Machine Learning Based Optimization Method for Vacuum Carburizing Process and Its Application

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This paper develops an optimized prediction method based on machine learning for optimal process parameters for vacuum carburizing. The critical point is data expansion through machine learning based on a few parameters and data, which leads to optimizing parameters for vacuum carburization in heat treatment. This method extends the data volume by constructing a neural network with data augmentation in the presence of small data samples. In this paper, the database of 213 data is expanded to a database of 2116800 data by optimizing the prediction. Finally, we found the optimal vacuum carburizing process parameters through the vast database. The relative error of the three targets is less than that of the target obtained by the simulation of the corresponding parameters. The relative error is less than 5.6%, 1%, and 0.02%, respectively. Compared to simulations and actual experiments, the optimized prediction method in this paper saves much computational time. It provides a large amount of referable process parameter data while ensuring a certain level of accuracy.

Keywords*: machine learning; heat treatment; neural networks; data augmentation; small sample*

1.introduction

Various heat treatment techniques, including hardening, carburizing, and tempering, are often used in material processing to provide critical components for aerospace, high-speed railroads, and automobiles with sufficient high strength and high resistance to friction and wear. However, deformation in the heat treatment process has been challenging to predict and control [1]. As early as 1992, scholars proposed the theory and simulation method of thermal phase transformation mechanics for heat treatment simulation, which includes the simulation calculation of vacuum carburization results[2]. The simulation of vacuum carburization requires a considerable amount of time and data costs. This study developed a method for data expansion and optimization of vacuum carburization parameters in heat treatment based on a few parameters and machine learning.This method extends the data volume by constructing a neural network with data augmentation in the presence of small data samples.

2. Theory and experimental methods

2.1 Theory

Heat treatment simulation software (e.g., COSMAP - Computer Simulation of Manufacturing Process) has been used to simulate the coupled diffusion analysis, temperature analysis, phase transformation, and deformation/stress distribution during carburizing and quenching processes (shown in Fig. 1) [3].

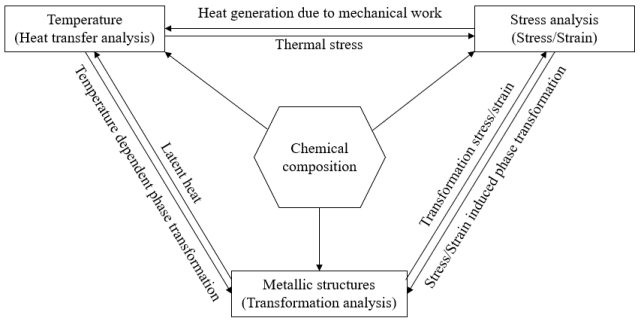

Figure 1: Basic theoretical diagram.

However, although simulation software (e.g., COSMAP) has been developed based on this theoretical foundation to simulate the temperature field, stress-strain field, and phase and hardness distributions in quenching under specified process conditions, multiple simulations and validations are necessary to find more reasonable process conditions. This obviously makes it difficult to improve process design and production efficiency. Therefore, the simulation results of vacuum carburizing quenching calculated by COSMAP were firstly used as the teacher signal for deep learning. And these teacher signals and the requirements and objectives given in the process design are used to optimize the selection and deep learning until the carburizing and quenching of automotive parts on product accuracy is achieved.

Based on the basic principles of heat treatment and COSMAP, a virtual heat treatment system (VHT) is proposed. The diagram of the heat treatment virtual manufacturing system is shown in Fig 2.

Figure 2 shows an overview of the current virtual heat treatment system, including the optimization process. First, the material, quenching, and process databases are constructed using material design, quenching-cooling, and carburizing process designs. We have established the carburizing and quenching knowledge base according to the actual production and experimental results. In this database, this paper can obtain about 30 groups of vacuum carburizing experimental data of cylinder model with different materials and use the materials represented by six data groups for research. From the data of these four databases, heat treatment simulations are performed to obtain characteristics regarding deformation, organization, carbon concentration distribution, and hardness distribution. However, the data characteristics are small, and the simulation and calculation could be more convenient. Therefore, 213 sets obtained from simulation and three experimental data sets are used as training data sets. The amount of data is expanded by machine learning to improve the speed of receiving process parameters from the demand, cross-checking with the database before putting them into the actual market, and finally responding to honest requests.

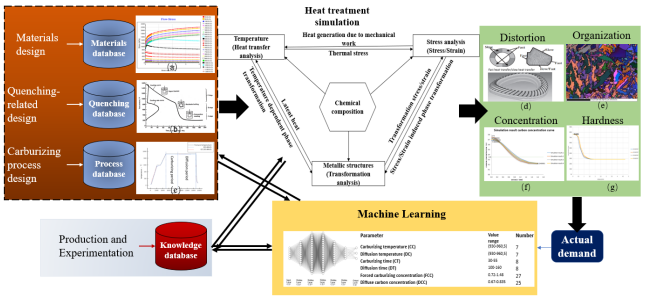

Figure 2: Overview of the heat treatment process.

2.2 Deep Learning Methods

The artificial neural network initially used in this paper is a Multilayer Perceptron. The number of nodes is 6 · 12 · 20 · 20 · 12 · 6 · 1. In the initial phase of vacuum carburizing, after obtaining the required target values from the customer, a certain quantity of vacuum carburizing process conditions is first listed based on physical laws and experience to form the basis for the initial parameter data. Carburized quenching simulations are then carried out using software such as COSMAP. Suppose the results of the simulation experiments contain results that match the target values. To overcome the difficulty of machine learning algorithms to obtain robust prediction results and excellent prediction accuracy with small samples, mega-trend-diffusion (MTD) is used to estimate the acceptable range of attributes for small data sets, to fill the information interval and to calculate the virtual sample value and the affiliation function value (the probability of occurrence of that sample value). This paper uses a multi-distribution mega-trend-diffusion (MD-MTD) technique based on the basic MTD, as shown in Fig 4 [4].

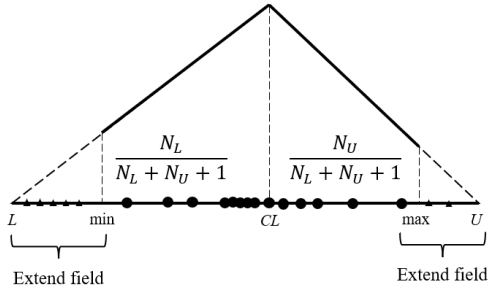

Figure 3: Diagram of MD-MTD

Given a sample set X = $\{x_1, x_2, ..., x_n\}$, the basic MTD estimates the acceptable bounds for X. The lower bound Eq gives L and the upper set U for the excellent range of X.

$$L = \{CL - Skew_L X\sqrt{-2\frac{\hat{S}^2_X}{N_L} X \ln ln\,(10^{-20})}\,,\ L \le min\ min, L > m \quad (1)$$

$$U = \{CL + Skew_U x\sqrt{-2\frac{\hat{S}^2_x}{N_L} x \ln ln\,(10^{-20})}\,,\ U \ge max\ max \quad (2)$$

Among them,

$$CL = (max + min)/2 \quad (3)$$

$$Skew_L = \frac{N_L}{N_L+N_U} \quad (4)$$

$$Skew_U = \frac{N_U}{N_U+N_L} \quad (5)$$

In Eq

$$\hat{S}^2_X = (\sum_{i-1}^{n} (x - \bar{x})^2)/(n-1) \quad (6)$$

n denotes the small sample set size, CL denotes the data center, $N_L(N_U)$ represents the number of sample values less than (greater than) CL, S^2 denotes the small sample set variance, and $skew_L$ $(skew_u)$ denotes the left (right) skewness describing the non $skew_L$ $(skew_u)$ denotes the left (right) skewness describing the non-symmetric diffusion characteristics of the data.

3.Results

In this paper, in order to determine the most suitable training frequency under the current neural network structure, we conducted multiple experiments and ultimately determined a training frequency of 5000.

This paper uses C# as the front end to call the Python program running on the back end. In this optimization result evaluation, the demand target values were set as follows: carburization layer depth 0.95, surface carbon concentration 0.69, and surface hardness 833. One set of experimental data from BMEI is consistent with the currently set requirements; therefore, data relating to a 1/4 cylinder of the same material and size were used in the COSMAP simulations, and the parameters for the simulations were obtained by optimization. The results of COSMAP simulations are read as shown in Figure 4. The 1/4cylinder model used for the simulation, which has diffusion coefficients designed concerning the full cylinder, can therefore be considered following the same physical laws as the full cylinder due to the symmetry. For the results to follow a consistent reading method with the experimental results, values close to the edges of the cylinder ends were chosen for reading surface hardness and surface carbon concentration.

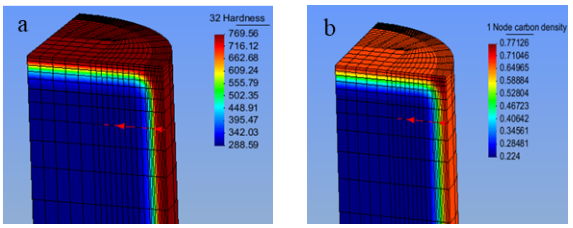

Figure 4: Selection of surface hardness(a)、surface carbon(b).

When reading the depth of the carburized layer, the value at 0.35% of the carbon content was read as the depth of the carburized layer. Analyze the effect of optimization on relative error by comparing it with simulation data and training data of the same parameters, as shown in Table 1.

Table 1: Optimization results, simulation results, relative errors between training data and experimental data

Parameter	CLD	SC	SH
Assumptions	0.95	0.69	833
Experimental	0.95	0.69	833
Optimization	0.97854	0.68676	833.12805
Result	3.00%	0.47%	0.0154%
Simulation1	0.907	0.68	767.5
Result	4.526%	1.449%	7.863%

Training result	0.95226 0.238%	0.75010598 8.711%	773.64301 7.126%

4. Discussion

The relative error of the optimization results is generally better than the simulated data under the corresponding parameters, and the relative error with the actual data is within the allowable range, and the total relative error is much higher than the optimal data in the training data. can justify this method of modifying the neural network. The limitation of this article is that the vacuum carburization data used are all of the same specified alloy material, and it is temporarily impossible to optimize and predict the parameters of vacuum carburization for any alloy.

5.Conclusions

This paper proposes a machine learning based optimization method for vacuum carburization process, which utilizes a multi-layer perceptron neural network to establish a vacuum carburization optimization prediction system. The vacuum carburization data is trained and expanded to obtain more small sample training and optimization parameters. Using the expanded database as a basis for predicting the optimal vacuum carburizing process parameters, the expected parameters for the three objectives had relative errors that were better than the corresponding simulated results, and the relative errors were all maintained below 5.6%, 7.414%, and 0.0154%, respectively. Compared with the standard calculation of vacuum carburizing process parameters, this method has the following characteristics: fast analysis and application of vacuum carburizing simulation data; The process parameter data obtained through optimization can be used as new data for the database within specific error tolerances.

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