Herd (SKH), has been employed in this paper to treat non-convex ED problems. The proposed KH has been modified using Stud selection and crossover (SSC) operator, to enhance the solution quality and avoid local optima. We are demonstrated SKH effects in two case study systems composed of 13-unit and 40-unit test systems to verify its performance and applicability in solving the ED problems. In the above systems, SKH can successfully obtain the best fuel generator and distribute the load requirements for the online generators. The results showed that the use of the proposed SKH method could reduce the total cost of generation and optimize the fulfillment of the load requirements.

***Keywords*—**Stud Krill Herd, economic dispatch, crossover, stud selection, valve-point effect.

I. Introduction

THE basic principle of the ED problem provides the best utilization of the power system, which creates economic and safe operating conditions for the planning and operation of the power system. In order to optimize the target function including cost, the ED problem depends on two kinds of operation limitations. These limitations are considered to be a constraint of equality and inequality. The ED problem is a non-convex optimization problem, and a large amount of computation is required if the high-power system is considered. Basically, the ED problem is considered static and non-linear, which is the most important function of the innovative energy management framework. Given the increased availability of control equipment and energy prices, the ED approach has become more relevant, as its starting point has shown its efficiency in managing various issues [1].

Recently, different techniques were explored in the literature, which revealed the ED problem studied in the past more than 20 years, and many algorithms have been created to solve it. A variety of conventional optimization methods have been produced [1] to tackle ED problems such as λ iterative method, gradient method, linear programming method and Newton method. The traditional programming technology is fast and reliable, but it is often unable to obtain the best solution to the highly complex non-linear objective function. While in the application of classical mathematical techniques, it is assumed that the fuel-cost-label generation unit is smooth and has a convex function. These technologies are sensitive to the initial solution and may fail because of the initial incorrect value of the variable. Because of its limited operation area, the valve point (VP) effect and the non-linear attribute of the piecewise quadratic cost function (Multiple fuel (MF) options), the actual power system is really difficult to solve with these classical mathematical techniques. Therefore, it is very necessary to deal with the problem of non-convex, non-linear and multi-modular power system. The drawbacks associated with these classical methods have led to the evolution and application of various artificial intelligence (AI) methods to solve the practical ED problem.

Although the AI methods are usually not able to ensure a global ideal solution, they can produce a feasible suboptimal solution in less computational time. Several AI techniques, like particle swarm optimization (PSO) [2], chaotic bat algorithm (CBA) [3], hybrid grey wolf optimizer (HGWO) [4], chaotic particle swarm optimization algorithm and sequential quadratic programming techniques (CPSO-SQP) [5], harmony search algorithm (HS) [6] and chaotic self-adaptive particle swarm optimization algorithm (CSAPSO) [7] are documented in the literature for solving non-convex ED problem (Only consider VP effects).

In this paper, a population-based swarm intelligence algorithm [8] called Stud Krill Herd (SKH) is first proposed to solve the large-scale ED problem considering VP effects. In SKH, an adaptive genetic reproduction mechanism is introduced to effectively overcome the problem of high dimensional complex problems. In fact, the SSC operators inspired by the stud genetic algorithm are used in the SKH algorithm. The main contribution features of this paper can be summarized as follows:

- The SSC operators are combined with KH to improve the main algorithm.
- Proposing an integrated SKH algorithm for solving ED with VP effects. It is investigated on two test systems and results verify the effectiveness and applicability of the SKH method.
- The obtained SKH results contrasted with the standard KH and other related methods documented in the literature.

The remainder of this paper is set out below: Section II describes the ED problem with VP effects. In Section III, the proposed SKH method is introduced, and its intrinsic difference is compared with other algorithms. In Section IV, the ED problem was solved by the proposed SKH method in five test systems, and the results were compared with the

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literature. Lastly, Section V provided the conclusion of this paper.

II. ED Problem

The ED problem involves the optimization of the generation output of each available generating unit, making it possible to minimize the general cost of generating electricity under the constrained conditions linked with the system. The problem objective functions and constraints are outlined as follows:

The goal of this problem is to reduce the total fuel cost F_C, which is represented by the sum of the costs generated by each available generator unit and expressed as:

$$F_C = \sum_{i=1}^{n} F_i\left(P_i\right) \tag{1}$$

where $F_i(P_i)$ is the fuel cost of the unit *i*th generating unit, *n* is the total number of generating units.

It represents the simplest cost characteristic function of an ED problem for a generating unit that can be represented as a single quadratic cost function:

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

where P_i is the real power generation of the ith generator unit *i*. a_i, b_i, and c_i are fuel cost coefficients of generating for unit *i* in [\$/MW^{2}h], [\$/MWh] and [\$/h], respectively, and *n* is the total number of generating units.

The power output of the generator units is controlled by multiple valves in the thermal energy plant. When the inlet steam valve is opened, a sudden rise in the loss is observed, resulting in a ripple formation in the cost characteristic curve. The occurrence of this phenomenon is called the valve-point loading effect. This takes into account the inclusion of multiple non-difference points in the cost feature function, which can be changed to a non-smooth function. It should be expressed as the following quadratic and sinusoidal functions:

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

where d_i and e_i are the coefficients that represent the load effect of the VP and $P_i^{\min}$ is the smallest output power generation of the *i*th generating unit.

The power balance and generation limits of different units without taken into account transmission line losses are considered for obtaining optimal power dispatch in this work. The summation of total power developed by each generating unit must be equal to the total load demand P_d, i.e., there should be power balance in the system as given below.

In the case of transmission line loss, the power balance and power generation limitation of different units are considered to be the best power dispatch in this work. The sum of the total power generated by each generator must equal the total load requirement P_d, that is, the power balance in the system should be shown below.

$$P_G = \sum_{i=1}^{n} P_i = P_d + P_L \tag{4}$$

The optimum power generation of the generating unit must be within its minimum and maximum power generation.

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \tag{5}$$

where $P_{gi}^{\min}$ and $P_{gi}^{\max}$ are the minimum and maximum real power generations of the *i*th generating unit, respectively.

III. Proposed Algorithm

A. Basic of Krill Herd Algorithm

In 2012, Gandomi and Alavi first proposed the Krill Herd (KH) algorithm [9]. The KH algorithm is based on the natural inspiration of behavior imitation of krill individuals in the krill population. The KH algorithm is inspired by krill activities such as [9]:

i. Inducing the movement of other krill individuals;
ii. Foraging activities;
iii. iii.Random diffusion.

The optimization algorithm has the ability to search unknown search space.

- Lagrangian model is extended to an n-dimensional decision space:

$$\frac{dx_i}{dt} = N_i + F_i + D_i \tag{6}$$

where N_k is the movement induced by other krill individuals; F_k is the feeding movement, and D_k is the physical diffusion of k_{th} krill.

The movement induced expresses the preservation of density by each individual. The algebraic formula reflects this behaviour, which is worded as follows:

$$N_k^{next} = N^{\max}\alpha_k + \omega_d N_k^{present} \tag{7}$$

$$\alpha_k = \alpha_k^{local} + \alpha_k^{t\arg et} \tag{8}$$

wherein $N^{\max}$ is the highest induced velocity, ω_n indicates the inertia weight in [0, 1], α_k^{local} and $\alpha_k^{t\arg et}$ indicate the local effect of the neighbor, which is the best solution of the k_{th} individual.

$\alpha_k^{t\arg et}$ is formulated by the following equations:

$$\alpha_k^{t\arg et} = C^{best}\hat{K}_{k,best}\hat{X}_{k,best} \tag{9}$$

$$C^{best} = 2\left(r_1 + \frac{I}{I_{\max}}\right) \quad (10)$$

C^{best} is the effective coefficient of the krill individual with the best fitness for the first k_{th} krill, r_1 is a random number of values between 0 and 1, and is used to improve exploration, I is the current number of iterations, and $I_{\max}$ is the maximum number of iterations.

Foraging activities/movements are mathematically calculated as follows:

The foraging action consists of two main parameters. First is the position of the food F_k^{next}, followed by the previous experience β_k about the position of the food.

$$F_i^{next} = V_f \beta_i + \omega_f F_i^{previous} \quad (11)$$

$$\beta_i = \beta_i^{food} + \beta_i^{best} \quad (12)$$

where V_f is the foraging speed, ω_f is the inertia weight of the foraging motion in the range [0, 1], $F_k^{previous}$ is the last foraging motion, β_k^{food} is the food attractive and β_k^{best} is the effect of the best fitness of each krill. Depending on the measured values of the foraging speed, take as 0.02 (ms-1).

The physical distribution is computed based on higher diffusion velocities and random direction vectors:

$$D_k = D^{\max}\delta \quad (13)$$

$$D_k = D^{\max}\left(1 - \frac{I}{I_{\max}}\right)\delta \quad (14)$$

wherein, $D^{\max}$ is the highest induction velocity, δ is the random direction vector [0, 1].

Finally, the location of each krill is updated to:

$$X_k^{next} = X_k^{current} + \Delta x_k(t) \quad (15)$$

$$\Delta x_k(t) = N_k(t) + F_k(t) + D_k(t) \quad (16)$$

where, t is the position of krill.

B. Stud Krill Herd Algorithm

As we are aware, the basic KH algorithm mainly depends on random search, therefore, KH may fail to find the final best solutions on high-dimensional complicated problems sometimes. In SKH, the adaptive genetic reproduction mechanisms were introduced with the aim of overcoming this disadvantage. In fact, a SSC operator, inspired by the Stud genetic algorithm, was used in SKH algorithm. In the basic KH algorithm, all the updated krill individuals will be accepted as the final krill individuals for the next generation, while in SKH, only the better krill individuals can be passed to the next generation. This updating mechanism makes SKH algorithm evolves towards the better directions. Algorithm 1 gives the mainframe of the SSC operator.

In fact, the SSC operator includes two sub-operators, which are selection and crossover. The selection operator is implemented by selecting the best krill individual and a random one. This indicates that SSC operator has less randomness. Subsequently, the two selected krill individuals are used to perform the crossover operator. This process is same with the standard GA. After implementing the selection and crossover operator (SSC), a new krill individual was generated, which will be evaluated by the fitness/objective function. If the newly-generated individual is better than the original one, it will be considered as the updated krill for the next generation; while, if not, the original krill individual will keep unchanged. This is a very greedy updating strategy.

Algorithm 1 *SSC operator*

Begin
- ***Perform selection operator***
  - *Choose the best krill (the Stud) to mate.*
- ***Implement crossover operator***
  - *Create new krill X_i' by crossover.*
- *Assess its quality/fitness F_i'.*
- ***if*** *($F_i' < F_i$)* ***then do***
  - *Accept the new generated solution X_i' as X_{i+1}.*
- ***else***
  - *Update the krill by* **Eq.** (16) *as X_{i+1}.*
- ***end if***

End.

Algorithm 2 *Stud KH algorithm*

Begin
- ***Step 1: Initialization.*** *Set the generation counter $t = 1$; initial population P of NP krill; setting the foraging speed V_f, maximum diffusion speed D^{max}, and maximum induced speed N^{max}; rossover p_c probability.*
- ***Step 2:*** *Assess the population based on their location to assess the krill population.*
- ***Step 3: While*** *t < MaxGeneration* ***do***
  - *Sort each krill according to their fitness.*
  - ***for*** *i=1:NP (all krill)* ***do***
    - *Implementation of three motions.*
    - ***Algorithm 1****, the position of krill i is updated by the SSC operator.*
    - *Each krill is evaluated according to its new location X_{i+1}.*
  - ***end for*** *i*
  - *Arrange all krill and find the best currently.*
  - *$t = t+1$;*
- ***Step 4: end while***
- ***Step 5:*** *Output the best solutions.*

End.

In SKH, at the start of the search, the basic KH algorithm implements global search in the whole search space. The greedy strategy, SSC operator, is a local search technology, which will refine the generated krill individual. SKH involves two important parts: the basic KH algorithm and SSC operator, which focus on global search and local search, respectively. Therefore, SKH can fully discover the advantages of KH and Stud GA. By merging the SSC operators of the above analysis together with KH, SKH has been developed and the SKH mainframe can be described in Algorithm 2. Here, *NP* is the size of the parent group P.

IV. Simulation Results

In order to illustrate the robustness and performance of SKH, two different case studies have been implemented to solve the problem of ED. The results obtained are compared with the different well-known algorithms presented in the literature. The Metaheuristic algorithm is always based on some random distributions, so it achieves approximately 50 times independent operation to obtain the most representative result. The proposed algorithm is developed and implemented using the MATLAB R2013b, and calculated under Intel (R) Core (TM), 2.40 GHz computers with 8 GB RAM.

A. Results of Case Study 1: 13-Unit System

This medium system comprises 13-generating units with valve-point loading as given in [1]. Therefore, the system has non-convex solution spaces and many local minima as a result of valve-point effects. The detail of the system as shown is gotten from [1]. As shown in Table I, the results of 13-generating units systems were tested for load demand of 2520 MW, and these results are in comparison with other algorithms. The proposed SKH offer a lower cost than SA, GA, GA-SA, PSO-SQP, ACO, HGA, EDSA and KH. From the results given here, we can imply that the suggested algorithm attained a high quality of results in term of the best cost. Accordingly, it has the capacity for reaching the exact solution through a swift balance between global and local search. These results corroborate the applicability of the suggested approach which have the ability to reach the global optimum for the cost function. Fig. 1 presents the SKH convergence; from this figure, the competence of the approach is mainly shown in a rapid convergence with a global solution.

TABLE I
ED Problem for 13-Generating UNITS [Load Demand=2520 MW]

Test System- 1			
ED using SKH		**Comparison with others algorithms**	
Unit No.	Power(MW)	Method	Cost ($/hr)
1	676,6918	SA [10]	24970.9
2	360	GA [10]	24398.2
3	360	GA-SA [10]	24275.7
4	173,61941	EP-SQP [10]	24266.4
5	63,855389	PSO-SQP [10]	24261.0
6	71,653188	UHGA [11]	24172.2
7	170,88848	GA-MU [12]	24170.7
8	109,62423	IGAMU [12]	24169.9
9	163,74404	ACO [13]	241169
10	40	HGA [11]	24169.9
11	102,84287	EDSA [14]	24169.9
12	107,78099	**KH**	**24168.4**
13	119.2996	**SKH**	**24166.5**

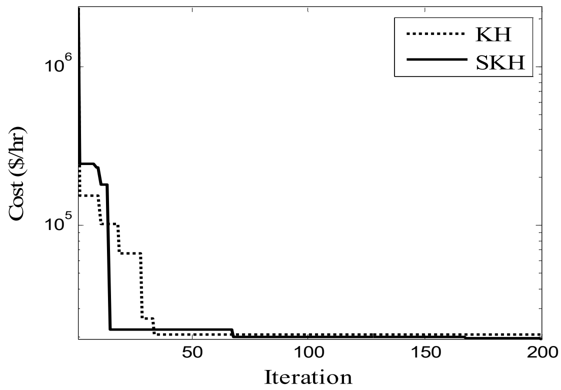

Fig. 1 Convergence characteristics of system 1

B. Results of Case Study 2: 40-Unit System

In this case study, the large test system is considered contain 40-generating units. In this system, because of the VP effect, the cost function is non-convex, and the global minimum value is difficult to determine. The load-effect coefficients of VPs are included in [15]. The system's data is listed in [15]. A 10500 MW Power Demand (PD) is used to solve ED problems. The best results obtained with the suggested algorithm for generation values, including best cost value is 121,412.35 $/hr, given in Table II. Table III illustrates best, mean, worst and computational time values. The minimum generation cost found by SKH is 121,412.35 $/hr, while the mean cost is 121,413.163 $/hr. Depending on these results, it can be stated that KH approach with the integration of SSC can produce feasible and good solutions. The average time of the SKH is 1.244 s, and such a computation time is very reasonable. Fig. 2 shows the convergence characteristics of SKH. From this figure, the capability of the approach is mainly shown in rapid convergence with a global solution.

TABLE II
ED Problem for 40-Generating Units [Load Demand=10500 MW]

Unit	Generation	Unit	Generation
1	110,110995	**21**	550
2	114	**22**	550
3	119,713715	**23**	550
4	187,023563	**24**	550
5	82,1859346	**25**	550
6	81,4774122	**26**	419,855184
7	300	**27**	11,2303944
8	300	**28**	10
9	297,813607	**29**	10
10	136,059592	**30**	97
11	361,427906	**31**	168,825151
12	154,683398	**32**	109,055185
13	125	**33**	177,22634
14	419,649934	**34**	200
15	252,370838	**35**	200
16	312,312144	**36**	200
17	488,051542	**37**	104,600713
18	380,431059	**38**	63,3314487
19	550	**39**	106,563912
20	550	**40**	550
Cost ($/hr)		**121,412.35**	

Results from the tested system prove that SKH given a little possibility to be trapped into local compared with KH. On the other hand, SKH with its solutions for two cases including generators system supplied a best cost than standard optimization algorithm. Thus, test results of the systems consisting of all online generators presents that SKH can be employed to compute the optimization trouble and supply practical outcomes for the mentioned problem, while considering fuel costs. The analyses of outcomes clearly express the assessment of this technique for a useful tool for power grid ED problem. Indeed, KH with SSC operators can seek for a best solution over the entire meaning area better than the basic algorithm.

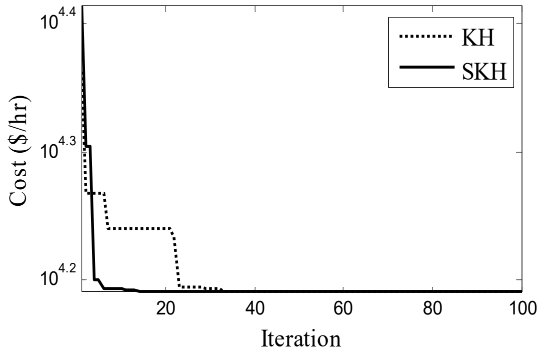

Fig. 2 Convergence characteristics of system 2

TABLE III
COMPARISON OF FUEL COSTS OBTAINED WITH DIFFERENT ALGORITHMS FOR TEST SYSTEM 2

Algorithm	Best fuel cost($/hr)	Mean fuel cost($/hr)	Max. fuel cost($/hr)	Standard deviation	Time (s)
SKH	121,412.35	121,413.163	121,413.564	0.5122	1.244
KH	121,413.26	121,414.357	121,415.874	1.02	1.54
CBA [3]	121,412.5468	121,418.9826	121,436.15	1.611	1.55
SQPSO [16]	121,412.57	121,455.7	121,709.5582	49.8076	47.24
MABC [17]	121,412.5918	121,431.5763	121,493.1885	18.16	1.92 min
DE [18]	121,412.68	121,439.89	121479.63	NA	31.503 s
CSO [19]	121,461.6707	121,936.1926	NA	32	NA
EP-SQP [22]	122,323.97	122,379.63	NA	NA	NA
PSO [20]	121,735.47	122,513.91	123,467.40	NA	NA
BBO [23]	121,426.95	121,508.03	121,688.66	NA	11.74
BF [21]	121,423.63	121,814.94	NA	124.876	NA

V. CONCLUSION

The non-convex ED has been positively solved with VP effects using Stud Krill Herd (SKH) algorithm. This new algorithm is validated on two tested systems with 10-unit and 40-unit system. SKH has been resulted by using the selection and crossover operator (SSC) in the basic KH algorithm. The obtained results were compared with others using a different methods documented in the literature. The proposed method is clearly proved its robustness and applicability for treating the non-convex ED problem with different tested systems.

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