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SHAPE MEMORY ALLOYS AND MACHINE LEARNING: A REVIEW

Shape memory alloys (SMAs) have found widespread application in various fields of science and technology due to their unique properties, such as superelasticity and shape memory effect. These alloys retain their initial form by memorising it between two transformation phases, which is temperature or magnetic field-dependent. The application of such materials is straightforward. The alloy can be deformed by force and recover to its initial shape or size after heating over a specific temperature. There are a lot of various kinds of SMA, for instance, Fe–Mn–Si, Cu–Zn–Al, and Cu–Al–N, and every type of SMA is applied specifically, though Nitinol Ni-Ti is ubiquitous because of its stable properties

SMAs are widely used in medicine, the aerospace industry, motor building, civil engineering, dentistry, etc. During their operation, structural elements made of SMAs undergo long-term cyclic loading that can lead to premature loss of functional properties, exhaustion of lifetime, and subsequent failure. Therefore, ensuring sufficient functional properties and endurance of SMA is necessary. Often, the experiments are quite costly and time-consuming and require expert knowledge. Therefore, it is crucial to model the functional and structural properties of SMAs by employing AI (Artificial intelligence) and machine learning (ML) methods.

AI can be employed to model SMA behaviour. AI is actively used in material science and fracture mechanics ML is a part of AI that can efficiently solve complicated tasks. This study aims to perform a comprehensive review of the application of ML methods to estimate various properties of shape memory alloys. A comprehensive analysis of ML methods was performed as applied to modelling various properties of SMAs. Several studies concern the application of methods of AI and ML to solve such problems. In general, AI and ML methods are promising and powerful tools to model the SMAs properties. Nevertheless, there is always room for improvement and further elaboration of the aforementioned methods and approaches for modelling the functional and structural properties of SMAs

Keywords: shape memory alloys, machine learning, artificial intelligence, neural network, functional properties.

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СПЛАВИ З ПАМ'ЯТТЮ ФОРМИ І МАШИННЕ НАВЧАННЯ: ОГЛЯД

Сплави з пам'яттю форми (СПФ) широко застосовують у різних галузях науки і техніки завдяки їхнім унікальним властивостям, таким як псевдопружність і ефект пам'яті форми. Загалом, згадані вище сплави зберігають свою початкову форму, запам'ятовуючи її між двома фазами перетворення, що залежить від температури або магнітного поля. Застосовувати такі матеріали нескладно. Сплав можна деформувати і відновити його початкову форму або розмір після нагрівання при певній температурі. Існує багато різних типів СПФ, наприклад, Fe–Mn–Si, Cu–Zn–Al та Cu–Al–N, і кожен тип СПФ застосовують окремо, хоча Nitinol Ni-Ti можна знайти повсюдним через його стабільні властивості.

СПФ широко застосовують у медицині, аерокосмічній промисловості, моторобудуванні, цивільному будівництві, стоматології та ін. Під час експлуатації елементи конструкцій з СПФ зазнають тривалих циклічних навантажень, що може призвести до передчасної втрати функціональних властивостей, вичерпання ресурсу та подальшого виходу з ладу. Тому необхідне забезпечення достатніх функціональних властивостей і довговічності СПФ. Часто експерименти є досить дорогими та тривалими та вимагають експертних знань. Для моделювання поведінки SMA можна використовувати штучний інтелект (AI). ШІ активно використовується в матеріалознавстві та механіці руйнування. Машинне навчання (МН) є частиною ШІ, яка може ефективно вирішувати складні завдання. Тому вкрай важливо моделювати функціональні та структурні властивості СПФ за допомогою методів ШІ та МН.

Мета даної статті - здійснити комплексний огляд застосування методів МН для оцінки різних властивостей СПФ. Проаналізовано методи МН для моделювання різних властивостей СПФ. Кілька досліджень стосуються застосування методів штучного інтелекту та машинного навчання для вирішення таких проблем. Загалом, методи ШІ та МН є перспективними та потужними інструментами для моделювання властивостей СПФ. Тим не менше, завжди є місце для вдосконалення та подальшої розробки вищезгаданих методів і підходів до моделювання функціональних та конструкційних властивостей СПФ.

Ключові слова: сплави з пам'яттю форми, машинне навчання, штучний інтелект, нейронна мережа, функціональні властивості.

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INTRODUCTION

Shape memory alloys (SMAs) gain a vast attention due to their unique shape memory effect (SME) and superelasticity (SE) caused by the martensitic transformation (MT) and its reverse transformation [1, 2, 3, 4].

SMAs are metallic alloys that can retain their initial form by memorising it between two transformation phases: temperature or magnetic field dependent. The application of such materials is straightforward. The alloy can be deformed by force and recover to its initial shape or size after heating over a specific temperature [5]. There are a lot of various kinds of SMA, for instance, Fe–Mn–Si, Cu–Zn–Al, and Cu–Al–N, and every type of SMA is explicitly applied, though Nitinol Ni-Ti is ubiquitous because of its stable properties [6]. SMA is widely used in medicine [7], the aerospace industry [8], motor building [9], civil engineering [10], etc. During their operation, such elements undergo long-term cyclic loading that can lead to premature loss of functional properties, exhaustion of their lifetime, and subsequent failure. Therefore, ensuring sufficient functional properties and endurance of SMA is necessary.

Often, the experiments are pretty costly and time-consuming and require expert knowledge. Therefore, it is crucial to model the functional and structural properties of SMAs by employing AI and ML methods.

MAIN PART

Some works are related to solving problems of fracture mechanics by employing AI and ML methods. For instance, the strength and lifetime of structural elements were predicted in the studies [11, 12]. One of the pioneers in the field of prediction of short cracks by NN was G. M. Seed and G.S. Murphy [13].

The endurance limit and fatigue limit at various stress ratios were forecasted in the paper [14]. The work determined the crack closure parameters by employing NN [15]. In the studies [16], the cumulative distribution function of fatigue lifetime was predicted using NN. The proposed model had two input neurons and one output neuron. The inputs of the mode were the stress value S, and time t, when the stress was applied. The input dataset was based on the experimentally determined S-N-P curves for steel SAE 8620. The number of neurons on the hidden layer was taken as 5, then increased to 10, and finally to 15. The value of the maximum likelihood function computed with the optimized lognormal distribution function was chosen as the loss function L. Therefore, a NN predicted the maximum likelihood function value better than that obtained with the lognormal distribution function. The neural network training was stopped when the value of L obtained with this model was superior to that achieved with the lognormal distribution. Afterwards, these approaches were further elaborated in the studies [17] to estimate the residual lifetime based on the analysis of the damage model in the case of a wide-band Gauss process with two peaks. In the study [18], an NN was employed to identify small fatigue cracks. In the paper [19], a fatigue growth rate was predicted using machine learning. In the work [20], a new approach was proposed to assess fatigue damage based on NN. It was shown that the NN-based approach showed a higher accuracy of lifetime prediction of chassis components for specific loading sequences in comparison with the Palmgren-Miner rule. In the study [21], an alternative method was proposed that allows the prediction of fatigue lifetime under random loading based on image recognition using NN. High correlation coefficient and best-fit coefficients were obtained in comparison with rainflow matrix method, which is based on Miner rule. Machine learning methods in recent years have frequently been employed to create SMAs with optimal functional properties and to predict their physical and mechanical properties, chemical composition and radii of elements atoms [22], temperature dependencies of pseudo-elastic recovery strain [23].

Artificial intelligence (AI) can be employed to model SMA behavior. This field has changed drastically in the course of history. AI is actively used in material science and fracture mechanics [24, 25].

Machine learning (ML) is a part of AI [26] that can efficiently solve complicated tasks. It showed remarkable success in the field of smart materials modelling [27, 28]. Material discovery is performed by AI methods [29].

In the study of [30], Artificial Intelligence Material Selection (AIMS) framework was developed and elaborated. This framework is sophisticated software based on machine learning methods that allow exploring and discovering SMA with desired properties. In this study. there were spotted SMA with a minimum transformation range and an actuation strain of at least 1.5% under an applied stress of 50 MPa or more. The dataset comprised of 88 features concerning materials composition, processing, and test parameters, and 26 material responses regarding the functional properties and microstructure characteristics. Random Forest, Extreme Gradient Boosting, and Deep Neural Network regressors were employed, and hyperparameters were tuned by Hyperopt. For the NN, a ReLU activation function was utilized at each layer. L2 regularization and dropout were employed with an optimum dropout rate of 0.4 to avoid overfitting. Early stopping also improved model robustness and the loss was analyzed with the binary cross-entropy (CE) method, comparing the ground truth and predicted properties and updating the weights and biases via back propagation and gradient descent to minimize the loss function.

The paper of [31] identified NiTiHf alloys that can be used as actuators in space. Seven machine learning (ML) models were tested, and the best-fit model was chosen to determine new alloy compositions with the pre-set transformation temperature (Ms), thermal hysteresis, and work output. There were ulitilized the following models: Linear regression model, Polynomial regression model, Support vector regression with linear kernel, Support vector regression with polynomial kernel, Support vector regression with rbf kernel, K-nearest neighbouring KNN, and NN. The algorithm employed was as follows. The transformation temperature (MS), thermal hysteresiss (TH), and work output (WO) were predicted by corresponding ML method. The algorithm starts with data collection and pre-processing. MLMS was trained, tested, and validated as the first step of the ML training process, identifying new NiTiHf alloy compositions. The number of compositions depends on the user's requirement and their customizability. Afterwards, MLTH was trained, tested, and checked. The composition identified from the MLMS was utilized to predict the TH for the compositions. The compositions with larger TH were brought forward. trained, tested, and validated via MLWO to find the WO for the compositions filtered from MLTH . The compositions with larger WO were chosen as final compositions. In that study, the K-nearest neighbours ML model showed the best results in discovering NiTiHf alloys with stable, functional properties with small root mean square errors (RMSE). For MS, RMSE = 5.11, as for TH, RMSE = 1.17, and, for WO, RMSE = 1.21.

In the paper of [32], the ML approach was proposed, which was specifically designed considering the dynamic SMA behavior. This approach effectively allows determining the thermodynamic parameters of SMA. The proposed method is based on feed forward artificial neural network (ANN) architecture. After training, the ANN can find the required model parameters from cyclic tensile stress-strain tests. The elaborated method was applied on SMA wires and agreed well with experimental data.

In [33], the aim was to find out whether video data analysis methods in conjunction with ML approaches can be employed to build a computer vision based predictive system to forecast a force generated by the movement of a SMA body. It was determined that video capture of the SMA body bending by means of computer vision method into a machine learning model, can forecast the amount of actuation force generated by the body. The elaborated approach combined computer vision and machine learning to describe novel SMA materials and estimate force generated by a moving SMA body under external excitement. The video of a moving SMA body was obtained via infrared digital camera, whilst measuring the force. The measured force was used ground truth for all future modelling. The change in the position and shape of the SMA body compared to its original position and shape under excitement, was taken from the video frames. This data about shape and position were correlated with the separately measured generated force for using the proposed predictive modelling. It was chosen to use vision based supervised Restricted Boltzmann Machine (RBM) approach together with a machine learning classifier algorithm to make this estimation. RBM based feature extraction and Random forest classification algorithms allowed to get 93 % force and stress prediction accuracy.

In the study of [34], a deep neural network (DNN) was used to improve the design of experiments of SMA electrochemical machining (ECM). The DNN employed in this paper had four layers. The input layer had 3 neurons. The first hidden layer had 50 nodes, the second layer comprised of 20 nodes, and the third layer consisted of 10 nodes. Each layer except the output utilized ReLU as an activation function and Softmax function was used on the output layer. A Back Propagation Algorithm with coefficients based on the Gradient Descent method was employed. To avoid overshooting, the learning rate was tested and the result was set at 0.001. Also, batch size was set to 3, and the Adam optimizer was taken with proper step direction and step size. The machining time, voltage and inter-electrode gap (IEG) were the inputs, and the hole size and depth were predicted by DNN. The DNN predicted that the values were quite consistent between 98.6% and 100.6%. It was determined that DNN is a more useful method than conventional approaches. The machining results were forecasted with high precision by applying ECM and DNN to SMA.

In the work of [35], SMA was employed in robotic hand. A reinforcement learning (RL) algorithm was applied to the above-mentioned hand actuated by SMA to control motion. The elaborated hand can achieve the required bending state and efficiently take the object with the attained bending state.

In the study of [36], a method was proposed to model the behavior of SMA by employing an NN. This ANN allows accurate and effective prediction of SMA displacement and temperature. There was presented a method to eliminate the position sensor using (NN) to compensate for the non-linearity. The proposed model predicts displacement and temperature. The study results show that NN are much more effective at modeling SMAs.

In the work of [37], AI that consisted of Computer Vision (CV) and ML approaches were applied to automate SMA characterization process. The authors discovered that an Extreme Gradient Boosting (XGBoost) regression model-based ML system trained on a quite large dataset can achieve 99% overall prediction accuracy. The elaborated system contributes largely towards material design optimization of machine SMA foils.

In [38], a deep learning method was utilized to study the behavior of hyperelastic materials in medicine. AI was utilized to various characteristics of smart materials, such as composites and sandwiches (CSs). The bending strength was modelled in [39]. The authors built ANNs in MATLAB and compared the modelling results with the experiments. The Levenberg–Marquardt (LM) algorithm for training was verified and its results were checked against the backpropagation algorithm. The metrics for the comparison were as follows: performance, regression correlation (R), and mean squared error (MSE).

CONCLUSIONS

A comprehensive analysis of machine learning methods was performed as applied to modelling various properties of shape memory alloys. The advantage of application such models is that it avoid in certain cases the direct experiment provided the sufficient amount of data exists. The experimental studies can be costly and require a lot of human labour, expensive laboratory equipment and time. As for the drawback of these models, sometimes they are not quite explainable and act in certain cases as a black box. In general, the type of ML model that is best in terms of chosen metrics depends heavily on the dataset and the solved problem. In some cases, NN are the best, while in the others KNN are best, and in some others SVM outperforms the others. There is no unique recipe which method will provide the best results and trials and errors method should be utilized. In general, the methods of AI and ML are quite promising and are powerful tools to model the properties of shape memory alloys.

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