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Application of artificial bee colony algorithm to select architecture of a optimal neural network for the prediction of rolling force in hot strip rolling process

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ABSTRACT

In the face of global competition, the requirement for dimensional accuracy, mechanical properties and surface properties has become a major challenge on aluminum manufacturing industries. Conventional rolling force formulas, however, provide not more than reasonably exact approximations. The mathematical modeling of the hot rolling process has long been recognized to be a desirable approach to aid in rolling operating practice and the design of mill equipment to improve productivity and quality. However, many factors make the theoretical analysis of the rolling process very complex and time-consuming. This paper presents a prediction method based on the Artificial Bee Colony algorithm and BP neural network, which was developed in order to improve the prediction of rolling force in hot strip rolling process. The architecture of BP neural network is optimized by Artificial Bee Colony algorithm. Comparing with the Sims mathematical model and BP neural network, the experimental results show that the prediction accuracy and error of rolling force is superior to the other two methods, and the predicted rolling force is very close to the practical rolling force.

Key words: rolling force; neural network; Artificial Bee Colony; mathematic model

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INTRODUCTION

Rolling force is playing a very important role in aluminum tandem hot rolling, which affects the rolling schedule, the thickness and strip shape of the products. Today, market demands are growing increasingly strict for high-quality products in hot rolling. Especially, the requirement for thickness precision is stricter than any other request. Good thickness precision is highly related with good rolling force prediction. However, the close coupling between the thermal, mechanical and material phenomena, the non-linear nature of the hot rolling process, and the multistep nature of optimization make the process difficult to model and solve. Therefore, adopting the traditional mathematical models to predict rolling force is not ideal, thus affects the quality of the products.

In order to improve the prediction of rolling force, a lot of researches have been done in depth. Orowan developed a comprehensive theory based on an extension of the slab method by introducing non-homogeneity of plastic deformation of the sheet and elastic deformation of the rolls [1]. Sims developed analytical expressions of pressure distribution, roll force and roll torque by avoiding most of the numerical integration in Orowan’s theory [2]. Ford and Alexander modified the Orowan’s model using limit analysis technology, and compared the results with the

Sims's ruselts for nonferrous metal [3]. However, due to the complexity of the modern rolling process, pure analytical models often require considerable simplification and assumptions, which inevitably lead to model errors when these assumptions are not satisfied.

In order to solve the defects of the mathematical model, one method is to use the finite element method (FEM) to predict rolling force, which is able to perform complicated calculations under realistic process constraints and various deformation conditions. Another approach is to use neural network to predict the rolling force. Portmann et al. presented an artificial neural network for presetting the rolling force in a temper mill. They tried to solve the network's performance degradation in aberrant points by using multiple networks per domain [4]. Zárate presented a model for the simulation of a cold rolling process based on ANN, which can be written in terms of the sensitivity factors and those can be obtained by differentiating an Artificial Neural Network (ANN) previously trained, reducing the computational time necessary [5]. Lee et al. presented a long-term learning method using neural network to improve the accuracy of rolling force prediction in hot rolling mill. They combined neural network method with the conventional learning algorithm in the pre-calculation stage to reduce the thickness error at the head–end part of the strip [6]. Son and Lee et al. proposed a new genetic algorithm (GA) to select the optimal architecture of the neural network in the hot rolling and compared with that of engineer's experience [7]. Lee and Choi presented an on-line adaptable network for the rolling force set-up and discussed such important matters as neural network structure, input selections, debugging, development environments and test results [8]. Son and Lee et al. presented an on-line learning neural network for both long-term learning and short-term learning was developed in order to improve the prediction of rolling force in hot-rolling mill [9]. Bittencout and Zárate presented an evolutionary mechanism based on GA, which was reinforced with the expert knowledge to find the ideal neurons quantity in the hidden layer of an MLP [10].

In this paper, a prediction method of rolling force based on the Artificial Bee Colony (ABC) algorithm and BP neural network is present, which is used in aluminum hot tandem rolling. The architecture of BP neural network is optimized by ABC. The results show that the new model is very successful in the prediction of rolling force.

ANALYSIS OF CONVENTIONAL MATHEMATIC MODEL OF ROLLING FORCE

Conventional mathematic model of rolling force：Sims's model is recognized as the most suitable for hot rolling, the rolling force model is described by Eq. (1).

$$P = Bl_c' Q_p K_m K_T \tag{1}$$

where P is the rolling force, B is the strip width, l_c' is the roll contact length, K_m is the average yield stress. According to Hill's experimental results,

$$l_c' = \sqrt{R'(H-h)} \tag{2}$$

$$Q_p = 0.786 + \frac{\sqrt{1-\varepsilon}}{2\sqrt{2(2-\varepsilon)}} \frac{l_c'}{h_m} \tag{3}$$

$$K_T = 1 - \frac{m\tau_f + (1-m)\tau_b}{K} \tag{4}$$

$$\varepsilon = \frac{H-h}{H} \tag{5}$$

where H and h are the input and output strip thicknesses, R' is the deformed work roll radius, m is a constant, v_{roll} is Poisson's ratio of the work roll, E_{roll} is Young's modulus of the work roll, R is the work roll radius, τ_f and τ_b are the front and back tension stresses at the stand.

Finally, if the rolling force prediction is given, then the setup of roll gap reference value is determined by Eq. (6).

$$S_d = h - \frac{P}{M} \tag{6}$$

where S_d is the roll gap reference value, h is the desired strip thickness, M is the mill spring constant.

Statistical analysis: The results of conventional mathematic model are analyzed using 1472 samples. The samples were collected from the finishing mills of aluminum tandem hot mill, when commercial pure aluminum (AA1050A) strips with dimension of 35 mm in thickness and 1365 mm in width were rolled in stand 2.

Fig. 1 shows the relationship between the output of current rolling force model and the measured rolling force, where x-axis and y-axis represent the output of rolling force model and the measured rolling force, respectively. The upper and lower lines represent 10% deviation from the centerline. There are 1097 samples outside the two lines, only 25.48% of the samples are in 10% deviation. As shown in Fig. 1, large variations and positive offset values of prediction error clearly show that the rolling-force model has more inherent errors in itself.

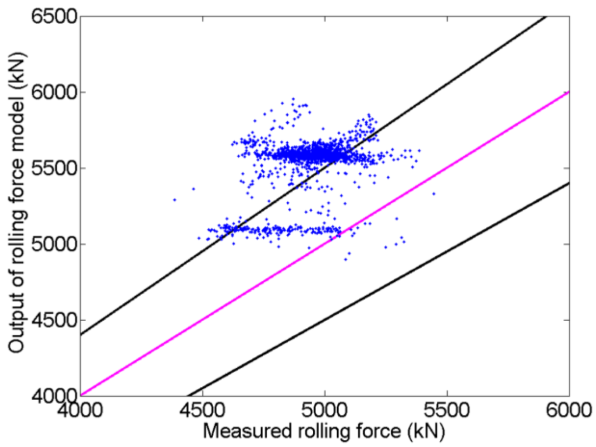

Fig. 1: Relationship between the output of rolling force model and the measured rolling force

ARTIFICIAL BEE COLONY (ABC) ALGORITHM FOR OPTIMIZATION OF ARTIFICIAL NEURAL NETWORK

Back-propagation neural networks (BPNN) for prediction of rolling force: The theory of neural networks is inspired by the structure of the brain and how it processes a huge amount of information [11]. Artificial neural networks are adaptive models that can learn from the data and generalize the things learned. They can be used to build mappings from inputs to outputs, giving information about how the phenomenon behaves in practice. BP neural network consists of an input layer, a number of hidden layers, and an output layer [12]. Each layer is formed by a number of neurons. Each neuron is connected by weights w_k. These weights are adapted during the training process by the back-propagation algorithm.

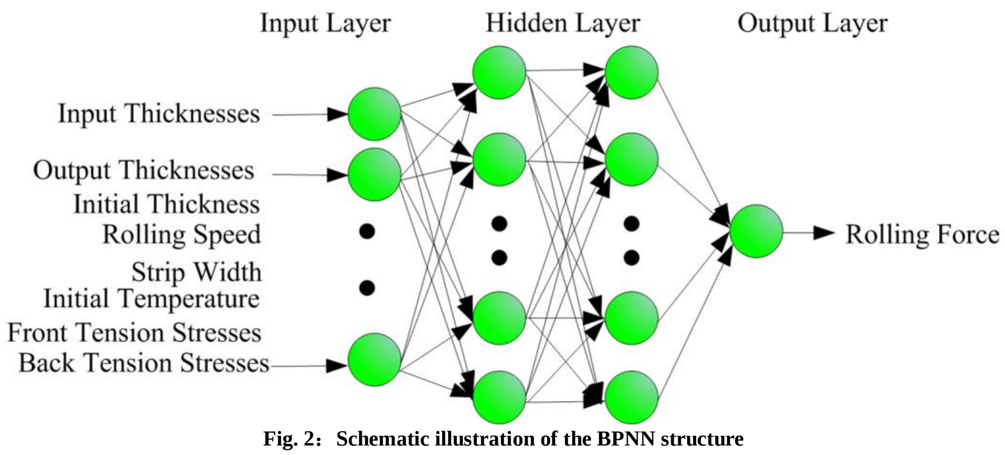

Fig. 2: Schematic illustration of the BPNN structure

In this paper, omitting the parameters which are not important benefits the development of the model, the independent input parameters are selected to be as the input and output thicknesses of strip, the initial thickness of strip, the rolling speed, the strip width, the initial temperature, the front and back tension stresses at the stand. The patterns of the neural network models for rolling force prediction according to the input parameters are shown in Fig. 2.

The expression for the output of each neuron is defined by Eq. (7).

$$y = f[\sum_{k=1}^{n} x_k w_k + b_k] \tag{7}$$

where n is the number of inputs, b_k is the bias of the neuron, x_k is the input value from the preceding layer neuron, w_k is the corresponding weight of each connection and f is the transformation function. The tangential sigmoid transfer function and linear functions are used in the hidden and output layers as the transformation function, respectively [13].

Typically for the conventional BP Training algorithm, the mean square error (MSE) function is used to be minimized.The mean square error (MSE) function is calculated by Eq. (8).

$$MSE = \frac{1}{Q \times K} \times \sum_{q=1}^{Q} \sum_{k=1}^{K} [d_k(q) - o_k(q)]^2 \tag{8}$$

Where Q is the number of samples, d_k and o_k are the desired output and the actual output of the kth output neuron, K is the total number of outputs.

The back-propagation algorithm is most widely used to minimize MSE by adjusting the weights of connection links. In this paper, the Levenverg-Marquardt algorithm is selected because it is the fastest method for training moderate-sized feed forward neural networks.

Principle of Artificial Bee Colony (ABC) Algorithm： The artificial bee colony (ABC) algorithm is inspired by the intelligent foraging behavior of honeybee swarm [14]. As a kind of optimization algorithm, ABC algorithm provides a search process based on population. Artificial bee colony is classified into three categories—employed bees, onlooker bees and scout bees. In ABC algorithm, the position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source represents the quality (fitness) of the solution. The number of the employed bees or the onlooker bees is equal to the number of solutions. The search process is summarized as follows:

Step 1: Generates a randomly distributed initial population P which consists of N_s solutions. Each solution x_i (i={1, 2, ..., N_s}) in P is a D-dimensional vector. D is the number of optimization parameters. Set cycle counter Cycle=0.
Step 2: Calculates the fitness values of each solution.

Step 3: An employed bee produces a new solution in the neighborhood by Eq. (9).

$$v_{ij} = x_{ij} + (x_{ij} - x_{kj}) \times (rand - 0.5) \times 2 \tag{9}$$

where i={1, 2, ..., N_s}, j={1, 2, ..., D}, k is a randomly chosen index form {1, 2, ..., N_s} but equal to I, rand is a uniform random number within [0,1].

Step 3: Calculates the fitness values of the new solution. If the fitness value of the new solution is greater than the old one, then the old solution is replaced by the new solution. Otherwise, the new solution is abandoned.

Step 4: An onlooker bee chooses a solution depending on the probability value P_i. P_i is defined as Eq. (10).

$$P_i = \frac{fit_i}{\sum_{n=1}^{N_s} fit_n} \tag{10}$$

where fit_i is the fitness value of the solution x_i and N_s is the number of solutions.

Step 5: Produces a new solution for the onlooker bee in the neighborhood by Eq. (9), and repeats step 3.

Step 6: Determines the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution by Eq. (11).

$$x_i = x_{\min} + rand \times (x_{\max} - x_{\min}) \tag{11}$$

where x_i is the abandoned source, x_{max} and x_{min} are the maximum and minimum values of population P, rand is a uniform random number within [0,1].

Step 7: Set Cycle= Cycle+1, and go back to step 2, until a termination criterion is met.

Optimizing BPNN with Artificial Bee Colony: The ABC-BPNN algorithm is an optimization algorithm combining the ABC with the BPNN. The objective of the optimization is to maximize the objective function which would lead to the minimization of the total MSE from Eq. (8). As seen in Eq. (7) and Eq. (8), the minimizing process of MSE value is the adjusting and optimizing process of the BPNN structure. Therefore, the ABC is used to optimize the architecture of the BPNN.

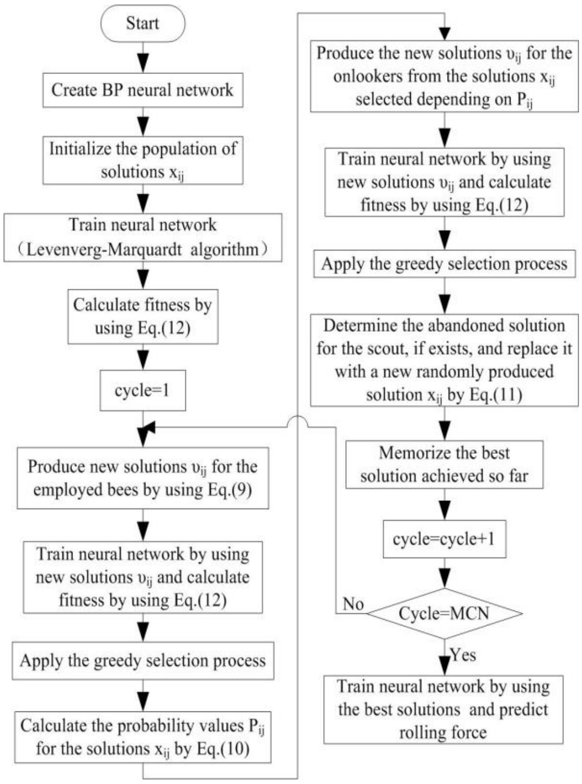

Fig. 3: Flowchart of ABC-BPNN

The steps of the ABC-BPNN algorithm are as follows:

Step 1: Creates a BP neural network.

Step 2: Employs ABC to select architecture of an optimal BP neural network, and trains neural network. The fitness function of the ith training sample is defined by Eq. (12).

$$Fitness(i) = \frac{1}{1 + \sqrt{1/Q \sum_{i=1}^{Q} (F_p(i) - F_m(i))^2}} \tag{12}$$

where Q is the number of the training samples, $F_p(i)$ is the prediction of rolling force with BPNN, $F_m(i)$ is the measured rolling force.

Step 3: Saves the optimal BP neural network.
Step 4: Uses the ABC-BPNN algorithm to predict the rolling force.

The overall programming procedure is carried out as shown in Fig. 3.

Based on using the ABC, the optimal architecture of the BPNN was constructed as 8–14–24–1, representing the number of inputs, neurons in first hidden layers, neurons second hidden layer and outputs, respectively.

APPLICATION OF ABC-BPNN IN HOT ROLLING PROCESS

The simulation performance of the ABC-BPNN model was evaluated on the basis of mean square error (MSE) and the correlation coefficients R. A R value greater than 0.9 indicates a very satisfactory model performance, while a R value in the range of 0.8–0.9 signifies a good performance and value less than 0.8 indicate an unsatisfactory model performance [15].

In order to evaluate the performance of the ABC-BPNN, a BPNN which is selected with engineer's experience in this paper is trained and tested by the same data sets used in the ABC-BP model. The architecture of the BPNN was constructed as 8-17-1, representing the number of inputs, neurons in hidden layers, and outputs, respectively.

Selection and pre-processing of dataset: The training and testing sets are 7500 samples. The samples were collected from the finishing mills of aluminum hot tandem rolling production line during Nov, 2012, when commercial pure aluminum (AA1050A) strips with dimension of 35 mm in thickness and 1365-1393 mm in width were rolled. The 5000 samples are selected randomly for neural network training, the rest of the samples are used for testing.

Before presenting the patterns to the BP network, it is usually necessary to normalize the input and target data so that they can fall into a specified range. All the input and target data are scaled in the range between [-1, 1] using the Eq. (13).

$$x_i = \frac{2(X - X_{\min})}{X_{\max} - X_{\min}} - 1 \qquad (13)$$

where X is the original data, X_{min} is the minimum value of X, X_{max} is the maximum value of X, and X_i is the unified data of the corresponding X.

Simulation results: Table 1 gives the MSE and R values for the two different models of the validation phases. These results show that ABC-BPNN has the capability of avoiding being trapped in local optimums and this is due to the combination of global searching ability of ABC and local searching ability of BP.

Table 1: Comparison between ABC-BPNN and BPNN

	ABC-BPNN	BPNN
MSE	0.00152	0.00510
R	0.9917	0.97187

Fig. 4 shows the relationship between the prediction of rolling force by BP neural network without ABC and the measured rolling force, where x-axis and y-axis represent the prediction of rolling force by BPNN and the measured rolling force, respectively. The black lines represent 10% deviation from the centerline, the green lines represent 3% deviation from the centerline. In 2500 test samples, there are 98.96% of the samples in 10% deviation, and there are 74.96% of the samples in 3% deviation.

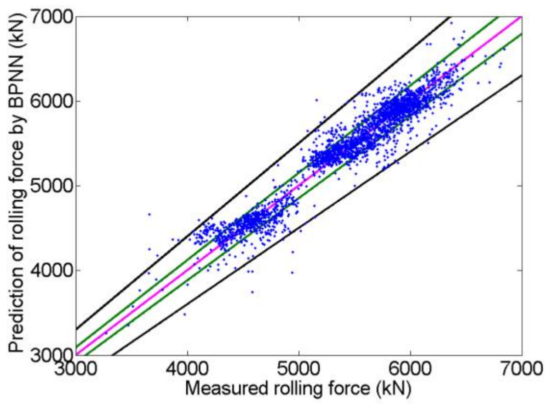

Fig. 4: Relationship between the prediction of rolling force by BPNN and the measured rolling force

Fig. 5 shows the relationship between the prediction of rolling force by ABC-BPNN and the measured rolling force, where x-axis and y-axis represent the prediction of rolling force by ABC-BPNN and the measured rolling force, respectively. In 2500 test samples, there are 99.60% of the samples in 10% deviation, and there are 90.16% of the samples in 3% deviation.

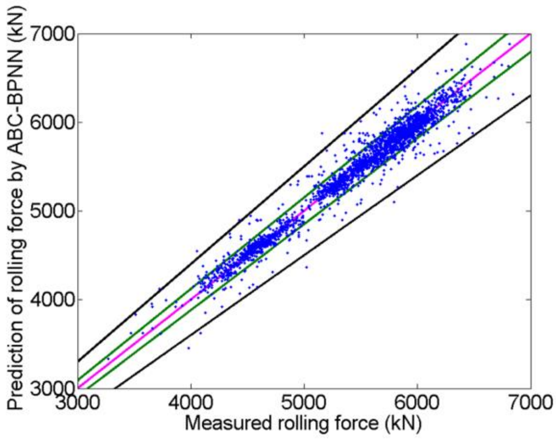

Fig. 5: Relationship between the prediction of rolling force by ABC-BPNN and the measured rolling force

The overall performances of Sims's model (conventional mathematic model), BPNN and ABC-BPNN were evaluated via mean absolute percentage error (MAPE), maximum percentage error (MPE) and the root mean-square error (RMSE). Table 2 gives the MAPE, MPE and RMSE of Sims's model, BPNN and ABC-BPNN.

Table 2: Statistical analysis of the prediction of rolling force by Sims's model, BPNN and ABC-BPNN

	Sims's Model	BPNN	ABC-BPNN
MAPE	11.76%	1.97%	1.17%
MPE	23.26%	23.08%	13.98%
RMSE	608.59kN	156.95kN	86.74kN

Through the above analysis, it can be observed that the performance of ABC-BPNN is much better than Sims's model and BPNN. The prediction of rolling force by ABC-BPNN is more accurate and robust than Sims's model and BPNN.

CONCLUSION

In this paper, an artificial bee colony-BP neural network (ABC-BPNN) is presented, which effectively combines the local searching ability of the gradient decent method and the global searching ability of ABC. The idea of ABC-BPNN is that the architecture of the neural network is selected by an artificial bee colony algorithm and the fitness of the ABC is determined by a neural network. The experiment with real data has showed that the predictive performance of the proposed model is better than that of the traditional BP neural network (BPNN) and Sims's model.

Further work will focus on the on-line adaptation capability due to changes in rolling conditions such as threading, tailing out, and the passing of a weld through the mill, etc.

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