Application research based on Artificial Fish-swarm Neural Network

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Abstract
Sinter tumbler strength is an important parameter in the sintering process, and has an important influence on the performance of finished sinter. Artificial fish swarm algorithm have good ability to acquire the global performance, the neural network has strong nonlinear ability and local optimization performance,; AFSA+BP algorithm combined with artificial fish swarm algorithm and BP algorithm, realizes the complementary artificial fish swarm algorithm global search capability and BP algorithm's local optimization combination of performance, an artificial fish swarm neural results show that the network combination algorithm, it is shown that comparing with the traditional BP neural network forecasting method, the presented forecasting method has better adaptive ability and can give better forecasting results. The artificial fish – swarm algorithm network is trained and checked with the actual production data this algorithm has strong generalization capability, predictive accuracy improved significantly, and speed up the convergence rate, provides an effective method for strength prediction. Which be used for off-line learning and prediction, a good basis for the online application.
Keywords: AFSA, ANN, COMBINATION PREDICTION, TUMBLER STRENGTH

1. Introduction

Artificial fish swarm algorithm (AFSA), proposed by Dr. Li Xiaolei from Shandong University in 2002, is a top-down adaption optimization algorithms enlightened by fish swarm behaviors. According to Dr. Li, this algorithm is applied to the following typical behaviors: foraging behavior, swarm behavior and following behavior. AFSA, as a new efficient adaption optimization algorithm, has the advantages--concurrency, simplicity, quick convergence, high optimization and fast escaping from a local optimum. Later on the basis of AFSA, the survival and competition mechanism were introduced to improve AFSA, making it a more successful swarm intelligence algorithm. Based on the animal autonomous agent, AFSA has both striking advantages and disadvantages. On the one side, it has such merits as high searching efficiency, good robustness, good global convergence, less sensitivity to the initial value and small errors of inversion results. But on the other hand, there exists low optimization accuracy, low convergence speed in the later period and other deficiencies. Artificial neural network is a mathematical model for the brain and its activities as well as a mathematical abstraction formed by the interconnection of a large number of processing units. Besides, it is also a large-scale nonlinear adaptive model. Artificial neural network is featured by high computing power, strong self- learning ability, adaptive capacity, nonlinear mapping ability and good fault tolerance. Therefore, it has been successfully used in pattern recognition, image processing, signal processing, system optimization, intelligent control and many other fields. By applying AFSA to the structure optimization and feature selection of neural networks, this study built stumbler strength optimization model. This model has not only reduced the computation of the system, greatly improved prediction accuracy and convergent speed, but also obviously improved the generalization of the system. As a good result, it has achieved complementary between the global searching ability of AFSA and the local optimization of BP algorithm.

2. Sintering Process

Sintering is a method that makes powdered materials (such as fine ore or preparation concentrate) into block mass under conditions involving incomplete fusion by heating to high temperature. Its production is sinter which is irregular and porous. The following parts are usually included in sintering process: acceptance and storage of iron-containing raw materials, fuel and flux; crushing and screening of raw materials, fuel and flux; batching, mix-granulation, feeding, ignition and sintering of mix material; crushing, screening, cooling and size-stabilization of sinter. The flowchart is shown in Fig. (1).

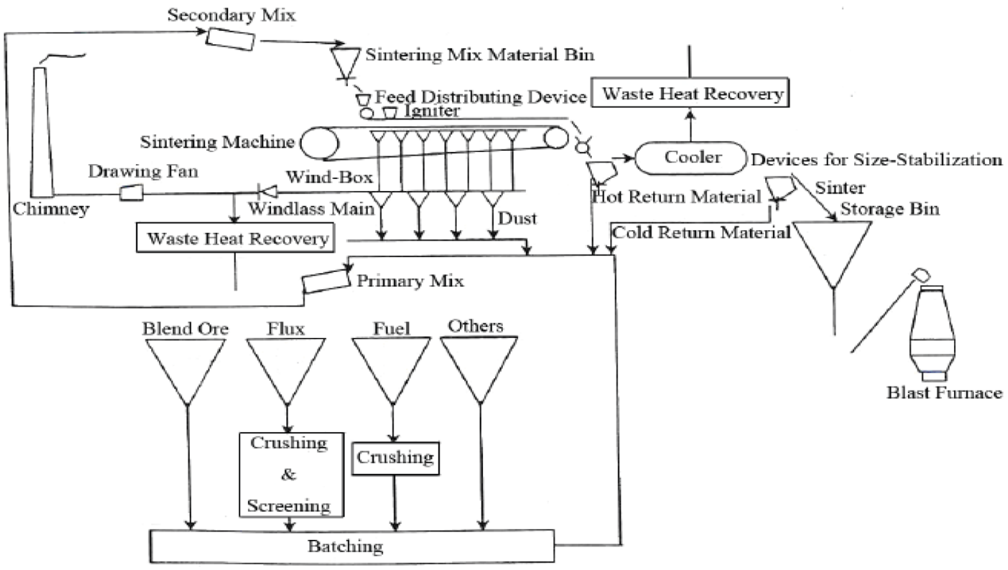

Figure 1. Sintering process

2. Combined Prediction Model for Artificial Neural Network

2.1. Principle of AFSA

Unlike human beings, fish don't have such advanced intelligence as logical reasoning and synthetic judgment capabilities. They achieve or express their aims through the simple act of individual or groups, which can be described as the following four behaviors.

2.1.1. Foraging Behavior

This is the most basic and primitive behavior of artificial fish. Besides, it is a behavior of food tropism for fish, which makes its selections by using the sight or smell to detect the physical qualities or concentration in the water.

Artificial fish searches for food in the water through vision or smell, and swim rapidly toward regions with more food. In the optimization-oriented process, based on its present location, artificial fish searches for more optimal location within visual after finite try-number. If not found, it will perform random walk behavior. Therefore, foraging behavior is the artificial fish's behavior of searching for more optimal location based on its location and capability, specifically, the process of searching for local and individual optimum.

Behavior description: set the current state of artificial fish as Xi, select a state at random as X_i .

$$X_j = X_i + Visual.Rand() \quad (1)$$

where Rand( ) represents a random number between 0 and 1. Then step forward toward that direction

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\left\| X_j - X_i^t \right\|}.Step.Rand() \quad (2)$$

Otherwise, reselect the random state at random to determine whether the condition of going forward is satisfied. If the condition cannot be met after several repeated try-number, it will move forward at random.

$$X_i^{t+1} = X_i^t + Visual.Rand() \quad (3)$$

2.1.2. Swarm Behavior

Fish will naturally gather in groups during swimming, and the artificial fish swam can be viewed as several groups of cluster center. These living habits are formed to ensure the survival of groups and avoid natural hazards. The formation of fish swarm is also a vivid life example. It is generally considered fish does not need a leader. Only if each member of a group follows the local interaction rule, the swarm phenomenon will stand out as a whole model or through individual local interaction. Fish swarm follows three rules: separation rule -- try not to be overcrowding with neighboring partners; alignment rule -- try to match the average direction with neighboring parters; cohesion rule -- try to move toward the center of neighboring partners.

Behavior description: Fish in nature will naturally gather in groups, mainly to protect their groups from dangers and to survive. In AFSA, rules over artificial fish are as follows: 1. To move toward the center of neighboring parters; 2. To Avoid overcrowding.

Set the current side of artificial fish as Xi, search for the number of partners nf within visual (dij≦Visual), and the center location Xc. If $\frac{Y_c}{n_f} \geq \delta Y_i$ it is a demonstration that there are enough food and space in the center of the parters. Then step forward toward the direction of the parters.

$$X_i^{t+1} = X_i^t + \frac{X_c - X_i^t}{\left\|X_c - X_i^t\right\|}.Step.Rand() \tag{4}$$

2.1.3. Rear-end Behavior

During the swimming of the fish swarm, when one or several of them find certain less crowd region with more food, the partners nearby will follow to reach the region. If the artificial fish finds the partner in the optimum location within perception, it will move step forward; otherwise, it will perform foraging behavior.

Rear-end behavior will always accelerate artificial fish to move toward the more optimal position. Rear-end behavior is an interpretation to be quicker, stronger and faster, which ensures the global optimal solution and convergence and rapidity of the algorithm.

Behavioral description: Rear-end behavior is the artificial fish's behavior of following its partner with highest fitness nearby. Optimization algorithm can be understood as the process of moving toward the optimum partner nearby. Set the current state of artificial fish i as Xi, the partner with maximum as Xj within visual(dij≦Visual). If , it shows that there are enough food in the center of Xj which is not crowed. Then step forward toward the direction of Xj.

$$X_i^{t+1} = X_i^t + \frac{X_c - X_i^t}{\left\|X_c - X_i^t\right\|}.Step.Rand() \tag{5}$$

2.1.4 Improved AFSA-jump Behavior

Strictly speaking, the three basic behavior of artificial fish swarm belong to the local optimization process. If the prediction accuracy does not change, it indicates the iterative process has fallen into local extreme. Since there is no point of executing the iteration, it might as well perform jump behavior. This study attempts to add the jump behavior for the reduction of prediction accuracy so as to obtain the iteration process out of the local extreme. This will undoubtedly increase the possibility of reaching global optimization and speed up the convergence speed as well. This seemingly negligible jump behavior can save the artificial fish deep in crisis.

2.1.5. Control Parameter Selections

Despite artificial fish's sensitivity to the initial value, it is still necessary to set control parameters. AFSA parameters include the number of attempts (try-number), sensing range(visual), step (step), the congestion factor(δ) and the number of artificial fish (N). AFSA is tolerant to the range of parameter value and also less strict in the initial value of the algorithms.

In short, the characteristic of artificial fish swarm is each of them will select the optimum orientation after comparing the results of rear-end, swarm and foraging. Rear-end behavior focuses on enhancing the rapidity and global superiority of algorithm convergence, swarm behavior enhances the global superiority of algorithm convergence on the early stage and the stability on the late stage. Yet the foraging behavior is the core and foundation of the whole algorithm, playing a vital role in guaranteeing the speed, stability and convergence of the algorithm and effectively avoiding the algorithm falling into local extremum.

2.2. Principle of BP Neural Network

ANNs are mathematical algorithmic models that imitate the neural network behavior characteristics of animals, and carry out parallel distributed information processing. These networks rely on the complexity of a system by adjusting large numbers of interconnected relationships between nodes for the purpose of processing information.

Among ANN models, the back-propagation (BP) neural network is the most well-known one. The steepest descent method is used as the learning rule of BP networks, with this method, the errors of the output of the BP network are propagated back to adjust the weights of interconnections to minimize the total .error.

BP neural network, short for the error back propagation neural network, consists of one input layer, one or more hidden layers and an output layer. Each layer is composed of a number of neurons. Just like the nerve cells of human beings, these neurons are correlated with each other. The structure is shown in Fig. (2).

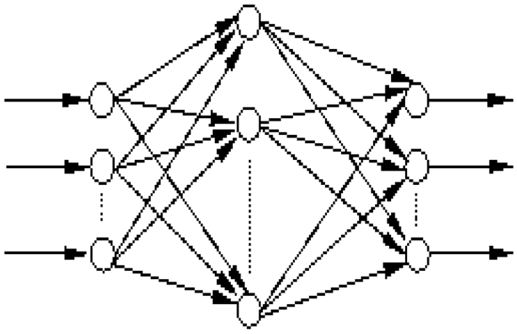

Figure 2. BP neural network Structure

The transmission of biological neuron signals is a complex electrochemical process passed synapse. As for artificial neural networks, this process is simplified and simulated as the continued changes and updates of a set of digital signals through certain learning rules. These digital signals are stockpiled in the weight connection between neurons. The network input layer simulates sensory neurons of the neuron system, receiving the input sample signals. Signals input via the input layer and output from the output layer after the complex calculation in the hidden layer. Make a comparison between the input signal and the expected output, if there exists error, let the error signal counter-propagates from the output layer to the input layer through the process of the hidden layer. In this process, the error is allocated to all unites of each layer via gradient descent algorithm. Then the error signal of each unit can be obtained. Revise the weight of each unit based on the error signal, thus the network weight is redistributed. When this process is finished, the input signal will enter the network again through the input layer to repeat the above process. This adjustment process of positive signal propagation and error back-propagation among weights in each layer will carry out repeatedly, until the network output error is reduced to the acceptable level, or the preset number of learning is reached. The continuous weight adjustment process is just the network's learning process.

3. Application Of Artificial Fish Swarm Neural Network Algorithm

MATLAB is a matrix based mathematical software package developed by Math Works Inc. with excellent computation and visualization abilities. MATLAB operates as a powerful programming language and also has an interactive computational environment. The neural network toolbox is used to develop various neural networks and allows the user to quantitatively and graphically monitor the network training process and analyze the results .

The stability of sinter tumbler strength is a performance index that has been put more emphasis by the enterprise. It is the key to maintain a good run for the entire iron-making system. The existing inspection method and mechanical equipments for sinter tumbler strength detection are too outdated to meet the demand of large-scale production process. Due to equipment problems, the inspection cycle is longer than 12 hours. The serious lag of inspection results has greatly hampered the development of sintering production. In particular, when the production quality is found abnormal, the sinter master-control room can't get the feedback timely, unable to adjust sintering production timely nor guide furnace production. The investigation shows that the majority of domestic enterprises have similar problems. This situation has seriously constrained sintering production and caused non-negligible losses to ironmaking production, which has been a bottleneck for the development of current ironmaking production. Therefore, it is an urgent need for sintering plants in China to develop the prediction model of sinter tumbler strength. Only by approximating or reaching the international advanced level in the same industry soon can these sintering plants create huge economic benefits, reduce unnecessary slag and waste so as to experience high-tech benefits from energy saving.

Sinter tumbler strength is one of the important indicators to evaluate the sinter quality and also the reflection of the sinter's mechanical strength, having a great influence on the technical-economic indicator of blast-furnace process. Therefore sinter tumbler strength prediction is very important. Since the sintering process has such characteristics as long time delay, strong coupling and nonlinear, adopting conventional algorithms is hard to achieve. Even some intelligence algorithms, including neural networks and support vector machine algorithm, have formidable shortcomings. Neural networks have both incomparable advantages and fatal disadvantages. On the one side, neural networks features the capability of high-speed operation, self-learning, self-adaption, nonlinear mapping and error-correction. However, they are also easily trapped into a local minimum and cannot extricate themselves. Besides, their weights and thresholds are hard to identify. These have contained the application of neural networks. The use of support vector machine algorithm to determine kernel function and regularization function is also time-consuming. The application of ASFA to optimize the neural network will greatly improve the global search capability of combination algorithm as well as the local search capability. Furthermore, the generalization and robustness of the algorithm also performs well.

Prediction parameters of ASFA are as follows: population size of artificial swarm is 50, sensing range 0.8, maximum moving step 0.56 and congestion degree factor 3.28. Structure parameters and performance parameters of fish swarm neural networks are: the input layer,10; neurons numbers of the hidden layer, 17; the output layer,1; the structure of artificial fish swarm neural networks as 10 × 17 × 1 similar to the empirical value; initial learning rate is 0.3, which varies dynamically with the further learning in BP networks; the action function slope of the hidden layer is 0.5. Through the optimization design of ASFA, BP neural network further calculates error back propagation for 1000 times. Used as predictive network for data testing, the single sample prediction time is no more than 12 ms. Iterative curve of artificial fish swarm neural network is shown in Fig.(2), and tumbler strength and CaO prediction in Fig.(3).

Fig.(2). shows the training performance of the designed neural network where the goal is set as 0.02. After 24 epochs, the total training error reduces to 0.02.

The squared error at this pattern is defined as

$$e_t(T)=\frac{1}{2}\sum_{k=1}^{24}\left(d_k^T-y_k^T\right), k=1,2,\ldots\ldots,24$$

As shown in Fig.(3)., square error convergence of artificial fish networks ais 3.85, and the prediction value of sinter tumbler strength in Figure3 is fit to the actual values, with only several big absolute errors at the points. These have been enough to meet the demands of sintering production.

4. Prediction with Afsa and BP Neural Neteork Model

Let λ_1 be AFSA prediction value, λ_2 be the prediction value by BP neural nerwork, while λ_c be prediction value by optimal combined model. The prediction errors are η_1, η_2 and η_c respectively. The corresponding weighted coefficients are ω_1, ω_2 and ω_c, and $\omega_1+\omega_2=1$

$$\eta_c=\varpi_1\eta_1+\varpi_2\eta_2 \tag{6}$$

$$\begin{aligned} &Var\left(\eta_c\right)=Var(\omega_1\eta_1+\omega_2\eta_2)=\\ &\omega_1^2Var\left(\eta_1\right)+\omega_2^2Var\left(\eta_2\right)+2\omega_1\omega_2Cov\left(\eta_1,\eta_2\right)\\ &=\omega_1^2Var\left(\eta_1\right)+2(1-\omega_1)^2Var\left(\eta_2\right)\\ &+2\omega_1(1-\omega_1)Cov\left(\eta_1,\eta_2\right) \end{aligned} \tag{7}$$

As to ω_1 , in order to determine the functional minimum value , let

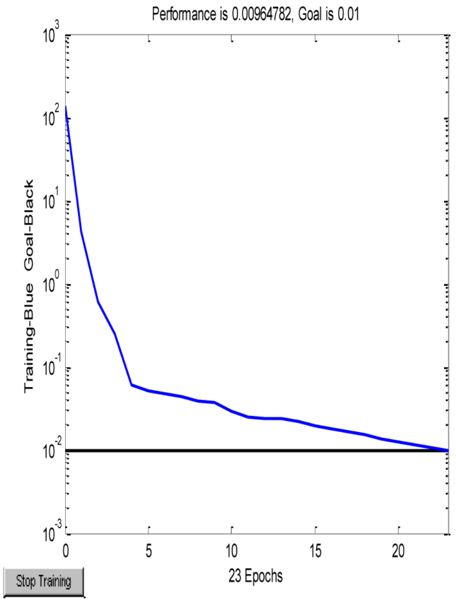

Figure 3. Convergence curve of training error

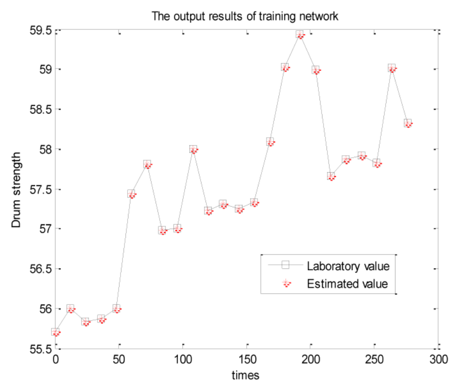

Figure 4. Predicition of sintering Drum strength based on AFSA-BPNN

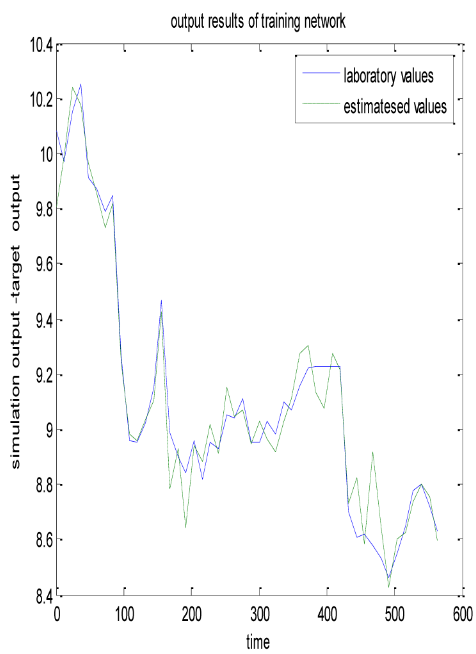

Figure 5. Predicition of sintering CaO based on AFSA-BPNN

$$\frac{\partial Var(\eta_c)}{\partial \omega_1}=0$$

and $\frac{\partial^2 Var(\eta_c)}{2\partial \omega_1^2}=Var(\eta_1)+Var(\eta_2)-2Cov(\eta_1,\eta_2)$

$$\omega_1=\frac{Var(\eta_1)-Cov(\eta_1,\eta_2)}{Var(\eta_1)+Var(\eta_2)-2Cov(\eta_1,\eta_2)},$$

because $Cov(\eta_1,\eta_2)=0$

Let $Var(\eta_1)=\gamma_{11}, Var(\eta_2)=\gamma_{12}$

Then the weighted coefficients of combined prediction are

$$\omega_1=\frac{\gamma_{12}}{\gamma_{11}+\gamma_{12}}, \omega_1=\frac{\gamma_{11}}{\gamma_{11}+\gamma_{12}} \tag{8}$$

5. Conclusions

This study seamlessly combined ASFA with artificial neural networks to build artificial fish swarm neural networks. Through the applied research of sinter tumbler strength prediction, the result shows that this algorithm can not only realize the global optimization, but greatly improve the convergence speed and generalization ability. Specifically, this algorithm is summarized as follows:

Seamless integration of ASFA and BP neural networks. This has accelerated the search process of BP algorithm, ensured the optimal selection of both nodes and action functions of the hidden layer as well as the optimization of network weight and threshold, resulting in complementary combination of ASFA's global searching ability and BP algorithm's local optimization ability.

Application of artificial fish swarm neural networks to sinter tumbler strength prediction. This can not only meet the accuracy requirement of tumbler strength prediction but the demands of a fast convergence speed and online real-time control. With good reliability and operability, this model has provided a scientific and effective method for tumbler strength prediction.

Conflict of Interest

The authors confirm that this article content has no conflict of interest.

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F2N-Rank: Domain Keywords Extraction Algorithm

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Abstract
Domain keywords extraction is very important for information extraction, information retrieval, classification, clustering, topic detection and tracking, and so on. TextRank is a common graph-based algorithm for keywords extraction. For TextRank, only edge weights are taken into account. We proposed a new text ranking formula that takes into account both edge and node weights of words, named F2N-Rank. Experiments show that F2N-Rank clearly outperformed both TextRank and ATF*DF. F2N-Rank has the highest average precision (78.6%), about 16% over TextRank and 29% over ATF*DF in keywords extraction of Tibetan religion.
Keywords: F2N-RANK, TEXTRANK, ATF*DF

1. Introduction

Domain keywords can serve as a highly condensed summary for a domain, and they can be used as labels for a domain. Domain keywords should be ordered by the “importance” of keywords.

In the study of keywords extraction, supervised methods [2-7] always depend on the trained model and the domain it is trained on. And in unsupervised methods [1, 8-11], algorithms based on term frequency and based on graph are the most common methods. Algorithms based on term frequency such as TF, ATF, ATF*DF, ATF*DF are easy to realize but their precisions are not very high. Algorithms based on graph, such as TextRank [1], are more effective than