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Data-Driven Welding Performance Prediction

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Abstract

With the widespread application of digital and intelligent production methods in the manufacturing industry, guiding companies to pay attention to and play the value of manufacturing big data is of great significance to innovative product process design. For laser welding, excessive deformation of the plate will lead to assembly accuracy. Research on problems that cannot be guaranteed, analyze process parameters, select welding current, welding voltage, welding speed, and welding diameter, and combine deep learning algorithms to build a welding performance prediction model. The simulation results show that the anti-deformation method is used for compensation control according to the predicted deformation.

Keywords

Deformation; Deep Learning; Layered Learning; Prediction Model; Compensation.

1. Introduction

Laser welding processing has the characteristics of small workpiece deformation, stable welding quality, fast welding speed and high degree of automation, which makes it widely used in automobile welding. With the continuous expansion of production scale, a large amount of process parameter data and quality will be generated in the process Performance data exists in the form of time series. It has the characteristics of randomness and non-linearity. By digging deeply into the laws of its existence, and finding the mapping relationship between these data, it provides a reliable basis for subsequent production, processing and quality control. Artificial Neural Networks (ANNs) is a data processing system that deals with nonlinear mapping relationships between variables. It can fully approximate arbitrarily complex nonlinear relationships and has strong self-learning capabilities. Optimization and other aspects have unique advantages and are widely used in artificial intelligence, robotics, statistics and other fields.The traditional welding predictive modeling method is only a simple predictive analysis of the data. In the face of massive, multi-source, heterogeneous big data, its prediction accuracy is limited. Therefore, this article selects welding current, welding voltage, welding speed and welding diameter as input, And use the neural network of the layered learning algorithm to predict the welding quality.Figure 1.

2. Layered learning algorithm

Step-by-step learning is the use of a step-by-step approach, according to the level of knowledge difficulty, and appropriate questions for teaching difficulties, so as to gradually guide students from the basic knowledge stage to the deep knowledge stage, so as to allow students to easily master the learning content. Learning is divided into three stages: preliminary homework, mid-term homework, and later homework. Similar to hierarchical reinforcement learning, a complex learning problem can be decomposed into several sub-problems and solved separately. The result is better than solving the whole problem directly [3]. Inspired by this, this paper proposes a layered learning algorithm to layer the data set according to the effective information content. As shown in the information pyramid in

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Figure 2, the bottom of the model is the data set with the lowest information content, which contains as the height increases. The effective information is constantly increasing.

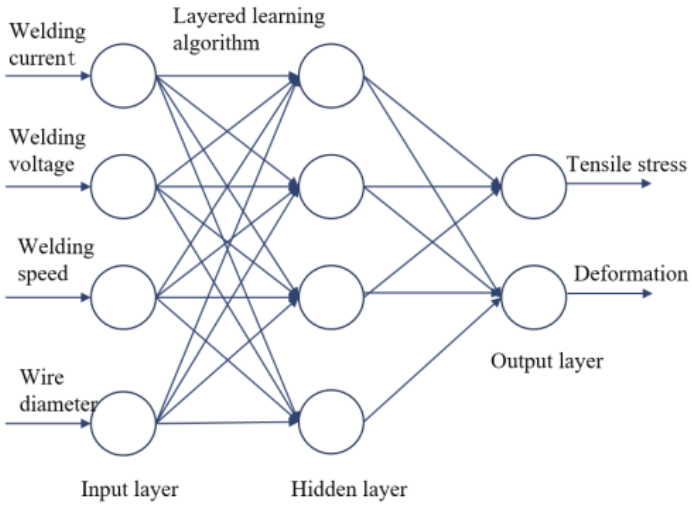

Figure 1:Neural network structure based on layered algorithm

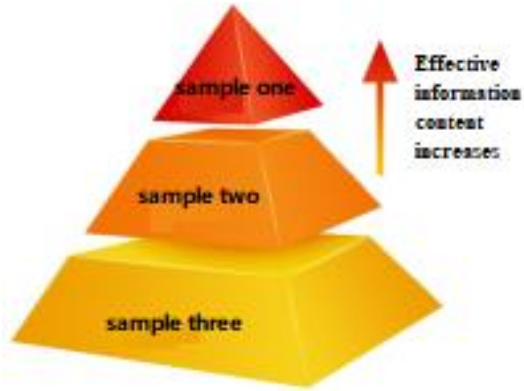

Fig 2: Information pyramid

The specific algorithm steps are as follows:

(1) Select the similarity coefficient m1, m2...mk corresponding to the k layer (m1<m2...<mk)

(2) The sequence is divided into {t1, t2...tm} The data tm that needs to be predicted and the historical data {t1, t2...tm-1} Find the similarity coefficient {s1, s2...sm-1}

(3) Compare the obtained {s1, s2...sm-1} with m1, and put it in sample 1 if it is less than m1

(4) Data selection of layer k-1, repeat step 3, when certain conditions are met, the algorithm ends.

3. Network model based on layered learning algorithm

3.1 Layered reconstruction training set

The characteristics of the data determine the upper limit of the prediction result, and the prediction method determines the lower limit of the prediction result. Before data prediction, the data most relevant to the predicted value must be selected from many historical data, which shows the importance of the training set[4] .

The training set reconstruction methods include: Euclidean distance, Mahalanobis distance, Hamming distance, etc. By setting a threshold, the training set is divided into two categories, and the sample set larger than the threshold is discarded, but this method exists The sequence window is difficult to divide, the subjectivity is too strong, and the sample set that cannot be discarded is all the disadvantages of invalid data. The traditional training set composed of data arranged in time series

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and the above-mentioned excessively subjective addition and deletion methods to the training set will all As a result, the training set obtained is not sufficiently hierarchical and not highly targeted. In this study, the training set was reconstructed according to the similarity. Use the entropy method to analyze the three indicators of dynamic time warping (DTW), cosine similarity, and symbolic aggregation approximation (Symbolic Aggregate Approximation, SAX) to obtain similarity coefficients, and then use the layered learning algorithm based on similarity coefficients to reconstruct the training set , From slightly similar to similar to more similar to the most similar, and the degree of similarity gradually increases. This method can accurately and efficiently extract and sort the effective features of historical data and improve the pertinence of the training model. Figure 3

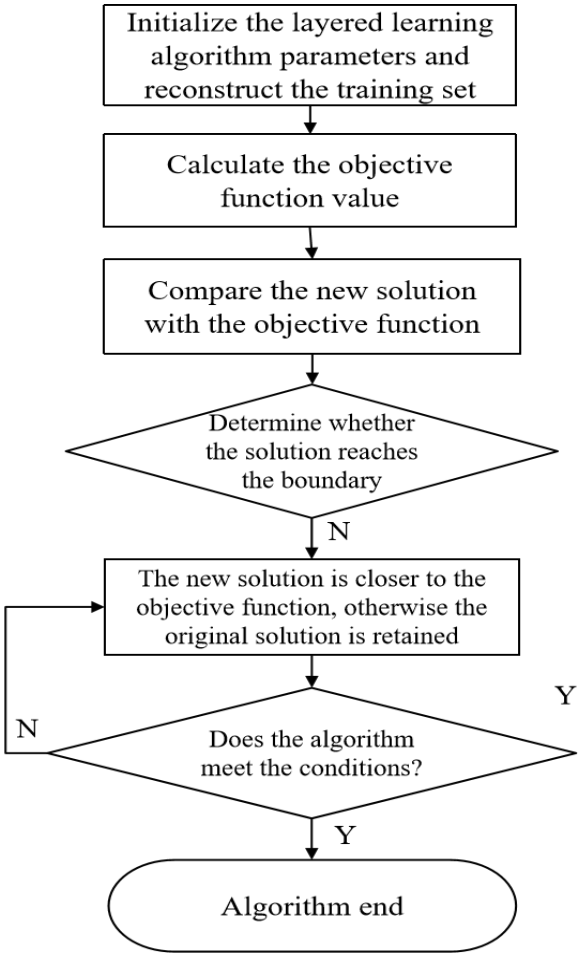

Figure 3:Training set reconstruction

The specific reconstruction steps are as follows:

(1) Initialization parameters: the number of layers of the information pyramid n, the similarity coefficient threshold t corresponding to each layer, the maximum number of updates p and the current number of updates q of the threshold in the algorithm, the number of samples that can be accommodated in each layer r, using the number of layers to learn The algorithm reconstructs the training set.

(2) Calculate the objective function value.

(3) Make difference between the new solution and the objective function, choose to update the number of layers and threshold, and judge whether the boundary conditions are met, if yes, output the result, otherwise go to the next step.

(4) Calculate the new objective function, if the new value is close to the objective function, keep it, otherwise keep the original solution.

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(5) Determine the termination condition of the algorithm. If the number of iterations q of the algorithm has reached the maximum number of iterations p, or a candidate solution whose objective function value satisfies the condition has been obtained, the algorithm terminates; otherwise, q=q+1, and return to step 3 to continue the algorithm loop.

3.2 Improved layered reconstruction training set

The layered[5]learning algorithm constructs different training sets according to the data to be tested. The data at the next moment needs to be re-established with a more targeted model. The advantage of this modeling is that the accuracy of prediction has been improved to a certain extent, but the cost is The calculation cost is too high, and there is a certain loss in calculation efficiency. Therefore, this chapter will start with improving efficiency, improving efficiency without reducing the prediction accuracy, so that the constructed model can be more adapted to the actual industrial needs. The following figure shows the improved model Build flowchart4

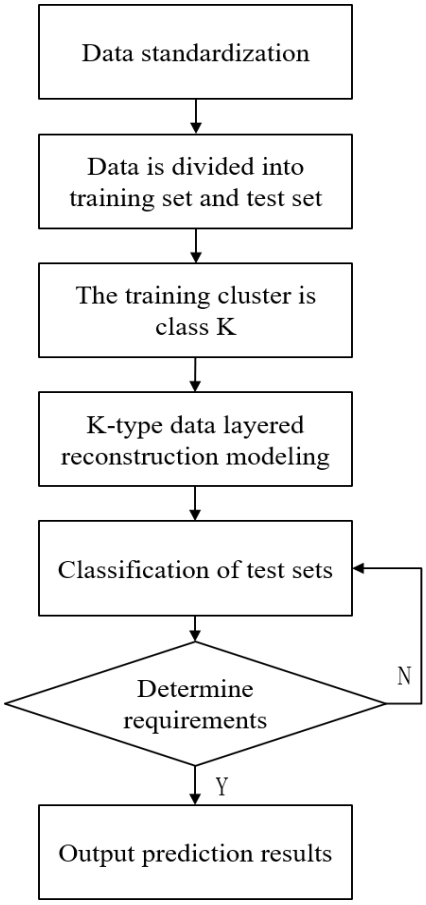

Figure 4: Improved layered reconstruction forecasting process

(1) Data preprocessing: By standardizing the data, the data can be reduced to a specified range, avoiding irregular data from affecting the construction of the model;

(2) The data set is divided: consult the literature, it can be found that 70% of the training set, 30% of the test set;

(3) Divide the training set into k categories. After literature research and investigation of the characteristics of the data, as well as multiple experiments, the K-mean algorithm is selected to extract the center distance of each category. It is necessary to take into account that the categories of efficiency points are not easy to be too many ;

(4) Model construction: For k types of data, use the layered reconstruction algorithm in the previous section to construct the model;

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(5) Test set classification: calculate the Euclidean distance for each type of data in the test set, and divide it into the closest category;

(6) Prediction: test sets of different categories are input into the corresponding training model for prediction

4. Error prediction of machine tools

4.1 Evaluation Index of Experimental Results

In order to quantitatively describe the prediction results, this paper uses root mean square error (RMSE) and average relative error (MAPE) as the final evaluation indicators. The expression is as follows[6]

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(T_i - \hat{T}_i\right)^2} \tag{1}$$

$$MAPE = \frac{1}{N}\sum |T_i - \hat{T}_i| \times 100/T_i \tag{2}$$

In the formula: N represents the sample size, T_i represents the real value, $\hat{T}_i$ represents the predicted value.

4.2 Experimental training network settings

For the setting of wavelet neural network training parameters, there is currently no fixed standard. Based on the existing experimental sequence data, the genetic algorithm proposed in [7] is used to optimize the experimental parameters in the training network. Compared with optimization algorithms such as steepest descent algorithm, Bayesian algorithm, particle swarm optimization, genetic algorithm has good convergence, robustness and fault tolerance when performing global search.

The parameters used in the final experiment are: parameter optimization algorithm using genetic algorithm [8]; input population size is 200; maximum evolutionary algebra is 2000; fitness function = 0.2; adaptive formula = 0.6. The wavelet neural network model structure is a single hidden layer, the number of hidden layer neurons is 125, the weight range is [-1, 1], the learning rate is 0.005, the excitation function is the Morlet wavelet function, and the loss function is the root mean square error RMSE . The operating environment is CPU Intel (R) Core (TM) i5-7500, memory 8 GB, frequency 3.41GHz, operating system Windows10[9].

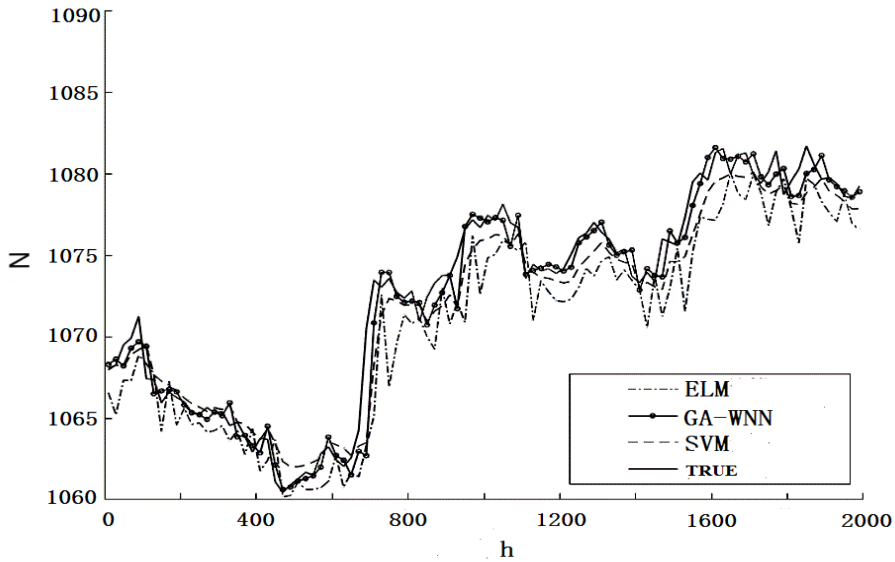

Figure.5: Comparison of three prediction models

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5. Comparative evaluation of experimental results

5.1 Use SVM, ELM, GA_WNN to analyze the prediction results

In order to illustrate the correctness of the selected neural network, the data extracted above was input into the SVM, ELM, and GA_WNN networks in order to construct the model. The prediction results are shown in Figure 5.

In order to further verify the innovation and superiority of the proposed layered learning algorithm in the deformation prediction method of the rotary kiln calcination zone, the prediction method is compared with the layered learning algorithm. Table 1 shows the mean square of the three prediction methods Comparison of root error (RMSE) and mean relative error (MAPE).

Table 1. Comparison table of various prediction errors

Training set type	Various forecasting methods	MAPE/%	RMSE/%
Reconstructed training samples	SVM	1.10	1.45
	ELM	1.99	2.51
	GA_WNN	0.67	0.93
The training sample has not been reconstructed	SVM	1.36	1.97
	ELM	2.57	2.92
	GA_WNN	0.74	1.26

Through the quantitative comparison of the above results, it is found that the GA_WNN prediction result is the best, the SVM prediction model is the second, and the ELM prediction model is the worst; the prediction model using the layered learning algorithm has greatly improved the original prediction accuracy. The analysis result of the layered learning algorithm is obviously better than the previous prediction model. This is because the training samples are extracted through the layered reconstruction analysis algorithm, so that the constructed prediction model is more targeted to the input data, greatly improving the generalization ability of the model, thereby improving the prediction accuracy.

5.2 Forecast compensation analysis

The traditional PID control is to adjust after the deformation is abnormal. After the prediction model in this paper obtains the prediction value based on the historical data, the staff can perform active deformation compensation in advance according to the prediction result, thereby making the rotary kiln system in a long-term effect Stable working condition. Compare the predicted value with the actual value, and divide the result into two deviations: over-compensation and under-compensation. Through simulation, the statistics of the compensation deviation results of the above prediction methods are shown in Table 2 below

Table 2. Compensation bias of various prediction methods

Predictive compensation method	Overcompensation /mm	Under-compensated/mm	Compensation times	average value/mm
ELM	42.255	-714.202	2000	0.378
SVM	21.273	-327.101	2000	0.174
GA_WNN	58.239	-177.608	2000	0.117

From the comparison of the results in the above table, it can be seen that the prediction method proposed in this paper is significantly better than other traditional prediction methods in terms of deformation compensation performance, and significantly improves the anti-interference ability of the rotary kiln.

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6. Summary

Aiming at reducing the time lag in the traditional welding control process, this paper proposes a wavelet neural network prediction method based on a layered learning algorithm, and verifies it with the help of actual welding deformation and tensile stress data. The root mean square error (RMSE) of the prediction results is between 0.9327 and 1.154, which meets the actual requirements of the project. The correlation coefficient is used for effective information extraction, and the layered learning algorithm is used for training set reconstruction, which greatly improves the pertinence of model training. According to the prediction results and using the anti-deformation method to compensate, good results are obtained.

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