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Predicting Mechanical Properties of Hot-Rolling Steel by Using RBF Network Method based on Complex Network Theory

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***Abstract*—Recently, producing high-precision and high-quality steel products becomes the major aim of the large-scale iron and steel enterprises. Because of the internal multiplex components of products and complex changes in the production process, it is too difficult to achieve precise control in hot rolling production process. In this paper, radial basis function neural network is used to complete performance prediction. It has the advantage of fast training and high accuracy, and overcomes shortcomings of BP neural network used previously, such as local minimum. When determining the center of radial basis function we make use of complex network visualization which can clearly figure out the relationship between input vectors and receive the center and width according to the relationship of the nodes.Experiments show that the method that is combining community discovery algorithm and RBF enjoy high stability, small training time which means to be suitable to analysis large-scale data. More importantly, it can reach high accuracy.**

I. Introduction

It has been a very long period of time that hot rolling strip steel production of our country was in a relatively backward stage. However, as the mid-90s of 20th century the major iron and steel enterprises introduced foreign advanced technology and equipment, the hot rolling strip steel production has been entered a rapid development epoch. In order to meet the market needs and enhance competitiveness, major companies are now focusing on producing high-precision and high-quality steel products. Research on steel products property prediction has important practical significance for increasing productivity and pursuing high value added products. According to the research and prediction of steel performance previously, people can adjust the steel components and processing technology to achieve the desired results. This method can both cut production costs and develop customer group targeted. Companies can produce different capability of hot rolling products according to their technology level, funds storage, market position and other factors, with the purpose of meeting the market demand and seeking to maximize their own development.

Since the complexity of the hot rolling products' internal structure and the physical and phase changes occurred in production process, it is even more difficult to have quality control of hot rolling steel production. In the previous research, scholars have used regression to analyze data, established a large number of data models [1]–[3],however, the effect of these data models was not very satisfied because of the complexity of steel manufacturing process, the large quantities of influencing factors besides the non-linear relations between various factors. Simulating the way of human nervous system's information transmission, artificial neural network method was proposed which has shown great advantages for steel production quality control. In recent years, researchers have carried out a large number of experiments using BP neural network method, and obtained certain results in steel performance prediction [4], [5]. Meanwhile, many optimization algorithms have also been proposed, such as the use of pruning algorithm to improve input data [6],the use of Bayesian algorithm to prevent the network "over training" occurring [7],the use of high-dimensional input method to raise network accuracy [8],the use of genetic algorithm to optimize the network weights to avoid local minimum [9],the use of two-stage hybrid algorithm to find the best approximation results [10]. We can notice that, however, BP neural network also has its limitations. It still has not been properly resolved problems such as how to determine the number of hidden layer nodes, what kind of training methods to be used and the long training time.

In this paper, we use radial basis function neural network which can overcome the problem generated in BP neural network for instance of how to select the hidden layer and long training time. In determining the hidden layer we use community discovery algorithm brought from complex network visualization. In line with the similarity between the input data we gain the number of hidden layer nodes and centers, and then paint them. This method solves the problem effectively which is how to select the hidden layer of nodes.

This paper is organized as follows: The second section describes the relevant work. The third section puts forward an advanced RBF model which is combined radial basis function and community discovery algorithm. The forth section shows the experiment results based on actual production data of iron and steel. The fifth section summarizes the work and shows our future work.

II. Related work

In 1985, Powell proposed a multi-variable interpolation Radical Basis Function(RBF) method. Radial basis function neural network developed by Moody and Darken in 1988, and has been proved to be the network which can close

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in any continuous non-linear function with any accuracy. RBF network is a three-layer feed-forward network, including input layer, hidden layer and output layer [11]. Unlike the previous BP neural network, the hidden layer of RBF network is meaningful. We can determine the number and value of hidden layer according to different input sources. The transfer function of hidden layer is RBF, which is a non-negative and non-linear function with the features of radial symmetry and attenuation regarding the center. The data of input layer is directly mapped to the hidden layer without weighted. The mapping relationship is immediately determined when the center of hidden layer determined. This process is non-linear mapping. From hidden layer to output layer is linear, that is, all nodes in the hidden layer reach the output layer after weighted. This process is linear mapping. For the output layer, the method of linear equations calculation can be used to compute weights, thus the learning speed of the network can be greatly accelerate.

There have been different algorithms to improve RBF method, cases of Yingsheng He using improved K-means algorithm to determining the center of RBF [18], Huali Wang using entropy clustering method automatically determining the RBF neural center and initial value [19]. This paper uses community discovery algorithm in complex network to determine the RBF centers and width.

Recently, complex network attracts a lot of attention of scholars [16], [17]. Many of the real world complex systems can be described by the complex network. Hot-rolling product performance prediction is also complex issue. As a powerful tool in studying complicated science and complicated systems, complex network combined with RBF model provides a new perspective for hot-rolling product performance prediction.

Complex network refers to a network with complicated connection relationship, which is composed with the node abstracted by various elements within the system and edges connected under the relationship of elements. This network reflects the topology of the system [15]. The community structure of complex network is an important direction of complex network research, which is defined as: the nodes in the same community are in the close connection, compared with loose connection between nodes in the different communities, which structure is called cluster, cohesive groups or modules. In the view of graph theory, community discovery is just the clustering problem, but it solves some of the traditional clustering problem, such as the number of clusters, the initial center nodes needed to pre-defined. Meanwhile, because it takes into account the complete topology characteristics between the nodes in complex network, clustering accuracy has been greatly improved.

With the advantages of community discovery method gradually emerging, more and more scholars began to carry out research on community discovery. A large number of community discovery algorithms have been proposed,including the clustering algorithm,division algorithm based on clique, division algorithm based on betweenness and similarity, division algorithm based on modularity, division algorithm based on graph, division algorithm based on the core point, information theory method, maximum likelihood method. Among that,fast GN based on modularity is common used currently. The efficiency of the algorithm is the research focus for scholars. In general,each algorithm has its advantages and limitations. What kind of algorithm will be perfect depending on the input data.

III. The combination of radial basis function and the community discovery algorithm

Our paper proposed the algorithm that combines radial basis function and community discovery algorithm. This approach not only guarantees high accuracy but also be able to handle large-scale data and clearly show the clustering results. The main steps as shown in algorithm 1:

Algorithm 1 Mechanical Properties Prediction

Input: Training Data TR and Testing Data TE.
Output: Predict Result PR.

```
Procedure Network building and prediction
    Cluster the data in TR,
    and determine center and width
    by community discovery algorithm ;
    Show the cluster result clearly
    by visualization of complex network
    so that we know the cluster effect ;
    Compute the hidden layer output
    according to RBF formula
    with center and width identified ;
    Compute weight between hidden and output layer
    by linear equations ;
    while (error rate) > (threshold)
        adjust network by gradient descent algorithm ;
    end while
    Predict TE using network built previously ;
    Receive PR ;
end Procedure
```

Just because of the feature of RBF taking node center and width into function, hidden layer nodes are no longer randomly generated, but associated with the input vector.

RBF is defined like:

$$\Phi_k(x_i) = \exp\left(-\frac{\| x_i - c_k \|^2}{2\sigma_k^2}\right), \tag{1}$$

in which x_i represents the i'th input vector, c_k represents the k'th hidden node center,σ_k represents the k'th hidden node width. We can see from the function that the input vector will be responded locally. If the input signal is close to the center of function, the hidden layer nodes will generat a larger output.This way to determine hidden node center and width is able to overcome week points such as local minimum which probability occurring in BP neural network. As a result, each hidden layer node will have an impact on certain number of input vectors.

The linear change between the hidden layer and the output layer is

$$y_j = \sum w_{kj}\Phi_k(x) + a_j, \tag{2}$$

in which y_j represents the j'th output value in output layer,w_{kj} the weight from the k'th hidden node to the j'th output node,$\Phi_k(x)$ the radial basis function values of the k'th hidden node,and a_j offsets.

According to the function definition and network structure, we can summarize that there are three main factors needed when building the network: hidden layer node center c_k, width σ_k and weight w_{kj} between hidden and output layer. Considering the property of network, the process of parameters training can be divided into two steps: first, use community discovery algorithm to determine the center and width of hidden layer, second, use linear equations method to determine weight and adjust by gradient descent algorithm.

A. Community discovery algorithm to determine center and width

Community discovery is a apply environment of complex network visualization. In this paper,make use of Pearson correlation coefficient which is shown as formula(3) to compute the similarity of input data, if the similarity is high between two input data, you can draw an edge between the two data. All the input data can be divided into different communities based on the density of edges. This clustering algorithm gives an effective solution of disadvantages in K-means algorithm which need to pre-determining the number of clustering.

$$r = \frac{\sum_{p=1}^{q}(x_p - \overline{x})((y_p - \overline{y})}{\sqrt{\sum_{p=1}^{q}(x_p - \overline{x})^2 \sum_{p=1}^{q}(y_p - \overline{y})^2}} \tag{3}$$

In our paper, we use the Fast GN algorithm [20] in community discovery which is used popular recently. Fast GN is based on the maximization of the modularity(Q) which was proposed by Newman. It is defined as:

$$Q = \frac{1}{2m}\sum_{ij} A_{ij} - \frac{k_i k_j}{2m}\delta(C_i, C_j), \tag{4}$$

in which A is the adjacency matrix, k_i is the degree of node i,m is the number of link in the network, $\delta(C_i, C_j)$ equals to 1 if node i and j belong to the same community, otherwise it equals to 0.

Fast GN is called a greedy scheme,which optimizes the community partition by optimizing the Q value, and appears perform well. The algorithm is in algorithm 2:

Algorithm 2 Fast GN Algorithm

Input: Graph G with n nodes of the network.
Output: Community Set CS.
Procedure Fast GN
  for every node i $\in$ CS do
    (c_i = i) $\rightarrow$ CS;
  end for
  for each two communities $\in$ CS do
    $\Delta Q = 2(e_{ij} - a_i a_j)$;
    $(c_{new} = c_i + c_j) \rightarrow CS$;
    delete c_i, c_j from CS;
    if size(CS) = 1 break;
    end if
  end for
  maxQ = max(Q);
  find the community set CS
    where Q = maxQ;
end Procedure

First of all, the algorithm divides the n nodes into n independent communities. Then combine the communities which have edges to each other. For a community with n nodes and m edges the time complexity is $O(nm)$. The whole time complexity of the entire community is $O(m^2 n)$. So it is faster than GN and shows good performance.

When the community is set up, the number of community is just the number of hidden layer node. We use the node center measure algorithm and node distance measure algorithm in complex network topologies when measuring the hidden layer center and width.

We use closeness centrality to find center, which defines the reciprocal of total d_{ij} representing the path of node i to other node j in the same community, shown as formula(5). Obviously, the node with larger value of CC_i is more important, defined to be hidden layer center. Additional, we use network diameter to compute hidden layer width, which defined the maximum $\max d_{ij}$ of shortest distance of center node i to other node j in the same community.

The closeness centrality is defined as:

$$CC_i = \frac{1}{\sum_j (d_{ij})}. \tag{5}$$

The research of complex network visualization assists people to tap effective information from complex relationship. A variety of visualization tools have been developed [12].Here, a visualization tool called NeSVA developed by our laboratory is used [21]. It can clearly display evolution process when divides input vectors into communities and shows the result finally.

B. determine the network weight and adjust by gradient descent algorithm

After getting center and width, the input vector can be reached through RBF in hidden layer. The weight between hidden layer and output layer can be determined according to linear equations [13], and then using gradient descent algorithm to reduce error rate [14].When the i'th input vector has trained in the network, the k'th center vector being $c_k(i)$ in hidden layer, the weight between the k'th hidden layer node and the j'th output layer node being $w_{kj}(i)$, then the $(i+1)$'th center vector and the weight are:

$$w_{kj}(i+1) = w_{kj}(i) - lw\frac{\partial E_i}{\partial w_{kj}(i)} \tag{6}$$

$$c_k(i+1) = c_k(i) - lc\frac{\partial E_i}{\partial c_k(i)}, \tag{7}$$

in which lw represents weight learning rate, lc represents center learning rate.Y_i represents the ideal output while y_i the actual after the i'th input vector training in the network.E_i represents the general errors between the ideal output and actual, shown as follows:

$$E_i = \sum (Y_i - y_i)^2/2 \tag{8}$$

From formula(6)(7)(8), we can conclude: the weight and center need to be adjusted each time are:

$$\begin{aligned}\Delta w_{kj} &= w_{kj}(i+1) - w_{kj}(i) = -lw\frac{\partial E_i}{\partial w_{kj}(i)} \\ &= lw \cdot (Y_i - y_i) \cdot \Phi_k(x)\end{aligned} \tag{9}$$

$$\begin{aligned}\Delta c_k &= c_k(i+1) - c_k(i) = -lc\frac{\partial E_i}{\partial c_k(i)} \\ &= lc \cdot \| \sum (Y_j - y_j) w_{kj} \| \cdot \frac{x_i - c_k(i)}{\sigma_k^2} \cdot \Phi_k(x)\end{aligned} \tag{10}$$

According to the adjusted center of hidden layer nodes, we can calculate the width of the new hidden layer nodes, loop this process and we can control the error rate in certain range.

IV. Experiments and results

Our experiment uses the actual product datas from iron and steel enterprises. There are totally 2000 sets of data divided into 1650 to be trained and 350 to be tested. First of all, use community discovery algorithm on training set determines the hidden layer node center and width of RBF neural network. Draw edges on training data and put them into communities due to their similarities. Figure 2 shows the community map.

According to formula(3), we can compute center node, meantime, use Euclidean distance to calculate the maximum value of the minimum path between nodes and center in each community. After that, hidden layer centers and width have been determined. Compute network weight by formula (1)(2), and adjust weight by gradient descent algorithm so as to decrease network error rate, finally, achieve the desired network accuracy.

As seen form figure(2)(3)(4), using the method we proposed, the predict error rates of the three mechanical properties are ±25Mpa for tensile strength, ±20Mpa for yield strength and ±3% for elongation rate, which are all in the error rate limits. Moreover, the training total time and frequency are much far less than the BP neural network algorithm and the way of using K-means algorithm to determine center and width.

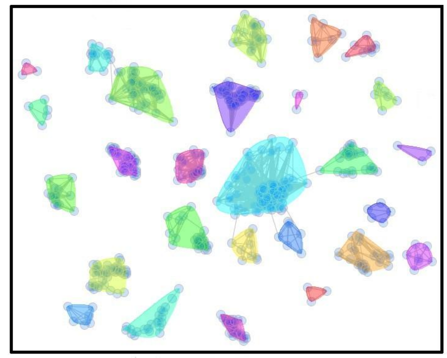

Fig. 1. The Community Diagram

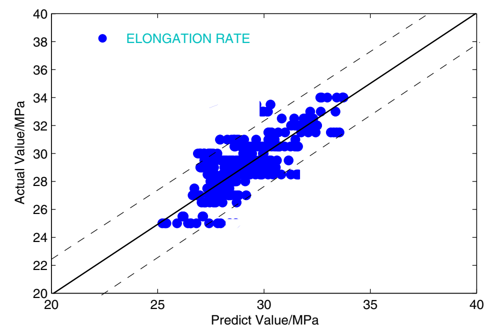

Fig. 2. The Predict Diagram of Elongation Rate

Table 1 shows comparison of training time and frequency between three methods. Method 1 represents combination of community discovery algorithm and RBF. Method 2 represents combination of K-means and RBF. Method 3 represents BP neural network.So are they in table 2.

From table 1 we know that our method need less training time of all since the community discovery algorithm assists us to find the hidden layer properly. Unlike K-means algorithm,

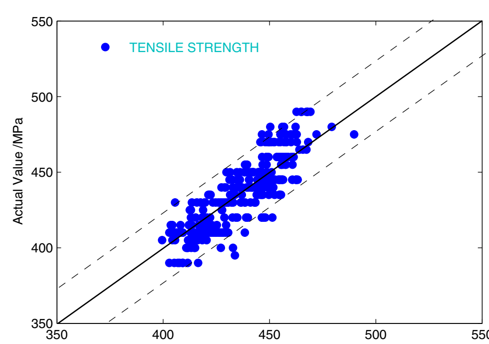

Fig. 3. The Predict Diagram of Tensile Strength

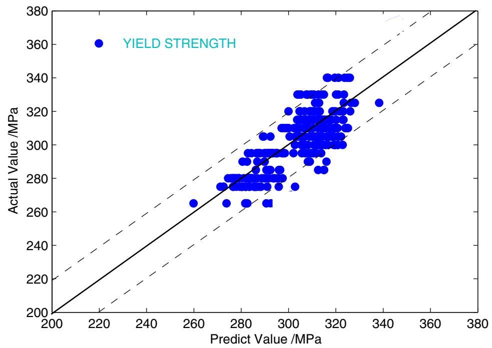

Fig. 4. The Predict Diagram of Yield Strength

we need not consider the initial number of hidden layer nodes. So this method can both raise speed and ensure high precision. As shown at table 2, error rate means the rate of the data which the error rate between true value and predict value is smaller than 0.05 in test data set.

TABLE I
COMPARISON OF TRAINING TIME AND FREQUENCY

Method	Training Time (M)	Frequency(Times)
1	15	20
2	30	100
3	60	10000

TABLE II
COMPARISON OF ERROR RATE

Method	1	2	3
Tensile Strength	93.2%	87.3%	85.6%
Yield Strength	86.7%	82.9%	82.7%
Elongation rate	80.3%	76.4%	75.3%

V. CONCLUSION

According to the theoretical and experimental analysis, we conclude that the use of RBF neural network to model and analysis the element and production process data of hot rolling steel can obtain a good accuracy, high stability, as well as shorter training time. Meanwhile, it is worth concerning that the different impact of the input value has been ignored by Pearson correlation coefficient. Because of that, some input vectors have great correlation, but have great different outputs. This is the most important reason for predict error. How to achieve determining the correlation according to different impact will be the next focus. In addition, considering that the clustering speed can be linear by community discovery algorithm, this method is suitable for large-scale data. We will take experiment on large-scale data sets and guide reality hot rolling production process in the future.

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