Coke Ratio Prediction Based on Immune Particle Swarm Neural Networks

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Abstract: The clonal selection mechanism and vaccination strategy of immune system are introduced into particle swarm optimization algorithm in this paper, in order to enhance the ability of global exploration of PSO, avoiding getting into local optimum and improving the accuracy of BP networks. The global Cauchy mutation operator and local Gauss mutation operator are used to improve the ability of searching global optimization and the accuracy of local optimization. Then the weights and thresholds of neural networks are trained by applying the immune particle swarm optimizer. Finally the coke ratio forecasting model is established based on the modified BP neural networks optimized by immune particle swarm optimizer. The result shows the forecast accuracy is more accurate than both the standard PSO and the traditional BP neural networks, and provides an effective way to reduce the coke ratio and achieve energy conservation and emission reduction for iron and steel enterprise.

Keywords: Coke ratio, immune, neural networks, particle swarm optimizer.

1. INTRODUCTION

Coke ratio is one of the most important criteria in blast furnace ironmaking and make a strong impact on energy consumption. There is a pressing need to reduce fuel consumption for energy conservation and emission reduction, cost reduction and environmental protection. The factors related with coke ratio involved various aspects in the blast furnace. Factors influencing the coke ratio are multitudinous with strong cross-coupling and the inner rules is very hard to master. Therefore, the relation between coke ratio and other parameters has strong nonlinear characteristics. The traditional prediction methods based on the experience or mathematical model would often not achieve anticipated performance. In recent years, applying the modern intelligence computing models to engineering areas is a new research interest in prediction technology.

Fan et al. [1] use the improved neural networks to predict the coke ratio in blast furnace. In [2], Zhou et al. combine the cluster analysis and neural networks model to predict the coke ratio, the results show the new prediction model can enhance the accuracy of the algorithm. Han et al. [3] apply the genetic algorithm to optimize the initial weights of neural networks and then establish forecast model for coke ratio. In [4], particle swarm optimization combined with chaotic local search is used to optimize the initial connection weights of the BP neural network model. Chen et al. [5] use generalized regression neural network to set up the neural network models of iron-making process. In [6], the particle swarm optimization is improved by immunity algorithm through using memory, density mechanism, vaccination and immune selection of IA. Li [7] propose an immune binary particle swarm optimization method to learn Bayesian networks structures. In [8], Sun et al. adopt clonal algorithm combined with the Gauss variation and Cauchy variation to optimize parameters of structure-changed fuzzy neural networks.

This paper lead the clonal selection mechanism and vaccination strategy into particle swarm optimization, set up a predictive model for coke ratio based on immune particle swarm neural networks (CSVS-PSO-BP). The global Cauchy mutation operator and local Gauss mutation operator are used in antibody variation process to improve the ability of searching global optimization and the accuracy of local optimization. Experimental results show that the proposed approach outperforms other compared algorithms on the coke ratio predictive problems.

2. PSO ALGORITHM

In PSO, a particle \( x_i = x_{i1}, x_{i2}, \ldots, x_{iD} \) represent a potential solution to a problem in a \( D \)-dimensional search space. The fitness function predefined decides the merits of a particle. The velocity for particle \( i \) is represented as \( v_i = v_{i1}, v_{i2}, \ldots, v_{iD} \). Every particle keeps a record of the best position that it has ever visited. Such a record is called the particle’s previous best position and denoted by \( p_i = p_{i1}, p_{i2}, \ldots, p_{iD} \). The best particle in the swarm is represented by \( p_g = p_{g1}, p_{g2}, \ldots, p_{gD} \).

In every iteration, the position and velocity of each particle are updated by following two formulas:
$v_{id}^{k+1} = w v_{id}^{k} + c_1 r_1 (p_{id} - x_{id}^k) + c_2 r_2 (p_{gd} - x_{id}^k)$ (1)

$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1}$ (2)

where $i = 1, 2, \cdots, M; d = 1, 2, \cdots, N$, and $M$ is the size of the swarm; $k$ determines the iteration number; $c_1, c_2$ are two positive constants, called cognitive and social parameter respectively; $r_1, r_2$ are two random functions in the range $[0,1]$. $w$ is called inertia weight which coordinate the global and local searching ability of PSO algorithm. Normally, $w$ is reduce gradually with the increase of iteration number.

3. THE IMPROVEMENT THOUGHT OF PSO

3.1. Affinity Calculation

In immune particle swarm algorithm, a particle is thought as antibody, Objective function is regarded as antigen. In iterative process of the algorithm, the clonal selection and mutation of an antibody are carried according to the affinity between antibody and antigen, so as to enhance the global exploration ability of the algorithm. Calculation affinity is as antibody, Objective function is regarded as antigen. In the improved algorithm, the swarm is divided into two sub-swarm by means of average affinity of the whole population.

3.2. Clone the Antibodies

The clonal mechanism of antibody in immune algorithm is used in CSVS-PSO. The antibodies with high concentration and low affinity are inhibited. Conversely, the antibodies with low concentration and high affinity are promoted. In this paper, the two indexes are taken into account to select antibodies. The selective probability $p_i$ of an antibody consist of two parts [6]: $p_i^1$ based on concentration and $p_i^2$ based on affinity. We have:

$p_i = \hat{p}_i^1 + (1-\alpha) p_i^2$

where

$p_i^1 = \frac{aff_i}{\sum_{i=1}^{n} aff_i}$

The antibody concentration is defined as:

$Diversity_i = \frac{1}{\sum_{i=1}^{M} |Fitness_i - Fitness_j|}$

hence,

$p_i^2 = \frac{Diversity_i^{-1}}{\sum_{i=1}^{M} Diversity_i^{-1}}$

Half of particles in each sub-swarm are selected in CSVS-PSO to be cloned according to the selective probability $p_i$.

3.3. Mutation

The idea of immune clonal algorithm is that in each evolution some clonal antibody are generated around candidate solutions according to affinity and concentration, then carry out antibody variation to expand search range of solutions. Two mutation operators are adopted in this paper[8]: global Cauchy mutation operator and local Gauss mutation operator. The global Cauchy mutation operator can search the global optimal solution on a large scale in solution space to get better global search ability. The local Gauss mutation operator can search the global optimal solution with high accuracy to enhance local search ability. The mixed mutation operators can increase search space as well as enhancing the local search capability.

3.2.1. Local Gauss Mutation

The local Gauss mutation is carried out for the antibody whose affinity is above average affinity of swarm so as to perform accurate search around the excellent solution. The formula is as follow:

$x_i' = x_i + \sigma_i N_j (0, 1)$

$\sigma_i = \frac{\sigma_j \exp(\tau'N_j (0, 1) + \tau N_j (0, 1))}{j = 1, 2, \cdots, n, \; i = 1, 2, \cdots, Size}$

3.2.2. Global Cauchy Mutation

The global Cauchy mutation is carried out for the antibody whose affinity is below average affinity of swarm so as to enlarge search space through increasing varying scope of position and effectively prevent local optimization. The formula is as follow:

$x_i' = x_i + \sigma_i C_j (0, 1)$

$\sigma_i = \frac{\sigma_j \exp(\tau'N_j (0, 1) + \tau N_j (0, 1))}{j = 1, 2, \cdots, n, \; i = 1, 2, \cdots, Size}$

$N(0,1)$ denotes a normally distributed one-dimensional random number with mean zero and standard deviation one. $N_j (0,1)$ indicates that the random number is generated anew for each value of $j$. $C_j (0,1)$ denotes a Cauchy random number for each value of $j$ centered at zero with a scale parameter of 1. The factors $\tau = \frac{1}{\sqrt{2\sqrt{n}}}$, $\tau' = \frac{1}{2\sqrt{n}}$.

After two mutation processes implemented in two sub-swarms respectively, we select twenty percent of excellent particles in result set according to the affinity of antibodies and replace ten percent of inferior particles in the original swarm. The essence of the hybrid mutation is to generate a new particle swarm near the promising candidate solution such that the search space is enlarged and the diversity of swarm is enhanced to trapping in local minima. In the meantime, the performance of the improved algorithm could be raised rapidly.
3.4. Vaccination Strategy and Immune Selection

Given an antibody, a vaccination means modifying the genes on a number of bits in harmony with priory knowledge so as to gain better affinity value [9]. In the immune particle swarm algorithm, we make the global optimal solution as the vaccine and the individual with the lowest affinity in swarm as the antibody to be vaccinated.

Supposed the size of genes in vaccine be \( n \), a string including character 0 and 1 with length \( n \) would be generated randomly. If a bit of the string is 1, it means the same bit of the antibody would be vaccinated. Otherwise, the gene-bit remain unchanged.

If the affinity of the antibody vaccinated is smaller than that of the parent, which means degeneration has happened in the evolution process, the parent would replace the current individual in the next generation.

4. THE IMMUNE PARTICLE SWARM OPTIMIZER

This paper introduces the clonal selection and vaccination strategy in artificial immune system to standard particle swarm optimization algorithm and propose an improved particle swarm optimization based on immune mechanism (CSV-S-PSO). The flow diagram of CSV-S-PSO is presented in Fig. (1). We can see from Fig. (1) that the algorithm initialize the population firstly, then calculate the fitness of each particle and obtain the \( pbest \) and \( gbest \) based on this. Subsequently, the next generation population is generated on which the immune clonal selection and vaccination strategy will be carried out. In the first dotted box, the immune clonal selection is inside. All the particles are viewed as antibodies, compute affinity of the antibodies and divide the population to two sub-swarms, clone antibodies according to affinity and concentration and perform two kinds of mutation respectively, finally choose some excellent antibodies to replace the original inferior ones to improve the performance of algorithm. In the second dotted box, part of vectors in global optimum are used as vaccine to plug into the antibodies with low affinity and immune selection is implemented afterward.

The new algorithm can be summarized as follows:

(1) Initialize position and velocity of all the particles randomly in the N dimension space.

(2) Calculate the fitness of all particles and obtain the global optimum position \( Gbest \) and the individual optimum position \( Pbest \).

(3) Generate the next generation \( XC \) according to the formula (1) and (2).

(4) Divide the swarm \( XC \) into two sub-swarms \( X_m \) with higher affinity and \( X_r \) with lower affinity by means of average affinity of the whole population.

(5) Calculate the selection probability of each particle according to both affinity and concentration, retain the better half particles \( X_{mh} \) and \( X_{rh} \).

(6) Perform Local Gauss mutation to \( X_{mh} \) and Global Cauchy mutation to \( X_{rh} \).

(7) Merge the mutation results and select twenty percent of excellent particles in result sets to replace ten percent of inferior particles in the original swarm.

(8) Select part of vectors in global optimum as vaccine randomly to plug into the antibodies with low affinity.

(9) Immune selection: If the affinity of the antibody vaccinated is smaller than that of the parent, the parent would replace the current individual in the next generation.

(10) Calculate the fitness of population and update \( Gbest \) and \( Pbest \).

(11) Repeat Step 3 - 10 until a stop criterion is satisfied or a predefined number of iterations are completed.

5. PREDICTION ALGORITHM BASED ON CSV-S-PSO AND BP

5.1. Neural Network Training

We use the improved PSO based on immune clonal selection strategy to optimize the weights and threshold of BP neural networks. When the neural works is trained, the connection weights between neurons and threshold of BP neural networks are encoded to real number string shown as a particle, \( x_t = (x_{i1}, x_{i2}, \cdots, x_{iL}) \), \( i = 1, 2, \cdots, N \), where
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\[ L = RS + ST + S + T \]

\( R, S \) and \( T \) represent the number of input layer, the number of hidden layer and the number of output layer.

In the executive procedure of algorithm, each particle is decomposed as weights and threshold of neural works and calculate the fitness of particles constantly until a stop criterion is satisfied or a predefined number of iterations are completed. The optimal particle is the training result of weights and threshold in neural works.

The fitness of individual in population is defined as mean square error of the sample data:

\[
\text{fitness}_i = \frac{\sum_{j=1}^{M} (y_{ij} - O_{ij})^2}{M}
\]

where \( M \) is the number of test sample, \( y_{ij} \) is predictive value of the \( i \)-th sample, \( O_{ij} \) is observed value of the \( i \)-th sample.

5.2. The Input Parameters

The coke ratio is affected by many factors with strong cross – coupling. It is difficult to clear and definite some mechanism and numerical relationship among those arguments. This make the relationship between coke ratio and other related arguments strong nonlinear characteristics. In the predictive model, we carefully select nine arguments as input values of neural works combined with data captured in the field and the associated degree with coke ratio. The selected arguments is as follows: coal ratio, air volume, rate of oxygen, hot blast temperature, permeability-index, peak Temperature, grade of feeding into furnace, silicon content, sulfur content. The coke ratio is as the output of neural works.

6. EXPERIMENTAL RESULTS

The iron making data in simulation come from the blast furnace with 3200m³ in a large steel enterprise from April 2012 to September 2012. There are 181 samples in all. The preceding 5 months with 151 samples is used as training samples and the data in September is used as test samples. Because the differences of value exist considerably between various input arguments of neural works, we use normalized treatment to the input variables and the output variables. The network structure is 9-9-1. The initial range of weights and threshold is [-1,1]. In order to test the performance of our
Table 1. Experimental results for different algorithms.

<table>
<thead>
<tr>
<th></th>
<th>Mean Absolute Percentage Error (MAPE)</th>
<th>Mean Absolute Difference (MAD)</th>
<th>Mean Square Error (MSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSVS-PSO-BP</td>
<td>0.0116</td>
<td>3.8167</td>
<td>27.2793</td>
</tr>
<tr>
<td>PSO-BP</td>
<td>0.0125</td>
<td>4.1423</td>
<td>28.9034</td>
</tr>
<tr>
<td>BP</td>
<td>0.0169</td>
<td>5.5494</td>
<td>42.2701</td>
</tr>
</tbody>
</table>

Fig. (4). The predictive result of BP.

The predictive results on the given dataset of CSVS-PSO-BP, PSO-BP and BP are shown in Figs. (2-4). The Mean absolute percentage error (MAPE), Mean absolute difference (MAD), Mean Square error (MSE) of the three predictive models are shown in Table 1. From Figs. (2-4), it can be seen that there are better fitting efficiency for the CSVS-PSO-BP than for the PSO-BP and BP. The results in Table I shows that the improved BP based on immune particle swarm optimization has more predictive precise with MAPE only 1.16 percent than PSO-BP and BP algorithms with MAPE percent 1.25 and percent 1.69 respectively. The results of simulation in the CSVS-PSO-BP predictive model agree well with the experimental data. The model can meet the demands of actual problem and are appropriately applied to predict the coke ratio in furnace.

CONCLUSION

This paper introduces a new form of the particle swarm optimizer through introducing the clonal selection mechanism and vaccination strategy, use it to optimize the performance of BP neural works, finally, set up a predictive model based on CSVS-PSO and BP algorithm for coke ratio. The results obtained show that approach CSVS-PSO-BP gives a better forecast in terms of accuracy for coke prediction in furnace. These works give a method for an in - depth study of energy saving and consumption reducing in producing process for furnace.

CONFLICT OF INTEREST

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

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