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Energy Consumption Prediction of Fused Deposition 3D Printer Based on Improved Regularized BP Neural Network

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Abstract: An energy consumption prediction method based on process parameters and neural network was proposed to study the inherent energy consumption characteristics of open source melt deposition 3D printer and improve energy efficiency. An improved regularized network is used for optimization to avoid over-fitting and under-fitting problems. The orthogonal test sample data were trained in MATLAB environment, and the predictive model between process parameters and energy consumption of open source melt deposition 3D printing was established. The energy consumption prediction results of BP networks and regularized networks are compared by analyzing convergence curves and network training charts. The results show that the BP network training has experienced over-fitting, resulting in a prediction energy consumption error of about 10%. The improved regularization method effectively avoids the over-fitting phenomenon and the error of energy consumption prediction is about 1%. It can effectively improve the calculation efficiency of energy consumption prediction, which shows the accuracy of this method in energy consumption prediction.

1. Introduction

As a new rapid prototyping technology, 3D printing is a new subject in the field of green manufacturing and a new direction of development [1]. Open source melt deposition 3D printing has become an important 3D printing process due to its low production cost and the features of being able to develop and design on open source hardware. Its energy form is mainly dominated by power consumption, and its energy consumption power is generally proportional to the melting point of printing materials. How to improve the power utilization efficiency of open source melt deposition 3D printers is of great significance for more efficient manufacturing of new mechanical products that are mainly made of engineering plastics and biomass materials.

Domestic and foreign scholars have preliminarily conducted some research on the energy consumption of 3D printing. Wang Qiang [2] et al. established energy consumption analysis based on process parameter response surface. Liu Anbang [3] et al. studied the power consumption and printing time efficiency of molten deposition printing plastic products, and obtained the power consumption and printing time consumption data of FDM printing plastic products with different model shapes, different model heights and section sizes, and different model placement locations. Jiang Kaiyong et al. [4] studied and established the heat transfer model of FDM process molding. CH Wang et al. [5] studied the effect of deposition and solidification of molten metal droplets on model shape. Baumers et
al. [6] compared and evaluated the power consumption of two mainstream polymer laser sintering platforms. The consumption of energy and materials varies with the process parameters and the environmental effects are different.

This paper focuses on the energy consumption characteristics of open-source fused deposition 3D printers, obtains a large number of experimental data samples through design experiments, and uses BP neural network method to train the model through MATLAB to obtain the relationship between process parameters and energy consumption. In order to avoid over-fitting and under-fitting, an improved regularization method is used to establish its energy consumption prediction model and verify the accuracy of the method.

2. Melt deposition 3D printer energy consumption model

The energy consumption during processing of FDM 3D printers is composed of energy consumption during the operation of all energy consuming components of 3D printers. It includes the energy consumption of XYZ shaft driving motor of 3D printer drive system, the energy consumption of extruder motor, the energy consumption of fan motor of cooling system, the energy consumption of heating bed of heating system, the energy consumption of sprinkler heating bar, the energy consumption of control system motherboard and other energy consumption, and the basic energy consumption of printer. The energy consumption composition system is shown in figure 1.

![Fused deposition 3D printer energy consumption composition system](image)

According to the whole processing process of 3D printers, the processing process can be divided into four stages: standby, preheating, processing and cooling. The power at each stage is different.

Therefore, the energy consumed by the whole process can be expressed as follows:

\[
E = \sum_{i=1}^{4} P_i T_i
\]

(1)

Where \(P_i\) and \(T_i\) indicate the power and time of each stage, respectively.

Since the power of each moment in the process is variable, the total energy consumption is obtained according to the integral of equation (1).

\[
E = \int_0^{T_1} + \int_0^{T_2} + \int_0^{T_3} + \int_0^{T_4} P(t) dt = \int_0^{T_1} P_1 dt_1 + \int_0^{T_2} P_2 dt_2 + \int_0^{T_3} P_3 dt_3 + \int_0^{T_4} P_4 dt_4
\]

(2)

3. Energy consumption prediction method

3.1 Regularized BP neural network

Artificial neural network [7] is a dynamic system constructed artificially with a directional topology.
Underfitting and overfitting [8] are common problems, especially in the field of neural network. The neural network model often has tens of thousands of parameters, so the deep network is more prone to overfitting. Regularization is used to reduce over-fitting. Adding a regularization term to the cost function, the smaller the cost, the better, but after the cost plus the regular term, in order to make the cost small, you can’t make the regular term larger. In other words, this reduces the complexity of the model and reduces the over-fitting. The training method with the diversity regular term has a faster convergence speed and a lower error rate [9].

In this paper, the relationship between process parameters of open source FDM 3D printers and equipment energy consumption is studied by using regularized neural network. The relationship between input process parameters and energy consumption is studied through neural network training and the energy consumption model of process parameters and equipment energy consumption is established. A four-layer neural network model is adopted, including one input layer, two hidden layers and one output layer. Its structure is shown in figure 2.

The activation function of the hidden layer of the first layer is sigmoid function, and the second hidden layer is linear function. These functions are defined as follows:

\[
1(1-x) + x = \frac{1}{1+e^{-x}} 
\]

\[
2(x) = 1 
\]

Their gradients can be given by the following formula:

\[
\frac{\partial f_1(x)}{\partial x} = f_1(x)(1 - f_1(x)) 
\]

\[
\frac{\partial f_2(x)}{\partial x} = 1 
\]

Given an eigenvector \(X_i \in \mathbb{R}^{N_i}\), where \(N_i\) represents the size of the process parameter, equal to the number of neurons on the input layer, and \(y_i\) represents the energy consumption under this condition. Since the goal of the model is to realize the mapping rule between machining parameters and equipment energy consumption, MSE is selected as the loss function of the regular neural network, as shown below:

\[
l(X_i) = \frac{1}{2}(\bar{y_i} - y_i)^2 
\]

\(\bar{y_i}\) indicates the predictive value of the model. In addition, the related regularized items are added to the objective function of the model.

Regularized terms can be defined as follows:

\[
R(W_1, W_2, W_3) = \|W_1\| + \|W_2\| + \|W_3\| 
\]

The objective function of regular neural network can be written as follows:

\[
O(X_i, W_1, W_2, W_3) = l(X_i) + \lambda \cdot R(W_1, W_2, W_3) 
\]

\(\lambda\) is the weight between the loss function and the conventional item. \(W_1\), \(W_2\), \(W_3\) are the weight of the model.
In order to optimize these weights, the back propagation algorithm (BP algorithm) is adopted as the optimization scheme. For this purpose, the "error rate" of each layer should be calculated, and then the gradient of the relevant parameters should be calculated according to the "error rate".

3.2 Algorithm parameter optimization
In this section, the parameters of the BP algorithm are optimized. First, calculate the error rate for the last layer.

\[ \delta_4 = y' - y \] (10)

It is easy to calculate the gradient of \( W_3 \) to \( B_3 \) according to the error rate of elements \( \delta_4 \) as follows.

\[ \frac{\partial l}{\partial W_3} = \delta_4 \times x_{2}\text{hat} + W_3 \delta_5 \] (11) \[ \frac{\partial l}{\partial B_3} = \delta_4 \] (12)

Similarly, the third layer's "error rate" can be given as follows.

\[ \delta_3 = (W_3 \delta_4) \circ f_3^{-1} \] (13)

Among them, the symbol "\( \circ \)" denotes the multiplication of elements. According to the error rate of \( \delta_3 \), it is easy to get the gradient of \( W_2 \) to \( B_2 \) as shown in equation (14).

\[ \frac{\partial l}{\partial W_2} = \delta_3 \times x_{3}\text{hat} + W_2 \frac{\partial l}{\partial B_2} = \delta_3 \] (14)

Finally, the error rate of the second layer is calculated:

\[ \delta_2 = (W_2 \delta_3) \circ f_2^{-1} \] (15)

After calculating the \( \delta_2 \), the gradient of \( W_1 \) to \( B_1 \) can be obtained as shown in equation (16).

\[ \frac{\partial l}{\partial W_1} = \delta_2 \times x_{1}\text{hat} + W_1 \frac{\partial l}{\partial B_1} = \delta_2 \] (17)

Based on the above equations, gradient descent method can be used to update the parameters of regular neural network.

4. Case Study

4.1 Laboratory equipment
The experimental equipment used the self-made open source fused deposition 3D printer, and the printing material was selected with PLA. The printing model was a simple cylinder with a diameter of 35mm and a height of 2mm. The energy consumption testing equipment is the WT1800 power analyzer, as shown in figure 3. This equipment can measure the harmonic, voltage, current, power and other conventional measurement items. It can monitor the real-time power of the printer in the four processing stages online and obtain energy consumption data.
4.2 The experimental scheme
The melt deposition printer has many process parameters. According to the experience obtained by many experiments, four main parameters, including thickness of layer, printing speed, temperature of sprinkler head and temperature of hot bed, are selected to study the influence on energy consumption.

According to the selection of four parameters for four factors three levels orthogonal experiment design, the layer thickness (mm), a printing speed b (mm/min), c (°C) and nozzle temperature hot bed temperature d (°C) as the experimental factors, each factor in three levels, a total of 81 kinds of experiments, to simplify the test times, choose L^{27} (3^{13}) orthogonal experiment. Experimental factors and levels are shown in Table 1.

| level | a (mm) | b (mm/min) | c (°C) | d (°C) |
|-------|--------|------------|--------|--------|
| 1     | 0.10   | 50         | 185    | 60     |
| 2     | 0.15   | 60         | 190    | 65     |
| 3     | 0.20   | 70         | 195    | 70     |

4.3 Results and analysis
The results measured according to the experimental scheme are shown in Table 2.

| NO   | a     | b     | c     | d     | E        |
|------|-------|-------|-------|-------|----------|
| 1    | 0.10  | 50    | 185   | 60    | 116075.16|
| 2    | 0.15  | 50    | 185   | 65    | 122429.52|
| 3    | 0.20  | 50    | 185   | 70    | 113828.04|
| 4    | 0.20  | 50    | 190   | 60    | 91161.36 |
| 5    | 0.10  | 50    | 190   | 65    | 142333.20|
| 6    | 0.15  | 50    | 190   | 70    | 130066.92|
| 7    | 0.15  | 50    | 195   | 60    | 103637.88|
| 8    | 0.20  | 50    | 195   | 65    | 106923.60|
| 9    | 0.10  | 50    | 195   | 70    | 156232.80|
| 10   | 0.20  | 60    | 185   | 60    | 89522.28 |
| 11   | 0.10  | 60    | 185   | 65    | 129034.44|
| 12   | 0.15  | 60    | 185   | 70    | 120893.04|
| 13   | 0.15  | 60    | 190   | 60    | 98683.20 |
| 14   | 0.20  | 60    | 190   | 65    | 99639.36 |
| 15   | 0.10  | 60    | 190   | 70    | 146212.92|
| 16   | 0.10  | 60    | 195   | 60    | 117141.12|
| 17   | 0.15  | 60    | 195   | 65    | 109681.92|
| 18   | 0.20  | 60    | 195   | 70    | 113824.08|
| 19   | 0.15  | 70    | 185   | 60    | 91158.84 |
| 20   | 0.20  | 70    | 185   | 65    | 97082.28 |
| 21   | 0.10  | 70    | 185   | 70    | 139609.08|
| 22   | 0.10  | 70    | 190   | 60    | 113374.08|
| 23   | 0.15  | 70    | 190   | 65    | 108600.48|
According to the experimental data results in Table 2, the experimental data were analyzed respectively by using the neural network programmed in MATLAB and the regularized neural network, and the BP algorithm and the training and prediction diagram of the energy consumption of the regularized BP algorithm were obtained. The data of NO (1–21) group and NO (22–27) group were selected as the model training set by the two neural network methods.

|    |    |    |    |    |    |
|----|----|----|----|----|----|
| 24 | 0.20 | 70 | 190 | 70 | 112581.72 |
| 25 | 0.20 | 70 | 195 | 60 | 89634.60  |
| 26 | 0.10 | 70 | 195 | 65 | 128627.28 |
| 27 | 0.15 | 70 | 195 | 70 | 122391.00 |

According to Fig. 4 (a), Fig. 4 (b), among the 21 groups of BP neural network training set, there are 19 groups of data with high fitting, and only 2 groups of data have deviation. However, in the 6 groups of prediction results, there are large errors, indicating that the BP network training process has overfitting phenomenon. Therefore, although BP neural network can fit the data better in the training process, excessive fitting data will lead to larger errors in the prediction results. Because this prediction method can’t achieve better results, it is not desirable. The error caused by over fitting can be solved well in the regularized neural network.

The training charts and prediction charts obtained by using regularized neural networks are as follows: Fig. 5 (a) the training charts of the regularized network; (b) the prediction charts of the regularized network.

The regularized network model is well trained to avoid the phenomenon of under-fitting and over-fitting of BP neural network, so the prediction results are more accurate. This is because in the neural network, the regularized network tends to have smaller weights. In the case of smaller weights, the random change of data will not affect the model of the neural network too much, so the possibility is less affected by the local noise of data. Without regularized neural network, the weight is large, it is easy to adapt to the data through larger model changes, and it is easier to learn local noise.
In order to verify the accuracy of regularized network prediction, six groups of predicted data were compared with the actual values, and the error rates of each group were calculated. The error rate is as follows.

\[ RE = \frac{E_{real} - E_{network}}{E_{real}} \times 100\% \ (18) \]

The error of the two networks is shown in Table 3.

| NO | BP network (RE) % | Regularized network (RE) % |
|----|-------------------|----------------------------|
| 22 | 9.9               | 0.9                        |
| 23 | 13.8              | -1.8                       |
| 24 | 13.1              | 2.1                        |
| 25 | -16.1             | -1.0                       |
| 26 | -5.9              | -0.7                       |
| 27 | -12.5             | 0.8                        |

According to Table 3, the error rate of BP network prediction value is about 10%, and the maximum error is 16.1%. The reason is that there is fitting in the training process, and the random change of data has a great impact on the model of neural network, while the regularization network produces less error, the error rate is about 1%, the maximum is only 2.1%. The reason is that the regularization term will not be affected by the local noise of data, so the energy consumption prediction will be more accurate.

5. Conclusion
The energy consumption model of the FDM process parameters with respect to the neural network is established by the method of neural network, and the experimental data is obtained by the orthogonal test method. The MATLAB is used to train and predict the experimental data respectively, and the model convergence curve, training chart and prediction graph are obtained. The energy consumption prediction error rate of BP neural network and regularized neural network is analyzed and compared. The results show that the BP network training process is overfitting, and the predicted results have a large error, which is about 10%. Regularization neural network can effectively avoid overfitting problem and reduce the prediction error of energy consumption. The error rate is about 1%. Compared with BP network, regularized BP network can be used to predict energy consumption more accurately, providing an accurate method for energy consumption prediction.

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References
[1] LIU F, ZHNAG H, YUE Hh. Green manufacturing - a sustainable development model for modern manufacturing [J]. China mechanical engineering, 1998, 9(6):76-78.
[2] WANG Q, ZHAO G, RUAN D et al. A Study on the Energy Consumption of FDM 3D Printer Based on Response Surface of Machining Parameters [J]. Modular Machine Tool & Automatic Manufacturing Technique, 2018(7).
[3] LIU Ab, MA Zy, CAO Wj. Research on Energy Consumption and Time Efficiency of Plastic Product 3D Printing Based on FDM [J]. China Plastics Industry, 2017(11):55-60.
[4] JIANG Ky, LIU Yw. Research on the Thermal Model and Process Control for Fused Deposition Modeling[J]. China mechanical engineering, 1999, 10(6):636-638.
[5] Wang C H, Tsai H L, Wu Y C, et al. Investigation of molten metal droplet deposition and solidification for 3D printing techniques[J]. Journal of Micromechanics & Microengineering, 2016, 26(9):095012.

[6] Gebler M, Uiterkamp A J M S, Visser C. A global sustainability perspective on 3D printing technologies[J]. Energy Policy, 2014, 74:158-167.

[7] Russell S J, Norvig P. Artificial intelligence: A modern approach. Prentice Hall Publishers, 1995, 733-736.

[8] QIN Gh, LI Zy. Over-fitting of BP NN research and its application[J]. Engineering Journal of Wuhan University, 2006, 39(6):55-58.

[9] QU Wy, YU Y. Exploring diversity regularization in neural networks [J]. JOURNAL OF NANJING UNIVERSITY(NATURAL SCIENCES) , 2017, 53(2):340-349.