Team Number:	0001

Problem Chosen:	B

The Influence of Chemical Element on Properties of Deformed Steel Bar

Abstract

What this paper studied is the problem of the influence of chemical element on properties of deformed steel bar. By developing the model of ***Optimal Properties Function*** *that is based on* ***factor analysis****,* ***gray relational analysis*** *and* ***Principal component analysis****, meanwhile the major chemical element and main mechanical performance index under different specifications, with which the issue of composition optimization scheme subsequent is reasonable solved on particular situations.*

Concerning the first issue, the data have been pretreated firstly by removing unreasonable data, through analyzing the data in lateral qualitative analysis, we can arrive at the significant difference of the chemical element between mechanical performance index by using ***One-way ANOVA****, and subsequently analyzing the data whether it exists significant difference among itself by using* ***LSD Multiple Comparison*** *in longitudinal quantitative analysis, and then estimating the correlativity by applying* ***Pearson Correlation Test*** *and* ***Polynomial Curve****. Finally, at a later* ***Factor Analysis****, the main factor and secondary factor are analyzed. Otherwise, positively correlated relationship between the former, they showed a negative correlation relationship with the latter.*

Concerning the second issue, analysis of five main elements C, Mn, S, Si, P firstly by using ***principal component analysis****, which subsequently the data of main chemical element are fitted through model of* ***Average Interval Polynomial Fitting****, and then it is concluded that element size and regularity of influence on the performance by using* ***Slope grey relational analysis*** *model. To tensile strength, the influence of the element is C>Mn>Si>P>S; To yield strength, C>Si>Mn>S>P; To percentage elongation after fracture, P>S>Mn>C>Si.*

Concerning the third issue, in order to draw between each element content and quantitative relationship between the performance index, through ***Stepwise Regression*** *to build the performance optimization function firstly, and then established in element content, price, cost as constraint conditions, to the best performance as the objective function of* ***Optimal Properties Function*** *model, and subsequently by using the* ***Lingo*** *software to calculate the content of each element of the optimal ratio and fixed interval.*

Finally, we validated our model using tests for rigor in both robustness and sensitivity.

Key words: *One-way ANOVA, LSD Multiple Comparison, Pearson Correlation Test, Factor Analysis, Slope grey relational analysis, Stepwise Regression*

Contents

1 Introduction

1.1 Problem Description

Hot-rolled ribbed bar is commonly known as deformed steel bar, its mainly used for skeleton of reinforced concrete component and it requires certain mechanical strength, bending and deformation properties, fabrication weldability in use. The chemical composition in steel is the basic element that influences the final structure property of hot rolled steel. Most deformed steel bar adopts microalloying method, that is to add expensive microelement (such as Mn alloy material, V alloy material, etc.) into steel, adjust the composition proportion and to improve structure property. A good composition design can guarantee the properties and control the production cost effectively at the same time. The element Cr in steel can significantly increase the strength, hardness and wear resistance. When the company uses mine rich in Cr, the Cr content in liquid iron will significantly increase. Therefore, there is a question: when Cr content increases, can we reduce alloy material amount in order to control the cost?

There is no clear dependency between the properties of deformed steel bar like tensile strength, yield strength and percentage elongation after fracture, elements like C, Mn, S, P, Si, Cr, Mo, Cu, Ni, Alt, V and other influence factors, so please apply modern mathematical and statistical methods in accordance with data in attachment 1 to model the influence of deformed steel bar properties on chemical element and optimize the composition.

1.2 Terminology and Definitions

Yield (engineering): *A yield strength or yield point is the material property defined as the stress at which a material begins to deform plastically. Prior to the yield point the material will deform elastically and will return to its original shape when the applied stress is removed. Once the yield point is passed, some fraction of the deformation will be permanent and non-reversible. In the three-dimensional principal stresses, an infinite number of yield points form together a yield surface.*

tensile strength: *often shortened to tensile strength (TS) or ultimate strength*[1][2] *is the capacity of a material or structure to withstand loads tending to elongate, as opposed to compressive strength, which withstands loads tending to reduce size. In other words, tensile strength resists tension (being pulled apart), whereas compressive strength resists compression (being pushed together). Ultimate tensile strength is measured by the maximum stress that a material can withstand while being stretched or pulled before breaking. In the study of strength of materials, tensile strength, compressive strength, and shear strength can be analyzed independently.*

1.3 Our work

This thesis is to study the influence of Chemical Element on Properties of Deformed Steel Bar, by studying the chemical elements content and the correlation between performance indicators, and the correlation between performance indicators, and design composition optimization scheme.

2 Problem Analysis

2.1 The Description of the Problem

(1) Analyze the main factors, secondary factors that influence properties of deformed steel bar like yield strength, tensile strength and percentage elongation after fracture, and analyze the correlation between these factors.
(2) Model the influence rule between deformed steel bar properties and chemical elements like C, Mn, Cr, V, Ni,etc.
(3) Research the reduction of alloy material like Mn and V in allowance range of deformed steel bar properties by Cr content increase, present the content modification scope of Mn, V, etc, and design composition optimization scheme.

2.2 Pre-built Solution

In view of the problem, first of all, the pretreatment of the sample data need to be properly, divided into two groups according to the specification data to deal with, and the lack of data objects are deleted and mean fill process. Based on a sample of each element and index data are normal distribution test, using the data of double overall independent T - test analysis of different specification of whether there is a significant difference between the independent samples, so the specification as single factor classifying sample data processing.
In view of the question 2, all kinds of elements in sample data for the first principal component analysis, pick out the main elements and minor elements, and then to simplify the data interval, and fitting analysis, through the observation to determine element and performance index of the relationship between.
For question 3, consider using grey correlation analysis, by constructing a new index function, to measure the relationship between the elements of steel performance index, consider using the optimization objective function method to obtain the best elements of the matching scheme.

2.3 Problematic Assumptions

1. Assuming that the sample data are reliable.

2. Assume that the sample data changes over time.

3. Assume that the main elements in the steel and the performance is not affected by other factors.

2.4 Explanation of Symbols

$a_{ij}, i = 1, 2, \cdots, n; j = 1, 2, \cdots, 15$ *is the first value of the first indicators of evaluation object;*

$\tilde{a}_{ij}, i = 1, 2, \cdots, n; j = 1, 2, \cdots, 15$ *Evaluate the first object of the first index of standardized index;*

$\overline{\mu_j}$, s_j *For the first index of the sample mean and sample standard deviation;*

r_{ij} *is the first with the first a correlation coefficient of indicators;*

b_j *is information on the first principal component contribution rate;*

$X(t)$ *is the system characteristic function;*

$Yi(t)(i = 1,2,\ldots,m)$ *is the Related factors function;*

λ_i *is the Element evaluation coefficient of tensile strength;*

φ_i *is the Element evaluation coefficient of yield strength;*

η_i *is the percentage elongation after fracture element evaluation coefficient;*

α, β, γ *is the Tensile strength, yield strength and percentage elongation after fracture of the principal component factor analysis.*

3 Models

Is more commonly used in steel with carbon steel or low alloy steel rolling, the so-called carbon steel, it is a chemical composition of iron and carbon is given priority to, and a small amount of manganese, silicon, sulfur and phosphorus and other elements.

Low alloy steel and carbon steel in different places, increase the content of manganese and silicon, some alloy steel also joined the small amounts of other alloying elements. But regardless of carbon steel, low alloy steel, cannot leave the carbon, silicon, manganese, sulfur and phosphorus. So, it is often said that steel is composed of five elements. Laboratory tests of reinforced and the five elements is usually inspection.

3.1 Basic model of the first question

In view of the problem a, to carries on the analysis from the following three steps, as shown in figure 1:

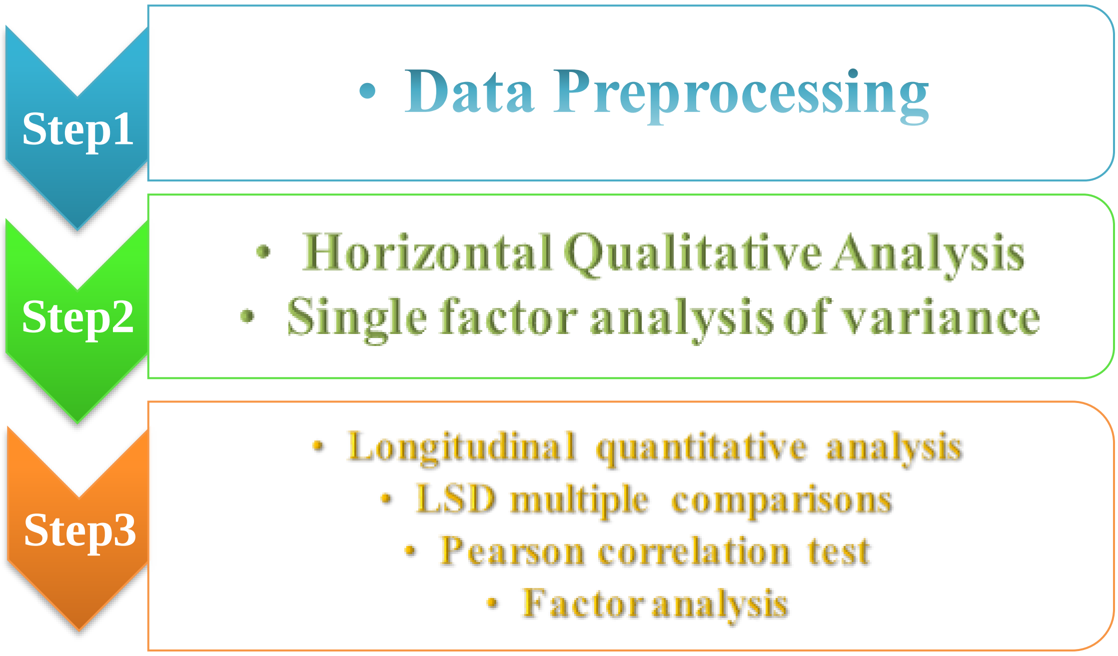


Fig 1. Solving steps of the first steps

3.1.1 Data preprocessing

Based on sample data filtering and sorting, found that some data is missing and numerical deviation phenomenon, because of the huge amount of data, so take a cut is made for the missing data and unreasonable data processing, in does not affect the quality of the whole sample data and the results of data analysis, to ensure the data more clearly the nature of the original sample.

First, type 1, 2, and mean to solve and compare the performance of each element[1]*, such as table 1 and figure 2, figure 3:*

Tab 1. Each element type 1, 2, and the average performance

specification	C	Mn	S	P	Si	Ceq	V	Cr	Ni	Cu	Mo	ALT	TS	YS	PEAF
1	0.215	1.428	0.025	0.026	0.533	0.465	0.0298	0.022	0.01157	0.0145	0.00093	0.00734	0.50	0.24	0.43
2	0.214	1.427	0.025	0.027	0.537	0.464	0.0299	0.021	0.01129	0.0142	0.00098	0.00755	0.46	0.24	0.44

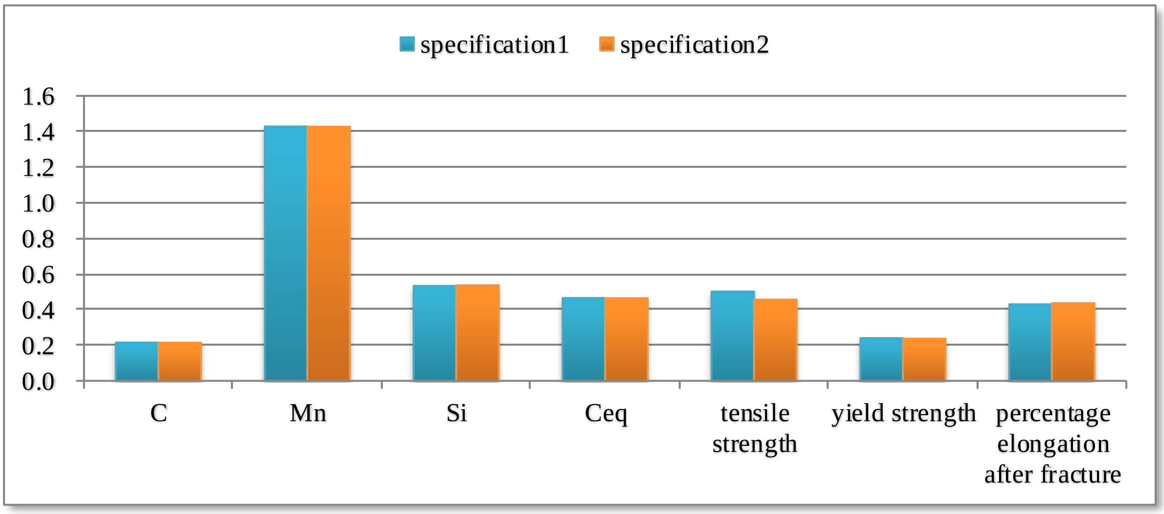


Fig 2. Some elements in type 1, 2, and the mean value of performance index

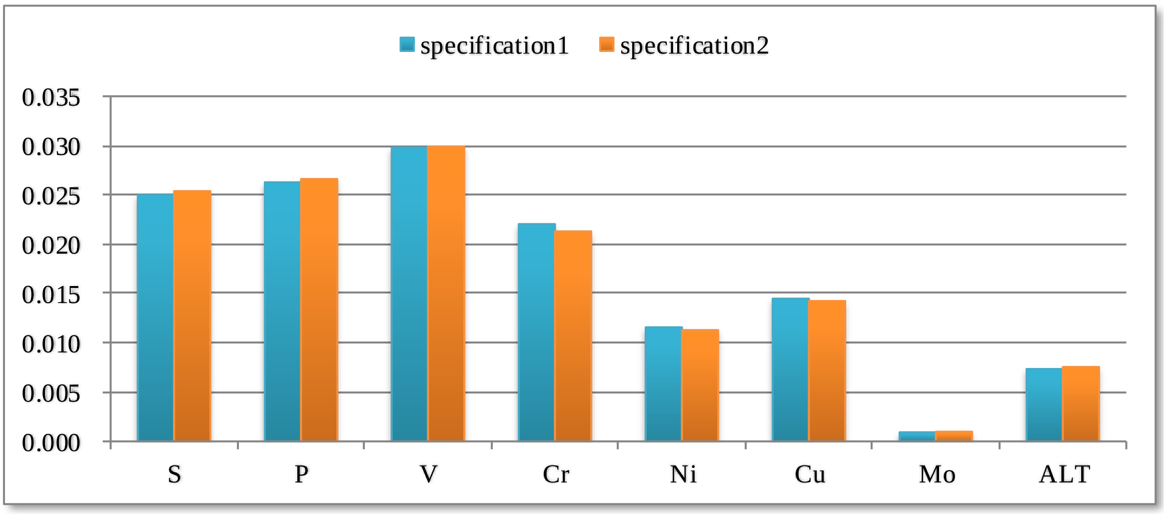
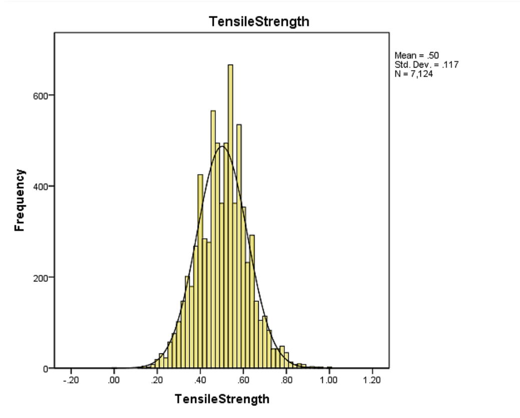


Fig 3. Mean value of some elements in type 1, 2

Second, using SPSS to three performance indicators: in type 1, 2, tensile strength, yield strength and percentage elongation after fracture normal distribution inspection. As shown in figure 4-9:



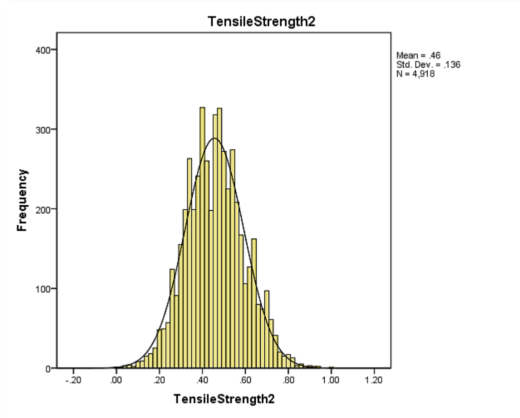
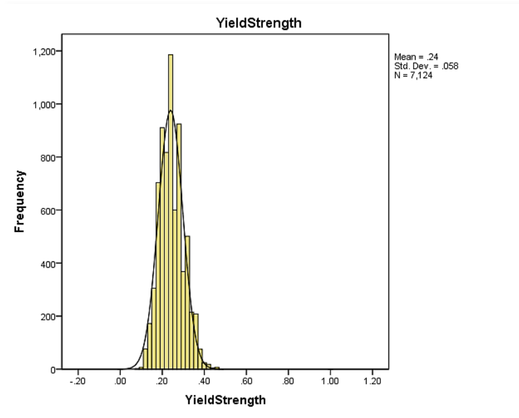


Fig 4-5. Type 1, 2 in the tensile strength of normal distribution frequency histogram



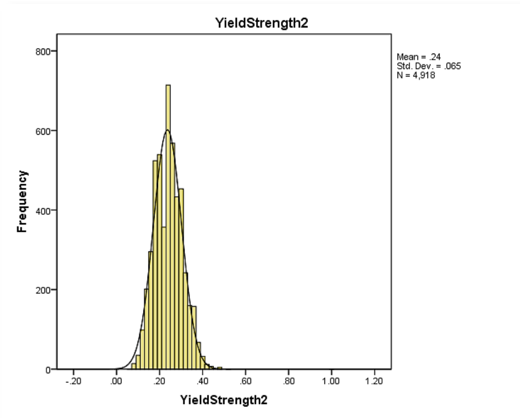
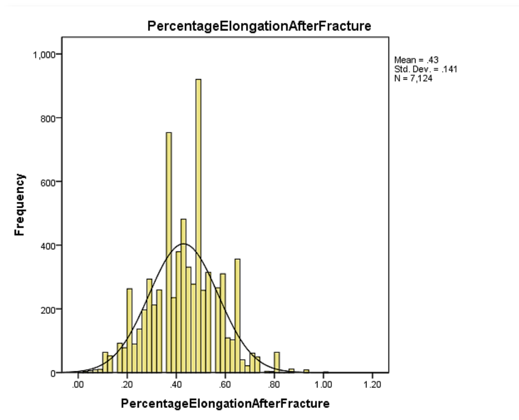


Fig 6-7. Type 1, 2, yield strength of normal distribution frequency histogram



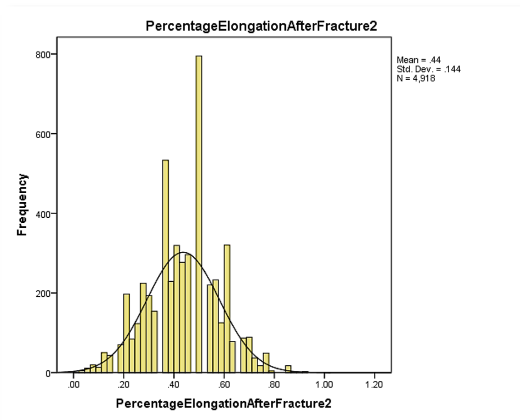


Fig 8-9. Type 1, 2 in the percentage elongation after fracture normal distribution frequency histogram

3.1.2 Horizontal qualitative analysis-Single factor variance analysis

To between type 1, 2, and for the same performance factor of single factor analysis of variance between, in group 1, 2 as a single variable factor, by using SPSS, respectively [2], on the properties of three independent sample data is analyzed, such as table 2-3, shown in figure 10.

Tab 2. Test of Homogeneity of Variances

Test of Homogeneity of Variances

TensileStrength3

Levene Statistic	df1	df2	Sig.
138.630	1	12040	0.000

Tab 3. ANOVA of Tensile Strength

ANOVA

TensileStrength3

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	5.966	1	5.966	382.580	0.000
Within Groups	187.764	12040	0.016	-	-
Total	193.730	12041	-	-	-

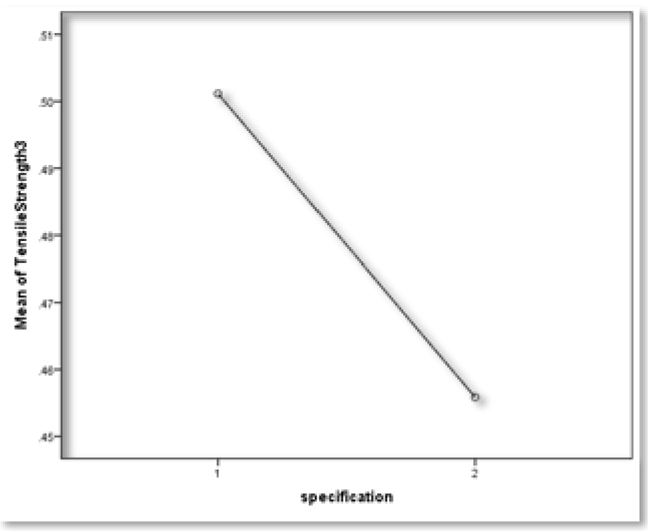


Fig 10. Mean of tensile strength

Through the above analysis, independent sample between type 1, 2 under the significance level of 0.05 has significant difference, so the choice of the two types of a group are studied in order to simplify the model, there needs to be discussed at the same time, the data of the type 1, 2, respectively.

3.1.3 Quantitative analysis of longitudinal-LSD, Pearson and Factor analysis

In view of the data type 1, 2, the three performance factors, significant difference of inspection first here using LSD multiple comparison analysis[3]; Then, to determine whether has the relationship between the three performance factors, first of all, drawing on data trends, found that roughly data presents the overall tendency, through SPSS Pearson correlation test for independent samples data; Finally, the three factors in factor analysis, through the main and second factors factor contribution analysis, and analyze the effect on the properties of materials between the three factors.

(1) The LSD multiple comparison analysis

Specific steps:

Step1: Put forward the hypothesis:

$$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$$

$$H_1 : \mu_1 \ , \mu_2 , \ \mu_3 , \ \mu_4 , \ \mu_5 \textit{Not all equal}$$

Step2: $\mu_1 , \mu_2 , \mu_3 , \ \mu_4 , \mu_5$ *are aged 9 to 17 ages mental state indicator.*

Step3: *A given significant level.* $\alpha = 0.05$.

Using SPSS software for different age groups of psychological state index variance analysis, the results are as follows:

Tab 3. Multiple Comparisons of type 1

Multiple Comparisons

Dependent Variable: Properties

LSD

(I) specification2	(J) specification2	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
tensile strength	yield strength	0.26173*	0.00185	0.000	0.2581	0.2654
	percentage elongation after fracture	0.07137*	0.00185	0.000	0.0677	0.0750
yield strength	tensile strength	-0.26173*	0.00185	0.000	-0.2654	-0.2581
	percentage elongation after fracture	-0.19036*	0.00185	0.000	-0.1940	-0.1867
percentage elongation after fracture	tensile strength	-0.07137*	0.00185	0.000	-0.0750	-0.0677
	yield strength	0.19036*	0.00185	0.000	0.1867	0.1940

*. The mean difference is significant at the 0.05 level.

Tab 4. ANOVA of Properties

ANOVA

Properties

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	260.812	2	130.406	10640.470	0.000
Within Groups	261.891	21369	0.012		
Total	522.704	21371			

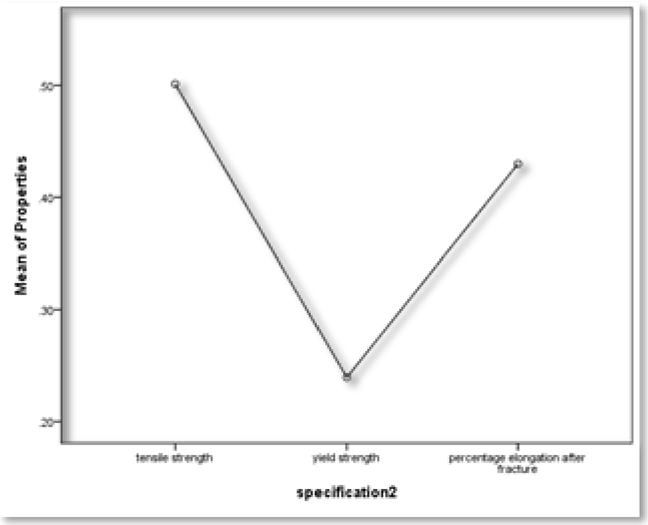


Fig 11. Mean of properties

Tab 5. Multiple Comparisons of type 2

Multiple Comparisons

Dependent Variable: Properties2

LSD

(I) specification3	(J) specification3	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
tensile strength	yield strength	0.21932*	0.00243	0.000	0.2146	0.2241
	percentage elongation after fracture	0.01910*	0.00243	0.000	0.0143	0.0239
yield strength	tensile strength	-0.21932*	0.00243	0.000	-0.2241	-0.2146
	percentage elongation after fracture	-0.20022*	0.00243	0.000	-0.2050	-0.1955
percentage elongation after fracture	tensile strength	-0.01910*	0.00243	0.000	-0.0239	-0.0143
	yield strength	0.20022*	0.00243	0.000	0.1955	0.2050

*. The mean difference is significant at the 0.05 level.

Tab 6. ANOVA of Properties2

ANOVA					
Properties2					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	145.165	2	72.582	4997.982	0.000
Within Groups	214.219	14751	0.015		
Total	359.383	14753			

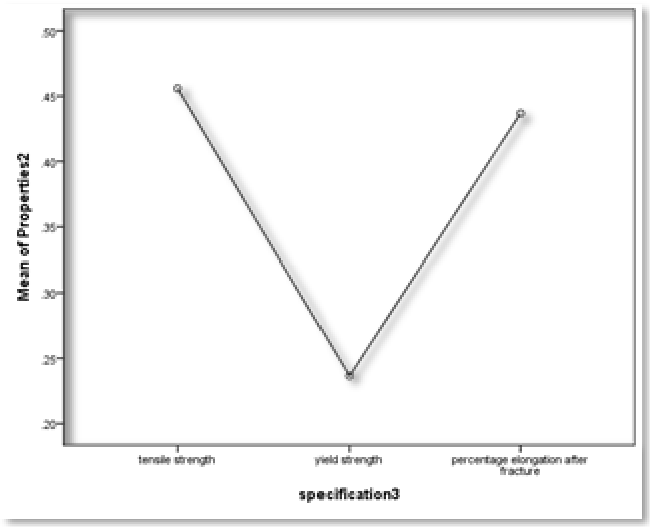


Fig 12. Mean of properties2

In the solution process, have verified the individual samples were accord with normal distribution, so by LSD multiple comparison test, found that three of the different types of performance factors between under the significance level of 0.05 has significant difference, so the relevant inspection.

(2) Data trend fitting figure

First of all, the data pretreatment, will large amounts of complex data sorting, then according to the interval range to merge, and then to use origin software to carry on the fitting, and watch the trend.

Standardization of data range in [0, 1], so the data according to [0, 0.2], [0.2, 0.4], [0.4, 0.6], [0.6, 0.8], [0.8, 1] is divided into five intervals, take the average interval data[4].

Tab 7. Type 1 interval average performance indicators

Section	tensile strength	yield strength	percentage elongation after fracture
[0,0.2]	0.18	0.13	0.53
[0.2,0.4]	0.35	0.18	0.47
[0.4,0.6]	0.51	0.24	0.43
[0.6,0.8]	0.67	0.31	0.38
[0.8,1.0]	0.86	0.39	0.31

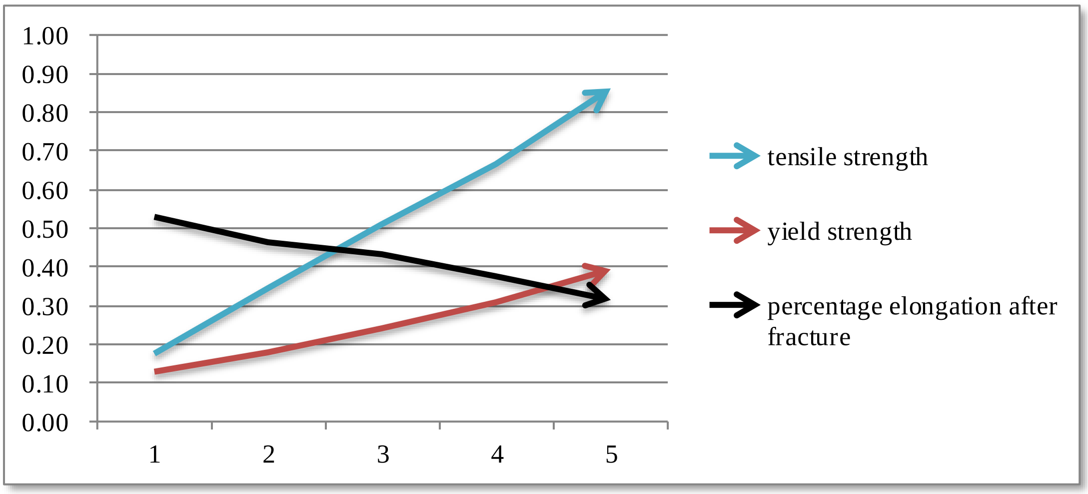


Fig 13. Type 1 interval average trend performance indicators

Tab 8. Type 2 interval average performance indicators

Section	tensile strength	yield strength	percentage elongation after fracture
[0,0.2]	0.16	0.14	0.52
[0.2,0.4]	0.33	0.19	0.47
[0.4,0.6]	0.49	0.25	0.43
[0.6,0.8]	0.67	0.31	0.38
[0.8,1.0]	0.86	0.38	0.33

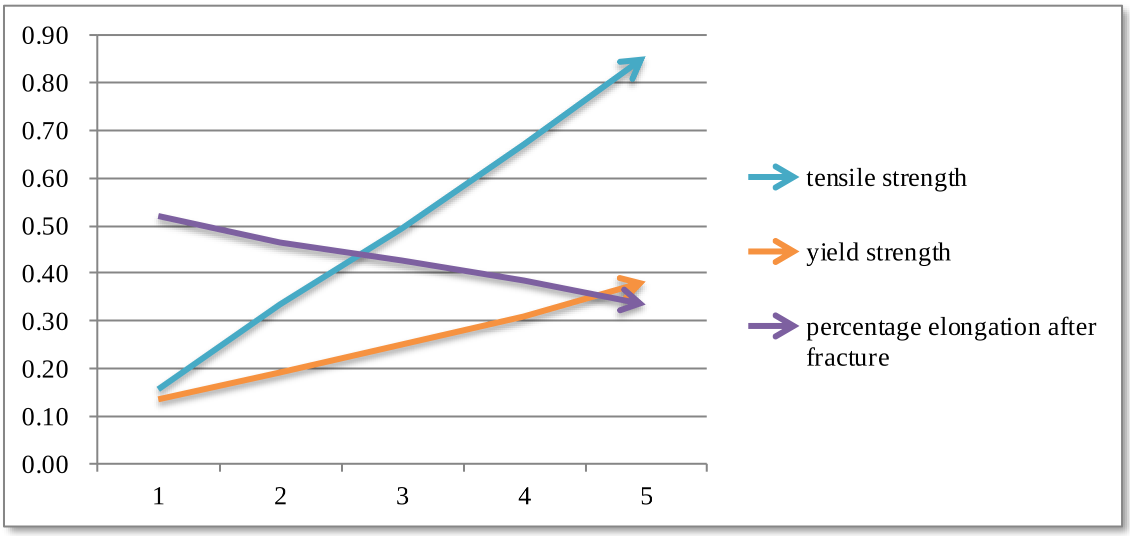


Fig 14. Type 2 interval average trend performance indicators

(3) Pearson correlation test

First of all, to multiple correlation Tensile Strength and Yield Strength Pearson test analysis:

Tab 9. Tensile Strength和Yield Strength的Correlations

Correlations		**TensileStrength1**	**YieldStrength1**
TensileStrength1	Pearson Correlation	1	0.799**
	Sig.	-	0.000
	N	7125	7125
YieldStrength1	Pearson Correlation	0.799**	1
	Sig.	0.000	-
	N	7125	7125

Thus, sig = 0.000 < 0.000, so the Tensile Strength and Yield Strength is not only consistent on the trend, and under the significance level of 0.05 relevant relations, thus can be concluded that there was a positive correlation between Tensile Strength and Yield Strength. Similarly, the Tensile Strength, Yield Strength, respectively for Percentage Elongation After Fracture under the significance level of 0.05 also have relevant relations, thus can be concluded that Tensile Strength, Yield Strength, respectively for Percentage Elongation After Fracture has a negative relationship.

Tab 10. The Correlations of three performance indicators

Correlations		Tensile Strength1	Yield Strength1	Percentage Elongation After Fracture1
Tensile Strength1	Pearson Correlation	1	0.799**	-0.213**
	Sig.	-	0.000	0.000
	N	7125	7125	7125
Yield Strength1	Pearson Correlation	0.799**	1	-0.247**
	Sig.	0.000	-	0.000
	N	7125	7125	7125
Percentage Elongation After Fracture1	Pearson Correlation	-0.213**	-0.247**	1
	Sig.	0.000	0.000	-
	N	7125	7125	7125

To sum up, type 1, 2, the Tensile Strength, Yield Strength and Percentage Elongation After Fracture under the significance level of 0.05 shows correlation, and are characterized by Tensile Strength and Yield Strength[5] was positively related to relationship, Tensile Strength, Yield Strength, respectively, and the Percentage Elongation After Fracture negative correlation.

(4) Factor analysis

Step1: To index the raw data

To eliminate the influence of different variables of dimension, first of all need t o standardize the variables. Factor analysis index variables are 5, respectively, x_1, x_2, x_3, x_4, x_5, The ith a first value of j indicators for evaluation objects $a_{ij}, i = 1, 2, \cdots, 133; j = 1, 2, \cdots, 5$. Convert each index into standardized index $\tilde{a}_{ij}$, there are:

$$\tilde{a}_{ij} = \frac{a_{ij} - \overline{\mu_j}}{s_j}, i = 1,2,\cdots,133; j = 1,2,\cdots,5,$$

Among them:

$$\overline{\mu_j} = \frac{1}{133}\sum_{i=1}^{133} a_{ij}, s_j = \sqrt{\frac{1}{133-1}\sum_{i=1}^{133}(a_{ij} - \overline{\mu_j})^2}$$

$\overline{\mu_j}$, s_j *are the first j a sample mean and sample standard deviation of the index.*

Conversely, the said:

$$\tilde{x}_j = \frac{x_j - \tilde{\mu}_j}{s_j}, j = 1, \cdots, 5$$

as standardized index variables.

Step2: Calculating the correlation coefficient matrix

The correlation coefficient matrix, $R = (r_{ij})_{m \times m}$,

$$r_{ij} = \frac{\sum_{k=1}^{133} \tilde{a}_{ki} \cdot \tilde{a}_{kj}}{133-1}, i, j = 1, 2, \cdots, 5,$$

Among them: $r_{ii} = 1$, $r_{ij} = r_{ji}$, r_{ij} *is the first ith with the first j a correlation coefficient of indicators.*

Step3: Elementary load matrix calculation

Calculate the correlation coefficient matrix[6] *eigenvalue of* R $\lambda_1 \ge \lambda_2 \ge \cdots \ge \lambda_5 \ge 0$, *and the corresponding eigenvectors* $\mu_1, \mu_2, \cdots, \mu_5$, *among them* $\mu_j = [\mu_{1j}, \mu_{2j}, \cdots, \mu_{5j}]^T$ *,Primary load matrix:*

$$\Lambda_1 = [\sqrt{\lambda_1}\mu_1, \sqrt{\lambda_2}\mu_2, \sqrt{\lambda_3}\mu_3, \sqrt{\lambda_4}\mu_4, \sqrt{\lambda_5}\mu_5]$$

Step4: Choose $m(m \le 5)$ ***main factors***

According to the primary load matrix, computing the contribution rate of each public factor, and choose $m(m \le 5)$ *main factors. To extract rotation of the factor loading matrix, matrix* $\Lambda_2 = \Lambda_1^{(m)} T$ *(among them* $\Lambda_1^{(m)}$ *si in* Λ_1 *'s top* m *columns,* T *is Orthogonal matrix), Tectonic factor model:*

$$\begin{cases} \tilde{x}_1 = \alpha_{11} F_1 + \cdots + \alpha_{1m} F_m \\ \tilde{x}_2 = \alpha_{21} F_1 + \cdots + \alpha_{2m} F_m \\ \tilde{x}_3 = \alpha_{31} F_1 + \cdots + \alpha_{3m} F_m \\ \tilde{x}_4 = \alpha_{41} F_1 + \cdots + \alpha_{4m} F_m \\ \tilde{x}_5 = \alpha_{51} F_1 + \cdots + \alpha_{5m} F_m \end{cases}$$

According to the above steps, using SPSS statistical software, this paper calculated the contribution rate of each factor in table 11:

Type 1:

Inspection: the method of correlation factor has a correlation coefficient matrix, reflect like correlation matrix, Bartlett sphericity test, KMO test.

Tab 11. Total Variance Explained

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.915	63.817	63.817	1.915	63.817	63.817
2	0.885	29.498	93.315	-	-	-
3	0.201	6.685	100.000	-	-	-

Calculation factor score: factor score for the ultimate sign of factor analysis, the specific numerical calculation of each factor on each sample, is the factor score, form variables called factor, in the following analysis of factor variables can be instead of the original data modeling, dimension reduction of a problem or simplify the process. Factor extraction and factor loading matrix solution: principal component analysis (pca) based on the principal component model, based on factor analysis model of the spindle factor method, maximum likelihood method, least square method, a factor extraction and image analysis. Principal component analysis (pca) can provide initial solution for factor analysis, facto r analysis is the extension and expansion of principal component analysis.

Name, rotating factor: in the factor loading matrix, multi-line, meet variable relation with multiple factors have larger, namely variable need multiple factors common explanation; Multiple columns, a factor can explain multiple variables[7] *at the same time. That one factor alone cannot represent the original variables, factor fuzzy, but the reality is a clear understanding, factor so factor rotation. Necessary, try to make a variab le on the less a few factors have higher load.*

Tab 12. Communalities

Communalities		
Communalities	Initial	Extraction
Tensile Strength1	1.000	0.841
Yield Strength1	1.000	0.858
Percentage Elongation After Fracture1	1.000	0.215
Extraction Method: Principal Component Analysis.		

By means of correlation coefficient matrix, reflect the correlation matrix, Bartlett sphericity test and KMO test method. Observe most of the correlation coefficient is higher, linear relationship is stronger, can extract the public factor, suitable for factor analysis. In the KMO, probability is less than the significance level of 0.05 0.000, reject the null hypothesis, *there was a significant difference with the unit matrix, KMO is 0.538, that is suitable for factor analysis.*

Tab 13. KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.538
Bartlett's Test of Sphericity	Approx. Chi-Square	7688.525
	df	3
	Sig.	0.000

Tab 14. Correlation Matrix

Correlation	Tensile Strength1	Yield Strength1	Percentage Elongation AfterFracture1
Tensile Strength1	1.000	0.799	-0.213
Yield Strength1	0.799	1.000	-0.247
Percentage Elongation After Fracture1	-0.213	-0.247	1.000

Each group of the column vector of meanings, characteristic value, variance contribution rate and cumulative variance contribution rate. The second column represents extraction, two factors together account for 93.315%, less loss of information. After the third column represents rotating factor, the total variance contribution rate has not changed, that is to say have no effect on the original joint degrees, redistribute[2] various factor to explain the variance of original variables, change the variance contribution rate of various factors.

Gravel figure: *y coordinate as the characteristic value, Abscissa to factor number. Characteristic value[9], the smaller the contribution to the original variable is small, can be ignored, so the two can also be extracted.*

Component matrix, the result is a variable is equal to two factor and the corresponding coefficient multiplication together after the results. Observation shows that the first factor and high degree of the correlation of all variables, and the second is not high, ambiguous, go against naming, so factor to rotate[11].

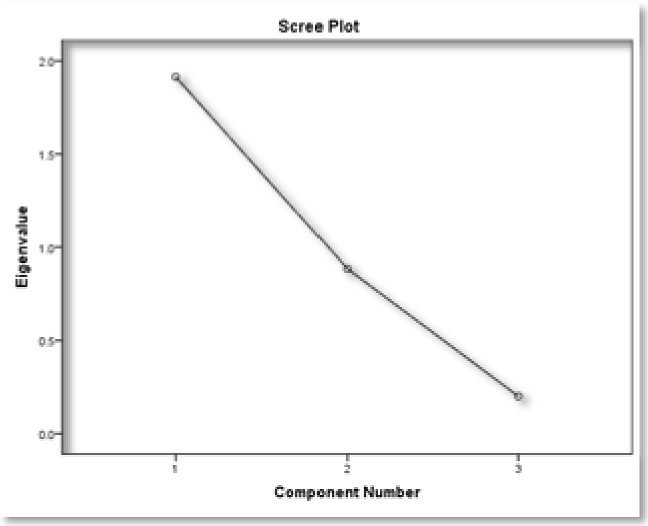


Fig 15. Eigenvalue

Factor named explanation[5]: by using factor loading matrix for the orthogonal method of varimax rotation to make the factor named explanatory. The first factor loading can be specified according to the output rotation factor loading after descending order. As shown in figure, the Tensile Strength and Yield Strength in the first factor is a high load, can be interpreted as the main factors influencing the performance[10] of spiral steel in the second-high performance of the load. Observe factor covariance matrix, linear correlation of two factors there is little, conforms to the effect of the factor analysis.

Table 15. Total Variance Explained of type 2

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.890	62.994	62.994	1.890	62.994	62.994
2	.841	28.042	91.036	-	-	-
3	.269	8.964	100.000	-	-	-
Extraction Method: Principal Component Analysis.						

Tab 16. Communalities of type 2

Communalities		
Communalities	Initial	Extraction
Tensile Strength2	1.000	0.782
Yield Strength2	1.000	0.817
Percentage Elongation After Fracture2	1.000	0.291

In type 2 performance factors in factor analysis of three groups of data, the second column represents extraction by two factors, together account for 91.036%, less loss of information.

Tab 17. KMO and Bartlett's Test of type 2

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.556
Bartlett's Test of Sphericity	Approx. Chi-Square	4177.261
	df	3
	Sig.	0.000

Tab 18. Correlation Matrix of type 2

Correlation	Tensile Strength2	Yield Strength2	Percentage Elongation After Fracture2
Tensile Strength2	1.000	0.728	-0.238
Yield Strength2	0.728	1.000	-0.298
PercentageElongationAfterFracture2	-0.238	-0.298	1.000

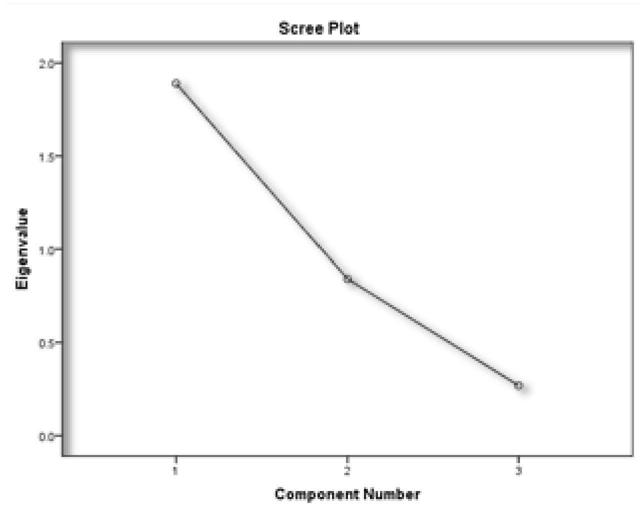
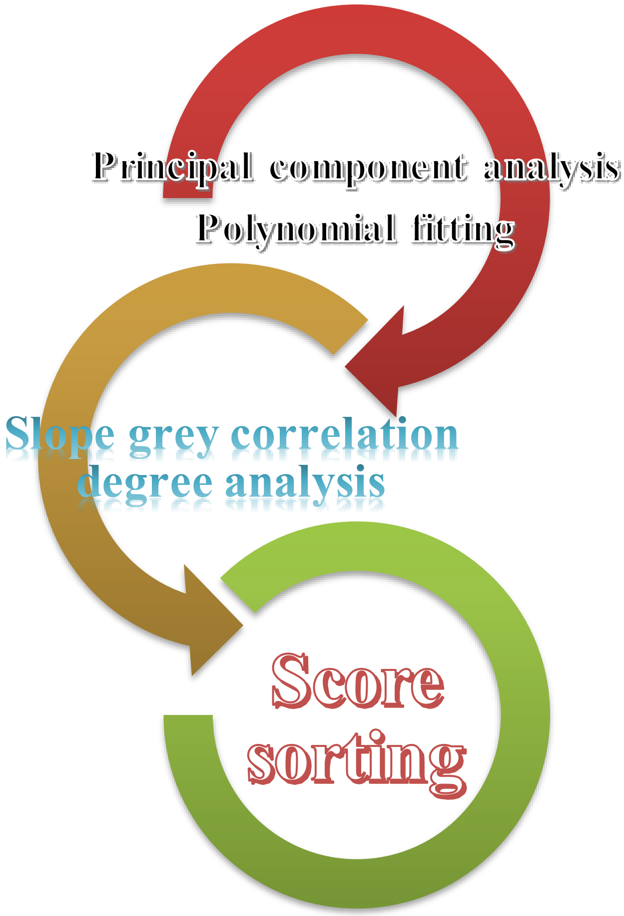


Fig 16. Eigenvalue of type 2

3.2 Basic model of the second problem

The solution of the problem two steps as shown in the figure below:



Tab 17. The solution of the problem two steps

3.2.1 Principal component analysis

(1) noun explanation[16]

①ceq is to convert all kinds of alloy element in steel carbon. Carbon steel in the key factors of strength and weldability are mainly carbon content. Besides carbon alloy steel (mainly low alloy steel) of various alloy elements on the strength of the steel and solderability also plays an important role.

Carbon steel and alloy structural steel carbon equivalent experience formula:

$$C\ equivalent = [C + Mn/6 + (Cr + Mo + V)/5 + (Ni + Cu)/15] * 100\%$$

Type:

C、 Mn、 Cr、 Mo、 V、 Ni、 Cu are the element content in the steel

Carbon equivalent Ceq can according to the following formula (percentage) values:

$$Ceq = C + Mn/6 + (Cr + V + Mo)/5 + (Cu + Ni)/15$$

(Yet carbon equivalent Ceq allowable deviation of + 0.03%)

②*Alt represents*[13] *the total aluminum content in steel, Als represent of acid soluble aluminum content in the steel. Steel in the aluminum acid soluble and acid insoluble, free acid chloride can be dissolved, known as the acid soluble, general requirements of acid soluble and full aluminum ratio greater than 90%. The greater the differenc e Alt, Als content, suggests that the more inclusions*[12].

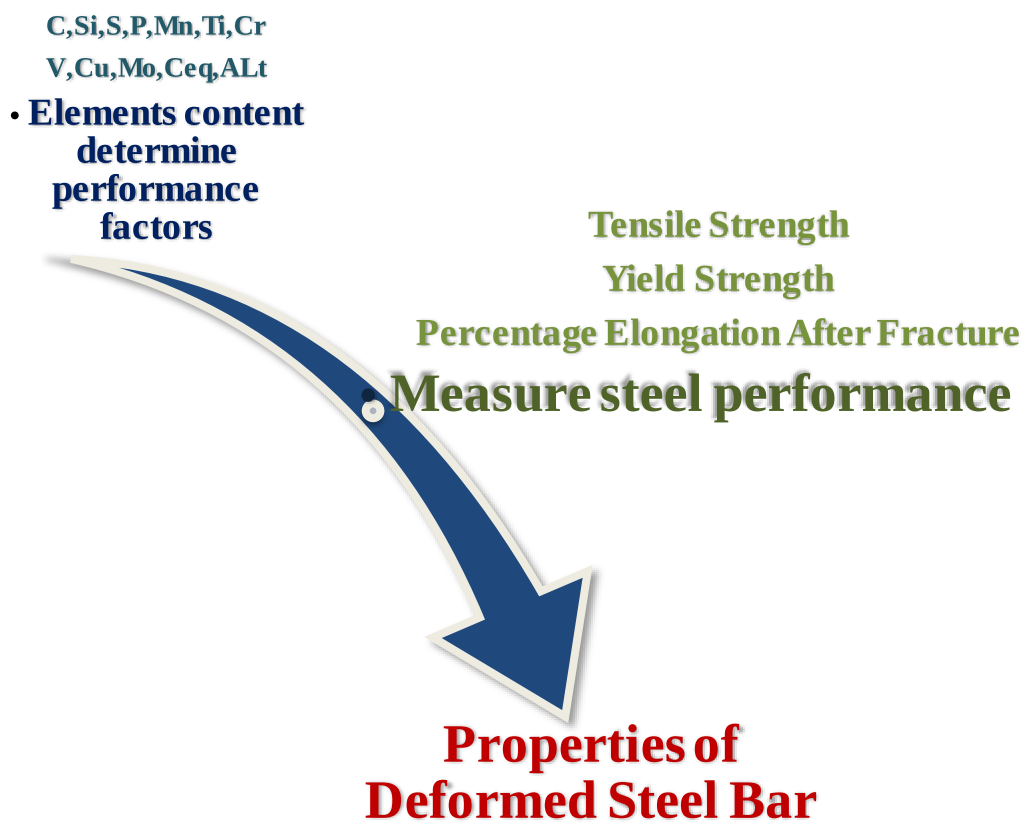


Fig 18. Element and performance index of the relationship

Step1: Standardized processing to the original data

Assuming that principal component analysis index variables[2] *have m* m *, respectively,* $\overline{x_1}, \overline{x_2}, \cdots, \overline{x_m}$ *, a total of* n *evaluation objects, and the first i the first j A index value of evaluation objects is* a_{ij}*. Each index* a_{ij} *into standardized parameter values* $\tilde{a}_{ij}$*, that is:*

$$\tilde{a}_{ij} = \frac{a_{ij} - \mu_j}{s_j}, i = 1, 2, \cdots, n; \ j = 1, 2, \cdots, m$$

Among them:

$$\mu_j = \frac{1}{n}\sum_{i=1}^{n} a_{ij} \text{ ,}$$

$$s_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(a_{ij} - \mu_j)^2} \text{ , } j = 1, 2, \cdots, m,$$

μ_j, s_j *is the first indicators of the sample mean and sample standard deviation. Conversely, the said:*

$$\tilde{x}_j = \frac{x_j - \mu_j}{s_j}, \; j = 1, 2, \cdots, m$$

as standardized index variables.

Step2: Calculating the correlation coefficient matrix R

The correlation coefficient matrix, $R = (r_{ij})_{m\times m}$*, that is*:

$$r_{ij} = \frac{\sum_{k=1}^{n} \tilde{a}_{ki} \cdot \tilde{a}_{kj}}{n-1}, i, j = 1, 2, \mathrm{L}, m,$$

Among them:

$r_{ii} = 1$, $r_{ij} = r_{ji}$, r_{ij} *is the first ith with the first j a correlation coefficient of indicators.*

Step3: Calculating eigenvalues and eigenvectors

Calculating the correlation coefficient matrix R *'s the eigenvalue* $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m \geq 0$*, the corresponding eigenvectors are* $\mu_1, \mu_2, \cdots, \mu_m$*, among the* m $\mu_j = [\mu_{1j}, \mu_{2j}, \cdots, \mu_{mj}]^T$*, by the eigenvalue of* m *a new indicator variables:*

$$y_1 = \mu_{11}\tilde{x}_1 + \mu_{21}\tilde{x}_2 + \cdots + \mu_{m1}\tilde{x}_m$$

$$y_2 = \mu_{12}\tilde{x}_1 + \mu_{22}\tilde{x}_2 + \cdots + \mu_{m2}\tilde{x}_m$$

$$\cdots$$

$$y_m = \mu_{1m}\tilde{x}_1 + \mu_{2m}\tilde{x}_2 + \cdots + \mu_{mm}\tilde{x}_m$$

y_1 *according to the first principal component,* y_2 *according to the second principal component,* y_m *according to the* m *principal component.*

Step4: To calculate $p(\, p \leq m\,)$ ***main ingredients, and Calculated value.***

① *Calculate the contribution rate* $\lambda_j(\, j = 1, 2, \cdots, m)$ *and cumulative contribution rate of* *information characteristic value*[14]*. That called:*

$$b_j = \frac{\lambda_j}{\sum_{k=1}^{m} \lambda_k}, \ j = 1, 2, L, m$$

As y_j *'s Contribution rate of information, and at the same time, there are:*

$$\alpha_p = \frac{\sum_{k=1}^{p} \lambda_k}{\sum_{k=1}^{m} \lambda_k}$$

as $y_1, y_2, \cdots, y_p$ *'s the cumulative contribution rate.*

When α_p *close to1(Usually take* $\alpha_p = 0.85, 0.9, 0.95$ *), Choose top* p *indicator variables* $y_1, y_2, \cdots, y_p$ *as the main ingredients, and instead of the original m index variable, thus p a principal component in comprehensive analysis.*

② *Calculating comprehensive score:*

$$Z = \sum_{j=1}^{p} b_j y_j$$

Among them: b_j *is the first* j *a principal component contribution rate of information, according to the comprehensive score values can be evaluated*[12]*.*

Through SPSS principal component analysis:

Tab 19. Total Variance Explained

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.432	20.266	20.266	2.432	20.266	20.266	2.284	19.030	19.030
2	2.092	17.430	37.695	2.092	17.430	37.695	1.836	15.296	34.326
3	1.247	10.390	48.085	1.247	10.390	48.085	1.605	13.371	47.698
4	1.086	9.054	57.139	1.086	9.054	57.139	1.097	9.140	56.838
5	1.025	8.541	65.680	1.025	8.541	65.680	1.061	8.842	65.680
6	0.960	8.004	73.684						
7	0.931	7.761	81.445						

8	0.859	7.161	88.606
9	0.668	5.568	94.174
10	0.423	3.523	97.697
11	0.256	2.131	99.828
12	0.021	0.172	100.000

Extraction Method: Principal Component Analysis.

Tab 20. Total Communalities

Communalities	Initial	Extraction
C	1.000	**0.837**
Mn	1.000	**0.700**
S	1.000	**0.710**
Si	1.000	**0.737**
P	1.000	**0.432**
Ceq	1.000	0.964
V	1.000	0.325
Cr	1.000	0.853
Ni	1.000	0.824
Cu	1.000	0.572
Mo	1.000	0.490
ALt	1.000	0.438

Extraction Method: Principal Component Analysis.

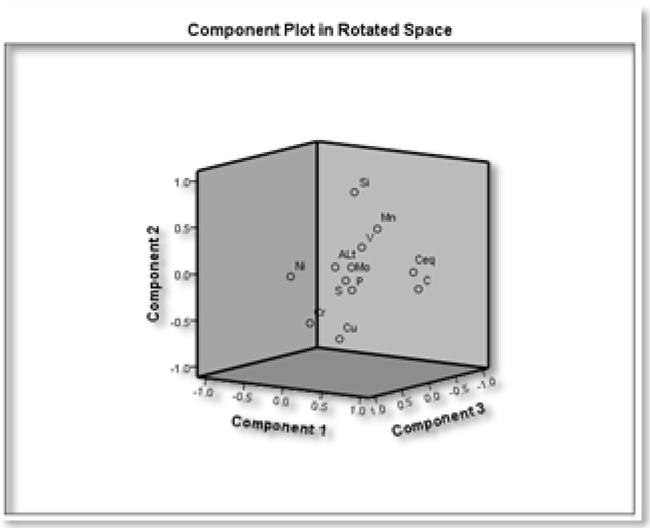


Fig 19. Component Plot in Rotated Space

Tab 21. KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.427
Bartlett's Test of Sphericity	Approx. Chi-Square	34289.198
	df	66
	Sig.	0.000

Tab 22. Correlation Matrix

Correlation Matrix		C	Mn	S	Si	P	Ceq	V	Cr	Ni	Cu	Mo	ALt
Correlation	C	1.000	0.234	0.039	0.046	0.059	0.870	0.143	0.072	0.035	0.071	0.025	0.041
	Mn	0.234	1.000	0.089	0.441	0.131	0.632	0.238	0.001	0.069	0.117	0.006	0.000
	S	0.039	0.089	1.000	0.022	0.017	0.012	0.044	0.026	0.017	0.044	0.021	0.006
	Si	0.046	0.441	0.022	1.000	0.117	0.193	0.141	0.357	0.002	0.402	0.010	0.024
	P	0.059	0.131	0.017	0.117	1.000	0.123	0.033	0.176	0.037	0.037	0.024	0.021
	Ceq	0.870	0.632	0.012	0.193	0.123	1.000	0.231	0.160	0.073	0.061	0.022	0.033
	V	0.143	0.238	0.044	0.141	0.033	0.231	1.000	0.045	0.005	0.073	0.054	0.009
	Cr	0.072	0.001	0.026	0.357	0.176	0.160	0.045	1.000	0.580	0.457	0.137	0.029
	Ni	0.035	0.069	0.017	0.002	0.037	0.073	0.005	0.580	1.000	0.106	0.013	0.014
	Cu	0.071	0.117	0.044	0.402	0.037	0.061	0.073	0.457	0.106	1.000	0.036	0.015
	Mo	0.025	0.006	0.021	0.010	0.024	0.022	0.054	0.137	0.013	0.036	1.000	0.064
	ALt	0.041	0.000	0.006	0.024	0.021	0.033	0.009	0.029	0.014	0.015	0.064	1.000

Fig 20. Scree Plot

Select contribution ranked in the top 5 five elements to carry on the comprehensive evaluation, it must:

$$Y_c = x_1 + 0.234x_2 + 0.039x_3 + 0.046x_4 + 0.059x_5 + 0.870x_6 + 0.143x_7 + 0.072x_8 - 0.035x_9 + 0.071x_{10} + 0.025x_{11} - 0.041x_{12}$$

$$Y_{Mn} = 0.234x_1 + x_2 - 0.089x_3 + 0.441x_4 + 0.131x_5 + 0.632x_6 + 0.238x_7 + 0.001x_8 + 0.069x_9 - 0.117x_{10} - 0.006x_{11}$$

$$Y_S = 0.039x_1 - 0.089x_2 + x_3 - 0.022x_4 - 0.017x_5 - 0.012x_6 + 0.044x_7 - 0.026x_8 - 0.017x_9 + 0.044x_{10} + 0.021x_{11} - 0.006x_{12}$$

$$Y_{Si} = 0.046x_1 + 0.441x_2 - 0.022x_3 + x_4 - 0.117x_5 + 0.193x_6 + 0.141x_7 - 0.357x_8 + 0.002x_9 - 0.402x_{10} + 0.010x_{11} + 0.024x_{12}$$

$$Y_P = 0.059x_1 + 0.131x_2 - 0.017x_3 - 0.117x_4 + x_5 + 0.123x_6 + 0.033x_7 + 0.176x_8 + 0.037x_9 + 0.037x_{10} + 0.024x_{11} + 0.021x_{12}$$

So:

$$Z = 20.266Y_c + 17.430Y_{Mn} + 10.390Y_S + 9.054Y_{Si} + 8.541Y_P$$

Through principal component analysis can be found that 12 elements, C, S, Si, Mn, P, the five elements as the main factors influencing the performance of the main elements, therefore, respectively on the Tensile Strength of the five elements, Yield Strength and Percentage Elongation After Fracture of fitting, and fitting equation are obtained.

3.2.2 Polynomial fitting equation

1.C element fitting curve and equation

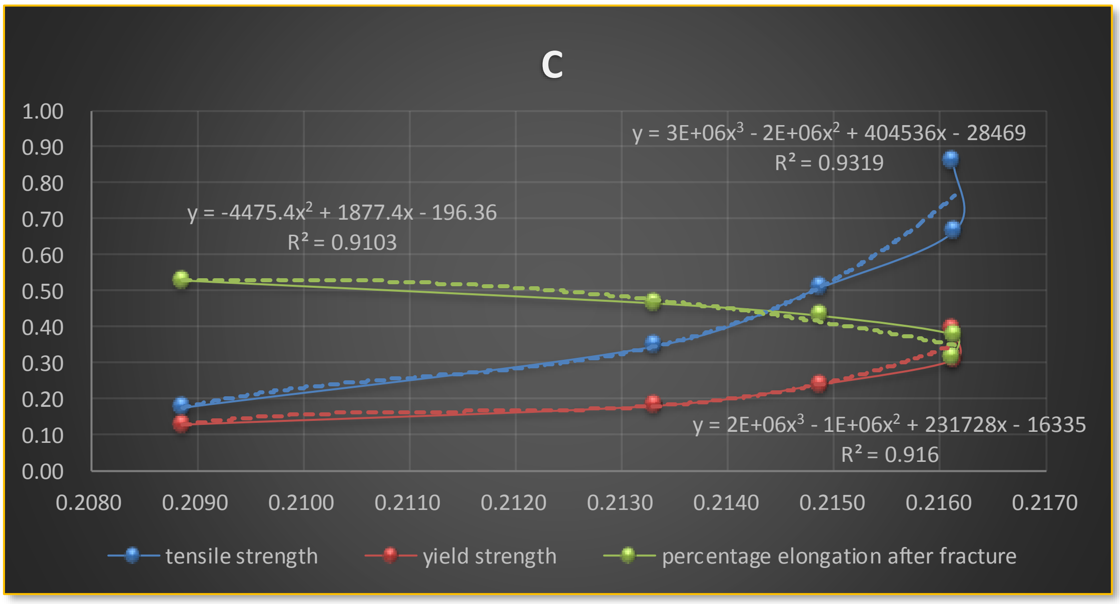


Fig 21. C element fitting curve

Tab 23. C element fitting equation

specification 1	Fitted Equation	R^2
C-Tensile Strength	$Y=3*10^6x^3-2*10^6x^2+404536x-28469$	0.9319
C-Yield Strength	$Y=2*10^6x^3-10^6x^2+231728x-16335$	0.916
C-Percentage elongation after fracture	$Y=-4475.4x^2+1877.4x-196.36$	0.9103

Carbon is the most important elements in steel. It plays a decisive role on steel performance. Carbon content in steel is little, the yield point, tensile strength and hardness of the steel is low, and the shape and toughness is better; On the contrary, if the carbon content of steel increases, the yield point, tensile strength and hardness of the steel can improve accordingly, but steel brittleness increases, that is getting down, such as elongation, cold bending performance degradation, especially the impact toughness drops is very obvious. So, by fitting curve and equation can be seen that with the increase of carbon content, tensile strength, yield strength and also will increase, on the contrary, percentage elongation after fracture.

2.Mn element fitting curve and equation:

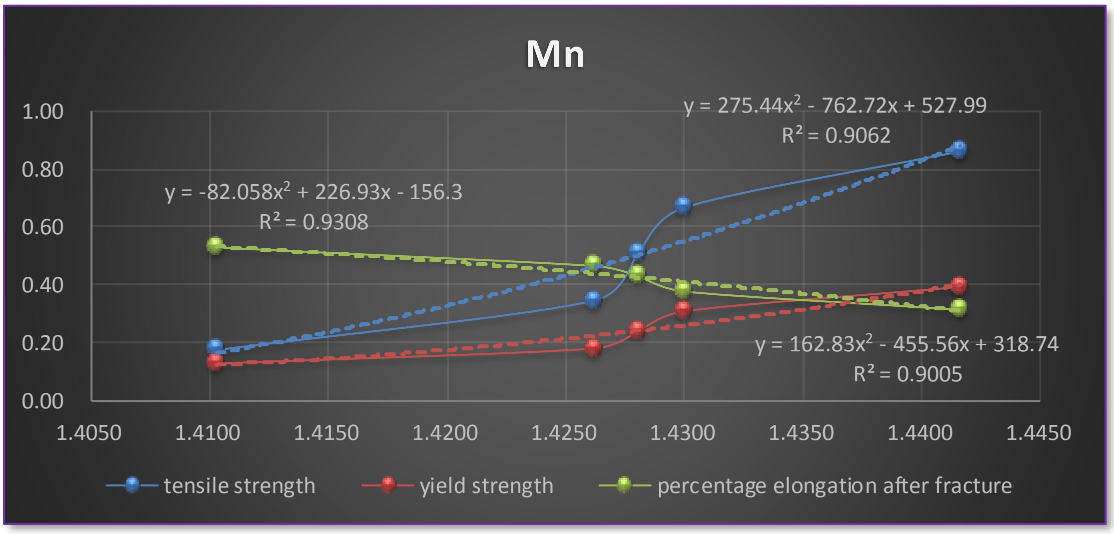


Fig 22. Mn element fitting curve

Tab 24. Mn element fitting equation

specification 1	Fitted Equation	R^2
Mn-Tensile Strength	$Y=275.44x^2-762.72x+527.99$	0.9062
Mn -Yield Strength	$Y=162.83x^2-455.56x+318.74$	0.9005
Mn-Percentage elongation after fracture	$Y=-82.058x^2+226.93x-156.3$	0.9308

Manganese is due to the steelmaking in ferromanganese alloys containing DNA and steel added, in the ordinary carbon steel, manganese content commonly less than 1%, no significant influence on the mechanical properties of steel. But the manganese content in the steel increase will make the yield point, tensile strength and hardness increased a lot, and elongation decrease little. When manganese content too much, not only can make the steel and impact toughness is reduced, but also prone to quenching organization and quenching cracks, serious influence on the performance of the steel can be welded. For low alloy steel, carbon content can be convert manganese, also known as carbon equivalent, use CH symbol, used it as a comprehensive index of measuring steel weldability. The approximate calculation formula of carbon equivalent is:

$$CH=(C+Mn/6)\%$$

Type C is in the carbon content, Mn is manganese content. Generally speaking, carbon equivalent CH within 0.55% better steel welding, and more than 0.55% of steel is difficult to welding.

By manganese element and the fitting curve and equation of performance factors, can be found that with the increase of manganese content, tensile strength and yield strength are increased, when Mn content is higher, the change of the yield strength flatten out, and the percentage elongation after fracture decreases, accords with the actual law of manganese element.

3.S element fitting curve and equation:

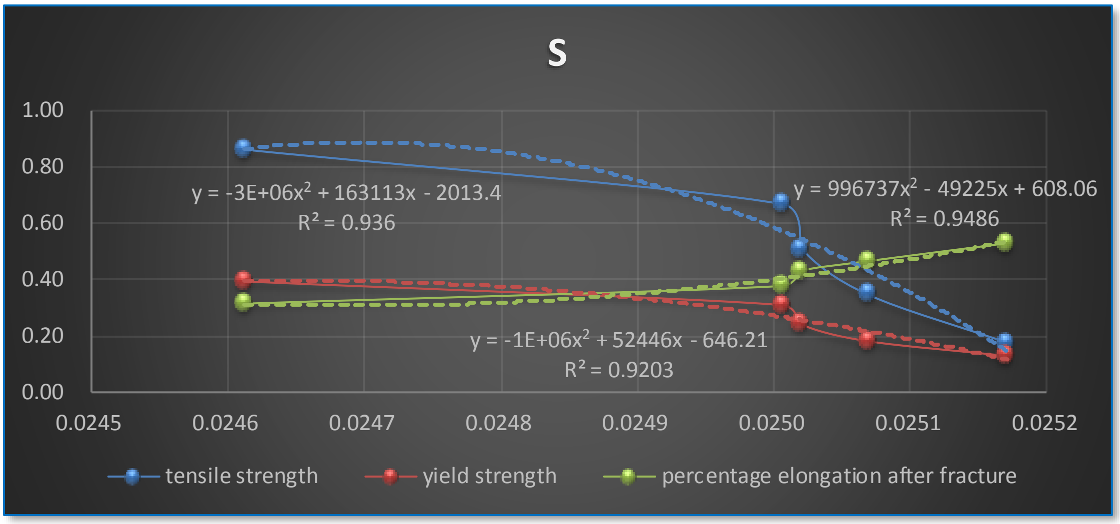


Fig 23. S element fitting curve

Tab 25. S element fitting equation

specification 1	Fitted Equation	R^2
S-Tensile Strength	$Y= -3*10^6x^2 + 163113x - 2013.4$	0.936
S -Yield Strength	$Y= -10^6x^2 + 52446x - 646.21$	0.9203
S-Percentage elongation after fracture	$Y= 996737x^2 - 49225x + 608.06$	0.9486

Sulfur into pig iron from iron ore and coke, again by the impurity in the iron into steel. It is a harmful impurity in steel, is famous for its hot short. When welding, sulfur can increase the fusion zone and heat affected zone of hot crack formation, so the Sulphur can make steel welding performance deteriorate significantly.

Sulfur will also reduce the impact toughness and fatigue strength of steel, also significantly reduce the corrosion resistance of steel. As a result, the performance of the sulfur because there are more than a lot of bad, so the construction of sulfur content in the steel must be controlled in less than 0.045 ~ 0.055%, within the scope of and if in production control sulfur content less than 0.02%, it can meet the standard requirements.

By fitting curve and equation of S element can be found that with the increase of sulfur content, tensile strength and yield strength decreases, and the percentage elongation after fracture will increase, so the sulfur element belongs to the harmful impurity in steel.

4. Si element fitting curve and equation:

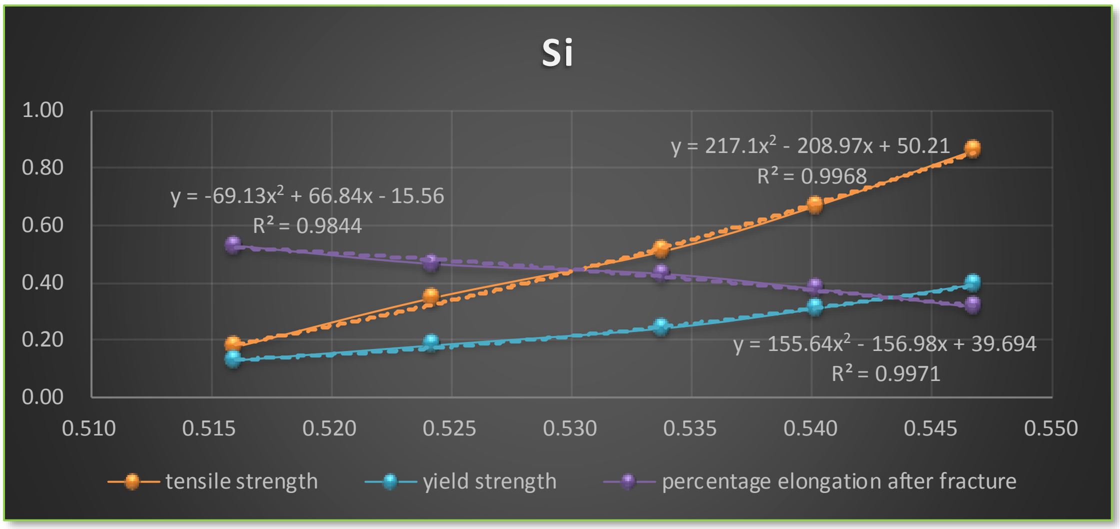


Fig 24. Si element fitting curve

Tab 26. Si element fitting equation

specification 1	Fitted Equation	R^2
Si-Tensile Strength	$Y= 217.1x^2 - 208.97x + 50.21$	0.9968
Si -Yield Strength	$Y= 155.64x^2 - 156.98x + 39.694$	0.9971
Si-Percentage elongation after fracture	$Y=-69.13x^2 + 66.84x - 15.56$	0.9844

Steel need to add some ferrosilicon, as deoxidizer, thus inevitably contain a small amount of silicon in steel. Silicon content in the steel increases within a certain range can strengthen the solid solution, improve the yield point and tensile strength of steel, and plastics and impact toughness is not falling.

When the silicon content is more than 0.6%, on the one hand, can lead to produce coarse grained steel, on the other hand will reduce carbon in austenite solubility, prompting the carbides in the grain boundary precipitation, not only reduces the abrasion resistance and toughness of steel, also increases the cracking tendency of steel.

When the silicon content is more than 1.0%, will make the welding performance of steel. But some main requirements of high strength steel used in construction, and on the shaping and welding performance requires only reaches a certain value, at that time, often adopt the method of increase of silicon content to improve the strength of the reinforcement.

We will usually silicon controlled within 0.3% ~ 0.6%, but in some special cases, if you need steel has good liquidity, we should increase the amount of silicon, the grain boundary conditions improve. Through the analysis of the fitting curve and equation of silicon, can be found that with the increase of silicon content, steel yield point and tensile strength increase, *and falling toughness and shape, namely, tensile strength and yield strength increase, and the percentage elongation after fracture.*

5. P element fitting curve and equation:

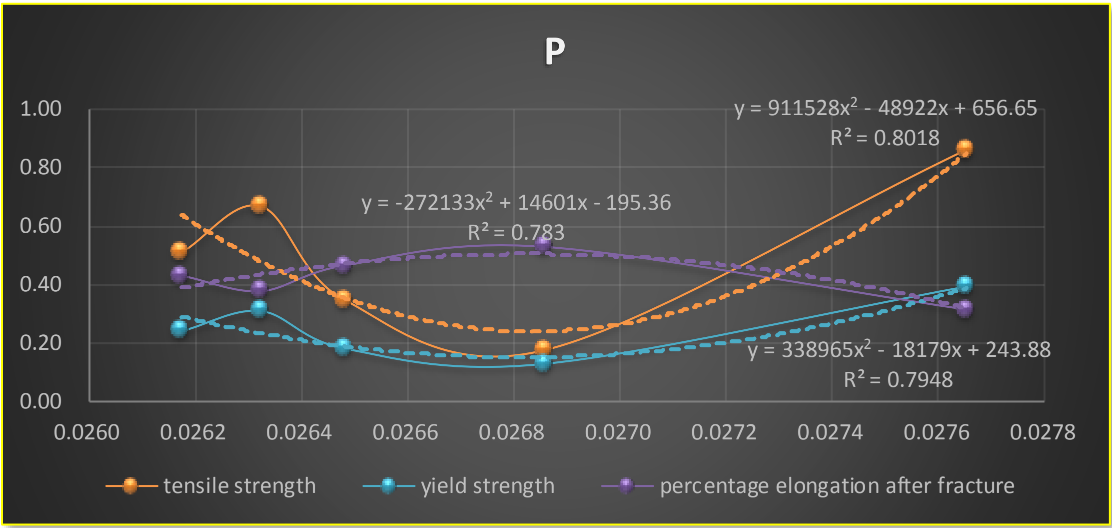


Fig 25. P element fitting curve

Tab 27. P element fitting equation

specification 1	Fitted Equation	R^2
P-Tensile Strength	$Y= 911528x^2 - 48922x + 656.65$	0.8018
P -Yield Strength	$Y= 338965x^2 - 18179x + 243.88$	0.7948
P-Percentage elongation after fracture	$Y=-69.13x^2 + 66.84x - 15.56$	0.783

Phosphorus is also a harmful impurity in steel, it is famous for its cold short. At low temperatures, phosphorus can make reinforced brittle, but at high temperatures and a lack of plastic, the welding performance is bad, make the cold bending property variation. Therefore, in the construction steel, the content of phosphorus is to control within the range is less than 0.045 ~ 0.05%.

In addition, the phosphorus also has promoted the role of manganese, carbon segregation, so should try to reduce the phosphorus content.

By fitting curve and equation of phosphorus can be found that with the increase of phosphorus content, tensile strength and yield strength increases first and then sharply lower, and then, when P reached high levels, and makes further improve tensile strength and yield strength, explain for enhancing steel ductile-brittle type, on the contrary, the percentage elongation after fracture before and after the change is small, effect is not very big.

6. Other elements: Cr, Mo, V, Ti, etc.

Chromium is mainly used in the steel elements, after water toughening treatment, chrome will mostly into austenitic steel, improve the stability of steel, but also accelerate the precipitation of the carbide during cooling.

Chromium is soluble in austenite, can improve the yield strength of steel, reduce the elongation and impact toughness of steel. In as-cast if chromium increases, it will also accelerate the precipitation of carbides, the soluble in austenite is relatively difficult, therefore not easy to get a single-phase austenitic, at this point, the water toughening of heating temperature should be based on the standard of high manganese steel by 30 ~ 50 ℃.When faced with a strong impact abrasion plus chromium steel its wear resistance is improved, but for the strong impact abrasive wear when its wear resistance increase is not much.

Molybdenum and iron binding force is stronger, at the same time, the size of the atom is bigger, diffusion velocity is small, so the molybdenum on as-cast will reduce the precipitation of the carbide content in steel, is no longer present on the austenitic grain boundary mesh, the molybdenum can also slowdown in steel needle-like carbide precipitation speed, reduce the precipitation temperature, the shape of high manganese steel under the as-cast and intensity increase benefit, is also very good make up for the insufficient due to chromium element to join. So, in chromium steel add molybdenum element is very beneficial.

Finally, several other alloying elements on the microstructure and mechanical properties of high cast steel, the influence of the first is vanadium and vanadium refining high manganese steel group, improve the steel yield strength and hardness of the original level of wear resistance. Followed by titanium, titanium can eliminate columnar crystals of high manganese steel, on wear resistance of steel and the improvement of the performance of the organization has a good effect. Finally, is the rare earth elements, it has the function of purifying molten steel, can reduce the number of inclusions and the size, can refine as-cast organization, reduce the columnar crystal, can improve the liquidity of molten steel, reduce the steel cold crack and the cracking tendency, improve the work hardening ability of steel, improve the process performance of high manganese steel.

3.2.3 Grey correlation analysis

Grey correlation analysis of the specific steps are as follows:

Step1: Sure to compare object and the reference sequence

Establish evaluation objects have a m, evaluation index have n, the reference sequence is

$x_0 = \{x_0(k) \mid k = 1,2,\cdots,n\}$, *and to compare the sequence is:*

$$x_i = \{x_i(k) \mid k = 1,2,\cdots,n\}, i = 1,2,\cdots,m.$$

Step2: Determine the weight of the corresponding parameter values

Available such as analytic hierarchy process (ahp) to determine the weight of each index corresponds $w = [w_1,\cdots,w_n]$, $w_k (k = 1,2\cdots,n)$ *is the first k corresponding evaluation indexes weights.*

Step3: Grey correlation coefficient calculation

$$\xi_i(k) = \frac{\min_s \min_t |x_0(t) - x_s(t)| + \rho \max_s \max_t |x_0(t) - x_s(t)|}{|x_0(k) - x_i(k)| + \rho \max_s \max_t |x_0(t) - x_s(t)|}$$

In order to compare the sequence x_i *to the reference sequence* x_0 *on the first* k *index of correlation coefficient, and* $\rho \in [0,1]$ *is distinguish coefficient.*

Among them, said $\min_s \min_t |x_0(t) - x_s(t)|$ *and* $\max_s \max_t |x_0(t) - x_s(t)|$ *are Two levels of minimum differential and the biggest difference. Generally speaking, distinguish coefficient* ρ *is greater, the resolution will greater;* ρ *is smaller, the resolution will smaller.*

Step4: Calculate the weighted grey correlation degree

Gray weighted correlation calculation formula is:

$$r_i = \sum_{k=1}^{n} w_i \xi_i(k)$$

Type: r_i *is the ith a weighted grey correlation degree of ideal object evaluation object*[10].

3.2.4 Slope grey correlation degree

Grey correlation analysis is mainly based on the relation of system data sequence comparison to analyze the correlation degree between various factors in the system, can reflect all kinds of factors influence each other relations in the system. Many current computation model, representing the correlation, the grey correlation degree, T correlation, etc., never tong fang face correlation was improved, and obtained a certain effect; These correlations are mostly similar to representing the correlation degree, cannot reflect the positive and negative correlation. In order to overcome the shortcomings of the above methods, this study slope with the improved gray correlation analysis method, the basic idea is: according to the factor of time series curve of average relative proximity to calculate the grey correlation degree of change trend.

X (t) for the system characteristic function, Yi (t) (i = 1, 2,..., m) for related factors function, said:

$$\delta_i(t)=\frac{1+\left|\frac{1}{\overline{x}}\cdot\frac{\Delta x(t)}{\Delta t}\right|}{1+\left|\frac{1}{\overline{x}}\cdot\frac{\Delta x(t)}{\Delta t}\right|+\left|\frac{1}{\overline{x}}\cdot\frac{\Delta x(t)}{\Delta t}-\frac{1}{\overline{y_i}}\cdot\frac{\Delta x(t)}{\Delta t}\right|}$$

X(t) and Yi(t) in t time gray slope correlation coefficient, $\frac{\Delta x(t)}{\Delta t}$ *is system characteristic function X(t) t to t* $+\Delta t$ *slope,* $\frac{\Delta y_i(t)}{\Delta t}$ *is factors associated with Yi(t) to t* $+\Delta t$ *slope, among them:*

$$\overline{x}=\frac{1}{n}\sum_{t=1}^{n}x(t),\Delta x=x(x+\Delta t)-x(t);$$

$$\overline{y_i}=\frac{1}{n}\sum_{t=1}^{n}y(t),\Delta y_i(t)=y_i(x+\Delta t)-y_i(t);$$

When X (t), Yi (t) (I = 1, 2,..., m) 1 - interval discrete sequences, X (t) and Yi (t) (I = 1, 2,..., m) in the t to t + Δ *t of grey slope incidence degree coefficient formula can be simplified as:*

$$\delta_i(t)=\frac{1+\left|\frac{\Delta x(t)}{\overline{x}}\right|}{1+\left|\frac{\Delta x(t)}{\overline{x}}\right|+\left|\frac{\Delta x(t)}{\overline{x}}-\frac{\Delta x(t)}{\overline{y_i}}\right|}$$

So:

$$\varepsilon_i=\frac{1}{n-1}\sum_{t=1}^{n-1}\xi_i(t)$$

For X (t) and Yi (t) slope grey correlation degree, if choose other interval incidence degree, concrete numerical value will change, but the overall trend will not change. Grey slope correlation coefficient reflects the variation of the two curves at some point, the consistent degree of slope and gray relational grade is on the whole interval grey slope correlation coefficient of average, X (t) and Yi (t) the rate of change of the closer the epsilon I.

3.2.5 Impact factor of slope grey correlation degree analysis

Calculates the factor correlation:

Tab 28. The correlation degree of elements with tensile strength

Factor **Tensile Strength**	**C**	**Mn**	**S**	**Si**	**P**
Correlation degree/ε	0.9667	0.9166	-0.8322	0.7544	-0.6617

Tensile strength, therefore, the principal component analysis and the five elements of the sensitive degree of sorting is: C > Mn > Si > S > p., the largest tensile strength is affected by C, Mn, once the content of C and Mn, the change of the performance of the steel in tensile strength is obvious.

Tab 29. The correlation degree of elements with yield strength

Factor **Yield Strength**	**C**	**Mn**	**S**	**Si**	**P**
Correlation degree/ε	0.9325	0.6956	-0.7862	0.7098	-0.5987

Yield strength, therefore, the principal component analysis and the five elements of the sensitive degree of sorting is: C > Si > Mn > S > p., the yield strength under the influence of C, Si, biggest once the content of C, Si, the performance of the steel in the change of the yield strength is obvious.

Tab 30. The correlation degree of elements with percentage elongation after fracture

Factor **percentage elongation after fracture**	**C**	**Mn**	**S**	**Si**	**P**
Correlation degree/ε	-0.7968	-0.8118	0.2762	-0.5006	0.2987

Thus, percentage elongation after fracture and principal component analysis of sensitivity of the five elements of sorts for: P > S > Mn > C > Si., the yield strength under the influence of S and P is the largest, once the content of S and P increased, the performance of the steel in the percentage elongation after fracture of change is obvious.

3.3 Basic model of the third problem

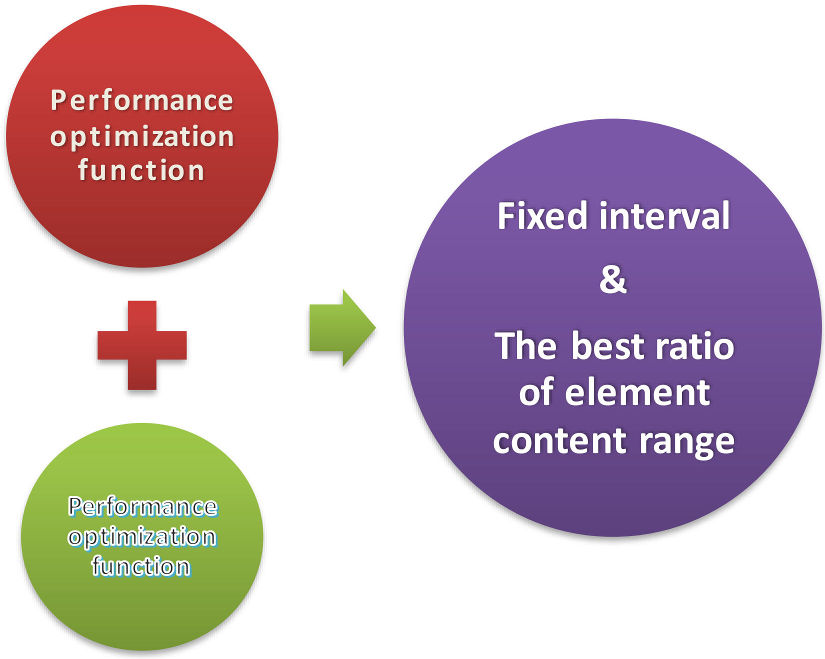


Fig 26. The problem of three steps

3.3.1 Build a performance optimization function-Stepwise regression

By increasing the content of Cr, Mn, reduce the alloy V, etc. The content of other elements, and finally calculated by optimization of the main chemical elements of the optimal.
In accordance with the above process can be found elements have the greatest influence on the properties of alloy steel C, Mn, Si, S, P, Cr and V, C, Mn, Si, Cr and V on the performance of the alloy steel plays a useful role, and S/P is not conducive to various properties of alloy steel. So, the following performance optimization function model, can establish performance for P, T of overall performance index for alloy steel, as judged by performance value, are:

$$P_{ST}=\lambda_1[C]+\lambda_2[Mn]+\lambda_3[Si]-\lambda_4[S]-\lambda_5[P]+\lambda_6[Cr]+\lambda_7[V]+C_1$$
$$P_{YT}=\varphi_1[C]+\varphi_2[Mn]+\varphi_3[Si]-\varphi_4[S]-\varphi_5[P]+\varphi_6[Cr]+\varphi_7[V]+C_2$$
$$P_{PEAF}=-\eta_1[C]-\eta_2[Mn]-\eta_3[Si]+\eta_4[S]+\eta_5[P]+\eta_6[Cr]+\eta_7[V]+C_3$$

Among them, ST, YT and PEAF is tensile strength, yield strength and percentage elongation after fracture of shorthand, and, respectively, λ_i, φ_i, η_i *are tensile strength, yield strength and percentage elongation after fracture element evaluation coefficient.*
In addition:

$$T_P=\alpha P_{TS}+\beta P_{YS}+\gamma P_{PEAF}$$

Among them, α, β, γ *are* P_{TS}, P_{YS}, P_{PEAF} *'s principal component factor analysis of tensile strength, yield strength and percentage elongation after fracture.*

According to the ***Steel for the reinforcement of concrete - part 2: Hot rolled ribbed bars*** *of the GB standard is:*

Tab 31. Chemical element content in the steel（<%）

C	Si	Mn	P	S
0.25	0.80	1.60	0.045	0.045

Tab 32. The mechanics properties of the steel index（>）

Tensile Strength/Mpa	Yield Strength/Mpa	Percentage elongation after fracture/%
335	455	17
400	540	16
500	630	15

(1) Element evaluation coefficient of stepwise regression

Take the dependent and independent variables in chemical composition[16] *and microstructure, strength, plasticity and impact work. Using stepwise regression algorithm, according to the size of the independent variable importance, gradually choose important variables from a set of independent variables into the regression equation. Here for the introduction and eliminate variables by F test value of 0.1, can guarantee a certain significance, and can be elected to the more independent variables. Regression results are as follows:*

$$P_{ST} = 415.90[C] + 137.18[Mn] + 144.03[Si] - 1717.26[S] - 3860.14[P] + 64.26[Cr] + 236.16[V] + 165.46$$

$$P_{YT} = 80.65[C] + 415.33[Mn] + 198.36[Si] - 203.45[S] - 1926.8[P] + 95.68[Cr] + 223.98[V] + 298.37$$

$$P_{PEAF} = -21.212[C] - 76.315[Mn] - 38.440[Si] + 382.632[S] + 22157.496[P] + 956.3[Cr] + 58.382[V] + 440.004$$

(2) Regression analysis results

1. The regression equation to a high level of reliability, the regression equation can be used for reference in the practical application.
2. The conventional elements, such as carbon, manganese, phosphorus, mainly appear in the return type, the description of the five common elements of steel is still stable quality control precision of the key factors.
3. The trace elements al, vanadium has certain influence to the mechanical properties, should pay attention. But copper does not appear in the return type, it shows that the content of copper (0.046 2%) impact on performance is not significant role.

3.3.2 Element content of optimization objective function

Problem by one factor analysis and calculation, the tensile strength, yield strength and percentage elongation after fracture of the principal component analysis factor were 62.994%, 28.042%, 8.964%. Therefore:

$$\alpha = 0.62994$$
$$\beta = 0.28042$$
$$\gamma = 0.08964$$

So:

$$T_P = 0.62994 P_{TS} + 0.28042 P_{YS} + 0.08964 P_{PEAF}$$

By actual steelmaking process add elements alloy and steel price per ton, the price of the building as a constraint condition[17], to maximize the performance as the objective function of optimization model, as follows:
The objective function:

$$MAX\ T_P = \alpha P_{TS} + \beta P_{YS} + \gamma P_{PEAF}$$

$$
s.t.\begin{cases}
\alpha = 0.62994; \\
\beta = 0.28042; \\
\gamma = 0.08964; \\
P_{ST} = 415.90[C] + 137.18[Mn] + 144.03[Si] - 1717.26[S] - 3860.14[P] + \\
64.26[Cr] + 236.16[V] + 165.46; \\
P_{YT} = 80.65[C] + 415.33[Mn] + 198.36[Si] - 203.45[S] - 1926.8[P] + 95.68 \\
[Cr] + 223.98[V] + 298.37; \\
P_{PEAF} = -21.212[C] - 76.315[Mn] - 38.440[Si] + 382.632[S] + 22157.496[P] + \\
956.3[Cr] + 58.382[V] + 440.004; \\
[C] \in (0.17, 0.25); \\
[Si] \in (0.15, 0.80); \\
[Mn] \in (1.20, 1.60); \\
[P] \in (0, 0.045); \\
[S] \in (0, 0.045); \\
[Cr] \in (0, 0.03); \\
[V] \in (0, 0.005); \\
Q_{Cr} = M_{Cr} \cdot q_{Cr} \\
Q_T = 5 \cdot Q_{Cr}
\end{cases}
$$

Calculated through the Lingo in the table below:

Tab 33. The calculation results

Specification	C	Si	Mn	P	S	Cr	V
GB （<）	0.25	0.8	1.6	0.045	0.045	-	-
Practical	0.2145	0.535	1.4275	0.0255	0.025	0.0215	0.02985
Setting (<)	[0.17,0.25]	[0.15,0.80]	[1.20,1.60]	0.045	0.045	0.03	0.005
Optimizing	0.2322	0.2736	1.3236	0.0199	0.0233	0.0293	0.00412
Correction	[0.19,0.25]	[0.25,0.40]	[1.2,1.50]	[0.0150,0.02]	[0.02,0.025]	[0,0.03]	[0,0.01]

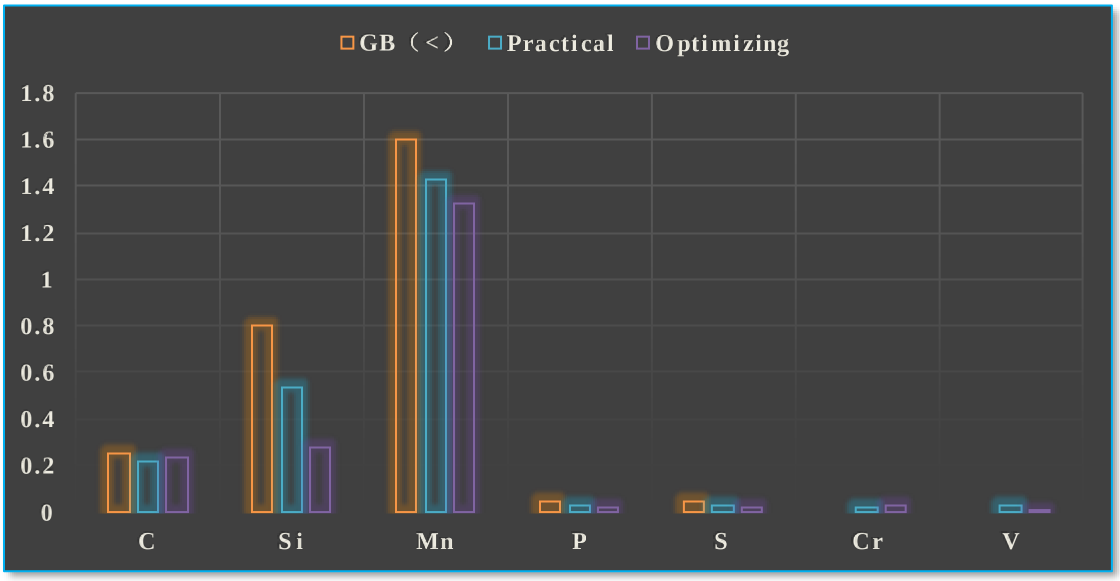


Fig 27. The calculation results

4 Conclusions

4.1 The results of the analysis on the first question

Through factor analysis, the Tensile Strength as the main factors that influence the performance of spiral steel, secondly, Yield Strength for the secondary factors, the Percentage Elongation After Fracture the secondary factors[20], and the Tensile Strength can directly reflect the most spiral steel material performance is good or bad, Can change in Tensile Strength, and the more, and predicting in advance to the problem with the material Yield Strength also can reflect in terms of Tensile Strength cannot judge the quality problem of the material, through the literature inquiry, to determine the Tensile Strength and Yield Strength can be used as two primary and secondary factors influencing the performances of materials.

But the correlation between the three factors, the Tensile Strength and Yield Strength was positively related to relationship, Tensile Strength, Yield Strength, respectively, and the Percentage Elongation After Fracture negative correlation. AS the Tensile Strength increased with the increase of the element or reduce caused by the change, change be subdivided with Tensile Strength, Yield Strength, and the Percentage Elongation After Fracture change instead.

4.2 The results of the analysis on the second question

In view of the question 2, the performance of the rebar to the influence of the content of each element in steel, concrete embodiment[19] in tensile strength, yield strength and percentage *elongation after fracture of three performance factors, is obtained by principal component analysis and polynomial fitting analysis, C, Mn, S, Si, P is the main factors influencing the performances of spiral steel, including the increase of the content of C, Mn and Si will make the tensile strength and yield strength of different level rise, and percentage elongation after fracture. And the element of S and P are harmful impurity in steel, will reduce the tensile strength and yield strength of steel, and the percentage elongation after fracture have minor influence of different level.*

4.3 The results of the analysis on the third question

Qualitative analysis is the role of spiral steel chemical elements:

Carburizing bearing steel, C content on the carburizing and quenching hardness and hardenability of parts after the core plays a decisive role, C content is too low, the hardness of hardenability and the core value is low, and the intensity decreased.

S is a harmful element in the carburizing bearing steel, should be strictly controlled on low temperature toughness of steel, the impact on the impact toughness is very big. Where impact resistance requirements, P is a harmful element, should reduce as far as possible. MN can dissolve in ferrite and ferrite matrix, improve the strength, hardness and hardenability of steel, but will reduce the plasticity and toughness slightly steel, Mn also can reduce the corrosion resistance of steel. Control Mn content in steel, to the comprehensive performance of steel to achieve the best. MN in carburizing bearing steel, control content shall not exceed 0.7%.

Si can also be solid soluble in ferrite and ferrite matrix, improve the strength and hardness of the steel, also can improve Quang ratio, the ratio of fatigue strength and tensile strength. Join the right amount of Si in steel can improve the hardenability, improve resistance to temper soften the organization. In carburizing bearing steel, Si and Mn composite effect can significantly increase the resistance to tempering stability of carburizing layer, the higher Si content, the better the performance of tempering stability, control of Si content less than 0.4%, so little effect on the toughness of the steel and plastic.

In the carburizing bearing steel, Ni is as alloy elements join, can reduce the surface of the ability to absorb carbon atoms in steel, accelerate the diffusion of carbon atoms in the austenite, reduce carbon concentration in carburized layer, Ni can slow down the carburizing speed, improve the toughness of the steel.

Cr in carburizing bearing steel, can improve the hardenability and improve the carburized layer of wear resistance, and can improve the mechanical properties of steel, at the same time Cr can make steel heat treatment process is stable.

Mo is the element of automatizing region was reduced. In carburizing bearing steel, Mo's *main function is to improve the hardenability, improve the toughness, wear resistance and carburizing performance, improve the mechanical properties*[21].

In front of the grey correlation analysis result, also can see that as a harmful chemical element of S, P in the carburizing bearing steel have been effectively controlled, even in the chemical composition of the sample, the highest and lowest levels S for 4 times, Si is 1.6 times, 1.4 times, P S and P on cardiovascular department minimum the influence of hardness, compared with the effects of Si is still poor[18].

Through the analysis of the front can be concluded that: when a C, Mn, Ni, Cr, Mo and other elements within the scope of the material composition of qualified fluctuation, the influence of hardness of Si content on cardiovascular department become the biggest factor, and the core hardness values increase or decrease with increase or decrease of Si content.

5 Future Work

5.1 Model Evolution

5.1.1 Model limitations

In question, because some cases, the amount of data relative to the sample data do not have the value of calculation and test, so for some elements of not considering the influence of performance indicators.

In addition, due to the limitation of time and other conditions, inevitably there will be an error when calculating the data, can only be made to the conclusion that is not another problem associated with psychological research conclusions of reference.

5.1.2 Single factor analysis of variance of normal distribution test

Single factor[18] *analysis of variance is also called a variance analysis, it tests by the single factor influence of one or more independent variables by the factors of each lev el grouping mean the difference between whether has statistical significance. Which age group as the factor analysis of variance, the study under the different types of single factor, embodied in the sample overall performance index is whether there is significant difference between.*

In addition, the single factor analysis of variance dependent variable belongs to the normal distribution overall process requirement. If the distribution of the dependent variable obvious is normal, can't use the process. So, before the variance analysis for different types of each independent normal distribution of the dependent variable, used here P - P figure test in the SPSS as shown.

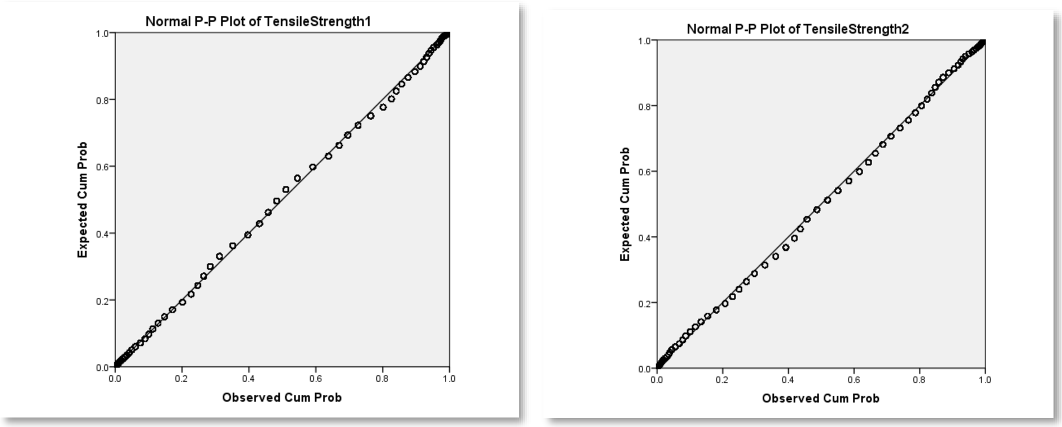


Figure 28-29. Normal P-P Plot of Tensile Strength

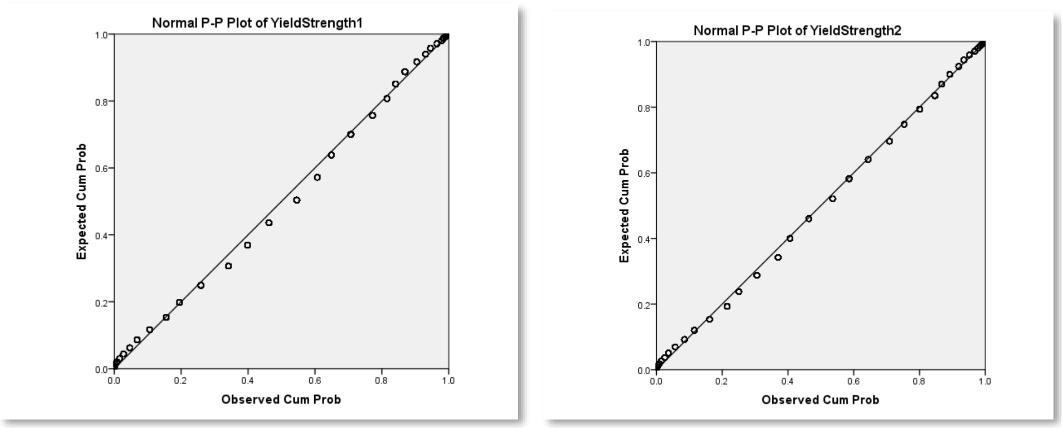


Figure 30-31. Normal P-P Plot of Yield Strength

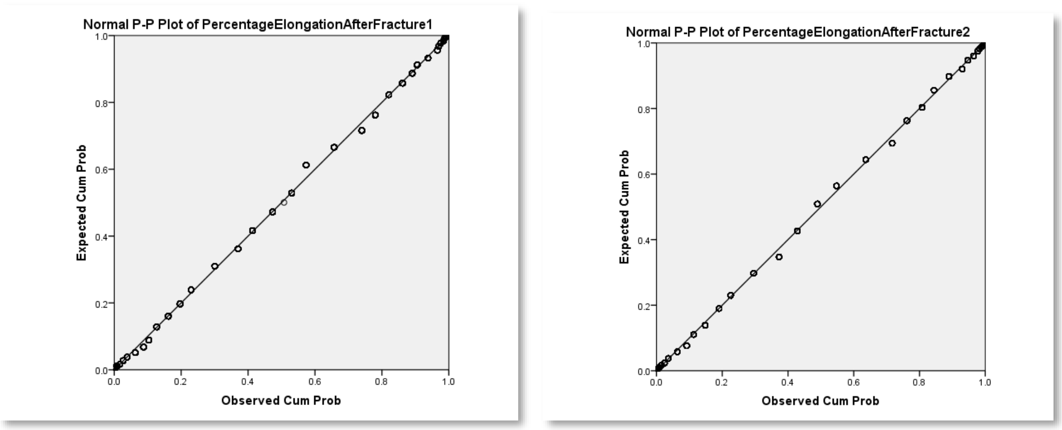


Figure 32-33. Normal P-P Plot of Percentage elongation after fracture

6 References

[1] *Sisonke Sun Shoaling, modeling algorithm and application, Beijing: national defense industry press, 2015*

[2] *Han Hogging, mathematical modeling method and application, Beijing: higher education press, 2009*

[3] *Jing, but march, mathematical modeling and mathematical experiments, Beijing: higher education press, 2000*

[4] *If so, how in SPSS distribution test (2), http://blog.sina.com.cn/s/blog_5efe471 10100d28n.html*

[5] *vanishing li, CEng Zhen incense, hang min, etc., principal component analysis (pica) in the multi-index comprehensive evaluation method, the application of journal of Hebei university of technology, 1999, 28 (1): 94-97*

[6] *Wang Jilin. Hot rolled ribbed steel bar of old and new standard comparison [J]. Journal of construction workers, 2010, 11:37, 38.*

[7] *lie Hua, Julius. The chemical composition of high manganese steel impact on organization and performance analysis [J]. Journal of science and technology association BBS (second half), 2010, 10, 101.*

[8] *Tian Yoshi Dong Fang, Feng Gaohu. In steel, chemical composition analysis of the impact of slab crack between [J]. Journal of thermal processing, 2014, 21:218-221.*

[9] *Wu Xinxiang. Talk about the chemical elements affect the performance of steel [J]. Journal of construction workers, 1980 practices: 27-29.*

[10] *Feng Chunhui. Discuss the role of alloying elements in steel [J]. Journal of metallurgy and quality standardization, 1996 preceding: 20-23.*

[11] *Ptilinum Jia Tingeing. Improvement on steel analysis method* —— *combined determination of MN, Cr element content in steel [J]. Journal of chemical industry in Shaanxi province, 1995,01:45 to 47.*

[12] *Lai Xining. 1499.2 GB - 2007 "steel reinforced concrete part 2: hot rolled ribbed steel bar, new change [J]. China standard review, 2008, 05:7 + 12.*

[13] *Zed-xi Yuan, Songsak Yu, Shi-qi Li, Ding-Xu Li, Wu Jun. Wesco steel chemical composition and performance relationship test study [J]. Journal of Wuhan technical university of metallurgy, 1998, 1998:30-34.*

[14] *Guo-Quang Yu, Zhan-bin li, goujon wan li and du. Groundwater dynamic BP neural network model and the improved grey slope correlation analysis [J]. Journal of Xian building university of science and technology (natural science edition), 2009, 566:566-570.*

[15] *Wu Xinxiang. Talk about the chemical elements affect the performance of steel [J]. Journal of construction workers, 1980 practices: 27-29.*

[16] *De-junk Kong, YE Undogged Wei, Wu-young Zheng, Long Dan. Microstructures and Plane Energy Spectra of X80 Pipeline Steel Welded Joints by Submerged Arc Automatic Welding[J]. Journal of Wuhan University of Technology (Materials Science Edition),2014,06:1265-1269.*

[17] *Zhen-Gudang Liu, Xu-Hua Gao, Chi Yu, Lin-Xu Du, Jian-Ping Li, Ping-Ju Hao. Corrosion Behavior of Low-Alloy Pipeline Steel with 1% Cr Under CO_2 Condition[J]. Acta Metallurgical Sonica (English Letters),2015,06:739-747.*

[18] *Xin Chaoyang, de-junk Kong. Microstructure and properties of steel after bromizing Cr12MoV analysis [J]. Journal of powder metallurgy materials science and engineering, 2015, 609:609-615.*

[19] *Xu Dangling lie-wee lie, phen-fen hang, Chen Hongjie. Several kinds of alloy elements on the influence of the oil casing steel CO_2 / H_2S corrosion [J]. Journal of petroleum and chemical corrosion and protection, 2008,01:20-23.*

[20] *Tension fracture behaviors of welded joints in X70 steel pipeline[J]. Theoretical & Applied Mechanics Letters,2011,03:39-43.*

[21] *Analysis of the influence of the hot-rolling material on galvanized product[J]. Boatel Technical Research,2010, S1:51.*

Appendix

1.T test the MATLAB program

```
X=xlsread('book.xlsx','A1:A117')';
Y=xlsread('book.xlsx','B1:B117')';
[H, P, CI] =ttest (X, Y)
%p<0.05 Reject H0 have significant difference
%Cl
  [Muhat, sigmahat, muci, sigmaci]=normfit(X)
% Muhat confidence intervals for mean muci for average 0.95
% sigmahat standard deviation sigmaci standard deviation 0.95 confidence interval
a=Muhat;
b=sigmahat;
Cx=b/a
[Muhat, sigmahat, muci, sigmaci]=normfit(Y)
% Muhat confidence intervals for mean muci for average 0.95
% sigmahat standard deviation sigmaci standard deviation 0.95 confidence interval
a=Muhat;
b=sigmahat;
Cy=b/a
%Cx < Y if the variation coefficient of Cy, shows more reliable than Y x
if Cx<Cy
    disp('x is smaller than y coefficient of variation, more stable, and the results more reliable')
else
     disp('y than x variation coefficient is small, more stable, the results more reliable')
end
```

2. Normal distribution test MATLAB program

```
A=xlsread('book.xlsx','A1:A117')';
A = A';
alpha = 0.05;
% Normal distribution
[mu, sigma] = normfit(A);
p1 = normcdf(A, mu, sigma);
[H1,s1] = kstest(A, [A, p1], alpha);
n = length(A);
```

```
if H1 == 0
    disp('the data source is normal distribution.')
else
    disp('the data source does not obey the normal distribution.')
end
```

3. Factor analysis

```
clear,clc
A=xlsread('book','sheet2','A2:F169');
n=size(A,1);
% Returns A number of rows of the matrix, the size (A, 2) returns the number of columns of the matrix, the size (A) is returned, and the number of columns
% Respectively, puts forward the independent variable x1: x4 and y values
x=A(:,[1:5]);y=A(:,6);
k=zscore(x);% The independent variable x standardization
r=corrcoef(k);% The correlation coefficient matrix of matrix k x standardization
[vec1,val,con1]=pcacov(r);% Principal component analysis related calculation
% Plus or minus characteristic vector transformation
f1=repmat(sign(sum(vec1)),size(vec1,1),1);
vec2=vec1.*f1;
% Primary load matrix
f2=repmat(sqrt(val)',size(vec2,1),1);
a=vec2.*f2;
% Interactive choose the number of main factors and main factor number less than or equal to 4
num=input('please select the number of main factors: ');
% Num is a main factor loading matrix is put forward
am=a(:,[1:num]);
% Am rotation transformation of the bm for rotating load matrix
[bm,t]=rotatefactors(am,'method','varimax');
% Rotating all factor loading matrix, after the first two rotation, behind not rotating
bt=[bm,a(:,[num+1:end])];
% Calculation factor contribution
con2=sum(bt.^2);
% Grasp rotation is the meaning of this statement, con1 is before rotating contribution
check=[con1,con2'/sum(con2)*100];
```

```
rate=con2(1:num)/sum(con2);
% Calculation factor contribution rate
coef=inv(r)*bm;
% Calculate the coefficient of scoring function
score=k*coef ;
% Calculate each factor score
weight=rate/sum(rate);
% To calculate weight score
Tscore=score*weight';
% Scores of each factor weighted sum, namely the composite scores for each enterprise
[STscore,ind]=sort(Tscore,'descend');
% To the enterprise
display=[score(ind,:)';STscore';ind'];
% The ranking results show
[ccoef,p]=corrcoef([Tscore,y]);
% Calculate the correlation coefficient F and the assets and liabilities
[d,dt,e,et,stats]=regress(Tscore,[ones(n,1),y]);
% Calculate the equation F and the assets and liabilities
d,stats
% According to regression coefficients, and related statistic value
```

4. Grey correlation analysis

```
clc,clear
a=xlsread('cook.xlsx','A1:C133');
[m,n]=size(a);
b=max(a')'
t=repmat(b,[1,n])-a;
mmin=min(min(t));
mmax=max(max(t));
rho=0.5;
xishu=(mmin+rho*mmax)./(t+rho*mmax)
guanliandu=mean(xishu)
[gsort,ind]=sort(guanliandu,'descend')
xlswrite('9X.xlsx',xishu);
xlswrite('9G.xlsx',guanliandu);
```

5. Principal component analysis

```
clc,clear
gj=xlsread('dook.xlsx','B2:H5');
gj=zscore(gj);% Data standardization
r=corrcoef(gj);% Calculating the correlation coefficient matrix
% Below, principal component analysis with correlation coefficient matrix, and the vec1 as a feature
vector of r, and the principal component factor
[vec1,lamda,rate]=pcacov(r)
% The eigenvalues of the lambda r, What is the contribution of each principal component
contr=cumsum(rate)
% Calculate the accumulative contribution rate
f=repmat(sign(sum(vec1)),size(vec1,1),1);
% Structure with vec1 dimension of the matrix elements of plus or minus 1
vec2=vec1.*f
% Modify the feature vector of plus or minus, make the weight of each feature vector and positive
num=2;
% The number of principal components in the num to choose
df=gj*vec2(:,1:num);
% Calculation of each principal component score
tf=df*rate(1:num)/100;
% Calculation of composite scores
[stf,ind]=sort(tf,'descend');
% The score according to the order from high to low
stf=stf',ind=ind'
format long
xlswrite('dook1.xlsx',vec1);
```

6.T Type 2 fitting data

tensile strength	yield strength	percentage elongation after fracture	C	Mn	S	P	Si
0.156305135	0.13529334	0.520091848	0.210820896	1.422686567	0.025738806	0.027074627	0.524850746
0.332289938	0.192353478	0.466185427	0.213096774	1.425278592	0.025504985	0.026523754	0.533120235
0.494367986	0.250579764	0.426725922	0.214468989	1.42646559	0.025529737	0.026571793	0.536835174
0.669137177	0.310737397	0.382768048	0.215619597	1.430835735	0.024525937	0.02679683	0.546123919
0.855406395	0.382523182	0.334160463	0.21483871	1.429032258	0.024967742	0.028064516	0.531935484