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Application of Adaptive Neuro Fuzzy Inference System (ANFIS) for Hardness Prediction of CK45 Based on Hot Rolling Parameters

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Abstract: Rolling stands as a crucial manufacturing technique that offers the dual benefit of enhancing steel's mechanical characteristics. Given the substantial time investment and financial burden associated with rolling experiment setups, implementing predictive models for mechanical properties can enhance precision while reducing both temporal and monetary costs. This study conducted hot rolling experiments on CK45 steel across two distinct environments. The specimens underwent rolling at five different temperature levels and five varying work-roll rotation speeds, maintaining consistent reduction percentages. Following the rolling process, the samples were rapidly cooled in ambient air and cold-water conditions, with hardness measurements obtained using specialized testing equipment. The research employed the Adaptive Neuro-Fuzzy Inference approach to forecast hardness values based on operational parameters. The model utilized rolling temperature and rotational speed of the rollers as input variables, while the hardness measurements post-quenching in both air and water environments served as output data. The analysis yielded R^2 values exceeding 0.99 between measured and predicted results for both environments, demonstrating ANFIS's effectiveness in accurately predicting sample hardness across various rolling speeds and temperatures.

Keywords: ANFIS, CK45, Hot Rolling, Mechanical Properties, Rolling Parameters

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Research paper

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1 INTRODUCTION

Rolling is one of the most common manufacturing processes for producing metallic products, such as steel, in different shapes and dimensions [1].

Flat rolling represents a cornerstone process in modern manufacturing, accounting for a substantial 40-60% of rolled product output in industrialized nations. This prevalent technique is executed through two primary methodologies: hot rolling and cold rolling, each selected based on factors such as product specifications, dimensional requirements, desired mechanical properties, and manufacturer objectives. The hot rolling process, characterized by deformation occurring above the material's recrystallization temperature, offers several notable advantages such as high deformation rates, Low required power for deformation, and no strain hardening in the work [2-3].

On the other hand, rolling process can be considered as a strengthening method of steel products in which the strengthening can be done by changing the grain sizes and plastic deformation. By using the rolling method as a manufacturing process, controlling the effective parameters of strengthening can be carried out at low costs and high rates [4-5]. Various studies have been conducted worldwide on the effect of rolling parameters on mechanical properties.

Nikan and colleagues [6] investigated the effect of hot rolling parameters on two-phase steels in their research. Based on their research results, the rolling temperature and reduction rate showed an effective change in mechanical properties. Mandana et al [7] evaluated the effect of hot rolling on the mechanical properties of low and high-carbon steels. They found out that the hot rolling process is an excellent method for eliminating the age hardening and increasing the yield strength in these kinds of steel.

Pitter et al [8] investigated the effect of hot rolling parameters such as reduction rate and rolling temperature on St60Mn in research. In this research, tensile strength, yield strength, hardening, modulus of elasticity, toughness and bending strength were measured based on the changes in rolling parameters.

As was mentioned earlier, the rolling process is a costly and time-consuming method, so creating an experimental setup for the evaluation of the effect of rolling parameters on mechanical properties is not feasible and cost-effective for all parameters. Therefore, creating a prediction model for predicting the mechanical properties of rolled products based on rolling parameters is necessary and can play a significant role in reducing costs.

During recent years, various artificial intelligence techniques, including fuzzy logic, neural networks, and adaptive neuro-fuzzy inference systems, have been employed to predict materials' mechanical properties. In their study, Abdul Syukor Mohamad Jaya and colleagues [9] introduced a novel methodology for forecasting the hardness of Titanium aluminum nitride (TiAlN) coatings by implementing the Adaptive Neuro-Fuzzy Inference System (ANFIS). G. Khalaj et al [10] studied a new approach based on the adaptive network-based fuzzy inference systems (ANFIS) to predict the Vickers micro hardness of the phase constituents occurring in five steel samples after continuous cooling. Ly et al [11] used ANFIS model for better prediction of the compressive strength of MSC (manufactured sand concrete).

M. Zare et al [12] explored the potential of ANN and ANFIS models to forecast yield strength (YS) and ultimate tensile strength (UTS) of a warm compacted molybdenum prealloy using existing data. Analysis of ANFIS modeling versus ANN model results indicates superior performance during the training stage. Le et al [13] used an adaptive neuro-fuzzy inference system for the prediction of the critical buckling load of steel columns. Yadollahi et al [14] developed an adaptive network-based fuzzy inference system (ANFIS) model and two linear and nonlinear regression models to predict the compressive strength of geopolymer composites.

Xie, Q et al [15], in their research, utilized the machine learning method for predicting the mechanical properties of several steel alloys after the welding operations. The results indicated that the error percentage in predicting these properties ranges between 36.2% to 2.16%. Soleymani, M et al [16] used neural networks for predicting the mechanical properties of steel plates made of St37 during the welding operations. The preliminary results were previously announced. Xu, H et al [17] identified a specific chemical composition of a steel alloy after the welding operations.

In this research, the hot rolling operation was carried out in two different environments on CK45 steel. The samples were rolled at five levels of temperature and five levels of rotational speeds of work-rolls under the same reduction percentage. They were then quickly cooled down in room atmosphere and cold water, and the hardnesses were measured by a hardness testing machine.

The Adaptive Neuro-Fuzzy Inference method was used for predicting the hardness based on the input parameters. Rolling temperature and the rotational speed were considered as the inputs, and the measured hardness after quenching in two air and water environments were considered as the output of the model. The obtained R^2 for the measured and estimated results for each environment was above 0.99, which shows that the ANFIS method can effectively predict the hardness of the samples based on different rolling speeds and temperatures.

2 EXPERIMENTS

CK45 steel was used as the main material for hot deformation. The chemical composition of CK45 is given in “Table1”.

Table 1 Chemical composition of CK45 steel

C	Mn	Si	P	S	Fe	Element
0.45	0.65	0.25	0.01	0.035	balance	%wt

A resistance furnace produced by Azar Furnace with the F11L model and with a nominal temperature of 1250 ^{o}C was used to heat the material. The sample dimensions are given in “Fig. 1”.

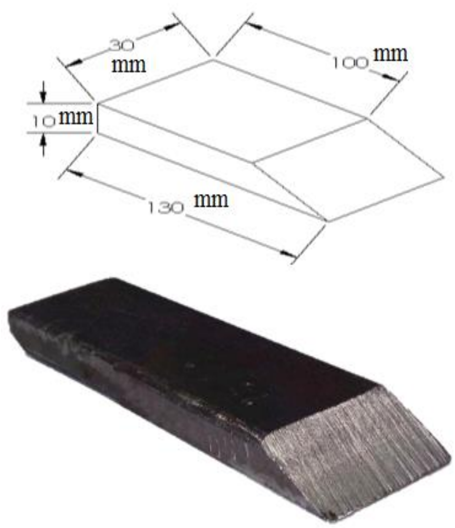

Fig. 1 The prepared sample for operation.

Fig. 2 The Vickers Hardness testing machine used for hardness measurement.

The rolling machine existing in the manufacturing workshop of Tabriz University of Sahand (IMK-1000h) was used for rolling operation. The power of this machine is 1000hp, and the roller diameter and roller length are 35cm and 40cm, respectively. An ESE WAY DVS B-P series of hardness testing machines (“Fig. 2”) was used for measuring the material hardness.

The rotational speed of the rollers and the rolling temperature in five levels were used for the rolling operation. “Table 2” shows the rolling parameters used for the experimental procedure.

Table 2 Rolling parameters used for experiment

Rotational speed (rpm)	Temperature (^{o}C)
10	850
12	900
15	950
17	1000
20	1050

3 EXPERIMENTAL PROCEDURES

After preparing the samples and increasing the furnace temperature to 950 ^{o}C, they were austinitized in furnace for two hours. They were then rolled immediately after being taken out of the furnace with 62 per cent of plastic deformation, at five rolling temperatures and five roller speeds. Figure 3 shows the rolling process. The samples were rapidly quenched in either ambient air (room temperature) or cold water (-100 ^{o}C), and they were then evaluated using a hardness testing machine using the Vickers method (30Kgf load and a pyramid diamond tool). The testing operations were repeated 5 times for each sample, and the averages were obtained and considered as the final hardness values for all of the samples. The value of the resultant force is obtained by the following equation:

Fig. 3 The samples under rolling.

4 ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS), introduced by Jang in 1993, represents a significant advancement in modeling nonlinear systems [9], [18-19]. This Takagi-Sugeno type model integrates fuzzy-based human knowledge with data-driven learning, creating a robust input-output mapping framework. ANFIS operates within the structure of adaptive networks, employing a hybrid learning procedure. This innovative approach combines the strengths of artificial neural networks (ANN) and fuzzy inference systems (FIS), resulting in a model capable of both reasoning and self-learning. The fuzzy rules in ANFIS can be expressed as follows:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$.
Rule 2: If x is A_2 and y is B2, then $f_2 = p_2x + q_2y + r_2$.

In which p_1, p_2, q_1, q_2, r_1, and r_2 represent linear coefficients in the consequent section, while A_1, A_2, B_1, and B_2 denote nonlinear coefficients. Figure 4 shows the matching ANFIS structure for dual-input first-order Sugeno fuzzy systems with two rules.

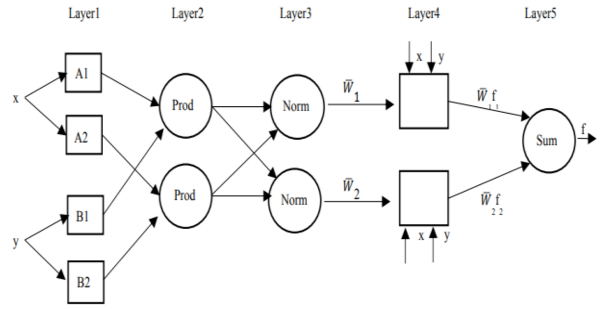

Fig. 4 Architecture of ANFIS model [13], [18].

The adaptive neuro-fuzzy inference system comprises a five-layer architecture: the fuzzy layer, product layer, normalized layer, de-fuzzy layer, and total output layer [13], [18], [20]. Each layer contains nodes with specific functions, as detailed below:

Layer 1: This initial layer, designated as the fuzzy layer, features adjustable nodes represented by square symbols and labeled A_1, A_2, B_1, and B_2. These nodes correspond to the system's inputs, x and y. The labels A_1, A_2, B_1, and B_2 serve as linguistic descriptors utilized in fuzzy theory to delineate the membership functions (MFs). Within this layer, the node functions establish the membership relationship between the input and output functions, which can be expressed mathematically as:

$$O_j = \mu A_j(x); \quad j = 1,2, \ldots \tag{1}$$

$$O_i = \mu B_i(y); \quad i = 1,2, \ldots \tag{2}$$

In this system, $O_{1,i}$ and $O_{1,j}$ represent the output functions, while μ_{Ai} and μ_{Bj} denote the corresponding membership functions (MFs). These MFs may take various forms, including triangular, trapezoidal, or Gaussian functions, among others.

Layer 2: This layer, known as the product layer, consists of fixed nodes depicted as circles and labeled "Prod." This layer generates outputs w_1 and w_2, which serve as weight functions for the following layer. The output of each node in this layer, denoted as $O_{2,i}$, is calculated by multiplying all incoming signals, as follows:

$$O_{2,i} = w_i = \mu A_j(x). \mu B_i(y); \quad i = 1,2, \ldots.. \tag{3}$$

The output signal from each node, w_i, indicates the activation level of a rule.

Layer 3: This is the normalization layer where each node is a fixed node, denoted by a circle node and marked as Norm. The nodes compute normalized activation levels by calculating the ratio of this node's activation strength to the total sum of all activation strengths.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}; \quad i = 1,2, \dots \tag{4}$$

Layer 4: This is the defuzzification layer containing adaptive nodes and indicated by square nodes. Each node i in this layer is an adaptive node with a node function:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + z_i) \tag{5}$$

Where w_i represents the normalized firing strength output from layer 3 and pi, qi, and ri constitute the parameter set for this node. These parameters follow a linear pattern and are known as consequent parameters of this node.
Layer 5: This layer contains one fixed node, indicated by a circle and labeled sum, which calculates the final output by adding all incoming signals together as:

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{6}$$

The quantity of fuzzy sets corresponds to the number of nodes present in the initial layer. Meanwhile, the dimensionality of layer 4 reflects the total number of fuzzy rules integrated into the framework, demonstrating the sophistication and adaptability of the ANFIS structure. When compared to neural networks, fuzzy rules can be viewed as analogous to neurons.
An ANFIS system can undergo supervised training to progress from a given input toward a specific desired output. During the forward phase of the ANFIS hybrid algorithm, node outputs advance until layer four, and the consequent linear parameters (p_i, q_i, r_i) are calculated using the least-squares approach with training datasets. During the backward phase, error signals travel in reverse, and the premise nonlinear parameters (A_i, B_i, C_i) are modified through gradient descent. Research has demonstrated that this hybrid methodology is remarkably effective in ANFIS training [9], [13], [18-19].

5 RESULTS AND DISCUSSION

An ANFIS model was created for predicting the hardness of the rolled material based on the rotational speed of the rollers and the rolling temperature. The MATLAB program was used to develop the ANFIS model. To map the mentioned effective parameters to the material hardness and fuzzifying the inputs, Gaussian membership function was found to be the best fuzzifying function among the other membership functions.
When compared with other methods, Gaussian family methods had the most accurate results. The Gaussian-based membership function is defined by a central value m and a standard deviation k > 0 as illustrated below (“Fig. 5”):

$$\boldsymbol{\mu(x) = e^{\frac{-(x-m)^2}{2k^2}}}$$

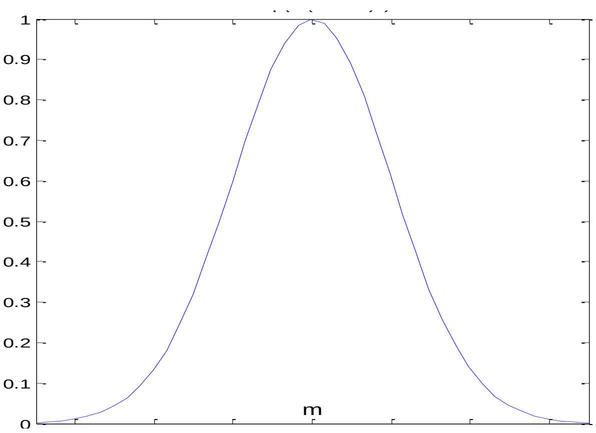

Fig. 5 Gaussian membership function.

After selecting the membership functions, the ANFIS model structure was created based on the experiments and defined fuzzy sets. In the designed structure, the rotational speed (V) and the rolling temperature (T) are defined as input, and the Vickers hardness (VH) as output of the model. The input and outputs of the model are given in “Fig. 6”.
In the developed model, five fuzzy sets were implemented to fuzzify the rolling parameters, corresponding to their five distinct levels. Given that the experimental design comprised 25 tests, a total of 25 fuzzy sets were established for both rotational speed and temperature as the primary variables. The rule count was matched to the number of experiments, resulting in 25 fuzzy rules being formulated for the hardness prediction model. Following the model construction, the ANFIS model training was executed using MATLAB software, and the outcomes were generated according to the model specifications. The ANFIS model architecture for predicting the material hardness after rolling is illustrated in “Fig. 7”.

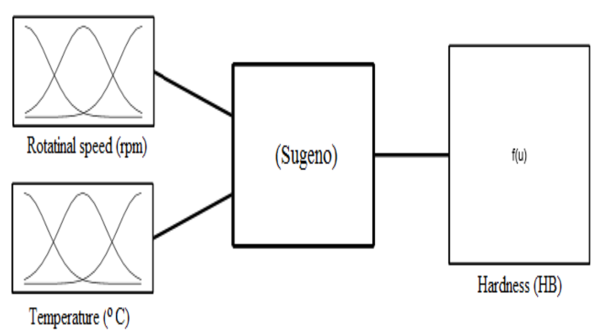

Fig. 6 Inputs and outputs of the ANFIS system.

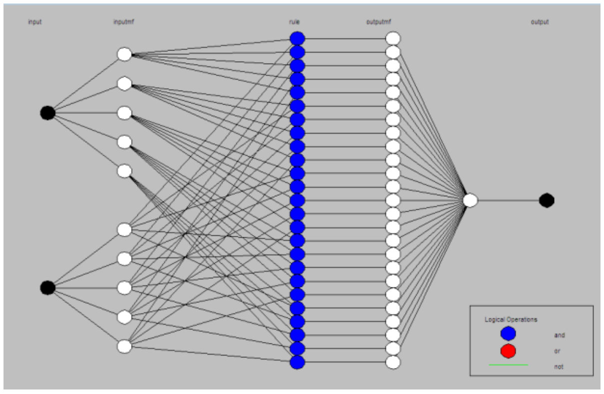

Fig. 7 The structure of ANFIS model.

As was mentioned earlier, after the rolling process, the samples were cooled separately in two environments, including air and water and the hardness values were measured using a Vickers test hardness machine. Two different ANFIS models were designed for each of the environments, and the predicted results of the models for these environments were estimated.

Graphical result of the ANFIS model was also created to evaluate the effects of the criterion variables. The effect of the rotational speed of the rollers and the rolling temperature on the hardness of the rolled samples is given in three-dimensional graphic in "Fig. 8". As is seen in the figure, both variables have a nonlinear effect on the material hardness. Figure 6 shows the result of the model for air quenching. As is seen in the figure, by increasing the rotational speed, the hardness increases too. While by increasing the rolling temperature a dramatic decrease is happened in rolled material hardness values.

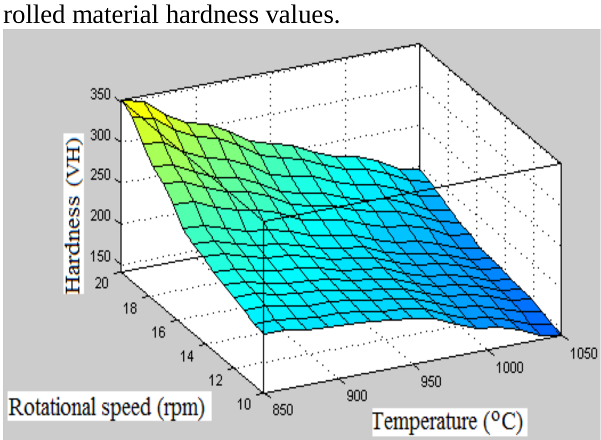

Fig. 8 The effect of rotational speed of rollers and rolling temperature on the hardness using of ANFIS model (air quenching).

Figure 9 shows the results of the model for water quenching. As is seen in the figure, by increasing both the rotational speed and the rolling temperature, the diagram shows an increase in rolled material hardness values. Moreover, by comparing the figures in air and water environments, it is found that the average hardness is higher in water quenching in relation to air quenching.

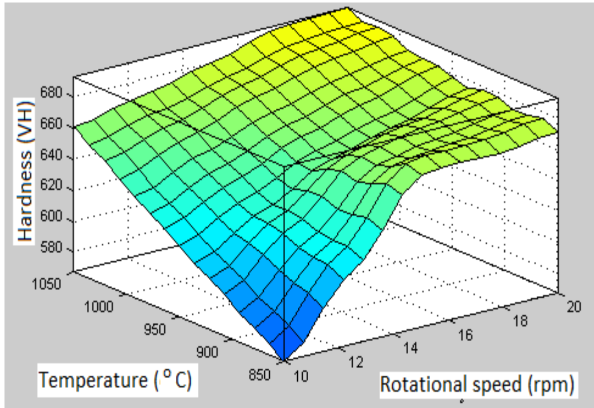

Fig. 9 The effect of rotational speed of rollers and rolling temperature on the hardness using the ANFIS model (water quenching).

The comparison diagram of the measured and estimated hardness is also conducted to obtain the R^2 values. Based on the comparison result, the R^2 value of the model is 0.9983 for air quenching and is 0.9947 for water quenching. It again confirms the ANFIS model accuracy and its contribution to the reliable estimation of rolled material hardness. Figures 10 & 11 show the comparison diagram of the measured and estimated hardness for air and water quenching, respectively.

In this research, the ANFIS method was used to predict the hardness, which, according to the authors of the paper, has not been previously reported in any research using this method. Given that the volume of experiments is usually low due to the high cost of rolling operations, compared to previous research done for similar cases using other methods, the aforementioned method has predicted the results with high accuracy by utilising the advantages of both fuzzy and neural models.

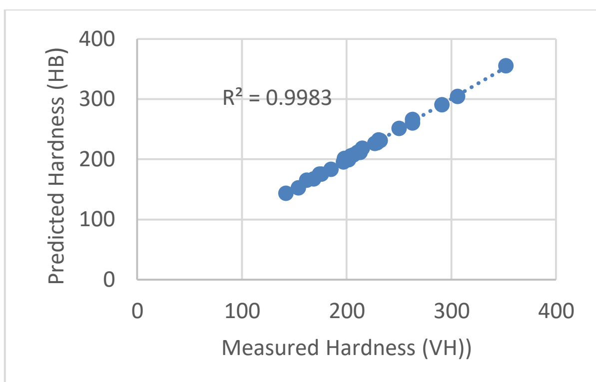

Fig. 10 Comparison of the measured and estimated results (air quenching).

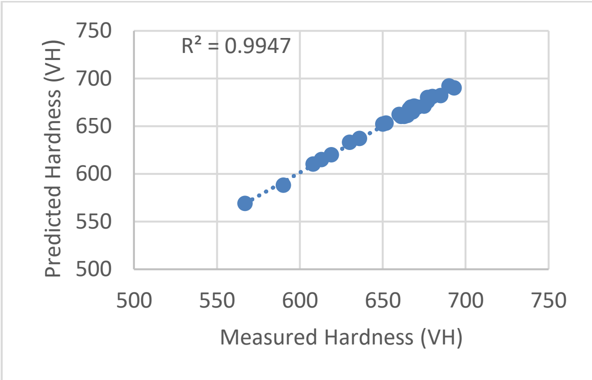

Fig. 11 Comparison of the measured and estimated results (water quenching).

6 CONCLUSIONS

This study investigated the impact of hot rolling process variables on the hardness properties of CK45 steel after air and water quenching treatments. The investigation focused on two key rolling parameters—temperature during rolling and the rollers' rotational velocity—as variables affecting material hardness. Multiple specimens underwent rolling processes at five distinct temperatures and five different roller speeds while maintaining consistent reduction ratios. Subsequently, the samples were rapidly cooled using ambient air and cold water, with hardness measurements obtained through specialized testing equipment.

A predictive ANFIS framework was developed to forecast hardness values using operational parameters. The model incorporated temperature and rotational speed as input variables, while the measured hardness results from both air and water cooling served as output data. Analysis revealed that modifications to rolling parameters consistently produced noticeable alterations in the material's grain structure, consequently affecting mechanical characteristics, including specimen hardness.

The ANFIS model's predicted outcomes were validated against actual hardness measurements from testing equipment. The comparative analysis demonstrated that the ANFIS system accurately forecasts hardness values, establishing it as a reliable methodology for predicting results across various rolling parameter ranges not directly tested in the experimental phase.

REFERENCES

[1] Ray, S., Introduction to Rolling Process, In Principles and Applications of Metal Rolling. Cambridge: Cambridge University Press, 2016, pp. 1-29.

[2] Wang, S. F., Peng, Y. A., and Zhi-Jie, L., Work-Hardening and Deformation Mechanism of Cold Rolled Low Carbon Steel, Research Journal of Applied Sciences, Engineering and Technology, Vol. 5, No. 3, 2013, pp. 823-828.

[3] Zhang, X., Wang, H., Scattergood, R. O., Narayan, J., and Koch, C. C., Modulated Oscillatory Hardening and Dynamic Recrystallization in Cryomilled Nanocrystalline Zn, Acta Materialia, Vol. 50, No. 16, 2002, pp. 3995-4004.

[4] Ueji, R., Tsuji, N., Minamino, Y., and Koizumi, Y., Effect of Rolling Reduction on Ultrafine Grained Structure and Mechanical Properties of Low-Carbon Steel Thermomechanically Processed From Martensite Starting Structure, Science and Technology of Advanced Materials, Vol. 5, No. 1-2, 2004, pp. 153-162.

[5] Sun, J. J., Lian, F. L., Liu, H. J., Jiang, T., Guo, S. W., Du, L. X., and Liu, Y. N., Microstructure of Warm Rolling and Pearlitic Transformation of Ultrafine-Grained GCr15 Steel, Materials Characterization, pp. Medium: X; Size: page(s), 2014, pp. 291-298.

[6] Niakan, H., Najafizadeh, A., Effect of Niobium and Rolling Parameters on The Mechanical Properties and Microstructure of Dual Phase Steels, Materials Science and Engineering: A, Vol. 527, No. 21, 2010, pp. 5410-5414.

[7] Zebarjadi Sar, M., Barella, S., Gruttadauria, A., Mombelli, D., and Mapelli, C., Impact of Warm Rolling Process Parameters on Crystallographic Textures, Microstructure and Mechanical Properties of Low-Carbon Boron-Bearing Steels, Metals, Vol. 8, No. 11, 2018, pp. 927.

[8] Nwachukwu, P. U., Oluwole, O. O., Effects of Rolling Process Parameters on The Mechanical Properties of Hot-Rolled St60Mn Steel, Case Studies in Construction Materials, Vol. 6, 2017, pp. 134-146.

[9] Abdul Syukor Mohamad Jaya, A. S. H. B., Siti Zaiton Mohd Hashim, Habibollah Haron Muhd, R. M., and Md. Nizam Abd, R., Application of ANFIS in Predicting of TiAlN Coatings Hardness, Australian Journal of Basic and Applied Sciences, Vol. 5, No. 9, 2011, pp. 1647-1657.

[10] Khalaj, G., Nazari, A., and Livary, A. K., Application of ANFIS for Modeling Of Microhardness of High Strength Low Alloy (HSLA) Steels in Continuous Cooling, Materials Research, Vol. 16, No. 4, 2013, pp. 721-730.

[11] Ly, Pham, Dao, and Le, Improvement of ANFIS Model for Prediction of Compressive Strength of Manufactured Sand Concrete, Applied Sciences, Vol. 9, No. 18, 2019, pp. 3841.

[12] Zare, M., Vahdati Khaki, J., Prediction of Mechanical Properties of A Warm Compacted Molybdenum Prealloy Using Artificial Neural Network and Adaptive Neuro-Fuzzy Models, Materials & Design, Vol. 38, 2012, pp. 26-31.

[13] Le, L. M., Ly, H. B., Pham, B. T., Le, V. M., Pham, T. A., Nguyen, D. H., Tran, X. T., and Le, T. T., Hybrid Artificial Intelligence Approaches for Predicting Buckling Damage of Steel Columns Under Axial Compression, Materials, Vol. 12, No. 10, 2019, pp. 1670.

[14] Yadollahi, M. M., Benli, A., and Demirboga, R., Application of Adaptive Neuro-Fuzzy Technique and Regression Models to Predict the Compressive Strength of Geopolymer Composites, Neural Computing and Applications, Vol. 28, No. 6, 2016, pp. 1453-1461.

[15] Xie, Q., Suvarna, M., Li, J., Zhu, X., Cai, J., and Wang, X., Online Prediction of Mechanical Properties of Hot Rolled Steel Plate Using Machine Learning, Materials & Design, Vol. 197, 2021, pp. 109201.

[16] Soleymani, M., Khoshnevisan, M., and Davoodi, B., Prediction of Micro-Hardness in Thread Rolling of St37 by Convolutional Neural Networks and Transfer Learning, The International Journal of Advanced Manufacturing Technology, Vol. 123, No. 9, 2022, pp. 3261-3274.

[17] Xu, H., Xu, Z., and Zhang, K., Mechanical Properties Prediction for Hot Roll Steel Using Convolutional Neural Network, In Bio-inspired Computing: Theories and Applications, Singapore, L. Pan, J. Liang, and B. Qu, Eds., Springer Singapore, 2020, pp. 565-575.

[18] Ginarsa, I. M., Nrartha, I. M. A., Muljono Agung, B., and Ardana, I. P., Application of Adaptive Neuro-Fuzzy Inference System Control in Power Systems, In Adaptive Neuro-Fuzzy Inference System as a Universal Estimator, V. Constantin Ed. Rijeka: IntechOpen, 2024, pp. Ch. 4.

[19] Mohammadi, K., Shamshirband, S., Petković, D., Yee, P. L., and Mansor, Z., Using ANFIS for Selection of More Relevant Parameters to Predict Dew Point Temperature, Applied Thermal Engineering, Vol. 96, 2016, pp. 311-319.

[20] Khalaj, G., Nazari, A., and Livary, A. K., Application of ANFIS for Modeling of Microhardness of High Strength Low Alloy (HSLA) Steels in Continuous Cooling, Materials Research-Ibero-American Journal of Materials, Vol. 16, 2013, pp. 721-730.