Hindawi
Mathematical Problems in Engineering
Volume 2017, Article ID 4393279, 11 pages
https://doi.org/10.1155/2017/4393279

Research Article

Research on NDT Technology in Inference of Steel Member Strength Based on Macro/Micro Model

Beidou Ding,[1,2] Naiqiang Xiao,[2] Shuxun Zhang,[3] and Yong Wang[3]

[1] *State Key Laboratory for Geomechanics & Deep Underground Engineering, China University of Mining and Technology, Xuzhou 221116, China*
[2] *Jiangsu Key Laboratory of Environmental Impact and Structural Safety in Engineering, China University of Mining and Technology, Xuzhou 221116, China*
[3] *National Space Frame and Steel Structures Quality Supervision and Inspection Center, Xuzhou 221006, China*

Correspondence should be addressed to Beidou Ding; dbdstar@163.com

Received 10 February 2017; Revised 5 June 2017; Accepted 11 June 2017; Published 16 July 2017

Academic Editor: Marek Lefik

In consideration of correlations among hardness, chemical composition, grain size, and strength of carbon steel, a new nondestructive testing technology (NDT) of inferring the carbon steel strength was explored. First, the hardness test, chemical composition analysis, and metallographic analysis of 162 low-carbon steel samples were conducted. Second, the following works were carried out: (1) quantitative relationship between steel Leeb hardness and carbon steel strength was studied on the basis of regression analysis of experimental data; (2) influences of chemical composition and grain size on tension properties of carbon steel were analyzed on the basis of stepwise regression analysis, and quantitative relationship between conventional compositions and grain size with steel strength was obtained; (3) according to the macro and/or micro factors such as hardness, chemical compositions, and grain size of carbon steel, the fitting formula of steel strength was established based on MLR (multiple linear regressions) method. The above relationships and fitting formula based on MLR method could be used to estimate the steel strength with no damage to the structure in engineering practice.

1. Introduction

The hardness and strength are two macroscopic performance indexes of steel material. The tensile strength is usually the main parameter evaluating the bearing capacity of structure or components. As detection of steel hardness is simple and rapid and will not damage structure or component, establishment of mathematical model with "macro" index such as steel hardness and strength is convenient for evaluation of material strength of steel structure in service. In addition, internal crystal structure and chemical composition are "micro" constitution of carbon steel. In fact, besides carbon composition, carbon steel also contains a small quantity of Mn, Si, S, P, O, N, and other compositions.

Metal harness has correlation with strength as expressed in Jiangsu engineering construction standard DGJ32/TJ 116-2011 [1] and international ISO standard ISO/TR10108 [2]. In recent years, many researchers [3–6] have used mathematical statistical analysis method to establish correlations between steel tensile strength with Brinell hardness and Rockwell hardness, and regression analysis method is used to solve their expressions. Over the past decades, steel mills have obtained many achievements in researches on quantitative relationship between mechanical properties and chemical composition of rebar. Furthermore, some regression models were formed according to their own production practices and used to guide design of chemical composition and formulation of internal control standard [7, 8]. A neural network with feed-forward topology and back propagation algorithm was used to predict the effects of chemical composition and tensile test parameters on hardness of heat affected zone (HAZ) in X70 pipeline steels [9]. The existences of minor compositions also affect the carbon steel quality and performance greatly. Influences of chemical composition of carbon steel and internal lattice size "micro" model on strength needed to be studied and integrated

into the regression model. However, there is a lack of researches on significance of minor chemical compositions to the mechanical properties of the steel. With development of technologies like mathematical method, physical metallurgy, and rolling, relationship between microstructure of hot rolling product and mechanical properties as well as mathematical model evolving from microstructure has obtained rapid development. Researches have carried out a large quantity of work in studying quantitative relationship between grain size and mechanical properties of steel, where the most important is Hall-Petch formula with the most extensive application [10–12]. All in all, at present, many model researches consider influences of single factors among carbon steel hardness, microstructure, and chemical composition on carbon steel strength, respectively. However, there are few model researches on inference of carbon steel strength by combining micro factors, chemical composition and grain size of carbon steel, and macro factor, hardness [13–16].

The main objective of the present paper is to develop MLR (multiple linear regressions) method for inferring the carbon steel strength with its hardness, chemical compositions, and grain size. In order to acquire the correlations among steel hardness, chemical composition, and strength, hardness test and metallographic analysis of carbon steel were carried out in this paper. MLR method was used to propose a macro/micro mathematical model based on experiment data of hardness, grain size, and chemical compositions of carbon steel. The models could be used to infer carbon steel strength to verify its effectiveness. This paper is arranged as follows. First, regression analysis method is introduced which consists of the establishment of the regression model, least squares estimation of regression coefficients, and the significance test of linear regression model. Second, the hardness test, chemical composition analysis, and metallographic analysis of 162 low-carbon steel samples were conducted. The following works were completed: (1) quantitative relationship between steel Leeb hardness and carbon steel strength was studied on the basis of regression analysis of experimental data; (2) influences of chemical composition and grain size on mechanical properties of carbon steel were analyzed on the basis of stepwise regression analysis, and quantitative relationship between conventional compositions and grain size with steel strength was obtained; (3) according to the macro and/or micro factors such as hardness, chemical compositions, and grain size of carbon steel, the fitting formula of steel strength was established based on MLR (multiple linear regressions) method. The above relationships and fitting formula could be used to estimate the carbon steel strength in different NDT engineering practice.

2. Regression Analysis Methods

Regression analysis method is a commonly used method in statistical analysis and mathematical modeling of relationships between random variables. As most random variables are randomly obtained through the experiment, the validity and significance of random variables in this model need further verification with statistical experiment. For regression analysis, it is necessary to establish a mathematical model, namely, common functional relationship. In the function model, its independent variables are regression variables and its dependent variables are called response variables. If there is only one variable in the model, it is then called single regression model, and if there are multiple variables, then it is called multiple regression model.

2.1. Regression Model. It is assumed that response variable $y(u)$ and m regression variables $\varphi_i(u)$ have linear relationship, and then general form of multiple linear regression models is

$$y(u) = \beta_1\varphi_1(u) + \beta_2\varphi_2(u) + \cdots + \beta_m\varphi_m(u). \quad (1)$$

Suppose that the experiment is conducted for n times and n groups of measured values are obtained:

$$\begin{bmatrix} u_1 & y_1 \\ \vdots & \vdots \\ u_{n-1} & y_{n-1} \\ u_n & y_n \end{bmatrix}. \quad (2)$$

Equation (3) can be obtained by substituting (2) into (1)

$$y_i = \beta_1\varphi_1(u_i) + \beta_2\varphi_2(u_i) + \cdots + \beta_m\varphi_m(u_i) + \varepsilon_i, \quad i = 1, 2, \ldots, n. \quad (3)$$

It is expressed in the form of matrix as

$$\mathbf{Y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix},$$
$$\mathbf{X} = \begin{bmatrix} \varphi_1(u_1) & \varphi_2(u_1) & \ldots & \varphi_m(u_1) \\ \varphi_1(u_2) & \varphi_2(u_2) & \ldots & \varphi_m(u_2) \\ \vdots & \vdots & & \vdots \\ \varphi_1(u_n) & \varphi_2(u_n) & \ldots & \varphi_m(u_n) \end{bmatrix},$$
$$\boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix}, \quad (4)$$
$$\boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}.$$

In (4), $\mathbf{X}$ is called regression variables matrix. $\mathbf{Y}$ is response variable matrix and $\mathbf{Y} \sim N_n(X \cdot \beta, \sigma^2 I)$, while $\boldsymbol{\varepsilon}$ is a unobservable random error variable and $\boldsymbol{\varepsilon} \sim N_n(0, \sigma^2 I)$,

in which I is unit matrix. $\boldsymbol{\beta}$ is vector consisting of regression coefficients $\beta_1, \beta_2, \ldots, \beta_m$, and u is unknown constant vector.

Then (4) can be expressed in the form of matrix as

$$\mathbf{Y} = \mathbf{X} \cdot \boldsymbol{\beta} + \boldsymbol{\varepsilon}. \tag{5}$$

2.2. Least Squares Estimation of Regression Coefficients. The regression coefficients $\boldsymbol{\beta}$ can be estimated by the least square method. To an estimated values of $\boldsymbol{\beta}$, if the least square of the random errors $\boldsymbol{\varepsilon}$ of the regression equation is minimum, the fitting effect of the regression equation is the best. Order the estimated value of β and record it as $\widehat{\beta}$; then the appropriate $\widehat{\beta}$ is to minimize the quadratic sum of random errors; namely,

$$\begin{aligned} \min_{\beta} \boldsymbol{\varepsilon}^T \cdot \boldsymbol{\varepsilon} &= \min_{\boldsymbol{\beta}} (\mathbf{Y} - \mathbf{X} \cdot \boldsymbol{\beta})^T \cdot (\mathbf{Y} - \mathbf{X} \cdot \boldsymbol{\beta}) \\ &= \left(\mathbf{Y} - \mathbf{X} \cdot \widehat{\boldsymbol{\beta}}\right)^T \left(\mathbf{Y} - \mathbf{X} \cdot \widehat{\boldsymbol{\beta}}\right) \triangleq Q\left(\widehat{\boldsymbol{\beta}}\right). \end{aligned} \tag{6}$$

It is written into form of components as below

$$\begin{aligned} &\mathbf{Q}(\beta_1, \beta_2, \ldots, \beta_m) \\ &= \sum_{i=1}^{n} \left[y_i - \beta_1 \varphi_1(u_i) - \beta_2 \varphi_2(u_i) - \cdots - \beta_m \varphi_m(u_i)\right]^2. \end{aligned} \tag{7}$$

Then

$$\mathbf{Q}\left(\widehat{\beta}_1, \widehat{\beta}_2, \ldots, \widehat{\beta}_m\right) = \min_{\beta_i} \mathbf{Q}(\beta_1, \beta_2, \ldots, \beta_m). \tag{8}$$

Order $\partial \mathbf{Q} / \partial \beta_j = 0$, $j = 1, 2, \ldots, m$; then (9) can be obtained by taking necessary conditions of extreme values according to multivariate function; namely,

$$\mathbf{X^T} \cdot \mathbf{X} \cdot \widehat{\boldsymbol{\beta}} = \mathbf{X^T} \cdot \mathbf{Y}. \tag{9}$$

It can be proved that, for any given $\mathbf{X}$, $\mathbf{Y}$, when X is full rank, $r(X) = r(X^T \cdot X) = m$, to get minimum quadratic sum of random errors of (10); namely,

$$\mathbf{Q}\left(\widehat{\boldsymbol{\beta}}\right) = \min_{\boldsymbol{\beta}} \mathbf{Q}(\boldsymbol{\beta}), \tag{10}$$

and the solution of normal equations system is $\widehat{\boldsymbol{\beta}} = (\mathbf{X^T} \cdot \mathbf{X})^{-1} \cdot \mathbf{X^T} \cdot \mathbf{Y}$, namely, estimated value of regression coefficients.

2.3. Significance Test of Linear Regression Model. This process mainly checks whether the model certainly has close relationship with regression variables, namely, whether it accords with (1). It is assumed that y is independent of u; namely, $y(u) = \beta_0$, and the mean experiment value is $\overline{y} = (1/n) \sum_{i=1}^{n} y_i$, and the quadratic sum of total deviations is named as SST; namely,

$$\begin{aligned} \mathrm{SST} &= \sum_{i=1}^{n} (y_i - \overline{y})^2 = \sum_{i=1}^{n} (y_i - \widehat{y}_i + \widehat{y}_i - \overline{y})^2 \\ &= \sum_{i=1}^{n} (y_i - \widehat{y}_i)^2 + \sum_{i=1}^{n} (\widehat{y}_i - \overline{y})^2 + 2\sum_{i=1}^{n} (y_i - \widehat{y}_i)(\widehat{y}_i - \overline{y}) \\ &= \mathrm{SSE} + \mathrm{SSR}, \end{aligned} \tag{11}$$

where the quadratic sum of residual is

$$\begin{aligned} \mathrm{SSE} &= \sum_{i=1}^{n} (y_i - \widehat{y}_i)^2 = \left(\mathbf{Y} - \mathbf{X} \cdot \widehat{\boldsymbol{\beta}}\right)^T \left(\mathbf{Y} - \mathbf{X} \cdot \widehat{\boldsymbol{\beta}}\right) \\ &= Y^T \cdot \mathbf{Y} - \mathbf{Y}^T \mathbf{X} \cdot \widehat{\boldsymbol{\beta}}. \end{aligned} \tag{12}$$

The quadratic sum of regression is

$$\mathrm{SSR} = \sum_{i=1}^{n} (\widehat{y}_i - \overline{y})^2. \tag{13}$$

Multiple correlation coefficients $R = \mathrm{SSR}/\mathrm{SST}$ are hereby defined and used to evaluate the fitting effect of the regression equation on the sample data. The greater the R value is, the closer the relationship between regression variables and response variables is and vice versa.

Hence, it is necessary to build statistical magnitude to determine value of R in this paper. Firstly, the freedom degree should be confirmed. The freedom degree of the total deviations quadratic sum and the regression quadratic sum are $f_T = n - 1$ and $f_R = m - 1$, respectively. Then the freedom degree of the residual quadratic sum is $f_E = f_T - f_R = n - m$. Naturally, the mean-square values of the quadratic sum of residual and the quadratic sum of regression are defined as $\mathrm{MSR} = (1/(m-1))\mathrm{SSR}$ and $\mathrm{MSE} = (1/(n-m))\mathrm{SSE}$, respectively.

It can be proved that when $y = \beta_0$, $y_i \sim N(0, \sigma^2)$; then $E(\mathrm{MSR}) = E((1/(m-1))\mathrm{SSR}) = \sigma^2$, $E(\mathrm{MSE}) = E((1/(m-1))\mathrm{SSE}) = \sigma^2$. It is indicated that MSE is unbiased estimation of σ^2; namely,

$$\begin{aligned} \frac{\mathrm{SSE}}{\sigma^2} &\sim \chi^2(n-m), \\ \frac{\mathrm{SSR}}{\sigma^2} &\sim \chi^2(m-1). \end{aligned} \tag{14}$$

In the meantime, SSR and SSE are mutually independent, and then statistical magnitude of F is constructed as

$$\begin{aligned} F &= \frac{\mathrm{MSR}}{\mathrm{MSE}} = \frac{\mathrm{SSR}/(m-1)}{\mathrm{SSE}/(n-m)} \sim F(f_R, f_E) \\ &= F(m-1, n-m). \end{aligned} \tag{15}$$

After a significance level is taken, $F_\alpha(m-1, n-m)$ is calculated and compared with $F(m-1, n-m)$. When $F(m-1, n-m) < F_\alpha(m-1, n-m)$, it is believed that the model is significant; then $y = \beta_0$ does not hold; namely, η has obvious functional relationship with u. At the moment $F(m-1, n-m) < F_\alpha(m-1, n-m)$; it is believed that the model is not significant; then $y(u) = \beta_0$ holds; namely, $y(u)$ does not have obvious functional relationship with u.

3. Experimental Study of Inference of Carbon Steel Strength Based on Leeb Hardness

To obtain the correlation between hardness and strength, the experiments of steel hardness and tensile strength were conducted, a comparative analysis of experimental data was implemented, and corresponding mathematical model was obtained on the basis of mathematical regression method.

Figure 1: Test specimen.

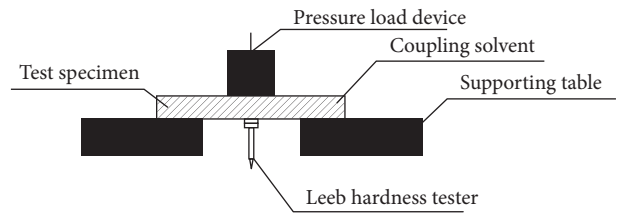


Figure 2: Test scheme.

3.1. Experimental Principles. Leeb hardness tester is manufactured according to principles of elastic impact and it is used to measure hardness of steel materials. When the impact device of the hardness tester is used to release the impact body made of tungsten carbide or diamond bulb from a fixed position, the specimen surface of the sample is impacted. The impact speed and rebound speed of the bulb on specimen surface are measured, and its Leeb hardness value is expressed with ratio of rebound speed to impact speed of the bulb. And the calculation formula of Leeb hardness is as below:

$$\mathrm{HL} = 1000 \times \frac{V_R}{V_A}. \tag{16}$$

In the equation, HL is Leeb hardness value; V_R is impact speed of the bulb; V_A is rebound speed of the bulb. Leeb hardness tester can be configured with six kinds of impact heads, that is, D, DC, D + 15, G, E, and C type pressure heads, respectively. Except that E type plunger chip is made of diamond, other forms are made of tungsten carbide.

3.2. Experimental Scheme. Steel plates used in the experiment came from 162 groups of steel plates from different steel plants in Jiangsu Province of China, including 82 Q235 steel plates and 80 Q345 steel plates, totally 162 experimental steel plates. Their thicknesses were, respectively, 6 mm, 8 mm, 10 mm, 12 mm, 14 mm, 30 mm, and so forth, their masses satisfied 2 kg < m < 5 kg, and material sampling was as seen in Figure 1. The experimental aim was to find empirical formula between Leeb hardness and tensile strength of structure steel. Based on the experimental aim, D type impact head was used for measurement in this experiment, and experimental scheme was as seen in Figure 2.

During experiment process of Leeb hardness measuring of carbon steel plates, Leeb hardness tester EQLI-OTIP3UNITD was used to measure Leeb hardness values of carbon steel plates (seen in Figure 3(a)) and standard test block of D type pressure head of Leeb hardness tester was used to calibrate Leeb hardness values (seen in Figure 3(b)).

3.3. Experimental Process and Results. It is required that specimens of the steel plates should have enough mass and rigidity in experimental standard and will not go through displacement or springing during impact process. Mass range of specimens participating in the experiment was 2 kg < m < 5 kg; in order to meet experimental requirements, specimens should be coupled so as to reduce energy loss under impact and avoid affecting calibration Leeb hardness values. Combined with field operating conditions, impact device adopted in this paper turned upward (seen in Figure 3(b)). Before specimens were measured, standard test block was tested. Leeb hardness value of the standard test block was 538 HLD, and measuring results were as shown in Table 1 for the convenience of correction of experimentally measured data.

It can be known from Table 1 that error between measured value and calibration value of standard test block is smaller than 12 HLD which meets national standard requirements. According to experimental standard requirements, each group of specimens should be measured for nine times, distance between indentations of every two points should be greater than 3 mm, and the distance from each point to specimen edge was greater than 5 mm. Two maximum values and two minimum values were excluded among nine measured values which met conditions to solve average value of five measured values, and then this average value was modified, which was the final Leeb hardness value. Table 2 is some partial testing results of the specimens measured by Leeb hardness.

3.4. Inference of Regression Equation of Carbon Steel Strength Based on Leeb Hardness. In order to infer the correlation between hardness and yield strength of carbon steel, the data of hardness and yield strength were regressed by the least square method and statistical method for the 162 test data. The correlation coefficient r^2 and the F value of regression equation fitting were analyzed. At the same time, through residual analysis the optimal regression model was determined and the large residual outliers were removed from the experimental data. Changes of HLD-Re linear regression model statistics were shown in Figure 4. From Figure 4, the correlation coefficient $r2$ and the F value increased with the optimization number, while the residual value decreased. After five optimization times, the correlation coefficient $r2$ was increased from 0.6 to 0.697; F value increased from 191.8 to 301.9, while the residual value $\sigma 2$ decreased from 1070.2 to 620.5. It was shown that this statistic reached the optimal value and the regression model better met the original data.

Experimental data of all steel plants were put together, linear regression analysis method was used to analyze experimental data, corresponding relation between Leeb hardness

(a) Leeb hardness gauge (b) Steel hardness test

Figure 3

Table 1: Testing data of standard test block of Leeb hardness tester.

Calibration value (HLD)	Testing data (HLD)					Mean value (HLD)
538	540	538	538	537	539	538.4

Table 2: Results of Leeb hardness test (partial data).

Number	Testing data					Modified value
FK00001	393	392	399	397	394	395.0
FK00001	410	412	412	407	409	410.0
FK00002	410	412	412	412	412	411.6
FK00002	426	425	424	428	426	425.8
FK00004	416	416	411	414	409	413.2
FK00004	443	442	444	442	442	442.6
FK00005	381	384	384	388	384	384.2
FK00005	424	422	423	424	432	425.0
FK00006	434	431	433	434	431	432.6
FK00006	443	444	445	445	445	444.4

Table 3: Regression analysis summary between HLD and yield strength R_e and ultimate tensile strength R_m.

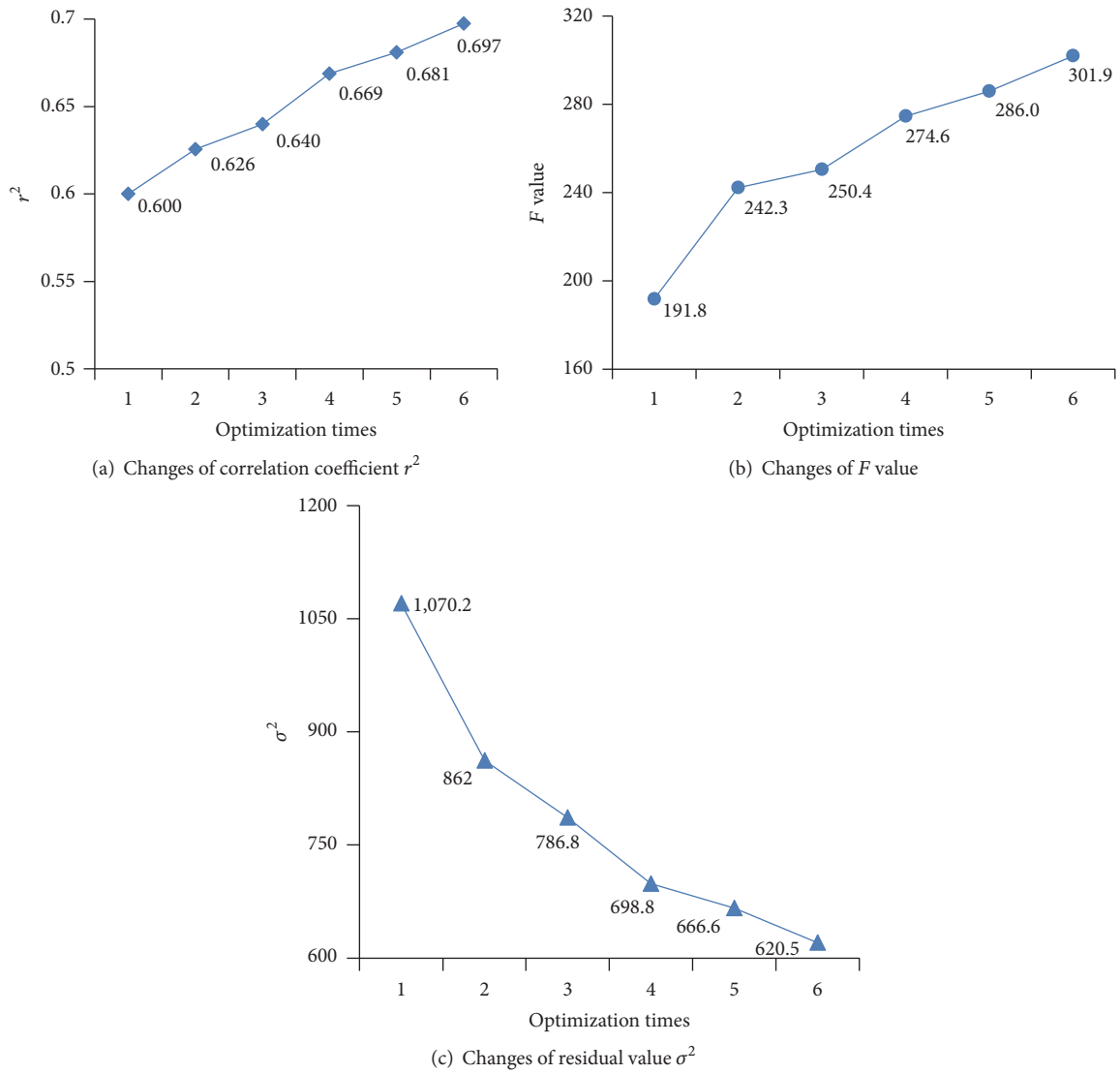
Function expression	Correlation coefficient r^2	Significant level α	F value	Test number
$R_e = -477.1893 + 2.0090\ \text{HLD}$	0.6974	0.05	301.8938	133
$R_m = -405.7281 + 2.164\ 5\text{HLD}$	0.6000	0.05	210.7	141

and strength of steel was obtained, and summary sheet of data regression analysis was as shown in Table 3. The quantitative relationships between Leeb hardness with yield strength R_e and ultimate tensile strength R_m of steel plants in Jiangsu were obtained through regression analysis method. It was found that, based on portable Leeb hardness tester, incorporating NDT technology of inferring steel strength with Leeb hardness method into the standard was feasible.

3.5. Comparisons Analysis of the Regression Equation. Figure 5 was the comparisons analysis of the regression equation among Duan et al.'s [3] paper and specifications in DGJ32/TJ 116-2011 [1]. DGJ32/TJ 116-2011 has an upper and lower limit of tensile strength in the same hardness value, so the converted tensile strength corresponding to the measured Leeb hardness was in a range, and it was not much practical effectiveness. From Figure 5, the values of Leeb hardness test were in the range 366~454 HLD and the most tensile strength test values were within the certain range. The inferred tensile strength according to Duan et al.'s [3] paper was close to the upper limit of converted tensile strength according to the specification in DGJ32/TJ116-2011. The formula based on multiple linear regressions method fitted the experimental data well. Furthermore, the inferred tensile strength was in the middle of the upper and lower bounds and could be used to estimate the steel strength in different engineering practice.

4. Experimental Study of Inference of Carbon Steel Strength Based on Micro Model

Besides carbon composition, carbon steel also contains compositions like Mn, Si, S, P, O, and N. The existence of minor



(a) Changes of correlation coefficient r^2

(b) Changes of F value

(c) Changes of residual value σ^2

Figure 4: Changes of HLD-Re linear regression model statistics.

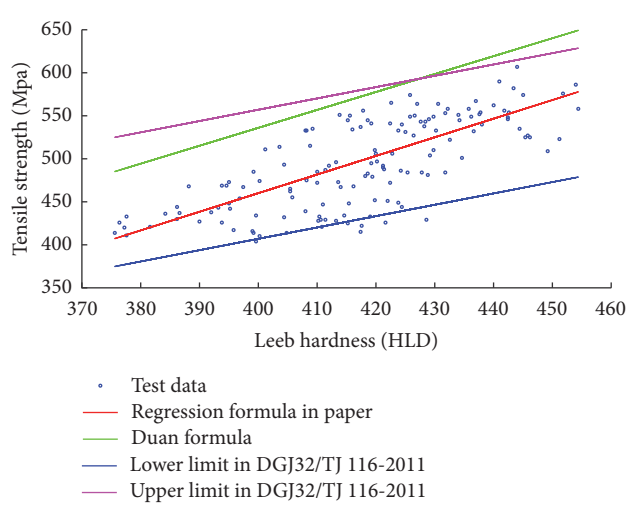


Figure 5: Comparisons analysis of the regression equation among Duan et al.'s [3] paper and specifications in DGJ32/TJ 116-2011 [1].

(a) Sample for determination of chemical compositions

(b) Bruker direct-reading spectrometer

Figure 6

Table 4: Percentages of regular compositions of test specimens (partial data).

Number	C%	Si%	Mn%	P%	S%
FK00001	0.136	0.125	0.337	0.026	0.023
FK00001	0.117	0.22	0.287	0.018	0.016
FK00002	0.146	0.331	1.474	0.02	0.0033
FK00002	0.118	0.338	1.412	0.025	0.024
FK00004	0.124	0.282	1.254	0.019	0.0093
FK00004	0.145	0.384	1.299	0.015	0.013
FK00005	0.112	0.159	0.423	0.021	0.018
FK00005	0.13	0.348	1.325	0.016	0.014

compositions will affect quality and performance of carbon steel greatly. Through test of chemical compositions in the steel specimens, their influences on steel performance were analyzed.

4.1. Test of Spectrograph Determination of Chemical Composition. Spark source atomic emission spectrometer takes spark discharge as excitation light source to sputter and excite the sample. Then, the qualitative and quantitative analysis of atoms in the tested sample can be conducted by detecting emission of composition spectrum happening in this process. As five major conventional compositions, C, Si, Mn, S, and P, have great influences on mechanical properties of steel, this experiment concentrated on detecting contents of C, Si, Mn, S, and P compositions. The experimental samples were 162 groups of carbon steel plates mentioned in previous section. For the convenience of experimental operation, steel plates used in this experiment were small steel plates cut from 162 groups of large steel plates.

In research process of this experiment, operations were as below: (1) 162 groups of steel plates (shown in Figure 6(a)) were processed, and for the convenience of experimental operations, steel plates were processed into small steel plates being about 10 cm × 5 cm. (2) Surface treatment of small steel plates was conducted: surface dust and external pollutants and greasy dirt were removed to avoid affecting measurement of chemical composition. (3) Bruker direct-reading spectrometer (shown in Figure 6(b)) was calibrated, excitation light source was used to excite specimen surface, and contents of various compositions were obtained through quantitative spectral measurement. (4) Measuring channels of chemical compositions were opened, contents of five major conventional compositions of 162 groups of steel plates were measured, and partial measuring results were as seen in Table 4.

4.2. Inferring Strength of Steel Based on Stepwise Regression. Stepwise function in statistical toolkit was used to build multiple linear regression models of chemical composition and strength, and analysis results were as seen in Table 5. The greater the regression sums of squares, the better the results of regression equation. It can be seen from Table 5 that Mn and S have great influences on yield strength R_e of carbon steel, while for its ultimate tensile strength R_m, besides Mn, S and P also have great influences. Hence, the above compositions were imported into regression equation.

After variables Mn, S, and/or P, namely, compositions were introduced, coefficient of determination and root-mean-square (RMS) error decreased. Meanwhile the corresponding regression model of yield strength R_e and ultimate tensile strength R_m of carbon steel could be defined as

$$R_e = 334.914 + 59.1846\,[\mathrm{Mn}] - 1492.38\,[\mathrm{S}]\,,$$

Table 5: Partial regression squares on the relationship between the determination of chemical composition and strength.

	C	Si	Mn	S	P
Yield strength (R_e)	0.157	0.024	1.428	0.561	0.115
Tension strength (R_{em})	0.00129	0.088	0.719	0.037	0.154

(a) (b)

Figure 7: (a) Test specimen; (b) DMI5000 Leica metallographic microscope.

$$R_m = 421.399 + 36.1576\,[\mathrm{Mn}] - 1492.38\,[\mathrm{S}] + 8.70659\,[\mathrm{P}]\,. \tag{17}$$

5. Experimental Studies of Microstructures of Carbon Steel Plates

5.1. Experimental Study of Microstructures. Metallographic microstructure test of specimens was conducted, their internal organization structures were analyzed, grain size d was calculated, and influence of grain size on material strength was analyzed. The main experimental processes were as below: (1) cut out specimens: according to experimental requirements, grinding wheel slicer was used for cutting and cooling measures should be taken during cutting process to reduce structural change of specimens caused by heating (as shown in Figure 7(a)). (2) Polish the cut specimens: this procedure was conducted step by step from rough grinding to fine grinding, and damage of surface layer should be reduced during grinding process of metallographic specimens as much as possible. (3) Remove deformed layer left in grinding procedure and make the deformed layer generated by polishing not to affect observation of microstructure. (4) Observe chemical corrosion of specimens. During the operation, the polished specimens were corroded in 4% nitric acid alcohol solution, and angle of microscopic plane was different from that of original grinding plane after corrosion. Under irradiation of vertical light rays, light rays entering objective lens through reflection were different, and grains with different shades could be seen (as shown in Figure 8). (5) DMI5000 metalloscope was used to observe the prepared metallographic samples and take photos through computer and image acquisition software (seen in Figure 7(b)).

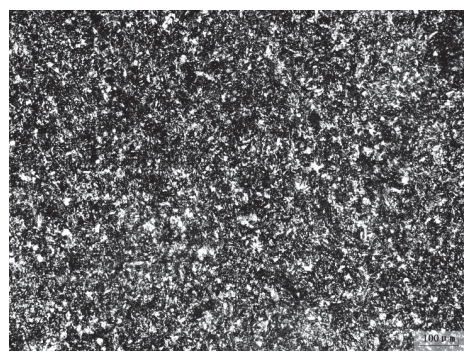


Figure 8: Metallurgical structure of test specimen (×100).

5.2. Experimental Analysis. According to dislocation piling up theory of single-crystal and polycrystalline materials, relationship between material tension strength and grain size was concluded, namely, Hall-Petch formula [14]:

$$\sigma = \sigma_0 + kd^{-1/2}. \tag{18}$$

Experimental data of ten groups of specimens extracted in this paper were as shown in Table 6, mathematical regression analysis was implemented, and it is obtained that yield strength and tensile strength satisfied positively related mathematical linear relationships with grain size $d^{-1/2}$. This was because after metal grains were refined, ratio of grain boundaries increased, and grain boundary's effect on hindering dislocation piling up was enhanced, and as dislocation piled up nearby the grain boundary, carbon steel strength increased as grains were refined. Actually as grain size decreased, grain boundaries increased, and then more energy would be consumed when the specimen was damaged, and thus it could be seen that carbon steel strength had linear

Table 6: Grain size and R_e of steel plate.

Number	Yield strength (Mpa)	Tensile strength (Mpa)	Grain size (mm)	$d^{-1/2}$
1	303	445	0.201632	2.227
2	309	450	0.128744	2.787
3	314	454	0.0945	3.253
4	321	460	0.065578	3.905
5	328	467	0.048155	4.557
6	331	469	0.042741	4.837
7	345	482	0.026508	6.142
8	353	489	0.021083	6.887
9	358	493	0.018496	7.353
10	365	499	0.015621	8.001

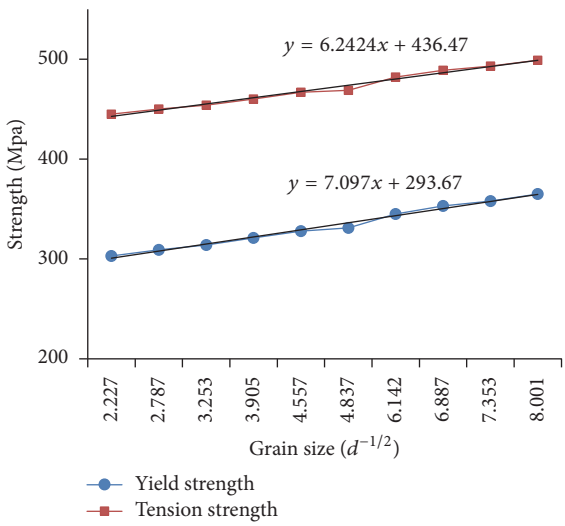


Figure 9: Relationship between grain size and steel strength.

relationship with grain size $d^{-1/2}$. It was concluded that the relationship between the tensile strength (yield strength) and the grain size of low-carbon steel complied the Hall-Petch formula with different coefficients, as shown in Figure 9.

6. Regression Analysis of Experimental Data in Inferring Carbon Steel Strength Based on Macro/Micro Model

With the combination of previous contents and comprehensive consideration, the macro/micro factors, which are steel hardness, five major conventional chemical compositions, and grain size, were used to infer strength formula of carbon steel with a comprehensive MLR analysis. During comprehensive analysis process, SPSS mathematical statistics software based on least square method was used to conduct MLR analysis. The residual analysis showed that residual errors complied with normal distribution, and it was indicated that the model met assumptions of least square method. On the condition that the macro-micro model met assumptions of normal distribution, coefficients of yield strength and tensile strength models of steel were estimated; estimated values of coefficient matrixes were, respectively, seen in Tables 7 and 8.

According to estimated coefficient values of independent values and constant terms in Table 7, yield strength was used to express mathematical regression models of factors as

$$\begin{aligned} R_e = {} & -314.302 - 174.066\,[\mathrm{C}] - 2.324\,[\mathrm{Si}] \\ & + 37.646\,[\mathrm{Mn}] + 609.908\,[\mathrm{P}] - 217.509\,[\mathrm{S}] \\ & + 1.526\,[\mathrm{HLD}] + 3.318 d^{-1/2}. \end{aligned} \tag{19}$$

According to estimated coefficient values of independent variables and constant terms in Table 8, the mathematical regression models of yield strength R_m were expressed as

$$\begin{aligned} R_m = {} & -227.221 + 171.233\,[\mathrm{C}] + 62.335\,[\mathrm{Si}] \\ & + 54.287\,[\mathrm{Mn}] + 1296.782\,[\mathrm{P}] - 213.827\,[\mathrm{S}] \\ & + 1.469\,[\mathrm{HLD}] + 1.571 d^{-1/2}. \end{aligned} \tag{20}$$

The regression analysis of yield strength R_e based on macro/micro model was also shown in Table 9, and the regression analysis of tensile strength R_m based on macro/micro model was shown in Table 10.

It can be found that the value of fitting degree r^2 and statistical magnitude F of yield strength were 0.686 and 45.952, respectively, while those of tensile strength were 0.763 and 67.778. Thus it can be known that when the micro factors such as conventional chemical compositions and grain size were incorporated into the mathematical model, the updated macro-micro model was improved.

7. Conclusions

Quantitative relationships between mechanical properties of steel with hardness and chemical composition were mainly studied in this paper, and a new NDT technology of steel strength inferring was explored. During research process, steel plates which were commonly used in steel structure were mainly used in this paper and they came from 86 steel plants of Jiangsu Province, steel plate thicknesses included 6 mm, 7 mm, 8 mm, 10 mm, 12 mm, 14 mm, 18 mm, 20 mm,

Table 7: Coefficient estimates of yield strength model.

Yield strength model	Coefficient β estimates	95% confidence interval of β	
		Lower limit	Upper limit
Constant	−314.302	−443.432	−185.173
HLD	1.526	1.212	1.840
$d^{-1/2}$	3.318	0.720	5.917
C percentage (%)	−174.066	−334.770	−13.363
Si percentage (%)	−2.324	−88.397	83.749
Mn percentage (%)	37.646	19.459	55.832
P percentage (%)	609.908	−244.132	1463.948
S percentage (%)	−217.509	−962.534	527.516

Table 8: Coefficient estimates of tensile strength model.

Tensile strength model	Coefficient β estimates	95% confidence interval of β	
		Lower limit	Upper limit
Constant	−227.221	−349.639	−104.803
HLD	1.469	1.171	1.767
$d^{-1/2}$	1.571	−0.893	4.035
C percentage (%)	171.233	18.882	323.583
Si percentage (%)	62.335	−19.265	143.934
Mn percentage (%)	54.287	37.046	71.529
P percentage (%)	1296.782	487.133	2106.431
S percentage (%)	−213.827	−920.127	492.474

Table 9: Regression analysis of yield strength R_e based on macro/micro model.

Regression formula (5)	$R_e = -314.302 - 174.066\,[\mathrm{C}] - 2.324\,[\mathrm{Si}] + 37.646\,[\mathrm{Mn}] + 609.908\,[\mathrm{P}] - 217.509\,[\mathrm{S}] + 1.526\,[\mathrm{HLD}] + 3.318d^{-1/2}$
Regression model statistics	$r^2 = 0.686$ $F = 45.952$ RMSE = 28.059

Table 10: Regression analysis of tensile strength R_m based on macro/micro model.

Regression formula (6)	$R_m = -227.221 + 171.233\,[\mathrm{C}] + 62.335\,[\mathrm{Si}] + 54.287\,[\mathrm{Mn}] + 1296.782\,[\mathrm{P}] - 213.827\,[\mathrm{S}] + 1.469\,[\mathrm{HLD}] + 1.571d^{-1/2}$
Regression model statistics	$r^2 = 0.763$ $F = 67.778$ RMSE = 26.601

and 30 mm, hardness value test and detection of chemical composition as well as metallographic test of these steel plates were conducted, and the following conclusions were drawn:

(1) Through analysis of experimental data from different perspectives, it is known that Leeb strength had quantitative relationships with yield strength and tensile strength of steel, and then the fitting formulas between Leeb hardness with yield strength and tensile strength were obtained (see Table 11).

(2) Influences of chemical compositions on mechanical properties of steel were analyzed on the basis of stepwise regression analysis method, and it is obtained that Mn, S, or P compositions had great influences on yield strength and tensile strength. Stepwise regression analysis was conducted, stepwise test was made, and then fitting formulas (3) and (4) about quantitative relationships between conventional compositions and mechanical properties of steel were obtained.

$$R_e = 334.914 + 59.1846\,[\mathrm{Mn}] - 1492.38\,[\mathrm{S}]\,,$$
$$R_p = 421.399 + 36.1576\,[\mathrm{Mn}] - 1492.38\,[\mathrm{S}] + 8.70659\,[\mathrm{P}]\,. \quad (21)$$

(3) Metallographic microstructures of steel had different morphologies and the relationship between the tensile strength (yield strength) and the grain size of low-carbon steel complied with the Hall-Petch formula with different coefficients.

(4) Based on the built conversion methods of steel hardness, chemical compositions, and strength, metallographic theory was introduced, mathematical macro/micro models between strength with hardness, grain size, and chemical compositions were built, and corresponding fitting formulas were obtained (see Table 12).

Table 11

Regression formulas (1) and (2)	Regression model statistics	
	r^2	F
$R_e = -477.1893 + 2.0090\ \text{HLD}$	0.6974	301.8938
$R_m = -405.7281\ \text{HLD} + 2.1645$	0.6000	210.7000

Table 12

Regression formula (5)	$R_e = -314.302 - 174.066\,[\text{C}] - 2.324\,[\text{Si}] + 37.646\,[\text{Mn}] + 609.908\,[\text{P}] - 217.509\,[\text{S}] + 1.526\,[\text{HLD}] + 3.318d^{-1/2}$		
Regression model statistics	$r^2 = 0.686$	$F = 45.952$	RMSE = 28.059
Regression formula (6)	$R_m = -227.221 + 171.233\,[\text{C}] + 62.335\,[\text{Si}] + 54.287\,[\text{Mn}] + 1296.782\,[\text{P}] - 213.827\,[\text{S}] + 1.469\,[\text{HLD}] + 1.571d^{-1/2}$		
Regression model statistics	$r^2 = 0.763$	$F = 67.778$	RMSE = 26.601

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The authors would like to express their sincere appreciation for the financial support from the Fundamental Research Funds for the Central Universities (Grant no. 2017XKQY051).

References

[1] Technical specification for testing tensile strength of steel construction in site by Leeb-hardness tester (DGJ32/TJ 116-2011), Jiangsu engineering construction standard, 2011.

[2] "Steel; conversion of hardness values to tensile strength values (ISO/TR 10108: 1989)," ISO/TC 17, 1989.

[3] Xiang-sheng Duan, Xiao-tan Di, Yan Zhou, and Li Tao, "Experimental Study on Conversion Steel Leeb-hardness and Tensile Strength," *Building Science*, vol. 19, no. 3, pp. 48–53, 2003 (Chinese).

[4] Suo-cai LI, "Probe into relationship between tensile strength and brinell hardness of 35CrMoV steel," *PTCA (Part A:Physical Testing)*, vol. 37, no. 12, pp. 514–530, 2001 (Chinese).

[5] A. Ghosh, J. Arreguin-Zavala, H. Aydin, D. Goldbaum, R. Chromik, and M. Brochu, "Investigating cube-corner indentation hardness and strength relationship under quasi-static and dynamic testing regimes," *Materials Science and Engineering A*, vol. 677, pp. 534–539, 2016.

[6] X. Xu, F. H. Ederveen, S. van der Zwaag, and W. Xu, "Correlating the abrasion resistance of low alloy steels to the standard mechanical properties: A statistical analysis over a larger data set," *Wear*, vol. 368-369, pp. 92–100, 2016.

[7] Du Mingshang, Feng Yunli, and Qi CHangfa, "Regression Analysis on Property and Composition of Second-Grade 20MnSi Reinforcing Bar," *PTCA (Part A:Physical Testing)*, vol. 35, no. 3, pp. 127–129, 1999 (Chinese).

[8] Liu Mei-shan, Huang Long-chang, and You Hua, "Regression Analysis and Discussion on Relationship Between Mechanical Properties and Chemical Composition of Twisted Ribbed Steel Bar," *PTCA (Part A:Physical Testing)*, vol. 38, no. 2, pp. 61–63, 2002.

[9] H. Pouraliakbar, M.-J. Khalaj, M. Nazerfakhari, and G. Khalaj, "Artificial Neural Networks for Hardness Prediction of HAZ with Chemical Composition and Tensile Test of X70 Pipeline Steels," *Journal of Iron and Steel Research International*, vol. 22, no. 5, pp. 446–450, 2015.

[10] R. Pamnani, V. Karthik, T. Jayakumar, M. Vasudevan, and T. Sakthivel, "Evaluation of mechanical properties across micro alloyed HSLA steel weld joints using Automated Ball Indentation," *Materials Science and Engineering A*, vol. 651, pp. 214–223, 2016.

[11] M. J. Faizabadi, G. Khalaj, H. Pouraliakbar, and M. R. Jandaghi, "Predictions of toughness and hardness by using chemical composition and tensile properties in microalloyed line pipe steels," *Neural Computing and Applications*, vol. 25, no. 7-8, pp. 1993–1999, 2014.

[12] X. Chen, J. Yan, and A. M. Karlsson, "On the determination of residual stress and mechanical properties by indentation," *Materials Science and Engineering A*, vol. 416, no. 1-2, pp. 139–149, 2006.

[13] M. Zhou, L.-X. Du, and X.-H. Liu, "Relationship Among Microstructure and Properties and Heat Treatment Process of Ultra-High Strength X120 Pipeline Steel," *Journal of Iron and Steel Research International*, vol. 18, no. 3, pp. 59–64, 2011.

[14] K. Tho, S. Swaddiwudhipong, J. Hua, and Z. Liu, "Numerical simulation of indentation with size effect," *Materials Science and Engineering: A*, vol. 421, no. 1-2, pp. 268–275, 2006.

[15] P. Ning-song, "The Quantitative Relationship Between σb and d in the Microstructure of 45 Qualitative Adjustment Steel," *Metal Forming Technology*, vol. 20, no. 1, pp. 46-47, 2002 (Chinese).

[16] C. SHou-gui, "The Effect of Grain Size on Mechanical Properties and Formability in Vanadium-alloyed Steel," *The Master's Dissertation of JiangSu University*, pp. 31–35, 2008 (Chinese).