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Article

Bending Force of Hot Rolled Strip Based on Improved Whale Optimization Algorithm and Twinning Support Vector Machine

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Abstract: Bending control is one of the main methods of shape control for the hot rolled plate. However, the existing bending force setting models based on traditional mathematical methods are complex and have low control accuracy, which leads to poor strip exit shapes. Aiming at the problem of complex bending force setting of the traditional algorithm, an improved whale swarm optimization algorithm and twin support vector machine-based bending force model for hot rolled strip steel (LWOA-TSVR) is proposed. Based on the hot rolling field production data of a steel plant, the research group established the bending force prediction model by using the nonlinear approximation ability of the twin support vector machine. The introduction of the Levy flight improvement algorithm improves the generalization ability, prediction accuracy, and convergence speed of the whale swarm optimization algorithm with the help of the convergence of coefficient vectors, solves the problem of a random selection of the parameters of the traditional whale swarm optimization algorithm and optimizes the ability of the whale swarm algorithm to jump out of the local optimum. Based on the actual rolling database, the hit rate of the proposed method reaches 91% (from −5 to 5 KN), which fully meets the requirements of the detection accuracy on the actual production line. The model is not only able to overcome the local search to obtain the global optimal solution, but also has the advantages of fast convergence and higher prediction accuracy. A comparison of the model with twin support vector machines and traditional whale swarm algorithms shows that the prediction accuracy is higher. The experimental results also show that this model has advantages over existing bending force prediction models in terms of improving the accuracy of the strip shape control and providing theoretical guidance for practical bending force settings.

Keywords: bending force; improved whale optimization algorithm; levy flight algorithm; plate shape control; twin support vector machine

Citation: Shi, C.; Wang, B.; Chen, J.; Zhong, R.; Guo, S.; Sun, P.; Ma, Z. Bending Force of Hot Rolled Strip Based on Improved Whale Optimization Algorithm and Twinning Support Vector Machine. *Metals* **2022**, *12*, 1589. https://doi.org/10.3390/met12101589

Academic Editor: Young-Sik Pyun

Received: 13 August 2022
Accepted: 19 September 2022
Published: 24 September 2022

1. Introduction

The control of bending force is one of the main methods of hot rolled strip shape control, which is based on the principle of applying hydraulic bending force to the work roll and support roll neck to change the roll seam convexity and thus influence the roll seam shape during rolling, prompting the strip to change along the width direction, compensating for the poor plate shape caused by changing in other rolling process factors, and thus ensuring the accuracy of the strip exit plate shape. The forecast accuracy of roll bending force has an important impact on the flatness and profile control accuracy [1,2].

In the actual production process, the optimal setting value of bending force is not easy to obtain, and it is usually obtained by calculation based on the influencing factors such as temperature, thickness, width, rolling force, material, thermal expansion of rolls, roll wear and flatness and convexity of strip steel. Generally, it is complex to obtain the configuration model of hot rolling bending force because some rolling factors related to the model are nonlinear and have strong coupling, as well as the very large detection error, which seriously affects the improvement of the accuracy of the bending force setting model. The mathematical model established by the traditional theory has low control accuracy in production practice [3–5]. Moreover, the development of the traditional bending force setting theory research has not improved the deficiency of the machine model in the non-stationary process, and this situation has seriously restricted the control accuracy and product quality. In recent years, rich results have been achieved in related research on bending force prediction, and the high-precision bending force prediction model plays a very important role in the control of plate shape. Therefore, the correct investigation of bending force prediction models is a very important but challenging job for strip steel production and plate control. Researchers have started to think about the use of an artificial intelligence approach to solving the above problems. The research on the hot rolled strip model based on the intelligent method is the development trend of bending force prediction, and a neural network is the main method to establish the bending force prediction model. However, the traditional BP (back propagation, a multi-layer feed-forward neural network trained according to an error back propagation algorithm, is one of the widely used neural network models) neural network model has the local minimum value problem, which leads to the non-uniqueness of model parameters and increases the difficulty of modeling. Moreover, if the number of samples is too small, the modeling effect is difficult to guarantee [6–8]. To solve the above problems and achieve a higher quality of plate shape, it is necessary to improve the accuracy of model prediction and computational speed to ensure the control effect of bending force, and to provide the theoretical basis for exploring new model methods for bending force setting.

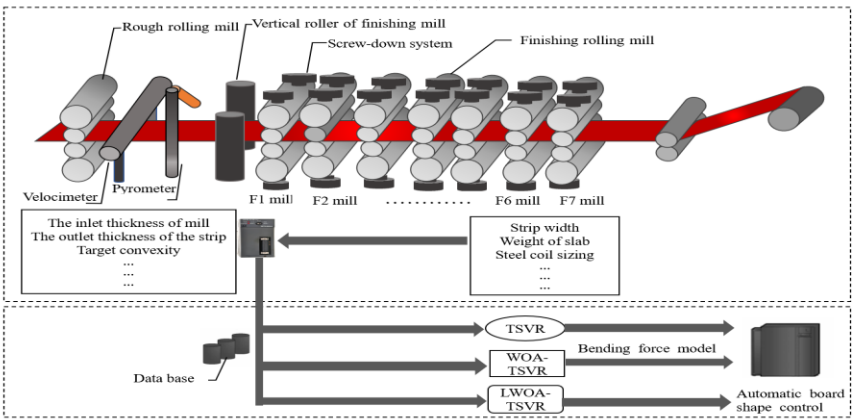
The group used the hybrid intelligent optimization algorithm of an improved whale swarm optimization algorithm and a twin support vector machine (LWOA-TSVR). Compared with the BP neural network algorithm, the algorithm model can not only overcome the local optimization to obtain the global optimal solution but also has the advantages of fast convergence speed and higher prediction accuracy, which can well solve the problem of easy to fall into local minimum in the neural network algorithm [9–11]. As a new intelligent algorithm, LWOA-TSVR can establish the final model of bending force setting based on actual industrial production sample data and through correlation analysis between sample data, which can solve the internal complex system modeling [12]. Firstly, the bending force forecasting model is established based on the testing data on the hot rolling line of a steel mill, using the initial information of the hot rolled strip and the raw material dosage, and other information [13,14]. Secondly, the feedback value of the prediction model is used to adjust the variables to be optimized for the target parameters, and SPSS is used to filter the influencing factors of the bending force to obtain the correlation coefficients between the influencing parameters and the bending force. Finally, the optimal value of the bending force is set. Although the traditional twin support vector machine model greatly reduces the difficulty of obtaining the bending force, the calculation speed and hit rate still need to be improved. To address this problem, the TSVR algorithm is first improved by combining the Levy flight algorithm to improve the modeling efficiency and generalization performance of the algorithm, and finally, the LWOA-TSVR model is built using the improved algorithm. To investigate the prediction effect of the LWOA-TSVR algorithm compared with traditional algorithms, four algorithms (BP, TSVR, WOA-TSVR, and LWOA-TSVR) are used to build the corresponding models and compared in the training set and testing set respectively. The research shows that the proposed model is feasible and can be applied to predict the bending force of hot rolled strips and provide a new research method for rolling optimization [15–18].

The subject belongs to the latest application in the field of metallurgical intelligent manufacturing, combining metallurgical technology with predictive technology in a favorable way. It is another new milestone in the development of metallurgical technology, breaking the deficiencies of bending force control in the traditional process and transforming what might otherwise be produced as unqualified products into qualified products by pre-adjusting the process parameters online and through the finishing rolling unit. It reduces the scrap rate and reduces production costs at the same time.

2. Industrial Trials

During the process of industrial trials, the F7 mill is taken as the object of study, the position of the bending roll is shown in Figure 1a. The relevant variable parameters are collected as the input of the model. After the strip passes through the exit of the roughing mill, the speed meter measures the entrance speed of the strip when it enters the finishing mill. A set of the pyrometer is designed and installed in front of the entrance of the finishing mill (using three pyrometers to measure at multiple points at the same time to take the average value), and the pyrometer is used to measure the entrance temperature of the strip at this time, and the thickness, width and temperature value measured at the roughing exit are sent to the second model as the set value of the roll gap, rolling speed, strip width and plate type of each stand when the strip is put through the finishing mill. When the strip enters the finishing area, the rolling force in the corresponding stand is measured using the nip mounted on the upper end of the finishing unit. The work roll traverse is calculated by measuring the angle which the press-down motor shaft has turned using magnetic tape. The strip exits the finishing area and the parameters such as exit thickness and target convexity of the strip are measured using the thickness gauge and convexity gauge installed at the rear of the F7 finishing mill stand, respectively. The finishing process flow and the principle of F7 mill bending force during the industrial trials are shown in Figures 1b and 2.

(**a**)



(**b**)

Figure 1. Layout of finishing the mill line: (**a**) Bending roll of finishing mill; (**b**) Equipment layout of hot continuous rolling mill line.

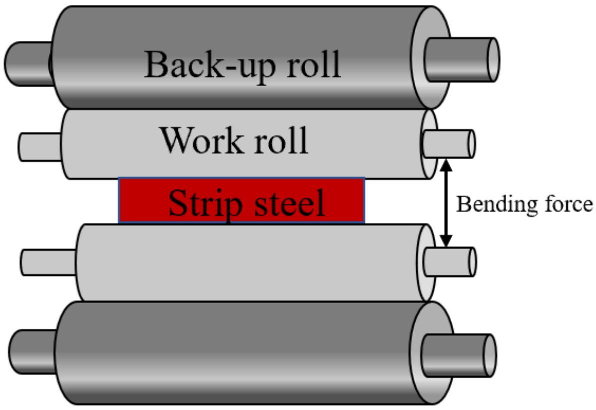


Figure 2. F7 mill hydraulic roll bending schematic.

3. Establishment of LWOA-TSVR Model

3.1. Static Control Model Based on LWOA and TSVR

In this paper, a static component control model based on LWOA and TSVR is established. The system block diagram of this control model is shown in Figure 3. The control model consists of a bending force prediction model, an input variable optimization model (LWOA), a parameter adjustment unit R_1, a rolling area, and a plate control section. The prediction model of bending force is established. The input of the prediction model is the inlet temperature of strip steel, entry thickness, exit thickness, strip width, rolling force, rolling speed, work roll shifting, yield strength of strip steel, and target convexity. And the output is the bending force.

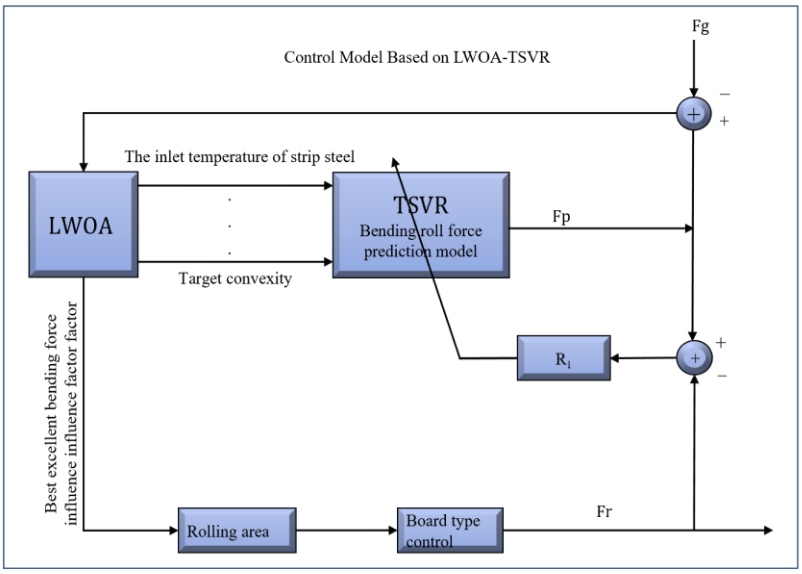


Figure 3. Static component control model based on LWOA-TSVR algorithm.

In the improved whale population optimization algorithm for pre-optimization of experimental data, the population size of the whale population is first initialized, then the fitness of each whale population is evaluated, and the fitness value of each whale population is compared to find the individual optimal solution, then the individual optimal value is compared to the global optimal solution, the global optimal solution is found and the current position of the whale population is updated, finally the position of the whale population is updated if it is judged to be at the global optimal value at this point and the data is fed to the kernel function parameters and penalty factors in the TSVR algorithm.

In the adjustment unit R_1, the model parameters are adjusted according to the principle of minimizing the error between the predicted value of the bending force Fp and the practical value Fr. Finally, the testing samples are substituted into the trained model to verify the relevant performance indicators. Once the system parameters have been determined, the static control model is built, and the parameters of the system are stored in the TSVR model. After the model has been built, a modified whale swarm optimization algorithm is used to optimize the output value Fp of the bending force against the target value Fg. The optimized results are then passed back to the rolling area. The rolling area can control the plate shape according to the specific values of the influencing factors. The initial information about the current mill and the desired predictions are fed into the static control model, which will calculate the value of the bending forces required to achieve optimum plate control. The final control of the bending force is achieved by executing the plate control section to achieve the target desired plate shape.

3.2. Sample Data Processing

The data collected in this paper are actual production data of SPCC steel grades in a steel mill. Because of the large variety of parameters influencing the bending force and the fact that there is no firm basis for concluding the magnitude of the influence of these factors on the bending force, SPSS (IBM SPSS Statistics 25, Norman H. Nie, C.Hadlai (Tex) Hull and Dale H. Bent, Chicago, IL, USA) is used to carry out a correlation analysis to measure the degree of correlation between the variables and the bending force and to filter out the most important influencing parameters. The input variables with high correlation are identified as: the inlet temperature of strip steel, entry thickness, exit thickness, strip width, rolling force, rolling speed, work roll shifting, yield strength of strip steel, and target convexity. The correlation result is obtained as shown in Table 1.

Table 1. Correlation statistical table of influencing factors.

Dependent Variable	Independent Variable	Correlation Coefficient
Bending force	Work roll shifting	0.001
	Rolling force	0.011
	Entry thickness	0.211
	Rolling speed	0.163
	The inlet temperature of strip steel	0.102
	Target convexity	0.383
	Yield strength of strip steel	0.074
	Strip width	0.348
	Exit thickness	0.544

3.3. Bending Force Optimization Model Based on LWOA-TSVR Hybrid Intelligent Algorithm

In the process of hot strip rolling, the bending state of the work roll is affected by many rolling factors, such as elastic deformation between rolls, rolling speed, rolling force, etc. Considering the complexity of bending force calculation, the improved whale swarm optimization algorithm is integrated into the bending force prediction model of the twin support vector machine. Finally, the bending force prediction model based on the LWOA-TSVR algorithm is obtained, and the specific process is shown in Figure 4.

The penalty parameter C and kernel function parameter σ of TSVR are optimized by the LWOA algorithm. The relational flow chart of the LWOA optimized TSVR is obtained as shown in Figure 5. Firstly, the rolling data are extracted and normalized, the parameter-seeking process of the twin support vector machine is optimized by the improved whale swarm algorithm, and the corresponding kernel function is selected; secondly the regression model is trained and tested by combining the optimal solution and the kernel function; finally, the bending force model is obtained by inverse normalization of the regressed rolling data.

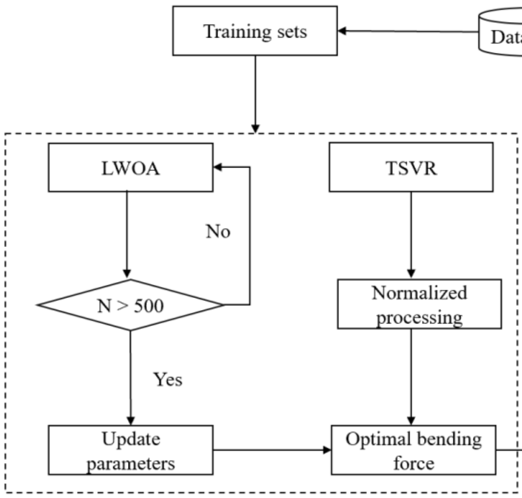


Figure 4. Flow chart of the bending force prediction model.

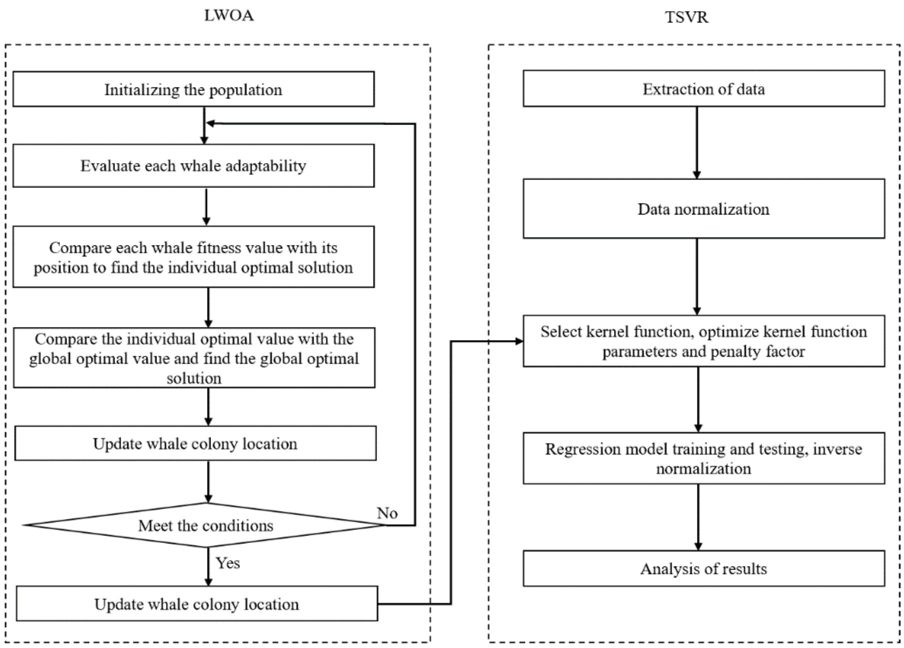


Figure 5. The process of LWOA optimized TSVR.

Using the input variables to the model and incorporating the principles of twin support vector regression machines, the following modeling steps can be identified:

Step 1: Input the training data for LWOA optimization and pre-process the experimental data;

Step 2: Initialize or update model parameters C1, C2, ε1, ε2, σ;

Step 3: Initialize the number of optimized whale populations;

Step 4: Substitute 1500 groups of training samples into Equations (1) and (2), and solve the optimization problem according to the optimization strategy of Equation (3) until the maximum number of iterations is satisfied to obtain the optimal solution vector α and β;

Step 5: Substitute the optimal vector into the weight vector and the bias vector to obtain ω1, b1, ω2, b2, and obtain the vector $[\omega1, b1]^T$, $[\omega2, b2]^T$. Substitute the results into $f_w(x)$ (bending force), that is, the bending force prediction model of the hot rolled strip is obtained;

Step 6: Calculate the hit rate, if the index reaches the required model accuracy, the model building is completed, otherwise repeat steps 2 to 6 until the index reaches the set value.

$$\begin{gathered}\min\tfrac{1}{2}\alpha^{T}H(H^{T}H)^{-1}H^{T}\alpha + f^{T}H(H^{T}H)^{-1}H^{T}\alpha - f^{T}\alpha \\ 0 \leq \alpha \leq C_1 e\end{gathered} \tag{1}$$

$$\begin{gathered}\min\tfrac{1}{2}\beta^{T}H(H^{T}H)^{-1}H^{T}\beta + h^{T}H(H^{T}H)^{-1}H^{T}\beta - h^{T}\beta \\ 0 \leq \beta \leq C_2 e\end{gathered} \tag{2}$$

$$X(t+1) = \begin{cases} \begin{cases} X^*(t) - lH, \text{if } a < 1 \\ X_{rand}(t) - lH, \text{if } a \geq 1 \end{cases}, \text{if } n < 0.5 \\ X^*(t) + \tau_p e^{\varepsilon \cdot m} \cdot \cos(2\pi m), \text{if } n \geq 0.5 \end{cases} \tag{3}$$

3.3.1. Improved Whale Optimization Algorithm

Compared with other optimization algorithms, the whale optimization algorithm has a faster operation speed, simple adjustment parameters, and a certain ability to jump out of the local optimum. However, since the algorithm itself only uses a random system for exploration, and the excessive dependence on random limits the search speed of the WOA algorithm, the convergence speed and convergence accuracy of the WOA algorithm are further accelerated. In addition, due to the limitation of coefficient vector B, the WOA algorithm will lose the ability to jump out of the local optimum when the number of iterations reaches half of the maximum set number of iterations. Therefore, the WOA algorithm has a certain risk of falling into the local optimum, resulting in inaccurate prediction results of the algorithm. To solve the above defects of the WOA algorithm, this paper proposes an improved whale optimization algorithm. Levy flight is used to improve the whale optimization algorithm. The improved algorithm has a faster convergence speed and higher convergence accuracy and has a better ability to jump out of the local optimum. Levy flight is a search based on Levy distribution, which is a random way of small range search and large range jump. Established using the following mathematical model for the predatory strategy of humpback whales:

$$X(t+1) = X^*(t) - BD_1 \tag{4}$$

where:

t, the current number of iterations;

B and M, coefficient vectors.

$$B = 2a\mathrm{Levy}(\lambda) - a \tag{5}$$

$$M = 2r_2 \tag{6}$$

The whale optimization algorithm is used to solve the optimization problem for TSVR. The whale optimization strategy is shown in Equation (3). The whale optimization algorithm is iterated iteratively to find the final solution.

where:

l, constant; update the magnitude of the distance;

H, vector of coefficients;

X*(t), the position vector of the current optimal solution;

X(t), the current position vector of the humpback whales;

Xrand(t), the random position vector of the whale population;

τ_p, the distance between the whale population and the prey;

a, the variable that decreases from 2 to 0;

ε, describes the shape of the spiral motion;

m, a random vector in the interval [–1, 1];

n, probability variable.

In the established model process, the industrial trial data are quickly used and normalized. Then the input variables are determined, and nine input variables are optimized by the LWOA optimization algorithm. The search range of variables is [–1, 1], the number of populations is 30, and the number of iterations is 500. The first iteration randomly generates 30 groups of initial solutions, calculates the fitness of each group of solutions, and saves the group of solutions with the smallest fitness as the current optimal solution to complete this iteration. When entering the next iteration, according to the whale optimization strategy, the positions of 30 solutions are updated, and a group of solutions with the smallest fitness are compared with the current optimal solution to save the group of solutions with smaller fitness. After 500 iterations, the group of solutions with the smallest fitness is the global optimal solution, and then the optimization value of the input variable is obtained by inverse normalization processing, and the optimization process is completed.

3.3.2. LWOA-TSVR Algorithm

Firstly, the testing data (total 2000 groups) processed by the LWOA algorithm are selected, secondly 1500 groups of them are selected as training data, and the remaining 500 groups are used as testing data, finally, the training set is selected to train the model, and the model is continuously adjusted according to the parameters, and the best model is recorded for each parameter setting, and then the accuracy of the final model is evaluated with the testing set. Because of the large number and complexity of the original data, large forecasting errors caused by order-of-magnitude differences in the different dimensions of the data are eliminated. Therefore, the input and output of the established model need to be normalized, and the input and output data are mapped to the [–1, 1] interval data normalization using the following equation:

$$y_i' = \frac{y_i - \min(y_i)}{\max(y_i) - \min(y_i)},\ i = 1, 2, 3, \cdots, m \tag{7}$$

where:

$\min(y_i)$, the minimum value of the model input or output raw data;

$\max(y_i)$, the maximum value of the model input or output raw data;

y_i, the raw data of the model input or output.

TSVR obtains the objective function by solving two quadratic programming problems to obtain two regression functions. Assuming that the training sample population is an n-dimensional vector, it can be expressed as (x_1, y_1), ... , (x_p, y_p), and the number of training samples is p.

$$A = [x_1, \ldots, x_p]^T \in R^{p*n} \tag{8}$$

$$Y = [y_1, \ldots, y_p]^T \in R^{p*n} \tag{9}$$

$$e = [1, \cdots, 1]^T \tag{10}$$

where:

A, input training sample;

Y, output training samples;

e, unit vector of appropriate dimensionality.

The hot rolled bending control is a multi-input single-output nonlinear system. The kernel function needs to be introduced:

$$K(x^T, A^T) = \exp\left(-\frac{||x^T - x_i^T||^2}{2\sigma^2}\right)\sigma > 0 \tag{11}$$

The sample is mapped to a high-dimensional space, and then linear regression is performed through the high-dimensional feature space to obtain the regression function.

$$f_{w1}(x) = K(x^T, A^T)\omega_1 + b_1 \tag{12}$$

$$f_{w2}(x) = K(x^T, A^T)\omega_2 + b_2 \tag{13}$$

By introducing Lagrange multipliers α and β vectors combined with KTT conditions, the pairwise problem of the objective function can be obtained as shown in Equations (1), and (2) above.

where:

C1, C2 > 0, adjust the parameters.

$$H = [K(x^T,\ A^T)e] \tag{14}$$

$$f = Y - e\varepsilon_1 \tag{15}$$

$$h = Y - e\varepsilon_2 \tag{16}$$

where:

$\varepsilon 1$, $\varepsilon 2 \geq 0$, adjusting the parameters.

Using the optimal solution, the weight vector and the bias vector are obtained as follows:

$$[\omega_1, b_1]^T = (H^T H\ +\ \gamma I)^{-1} H^T (f\ -\ \alpha) \tag{17}$$

$$[\omega_2, b_2]^T = (H^T H\ +\ \gamma I)^{-1} H^T (h\ +\ \beta) \tag{18}$$

where:

γ, the normal number;

I, unit matrix of appropriate dimensions.

The value of the weight vector and bias are brought into the regression functions $f_{w1}(x)$ and $f_{w2}(x)$. Using these two objective regressions forecasting functions, the bending force forecasting model can be determined according to the principle of the TSVR algorithm, and the objective function of the bending force forecasting model is finally derived as:

$$f_W(x) = K(x^T, A^T)\frac{(\omega_1 +\ \omega_2)}{2} + \frac{(b_1 + b_2)}{2} \tag{19}$$

Through the analysis of the above optimization process, the parameters with the greatest influence on the model are σ (kernel function parameter) and C (penalty parameter). To obtain the optimal σ and C, this paper proposes to use an improved whale optimization algorithm to find the optimal solution, combining the optimization strategy in Equation (3), while adjusting these 25 variables, each iteration substitutes the adjusted variables into the bending force forecasting model to obtain the corresponding bending. The group of variables with the smallest error between the forecast value and the target value after completing the specified number of iterations is the optimal value of the bending force, and the whole optimization process can be summarized as the expression of the fitness function for solving the following optimization problem is:

$$\begin{gathered} \min_{x}(f_W(x) -\ \text{Desiredvalue}_W)^2 \\ -1e\ \leq\ x\ \leq\ 1e \end{gathered} \tag{20}$$

where:

x, consisting of 25 normalized variables;

$f_W(x)$, the forecast value of the bending force forecasting model;

Desiredvalue_W, the target value of the endpoint bending force.

The specific optimization process can be described as follows:

Step 1: Read the hot rolled strip steel production data to be optimized and normalize the data;

Step 2: Initialize the model parameters, such as the number of variables, the upper and lower bounds of the variables to be optimized, the number of populations, and the number of iterations;

Step 3: Randomly generate initial solutions for the number of populations, and merge each set of solutions with the input variables in Table 1 as input data to be substituted into the bending force forecasting model to obtain the forecast value of bending force;

Step 4: Calculate the fitness of each group of solutions according to the fitness function $f_{fit(x)}$, and save the optimal solution with the smallest current fitness;

Step 5: If the current number of iterations is less than the maximum number of iterations, update a, r, P, v, p to determine the solution required for the next iteration using Equation (4), detect whether there is a solution that exceeds the search space if so, map it to a random position in the feasible domain, and repeat steps 4–5. otherwise, return the optimal solution to complete the optimization of the bending force influencing factors.

Through the above steps, the predicted result of the LWOA-TSVR algorithm is finally compared with the actual data, as shown in Figure 6.

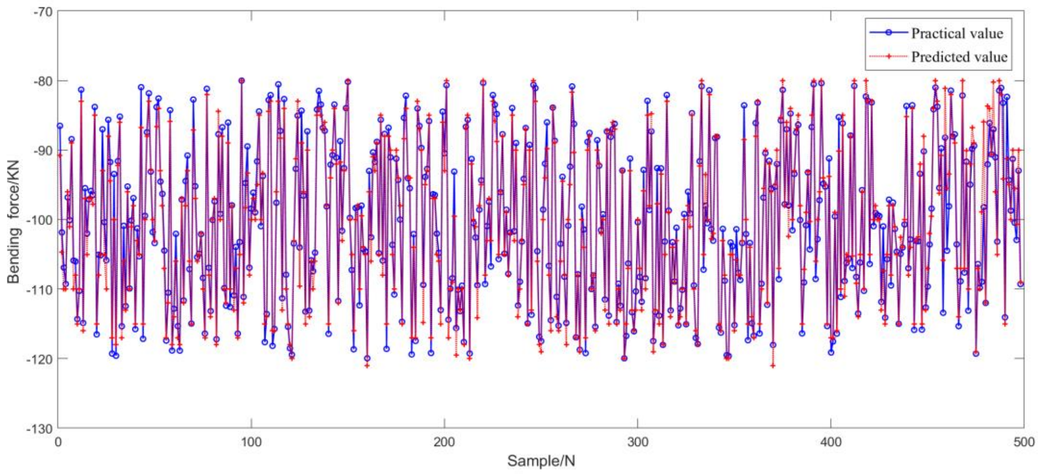


Figure 6. LWOA-TSVR prediction effect graph.

3.3.3. Results and Discussion

To describe the prediction effect of the LWOA-TSVR model, the SSR/SST value and the SSE/SST value are used. The closer the SSR/SST value is to 1, the closer the model prediction is to the same degree of oscillation as the practical value. The smaller the SSE/SST value is, the better the fitting degree between the predicted value and the practical value of the model is. The formulas for the corresponding judging indicators are shown in Equations (21) and (22).

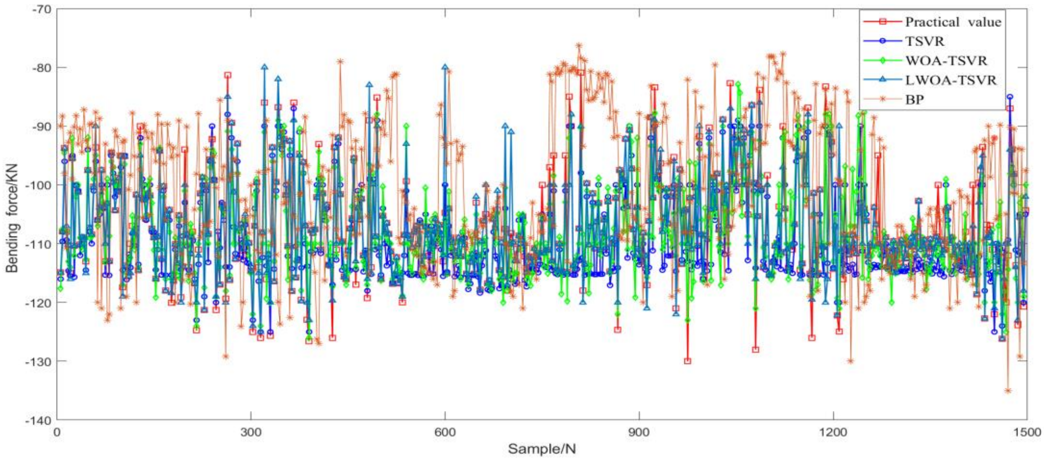
$$\mathrm{SSE/SST} = \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}_i\right)^2} \tag{21}$$

$$\mathrm{SSR/SST} = \frac{\sum_{i=1}^{n}\left(\hat{y}_i - \bar{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}_i\right)^2} \tag{22}$$

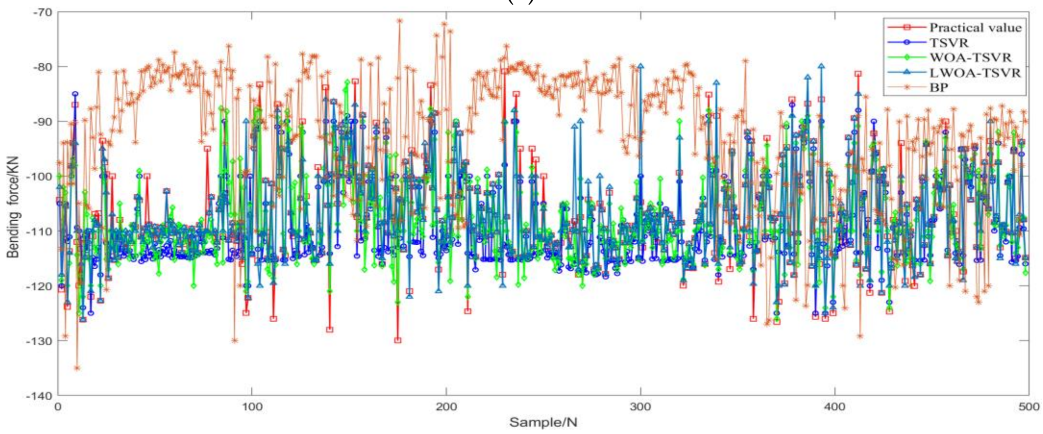
The calculated SSR/SST value of the LWOA-TSVR model is 0.9582, which is close to 1, so the predicted value of the LWOA-TSVR bending force model is very close to the oscillation degree of the practical value. The SSE/SST value is 0.0418, which indicates that the fitting degree of the model is good. In summary, it can be concluded that the LWOA-TSVR prediction effect is good and can meet the process requirements.

3.3.4. Comparative Analysis of The Models

To investigate the prediction effect of the LWOA-TSVR algorithm compared with traditional algorithms, four algorithms (BP, TSVR, WOA-TSVR, and LWOA-TSVR) were used to build the corresponding models and were compared in the training set and testing set respectively. Firstly, the SSE/SST and SSR/SST value is used to judge the fitting effect of the models, secondly the MAE (mean absolute error), RMSE (root mean square error), and relative errors are used to evaluate the prediction accuracy of the model, finally, the HR (hit rate) is used to examine the degree to which the models met the standards. The parameters of the BP algorithm are set as follows: the input quantity, output quantity, and the number of nodes in the hidden layer: 9, 1, 8 respectively. The predicted values of the four algorithms are compared with the actual production data and the results are shown in Figure 7.



(**a**)



(**b**)

Figure 7. Comparison results of four types of bending force models: (**a**) Bending force on the training set; (**b**) Bending force on the testing set.

As can be seen from Figure 7, the deviations from the actual production data of the four models are in the order of small to large: LWOA-TSVR, WOA-TSVR, TSVR, and BP. According to the SSE/SST value and SSR/SST value of the four models in Table 2, compared with the other three algorithms, the LWOA-TSVR model has the lowest SSE/SST value and the best fit obtained by the model; The SSR/SST value is closer to 1, the oscillation between the predicted and practical value is closer.

Table 2. Comparison of the regression effects of the four models.

Evaluating Indicator		**Training**	**Testing**
		Rolling Force	**Rolling Force**
SSE/SST	BP	0.1201	0.2021
	TSVR	0.1014	0.1304
	WOA-TSVR	0.0693	0.0933
	LWOA-TSVR	0.0418	0.1235
SSR/SST	BP	0.8799	0.7979
	TSVR	0.8986	0.8696
	WOA-TSVR	0.9307	0.9067
	LWOA-TSVR	0.9582	0.8765

To investigate the prediction accuracy of these models, MAE (mean absolute error), RMSE (root mean square error), and relative errors are used to analyze the models. The smaller the value of MAE, RMSE, and relative errors, the higher the prediction accuracy of the model. The calculation equations are Equations (23)–(25), and the calculation results are shown in Figures 8 and 9.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|}{n} \tag{23}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{n}} \tag{24}$$

$$\delta = \frac{\left|\hat{y}_i - y_i\right|}{y_i} \tag{25}$$

where:

n, the number of testing sample;

y_i, the practical output of the testing sample;

$\hat{y}_i$, the forecast value of the model;

δ, relative error.

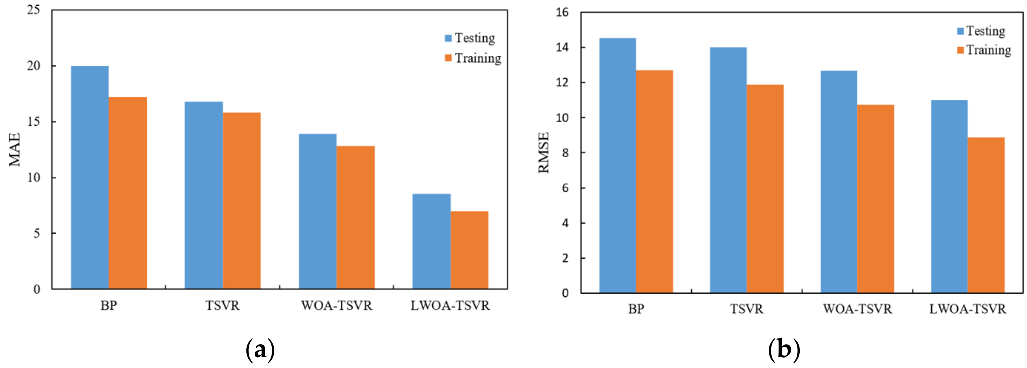


Figure 8. Error histogram for the four models: (**a**) MAE value for the four models;(**b**) RMSE value for the four models.

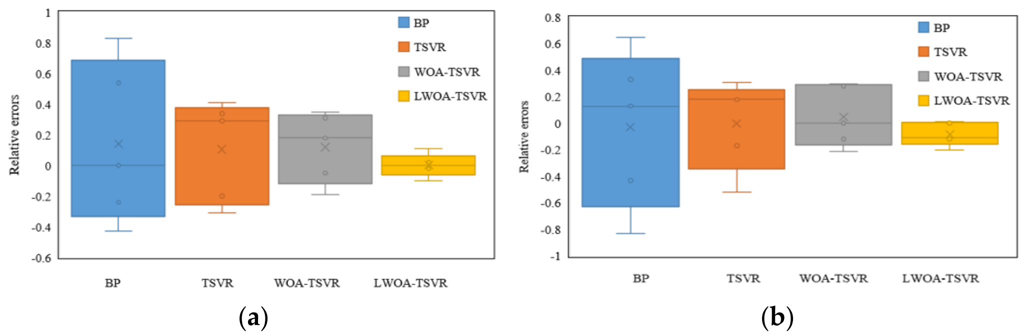


Figure 9. Comparison of relative errors of four models: (**a**) Relative error of the training set; (**b**) Relative error of the testing set.

From Figures 8 and 9 we can see that the MAE values of BP, TSVR, WOA-TSVR, and LWOA-TSVR in the training set tests are: 17.1872, 15.7865, 12.8261, and 6.9997, respectively, and the corresponding RMSE values are: 12.6811, 11.8907, 10.7386 and 8.8761, respectively. δ (relative error) values are:0.83, 0.41, 0.35, and 0.11. Relative error values are: 0.83, 0.41, 0.35, and 0.11, respectively. In the testing set tests, the MAEs of BP, TSVR, WOA-TSVR, and LWOA-TSVR are: 19.9876, 16.7882, 13.8766, and 8.5322, respectively, and the corresponding RMSEs are 14.5292, 13.9881, 12.6782 and 10.9882, respectively. The values of δ (relative error) are: 0.65, 0.31, 0.30, and 0.01, respectively.

To investigate the degree of compliance of the model, the HR (hit rate) performance index is used for analysis, and during the analysis process, the bending force is considered as a hit when it satisfies Equation (26), and the corresponding hit rate calculation equation is shown in Equation (27). As can be seen from Table 3, the LWOA-TSVR bending force has the highest hit rate under the same conditions, which shows that the prediction accuracy of this method is better than that of other algorithms.

$$C_S * (100\% - k) < C_y < C_S * (100\% + k) \tag{26}$$

where:

C_S, the measured result of the bending force;

C_y, bending force forecast results;

k, hitting accuracy.

$$HR = \frac{\left(\left|y_i - \hat{y}_i\right| \leq n_e\right)}{n} * 100\% \tag{27}$$

Table 3. Hit rate of bending force.

Error Scope	Model			
	BP	TSVR	WOA-TSVR	LWOA-TSVR
From −5 to 5 KN	69%	76%	85%	91%
From −10 to 10 KN	78%	80%	87%	95%

In summary, through the comparison of SSE/SST, SSR/SST, MAE, RMSE, relative errors, and HR, the LWOA-TSVR model has the best performance evaluation index, which shows that the LWOA-TSVR algorithm has higher approximation precision. Therefore, the LWOA-TSVR prediction model has higher prediction performance.

4. Application and Validation

To verify the practical application of the established LWOA-TSVR bending force prediction model, the model is applied to the actual production line of a hot strip mill for testing (200 slabs in total). The main rolling process parameters are shown in Table 4, and the final hit rate is 91% for bending force within −100 KN ± 5 KN and 95% for −100 KN ± 10 KN. Compared with the conventional bending force control function, the intelligent control capability of this model is significantly more effective. The results of the bending force model forecast, and practical values are shown in Figure 10. The validity of the bending force model is verified by randomly selecting the rolling data of the same rolled strip. The results show that the bending force is highly consistent with the trend of bending force in the field, which verifies the good forecasting performance of the bending force model and improves the accuracy of plate shape control.

Table 4. Configuration parameters for rolling mill equipment.

Parameter	Value
Clearance between rolls	11.78 mm
String speed	3.15 m/s
Power of rolling mill	2595.23 KW
Looper tension	10.06 MPa
Work roll size	Φ1 110/1210 × 5300 mm
Support roller size	Φ2 100/2300 × 4950 mm
Maximum rolling force	120,000 KN
Rated torque	20,000 KN·m
Loop angle	26.00 deg
The initial thickness of the strip	5.7 mm

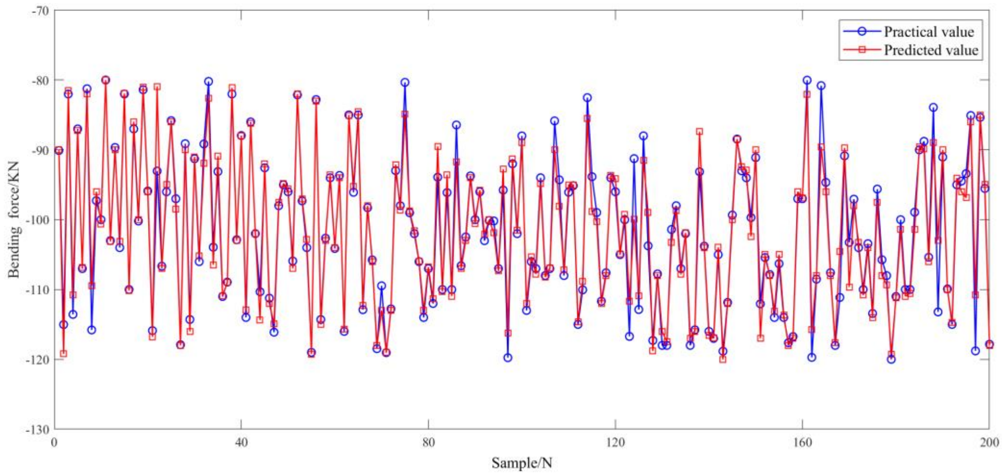


Figure 10. Comparison of model predicted value with practical value in the application.

5. Conclusions

In this paper, a forecasting model based on twin support vector machines is proposed and an improved whale swarm optimization algorithm is used for data analysis. Through analysis of field-testing data, the main factors affecting the magnitude of the bending force are obtained as follows: the inlet temperature of strip steel, entry thickness, exit thickness, strip width, rolling force, rolling speed, work roll shifting, yield strength of strip steel, and target convexity.

(1) The experimental study shows that the LWOA-TSVR model can accurately predict the bending force, compensate for the defects of slow convergence speed and low convergence accuracy of traditional modeling, improve the generalization ability, accuracy and implementation efficiency of the model and the model is simple in structure and can handle complex problems such as non-linearity and strong coupling.

(2) The model is tested by field application. The results show that within the tolerance range: the hit rate of bending force within -100 ± 5 KN is 91%, and the hit rate within -100 ± 10 KN is 95%. This is higher than the current advanced method.

(3) The proposed bending force prediction model is compared with four prediction methods for verification. The results show that the LWOA-TSVR model has the smallest optimal relative error and the best following effect in the evaluation of MAE and RMSE indicators, thus verifying the good generalization ability of the LWOA-TSVR forecasting model. The model provides theoretical guidance and an experimental basis for the practical bending force setting method in the hot rolling production process.

Author Contributions: Conceptualization, C.S. and B.W.; methodology, C.S. and B.W.; software, J.C.; validation, C.S., B.W. and R.Z.; formal analysis, S.G.; investigation, P.S.; resources, C.S.; data curation, B.W.; writing—original draft preparation, B.W.; writing—review and editing, C.S. and B.W.; visualization, Z.M.; supervision, C.S. and B.W.; project administration, C.S.; funding acquisition, C.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research is supported by the basic scientific research fund projects of the Educational Department of Liaoning Province in 2021(LJKZ1071), the natural science fund program projects of the Department of Science & Technology of Liaoning province in 2022(2022-BS-297), and the industrial research and industrialization (key R&D project) (2020JH2/10100019).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw/processed data required to reproduce these findings cannot be shared at this time as the data also forms part of an ongoing study.

Conflicts of Interest: The authors declare no conflict of interest.

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