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Research Article

Prediction of rolling force and spread in hot rolling process by artificial neural network and multiple linear regression

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ABSTRACT

The aim of this study is to compare the performance of multiple linear regression (MLR) and artificial neural network (ANN) models in predicting rolling force and spread during free rolling in the hot rolling process. Accurate prediction of rolling force and spread in hot rolling is critical for ensuring homogeneous load distribution across rolling stands, enhancing energy efficiency, reducing failure stops, and achieving dimensional accuracy and high-quality final products. The data used in this study were generated through FEM analysis, with a portion of the results verified experimentally. The dataset includes variables such as material temperature, rolled material dimensions, reduction amount, and rolling speed, all of which influence rolling force and spread. A maximum acceptable error rate of 2.9% for spread and 6.7% for rolling force was determined. Both MLR and ANN models were applied to the dataset, and their prediction performances were compared using the mean square error (MSE). For rolling force estimation, the ANN model achieved a training R value of 0.9888 and a test R value of 0.9844, while the MLR model obtained an R^2 value of 0.9651 and an adjusted R^2 value of 0.9829. In spread estimation, the ANN model achieved a training R value of 0.9947 and a test R value of 0.9844, compared to the MLR model's R^2 value of 0.9871 and adjusted R^2 value of 0.9863. The results indicate that both models perform comparably well in estimating rolling force and spread. However, the artificial neural network model demonstrates a slight advantage, offering marginally superior prediction performance.

1. Introduction

In recent years, reducing carbon emissions and dependency on oil for energy has become a priority. Increasing energy efficiency and optimizing production processes to produce the same quality products at lower costs have gained significant importance. Particularly in the steel sector, where energy consumption is high, the rolling process remains one of the most widely used production methods. In hot bar rolling mills, the number of passes and their design are critical parameters for ensuring product quality and energy efficiency. A correct pass design not only enhances energy efficiency but also reduces initial investment costs by enabling the selection of an optimal number of rolling stands and appropriately powered motors during the investment phase [1, 2].

During the rolling pass design process, the accurate calculation of rolling loads and spread is crucial. These calculations are essential to achieving the desired product properties and ensuring correct pass design. Rolling loads refer to the forces exerted on the material during rolling and depend on numerous factors, such as the dimensions, temperature, chemical composition, and section reduction of the rolled material. Accurate calculations of these loads are vital to controlling deformations and stresses during bar shaping. For instance, Houpping Hong (2019) calculated material sections and rolling loads in a six-pass design [3].

Material deformation at high temperatures plays a significant role in determining product quality and productivity. Specifically, the rolling force and spread of the material during rolling influence several parameters, including the dimensional accuracy of the final product, the power requirements of the rolling stands, roll wear, and energy consumption. In a study by D.H. Kim et al. (2002), roll wear was measured based on pass shapes, and its impact on the product cross-section was evaluated [4, 5].

The spread of the material determines how its dimensions change during shaping, ultimately affecting

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the rod's final shape. Accurate spread calculations are critical for achieving the desired product dimensions and shapes. In 1961, L.G.M. Sparling and B. Eng developed an empirical model to calculate the spread [6].

Numerous empirical formulas have been developed to calculate rolling forces and spread. While some provide accurate results under specific conditions, others are more reliable in particular scenarios [6]. With advancements in computer technology, the finite element method (FEM) has emerged as a powerful tool for calculating rolling forces and spread. FEM offers advantages over empirical formulas, such as the ability to handle a broader range of parameters and geometries. In 2014, J. Bartnicki modeled the rolling of hollow round materials using FEM and demonstrated its agreement with experimental results. More recently, Ana Claudia González-Castillo et al. (2021) utilized FEM analysis to predict mechanical properties in thermomechanical rolling, while Shafaa Al-Maqdi et al. (2020) performed FEM analyses under various rolling conditions for hot billet rolling processes [7–11].

Despite its accuracy, FEM faces limitations in industrial applications due to its computational complexity, long processing times, and the high cost of software licenses. However, it remains a flexible tool for studying parameters affecting rolling force by allowing the simulation of different experimental scenarios and adjustments to hot rolling models. For example, Zhenhua Wang et al. (2019) established a regression model of rolling force using FEM data for hot sheet rolling [12, 13].

Traditional approaches such as multiple linear regression (MLR) have been widely used to estimate critical process parameters. MLR models analyze linear relationships between input and output variables. However, the nonlinear and complex relationships inherent in hot rolling processes limit the performance of MLR models. In 2005, D.M. Jones et al. developed an MLR model based on data from a hot rolling mill and reported its performance metrics [12, 14].

In contrast, data-driven modeling techniques like artificial neural networks (ANN) have shown superior performance in modeling nonlinear systems. ANN models can effectively learn and predict input-output relationships, outperforming traditional methods like MLR. For instance, Mahdi Bagheripoor and Hosein Bisadi (2013) developed an ANN model for estimating rolling parameters in hot rolling processes, utilizing FEM analysis results for training. Ruihua Jiao et al. (2021) further advanced the field by introducing a deep learning model based on regenerative neural networks to predict roll wear in hot rolling processes [14–22]. ANN methods have also been applied successfully in optimizing production times and predicting diesel engine performance and emission parameters [23, 24].

The literature highlights FEM as a powerful approach for calculating rolling parameters, offering precise results. However, its application to rolling pass design is time-intensive and costly. Recent research has extensively examined MLR and ANN methods for estimating rolling parameters, yet studies focusing on the hot billet rolling process remain insufficient.

This study aims to comprehensively compare the performances of multiple linear regression (MLR) and artificial neural network (ANN) models in predicting rolling force and spread during the hot billet rolling process. By analyzing experimentally verified data generated through FEM, this research provides valuable insights for optimizing hot rolling processes and serves as a key resource for industry professionals. Unlike existing studies, which primarily examine these methods separately, this study fills a gap in the literature by directly comparing the two methods. Furthermore, the findings contribute to improving production efficiency and reducing costs by guiding the development of optimization strategies for multi-pass hot rolling.

2. Materials and Method

2.1 Hot Rolling Process and Obtaining Experimental Data

In the steel industry, hot rolling plays a critical role in producing high-quality products. In the hot rolling process used for manufacturing rebar and coils, steel billets are heated in annealing furnaces at temperatures ranging from 1000 to 1250 °C and subsequently rolled in rolling mills to achieve the desired section and shape. The length of the steel billets used in the continuous rolling process typically ranges from 6 to 12 meters.

In this study, experimental results obtained from the rolling mill of a rebar manufacturing company were utilized. Free rolling with uncalibrated flat rolls was examined. Steel billets measuring 150 mm × 150 mm and 12 meters in length were rolled under the parameters specified in Table 1.

The results of six experiments carried out on hot rolling processes are presented in Table 1. The column headings in the table explain the basic parameters and results of each experiment. The dimensional measurements of the rolled material are given in the first, second and third columns as shown in Figure 1, the material speed in meters/second in the fourth column, and the temperature of the rolled material in °C in the fifth column. The experimental results are given as the spread (width) of the rolled material in column six and the rolling force in kilonewton in column seven.

The spread of material was obtained by measuring the width of the material coming out of the rolling mill with the measuring caliper shown in Figure 2. In the measuring caliper, the material is squeezed between the two ends of the tongs to measure the width and height, and the thickness of the material is found by measuring the tongs distance with a caliper. The rolling forces were obtained from the rolling mill automation. The material chemical analysis results are given in Table 2.

Table 1. Experimental parameters and results

Input Height H1 (mm)	Input Width W1 (mm)	Output Height H2 (mm)	Rolling Speed U (m/sec)	Material Temp. T (°C)	Output Width W2 (mm)	Rolling Force F (kN)
150	150	100	0.31	1100	175	1120
150	150	110	0.31	1100	170	1000
150	150	120	0.31	1100	163	850
150	150	100	0.31	1050	176	1200
150	150	100	0.31	1150	177	950
150	150	100	0.21	1100	172	1000

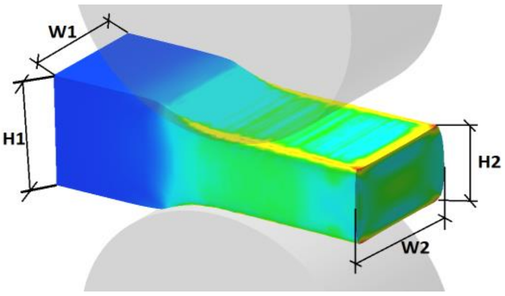

Figure 1. Rolled material measurement


Figure 2. Rolling stand and measuring caliper

Table 2. Chemical composition

%C	%Si	%Mn	%P	%S	%Cr	%Ni	%Mo
0.2028	0.1796	0.5651	0.024	0.0161	0.1257	0.1035	0.0172

2.2 Finite Element Method And Obtaining Results

Experiments in hot rolling processes are extremely costly and difficult to conduct. On the other hand, the finite element method gives very good results in the simulation of hot rolling processes.

In this study, SIMUFACT program was used for FEM analysis and in this program St32-2, which is the material closest to the chemical properties of rebar quality according to DIN 1700 standard, was used. It was defined with the code St37-2_h in Simufact forming software. Table 3 shows the chemical structure of St37-2 material according to DIN 1700 standard.

Table 3. St37-2 chemical composition according to DIN 1700 standard

%C	%Mn	%P	%S	%N	%Cu	CEV
Max. 0.2	Max. 1.4	Max. 0.04	Max. 0.04	Max. 0.012	Max. 0.55	Max. 0.38

The workpiece dimensions, rolling amount, rolling speed and rolling temperature minimum and maximum values are shown in Table 4. The workpiece length was taken as 400 mm in each analysis. A total of 87 different FEM analyses were performed in these intervals. Since the diameter of the roller used in the experiments was Ø420 mm, the same diameter roller was used in the FEM analysis.

In literature studies, it has been observed that the friction coefficient depends on the rolling speed and material temperature and is used between 0.30 and 0.45 [25-27]. In this study, the friction between the rolls and the workpiece during modeling in the FEM software was defined as 0.4 according to the Coulomb model.

In the modeling, the heat transfer coefficient between the workpieces was defined as 50 W/(m^2.K) and the heat radiation emission coefficient as 0.25. The initial temperature of the rolls was determined as 50 °C in accordance with industrial applications [28].

Hexahedral mesh was used for the analysis and the mesh spacing was determined as 2.6, and elements between 44,800 and 62,890 were used according to the workpiece dimensions.

The spread as a result of the simulation was obtained by measuring the material with a measuring tool in the result display window, as seen in Figure 3. The rolling force was taken with a 10% average from the graphic drawing window. The rolling force graph is shown in Figure 4.

Table 4. Value ranges in which the experiments were performed

	Input Height H1 (mm)	Input Width W1 (mm)	Output Height H2 (mm)	Rolling Speed u (m/sn)	Material Temperature T (°C)
Minimum	120	120	80	0.22	900
Maximum	150	150	145	1.1	1200

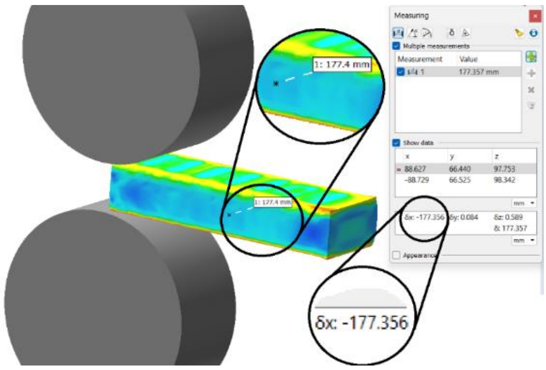

Figure 3. Measurement of the spread

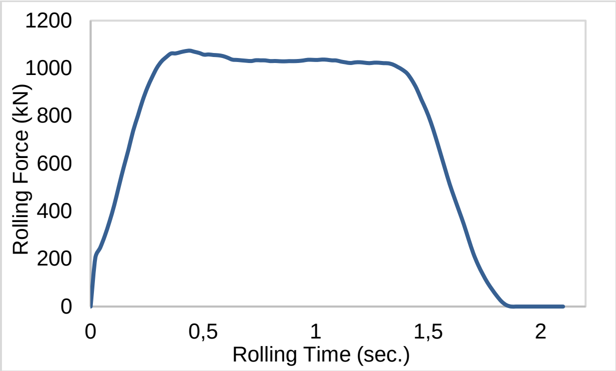

Figure 4. Rolling force graph

2.2 MLR and ANN Training

MLR analysis can be defined as a statistical technique in which the dependent variable is explained by more than one independent variable. This analysis allows determining how the dependent variable is affected by more than one independent variable and the relative effects of these variables on the dependent variable. In the analysis, the linear relationship between the dependent variable and the independent variables is modeled and the coefficients of the independent variables are calculated. Thus, it can be determined how much change a unit change in the independent variables causes in the dependent variable. MLR is a powerful tool for examining complex relationships between variables and making predictions. Multiple linear regression is as follows:

$$Y = a_1 + b_1 x_1 + b_2 x_2 + b_3 x_3 + \cdots + b_i x_i \quad (1)$$

Here Y is the dependent variable to be determined; x_1, x_2, x_3 … x_i are known variables for which estimates will be made and a, b_1, b_2, b_3 … bi are coefficients and the values are determined by the least squares method. MLR analysis was used to determine the relationship between the crushing force and the material dimensions of the spread, the rolling amount, the rolling speed. The MLR analysis was performed using Minitab version 18.

Artificial neural networks are a machine learning algorithm inspired by the working principle of the human brain. Its basic structure includes an architecture consisting of interconnected artificial neurons and input, hidden and output layers, as shown in Figure 5. Artificial neurons receive inputs, apply an activation function and transfer them to other neurons in a weighted manner. The network learns the relationship between input and output by working iteratively on training data. During this learning process, the weights are constantly updated and the most appropriate weight values are determined. Artificial neural networks have powerful features such as being able to model complex nonlinear relationships, make high-accuracy predictions and solve classification problems.

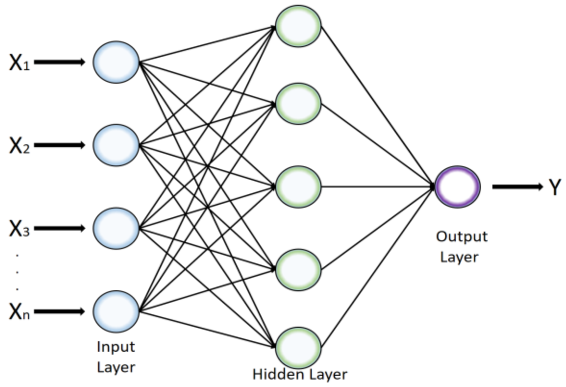

Figure 5. Schematic representation of artificial neural network

In this study, a 2-layer, 10-neuron neural network architecture was used to effectively model both the rolling force and the spread processes. The neural network, thanks to its ability to learn relationships between complex data, allows us to deeply analyze the interactions of these two critical parameters.

Various parameters were carefully determined in order to increase the effectiveness of the neural network training process. The model was trained for a total of 1000 epochs to provide an in-depth analysis of the learning process. During the iterations, the minimum gradient value was set to 10^{-7}, thus increasing the sensitivity of the network during the learning phase. The maximum error limit was set to 1000, thus clearly defining the acceptable error range of the model. The architecture used was determined as Feed-forward backpropagation type. Thanks to this structure, the weight ratios are updated backwards while the data is processed in the forward direction, thus optimizing the learning process for the network to produce more accurate results. During training, the Levenberg-Marquardt algorithm was preferred to provide fast and efficient learning; this algorithm provides high-speed convergence, allowing the model to reach optimal results in a shorter time. In addition, Gradient Descent with Momentum was used as the adaptation learning function. This method makes the learning process more stable, while a faster convergence is provided with the momentum contribution. Hyperbolic tangent sigmoid function is preferred as the transfer function; this function helps the model to learn non-linear relationships more effectively. As a result, the performance of the neural network will be evaluated with the mean square error criterion and thus the learning success will be revealed quantitatively [16].

3. Results and Discussion

Two different modeling approaches were used to estimate the spread and rolling force in the rolling process. First, numerical analysis was performed using the finite element method (FEM). In the FEM model, material spread and rolling forces were calculated. Then, FEM analyses were verified with experimental measurements and two different prediction models were developed using the obtained data.

3.1 Comparison of FEM Results with Experimental Results

The aim of the study was to verify the analysis results performed using the finite element method (FEM) with experimental data. In this context, experimental measurements were performed on six different samples. The material dimensions used in the experiment, rolling speeds, and the spreading amounts and crushing forces obtained as a result of the experiments are shown in Table 5. The experimental results were compared with the results obtained with the FEM analysis and the differences between them were examined. As a result of the analyses, it was seen that the FEM model was compatible with the experimental data and represented the behavior of the real system with high accuracy. The comparison graphs of the spreading amount are shown in Figure 7 and the crushing force are shown in Figure 8.

When the experimental results are compared with the FEM results, an error between 0.6% and 2.9% in the spread and 1.7% and 6.7% in the rolling force is observed. These error rates can be considered at an acceptable level for rough rolling. Y. Mahmoodkhani calculated the error rate as less than 10% in his study in 2016, stated that this error rate is negligible in the calculation of crushing forces and developed an adjustment tool with this error margin [29].

3.2 MLR Results

MLR analysis was conducted using a total of 87 data points to better understand the relationship between rolling force and various influencing factors. The results are presented through various tables and graphs. Specifically, the variance analysis performed for rolling force is detailed in Table 6, which highlights the explanatory power of the model and the interactions between variables. Table 7 presents the coefficients related to rolling force, providing insights into the model's accuracy and functionality.

In MLR analysis, coefficients play a critical role in quantifying the effects of independent variables on the dependent variable. Each coefficient indicates the extent of change in the dependent variable resulting from a one-unit change in the corresponding independent variable. This allows for a clear interpretation of the variables' effects. The signs of the coefficients determine the direction of the effect, while their magnitudes indicate the relative importance of these effects. Properly determined coefficients enhance the predictive capability of the model and ensure more reliable results. As such, the coefficients serve as an essential reference point for evaluating the model's performance and identifying which factors have a more substantial impact on the dependent variable.

Additionally, Table 8 provides the error rates calculated for rolling force, offering valuable information about the model's performance. Figure 9 visualizes the error term distributions for rolling force, presenting the error distribution and statistical properties of the model through graphical representations. These findings form a crucial basis for assessing and validating the effectiveness of the MLR model.

Table 5. Comparison of FEM and experimental results

					FEM Results		Experimental Results	
Input Height H1 (mm)	Input Width W1 (mm)	Output Height H2 (mm)	Rolling Speed u (m/s)	Material Temp. T (°C)	Output Width W2 (mm)	Rolling Force F (kN)	Output Width W2 (mm)	Rolling Force F (kN)
150	150	100	0.33	1100	177	1045	175	1120
150	150	110	0.33	1100	172.9	955	170	1000
150	150	120	0.33	1100	165	810	163	850
150	150	100	0.33	1050	177.5	1180	176	1200
150	150	100	0.33	1100	178	925	177	950
150	150	100	0.22	1100	177	951	172	1000

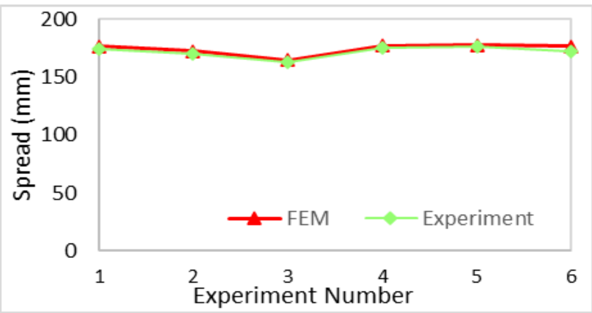

Figure 7. Comparison of spread FEM and experimental results

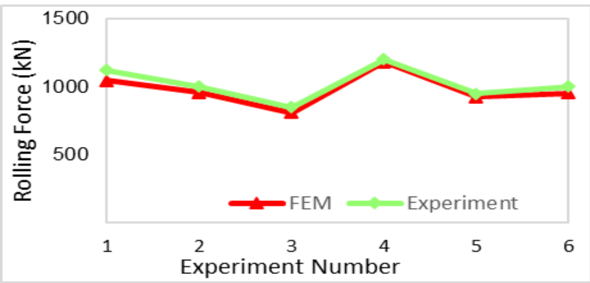

Figure 8. Comparison of rolling force FEM and experimental results

MLR analysis was performed according to the results of the spread for 87 analyses. This analysis was performed to better understand the relationship between the spread and various factors. The obtained data is presented with various tables and graphs. Table 9 presents the variance analysis for spread, while Table 10 includes the coefficients for spread. In addition, Table 11 includes the error rates calculated for spread, and these data help evaluate the performance of the model. Finally, the residual plots for spread are given in Figure 10. These graphs provide a better understanding of the results by visualizing the error distribution.

Table 6. Variance analysis for rolling force

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	5	6703984	1340797	447.91	0
Input Height	1	1137677	1137677	380.05	0
Input With	1	208485	208485	69.65	0
Output Height	1	3801779	3801779	1270.02	0
Rolling Speed	1	293421	293421	98.02	0
Material Temp.	1	789004	789004	263.57	0
Error	81	242471	2993		
Lack-of-Fit	79	231068	2925	0.51	0.851
Pure Error	2	11403	5701		
Total	86	6946455			

Table 7. Coefficients for rolling force

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	1768	265	6.68	0	
Input Height	16,868	0.865	19.49	0	1.04
Input With	7.42	0.889	8.35	0	1.04
Output Height	-16.419	0.461	-35.64	0	1.05
Rolling Speed	311,3	31.4	9.9	0	1.06
Material Temp.	-2.502	0.154	-16.23	0	1.03

Table 8. Model summary for rolling force

S	R-sq	R-sq(adj)	R-sq(pred)
54.7126	0.9651	0.9629	0.9615

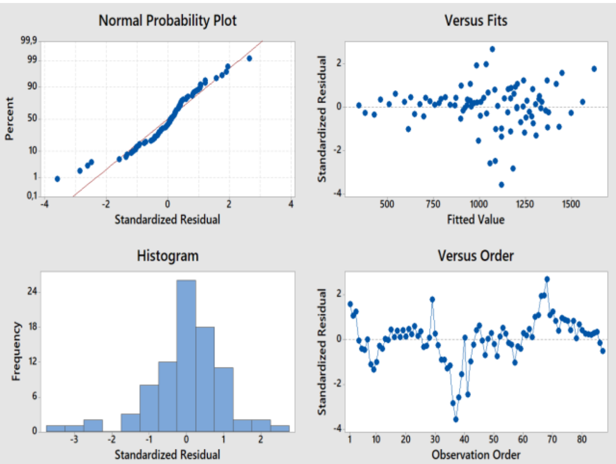

Figure 9. Residual Plots for Rolling Force

Table 9. Variance analysis for spread

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	5	13397.3	2679.46	1238.46	0
Input Height	1	1526.6	1526.65	705.63	0
Input Width	1	4558	4557.96	2106.72	0
Output Height	1	6506.4	6506.36	3007.28	0
Rolling Speed	1	920.3	920.3	425.37	0
Material Temp.	1	13.7	13.66	6.31	0.014
Error	81	175.2	2.16		
Lack-of-Fit	79	174.1	2.2	3.78	0.232
Pure Error	2	1,2	0.58		
Total	86	13572.5			

Table 10. Coefficients for spread

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-27.49	7.12	-3.86	0	
Input Height	0.6179	0.0233	26.56	0	1.04
Input Width	1.0972	0.0239	45.9	0	1.04
Output Height	-0.6793	0.0124	-54.84	0	1.05
Rolling Speed	17.435	0.845	20.62	0	1.06
Material Temp.	0.01041	0.0041	2.51	0.014	1.03

Table 11. Model summary for spread

S	R-sq	R-sq(adj)	R-sq(pred)
1.4709	0.9871	0.9863	0.9857

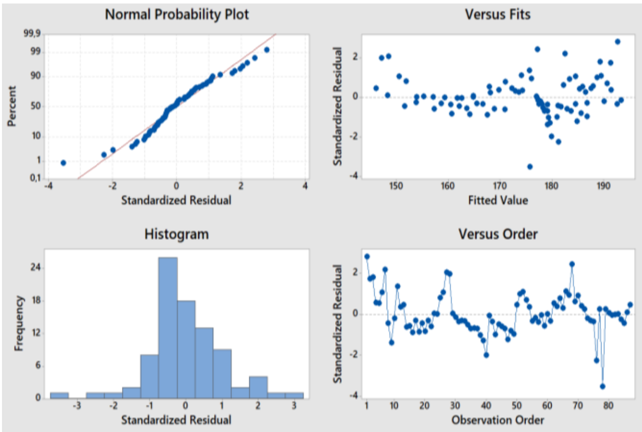

Figure 10. Residual Plots for Spread

3.3 ANN Results

A two-layer, ten-neuron artificial neural network model was developed to accurately predict the spread and rolling force of the material during the rolling process. This model allows us to better understand material behaviors thanks to its capacity to learn relationships between complex data. The learning performance of the rolling force is shown in detail in Figure 11. This visual reflects the results obtained during the training process of the neural network and the accuracy of the model. In addition, the error rates for the rolling force prediction are presented graphically in Figure 12.

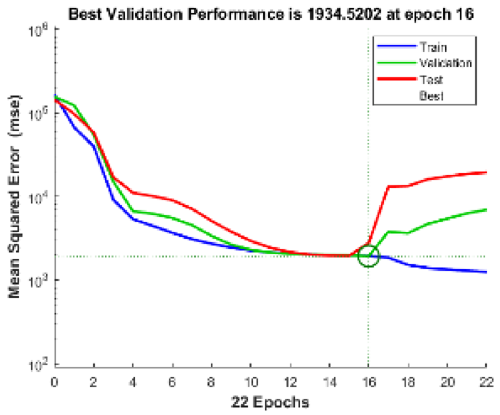

Figure 11. Training performance for rolling force

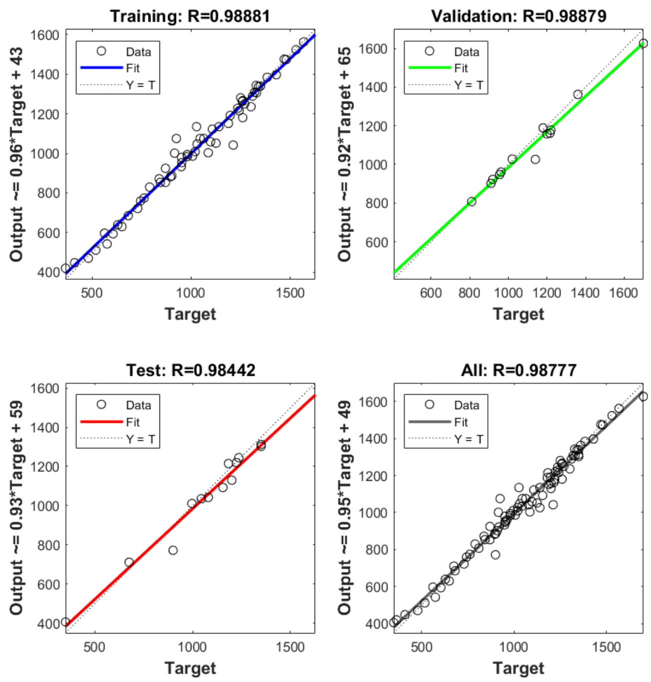

Figure 12. Regression results for rolling force

These graphics constitute an important source for evaluating the prediction performance of the model and visualizing the error distribution. These findings reveal the effectiveness of the neural network and provide valuable information for optimizing material processing processes.

The performance results obtained in the prediction of rolling force provide an important basis for evaluating the effectiveness and accuracy of the model. In the training phase, the R value of the model was calculated as 0,9888, which shows the high fit between the training data and the model. This high value reveals that the model successfully learned the data during the training process and has a strong ability to make predictions. In the validation phase, the R value was determined as 0,9887. This result shows that the model exhibits consistent performance with data other than training and has high generalization ability. The R value obtained in the testing phase was calculated as 0,9844, which shows that the model achieves successful results with data it has not used before. Finally, when all data are taken into account, the total R value was determined as 0,9877. This high value shows that the overall performance of the model is quite satisfactory and provides quite reliable results in the prediction of rolling force.

The learning performance for the prediction of the spread is presented in detail in Figure 13. This visual shows how effectively the model predicted the amount of spread during the training process and reflects the learning curve of the model. Figure 13 compares the results obtained during different iterations, showing the development and performance of the model over time. In addition, this graphic provides the opportunity to analyze the potential improvements in the learning process of the model and at which stages it is more successful. On the other hand, the regression results of the spread are shown graphically in Figure 14. These graphics clearly show the differences between the model's predictions and the actual values, visualizing the error distribution. The analysis of the error rates helps us understand under which conditions the model makes more errors and which factors affect the accuracy of the predictions. These two visuals provide a critical reference point for evaluating the prediction performance of the amount of spread and analyzing the effectiveness of the model.

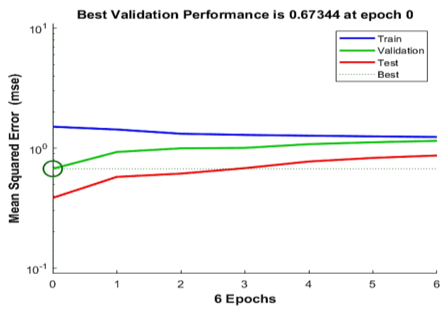

Figure 13. Training performance for spread

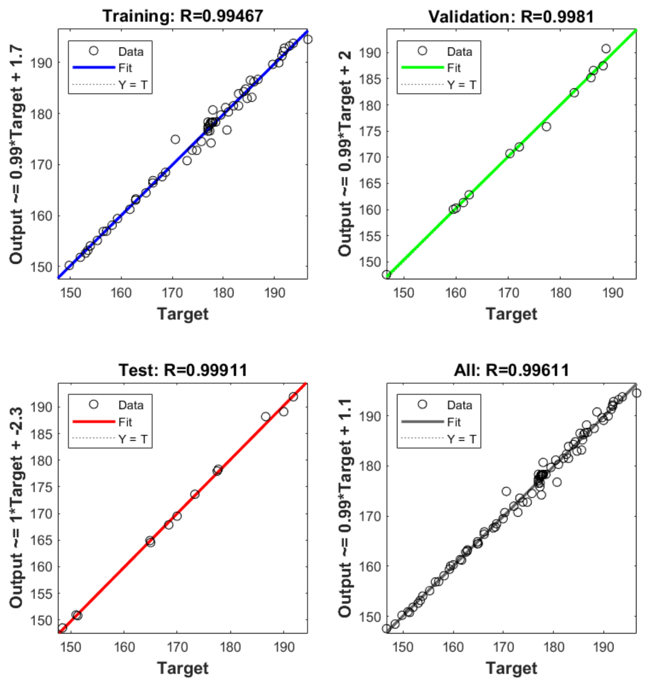

Figure 14. Regression results for spread

Table 12. MLR and ANN performance comparison

	Multi Liner Regression (MLR)			Artificial Neural Network (ANN)			
	R-sq	R-sq(adj)	R-sq(pred)	R (train.)	R (valid.)	R (test)	R (all)
Rolling Force	0.9651	0.9629	0.9615	0.9888	0.9887	0.9844	0.9878
Spread	0.9871	0.9863	0.9857	0.9947	0.9981	0.9991	0.9961

The results obtained in estimating the spread show a very good performance. The R value was calculated as 0,9946 in the training phase, which shows that the model provides excellent compatibility with the training data. The R value was determined as 0.9881 in the validation process, which shows that the model also shows consistent performance with new data. The R value obtained in the testing phase was calculated as 0.9991, which shows that the model achieved very successful results with data it had not seen before. The total R value was determined as 0.9961, which indicates that the results of the artificial neural network model showed a very high correlation with the data. These findings reveal that the model's ability to estimate the spread is extremely strong.

3.4 Comparison of MLR and ANN Results

MLR analysis is a traditional method often used to describe linear relationships between dependent and independent variables. The model is relatively simple to construct and interpret, but its ability to capture complex, nonlinear relationships is limited. On the other hand, artificial neural networks are capable of learning complex, nonlinear relationships between input and output data. In particular, artificial neural networks may be a more suitable option for understanding how small changes in input parameters affect outputs.

In this study, both modeling approaches were trained and tested using experimental and finite element analysis data. The R values for both models are shown in Table 12.

4. Conclusions

The prediction of material spread and rolling force in the hot rolling process is critically important for process control and optimization. In this study, two different modeling approaches, namely multiple linear regression (MLR) and artificial neural networks (ANN), were utilized and compared for predicting these parameters.

The maximum error rate in spread was observed to be 2.9%, with the FEM result recorded as 177 mm and the experimental result as 172 mm. The minimum error rate was found to be 0.6%, with the FEM result recorded as 178 mm and the experimental result as 177 mm. For rolling force, the maximum error rate was determined to be 6.7%, with the FEM result recorded as 1045 kN and the experimental result as 1120 kN, while the minimum error rate was 1.7%, with the FEM result recorded as 1180 kN and the experimental result as 1200 kN. The FEM and empirical results were found to be closely aligned and highly consistent.

In rolling force prediction, the training R value of the ANN model was 0.9888, and the test R value was 0.9844. In contrast, the R^2 value for the MLR model was 0.9651, with an adjusted R^2 value of 0.9829. For spread prediction, the ANN model achieved a training R value of 0.9947 and a test R value of 0.9844, while the R^2 value for the MLR model was 0.9871, with an adjusted R^2 value of 0.9863. Both models provided closely aligned predictions for rolling force and spread in the hot rolling process. However, the ANN model demonstrated slightly superior performance in rolling force prediction.

This study systematically compares the performance of MLR and ANN models, offering a novel contribution to both academic literature and industrial applications, thereby addressing a significant gap in this field. The findings have the potential to enhance production efficiency and reduce costs, facilitating the development of optimization strategies for multi-pass hot rolling processes.

Declaration

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The authors also declared that this article is original, was prepared in accordance with international publication and research ethics, and ethical committee permission or any special permission is not required.

Author Contributions

Fatih Yilmaz: Conceptualization, Methodology, Software, Visualization, Investigation. Mehmet Ali Guvenc: Investigation, Resources, Data curation, Writing - original draft and supervision. Selcuk Mistikoglu: Supervision.

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