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Prediction of Garment Production Cycle Time Based on a Neural Network

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Abstract
The process of garment production has always been a black box. The production time of different clothing is different and has great changes, thus managers cannot make a production plan accurately. With the world entering the era of industry 4.0 and the accumulation of big data, machine learning can provide services for the garment manufacturing industry. The production cycle time is the key to control the production process. In order to predict the production cycle time more accurately and master the production process in the garment manufacturing process, a neural network model of production cycle time prediction is established in this paper. Using a trained neural network to predict the production cycle time, the overall error of 6 groups is within 5%, and that of 3 groups is between 5% and 10%. Therefore, this neural network can be used to predict the future production cycle time and predict the overall production time of clothing.

Key words: *garment production, big data, cycle time, neural network, prediction.*

Introduction

The textile and garment industries are two of the most important in China. According to statistics of the World Trade Organization, in 2017 global textile and garment exports were worth 647.89 billion euros, while China's exports were 245 billion euros, ranking first in the international textile and garment trade pattern, with a market share of more than 1/3 [1]. In 2018, China's total import and export value for textiles and clothing reached 252.79 billion euros, up 3.7% year on year [2]. The contribution rate of exports was the largest among all the factors of garment demand, which means that exports were the most significant factor in driving the development of China's textile industry [3]. The EU is China's largest export market. The value of textile and garment products imported by the EU is nearly 114.8 billion euros, mainly from China, Bangladesh, Turkey, India and Cambodia [4]. With the development of production technology, such lean production methods as 5S management, VSM (Value Stream Mapping) and others are applied to garment production, China is also facing competition from low-cost labor forces in Southeast Asia and other countries. Thanks to the close relationship of the textile industry with agriculture and ancient culture, the Indian textile industry has the ability to produce a wide range of products suitable for various market segments, both in India and around the world [5]. After implementing lean tools in Indian garment enterprises, researchers observed a reduction in work-in-progress inventory, as well as increased production and efficiency of the production line [6]. Lean and digital production has become a new development direction to improve the efficiency of garment production.

However, the sewing process is still a black box. Influenced by factors such as proficiency, style, fabric, etc., the cycle time of each garment production is different, which decreases with an increase in the number of work pieces. The process of garment sewing production is a declining learning curve, which in theory is a smooth curve, as shown in ***Figure 1***. In fact, workers need time to adapt to the cycle time after the decline. The learning curve in actual production is shown in ***Figure 2***.

The abscissa of the image is the number of production pieces, and the ordinate is the cycle time. Wright was the first person to observe and study the learning curve in production and operation management [7]. Through the learning curve, managers can set more accurate labour standards, monitor actual production targets [8], as well as predict the available working hours of the process [9] and production volumes [10]. In production and operation management, the learning curve can describe employee performance improvement caused by repetition or experience, which makes it a useful tool for management decision [11]. Production big data combined with regression analysis can help managers choose the best learning curve model [12]. Through the proficiency rate, a functional relationship between different production days and the pipeline cycle time can be established [13]. However, there is no study on the cycle time of garment production using big data and a neural network.

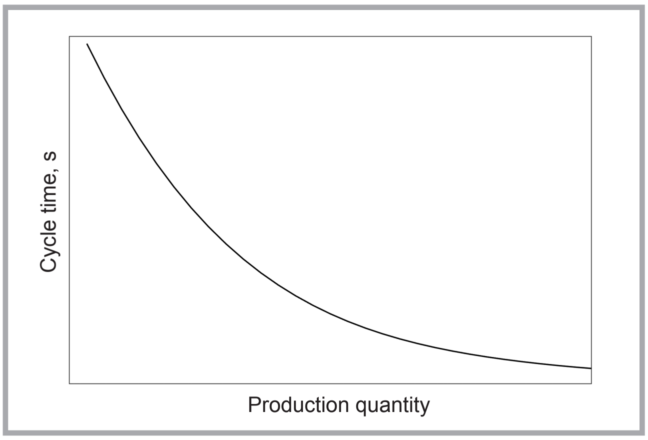

Figure 1. *Theory cycle time.*

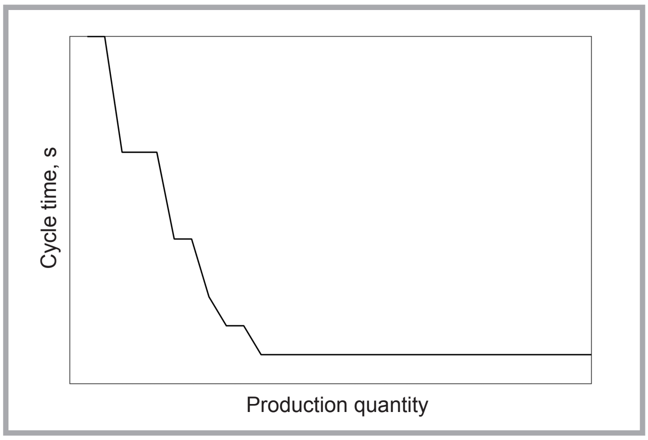

Figure 2. *Actual cycle time.*

Research methodology

An artificial neural network (ANN) is a mathematical model based on the working principle of a biological neural network. A neural network is one of the most basic forms of machine learning. In the textile and garment industry, a neural network has been used to deal with complex non-linear problems, such as prediction of fabric size and performance [14], classification of fabric defects [15], human body recognition [16], evaluation of the sewn thread consumption of jean trousers and so on [17]. In this paper, a BP (back propagation) neural network is used to predict the learning curve of the garment production cycle time. The curve is affected by many factors, but the logic relation is difficult to express with an accurate function relation. A BP neural network is a kind of forward tutor learning neural network with error reverse propagation. It does not need to determine the mapping relationship between the input and output in advance, but only learns some rules through its own training. Its basic idea is the gradient descent method, which uses gradient search technology to minimise the error mean square deviation of the actual output value and the expected output value of the network.

Training parameters

Production quantity: the larger the production quantity is, the more skilled the workers can be. The stable cycle time will be greatly reduced compared with the initial cycle time, but there is also a limit. The smaller the production quantity is, the shorter the learning time of the workers is. It is possible that the production has not reached the ultimate efficiency and the production has been completed.

GST per capita: General sewing time (GST) is a pre-set action time system specially designed for the clothing industry, which originated from the production therblig analysis proposed by F.B. Gilbreth. The GST programs the common actions in the sewing process and describe the actions in code form. Each code has a clear time value, and then a standard time is estimated according to the moving distance and action difficulty. In a garment factory, industrial engineers account for the GST of each garment. The calculation formula of GST per capita is:

$$GST\ per\ capita = \frac{GST}{number\ of\ people} \tag{1}$$

which reflects the production beat of the water line in an ideal state. However, in actual production, the GST per capita can only be used as a reference value. The final stable cycle time may be larger than the GST per capita due to factors such as the bottleneck process or complex style. It may also be smaller than the GST per capita due to factors such as workers being more familiar with the style and higher efficiency.

Initial cycle time: when the first garment of a production order is produced, the production cycle time is higher than the GST per capita due to the low proficiency of workers. The initial cycle time is the highest point on the production learning curve, which determines the starting point of the learning curve. The initial cycle time needs to be determined according to the bottleneck process on site, which cannot be calculated before production, and can reflect the production difficulty of a garment to a certain extent.

Building neural network

The structure of a BP neural network for clothing production cycle time prediction is shown in ***Figure 3***. There are three layers: the input layer, hidden layer and output layer. The input layer is responsible for receiving data, with three variables x_1, x_2 and x_3 representing the production quantity, GST per capita and initial cycle time.

The hidden layer is responsible for data decomposition and processing. There are 10 neurons, each of which is a processing unit receiving input from the upper layer. The activation function, also called the mapping function *tansig*, can transform the result of calculation in a non-linear way, so as to improve the expression

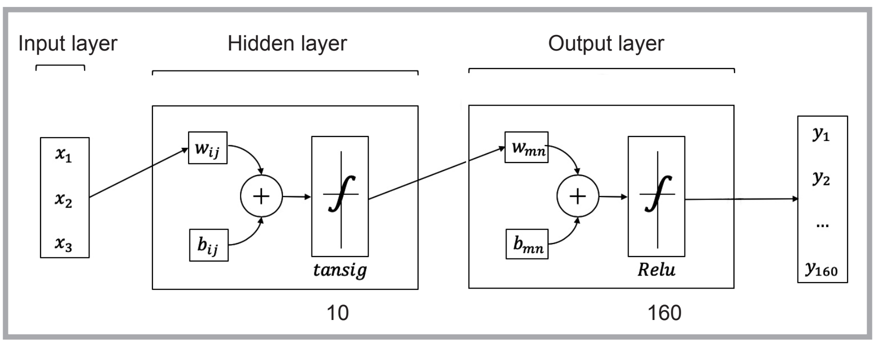

Figure 3. *Structure of cycle time prediction BP neural network.*

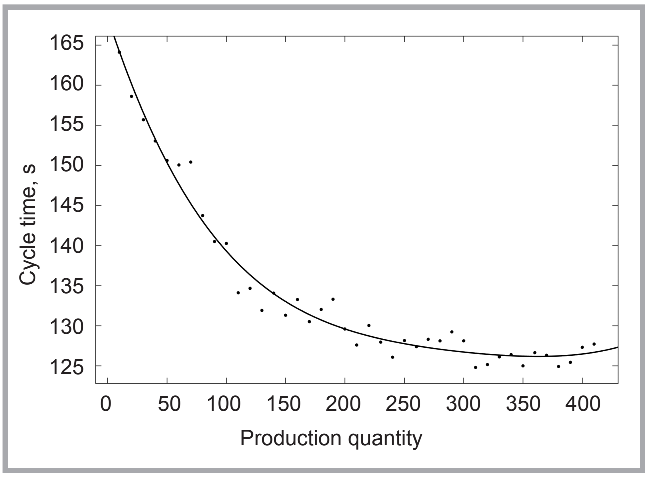

Figure 4. *Fitting of predicted cycle time.*

ability of the neural network and deal with the problem of linear indivisibility. w_{ij} is the hidden layer weight and b_{ij} is the hidden layer threshold. The *tansig* formula is as follows:

$$\tan sig(n) = \frac{2}{1+e^{-2n}} - 1 \qquad (2)$$

The output layer receives the output of the hidden layer and has 160 output y, which is divided into the cycle time from 10 pieces to 1600 pieces in the production process of a certain garment. According to experience [18], the output layer activation function selects the *Relu* function, which has a faster convergence speed than *sigmoid* and *tansig*. w_{mn} is the weight of the output layer, and b_{mn} is the output layer threshold. The *Relu* function is expressed as follows:

$$f(\mathrm{x}) = \max(0, x). \qquad (3)$$

Experimental

In this research, the production data of a women's clothing enterprise in Hangzhou, China, was used to carry out the experiment. 120 groups of production process data of the enterprise from May to July 2019 were obtained. 89 groups were selected for neural network training and 10 for a simulation test. The data experiment was carried out in MATLAB 2017b. Through the training of the neural network, 10 groups of prediction data were obtained, and curve fitting was carried out for the prediction data. Then the final prediction data were obtained according to the fitting curve, and finally compared with the real data.

1) Select 89 groups of production data, including five categories of dress, skirt, shirt, knitwear and coat; the minimum production quantity is 181 pieces, the maximum production quantity – 1823 pieces, the minimum GST per capita – 45 seconds, the maximum GST per capita – 277 seconds, the minimum initial cycle time – 60 seconds, and the maximum initial cycle time is 450 seconds. Because the input data size needs to be unified in the neural network, the cycle time of different production quantities is extended to 1600 pieces, with the last piece completed, and the interval being 10 pieces. For example, the production of one training group has been completed in 300 pieces, and the cycle time of the last one is 200 seconds; thus the cycle time of 300 pieces to 1600 pieces is set to 200 seconds. It should be noted that due to the small production quantity of this section, 300 pieces will complete the whole order. If the production quantity increases, the cycle time may be further reduced. In the neural network, because the production quantity is also an input variable, the influence of production quantity on the cycle time can be taken into account in the training of the neural network.

89 sets of data are used to train the neural network several times. The decision coefficient R^2 is stable at 0.95483. The calculation formula R^2 of is as follows:

$$R^2 = \frac{\left(l\sum_{i=1}^{l} \hat{y}_i y_i - \sum_{i=1}^{l} \hat{y}_i \sum_{i=1}^{l} y_i \right)^2}{\left(l\sum_{i=1}^{l} \hat{y}_i^{\,2} - \left(\sum_{i=1}^{l} \hat{y}_i \right)^2 \right)\left(l\sum_{i=1}^{l} y_i^{\,2} - \left(\sum_{i=1}^{l} y_i \right)^2 \right)} \qquad (4)$$

Where, y_i represents the true value of the i sample, $\hat{y}_i$ – the predicted value of the i sample, and l is the number of samples. The range of coefficient R^2 is between 0-1. The closer it is to 1, the better the fitting degree is.

The results show that the fitting degree of the trained neural network is good. 10 groups of production data of prediction samples are inputted to the neural network for simulation prediction, and 10 groups of prediction cycle time can be obtained.

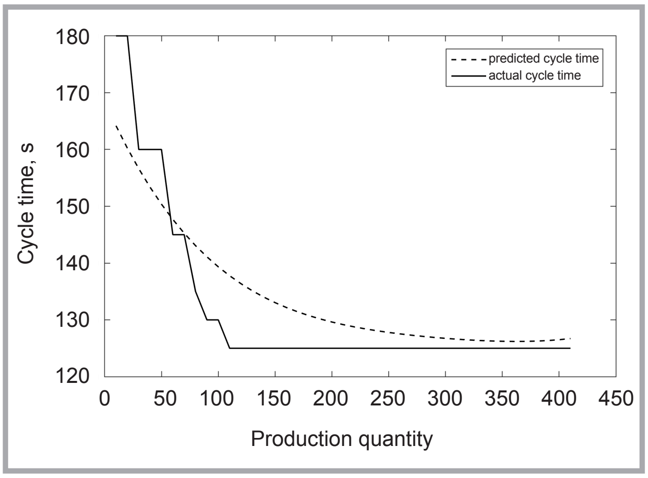

Figure 5. *Comparison of predicted cycle time and actual cycle time.*

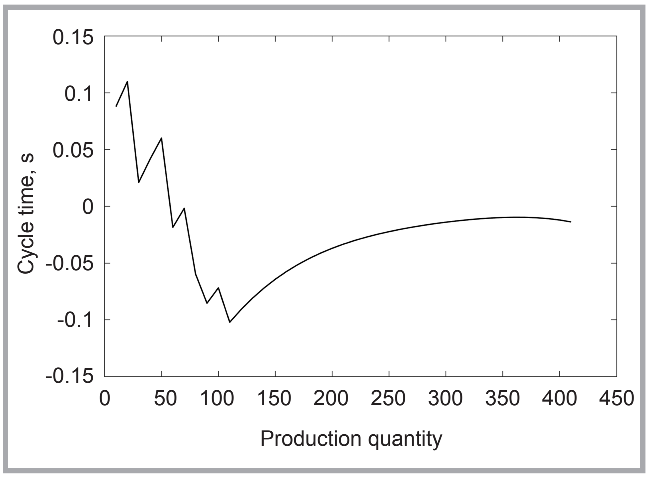

Figure 6. *Error percentage of predicted cycle time.*

2) Due to the disturbance of neural network prediction data, the latter prediction cycle may be larger than the former one, which violates the actual production logic. Therefore, curve fitting of the neural network output data is needed before the final prediction results are obtained. According to the production quantity, select the corresponding prediction cycle time, such as the first group of data. The production quantity is 407, therefore select a prediction cycle time from 10 to 410, and fit the curve in MATLAB through the 4th degree polynomial, and get the following fitting formula:

$$f(x) = 3.495e - 09 \times x^4 - 4.196e - 06 \times x^3 + \\ + 0.001986 \times x^3 - 0.4517 \times x^2 + 168.5 \quad (5)$$

Figure 4 shows the fitted production learning curve. Take 41 groups of production quantity into the formula to get the final 41 groups of predicted cycle time.

Results and discussion

Compare the final predicted cycle time with the real cycle time, as shown in ***Figure 5***, The error percentage is shown in ***Figure 6***. It can be seen that the sorting error is within 10%, and most of the errors are within 5%. Finally, the error of the complete production time is calculated. The predicted time is 5499.6 seconds, the actual time 5400 seconds, the error 99.6 seconds, and the overall error percentage is 1.8%. It can be seen that the trained neural network can predict the product cycle time and complete production time in a certain error range.

Take the above analysis method to predict the production cycle time of 10 test groups, the overall error of which is shown in ***Table 1***.

It can be seen from the prediction results that among the 10 groups of prediction results, the overall error of 6 groups is within 5%, and that of 3 groups is between 5% and 10%. The overall prediction results are better. The error of prediction results of group 9 is larger than others. After analysis, the initial cycle time of this group is 210 seconds, and the error of the prediction cycle time of the first 200 pieces of the neural network is within 5%. However, due to certain reasons, such as simple style, or high similarity with the previous one, the production cycle time drops rapidly to 150 seconds at 270 pieces, while the neural network prediction result is 180 seconds, and thus there is an error.

Table 1. *Predicted cycle time errors.*

No	Production quantity	Cycle time, s	Initial cycle time, s	Predicted production time, s	Actual production time, s	Error, %
1	407	110	180	5499.6	5400	1.8
2	300	115	230	5360.3	5190	3.3
3	300	140	180	4428.3	4590	3.5
4	820	211	390	19520.9	19030	2.6
5	525	216	260	11127.7	11820	5.9
6	410	122	200	6682.2	7045	5.2
7	870	164	230	13856.9	14181	2.3
8	595	206	220	10767.1	10450	3.0
9	445	180	210	8420.5	7520	11.9
10	190	157	180	2786.7	3010	7.4

Conclusions

In the production of clothing manufacturers, experience is often used to estimate the complete production time of orders, which is subjective and lacks scientific basis. Although a large amount of data have been accumulated in production, it cannot be combined with the results. As a machine learning model, a neural network can establish the potential relationship between nonlinear variables, and the larger the amount of data, the stronger the learning ability. In recent years, with the development and accumulation of big data, the neural network has risen again. As a traditional manufacturing industry, garment manufacturing has accumulated a lot of data and has certain rules.

By establishing a neural network model of garment cycle time prediction, we can predict the production cycle time. The result shows that the deviation between the prediction of the neural network and the real value fluctuates within 10% in each cycle time prediction, or is greater or less than the real value. In the prediction of the total production time, the error between the prediction results of the neural network and the real value is mostly concentrated in the range of 5%, and the average error of 10 groups of the prediction group is 4.69%. In the actual production, we can predict the total production time within a small error range, help the manufacturer to arrange the production plan reasonably, avoid the imbalance phenomenon of order accumulation or production waiting caused by the uncertain production time, improve the production efficiency, and realize lean production.

It should be pointed out that in some cases, e prediction of the production cycle time of the neural network will produce large deviation: for example, the sample data are not enough; or the production quantity is small, for instance, only 20 pieces; or the production cycle time is for personalised minority clothing. For example, in the 10 cases in this study, one has a large overall error. One possible reason is that there is no sample with a small amount of production and a rapid decline in the cycle time in the sample data. Compared with the prediction cycle time of the mathematical model, the neural network has the function of self-learning, that is, with an increase in data accumulation, the prediction accuracy can be further improved. In practical application, the neural network can be trained by a large number of data, which can avoid this kind of situation.

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