The Influence of Chemical Element on Properties of Deformed Steel Bar

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Abstract

The composition optimization schemecan of chemical element guarantee the performance of the deformed steel bar and control the production cost effectively. we use SPSS to draw the boxplot, and remove the abnormal data after analyzing image. Later, in order to analyze the main factors, secondary factors that influence properties of deformed steel bar, this paper mainly use factor analysis method. Next, we use the correlation coefficient method to analyze the correlation between the factors based on the results of the last step. In the same way, the correlation between the influencing factors of other performance indexes can be obtained. Then we found that the main and minor elements which influence various performances are not the same through the analysis of the problem. Therefore, we respectively establish the BP neural network model for the performance indexes of the three kinds of steel bars. We first use some data to test the model, and then we get the change curve that different element on the performance of the steel bar by control variable method. Finally, we analyze the results and know the influence rule between deformed steel bar properties and chemical elements.

Keywords

Factor Analysis, BP Neural Network Model, Improved Simulated Annealing Algorithm.

1. Introduction

Steel is a general designation of iron carbon alloy, which is between 2.06% and 0.02% mass percent of carbon content. Some researchers and manufacturers have put forward the content of residual elements in the steel, the removal of these residual harmful elements of the smelting process is also in the research and development[1].Xuan Wang Study found that different impurity elements have different effects on reinforcement, and analyzed their harmful effects[2].Yanwei Bao study shows that Mo, V and Nb elements can improve the yield strength, tensile strength and elongation of refractory steel[3].At home and abroad, the factors affecting the energy consumption of iron and steel enterprises are many, but it still needs to be systematic. Although there are a lot of research on the performance of the steel bar, but no comprehensive analysis of all the steel, it cannot directly reflect the relationship between the elements and properties of steel.

2. Data Processing

Statistical data may have quality problems. This problem is essentially an error problem, that is, the gap between the statistical data and the actual number of objective phenomena. We deal separately with the product 1, product 2 data. As the premise of the box line does not require normal distribution, the use of SPSS software to draw the box line diagram, analysis and removal of abnormal data. Box line diagram (Boxplot) is the use of the data in the five statistics: the smallest, the first four points, the median, the first three or four points and the maximum value to describe a method of data. It is true and intuitive to show the original features of the data shape; on the other hand, the box line chart to determine the standard value of the abnormal value of four points and four points distance based. According to the product 1, product 2 carbon content of the original data to draw the box line diagram, as shown in Figure 1

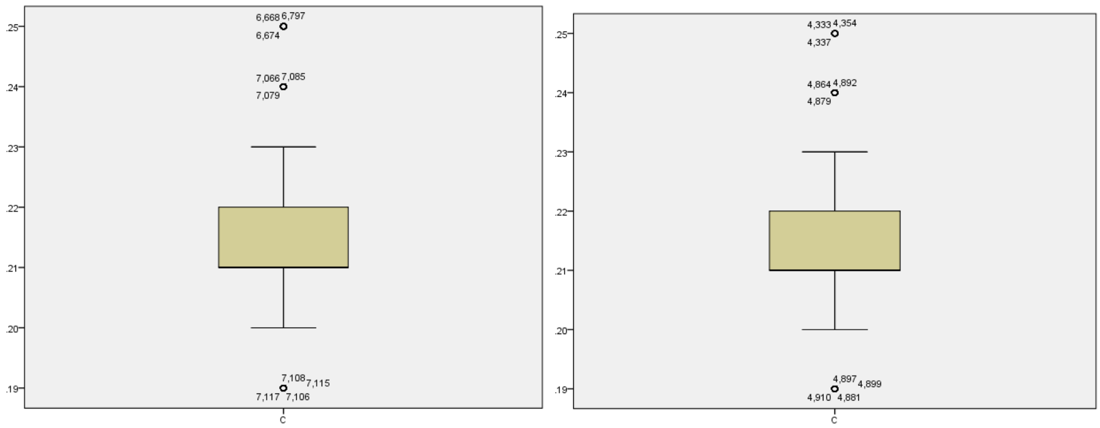

Fig.1 Distribution of carbon content in box

Can be seen from Figure 1, the product 1, product 2 carbon element content percentage has 10 data anomalies, while the other data excluding the line of the 20 data. Mn, S, strength yield, elongation after fracture percentage and other data with the same method to remove the abnormal data, in the end, we get a reasonable data set, so that after the work.

3. Factor Analysis

In order to analyze the main factors that affect the performance of deformed steel bars, such as yield strength, tensile strength and elongation at break, this paper mainly uses factor analysis method to analyze the main factors. Factor analysis is one of the commonly used multivariate statistical methods in multi index comprehensive evaluation. The basic idea is to transform a number of observation indicators into a few independent new indicators through the dimension reduction process.

Let $X'=(X_1,X_2,...,X_p)$ be a random vector of $P\times 1$, and its mean vector is $\mu'=(\mu_1,\mu_2,...,\mu_p)$ Co-variance matrix of X

$$Cov(X)=\sum \tag{1}$$

$F'=(F_1,F_2,...,F_m)$ is the standardization of the orthogonal common factor vector $m\times l$, that is, the assumption that $(m<p)$

$$E(F)=0 \quad Cov(F)=1 \tag{2}$$

It is a special factor (or error) vector of $\varepsilon'=(\varepsilon_1,\varepsilon_2,...,\varepsilon_p)$, and its mean is zero, and the co-variance matrix is diagonal matrix (which is the correlation between each $P\times 1$), $E(\varepsilon)=0$

$$Cov(\varepsilon) = \psi = diag(\psi_1, \psi_2, ..., \psi_p) = \begin{pmatrix} \psi_1 & & & \\ & \psi_2 & & 0 \\ 0 & & \ddots & \\ & & & \psi_p \end{pmatrix} \tag{3}$$

And it is assumed that the common factor $F_1, F_2, ..., F_m$ is not correlated with each other special factor $\varepsilon_1, \varepsilon_2, ..., \varepsilon_p$ (or F and ε)

$$Cov(\varepsilon, F) = 0 \tag{4}$$

Under the above assumptions, the orthogonal factor model can be written in the following matrix

$$\begin{array}{ccccccc} X & = & \mu & + & AF & + & \varepsilon \\ (p\times 1) & & (p\times 1) & & (p\times m)(p\times 1) & & (p\times 1) \end{array} \tag{5}$$

Factor analysis model can be written in detail:

$$\begin{aligned} X_1 &= \mu_1 + a_{11}F_1 + a_{12}F_2 + \ldots + a_{1m}F_m + \varepsilon_1 \\ X_2 &= \mu_2 + a_{21}F_1 + a_{22}F_2 + \ldots + a_{2m}F_m + \varepsilon_2 \\ &\vdots \\ X_p &= \mu_p + a_{p1}F_1 + a_{p2}F_2 + \ldots + a_{pm}F_m + \varepsilon_p \end{aligned} \tag{6}$$

Among them, the matrix $A = (a_{ij})$ is called the factor load matrix, A is the $p\times m$ matrix $(m < p)$ as follows

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1j} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2j} & & a_{2m} \\ \vdots & \vdots & & \vdots & & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{ij} & \cdots & a_{im} \\ \vdots & \vdots & & \vdots & & \vdots \\ a_{p1} & a_{p2} & \cdots & a_{pj} & \cdots & a_{pm} \end{pmatrix} \tag{7}$$

The load on any element of a_{ij}, A, indicates that the first i variable is the load on the first X_i factor j, and is the co-variance of the first F_j variable with the i common factor X_i, that is

$$Cov(X_i, F_j) = a_{ij} \tag{8}$$

If the observed variable X_i is also a standard variable, then the a_{ij} is the correlation coefficient between X_i and F_j, which indicates the close relationship between X_i and F_j.The factor load factor of the i line $a_{i1}, a_{i2}, ..., a_{im}$ shows that the first i variable X_i depends on the degree of each factor, and the factor load of the j column shows the relationship between the first j factor F_j and each variable.

4. Correlation Analysis Between Factors

To measure the degree of linear correlation between things or variables, and to use appropriate statistical indicators, the process is related to the analysis[4]. We use Pearson correlation coefficient method. Among them, the correlation coefficient formula is

$$r=\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{9}$$

r is correlation coefficient, $\bar{x}$、$\bar{y}$ is the average of x、y , x_i、y_i are variable x、y of the first i observation.

Use SPSS software to draw the relationship between the factors that affect the tensile properties, such as table1

Table 1. The relationship coefficient between the factors of tensile properties

1	Specification 1					Specification 2				
	C	MN	Ceq	V	Cr	C	MN	Ceq	V	Cr
C	.236**	.871**	.144**	.068**	.065**	1	.194**	.863**	.136**	.057**
MN	.236**	1	.632**	.241**	.000	.194**	1	.611**	.248**	-.002
Ceq	.871**	.632**	1	.234**	.157**	.863**	.611**	1	.232**	.149**
V	.144**	.241**	.234**	1	-.051**	.136**	.248**	.232**	1	-.109**
Cr	.068**	.000	.157**	-.051**	1	.057**	-.002	.149**	-.109**	1

From the table shows that the relationship between the main factors of the tensile properties of the product 1, MN and C are significantly positively correlated, and Ceq is also a positive correlation. Product 2, C and Ceq into a significant positive correlation, and MN also has a positive correlation. In the same way, it is concluded that the relationship between the main factors which affect the performance of the resistance is like table2.

Table 2. The relationship coefficient between the factors of resistance and yield

2	Specification 1					Specification 2				
	Mn	Si	Cu	P	V	Mn	Si	Cu	P	V
Mn	1	.438**	-.112**	.154**	.241**	1	.417**	.611**	.248**	-.002
Si	.438**	1	-.401**	-.127**	.144**	.417**	1	.187**	.194**	-.336**
Cu	-.112**	-.401**	1	.029*	-.072**	.611**	.187**	1	.232**	.149**
P	.154**	-.127**	.029*	1	.041**	.248**	.194**	.232**	1	-.109**
V	.241**	.144**	-.072**	.041**	1	-.002	-.336**	.149**	-.109**	1

From the table we can see that the relationship between the product 1 resistance to yield performance, Si and Mn into a positive correlation, and Cu into a negative correlation, therefore, Si and Cu negative correlation. Product 2, Mn and Si, Cu are all positive correlation.The results of the relationship between the main factors affecting the tensile properties are as the main factors

Table 3. The relationship coefficient between the factors of the tensile property

3	Specification 1						Specification 2				
	C	MN	Cr	Ni	CU		MN	S	P	Cr	Ni
C	1	.236**	.068**	-.036**	.065**	Mn	1	-.097**	.166**	-.002	.046**
Mn	.236**	1	.000	.065**	-.112**	S	-.097**	1	.029*	-.095**	-.093**
Cr	.068**	.000	1	.577**	.461**	P	.166**	.029*	1	.186**	.076**
Ni	-.036**	.065**	.577**	1	.119**	Cr	-.002	-.095**	.186**	1	.545**
Cu	.065**	-.112**	.461**	.119**	1	Ni	.046**	-.093**	.076**	.545**	1

From the knowledge, the relationship between the factors of the product 1 anti extension performance, Ni,Cu, Cr is positively correlated with each other, Mo and they are negatively correlated. Product 2, N,Cu,Cr is also related to each other, S and Ni Cr positive correlation, but negatively correlated with Cu.

5. Performance Prediction Model of Steel Bar Based on BP Neural Network

5.1 A Brief Introduction to the BP Neural Network

At present, the development of many mature theories and methods can predict the performance of steel materials, such as dislocation theory, regression analysis and so on. But these theories and methods have certain limitations, and the artificial neural network model is currently popular especially suitable for nonlinear system, we apply in the tensile properties of steel materials, anti-bending performance, tensile properties prediction[5].

BP neural network is the abbreviation of error back propagation neural network. It consists of an input layer, one or more hidden layers and one output layer, each time is composed of a certain number of neurons. These neurons, like people's nerve cells, are related to each other. Its structure as shown in figure:

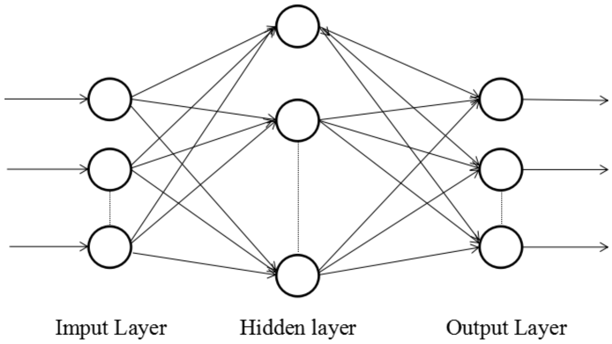

Fig.2 BP neural network model

5.2 The Establishment of BP Neural Network

5.2.1 Input and Output Samples

The first question through factor analysis, we have learned that the major and minor elements affecting the performance and the influence of different performance index elements vary greatly, so we in the primary and secondary factors as the input, the performance index as the output samples, respectively on the criterions of network building and training.

5.2.2 The Number of Nodes in the Hidden Layer

There is no clear theoretical basis for setting the number of nodes in the hidden layer, and the empirical formula is generally based on the empirical formula:

$l = \sqrt{m+n} + a$ or $l = \sqrt{0.43mn + 0.12n^2 + 2.54m + 0.77n + 0.35 + 0.51}$

Among them, m 、 n are the number of input nodes and the number of output nodes; a is the constant between C and 1~10.

5.2.3 Other Parameter Settings

Other parameters we follow the general rules set to:

Learning rate is 0.05,Maximum training times is 10000,Mean square error is 0.65*10^-3.

5.2.4 The Establishment of the Network

We establish a network to tensile strength specifications just in case: first, the data were randomly divided into 1:4, four of which were used to train the network, a network to verify the feasibility, then the data into MATALB and call the premnmx function to normalize the data, according to the empirical formula calculated the number of hidden nodes is 6. Call function newff to establish the network and training.

5.3 Network Feasibility Test

By using the network in front of the remaining data to predict and compare with the true value, draw:

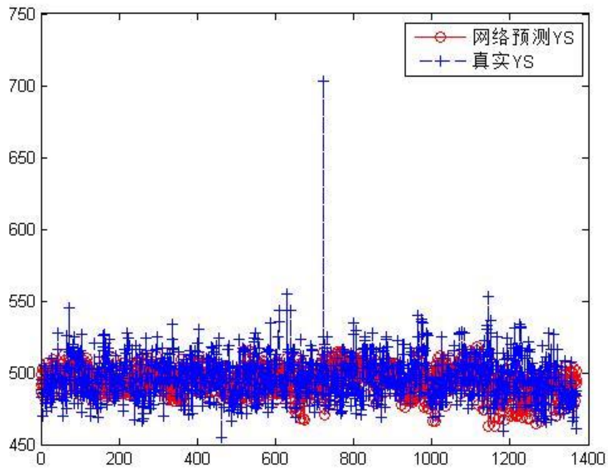

Fig.3 Test chart

The feasibility of the network is found to be higher, which can be used to predict the performance of steel bars.

6. Conclusion

The main and minor elements which influence various performances are not the same through the analysis of the problem. Therefore, we respectively establish the BP neural network model for the performance indexes of the three kinds of steel bars. We first use some data to test the model, and then we get the change curve that different element on the performance of the steel bar by control variable method. Finally, we analyze the results and know the influence rule between deformed steel bar properties and chemical elements.

References

[1] Shen Deng.Influence and control of residual elements on the quality of steel[J].Liuzhou Iron and Steel Technology,2016,02:10-15.

[2] Xuan Wang,Xueping Tang,Jieming Yang,Min Lei.Characteristics and influence of main impurity elements in steel[J].Special Steel Technology,2011,01:13-15.

[3] Yanwei Bao.Effects of V and Nb elements on Microstructure and mechanical properties of steelreinforced concrete structures[J].Foundry Engieering,2015,06:1376-1379.

[4] Qinghua Ma,Yonghong Li,Lisong Liang,Qin Li,Hai Wang,Yuanfeng Xu,YuboSun,Guixi Wang.Factor analysis and comprehensive evaluation on fruit quality of Winter jujube fine plant[J]. Chinese Agricultural Science,2010,12:2491-2499.

[5] Chunyan Wei,Xiaolin Lang.Application of MATLAB in mathematical modeling[M].Publishing Company of Beijing University of Aeronautics and Astronautics, 2007.