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Prediction of Mechanical Properties of Mortise and Tenon Lattice Structures by Fused Deposition Modeling Using Artificial Neural Network

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인공신경망을 이용한 융합증착 모델링에 의한 모티스와 테논 격자구조물의 역학적 특성 예측

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Abstract High strength, lightweight lattice structures are gaining increasing attention in aerospace, automotive, and other fields. Fused deposition modeling (FDM) is a widely used additive manufacturing technique that has significant advantages in the fabrication of lattice structures. However, deposition of inter layers phenomenon affects the mechanical properties of the FDM formed lattice structure, and it is difficult to establish the relationship between the parameters of the lattice structure and the mechanical properties. In this paper, FDM technology was used to prepare 23 groups of mortise and tenon lattice structures (MTLS) with different angles θ, height h and thickness t, and quasi-static compression tests were carried out on them. Artificial neural network (ANN) was used to establish a prediction model of specific energy absorption (SEA) of lattice structures, and the accuracy of the prediction model was verified by experiments. The results show that the SEA of MTLS decreases with increasing θ. With the increase of t and the decrease of h, SEA first increases and then decreases. The SEA values predicted by the ANN with "3-7-1" structure are in good agreement with the experimental values. The ANN tool are validated and can be a favourable tool for lattice energy prediction with available data.

Key Words : Fused deposition modeling, Artificial neural network, Mortise and tenon, Lattice structure, Mechanical properties

요 약 고강도 경량 격자 구조는 항공우주, 자동차 등 여러 분야에서 점점 더 주목받고 있다. 융합 적층 성형(FDM)은 격자 구조 제작에서 중요한 장점을 지닌 널리 사용되는 적층 제조 기술이다. 그러나 층간 적층 현상은 FDM으로 형성된 격자 구조의 기계적 특성에 영향을 미치며, 격자 구조의 매개변수와 기계적 특성 간의 관계를 확립하는 것이 어렵다. 본 논문에서는 FDM 기술을 사용하여 각기 다른 각도 θ, 높이 h, 두께 t를 가진 23개의 짜임 및 장부 격자 구조(MTLS)를 준비하고, 준정적 압축 시험을 수행했다. 인공 신경망(ANN)을 사용하여 격자 구조의 비에너지 흡수(SEA)를 예측하는 모델을 구축하였고, 실험을 통해 예측 모델의 정확성을 검증했다. 결과에 따르면, MTLS의 SEA는 θ가 증가함에 따라 감소하며, t가 증가하고 h가 감소할 때 SEA는 처음에 증가하다가 다시 감소하는 경향을 보였다. 3-7-1 구조의 ANN으로 예측된 SEA 값은 실험 값과 잘 일치하였고, ANN 도구는 기존 데이터를 기반으로 한 격자 구조 에너지 예측에 유리한 도구로 검증되었다.

주제어 : 융합 증착 모델링, 인공 신경망, 맞춤 및 장부, 격자 구조, 기계적 특성

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1. Introduction

Lattice structures offer advantages such as lightweight, high energy absorption, and high strength, making them widely used in aerospace, automotive, biomedical, and other fields[1,2,3]. Traditional preparation methods for lattice structures include investment casting, extrusion, stamping, and tensile mesh folding[4,5,6]. While these traditional processes achieve excellent performance through high-precision machining and a wide range of material options, they are hampered by complexity, high costs, long production cycles, and limited design flexibility, which constrain the further application of lattice structures[7].

Additive manufacturing (AM) technology provides significant design flexibility and the capability to produce complex structures[8]. Among the various additive manufacturing methods, Fused Deposition Modeling (FDM) stands out as a prevalent additive manufacturing technique, renowned for its cost-effectiveness and enhanced geometric flexibility, particularly when employed to fabricate lattice structures[9]. Deposition of inter layers phenomenon refers to the rapid heating and cooling process due to which the heated molten material deposited on the previously deposited cooled layer, causes in weak bonding between the deposited layers[10]. Due to weak inter layers adhesion and porous structure, the mechanical properties of FDM formed lattice structures are anisotropic[11,12]. A multitude of researchers have delved into the mechanical properties of FDM formed lattice structures, focusing on the interplay between lattice structure parameters and material behavior [13,14]. It has been consistently observed that the relationship between these parameters and the mechanical properties is characterized by multifactorial and nonlinear dynamics. This complexity has rendered the establishment of a direct mathematical model linking structural design variables to mechanical performance exceedingly challenging[15]. Experimental and finite element analysis methods often demand extensive computational resources and experimental data[16,17].

An ANN is a computational model inspired by the structure and function of the human brain's neural networks. ANNs are designed to simulate complex nonlinear relationships and predict output values based on training data[18]. By using data samples rather than entire datasets, artificial neural networks are able to make quick predictions, which saves both time and money.

Doodi et al.[19] used ANN and Levenberg-Marquardt algorithms to predict the energy absorption of their designed bionic lattice structures with parameters such as overlapping area, wall thickness and size of the unit cell. Hosseini et al.[20] used Levenberg-Marquardt et al algorithms to train ANN to predict the absorbed energy, dissipated energy and peak force value of sinusoidal shape memory unit made of PLA. Alwattar et al.[21] calculated the performance of BCC lattice structure through finite element analysis approach and theoretical calculations, the results are then used to develop an ANN model, in which the input data were the lattice strut diameters and the cell size, and the output data were the mechanical properties data of lattice structure. Vyavahare et al.[22] developed a machine learning model using neural networks to predict strength, stiffness, and specific energy absorption under flexural loading due to different lattice structural parameters (angle, width, and length of arm). Singh et al.[23] considering process parameters such as different raster patterns, built an artificial neural network prediction model to predict the response of tensile strength, material consumption, build time, and surface quality.

In this research, a novel mortise and tenon lattice structure (MTLS) is designed, which is inspired by traditional mortise-tenon structures used in architecture. ANN is used to develop a prediction model for the specific energy absorption

(SEA) of the MTLS, allowing for the forecasting of the energy absorption characteristics of the FDM-printed lattice structures. It provides an idea for rapid design and manufacture of lightweight and high energy absorbing new lattice structures.

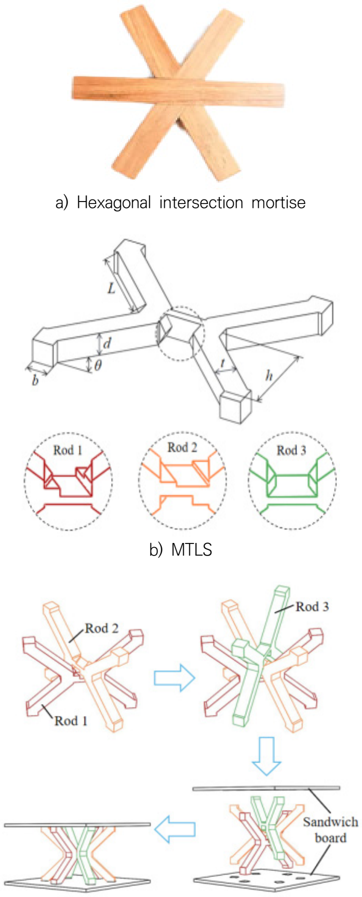
The rest of the paper is organized as follows: Section 2 details the design method of lattice structure, structure parameters, printing parameters, test parameters and ANN methods. Section 3 describes the parameter setting, prediction results and test results of ANN, and the experimental results are discussed. The conclusion is presented in Section 4.

2. Methods and Experiment

2.1 Methodology for design and fabrication of MTLS

In traditional construction, the mortise and tenon structure serves as the primary structural support and comprises components such as columns, beams, purlins, and other related elements. The tenon refers to the projecting part of the joint, while the mortise and tenon together represent the connection between two or more parts, with the tenon pin being the structural component inserted into the mortise hole.

Based on the characteristics of mortise and tenon structures and lattice structures, a typical hexagonal joint tenon is selected as the design object. The tenon is formed by three square materials inclined at a 60° angle to each other, with each square material's joint retaining 1/3 of its thickness, as shown in Fig. 1a). The designed MTLS members are illustrated in Fig. 1b). To ensure the stability of the MTLS during compression, upper and lower sandwich plates are incorporated into the design. The assembly process of the MTLS is shown in Fig. 1c).



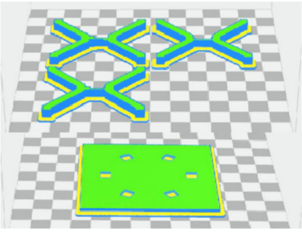
a) Hexagonal intersection mortise

b) MTLS

c) Installation process of MTLS

[Fig. 1] Design idea and structure of lattice structure

The MTLS was fabricated using a UP 300 FDM printer manufactured by Beijing Taiertimes. The mortise and tenon structure is printed separately from the sandwich plate, as shown in Fig. 2. For this process, 1.75mm diameter eSUN ABS+ filament, produced by Shenzhen Guanghua Weiye, was selected. The printing parameters include a nozzle temperature of 270℃, a platform temperature of 90℃, a layer thickness of 0.25mm, and a 100% infill rate, with all other settings using the printer's default parameters.



[Fig. 2] Installation process of MTLS

2.2 Lattice Structure Performance Test

The mass of the rod and sandwich plate of the MTLS was measured using a precision electronic balance with an accuracy of 0.0001 g. Compression experiments on the prepared lattice structures were conducted using a WDW-50 universal testing machine, with the force-displacement response of each sample recorded at a loading rate of 1 mm/min.

The specific absorbed energy (SEA) denotes the energy absorbed per unit mass for a specific structure. The specific expressions are provided below:

$$SEA = \frac{\int_0^{\delta} F d\delta}{m} \qquad (1.1)$$

Where F is the magnitude of the compression force, δ is the final compression displacement, and m is the mass of the structure.

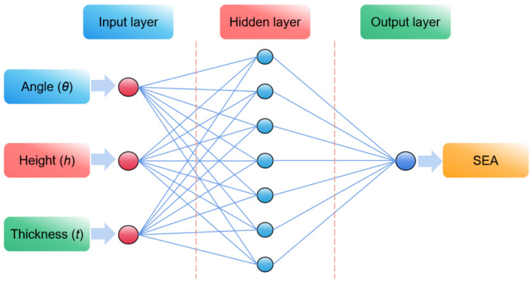
The Central Composite Design (CCD) method was used to design 23 groups of MTLS to reduce the number of experiments. MTLS compression parts are printed considering the experimental design mentioned in 〈Table 1〉. by varying the MTLS structural parameters combinations, and the SEA values are calculated according to the formula and listed in 〈Table 1〉.

〈Table 1〉 Experimental run and responses evaluated

θ/°	t/mm	h/mm	SEA/J·kg^{-1}
45	20	6	121.5166243
45	20	6	84.41400936
45	20	6	179.0595374
45	18	6	388.0309295
30	20	6	652.4079251
52.5	19	6.5	102.5699385
52.5	21	6.5	28.13124716
52.5	21	5.5	41.51734073
52.5	19	5.5	78.97687265
37.5	21	5.5	456.5170311
45	20	6	117.7743427
45	22	6	103.0100217
45	20	6	89.31266269
37.5	21	6.5	117.4193451
37.5	19	5.5	219.4160079
45	20	6	124.3306705
45	20	6	150.4812834
45	20	5	93.48500337
60	20	6	98.90377397
45	2	6	185.167787
37.5	19	6.5	142.5282631
45	20	7	94.03355364
45	20	6	134.9731326

2.3 Artificial Neural Network Model

In predicting the mechanical properties of MTLSs, the implementation of an ANN model involves selecting the number of neurons in the input, hidden, and output layers. The input layer consists of 3 neurons, representing the angle θ of the mortise and tenon lattice member, the height h from the center of the member to the plate, and the thickness t of the member. The output layer contains a single neuron, which represents the SEA. The structure of artificial neural network is shown in Fig. 3.



[Fig. 3] The structure of artificial neural network

3. Results and Discussion

3.1 Sample Pretreatment

Although there is no exact method to calculate the optimal number of neurons in the hidden layer, the following formula can be used as a rule of thumb during the design process:

$$h = \sqrt{m+n} + a \tag{1.2}$$

Where h is the number of neurons in the hidden layer, m is the number of neurons in the input layer, n is the number of neurons in the output layer, and a is a constant between 1 and 10. To achieve the best fit performance, a can be adjusted to minimize the prediction error. In this paper, the number of hidden layer neurons is determined using the trial and error method, resulting in an optimal artificial neural network structure of 3-7-1.

To ensure convergence, the sample data is normalized using the following formula:

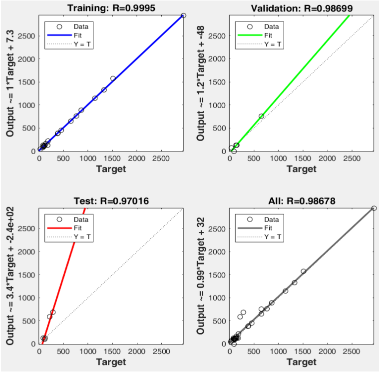
$$y_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{1.3}$$

Where x_i and y_i represent the original and normalized data of the i-th input, respectively. $\max(x_i)$ and $\min(x_i)$ denote the maximum and minimum values in the i-th input sample, respectively. After normalization, the data is scaled to fall within the range of 0 to 1.

The Levenberg-Marquardt backpropagation algorithm is employed to train the network. The data is divided as follows: 70% for training, 15% for testing, and 15% for validation, that is, the sample size for training data is 17, the sample size for test data is 3, and the sample size for verification data is 3. In order to better predict and improve the accuracy of the model, the subsequent validation test values are not used as the training test set.

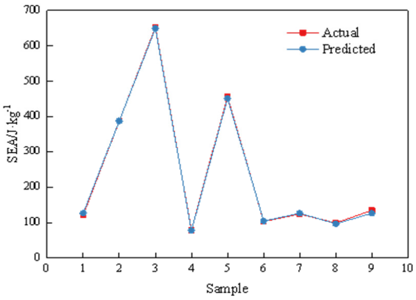
3.2 Model Prediction Results

The regression performance of the artificial neural network model is illustrated in Fig. 4, which shows a strong correlation between the experimental data and the predicted values.



[Fig. 4] The regression performance of the artificial neural network model

To verify the data training transparently, predicted and actual values are randomly selected from the experimental data and compared in a chart, as shown in Fig. 5. The comparison reveals that the error between the actual and predicted values is negligible within the available dataset of input and output values.



[Fig. 5] Comparison of the actual values with the ANN predicted values

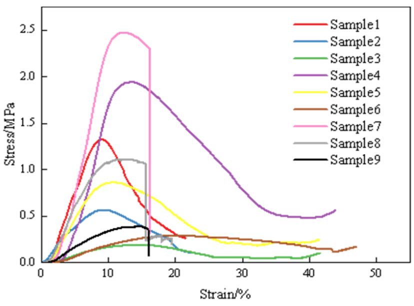
3.3 Experimental Verification

For the trained algorithm, 9 groups of MTLSs with different parameters are designed to predict the SEA value, and the specific parameters are shown in 〈Table 2〉.

〈Table 2〉 Structural parameters of MTLS for verification

No.	θ/°	t/mm	h/mm
1	30	5	17.5
2	45	5	17.5
3	60	5	17.5
4	30	6	17
5	45	6	17
6	60	6	17
7	30	7	16.5
8	45	7	16.5
9	60	7	16.5

Three-dimensional modeling of the MTLS, with parameters as shown in 〈Table 2〉, was performed. The structure was printed and assembled using an FDM printer and subsequently tested under quasi-static compression load. The resulting stress-strain curve of the MTLS is illustrated in Fig. 6.



[Fig. 6] Stress-strain curves of MTLSs

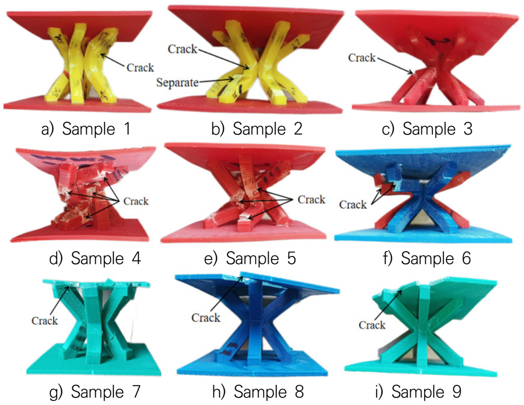
Fig. 6 illustrates that the forming method significantly affects the fracture properties of the lattice. The compression process of the MTLS can be described as follows:

First Stage: The stress-strain curve increases linearly. As θ decreases, stress rises rapidly. Stress also increases as t and h decrease.

Second Stage: Elastic deformation occurs, and the stress begins to gradually decrease.

Third Stage: Due to the fitting of the mortise and tenon matrix structure into the hole on the sandwich plate, the specimen starts to break and distort at multiple points, leading to a gradual decline in stress.

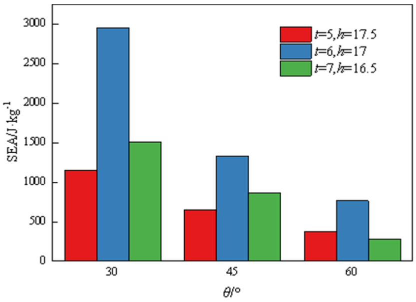
The samples with MTLS compressed is shown in Fig. 7.



[Fig. 7] The samples with MTLS compressed

As can be seen from Fig. 7a)-f), when t is 5 mm and h is 17.5 mm, or when t is 6 mm and h is 17 mm, the rods of the MTLS experience twisting, bending deformation, and extrusion, leading to the formation of cracks. Conversely, when t and h are 7 mm and 16 mm, respectively, the rods undergo elastic deformation, and the upper sandwich plate fails due to shear forces, this conclusion can be verified in Fig. 7g)-i).

The SEA values of 9 groups of samples were calculated using formula (1), as shown in Fig. 8.

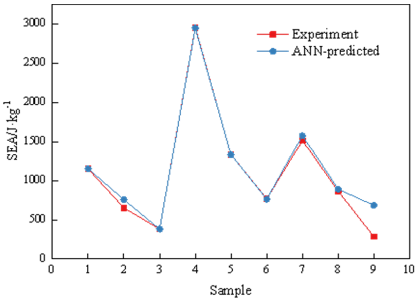


[Fig. 8] SEA experimental values of 9 test samples

As θ increases, the SEA of the MTLS decreases gradually. With increasing t and decreasing h, the SEA initially increases and then decreases. The SEA value is highest at 2954.4 J/kg when θ is 30°,

t is 6 mm, and h is 17 mm. Conversely, the SEA value is lowest at 285.28 J/kg when θ is 60°, t is 7 mm, and h is 16.5 mm.

The SEA values of 9 groups of samples were compared with the predicted values, as shown in Fig. 9.



[Fig. 9] Comparison of experimental and predicted values

It can be seen from Fig. 9 that the predicted results of the ANN model for 9 samples are in close agreement to the actual experimental values. From the comparative results, it can be concluded that well-trained neural network model is capable of predicting output responses of MTLS with higher level of accuracy.

4. Conclusion

In this paper, a lattice structure inspired by traditional mortise and tenon techniques is designed using 3D modeling software. The samples were fabricated using FDM technology and subjected to quasi-static compression tests. The SEA of each sample was calculated based on the test results. The mechanical properties of MTLS were predicted by ANN.

70% of the available data is used for training, 15% for testing, and 15% for validation. After multiple training iterations, the predicted values are compared with the actual data to enhance the accuracy of the training algorithm.

A compression test was conducted on 9 groups of MTLSs, and the SEA values were predicted using the ANN model. Comparison of the actual values with the predicted values shows a high level of consistency. As the angle θ increases, the SEA of the MTLSs decreases gradually. Additionally, with increasing t and decreasing h, the SEA initially increases and then decreases. The SEA reaches its maximum value at 2954.4 J/kg when θ is 30°, t is 6 mm, and h is 17 mm.

Although the prediction results from the model are promising, further investigation is needed to determine the optimal number of hidden layers. This will enhance the performance of the ANN model and reduce computational time.

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〈관심분야〉

digital communication systems, Big Data