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Model turbine heat rate by fast learning network with tuning based on ameliorated krill herd algorithm

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ABSTRACT

The krill herd (KH) is an innovative biologically-inspired algorithm. To improve the solution quality and to quicken the global convergence speed of KH, an ameliorated krill herd algorithm (A-KH) is proposed to solve the aforementioned problems and test it by classical benchmark functions, which is one of the major contributions of this paper. Compared with other several state-of-art optimization algorithms (biogeography-based optimization, particle swarm optimization, artificial bee colony and krill herd algorithm), A-KH shows better search performance. There is, furthermore, another contribution that the A-KH is adopted to adjust the parameters of the fast learning network (FLN) so as to build the turbine heat rate model of a 600MW supercritical steam and obtain a high-precision prediction model. Experimental results show that, compared with other several turbine heat rate models, the tuned FLN model by A-KH has better regression precision and generalization capability.

1. Introduction

With the rapid growth of energy consumption and the aggravation of environmental pollution, the steam turbine heat rate forecast problem of power plants attracts the attention of technology staffs and researchers. Heat rate refers to the calories required to produce a kilowatt-hour of energy. The steam turbine heat rate is an important economic indicator that reflects the process of energy conversion. During steam turbine operation, the operators aim to ascertain the real-time heat rate value to ensure the economical and safe operation of the steam turbine. So establishing a high-precision prediction model is very important for optimizing and monitoring the operations of power plants, many research works on how to model and forecast the heat rate of stream turbine have been published [1–5] in past ten years. The field calculation of heat rate is typically depended on precise mass and energy balance equations, or thermal performance experiments, which require numerous operation parameters. However, the operating characteristics of steam turbine are unstable, and the related operation parameters often deviate from design conditions, thus affecting the computational accuracy of heat rate.

The krill herd algorithm (KH) [6] is a new and efficient meta-heuristic optimization algorithm based on the herding behavior of krill, which is proposed by Gandomi et al. Like other population-based optimization methods such as biogeography-based optimization (BBO) [7], particle swarm optimization (PSO) [8,9], artificial bee colony (ABC) [10,11], gravitational search algorithm (GSA) [12], and evolutionary optimization (DE) [13,14], the KH algorithm is also a population-based optimization method and used to find the global optimum. In some searches [15,16], the performance of KH has already been compared with the other optimizition methods, such as bat algorithm (BA) [17], genetic algorithm (GA) [18] and harmony search (HS) [19]. The crucial advantage of KH algorithm is its strong diversity, simple operation and less adjustment parameters. In addition, the KH algorithm has been applied to some complex computational problems, such as design of planar steel frames, data clustering and mechanical design et al.

The fast learning network (FLN) [20] is a novel artificial neural network based on the thought of extreme learning machine (ELM), which is a double paralleled forward neural network and owns strong non-linear fitting capability, generalization and fault tolerance ability. In FLN, input weights and hidden layer biases are randomly generated, and the weight values of the connection between the output layer and the input layer and the weight values connecting the output node and the input nodes are analytically determined based on least squares methods.

Regression models and monitoring methods have been proposed to determine the mathematical relationship of the turbine heat rate. Liu et al. [21] proposed a soft computing method based

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on least squares support vector machine (LSSVM) and gravitational search algorithm to forecast turbine heat rate. Zhang et al. [22] provided a new approach for model-based monitoring of turbine heat rate. Chaibakhsh et al. [23] presented a non-linear dynamical model for heat recovery steam generator units. Li Hui [24] proposed a heat rate forecasting method based on the accurate online support vector regression algorithm (AOSVR). The neural network models [25,26] are usually applied in forecasting works. However, the linear processing of related operation parameters will affect heat rate calculation inevitably. In order to overcome above shortcomings, this paper proposes an integrated modeling method based on ameliorated krill herd algorithm (A-KH) and fast learning network (FLN).

In this paper, in order to improve the solution quality and to quicken the global convergence speed of KH, an ameliorated krill herd algorithm called A-KH is proposed. In A-KH, there are four major highlights: First, the opposition-based learning is adopted to initialize the population. Second, the linear decreasing C_t is used to maintain the balance between exploration and exploitation ability. Third, sine map is used to tune the inertia weights (ω_n,ω_f) during the process of the search. Finally, we propose to make three major changes by introducing the best-so-far solution, inertia weight and acceleration coefficients to modify the search process. In order to verify the validity of the proposed meta-heuristic A-KH algorithm, ten famous numerical optimization problems are adopted to test A-KH search performance and compared with other four algorithms (biogeography-based optimization, particle swarm optimization, artificial bee colony and krill herd algorithm). Experiment results show that the A-KH could find the global optimal solutions or the solutions close to the optimal solutions effectively, simultaneously have much faster convergence speed than other four methods on most numerical functions. In addition, the A-KH and other four state-of-art optimization algorithms are also used to adjust the input weights and hidden layer biases of FLN so as to obtain a high-precision prediction model of heat rate for a 600MW supercritical stream turbine. The results show that the A-KH-FLN model has better generalization ability and regression precision. Compared with related studies, the specialty place of this article is that an ameliorated krill herd algorithm is proposed and the results show that the A-KH method has better search performance proved by experiments. Then, the A-KH is adopted to adjust the parameters of the fast learning network (FLN) in order to obtain a high-precision prediction model of heat rate for a 600MW supercritical stream turbine, simulation results show that the A-KH-FLN model can predict turbine heat rate accurately and efficiently. So the A-KH method is suitable for application to optimize problems of various fields.

Specified parts of this paper are organized as follows: Section 2, introduce the summarization of the research work. Ameliorated krill herd algorithm is proposed in Section 3. Section 4, the A-KH is applied to optimize some classical benchmark functions and compared with BBO, PSO, ABC and KH. Section 5, describes the parameter optimization of FLN based A-KH. Finally, concludes the paper.

2. Review of related work

2.1. Krill herd algorithm

The krill herd (KH) algorithm is a new type of meta-heuristic swarm intelligence method for solving optimization tasks. This method is inspired by the herding of krill swarms when searching for the food and communicating each other [27]. The krill individuals include two main goals: (1) increasing krill density, and (2) reaching food. For each krill, the time-dependent position of an individual krill in *two*-dimensional surface is determined by three components described below [28]:

i Movement affected by other krill;
ii Foraging action;
iii Physical diffusion.

Regular KH approach adopted the following Lagrangian model in a D-dimensional decision space.

$$\frac{dX_i}{dt} = N_i + F_i + D_i \tag{1}$$

where N_i, F_i, and D_i are, respectively, the motion induced by other krill individuals, the foraging action, and the physical diffusion of the ith krill individual.

2.1.1. Movement affected by other krill

The direction of the first motion induced, α_i, is estimated from the local effect, target effect, and repulsive effect. For krill i, this movement can be modeled below:

$$N_i = N^{\max}\alpha_i + \omega_n N^{old} \tag{2}$$

where,

$$\alpha_i = \alpha_i^{local} + \alpha_i^{t\arg et} \tag{3}$$

and $N^{\max}$ is the maximum speed, N^{old} is the previous motion,ω_n is the inertia weight in the range [0,1], α_i^{local} and $\alpha_i^{t\arg et}$ are the local effect provided by the neighbors and the target direction effect provided by the best krill individual, respectively. According to the literature [6], we take $N^{\max}$ as $0.01(\mathrm{ms}^{-1})$ in our study.

2.1.2. Foraging motion

The second motion is influenced by the two main factors. One is the previous experience with respect to the food position, and another is the food location. For the ith krill individual, this motion can be provided below [29]:

$$F_i = V_f\beta_i + \omega_f F_i^{old} \tag{4}$$

where,

$$\beta_i = \beta_i^{food} + \beta_i^{best} \tag{5}$$

and, V_f is the foraging speed, F_i^{old} is the previous foraging, ω_f is the inertia weight of the foraging motion between 0 and 1, β_i^{food} and β_i^{best} are the food attraction and the effect of the best fitness, respectively. In our study, we set V_f to 0.02.

2.1.3. Physical diffusion

The third motion is considered to be a random process. This motion can be expressed according to two factor: a random directional vector and a maximum diffusion speed. It can be formulated as follows:

$$D_i = D^{\max}\delta \tag{6}$$

where $D^{\max}$ is the maximum diffusion speed, and $\delta$is the random directional vector in $[-1,1]$.

2.1.4. Motion process of the KH algorithm

The first and second motions include global and local schemes, respectively. These schemes can work simultaneously which makes KH a robust and an efficient method [30]. Using different effective parameters of the motion during the time, the position vector of a krill individual during the interval t to $t+\Delta t$ is given by following equation:

$$X_i(t+\Delta t) = X_i + \Delta t\frac{dX_i}{d_t} \tag{7}$$

It should be noted that Δt is one of the most important constants, because this parameter can be regarded as a scale factor of