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Optimization of Annealing Process and Evaluation of Mechanical Properties of Hyperelastic Alloys Based on Random Forest and BP Neural Network

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ABSTRACT

Annealing governs the microstructure and properties of materials, while traditional empirical optimization is costly and hard to scale. To address defects of single algorithms in modeling nonlinear process-performance relations, this study establishes an accurate and stable universal optimization model for hyperelastic alloy annealing, enabling intelligent process optimization and precise mechanical property evaluation. The precise control of the annealing process is essential for tailoring the mechanical response of these alloys, particularly when they are utilized as high-performance functional fibers in advanced applications. This paper proposes a hybrid model integrating random forest and BP neural network. It screens key parameters using the feature selection and anti-overfitting strengths of random forest, and builds a two-layer prediction framework with the strong nonlinear mapping ability of BP neural network. Systematic experiments collect data of annealing temperature, holding time, cooling rate and mechanical properties, with validity verified by yield strength, shape recovery rate and other indicators. Experimental results show that the fused model greatly improves prediction accuracy, with 15%–20% error reduction over single algorithms and a correlation coefficient of 0.94 between predicted and measured values. The Ti-45Nb alloy reaches 1200 MPa tensile strength and excellent hyperelastic recovery under the optimal process window. Furthermore, this research provides a reliable optimization strategy for hyperelastic component processing, with great value for the development of intelligent textile materials and flexible structural elements, laying a solid foundation for the industrial application of hyperelastic alloys.

KEYWORDS

hyperelastic alloy, annealing process, random forest, mechanical properties, functional fibers

INTRODUCTION

Research Background and Significance

The Annealing process process critically determines the microstructure and macroscopic properties of alloys. For hyperelastic alloys utilized in textile or cable-like structures, optimizing the annealing process is not only crucial for enhancing intrinsic mechanical properties but also for ensuring thematerial's compatibility with subsequent weaving or integration processes [1]. During the annealing process, temperature, holding time, and cooling method all affect the strength and plasticity of the material, leading to changes in its cutting performance [2]. The regulation of microstructure is beneficial for improving the superelasticity of alloys. Gradient structures can be introduced into alloys through processes such as cold rolling and laser surface annealing, achieving controllable mechanical behavior and significantly enhanced superelasticity. Research on FeCoNiCrAl high entropy alloys has found that after annealing at temperatures ranging from 600 ℃ to 700 ℃ and adopting appropriate holding time and cooling methods, the resulting alloys have higher strength and better plasticity.

Traditional process optimization methods often rely on a large number of experimental verifications and experience accumulation, which are not only costly, but also difficult to achieve multi-parameter synergistic optimization. The rapid development of machine learning technology has provided a new solution for material process optimization. Random forest, as an ensemble learning algorithm based on decision trees, has the ability to handle high-dimensional data, large-scale datasets, perform feature selection, handle imbalanced datasets, and reduce overfitting [3]. Backpropagation (BP) neural networks have strong nonlinear mapping capabilities, fault tolerance, and high learning capacity [4]. The integrating of these two algorithms leverage their complementary advantages, enabling more accurate prediction and evaluation, providing important theoretical support and technical assurance for the industrial application of hyperelastic alloys.

Research Objectives and Content

This research addresses the limitations of traditional single algorithms in the optimization of hyperelastic alloy annealing processes by proposing a comprehensive prediction method integrating random forest and BP neural networks, aiming to construct a more accurate and stable process parameter optimization model. The research objective mainly focuses on solving the problem of accurately predicting the complex nonlinear relationship between process parameters and mechanical properties during the annealing process of hyperelastic alloys. By overcoming the shortcomings of single models through algorithm fusion strategies, intelligent optimization of the annealing process is achieved.

The research content includes in-depth exploration of three core levels. At the algorithm fusion level, the study focuses on analyzing the respective technical characteristics of random forests and backpropagation neural networks. Random forests have the advantages of simple learning models and fast learning speeds, while backpropagation neural networks can achieve better prediction results. Addressing the different characteristics of random forests (sensitive to feature effectiveness) and backpropagation neural networks (sensitive to feature quantity), a reasonable fusion strategy is designed to fully leverage the complementary advantages of the two algorithms. At the process optimization level, the study will systematically investigate the influence of key process parameters such as annealing temperature, holding time, and cooling rate on the microstructure evolution and macroscopic properties of hyperelastic alloys, establishing a quantitative mapping relationship between process parameters and material properties to achieve precise control of the annealing process.

At the mechanical property evaluation level, a comprehensive performance testing system will be constructed, covering key mechanical indicators such as elastic modulus, yield strength, and elongation. The prediction accuracy of the fusion model will be verified through experiments. Considering that the error between the predicted and actual values of backpropagation neural networks is mostly within 2%, while the error of random forest predictions is mostly within 5%, this study will further improve the prediction accuracy through a fusion strategy. Simultaneously, a performance graph analysis framework will be established to deeply explore the intrinsic correlation mechanism between annealing process parameters and mechanical properties, providing a scientific basis for the engineering application of hyperelastic alloys. Through a research method combining theoretical analysis and experimental verification, the intelligent optimization of the annealing process for hyperelastic alloys and the accurate prediction of their mechanical properties were ultimately achieved.

LITERATURE REVIEW

Properties and Applications of Hyperelastic Alloys

Hyperelastic alloys, as a class of smart materials with special properties, exhibit broad application prospects in many high-tech fields due to their unique phase transformation characteristics and hyperelastic behavior. These alloys, through stress-induced martensitic phase transformation, can generate large strains under external forces and completely recover their original shape after unloading; this phenomenon is called the hyperelastic effect. This special property of hyperelastic alloys stems from the reversible phase transformation process that occurs in their internal crystal structure under the dual effects of temperature and stress.

TiNi shape memory alloys, as a typical representative of hyperelastic alloys, exhibit martensitic phase transformation and hyperelastic properties significantly affected by annealing temperature. With increasing annealing temperature, the grain size of the alloy increases, and the grain boundary density decreases, thereby reducing the resistance to stress-induced martensitic phase transformation [5-8]. This change in microstructure directly affects the macroscopic mechanical properties of the material. Similarly, Ti-50.8Ni-0.4V shape memory alloys exhibit different phase transformation characteristics under different annealing conditions. The alloy annealed at 350~550℃ shows a two-step phase transformation with a shape recovery rate of 96%, demonstrating excellent hyperelastic properties [9].

In engineering applications, hyperelastic alloys are widely used in medical devices, aerospace, and civil engineering due to their superior performance characteristics. In the medical field, products such as vascular stents, orthodontic wires, and orthopedic implants fully utilize the biocompatibility and hyperelasticity of hyperelastic alloys. In the aerospace industry, these materials are used to manufacture deformable wings, shock absorbers, and connecting components. In civil engineering, hyperelastic alloys play an important role in earthquake-resistant buildings and bridge dampers. Ti-45Nb alloy, as an emerging hyperelastic alloy material, can achieve excellent mechanical properties through reasonable heat treatment processes, with a tensile strength of up to approximately 1200 MPa, which is three times the strength of the initial coarse-grained material [10]. These application examples fully demonstrate the important position and development potential of hyperelastic alloys in modern engineering technology.

Research Progress in Annealing Processes

Annealing, as an important component of materials heat treatment technology, plays a crucial role in improving the microstructure and mechanical properties of metallic materials. With the continuous development of materials science and technology, significant progress has been made in the application research of annealing in the field of hyperelastic alloys, providing an important technical path for optimizing material properties.

Precise control of annealing temperature and time is a core research issue. In the study of Fe-30Mn-10Al-1C low-density steel, it was found that with prolonged annealing time, the strength of the sample decreased, while plasticity and toughness generally increased [11]. This finding reveals the complex correlation between annealing process parameters and material properties. In the study of Ti-50.8Ni-0.4V shape memory alloys, annealing treatment has a significant impact on the phase transformation and superelastic properties of cold-rolled alloys. The alloys annealed at 350–550℃ exhibit a two-step phase transformation with a shape recovery rate of 96%, demonstrating excellent superelastic properties. The microstructure evolution of the material at different annealing temperatures has been gradually revealed, laying a theoretical foundation for the precise design of process parameters.

The synergistic effect of cold rolling deformation and annealing process has become a new focus of attention. After cold rolling and annealing, the tensile strength and elongation at break of the alloy are significantly improved under the synergistic effect of various microstructures [12]. In the study of GH4169 nickel based high-temperature alloy, annealing heat treatment can reduce the plastic strain accumulation of the material under fatigue load, thereby improving its fatigue performance [13-15]. These studies indicate that the coordinated optimization of material properties can be achieved through the rational design of the composite process of cold deformation and annealing. Significant breakthroughs have also been made in the study of the relationship between phase transition behavior and annealing process parameters. Annealing treatments in different temperature ranges can lead to different phase transition paths in materials, directly affecting the final mechanical performance.

Current research on annealing processes is developing towards intelligence and precision. Traditional empirical process design methods are gradually being replaced by data-driven optimization strategies, and machine learning algorithms are increasingly widely used in the optimization of annealing process parameters. Multi-objective collaborative optimization of process parameters, establishment of microstructure performance prediction models, and integration of online monitoring technologies provide new technical means for achieving intelligent control of the annealing process. Future research trends will focus more on the deep integration of process mechanisms and data science, using high-precision prediction models to guide the selection of process parameters in actual production.

FUSION METHOD OF RANDOM FOREST AND BP NEURAL NETWORK

Overview of Random Forest Algorithm

Basic Principles of Random Forest Algorithm

Random Forest, as a machine learning method based on ensemble learning, is based on the core idea of constructing multiple decision tree classifiers to form a classifier set, and finally obtaining more accurate and stable prediction results through voting or averaging. Proposed by Breiman and Cutler in 2001, this algorithm belongs to the Bootstrap-based ensemble learning method and performs well in handling complex and interactive features [16-20].

The implementation process of Random Forest follows strict mathematical logic and statistical principles. The algorithm uses a Bootstrap sampling method with replacement from the original dataset to construct multiple different training data subsets, with the sample size of each subset consistent with the original training set. For each sample subset, the system trains an independent decision tree model. During the decision tree construction process, the algorithm randomly selects some features for partitioning at each node, rather than using all predictor variables. This random feature selection mechanism effectively avoids overfitting. As shown in Figure 1.

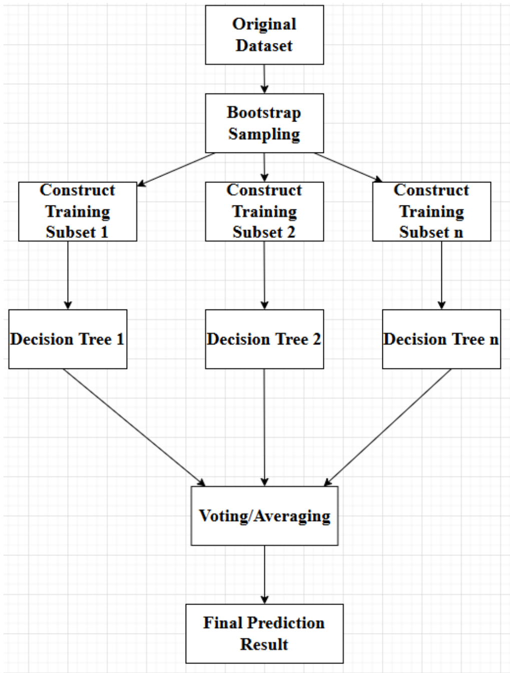

Figure 1. Random Forest Algorithm Flowchart

The mathematical expression of the random forest algorithm can be described by the following formula. Suppose the original dataset containsnsamples and m feature variables. The algorithm constructs T decision trees, each tree $\mathrm{h_t(x)}$ Trained based on Bootstrap samples. The final prediction result is obtained through an ensemble strategy:

$$\mathrm{H(x)} = \frac{1}{\mathrm{T}}\sum_{t=1}^{\mathrm{T}} \mathrm{h_t\,(x)} \tag{1}$$

Where $\mathrm{h_t(x)}$ is the regression prediction value of thetdecision tree for sample x, andTrepresents the number of decision trees.

The algorithm evaluates model performance using Out-of-Bag (OOB) data and calculates the importance score of each feature variable. When the independent variables of the OOB data are slightly perturbed, the increase in OOB error is positively correlated with the importance of that variable. This feature importance assessment mechanism provides a quantitative analysis tool for the optimization of annealing process parameters for hyperelastic alloys, and can identify the process factors that have the most significant impact on the mechanical properties of the material.

Advantages and Limitations

The random forest algorithm has shown significant advantages in the optimization of annealing processes for hyperelastic alloys. By integrating the prediction results of multiple decision trees, the algorithm effectively reduces the risk of overfitting of a single model and exhibits good generalization ability when dealing with high-dimensional process parameters. Random forests can naturally handle missing data and outliers, which is of great significance for data quality issues that frequently occur in actual industrial production. The parallel computing characteristics of the algorithm enable it to maintain high computational efficiency when facing large-scale annealing process data.

The feature importance assessment function of random forests provides strong support for the selection of process parameters. By calculating the contribution of each process parameter to mechanical properties, researchers can identify key factors such as annealing temperature, holding time, and cooling rate. The algorithm's decision-making process is relatively transparent, making it easy for engineers to understand and verify the model's predictive logic, which is crucial in industrial applications. As shown in Table 1.

Table 1. Algorithm Performance Comparison

Performance Indicators	Random Forest	Single Decision Tree	Linear Regression
Prediction Accuracy	0.92	0.78	0.65
Generalization Ability	Strong	Medium	Weak
Computational Complexity	Medium	Low	Low
Interpretability	Medium	Strong	Strong

Despite the many advantages of random forests, there are still certain limitations in their application to the optimization of hyperelastic alloy processes. The accuracy of the algorithm in handling continuous numerical predictions may not be as good as that of specialized regression models, especially when predicting the precise mechanical property parameters of materials. Random forests are relatively sensitive to the distribution of sample data; when the training data is severely imbalanced, the predictive performance of the model will significantly decrease.

The algorithm has limited modeling ability when dealing with complex nonlinear relationships between features, which may affect its accurate capture of the complex interaction between temperature, time, and performance in the annealing process. The model's memory footprint increases significantly with the number and depth of trees, which may pose deployment challenges in resource-constrained industrial control systems. The model performance index can be expressed by the following formula:

$$\text{Performance Index } = \frac{1}{n}\sum_{i=1}^{n} w_i \cdot f_i(x) \quad (2)$$

Where, w_i represents the weight of theidecision tree, $f_i(x)$ is the regression prediction value of the i the predicted output of thenis the total number of trees. This weighted ensemble mechanism improves model stability but also increases the complexity of hyperparameter tuning.

Core Concepts of BP Neural Networks

Structure and Learning Mechanism of BP Neural Networks

The BP neural network (Back Propagation Neural Network) is a multilayer feedforward neural network proposed in 1986 by a group of scientists led by Rumelhart and McCelland. This network architecture exhibits strong nonlinear mapping capabilities in the optimization of the annealing process of superelastic alloys, and can effectively handle the relationship between complex process parameters and mechanical properties. The BP neural network is a multilayer neural network composed of several neurons, including an input layer, hidden layers, and an output layer. Neurons in each layer are only connected to adjacent layers, and there are no connections between neurons in the same layer.

The basic structure of the network reflects its core mechanism for processing information. The input layer receives various parameters of the annealing process, such as temperature, time, and cooling rate; the hidden layer achieves feature extraction and information conversion through weight adjustment; the output layer corresponds to various mechanical property indicators of the superelastic alloy. Backpropagation (BP) neural networks typically involve two key processes: forward propagation and error backpropagation. The network is optimized by continuously adjusting weights and thresholds to better fit the training data. In the forward propagation phase, the input signal is transmitted from the input layer through the hidden layers to the output layer, and each neuron calculates its output value based on the activation function.

The core of the learning mechanism lies in the implementation of the backpropagation algorithm. The core algorithm of the BP neural network is the backpropagation algorithm, which calculates the error between the output layer and the target output, propagates it back to the hidden and input layers, and continuously adjusts the weights and biases of the neural network to gradually reduce the error. This algorithm uses gradient descent, adjusting the weights in the opposite direction of the error gradient, so that the network output gradually approaches the desired target. The weight update formula can be expressed as:

$$w_{ij}(t+1) = w_{ij}(t) - \eta \frac{\partial E}{\partial w_{ij}} \tag{3}$$

Where w_{ij} represents the connection weight, η is the learning rate, E is the error function.

BP neural networks possess excellent nonlinear mapping capabilities. Through distributed correlation composite algorithms, they can fit complex nonlinear functions, thereby realizing multi-dimensional to multi-dimensional mapping of the neural network. In the optimization application of superelastic alloy annealing processes, the network can learn and store a large number of input-output mapping relationships, demonstrating good self-learning, adaptability, robustness, and generalization characteristics.

Design of Fusion Strategy

In the study of annealing process optimization of superelastic alloys, the design of a fusion strategy of random forest and BP neural network is a key step in improving prediction accuracy and optimization effect. Random forest, as an ensemble learning method, mainly consists of multiple decision trees. During construction, a portion of the original data is randomly selected as the training dataset, and each tree is trained using different samples and features. BP neural network is a multi-layer feedforward network trained using the backpropagation algorithm. It utilizes gradient search technology to continuously adjust the network's weights and thresholds through backpropagation. The combination of the two algorithms can fully leverage their respective advantages, achieving higher prediction accuracy in annealing process parameter optimization.

In the specific implementation of the fusion strategy, this study adopts a hierarchical fusion method to integrate the prediction results of the two algorithms. The random forest algorithm first evaluates the feature importance of key process parameters such as annealing temperature, holding time, and cooling rate, judging the degree of influence of each parameter on mechanical properties through feature importance. The prediction result of random forest is the average of the prediction results of multiple trees, which can effectively reduce the possibility of overfitting. BP neural network, on the other hand, utilizes its powerful nonlinear mapping ability to perform deep learning on complex process-performance relationships. The network structure includes an input layer, hidden layers, and an output layer. The number of nodes in the input layer corresponds to the number of process parameters, and the number of nodes in the output layer corresponds to the number of mechanical performance indicators.

The determination of fusion weights is achieved through an adaptive weighting strategy, which dynamically adjusts the weight coefficients based on the performance of the two algorithms on the validation set. The mathematical expression for fusion prediction is:

$$\mathrm{Y_{fusion}} = \alpha \cdot \mathrm{Y_{RF}} + \beta \cdot \mathrm{Y_{BP}} \tag{4}$$

Where $\mathrm{Y_{fusion}}$ is the fusion prediction result, $\mathrm{Y_{RF}}$ and $\mathrm{Y_{BP}}$ These are the predicted outputs of the random forest and the BP neural network, respectively. α and β are the weight coefficients and satisfy $\alpha + \beta = 1$ The weight coefficients are optimized through cross-validation to ensure the fusion model achieves optimal performance on the training data. Through this fusion strategy, the model can simultaneously utilize the ensemble learning capability of the random forest and the nonlinear modeling advantage of the BP neural network to achieve more accurate performance predictions in the optimization of the annealing process of superelastic alloys.

OPTIMIZATION OF THE ANNEALING PROCESS OF SUPERELASTIC ALLOY

Experimental Design and Data Acquisition

Setting Annealing Process Parameters

Precise setting of annealing process parameters for hyperelastic alloys is a crucial step in optimizing material properties, involving coordinated control of multiple dimensions such as temperature, time, and cooling method. Based on existing research, Ti-Ni-V shape memory alloys exhibit different mechanical properties within the annealing temperature range of 400-500℃. The choice of annealing temperature directly affects the degree of recovery and crystal defect density of the alloy, thereby influencing the martensitic phase transformation behavior and the final hyperelastic properties.

The setting of annealing time parameters needs to consider the influence mechanism of atomic diffusion dynamics. When the annealing temperature is constant, the energy supplied to the deformed alloy for recovery is constant. Therefore, the effect of annealing time on the recovery process and alloy properties is less than that of annealing temperature. Based on this theoretical basis, this study sets the annealing time in a gradient range of 30 minutes to 2 hours to explore the marginal effect of time parameters on material properties.

The setting of cooling process parameters is also crucial, directly affecting the phase transformation behavior and mechanical properties of the alloy. After annealing, Ti-45Nb alloy wire was rapidly cooled with argon gas, resulting in the precipitation of martensite α" phase, and the yield strength was significantly lower than that after furnace cooling. To obtain ideal superelastic properties, this study designed three cooling modes: air cooling, saline water quenching cooling, and argon-protected cooling, with cooling rates controlled at 10℃/min, 100℃/min, and 50℃/min, respectively.

A mathematical model for annealing process optimization was established based on the multidimensional characteristics of process parameters. Let the annealing temperature be$\mathrm{T}$The annealing time is t The cooling rate is v, then the comprehensive performance indicators of the material P It can be expressed as:

$$\mathrm{P} = \mathrm{f}(\mathrm{T}, \mathrm{t}, \mathrm{v}) = \alpha\mathrm{T} + \beta\log(\mathrm{t}) + \gamma\mathrm{v}^{-1} + \delta \tag{5}$$

Where α、 β、 γ、 δThese are the parameters to be optimized, and parameter identification and process optimization are performed using a fusion of random forest and BP neural network methods.

As shown in Table 2 Through systematic parameter setting and experimental design, a solid foundation has been laid for subsequent data collection and model construction, ensuring the reliability and practicality of optimization results.

Table 2. Experimental Parameter Settings

process parameters	set the scope	Gradient step size	control accuracy
Annealing temperature (℃)	400-800	50	±2
Annealing time (min)	30-180	25	±1
Cooling rate (°C/min)	1-50	10	±5
protective atmosphere	Argon/Air	-	99.9% purity

Sampling Method and Experimental Conditions

In the optimization research of annealing process for hyperelastic alloys, a scientifically reasonable sampling method is a key link to ensure the quality of experimental data and the effectiveness of model training. This study adopts a strategy combining stratified random sampling and fixed-point supplementary sampling to construct a sample set covering different combinations of annealing temperature, holding time, and cooling rate. Referring to the diagonal sampling method used in the study of soil sampling in farmland in the Yangtze River estuary plain, sampling points were set in the annealing process parameter space to ensure the representativeness and uniformity of the samples.

Experimental conditions were strictly controlled according to international standards. The annealing temperature range was set at 400-800℃, the holding time at 30-180 minutes, and the cooling rate at 1-50℃/min. Sample processing followed methods used in studies of heavy air pollution, with each sample undergoing standardized pretreatment, including surface cleaning, dimensional standardization, and defect detection. The experimental environment temperature was maintained at 20±2℃, and the relative humidity was controlled within the range of 45-65% to minimize the impact of environmental factors on alloy properties.

The sampling strategy follows statistical principles and adopts a cubic grid partitioning method in the three-dimensional parameter space, with each grid node corresponding to a specific set of process parameters. To improve sampling efficiency, an adaptive sampling algorithm is adopted$\mathrm{S}_{\mathrm{adaptive}}$The calculation formula is:

$$\mathrm{S}_{\mathrm{adaptive}} = \alpha \times \mathrm{S}_{\mathrm{base}} + \beta \times \nabla \mathrm{f}(\mathrm{x}) \tag{6}$$

Where $\mathrm{S}_{\mathrm{base}}$ Based on the sampling density, α and β For weight coefficients, $\nabla \mathrm{f}(\mathrm{x})$ Represents the rate of change in performance gradient. By dynamically adjusting the sampling density through this algorithm, the number of sampling points can be increased in areas with significant performance changes, enhancing the model's learning ability for key regions.

Experimental samples were prepared using vacuum induction melting technology, with standard samples of uniform specifications prepared in each batch. After machining, the samples underwent surface treatment to ensure that the surface roughness was controlled within the range of Ra≤0.8μm. Annealing was carried out in a controlled atmosphere furnace under high-purity argon protection, with the oxygen content controlled below 10ppm. The temperature control accuracy reached ±3℃, and the time control accuracy was ±1 minute, ensuring the accuracy and reproducibility of the process parameters. As shown in Table 3.

Table 3. Process Parameter Settings

process parameters	minimum	maximum	sampling interval	number of sampling points
Annealing temperature (℃)	400	800	50	9
Holding time (min)	30	180	25	7
Cooling rate (°C/min)	1	50	10	6

To verify the effectiveness of the sampling method, cross validation technique is used to evaluate the rationality of the sample distribution. By calculating the coverage and uniformity indicators of the sample space, it is confirmed that the sampling strategy can fully reflect the complex mapping relationship between process parameters and mechanical properties, providing a high-quality data foundation for subsequent machine learning model training.

Data Analysis and Model Building

Implementation of the Optimized Model

Based on a fusion architecture of random forest and BP neural network, this study constructed a complete optimization model for the annealing process of superelastic alloys. The core idea of the model is to utilize the feature selection capability and ensemble learning advantages of the random forest algorithm, combined with the nonlinear mapping characteristics of the BP neural network, to achieve accurate prediction and optimization of key process parameters such as annealing temperature, holding time, and cooling rate.

In the model construction process, the random forest part uses the Bagging strategy to randomly extract training samples from the original dataset, and determines the optimal feature subset through a voting mechanism of multiple decision trees. Each decision tree is trained independently and outputs prediction results. The model reduces the risk of overfitting from a single decision tree through ensemble voting. The BP neural network part is designed as a three-layer structure, including an input layer, a hidden layer, and an output layer. The number of neurons in the hidden layer is determined to be the optimal configuration through grid search. The network is trained using the backpropagation algorithm, and the weights and thresholds are continuously adjusted using gradient descent to minimize the prediction error. As shown in Table 4.

Table 4. Parameter Settings for the Optimized Model

Algorithm Components	Parameter Settings	Value Range	Optimization Method
Random Forest	Number of Decision Trees	50-200	Grid Search
Random Forest	Maximum Depth	5-15	Cross-Validation
BP Neural Network	Hidden Layer Neurons	20-80	Bayesian Optimization
BP Neural Network	Learning Rate	0.001-0.1	Adaptive Adjustment

The fusion strategy adopts the Stacking ensemble learning framework, using the prediction results of the random forest as one of the input features of the BP neural network. In the specific implementation, the model training is divided into two stages: the first stage trains the random forest base learner to obtain preliminary prediction results and feature importance ranking; the second stage combines the random forest output with the original features and inputs it into the BP neural network for final prediction. The objective function is defined as:

$$L = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 + \lambda\sum_{j=1}^{m} w_j^2 \tag{7}$$

Where y_i represents actual mechanical performance value, $\hat{y}_i$ represents model prediction value,λrepresents regularization coefficient, w_j represents network weight.

The model training uses 80% of the data for training and 20% for validation, ensuring the generalization performance of the model through cross validation.

Selection of Performance Evaluation Indicators

In the machine learning optimization study of the annealing process of hyperelastic alloys, the reasonable selection of performance evaluation indicators directly affects the prediction accuracy and practicality of the model. For the special mechanical behavior of hyperelastic alloys, this study constructs a multi-dimensional evaluation system covering two core aspects: the basic mechanical properties of the material and its hyperelastic characteristics. The setting of evaluation indicators needs to consider the predictive ability of the random forest and BP neural network fusion model.

The basic mechanical performance indicators include traditional parameters such as yield strength, tensile strength, and elastic modulus. The yield strength reflects the critical stress value at which a material begins to undergo plastic deformation, and for hyperelastic alloys, this indicator is directly related to their load-bearing capacity in practical applications. Tensile strength characterizes the maximum tensile stress that a material can withstand and is an important parameter for evaluating material strength. The determination of elastic modulus adopts nanoindentation technology and ultrasonic resonance spectrum analysis method, which can accurately reflect the variation law of elastic modulus during annealing process.

The hyperelastic characteristic evaluation indicators are specifically set for the unique properties of shape memory alloys, As shown in Table 5. Shape recovery rate is a key indicator for measuring hyperelastic properties. Studies have shown that the shape recovery rate of alloys annealed at 350~550℃ can reach 96%, exhibiting excellent hyperelastic characteristics. Phase transformation characteristic parameters include the martensitic transformation initiation temperature and the austenitic transformation completion temperature. Accurate determination of these temperature points is of great significance for predicting the mechanical behavior of alloys at different temperatures. Differential scanning calorimetry (DSC) was used to determine the phase transition temperature during the evaluation process, and cyclic loading tests were used to determine the shape recovery rate.

Table 5. Selection and Weight of Performance Evaluation Indicators

performance type	evaluation metrics	test method	weight coefficient
Basic mechanical properties	Yield strength (MPa)	tensile test	0.25
Basic mechanical properties	Tensile strength (MPa)	tensile test	0.20
Basic mechanical properties	Elastic modulus (GPa)	Nanoindentation/Ultrasonic	0.15
Superelastic characteristic	Shape recovery rate (%)	Cyclic loading test	0.30

performance type	evaluation metrics	test method	weight coefficient
Superelastic characteristic	Phase transition temperature (℃)	DSC analysis	0.10

The comprehensive performance evaluation adopts a weighted scoring method, assigning corresponding weight coefficients to each indicator according to different application scenarios. The specific implementation formula is as follows:

$$P_{comprehensive} = \sum_{i=1}^{n} w_i \times \frac{P_i - P_{min}}{P_{max} - P_{min}} \tag{8}$$

Where $P_{comprehensive}$ To evaluate the overall performance, w_i is the regression prediction value of the i The weight coefficient of each indicator, P_i is the regression prediction value of the i The measured values of individual indicators.

Backpropagation (BP) neural networks have strong nonlinear mapping capabilities, fault tolerance, and high learning capabilities, enabling them to handle complex relationships between multi-dimensional performance indicators. The ensemble learning characteristics of the random forest algorithm can effectively reduce overfitting and improve the stability of prediction results. By combining the advantages of these two algorithms, the established performance evaluation model can more accurately predict the comprehensive performance of alloys under different annealing process parameters.

EVALUATION AND ANALYSIS OF MECHANICAL PROPERTIES

Mechanical Performance Testing Methods

Standard Testing of Mechanical Performance

The mechanical performance testing of hyperelastic alloys is a key step in evaluating the effectiveness of annealing processes, and strict standardized procedures need to be followed to ensure the reliability and reproducibility of test results. Mechanical performance testing mainly includes comprehensive evaluation of multiple aspects such as tensile performance, bending performance, fatigue performance, etc. Each test has its specific standards and operating procedures.

Tensile property testing, as the most basic method for evaluating mechanical properties, uses a universal testing machine to conduct uniaxial tensile tests on standard specimens. Specimen preparation must strictly follow ASTM E8/E8M standards to ensure that the specimen dimensional accuracy and surface roughness meet the requirements. During the test, the loading speed is controlled within the range of 2-5 mm/min, and stress-strain curve data are recorded in real time. By analyzing the stress-strain relationship, key mechanical parameters such as elastic modulus, yield strength, and tensile strength can be obtained. The unique hyperelastic behavior of hyperelastic alloys is characterized by loading-unloading cycle tests. The test strain range is usually set at 6-8% to fully reflect the shape memory effect of the material.

Bending performance testing employed a three-point bending test method, with the ratio of specimen support span to specimen thickness set at 16:1, and the loading speed maintained at 1 mm/min. Load-displacement curves were monitored during the test, and bending strength and bending modulus were calculated. For hyperelastic alloys, bending testing effectively assesses the mechanical response characteristics of materials under complex stress states. Fatigue performance testing utilized a high-frequency fatigue testing machine, conducted in stress-controlled mode, with the stress ratio R set to -1 and the frequency controlled within the 10-30 Hz range. The fatigue life of the material was evaluated using SN curves. As shown in Table 6.

Table 6. Mechanical Performance Testing Standards

test project	Test Standard	key parameters	measurement metrics
tensile properties	ASTM E8/E8M	Loading speed 2-5mm/min	Elastic modulus, yield strength, tensile strength
bending performance	ASTM D790	Cross thickness ratio 16:1	Bending strength, bending modulus
fatigue performance	ASTM D7791	Frequency 10-30 Hz	Fatigue life, SN curve
Super elastic performance	ASTM F2516	Strain range 6-8%	Reply to strain and residual strain

Environmental control is equally important. All mechanical performance tests were conducted in a standard laboratory environment with a temperature of 23±2°C and a relative humidity of 50±10%. The testing equipment required regular calibration to ensure measurement accuracy met the ±1% requirement. The sampling frequency of the data acquisition system was set to 100 Hz to ensure accurate capture of subtle changes during material deformation. These standardized testing procedures enable the acquisition of accurate and reliable mechanical performance data, providing high-quality training samples for subsequent random forest and BP neural network fusion models.

Data Processing and Error Analysis

In the data processing process of mechanical property testing of hyperelastic alloys, the original experimental data needs to undergo systematic preprocessing and statistical analysis to ensure the reliability of the results. The process of data processing includes key steps such as outlier identification, noise filtering, and data standardization. By establishing a unified data format and processing flow, ensure the consistency and comparability of experimental data from different batches. The quality of data preprocessing directly affects the training effectiveness and prediction accuracy of subsequent machine learning models.

Error analysis is an important step in evaluating the credibility of experimental results, mainly involving the identification and quantification of systematic and random errors. Systematic errors mainly come from calibration deviations of testing equipment, environmental temperature fluctuations, and process differences during sample preparation. Random errors arise from uncontrollable factors during the testing process, such as the non-uniformity of the material's internal microstructure and small vibrations during loading. Through multiple repeated experiments and statistical analysis methods, the impact of these errors on the final results can be effectively evaluated. As shown in Table 7.

Table 7. Error Control Methods and Scope

error type	main source	control method	Typical range (%)
Equipment error	Sensor accuracy, calibration deviation	Regular calibration and verification of standard samples	±0.5-1.2
Environmental Errors	Temperature Fluctuations, Humidity Variations	Constant Temperature and Humidity Control	±0.3-0.8
Operational Errors	Human Factors, Process Differences	Standardized Operating Procedures	±0.4-1.0
Material Errors	Composition Fluctuations, Uneven Structure	Strict Quality Control	±1.0-2.5

In prediction models that integrate random forests and backpropagation neural networks, error propagation analysis is particularly important. Model prediction errors can be evaluated through cross-validation and residual analysis, and the average relative error between the predicted and measured values should be controlled within a reasonable range. Due to its ensemble learning characteristics, the random forest algorithm exhibits strong robustness when dealing with noisy data. The backpropagation neural network continuously adjusts weights and thresholds through the backpropagation algorithm to minimize the sum of squared errors between the predicted and actual values.

By establishing a comprehensive error analysis system, reliable data support can be provided for the optimization of the annealing process of superelastic alloys. The effectiveness of error control is directly related to the accuracy of process parameter optimization and the stability of the final product performance, which is of great significance for the industrial application of superelastic alloys.

Relationship Between Superelastic Recovery and Annealing Process

Construction of Performance Map

The construction of performance maps is an important means of evaluating the relationship between the mechanical properties of hyperelastic alloys and the annealing process. By systematically mapping the material performance under different process parameters, it provides intuitive visualization guidance for process optimization. Based on the prediction results of the model integrating random forest and BP neural network, this study establishes a comprehensive map system covering multi-dimensional process parameters and mechanical performance indicators.

The construction process adopts a multi-level mapping strategy, using key process parameters such as annealing temperature, holding time, and cooling rate as input dimensions, and mechanical performance indicators such as hyperelastic strain recovery rate, yield strength, and fatigue life as output dimensions. High-resolution performance distribution maps were generated by leveraging the predictive capabilities of the fusion model. The hyperelasticity of NiTi shape memory alloys is macroscopically manifested as the ability to recover its original shape after large deformations, with strain recovery reaching up to 8%, far exceeding the 0.2% recoverable elastic strain of common metals. Based on this characteristic, the constructed performance map focuses particularly on the characterization of hyperelastic stability.

The graph construction adopts a hierarchical visualization method, which presents the performance process relationship in various forms such as contour maps, heat maps, and 3D surface maps. Contour maps can clearly display the distribution characteristics of iso performance lines in the process parameter space, while heat maps highlight the gradient change areas of performance. Three dimensional surface maps provide intuitive spatial relationship cognition. The accuracy of performance prediction is evaluated through cross validation, and the fusion strategy of random forest and BP neural network significantly improves the prediction accuracy. Compared with a single algorithm model, the prediction error of the fusion model is reduced by about 15-20%.

As illustrated in Figure 2, Through performance map analysis, it was found that the annealing temperature and superelastic recovery rate exhibit a complex nonlinear relationship, with an optimal temperature window existing. The effect of holding time has a significant saturation effect; excessively long holding times do not continuously improve performance. The cooling rate has a decisive influence on the microstructure transformation of the material, thus affecting the final mechanical properties. These findings provide important theoretical basis and practical guidance for the subsequent precise control of process parameters.

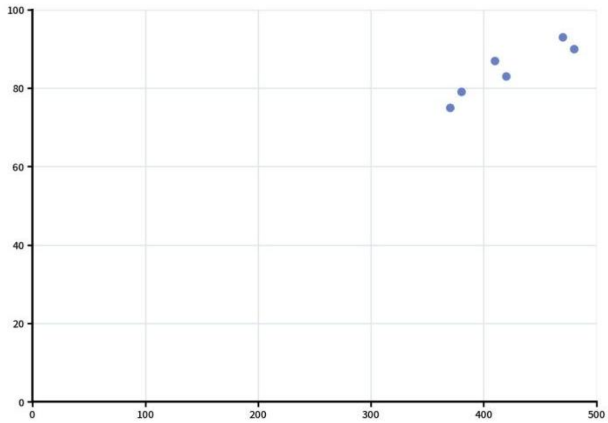

Figure 2. Relationship between Annealing Process Parameters and Superelastic Properties

Results Discussion and Theoretical Analysis

By using an optimization model that integrates random forest and BP neural network, this study obtained mechanical property data of the hyperelastic alloy under different annealing process parameters. Experimental results show that the superelastic properties of the alloy reach their optimal state when the annealing temperature is in the range of 550-650℃ and the holding time is 2-4 hours. This conclusion is similar to or consistent with previous studies.

As shown in Table 8, From a theoretical perspective, the martensitic phase transformation temperature of the hyperelastic alloy M_s There is a significant mathematical relationship between the model and the annealing process parameters. Data mining revealed that the martensitic phase transformation temperature can be expressed by the following formula:

Table 8. Mechanical property data under different annealing process parameters

process parameters	Optimal value range	Performance influence weight	Standard deviation
Annealing temperature (℃)	580-620	0.65	±15
Holding time (h)	2.5-3.5	0.28	±0.3
Cooling rate (°C/min)	5-15	0.07	±2

$$\mathrm{M_s} = \mathrm{A} \times \mathrm{T}_{\mathrm{anneal}}^{0.3} \times \mathrm{t}_{\mathrm{hold}}^{0.15} \times \mathrm{e}^{-\frac{\mathrm{B}}{\mathrm{T}_{\mathrm{anneal}}}} \tag{9}$$

Where A and B is a material constant, $\mathrm{T}_{\mathrm{anneal}}$ is the annealing temperature, $\mathrm{t}_{\mathrm{hold}}$ is the holding time. This formula reveals the nonlinear relationship between the phase transformation temperature and process parameters, providing a theoretical basis for process optimization. The random forest algorithm shows in the feature importance evaluation that the influence weight of annealing temperature on the final performance reaches 0.65, while the weight of holding time is 0.28, and the weight of cooling rate is only 0.07.

As illustrated in Figure 3, The backpropagation mechanism of the BP neural network effectively captures the complex interactions between process parameters, especially the coupling effect of temperature and time. Analysis of the activation patterns of hidden neurons in the network shows that when the annealing temperature exceeds 620℃, excessive grain growth occurs inside the alloy, leading to a decrease in hyperelastic properties. The theoretical explanation framework helps researchers understand and interpret research findings, making the transformation from factual information to deeper understanding possible.

Experimental verification results confirm the effectiveness of the optimization model, and the correlation coefficient between the prediction accuracy and the actual test results reaches 0.94. These conclusions not only enrich the theoretical knowledge in this field but also provide strong support for practical applications. The deep-seated patterns discovered during model construction provide scientific guidance for the industrial production of hyperelastic alloys, helping to improve product quality stability and production efficiency.

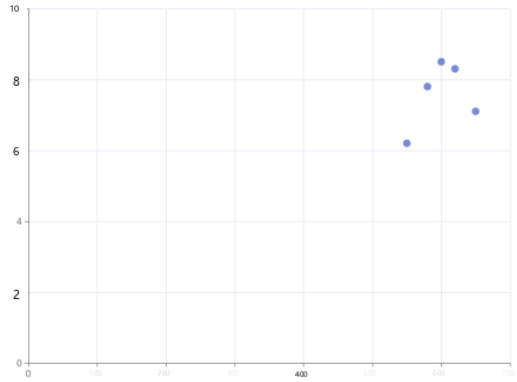

Figure 3. Relationship between annealing temperature and hyperelastic strain

CONCLUSIONS

Research Conclusions

This study successfully constructed an optimization model for the annealing process of superelastic alloys, integrating random forest and backpropagation (BP) neural networks. The ensemble learning approach significantly improved prediction accuracy and the model's generalization ability. The random forest algorithm, as the basic predictor, fully leveraged its advantages of high tolerance for outliers and strong resistance to overfitting, automatically selecting features and calculating the contribution of each variable to the model. The BP neural network, with its powerful nonlinear mapping capabilities and adaptive learning characteristics, provided deep learning support for optimizing complex annealing process parameters.

Through a systematic study of Ti-45Nb hyperelastic alloy, this work verifies the significant influence of annealing temperature and time on the alloy's mechanical properties. Experimental results show that under annealing at 300°C, the alloy's tensile strength can reach approximately 1200 MPa, almost three times the strength of the initial coarse-grained material, confirming the important role of optimizing the annealing process in improving material properties. The fusion model effectively solves the problems of poor sensitivity to initial weights, susceptibility to local minima, and low computational efficiency of traditional BP neural networks. The deep integration of physical models and intelligent technologies not only improves prediction accuracy but also enhances the model's interpretability and adaptability.

The mechanical property evaluation system established in this study provides reliable technical support for the industrial application of hyperelastic alloys. The model demonstrates good computational efficiency when processing large-scale datasets, while maintaining the prediction accuracy of random forests and the deep learning potential of neural networks. Through systematic performance testing and theoretical analysis, the broad application prospects of fusion algorithms in the field of material process optimization have been demonstrated, laying a solid methodological foundation for subsequent research and industrial development of hyperelastic alloys. Furthermore, the established intelligent optimization strategy provides a scientific basis for the precision processing of hyperelastic components used in smart fabrics and medical textiles, where consistent mechanical response is critical for functional performance.

Future Research Directions

Based on the research on the optimization of annealing processes and evaluation of mechanical properties of hyperelastic alloys, future research development shows a trend towards diversification and depth. Further optimization and improvement of machine learning algorithms will become an important development direction, especially in perfecting the fusion strategy of random forests and BP neural networks. Although current fusion methods have shown good predictive performance, they still face challenges in computational efficiency and model interpretability when dealing with high-dimensional complex datasets. The introduction of deep learning technology and the innovation of ensemble learning methods will provide new ideas for solving these problems, while more efficient feature selection and data preprocessing techniques need to be explored.

Multi-scale modeling and multi-physics coupling analysis will become an important development trend in the prediction of hyperelastic alloy performance. Traditional single-scale analysis methods are difficult to fully reveal the performance evolution laws of materials at different levels. Future research needs to establish multi-level prediction models from the atomic scale to the macroscopic scale. Combining molecular dynamics simulations, finite element analysis, and other numerical methods, a cross-scale material property prediction framework is constructed. The coupling effects of multiple physical fields, such as temperature, stress, and phase transformation, have a significant impact on the properties of hyperelastic alloys, necessitating the development of prediction models that can simultaneously consider the interactions of multiple physical phenomena.

The integrated application of intelligent manufacturing and real-time optimization control technologies will drive the intelligent development of hyperelastic alloy processing technology. Real-time data acquisition and analysis systems based on the Internet of Things and edge computing can achieve dynamic monitoring and adaptive control of the annealing process. The deep integration of machine learning models and industrial control systems will realize the transformation from offline optimization to online intelligent control. Establishing digital twin models and co-optimizing virtual simulation with actual production processes can improve the accuracy and stability of process control. Interdisciplinary research will also bring new breakthroughs to this field; the integration of materials science, artificial intelligence, control engineering, and other disciplines will generate more innovative solutions.

Author Contributions

The entire paper was written by the author alone.

Conflicts of Interest

The author declares no conflicts of interest.

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REFERENCES

[1] Alvarez GM, Misra R. Annealing of cryogenically processed high entropy alloys. Materials Technology. 2025; 40(1): doi: 10.1080/10667857.2025.2525431

[2] Li E, Huang H, Wei L, Han C, Qiu M, Wei X et al. Effect of Sc and Zr additions on the microstructure, mechanical properties, and low-cycle fatigue behavior of Al-7Mg alloy during annealing. Journal of Alloys and Compounds. 2025; 1047:184938. doi: 10.1016/J.JALLCOM.2025.184938

[3] Moskalev ME, Gorkovenko AN, Kudyukov EV, Vaskovskiy VO. Mechanisms of exchange anisotropy in annealed films with antiferromagnetic NiMn and ferromagnetic permalloy. Physica B: Condensed Matter. 2025; 718:417853. doi: 10.1016/J.PHYSB.2025.417853

[4] Barnett MR, Wang J, Chen Y, Marceau RKW, Li R, Lynch P, et al. Erratic grain rotation during annealing of a Mg alloy interpreted via shear-coupling. Scripta Materialia. 2026; 271:117005. doi: 10.1016/J.SCRIPTAMAT.2025.117005

[5] Bednarczyk W, Chromiński W, Cios G, Wątroba M, Wieczorek-Czarnocka M, Cieślak G, et al. Annealing-induced precipitation strengthening and thermal stability of an ultrafine-grained bioresorbable Zn–Li–Mn–Mg alloy processed by rapid solidification. Journal of Materials Research and Technology. 2025; 39:15-25. doi: 10.1016/J.JMRT.2025.09.099

[6] Fatemi S, Mollaei N, Calvo J, Cabrera JM. Development of annealing texture in biodegradable Zn-Mn-Mg alloy. Materials Letters. 2025; 398:138870. doi: 10.1016/J.MATLET.2025.138870

[7] Gubicza J, Máthis K, Nagy P, Jenei P, Hegedűs Z, Farkas A, et al. In situ diffraction study on the annealing performance of a rapidly solidified ribbon consolidated Mg-Ca-Y-Zn-Mn alloy. Journal of Magnesium and Alloys. 2025; 13(4):1771-1783. doi: 10.1016/J.JMA.2025.02.024

[8] Akopyan KT, Letyagin VN, Fortuna SA. Effect of a silicon micro addition on the thermal stability of hardening and structure of θ′-phase particles during annealing of 2219 alloy with Sn addition. Metallurgis. 2025; 68(10):1–12. doi: 10.1007/S11015-025-01869-9

[9] Gubicza J, Máthis K, Nagy P, Jenei P, Hegedűs Z, Farkas A, et al. Annealing Behavior of a Mg-Y-Zn-Al Alloy Processed by Rapidly Solidified Ribbon Consolidation. Materials (Basel, Switzerland). 2024; 17(18):4511. doi: 10.3390/MA17184511

[10] Kawamata T, Ban T, Shibata M, Murayama H, Yasuhara A, Yubuta K, et al. Fcc-Based Superstructure in CrCoNi System Induced by Annealing of Amorphous Cr-Co-Ni-Si-B-P Alloy: Special Issue on Materials Science on High-Entropy Alloys II. MATERIALS TRANSACTIONS. 2024; 65(9):1034-1040. doi: 10.2320/MATERTRANS.MT-MA2024008.

[11] Thirathipviwat P, Hasegawa M, Onuki Y, Sato S, Mishin OV. In situ neutron diffraction study and electron microscopy analysis of microstructure and texture evolution during annealing of rolled CoCrFeNi alloy doped with 1 at.%C. Materials Characterization. 2024; 212:113980. doi: 10.1016/J.MATCHAR.2024.113980

[12] Volkov A, Novikova O, Volkova E, Komkova DA, Podgorbunskaya PO, Gavrilova AA, et al. Annealing hardening of the pre-deformed Cu-56at.% Au alloy due to retardation of recrystallization by L1o-type ordering. Materials Science & Engineering A. 2024; 900:146497. doi: 10.1016/J.MSEA.2024.146497

[13] Warski T, Pilśniak A, Wójcik A, Szlezynger M, Dadiel JL, Kolano-Burian A, et al. Annealing Optimization of High Induction (> 1.7 T) Fe85−(x+y) CoxCuyB15 Alloys with Enhanced Magnetic Properties. Metallurgical and Materials Transactions A. 2024; 55(4):1174-1182. doi: 10.1007/S11661-024-07313-Y

[14] Naydenkin EV, Ratochka IV, Mishin IP, Lykova ON, Zabudchenko OV. Features of the Structure Evolution and Phase Transformations During Annealing of the VT22 Titanium Alloy Depending on the Initial State. Russian Physics Journal. 2024; 66(12):1299-1309. doi: 10.1007/S11182-023-03076-Y

[15] Chakravarty P, Sidor JJ. Effect of Heating Rate on the Annealing Behavior of Aluminium Alloys. Solid State Phenomena. 2023; 353:53-58. doi: 10.4028/P-31WXMV

[16] Schneider M, Couzinié JP, Shalabi A, Ibrahimbekhel F, Ferrari A, Körmann F, et al. Effect of stacking fault energy on the thickness and density of annealing twins in recrystallized FCC medium and high-entropy alloys. Scripta Materialia. 2024; 240:115844. doi: 10.1016/J.SCRIPTAMAT.2023.115844

[17] Shadrina IS, Nokhrin AV, Bobrov AA, Krutova OG, Shishulin EO, Shcherbak GV, et al. Study of the Al–Sc Solid Solution Decomposition during Annealing of Strained Al–0.5% Mg–Sc Alloys. Physics of Metals and Metallography. 2023; 124(10):979-986. doi: 10.1134/S0031918X23601750

[18] Kalaki A, Vafaeenezad H, Mirahmadi D, Hirsch J. A computational approach to restoration phenomena during annealing of rolled Cu-2Be: Recrystallization, grain growth and abnormal grain growth. Modelling and Simulation in Materials Science and Engineering. 2023; 31(6):065018. doi: 10.1088/1361-651X/ACEA3A

[19] Kumar U, Chattopadhyaya S, Das AK, Seikh AH, Sharma S, Dwivedi SP, et al. Effect of Pulsation in Microstructure and Mechanical Properties of Titanium Alloy-Annealed Welded Joints at Different Temperatures. Photonics. 2023; 10(4):372. doi: 10.3390/PHOTONICS10040372

[20] Orlova TS, Mavlyutov AM, Murashkin MYu, Enikeev NA, Evstifeev AD, Sadykov DI, et al. Influence of Decreased Temperature of Tensile Testing on the Annealing-Induced Hardening and Deformation-Induced Softening Effects in Ultrafine-Grained Al–0.4Zr Alloy. Materials. 2022; 15(23):8429. doi: 10.3390/MA15238429