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# A chaos genetic algorithm for optimizing an artificial neural network of predicting silicon content in hot metal

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**Abstract:** A genetic algorithm based on the nested intervals chaos search (NICGA) has been given. Because the nested intervals chaos search is introduced into the NICGA to initialize the population and to lead the evolution of the population, the NICGA has the advantages of decreasing the population size, enhancing the local search ability, and improving the computational efficiency and optimization precision. In a multi-layer feed forward neural network model for predicting the silicon content in hot metal, the NICGA was used to optimize the connection weights and threshold values of the neural network to improve the prediction precision. The application results show that the precision of predicting the silicon content has been increased.

**Key words:** blast furnace; optimization; chaos genetic algorithm; neural network; silicon content prediction

## 1 Introduction

In blast furnace (BF) ironmaking process, the control of the thermal state of a BF is one of the important factors ensuring the BF stable operation. The silicon content of hot metal is directly related to the BF thermal regime [1,2], so the prediction of the silicon content of BF hot metal is used to estimate the thermal state.

The multi-layer feed forward neural network based on BP learning algorithm is recently emerging as an important tool to predict the silicon content of hot metal in artificial intelligent control of BF ironmaking [3-6], while the BP neural network has the drawbacks of local convergence and spends much time in learning because of the inherent problems of BP learning algorithm [7].

Based on the chaotic properties of ergodicity, stochastic property, and "regularity", chaos optimization is a novel optimization algorithm which is more liable to skip the local minimum by using the chaos variables to search the optimum in the solution space. Compared with the prior chaos optimization algorithms, the nested interval chaos search method avoids the blindness of chaos search and improves ergodicity by taking full advantage of the probability distribution characteristics of Logistic map [8]. In the paper, a genetic algorithm based on the nested intervals chaos search (NICGA) was proposed by introducing the nested intervals chaos search into the genetic algorithm to initialize the population and to lead the evolution of population. Furthermore, the NICGA was utilized to optimize the connection weights and threshold values of the multi-layer feed forward neural network to improve the silicon content prediction precision.

## 2 A genetic algorithm based on the nested intervals chaos search

The optimization problem is described as follows:

$$\min f(X), \quad X=[x_1,x_2,\cdots,x_l], \quad x_i\in[a_i,b_i], \quad i=1,2,\cdots,l \tag{1}$$

### 2.1 Nested intervals chaos search [8]

Logistic map is defined as follows:

$$z_{n+1}=\mu z_n(1-z_n), \; z_n\in(0,1) \tag{2}$$

It is a typical chaotic system and is frequently used in chaos optimization algorithm. When $\mu=4$, Logistic map is in chaotic state.

When Logistic map is in chaotic state, its theoretical probability density can be gained as follows [8]:

$$p(z)=\frac{1}{\pi\sqrt{z(1-z)}} \tag{3}$$

Considering the probability distribution characteristics of Logistic map, $m_i^k$ is selected as an ordinal subset of a number sequence (0.4, 0.3, 0.2, 0.1, 0.05, 0.03, 0.01, 0.005, 0.003, $\cdots$).

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Nested intervals are established as following:

(1) If $[a_i, b_i] \subseteq [-\text{dis}, \text{dis}]$, then there is only one interval in the nested intervals, which is $[a_i, b_i]$.

(2) If $[a_i, b_i] \supset [-\text{dis}, \text{dis}]$, then nested intervals are established as follows.

$$a_i^1 = a_i,\quad b_i^1 = b_i,\quad d_i = b_i - a_i,\quad c_i = \frac{a_i + b_i}{2},$$

$$\begin{aligned} a_i^k &= c_i - m_i^k d_i \\ b_i^k &= c_i + m_i^k d_i, \\ i &= 1,2,\cdots,l,\ k = 2,\cdots,N \end{aligned} \tag{4}$$

Nested intervals:

$$\begin{aligned} &[a_i^1, b_i^1] \supset [a_i^2, b_i^2] \supset \cdots \supset [a_i^k, b_i^k] \\ &\supset \cdots \supset [a_i^N, b_i^N] \end{aligned} \tag{5}$$

Parameters dis, $m_i^k$ are selected according to the size of optimization objects' definition interval. Based on the selection of $m_i^k$, parameter $N$ is determined as:

$$b_i^N - a_i^N \le 2\text{dis} - 0.5 \tag{6}$$

When $\mu = 4$ and equation (2) is endowed with initial numbers as $z_{0,i}$ ($i = 1, 2, \cdots, l$) which have little difference and cannot be fixed points, $l$ chaos variables in different trajectories can be gained as $z_{n,i}$ ($i$=1, 2, $\cdots$, $l$). Nested intervals chaos search will be realized when $z_{n,i}$ ($i$=1, 2, $\cdots$, $l$) are mapped into nested intervals according to the following equation:

$$x_{n,i}^k = a_i^k + (b_i^k - a_i^k) z_{n,i} \tag{7}$$

### 1.2 Genetic algorithm based on the NICGA

The algorithm can be realized through the following eight steps.

Step 1 Determine the fitness function $g(X)$, initialize the parameters: population size $M$, probability of crossover $P_c$.

Step 2 Initialize the population.

The initial population is $\boldsymbol{P}=(\boldsymbol{X}_1, \boldsymbol{X}_2, \cdots, \boldsymbol{X}_M)$, and $\boldsymbol{X}_i$ ($i$=1, 2,$\cdots$, $M$) are sought by chaos search to make the fitness function $g(\boldsymbol{X})$ maximum.

Step 3 Code.

Code the individual of population into binary or decimal genes.

Step 4 Selection.

Select the proper selection operator and perform the selection operation.

Step 5 Crossover.

Select the proper crossover operator and perform the crossover operation on the selected individuals with the probability of crossover $P_c$.

Step 6 Decode the individuals, calculate the fitness of every individual and sort the individual according to the fitness.

Step 7 Mutation operation of the nested intervals chaos search.

On several individuals with maximum fitness, perform the nested intervals chaos search nearby the individuals respectively. If the fitness of new individuals searched is larger than that of old individuals, the old individuals will be replaced by the new ones. Otherwise, reserve the old ones.

Step 8 Judge whether the termination condition is satisfied. If it is satisfied, end. Otherwise, go to step 3.

Declaration of some parameters:

(1) The number of intervals in nested intervals $N$: $N \le 10$ when initializing the population through nested intervals chaos search; $N \le 2$ when leading the evolution of population by nested intervals chaos search.

(2) The length of every chaos variable serial is usually 30.

(3) The probability of crossover is: $P_c$ = 0.5-1.0.

(4) Considering the ergodicity of nested intervals chaos search, the population size $M$ = 20.

## 3 Practical application of NICGA

### 3.1 ANN model for predicting Si content

(1) Structure of the ANN.

A three-layer feed forward neural network is selected, in which the number of input nodes is taken to be the same as the number of state variables that mainly affect the silicon content, and the output node represents the silicon content. The number of hidden nodes can be changed in accordance with the requirement of the prediction precision. **Figure 1** shows the neural network's topology structure.

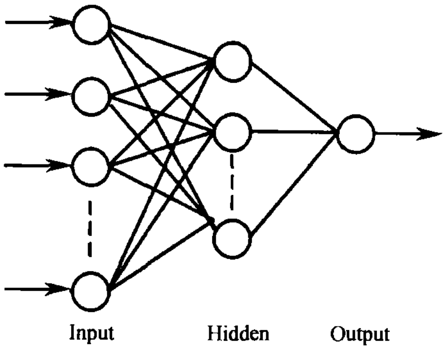


**Figure 1 The ANN structure.**

(2) Input parameters [4, 9].

There are many factors, which have influences on the BF temperature level, including the charging method, hot blast temperature, mass of fuel and so on. According to the correlation degree of the factors with BF thermal state, the following variables is finally selected to predict the silicon content of BF hot metal:

- Hot blast temperature, ℃;
- Hot blast pressure, MPa;
- Blast volume flow rate, $m^3$/min;
- Pulverized coal injection, kg/t;
- Enriched oxygen volume fraction, %;
- Top gas pressure, MPa;
- $CO_2$ volume fraction of top gas, %;
- TFe mass fraction, %;
- Coke rate, kg/t.

### 3.2 The application of NICGA

(1) Fitness function [10].

Let $E$ be the error function of the ANN, then the fitness function is defined as: $g = 1/E$. $E$ is calculated as follows:

$$E=\sum_k (Y_k-\overline{Y}_k)^2 \tag{8}$$

where $Y_k$ and $\overline{Y_k}$ are the predicted and the actual silicon content of the $k$-th sample respectively. $Y_k$ is determined by the following steps:

(a) Assuming that $\{I_l\}_k$ denotes the input of the $k$-th sample, the output of every node of the input layer equals to the input.

(b) The output $U_j$ of the hidden layer is given by

$$U_j=f(\sum_i W_{ij}\cdot I_i-\theta_j) \tag{9}$$

where $\{W_{ij}\}$ represents the connection weight set between the units of the input layer and of the hidden layer, and $\{\theta_j\}$ represents the threshold set of the hidden layer's units.

(c) The final output of the $k$-th sample is as follows:

$$Y_k=f(\sum_j V_j\cdot U_j-\lambda) \tag{10}$$

where $\{U_j\}$ represents the connection weight set between the units of the hidden layer and of the output layer, and $\lambda$ represents the threshold of the output layer's unit.

(d) The above function $f(x)$ is defined as

$$f(x)=\frac{1}{1+e^{-x}} \tag{11}$$

(2) Coding and decoding method.

When the number of hidden nodes is taken to be 8, there are 89 connection weights and threshold values to be optimized by NICGA. In order to prevent the optimized variables' code length from being too long, the decimal coding method is used. One individual of the population is coded as: $d_1d_2d_3\ldots d_{80}d_{81}d_{82}\ldots d_{89}$, where $d_i$ is a plus integer and $d_i\in[0, 9]$.

Accordingly, the decoding method is given as follows:

$W_{ij}=W_{\min}+(W_{\max}-W_{\min})\cdot d_i/10,\quad i=1\text{-}80;$

$V_j=V_{\min}+(V_{\max}-V_{\min})\cdot d_j/10,\quad j=81\text{-}89.$

where $W_{\max}$, $W_{\min}$ and $V_{\max}$, $V_{\min}$ can be obtained from the nested intervals chaos search in the 2-th step of NICGA.

(3) Selection operator.

Considering the ergodicity of nested intervals chaos search, Deterministic Sampling [11] is adopted as GA's selection operator to protect the elitist found by chaos search from destroying by GA's crossover operation.

(4) Crossover and mutation operator.

Select the simple crossover operator, and select the mutation operator of the nested intervals chaos search to improve the mutated individuals' precision, which is more important for optimizing the connection weights and threshold values of the ANN.

### 3.3 Application result

According to the characteristics of the NICGA, the population size is 20, the crossover probability is 0.8, and the mutation probability is 0.25.

After the data were gathered from AnYang Iron and Steel Corporation Ltd. in China in a defined time interval and were preprocessed by certain methods, a total of 200 patterns were represented to be used in optimizing the ANN model. The optimal ANN obtained after 200 generations evolution was tested through another 100 sets of data, and the results of testing are shown in **figure 2**. Assuming that the predicting errors are within ±0.1, the hit ratio is 90%. Compared with references [2], [3] and [10], the prediction precision was improved. The comparison is shown in **table 1**.

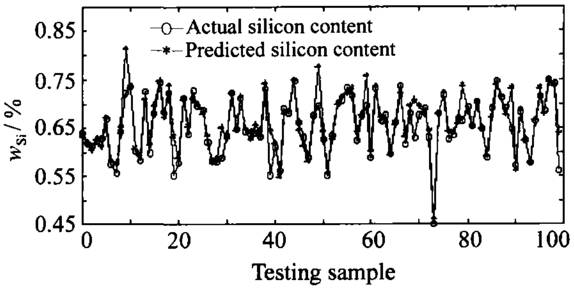


**Figure 2 The silicon mass fraction ($w_{Si}$) comparison between predicted and real data.**

**Table 1 Comparison of the prediction precision**

| This paper | Ref. 2 | Ref. 3 | Ref. 10 |
|---|---|---|---|
| 90% | 87% | 80% | 86% |

## 3 Conclusions

The presented NICGA not only preserves the advantages of genetic algorithm, but also overcomes some disadvantages of genetic algorithm by decreasing the population size, enhancing the local search ability, and improving the optimization variables' precision. When the NICGA is utilized to optimize the connection weights and threshold values of the multilayer feed forward neural network, the local minimum can be skipped. The practical results show that the precision of predicting the silicon content has been increased.

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