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Optimized Design of Ceramic Materials Based on Improved Hopfield Neural Network

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Abstract. Ceramic materials are widely used in various fields because of their excellent properties such as high hardness and high strength. Ceramic materials and their production raw materials have a significant impact on their performance, so the optimization of ceramic materials for the production of high-performance ceramics is of great importance. Traditional ceramic material optimization method is easy to fall into the local optimum, the absolute error is large, to deal with this issue, this article suggests a ceramic material optimization design method based on the enhanced Hopfield neural network (EHNN). Firstly, the HNN is enhanced relied on the neuron excitation threshold and the adjustment rate correction weights, so that the neuron states finally converge to the expected attractor neighborhood. Secondly, the connection relationship between the synapses on the neurons is adopted to establish the correlation between the ceramic materials and the weights, and then the model structure of ceramic material optimization is constructed relied on the EHNN, which encodes the ceramic materials with the help of the input matrix as the input of the EHNN network, and automatically adjusts the connection weights between the neurons within a certain range, which assists the network in generating the desired energy minima as the optimal output of the ceramic materials. The experimental outcome indicates that the designed ceramic material optimization method has high flexural strength, hardness, fracture toughness and low absolute error, which verifies the high efficiency of the offered method.
Keywords: Ceramic material; Hopfield neural network; Excitation threshold; Correction weight; Absolute error

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1. **Introduction.** Ceramic sculpture, as an ancient and creative art form, is a perfect fusion of natural beauty and creative beauty [1]. In the long history, ceramic sculpture because of its flexible and rich choice of materials, through the clay material, glaze material and decorative materials of the mutual cooperation, shaping a rich variety of ceramic art image, expressed the social life and the artist's inner feelings. For a long time, the research method of ceramic sculpture materials mainly adopts the "trial-and-error method", but this traditional design method has the shortcomings of long development cycle, high research cost, and great waste of human and material resources [2, 3, 4]. Due to the

existence of a large number of unrationalized empirical and experimental laws, it is impossible to realize the optimization without relying on experience and exploring materials for quite a long time [5, 6]. As the computational intelligence technology rapidly growing, high-performance and highly reliable ceramic materials have become the current research hotspot in the field of ceramic sculpture, the use of artificial intelligence methods with fewer experiments to obtain more ideal materials, to achieve twice the result with half the effort [7].

1.1. **Related work.** Scott et al. [8] introduced the artificial neural network ANN technique into the study of dielectric ceramic formulations, using the influence of each component in the formulation on the desired index and optimization calculations. Li et al. [9] used BP neural network to develop a model for predicting the percentage content of each component of a complex phase ceramic material. Zhang et al. [10] used the back propagation learning algorithm (BP algorithm) with multilayer feedforward neural networks to optimize the network model of ceramic kiln temperature zone distribution, but the absolute temperature difference of the prediction results was large. Sharath et al. [11] successfully applied the artificial neural network technology in the identification and prediction of the mechanical properties of ceramic materials, process optimization, and so on. He et al. [12] used BP algorithm to optimize the preparation process of reaction sintered ceramic sculptural materials and forecast the generation. Xiong et al. [13] used RNN neural network to realize the nonlinear mapping relationship between component content and mechanical properties to optimize the mechanical properties of ceramic materials under different sintering process conditions. Kumar et al. [14] applied genetic algorithms to the optimal design of ceramic materials, through the selection of material varieties and the thickness of each layer of the material to achieve the best performance. Zhang et al. [15] used genetic algorithms hybrid neural networks to optimize the injection molding process on ceramic sculptures, avoiding the process of the trial-and-error of the application of CAE analysis. Correia et al. [**?**] used a good simulated annealing algorithm to establish an optimization model for predicting the flexural and tensile strength of hot press molds based on sample data of ceramic materials, but the error in the mechanical property index is large.

Optimization of ceramic materials is a nonlinear optimization problem, and traditional mathematical methods such as genetic algorithms and simulated annealing algorithms are difficult to meet its requirements. Hopfield Neural Network (HNN) is a fully-connected neural network, which can be used to solve the associative memory and constrained optimization problems by using different structural features and learning methods than hierarchical neural networks [16]. Wang and Deng [17] simulated the synaptic crosstalk phenomenon between neurons by using fractional-order voltage-controlled memristors, and constructed a fractional-order memristor HNN, but there is a crosstalk problem in the memory samples. Obeidat [18] proposed a self-adjusting step-size method to improve the convergence speed of the network, and the simulated annealing method was combined with the HNN to avoid falling into a local minimum in the process of solving the problem. Li et al. [19] proposed to introduce the traditional HNN into the design model of ceramic materials to ensure that any starting point can converge to the optimal solution, but the absolute error of the designed materials is large.

1.2. **Contribution.** Intending to the issue that the current optimization methods for ceramic materials are simple to fall into local minima, leading to large absolute errors of the optimized materials, this article suggests an optimization design method for ceramic materials relied on the Enhanced Hopfield Neural Network (EHNN). Firstly, the traditional HNN algorithm is improved, and the weights are corrected based on the neuron excitation threshold and the adjustment rate, so that the neuron states finally converge to the desired attractor neighborhood. Secondly, the raw materials of ceramics production are used as the sample set to establish the association between raw materials and weights, and then the model structure of ceramic material optimization is constructed based on EHNN, which encodes the ceramic raw materials with the help of input matrix, automatically adjusts the connection weights between neurons within a certain range, establishes the objective function, and transforms the optimization problem of ceramic materials into the problem of solving the optimal solution of the EHNN model. The experimental outcome indicates that the optimization method of ceramic materials designed in this article has improved the effect on flexural strength, hardness, fracture toughness, and absolute error indexes, which illustrates the effectiveness of the optimization method in this article.

2. **Theoretical analysis.**

2.1. **Hopfield neural network.** Hopfield neural networks have been widely used in the parallel implementation of machine learning, associative memory, pattern recognition and material optimization in artificial intelligence [20, 21, 22]. The discrete Hopfield neural network is a binary neural network, compared with the BP neural network, it has more powerful associative memory function and self-learning and training ability, and still has the ability of self-learning and self-adaptive associative memory learning in complex situations, and it can have stronger global stability through feedback, and its topology is indicated in Figure 1.

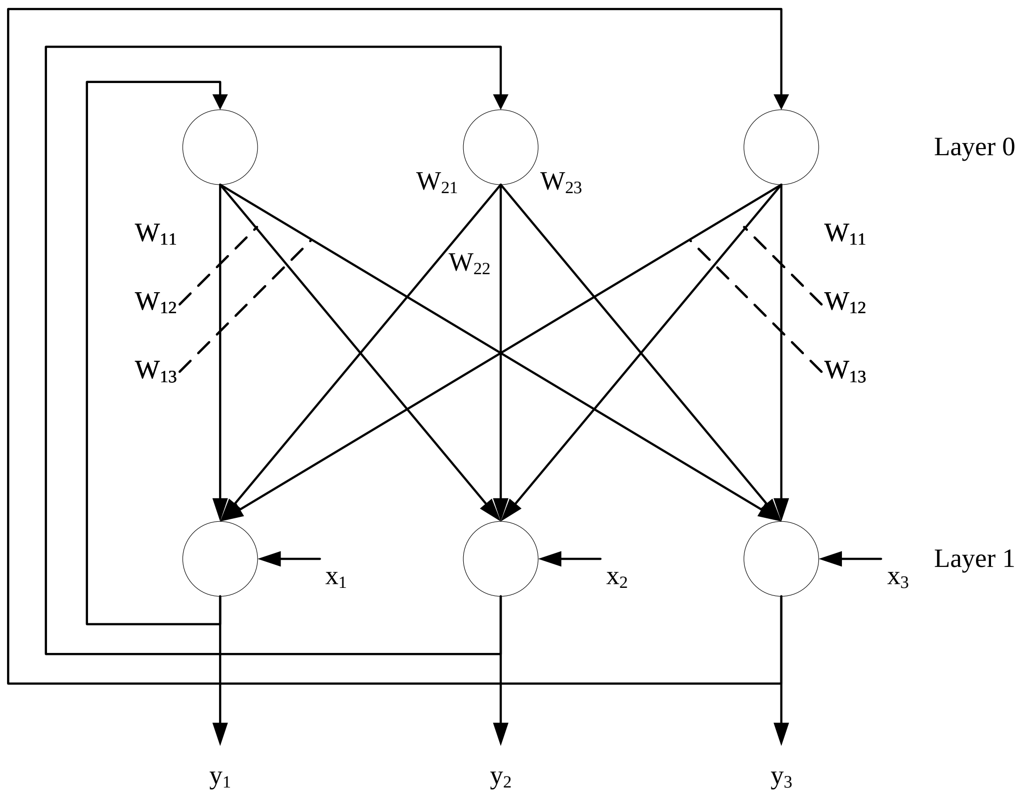

Figure 1. Network topology of HNN

Each neuron in the Hopfield network has the same function and takes the values of 0 and 1, and the weight between neuron i and neuron j is determined by v_{ij}. Take a discrete Hopfield neural network consisting of 3 neurons as an example, the neurons have current state w_i and output state y_j. The relationship between the input and output states of the neurons is indicated below.

$$u_j(t+1) = \sum_{j=1}^{m} v_{ij} y_j(t) + I_j \tag{1}$$

where I_j is the continuous external input to the neuron and the nonlinear function f is the activation function as bellow.

$$y_j(t+1) = f\left(u_j\right) = \begin{cases} 1, & u_j \geq \delta_j \\ 0, & u_j < \delta_j \end{cases} \tag{2}$$

The output state of a neuron in a Hopfield network at time $t+1$ is related to the output state at time t. When the network is updated, if the weight matrix is symmetric with a non-negative diagonal, for a given initial state, it evolves with decreasing capacity and eventually reaches a stable state, i.e., the following energy function is guaranteed to be minimized.

$$E = -\frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} v_{ij} y_i y_j - \sum_{j=1}^{m} I_j y_j \tag{3}$$

2.2. **Design principles for ceramic materials.** Finding regularities and determining the best performing ceramic material combinations through extensive experiments is a common material design method used by researchers [23]. The properties of the material, however, are determined by the components and preparation process of the material from a macroscopic point of view. Thus, the key to designing materials is to be able to determine the mathematical relationship between the material properties and the influencing factors such as the type of raw material, the amount of raw material, and the preparation process. This allows for the design of materials that meet performance requirements without understanding the detailed mechanisms within the material.

The design of ceramic materials must follow the following principles [24].

(1) Principle of chemical compatibility. It means that there must be good chemical compatibility between the reinforcing particles and the matrix without any chemical reaction during sintering and use.

(2) Physical property matching principle. Refers to the matching between the reinforcing particles and the matrix in the modulus of elasticity and coefficient of thermal expansion.

(3) Principle of the finest raw material powder. Refers to all the raw materials should be as fine as possible, which is conducive to the formation of intracrystalline and composite ceramic materials.

(4) Sintering system control principle. On the basis of ensuring dense sintering of raw materials, the higher the sintering heating rate, the lower the sintering temperature, the shorter the holding time, the more favorable to the formation of ceramics.

(5) composition control principle. In the preparation of complex phase ceramics, to control the proportion of raw materials in the porcelain body. The lower the reinforcing phase content, the weaker the hindering effect on the migration of matrix grain boundaries, so that the particles are more easily wrapped into the matrix grain interior.

3. **Enhancement of hopfield neural network.** The HNN memory demonstrates the construction of the weight matrix, and the samples waiting to be memorized are input into the weight matrix through the network, so there are problems of omission of memorized

samples and crosstalk between similarly memorized samples, and an improved HNN algorithm relied on the neuron excitation threshold and the adjustment rate of the corrected weights is proposed.

As indicated in Section 2.1, the final convergence state of each neuron in the HNN depends only on the weight matrix and the excitation threshold of the neuron. According to the principle of HNN, if the neuron converges to the desired attractor neighborhood, the weight matrix and the neuron excitation threshold should satisfy the following conditions

$$y_i = \begin{cases} \sum_{j=1}^{n} v_{ij} p_j^{(l)} - U_i > 0, & p_i^{(l)} = 1 \\ \sum_{j=1}^{n} v_{ij} p_j^{(l)} - U_i \leq 0, & p_i^{(l)} = -1 \end{cases} \tag{4}$$

where $p_i^{(l)}$ is the i-th element of the l-th memory pattern sample data vector to be stored in the HNN, $i = 1, 2, \ldots, m$.

Step 1: To binarize the stored data matrix $P^{(l)}$ into vector $p^{(l)}$. Since the HNN neuron has only two states, +1 (excitatory) and -1 (inhibitory), vector $p^{(l)}$ is coded according to Equation (5).

$$p^{(l)} = p^{(l)} * 2 - 1 \tag{5}$$

Step 2: The samples of memory patterns to be stored are sequentially added to the HNN by using the outer product learning method as indicated in Equation (6).

$$V = \sum_{l=1}^{n} \left(p^{(l)} p^{(l)\mathrm{T}} - E \right) \tag{6}$$

where $l = 1, 2, \ldots, n$, E is the unit matrix.

Step 3: Assuming that the HNN system converges to the attractor at a certain point in time, the internal state value of the i-th neuron is computed according to Equation (7) for different memory sample inputs, based on the weight matrix V obtained.

$$temp_i^{(l)} = \sum_{i=1}^{m} \sum_{q=1}^{n} v_p^q p_i^{(l)} \tag{7}$$

where $j = 1, 2, \ldots, m$, $temp_i^{(l)}$ are the internal state values of the i-th neuron after one moment of the l-th memory pattern sample as the initial state input, and v_p^q denotes the weights of the q-th neuron in the p-th row.

Step 4: Store the internal state values of the i-th neuron after a moment in different memory sample patterns into the array $temp\_array_i$, and obtain the upper and lower thresholds of each neuron according to Equation (8).

$$\begin{cases} W_{i\_max} = \min(temp\_array_i)_{p_i^{(l)}=1} - 1 \\ W_{i\_min} = \max(temp\_array_i)_{p_i^{(l)}=-1} \end{cases} \tag{8}$$

where U_{i_max} is the upper excitation threshold of the i-th neuron, U_{i_min} is the lower excitation threshold of the i-th neuron, $(temp\_array_i)_{p_i^{(l)}=1}$ is the element in array $temp\_array_i$ whose corresponding neuron's expected state is +1 (excitation) when the HNN converges to the correct attractor, and $(temp\_array_i)_{p_i^{(l)}=-1}$ is the element in array $temp\_array_i$ whose corresponding neuron's expected state is -1 (inhibition) when the HNN converges to the correct attractor.

Step 5: Let the network have memory samples L^m with m input patterns, and after the network has smoothed over several iterations, the output matrix $Y(t)$ should also be an input pattern L^m, as indicated below.

$$y_p^q(t) = \operatorname{sgn}\left(\sum_{q=1}^{n}\sum_{p=1}^{m} v_p^q(t) l_p^q(t)\right) \tag{9}$$

where $l_p^q(t)$ denotes the value of the neuron in the p-th row and q-th column of the input pattern L^m of the HNN. The learning rate μ is introduced in Equation (9) to adjust the network weights.

$$v_p^q(t) = \mu \sum_{q=1}^{n}\sum_{p=1}^{m} l_p^q(t) \tag{10}$$

In the case where the input patterns are not orthogonal, the HNN's stable output $y_p^q(t)$ after several iterations may not converge reasonably well to the memorized L^m due to the multiple adjustments of the weight matrix, and it is necessary to apply the adjustment rate ϑ to correct the weight matrix to ensure that the network can memorize L^m reasonably well.

$$v_p^q(t+1) = v_p^q(t) + \Delta v_p^q(t) \tag{11}$$

where $\Delta v_p^q(t)$ denotes the increment of connection weights from neurons in row p, column q to neurons in row q, column q in HNN at the t-th iteration.

$$\Delta v_p^q(t) = \vartheta\left(l_p^q(t) - y_p^q(t)\right) \tag{12}$$

With the above learning methods, the network is optimized by learning the correlation patterns of the memory samples L_v^m with m patterns, and judging the weight matrix by repeated learning, so as to optimize the network's memory performance.

4. **Optimized design of ceramic materials based on enhanced hopfield neural network.**

4.1. **Association of HNN weights with ceramic raw materials.** Existing neural network-based ceramic material optimization methods are prone to fall into local minima, resulting in large absolute errors in the optimized materials. To deal with the above problems, this paper proposes a ceramic material optimization design method relied on EHNN. Firstly, the association between ceramic materials and weights is established based on the connection relationship between synapses on neurons, and then the model structure of ceramic material optimization is constructed based on EHNN, which encodes ceramic materials with the help of the input matrix as the input of the EHNN network and outputs the optimal ceramic materials. The entire model structure is indicated in Figure 2.

Ceramics is based on a certain component design, using a variety of selected oxides, nitrides, carbides and borides as the initial raw materials, based on different toughening and reinforcing mechanisms to add different phases for microstructural design, so as to obtain a variety of ceramic materials with good overall performance [25]. In this paper, the initial raw material of ceramics is the sample set $X = \{x_1, x_2, \ldots, x_i\}$ as the input, and the synaptic strength (weight) of HNN is denoted by v_i. Assuming that the weights on each of the many synapses of the neuron can have different values at a given known moment, the input material samples will sum to a collective effect or net input. Thus, input summation is the simple sum of the functions connecting these quantities over a given time interval as the product of the input material samples x_i and their corresponding weights v_i, expressed as follows.

$$u_i = v_1 x_1 + v_2 x_2 + \ldots + v_i x_i \tag{13}$$

Then using a set of connections (corresponding to the synapses of neurons), the connection strength is expressed by the weights on each connection, the weights are positive for excitation, negative for inhibition, using a nonlinear activation function, the neuron output amplitude is limited to a certain range generally limited to between $(0,1)$ or $(-1,+1)$. The correlation relationship between the obtained weights and ceramic material is indicated below.

$$\frac{du_i}{dt} = \sum_{j=1}^{n} T_{ij} v_j - \frac{u_i}{R_i} \tag{14}$$

where u_i and v_j are the input sample sum and weight of neuron i and neuron j, respectively; and R_i is the real value of the transfer function of neuron i.

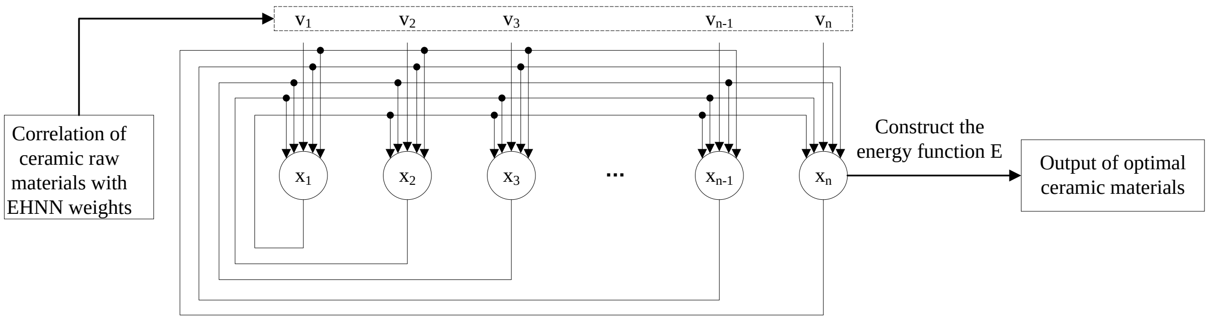

Figure 2. The whole model framework of the suggested model

4.2. **Construction of optimized model structure for ceramic materials.** After associating ceramic raw materials and EHNN weights, the EHNN network structure for ceramic material optimization is established. Assuming a total of $n \times m$ binary neurons, the initial state of the neurons is coded for ceramic material $x_i(t)$. The outputs 1 and -1 represent the excitatory and inhibitory states of the neurons, respectively. The results obtained are the synthesized optimized outputs of the stabilized EHNN neural network.

(1) Initialization. Let the number of HNN iterations be t, the network weights and thresholds are assigned with small random values $v_p^q(t) \in [-1,1], \vartheta(t) \in [-1,1]$.

(2) Neuronal input. During the t iteration of HNN, the neuron input is equal to the weighted output of other neurons. The neuron input of the first row and first column are described below.

$$u_{i1}^1(t) = \begin{pmatrix} v_{11}^{11}(t)x_1^1(t) & \ldots & v_{1i}^{1i}(t)x_i^i(t) \\ v_{12}^{11}(t)x_2^1(t) & \ldots & v_{12}^{1i}(t)x_2^i(t) \\ \vdots & \ddots & \vdots \\ v_{1n}^{11}(t)x_n^1(t) & \ldots & v_{1n}^{1i}(t)x_n^i(t) \end{pmatrix} \tag{15}$$

where $u_{i1}^1(t)$ denotes the input matrix of the neuron in row 1, column 1 of the EHNN at the t-th iteration, and $v_{1p}^{lq}(t)$ denotes the neuron weights of the neuron in row p, column q of the EHNN connecting to the neuron in row 1, column 1 of the EHNN at the t-th iteration.

(3) In the process of accounting for EHNN neurons, it needs to multiply the input information by the weights, and the formula for neurons in row 1 and column 1 is as bellow.

$$r_1^1(t) = \sum_{q=1}^{n} \sum_{p=1}^{m} v_{1p}^{lq} x_p^q(t) \tag{16}$$

where $r_1^1(t)$ denotes the formula for the neuron in row 1, column 1 of the EHNN optimized ceramic material model.

(4) Output of neurons. Based on the input ceramic initial raw materials, the output matrix of the EHNN is obtained from the output of the neurons in row 1, column 1 at the t-th iteration as bellow.

$$f(Net) = f(u - \vartheta) = f\left(\sum_{q=1}^{n} \sum_{p=1}^{m} v_p^q x_p^q - \vartheta\right) \tag{17}$$

where x_p^q is the input ceramic raw material, v_p^q is the weights of the neurons. u is the result of the combination of raw material and weights, ϑ is the threshold, Net is the net input, and $f(Net)$ is the activation function.

The essence of ceramic material optimization is to determine the correlation of the initial feedstocks with each other and the correlation of each feedstock with the final properties of the material. In terms of obtaining the output based on the input feedstock x_p^q, the EHNN consists of two steps, the first step being the net input Net obtained from the above calculations. the second step is to perform a nonlinear transformation on the net input $f(Net)$ as bellow.

$$\hat{f}(net) = \frac{1 - \exp\big(-\big(\sum_{q=1}^{n} \sum_{p=1}^{m} v_p^q x_p^q - \vartheta\big)\big)}{1 + \exp\big(-\beta \cdot \big(\sum_{q=1}^{n} \sum_{p=1}^{m} v_p^q x_p^q - \vartheta\big)\big)} \tag{18}$$

where $\beta > 0$ controls its slope.

4.3. **Optimized design of ceramic materials.** The mathematical model of the traditional HNN is shown in Equation (1). In this paper, based on the improved HNN network in Section 3, the mathematical model of EHNN is obtained as indicated below.

$$u_p^q(t+1) = -\alpha \sum_{q=1}^{n} \sum_{p=1}^{m} u_p^q(t) + \mu\left(\sum_{q=1}^{n} \sum_{p=1}^{m} V_p^q O_p^q(t) + I_p^q\right) - P_p^q(t)(O_p^q(t) - \hat{f}(net)) \tag{19}$$

where α is the attenuation factor of neuron inner membrane, α is 1 for analysis, μ is a positive parameter, $u_p^q(t)$ and $O_p^q(t)$ are the internal states and outputs of neurons, V_p^q is the synaptic connection weights of neurons in the p-th row and q-th column, I_p^q is the continuous external inputs of neurons, $P_p^q(t)$ is the negative feedback term, and $\hat{f}(net)$ is the net inputs of ceramic materials. When the value of $P_p^q(t)$ is large enough, the system will show complex mechanics; when $P_p^q(t)$ decreases gradually, the network will slowly change from a chaotic state to a stable state.

For the optimization of ceramic materials, the first step is to solve for the synaptic weights of the network that can ensure the stability of the EHNN network. In EHNN, since the connection weights of the network are fixed and the current state of the neurons is related to the previous state, the stability of the Hopfield is determined by the energy function, and the energy function E is constructed as below.

$$E = \alpha \sum_{q=1}^{n} \sum_{p=1}^{m} v_p^q(t) + \mu u_p^q(t) \tag{20}$$

Adopting the Lagrange multiplier method, the above constrained optimization problem is evolved into a multi-objective optimization problem by multiplying it with appropriate weighting coefficients, and the optimization objective function of ceramic materials can be obtained as follows, and the optimization problem of ceramic materials is transformed into the problem of solving the optimal solution of the EHNN model.

$$f(t) = \min \left[\sum_p \sum_q \frac{du_p^q(t)}{dt} \left(-\frac{\alpha}{2} v_{p-1}^q(t) + \frac{\mu}{2} v_{p+1}^q(t) \right) \right] \tag{21}$$

5. Performance testing and analysis.

5.1. Comparison of classification performance. For the goal of verifying the performance of optimized design of ceramic materials relied on EHNN, this article adopts 20 kinds of ceramic materials in the literature [26] as the experimental dataset, and carries out simulation experiments based on MATLAB R2021a, the learning rate is set to 0.01, and the neurons' action functions during training are all tansig. Before training, all inputs and outputs are linearly normalized. The normalization range is 0.1-0.9. The MATLAB Neural Network Toolbox is used to build an HNN network with ceramic material as the output. Then train the network. The trained optimal ceramic material is obtained. The hardware parameters used are 120Hz Intel Core i7-13700H00H processor, 16 GB RAM and Windows 11 operating system.

In this article, a combination of Bending Strength (BS), Hardness (HA), Fracture Toughness (FT) [27], and Absolute Error (AE) [28] performance metrics of ceramic materials are used to perform comparative experiments on the optimized ceramic material EHNN-OCM in this paper, and the already existing optimization methods, BP-ACU [12] and HNN-ACI [19]. Table 1 demonstrates the comparison of experimental values with optimal solution results for different models, where E-Value denotes experimental value, O-Value denotes optimization value.

Method	**BS (MPa)**		**HA (GPa)**		**FT (MPa.m$^{1/2}$)**	
	E-Value	O-Value	E-Value	O-Value	E-Value	O-Value
BP-ACU	472	431	4.2	4.51	16.73	17.36
HNN-ACI	598	629	4.8	4.97	17.21	16.93
EHNN-OCM	709	724	5.3	5.19	19.68	19.84

As can be seen from Table 3, EHNN-OCM has achieved the best performance in BS, HA and FT indexes, in which the experimental value of EHNN-OCM is increased by 50.21%, 26.19% and 17.63%, respectively, compared with BP-ACU method. Compared with HNN-ACI method, the results were 18.56%, 10.42% and 14.35% higher, respectively. This is because the BP-ACU method is based on genetic algorithm to optimize the BP neural network to optimize the ceramic material, and the input data is the raw material parameters of the ceramic. Because the raw material parameters are not associated with the weight of the BP neural network, the optimization effect is far worse than that of HNN-ACI and EHNN-OCM. HNN-ACI is based on the traditional HNN neural network to optimize ceramic materials, which is relatively better than the optimization effect of BP-ACU method. However, the raw material of ceramic design is not closely combined with HNN, nor is HNN optimized, resulting in a lower optimization effect than EHNN-OCM. In the optimization process of ceramic materials, EHNN-OCM not only corrects the weight and threshold value of traditional HNN, but also closely combines the initial raw material of ceramic production with the weight until a better material is obtained, thereby improving its performance in the optimization of ceramic materials, which makes EHNN-OCM perform best in various indicators.

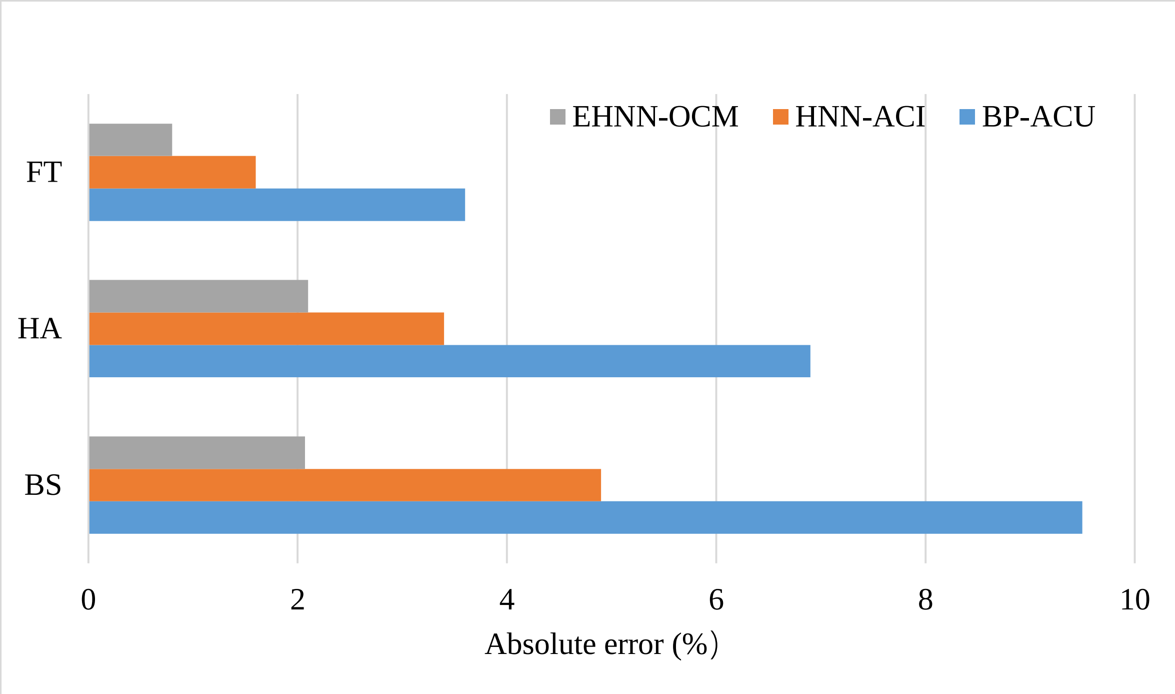

Figure 3. Comparison of absolute errors of different optimization methods

In addition, through Table 3, a comparison of the absolute errors of the experimental and optimized values for BP-ACU, HNN-ACI and EHNN-OCM on different metrics can be obtained as shown in Figure 3. The absolute errors of BS, HA and FT for EHNN-OCM are 2.07%, 2.1% and 0.8%, respectively, and those for HNN-ACI are 4.9%, 4.4% and 1.6%, respectively, 3.4% and 1.6%, and the absolute errors of BS, HA and FT for BP-ACU are 9.5%, 6.9% and 3.6%, respectively. This indicates that the EHNN-OCM method proposed in this paper optimizes the ceramic materials with high accuracy, and the theoretically optimized values are almost the same as the results of the imitation experiments. The BP-ACU method, on the other hand, has a larger absolute error, due to the problem of local convergence of the BP neural network, which leads to a larger network fitting error.

5.2. **Tensile strength and time delay analysis.** The intensity of the emission spectra of ceramic materials is closely related to the output energy of ceramic materials generated by the interaction of various natural and synthetic raw materials. The time-resolved mode was set in MATLAB, the wavelength was set to 541 nm, the focusing point was located 4 mm below the sample surface, and the acquisition time delay was 10 μs. The evolution curves of the tensile strength of the ceramic materials optimized by EHNN-OCM with time were obtained under the conditions of single-pulse output energies of 10, 20, 30, 50, and 80 mJ, respectively.

As can be seen in Figure 4, the same output energy, tensile strength at any time delayed by the trend of increasing and then decreasing; when the output energy of a single pulse from 10 mJ increasing, tensile strength but gradually decreased, and the maximum value of the time of the appearance of the energy with the increase and the backward shift. This is due to the tensile strength of ceramic materials is mainly produced by the vibration and rotation of silicate molecules, with the increase in energy, ablation produced by the molecular body temperature continues to rise, high-temperature environment has a destructive effect on the molecular bonding, hindering the formation of raw materials, which led to the weakening of the tensile strength. At the same time, the higher the energy, the larger the volume and temperature of the molecules produced by ablation, and the longer the time required for expansion and cooling to form the ceramic material, resulting in a shift in the time to the maximum tensile strength with the increase in pulse energy.

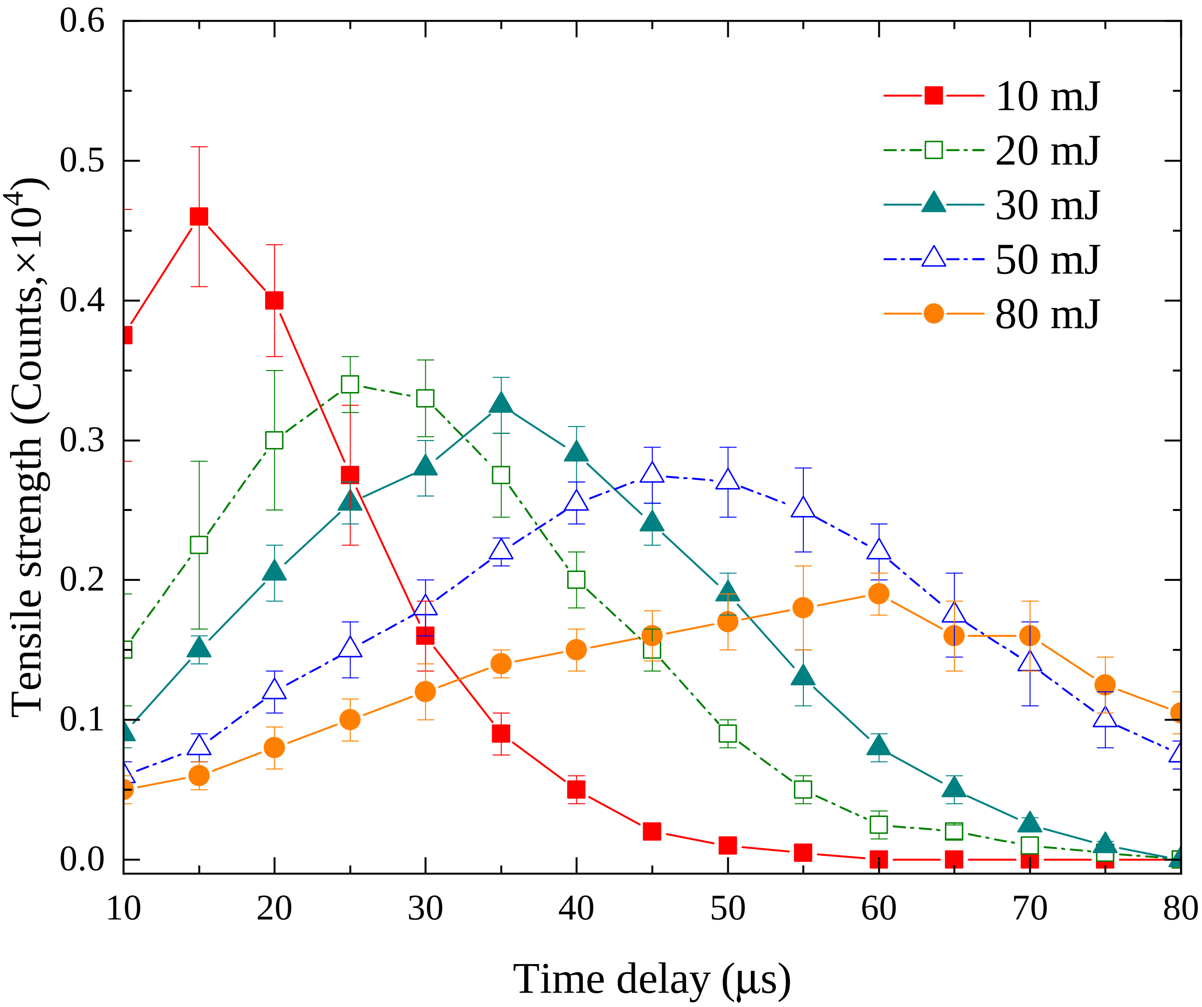

Figure 4. Relationship between tensile strength and time delay of ceramics at different energies

6. **Conclusion.** Focusing on the issues of slow convergence speed and large absolute error of existing ceramic material optimization methods, this paper proposes a ceramic material optimization design method based on EHNN. Firstly, the traditional HNN algorithm is improved, and the weights are corrected based on the neuron excitation threshold and the adjustment rate, so that the neuron states finally converge to the desired attractor neighborhood. Secondly, the raw materials for the production of ceramics are used as the sample set to establish the correlation between the raw materials and the weights, and then the model structure for the optimization of ceramic materials is constructed

based on the EHNN, which encodes the ceramic materials with the help of the input matrix as the input of the EHNN network, and automatically adjusts the connection weights between the neurons within a certain range, assisting the network in generating the desired energy minima, which is used as the optimal output of ceramic materials. The experimental outcome indicates that the suggested ceramic material optimization method has higher flexural strength, hardness, fracture toughness and lower absolute error compared with the comparison methods, and can be better applied to the field of ceramic material optimization design.

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