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AN OPTIMISED STACKING ENSEMBLE MACHINE LEARNING MODEL FOR PREDICTING THE HYSTERESIS BEHAVIOUR OF SHAPE MEMORY ALLOYS

OPTIMIZOVANI STACKING ANSAMBL MODEL MAŠINSKOG UČENJA ZA PREDVIĐANJE HISTEREZISNOG PONAŠANJA MEMORIJSKIH LEGURA

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Keywords
- shape memory alloys (SMA)
- hysteresis behaviour
- machine learning
- stacking model
- ensemble model

Abstract

The study investigates the possibility of predicting the hysteresis behaviour of a NiTi shape memory alloy (SMA) under cyclic loading using machine learning methods. Based on experimental test data obtained from SMA wire specimens, an ensemble model of the Stacking Regressor type is developed, combining the Random Forest, Gradient Boosting, Extremely Randomised Trees, k-Nearest Neighbours, Support Vector Regression, and Multi-Layer Perceptron algorithms. The ElasticNet algorithm is employed as the meta-model. The ensemble structure and model hyperparameters are optimised using the GridSearchCV procedure with group cross-validation. The results demonstrate high accuracy in strain prediction across different cyclic loading frequencies. The coefficient of determination R^2 for the test data exceeds 0.996. The proposed model also exhibits strong generalisation when predicting material behaviour beyond the training range and accurately reproduces the shape of hysteresis loops in the stress-strain diagram.

Ključne reči
- memorijske legure (SMA)
- histerezisno ponašanje
- mašinsko učenje
- stacking model
- ansambl model

Izvod

U radu je istražena mogućnost predviđanja histerezisnog ponašanja NiTi memorijske legure tokom cikličnog opterećenja primenom metoda mašinskog učenja. Na osnovu eksperimentalnih podataka dobijenih ispitivanjem SMA žice razvijen je ansambl model tipa Stacking Regressor, koji kombinuje algoritme Random Forest, Gradient Boosting, Extremely Randomised Trees, k-Nearest Neighbours, Support Vector Regression i Multi-Layer Perceptron. Kao metamodel primenjen je algoritam ElasticNet. Optimizacija strukture ansambla i hiperparametara modela izvršena je primenom metode GridSearchCV uz korišćenje grupne kros-validacije. Dobijeni rezultati pokazuju visoku tačnost predviđanja deformacije za različite frekvencije cikličnog opterećenja. Vrednosti koeficijenta determinacije R^2 za ispitne podatke prelaze 0.996. Model takođe pokazuje dobru sposobnost generalizacije pri predviđanju ponašanja materijala izvan opsega ciklusa korišćenih za obuku i pravilno reprodukuje oblik histerezisnih petlji na dijagramu napon-deformacija.

INTRODUCTION

Shape memory alloys (SMAs) belong to a class of smart materials characterised by unique functional properties, most notably the shape memory effect and superelasticity. These phenomena are caused by reversible phase transformations between the martensitic and austenitic phases, enabling the material to withstand significant deformation and recover its original shape after unloading or heating. Owing to these properties, SMAs have found wide applications in medicine /1/, aerospace engineering /2/, space technology /3/, robotics /4/, civil engineering /5/, and automation /6/.

One of the characteristic features of the mechanical behaviour of SMAs under cyclic loading is the formation of hysteresis loops in the stress-strain relationship. These loops reflect the complex interaction between phase transformations, energy dissipation processes, and the evolution of the material's internal structure.

The area of the hysteresis loop corresponds to the energy dissipated during a single loading-unloading cycle. Quantitatively, the dissipated energy can be calculated using the following expression:

$$W_{diss} = \int_{\varepsilon_{\min}}^{\varepsilon_{\max}} (\sigma_1(\varepsilon) - \sigma_2(e))d\varepsilon \,, \qquad (1)$$

where: σ is mechanical stress (MPa); ε is relative strain (dimensionless); $\sigma_1(\varepsilon)$ and $\sigma_2(\varepsilon)$ represent stress-strain relationships during the loading and unloading stages of a single cycle, respectively.

The value of W_{diss} is an important functional property of SMAs, as it reflects the material's ability to dissipate mechanical energy and damp vibrations.

The geometry of the hysteresis loop and the magnitude of the dissipated energy are determined by a combination of thermodynamic, kinetic, and operational parameters of the material. Among the key characteristics are the start and finish temperatures of the forward martensitic transformation, M_s and M_f, as well as those of the reverse austenitic transformation, A_s and A_f. These parameters define the conditions the phase transformations occur in the alloy. The frequency of the applied cyclic loading f (Hz) also signifi-

cantly influences the shape and area of the hysteresis loop. In addition, the nature of the hysteretic response evolves with an increasing number of loading-unloading cycles *N*.

The frequency of the applied external loading is one of the important factors determining the functional properties of shape memory alloys /7/. Its influence becomes particularly evident under repeated cyclic loading, when forward and reverse martensitic-austenitic phase transformations are periodically activated. Changes in frequency directly affect the processes occurring in the material during deformation. At high frequencies, self-heating of the material may occur due to insufficient heat dissipation generated during phase transformations. This leads to a local temperature increase and a shift in phase transition temperature limits. Loading frequency significantly influences the shape of the hysteresis loop in the stress-strain diagram. As the frequency increases, the loop geometry changes, directly affecting its area and, consequently, the amount of energy dissipated during a single loading-unloading cycle, /8/.

Accurate prediction of hysteresis behaviour is crucial for assessing the reliability, durability, and operational efficiency of structures employing shape memory alloys. At the same time, modelling the nonlinear behaviour of SMAs remains a challenging scientific problem. Classical constitutive models often require complex mathematical formulations and a large number of parameters. Moreover, such approaches are not always able to adequately reproduce the evolution of hysteresis behaviour under repeated loading cycles.

In this context, increasing attention has recently been devoted to approaches based on machine learning which enable modelling of complex nonlinear relationships without the need for explicit formulation of physical equations /9-11/. The use of machine learning algorithms enables the identification of hidden patterns in large experimental datasets and the development of highly accurate predictive models of the mechanical behaviour of materials, /12-14/.

The aim of this study is to develop a stacking-based ensemble machine learning model to predict the hysteresis behaviour of a NiTi alloy under cyclic loading conditions. The results obtained make it possible to evaluate the effectiveness of a data-driven approach for reproducing the complex, nonlinear behaviour of SMAs and predicting the evolution of hysteresis loops during cyclic loading.

MATERIAL AND METHODS

Experimental setup and material description

To construct the dataset used for training and testing the machine learning models, experimental results obtained from tests of a NiTi shape memory alloy wire are used. The experiments are conducted on wire specimens with a diameter of 1.5 mm and length of 210 mm during low-cycle fatigue tests /15/.

Experiments were carried out at room temperature using a servo-hydraulic testing machine STM-100 which provides controlled cyclic loading of the specimen (Fig. 1).

The chemical composition of the investigated alloy was 55.78 % Ni and 44.12 % Ti, while the total content of impurities (Co, Cu, Cr, Fe, Nb, C, H, O, N) did not exceed 0.1 %.

Figure 1. Experimental setup on the servo-hydraulic testing machine STM-100.

Dataset structure and feature definition

The constructed dataset includes the following input features: material stress σ (MPa), denoted as stress; the loading-unloading cycle number *N*; and an indicator of the loading or unloading stage (the UpDown variable). The material strain ε (%) is selected as the target variable (strain).

The dataset contains strain and stress measurements obtained during cyclic loading of the SMA specimen at 0.3, 0.5, 1, 3, and 5 Hz. In this study, experimental data corresponding to 100-250 loading-unloading cycles of the SMA are used. The selection of this cycle range is explained by the fact that, within this interval, the hysteresis loops exhibit a relatively stable shape, which is associated with the stabilisation of functional properties after the initial stage of cyclic loading. This ensures the formation of a representative dataset suitable for training machine learning models.

The number of samples (measurements) in the dataset for each of the five frequencies is presented in Table 1.

Table 1. Number of samples in the dataset for loading frequencies.

Frequency (Hz)	0.3	0.5	1	3	5
Number of samples	16912	3051	16006	18573	14949

Data splitting and cross-validation strategy

To construct the training and test sets, the GroupShuffle Split method implemented in the Python scikit-learn library is applied. This method ensures a random split of the data into training and test subsets while accounting for the group membership of observations. In this study, the loading cycle number *N* is used as the grouping index. This prevents data from the same cycle from appearing simultaneously in both the training and test sets, thereby avoiding information leakage during model evaluation. The data are split at an 80/20 ratio, with 80 % used for model training and the remaining 20 % for independent evaluation of generalisation.

Stacking ensemble model construction

Based on the prepared datasets, an ensemble model of the Stacking Regressor type is developed /16/. One of the key stages in constructing such an ensemble is selecting an optimal combination of base algorithms.

To determine the optimal structure of the stacking ensemble, a search is conducted among different combinations of

base machine learning algorithms. Six regression algorithms representing different approaches to modelling nonlinear relationships are selected as candidates for forming the ensemble: Random Forest (RF) /17/, Gradient Boosting Regressor (GBR) /18/, Extremely Randomised Trees (ET) /19/, K-Nearest Neighbors /20/, Support Vector Regression (SVR) /21/, and Multi-Layer Perceptron (MLP) /22/.

To investigate the influence of ensemble composition on prediction quality, all possible combinations of the selected models are generated. Each combination is considered as a separate configuration of the stacking ensemble. This approach enables evaluation of how model accuracy changes with the set of algorithms in the ensemble.

To avoid overly simple ensemble structures, the number of base models in each combination is limited. In this study, ensembles containing from three to six base algorithms are considered. Such an approach ensures sufficient model diversity within the ensemble while maintaining computational efficiency.

For each generated combination, a stacking model is constructed, with the base algorithms' predictions are used as input features for the ElasticNet meta-model /23/. This allows the ensemble to combine the strengths of different algorithms and better capture complex nonlinear relationships between the input features and the target variable. Such an approach provides a comprehensive exploration of the space of possible ensemble structures and enables identification of the configuration of models that achieve the best balance between prediction accuracy and stability.

ElasticNet algorithm combines the properties of Lasso and Ridge regularisation, enabling simultaneous selection of informative features and reduction of model overfitting.

Model optimisation and selection criteria

The optimal hyperparameter values for the base models and the meta-model are selected using the GridSearchCV method /24/ with the neg_mean_squared_error metric. To ensure a reliable evaluation of the model while accounting for the structure of the data, a specialised wrapper Group KFoldWith Groups is applied. This approach enables cross-validation while accounting for observations' group membership. In this study, the loading cycle number N is used as the grouping index, which prevents data from the same cycle from appearing in different subsets during the validation process.

During cross-validation, the dataset is divided into $K_f = 5$ subsets (folds). For each fold, the model is trained on $K_f - 1$ subsets and evaluated on the remaining part of the data. Prediction performance is assessed using the Mean Squared Error (MSE) metric, which for the k-th fold is defined as:

$$MSE_k = \frac{1}{n_k}\sum_{i=1}^{n_k}(y_i - \hat{y}_i)^2 \tag{2}$$

where: y_i is experimental strain value for the i-th measurement; $\hat{y}_i$ is the value predicted by the Stacking model for the i-th observation; and n_k is number of observations in the k-th fold.

In general form, the prediction of the ensemble Stacking model is defined as a linear combination of the predictions of base models:

$$\hat{y} = b + \sum_{j=1}^{m} w_j \hat{y}_j \tag{3}$$

where: $\hat{y}$ is final ensemble prediction; $\hat{y}_j$ is prediction of the j-th base model; w_i is weighting coefficient determined by the ElasticNet meta-model; b is bias (intercept); and m is number of base models.

The coefficients w_i represent the contribution of each base model to the final ensemble prediction. Their values are determined during training by the ElasticNet meta-model, which minimises the loss function with regularisation, thereby reducing the influence of less informative or highly correlated base models. Parameter b is the intercept of the model, defining the baseline level of predicted variable and shifting the prediction hyperplane relative to the origin. The presence of this parameter allows compensation for systematic deviations of base models and improves the accuracy of the approximation.

The optimal structure of the stacking ensemble is determined based on two criteria: prediction accuracy and model stability. The optimal structure of stacking ensemble is determined based on two criteria: prediction accuracy and model stability. For each considered combination of base algorithms, the mean squared error obtained from cross-validation is calculated as:

$$\text{meanMSE} = \frac{1}{K_f}\sum_{k=1}^{K_f}\text{MSE}_k \ . \tag{4}$$

This metric characterises the model's overall prediction accuracy. In addition, the variability of the error across cross-validation folds is evaluated, which is defined as the standard deviation of MSE values:

$$\text{std MSE} = \sqrt{\frac{1}{K_f}\sum_{k=1}^{K_f}(\text{MSE}_k - \text{meanMSE})^2} \ . \tag{5}$$

This metric reflects the model's stability across changes in training and validation subsets. A low standard deviation indicates consistency across different parts of the dataset and better generalisation capability of the model.

The comparison of different base-algorithm combinations is performed by analysing the metrics across all investigated ensemble configurations. The optimal configuration is the combination of base models that minimises the mean prediction error while maintaining low variability across folds. Additionally, the ensemble's complexity, particularly the number of base models, is taken into account. This enables avoiding excessive model complexity and selecting a configuration that optimises prediction accuracy, stability, and computational efficiency.

Model evaluation metrics

After determining the optimal configuration of the stacking ensemble based on cross-validation results, the model is finally trained on the training dataset and subsequently evaluated on an independent test subset. This approach allows an objective assessment of the model's generalisation capability using data that are not involved in training or hyper-parameter tuning stages. The prediction quality is evaluated by comparing predicted strain values with corresponding experimental data. To assess the performance of the ensemble model, standard regression analysis metrics are employed to provide a quantitative evaluation of prediction accuracy

and level of agreement between predicted and experimental values, /25/. In particular, the following metrics are used: Mean Squared Error (MSE), Mean Absolute Error (MAE), coefficient of determination (R^2), and Mean Absolute Percentage Error (MAPE).

The MSE is defined as:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 , \tag{6}$$

where: n is number of measurements in the test dataset.

The MAE is calculated as:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| . \tag{7}$$

The coefficient of determination characterises the degree of agreement between predicted and experimental values and is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{8}$$

where: $\bar{y}$ is mean value of experimental data.

The MAPE is defined as:

$$\mathrm{MAPE} = 100\% \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| . \tag{9}$$

Combined analysis of these metrics enables comprehensive evaluation of model performance by accounting for both the absolute magnitude of the prediction error and the degree of agreement between predicted and experimental values.

RESULTS AND DISCUSSION

Optimisation of the Stacking ensemble structure

At the first stage of the study, a search is performed to determine the optimal stacking ensemble structure and to tune the hyperparameters of base models and meta-model. For this purpose, various combinations of machine learning algorithms are considered as base models of the ensemble, while the ElasticNet algorithm is used as meta-model. The optimal hyperparameter values are determined using Grid SearchCV with cross-validation, enabling systematic exploration of parameter space and selection of model configurations that achieve the best predictive performance.

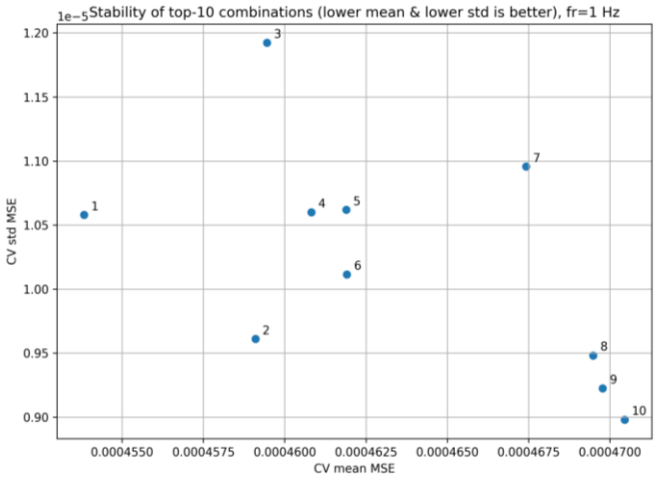


Figure 2. Ten best stacking ensemble combinations at a frequency of 1 Hz according to meanMSE and stdMSE metrics.

The performance of each ensemble configuration is evaluated using cross-validation results and meanMSE and stdMSE metrics which characterise prediction accuracy and model stability, respectively. This approach enables comparison of different combinations of base algorithms and identification of the ensemble structure that minimises prediction error while maintaining low variability across cross-validation folds.

Figure 2 presents the results of the performance analysis for the ten best combinations of base models in the stacking ensemble at a loading frequency of 1 Hz. Each point corresponds to a specific combination of base algorithms in the ensemble, and its index identifies the model configuration.

Figure 3 presents the cross-validation results for 10 best base-model combinations in the stacking ensemble at a loading frequency of 1 Hz.

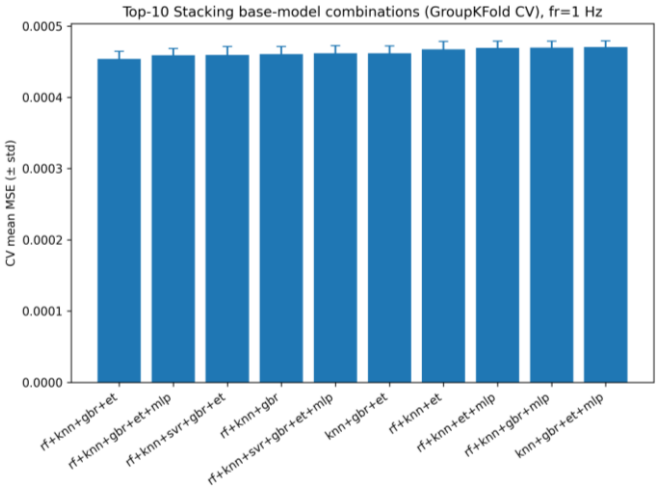


Figure 3. Values of meanMSE (± std) for 10 best combinations of base models in the stacking ensemble at loading frequency of 1 Hz.

For each configuration, the mean value of Mean Squared Error (meanMSE) and its standard deviation across folds (± std) are presented. The results show similar error values across different model combinations, indicating the stability of the ensemble approach for predicting the hysteresis behaviour of SMAs.

Similar results are also obtained for other cyclic loading frequencies (0.3, 0.5, 3, and 5 Hz), for which corresponding plots of meanMSE and stdMSE distributions are constructed for the best model combinations. Such an analysis enables visual comparison of the performance of different model configurations.

Optimal model configuration and hyperparameters

Based on the analysis, the optimal stacking ensemble configuration and corresponding values of model hyperparameters are determined, yielding the most accurate reproduction of the relationship between stress and strain in the NiTi alloy under cyclic loading. The results are presented in Table 2 and are used to further evaluate the model on an independent test dataset.

Prediction accuracy and generalisation ability

The accuracy of the developed ensemble model is evaluated using standard regression analysis metrics. These indicators are calculated both for the test dataset within the range of training cycles (100-250) and for individual cycles (300

and 400) that were not used for training, validation, or testing. Such an approach allows assessing not only the model accuracy within the training range but also its generalisation capability when predicting material behaviour beyond the experimental data used for training (extrapolation). Results of the quantitative accuracy evaluation are presented in Table 3.

Table 2. Optimal stacking ensemble models and key hyperparameters for different loading frequencies.

Freq. (Hz)	Model	Key hyperparameters
0.3	ElasticNet	α = 0.01, l1_ratio = 0.8, max_iter = 1000
	RF	n_estimators = 200, max_depth = None
	KNN	n_neighbors = 5, metric = minkowski (p = 2)
	GBR	n_estimators = 200, learning_rate = 0.1, max_depth = 3
	ET	n_estimators = 200, max_depth = None
	MLP	hidden_layer_sizes = (16,32), learning_rate = adaptive, max_iter = 2000
0.5	ElasticNet	α = 0.01, l1_ratio = 0.8, max_iter = 1000
	RF	n_estimators = 200, max_depth = None
	KNN	n_neighbors = 5, metric = minkowski (p = 2)
	GBR	n_estimators = 250, learning_rate = 0.1, max_depth = 3
	ET	n_estimators = 300, max_depth = None
1	ElasticNet	α = 0.01, l1_ratio = 0.8, max_iter = 1000
	RF	n_estimators = 250, max_depth = None
	KNN	n_neighbors = 5, metric = minkowski (p = 2)
	GBR	n_estimators = 300, learning_rate = 0.1, max_depth = 3
	ET	n_estimators = 400, max_depth = None
3	ElasticNet	α = 0.05, l1_ratio = 0.9, max_iter = 1000
	RF	n_estimators = 300, max_depth = 25
	KNN	n_neighbors = 7, metric = minkowski (p = 2)
	GBR	n_estimators = 300, learning_rate = 0.05, max_depth = 3
	ET	n_estimators = 450, max_depth = 25
	MLP	hidden_layer_sizes = (8, 16, 8), learning_rate = adaptive, max_iter = 2000
5	ElasticNet	α = 0.05, l1_ratio = 0.9, max_iter = 1000
	RF	n_estimators = 400, max_depth = 25
	KNN	n_neighbors = 9, metric = minkowski (p = 2)
	SVR	C = 10, kernel = RBF
	GBR	n_estimators = 400, learning_rate = 0.05, max_depth = 3
	ET	n_estimators = 550, max_depth = 25
	MLP	hidden_layer_sizes = (32, 16, 32), learning_rate = adaptive, max_iter = 2000

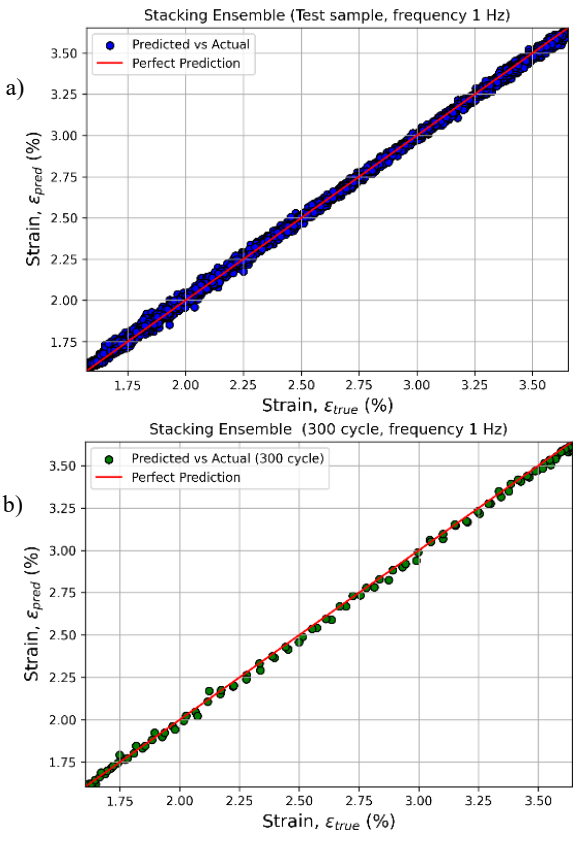
The results presented in Table 3 demonstrate the high accuracy of strain prediction for the NiTi alloy using the ensemble Stacking model within the training cycle range. For the test dataset, the coefficient of determination R^2 exceeds 0.996 at all frequencies investigated, while values of MSE and MAE remain very low. This indicates that the model can accurately reproduce the nonlinear relationship between stress and strain during cyclic loading of the SMA. The MAPE for the test data is 1.21 %, confirming high agreement between model predictions and experimental results.

Table 3. Prediction errors.

Cycles	Frequency (Hz)	MSE	MAE	R^2	MAPE (%)
Test	0.3	0.0008	0.0216	0.9997	0.69
	0.5	0.0004	0.0162	0.9992	0.57
	1	0.0004	0.0173	0.9990	0.73
	3	0.0006	0.0207	0.9979	0.99
	5	0.0006	0.0211	0.9961	1.21
300	0.3	0.0015	0.0290	0.9994	0.84
	0.5	0.0015	0.0321	0.9969	1.10
	1	0.0005	0.0196	0.9988	0.75
	3	0.0013	0.0305	0.9969	1.45
	5	0.0084	0.0688	0.9692	5.32
400	0.3	0.0075	0.0719	0.9969	1.97
	0.5	0.0127	0.1028	0.9726	3.53
	1	0.0010	0.0261	0.9978	1.10
	3	0.0020	0.0342	0.9958	1.51
	5	0.0133	0.0918	0.9595	6.80

Additional model evaluation is performed on cycles 300 and 400, which were not used during training, to assess the model's extrapolation capability. The obtained results show that beyond the training range the model maintains a high level of prediction accuracy. Although a slight increase in prediction errors is observed with increasing number of cycles (especially at 5 Hz), the R^2 value remains high (up to 0.9595 at cycle 400). Such deviations are associated with the further accumulation of fatigue effects and the evolution of the material's mechanical properties, which the models reproduce within the limitations imposed by their structure.

Despite this, the models demonstrate strong generalisation and accurately reproduce material behaviour under long-term cyclic loading.



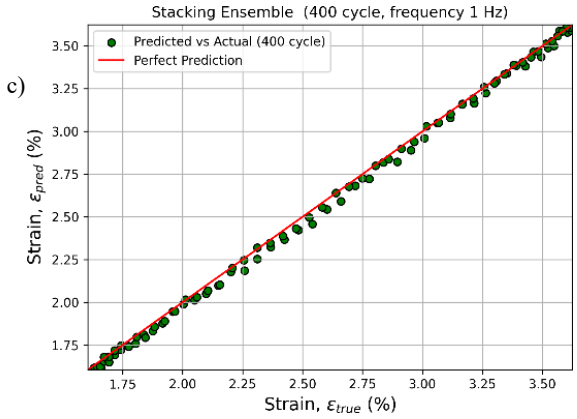


Figure 4. Agreement between experimental and predicted strain values for: a) test dataset; b) cycle 300; c) cycle 400, obtained using the ensemble Stacking model, loading frequency 1 Hz.

Figure 4 presents agreement plots between the experimental and predicted strain values obtained using the ensemble Stacking model at a loading frequency of 1 Hz. The figure shows results for the test dataset within the training cycle range, as well as for cycles 300 and 400, which were not used during model training. As shown in Fig. 4, the predicted strain values are in good agreement with experimental data. For test dataset (Fig. 4a), most points lie directly along the ideal prediction line, indicating high model accuracy in reproducing the relationship between stress and strain over the training cycle range. For cycle 300 (Fig. 4b), a similarly high correspondence between experimental and predicted values is observed. In the case of cycle 400 (Fig. 4c), a slightly greater dispersion of points relative to the ideal prediction line appears, which is consistent with the moderate increase in prediction errors reported in Table 3. Similar plots are also constructed for the remaining loading frequencies.

Reproduction of hysteresis loops

For a more comprehensive evaluation of prediction quality, it is important to assess model ability to reproduce the shape of hysteresis loops in the stress-strain diagram. The geometry of these loops reflects characteristics of martensitic-austenitic phase transformations as well as the energy dissipation processes occurring in the material during cyclic loading.

Figure 5 compares experimental hysteresis loops with those predicted by the ensemble Stacking model for cycles 300 and 400, loading frequency 1 Hz. As shown in Fig. 5, the model-predicted curves closely reproduce the shapes of experimental hysteresis loops during both loading and unloading. Similar plots are also constructed for other investigated loading frequencies, and in all cases a good agreement between experimental and predicted relationships is observed.

Overall, the results indicate that the developed models correctly capture the material's nonlinear behaviour and accurately predict the hysteresis of the NiTi shape memory alloy under cyclic loading.

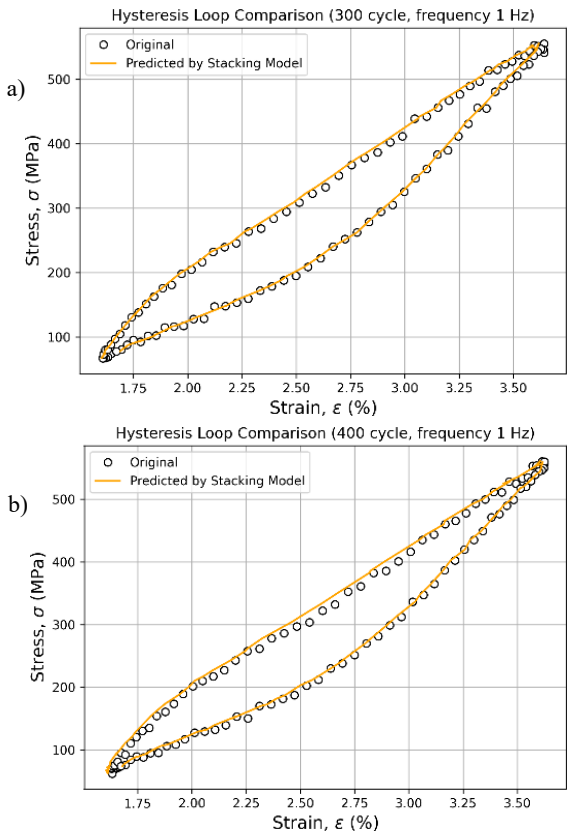


Figure 5. Comparison of experimental and predicted hysteresis loops for: a) cycle 300, and b) cycle 400, obtained using the ensemble Stacking model at a loading frequency of 1 Hz.

CONCLUSIONS

In this study, an ensemble Stacking Regressor machine learning model is developed to predict the hysteresis behaviour of a NiTi shape memory alloy under cyclic loading. The model combines the outputs of several base machine learning algorithms, including Random Forest, Gradient Boosting, Extremely Randomised Trees, k-Nearest Neighbours, Support Vector Regression, and Multi-Layer Perceptron, and uses the ElasticNet meta-model to generate the final prediction. The optimal ensemble structure and model hyperparameters are determined using GridSearchCV with group cross-validation, which accounts for the cyclic structure of the experimental data and prevents information leakage between subsets.

The obtained results demonstrate high prediction accuracy of the NiTi alloy strain within the training cycle range (100-250). The coefficient of determination R^2 for the test data exceeds 0.996 for all investigated loading frequencies, while the values of MSE, MAE, and MAPE remain low, indicating a high level of agreement between experimental and predicted values. Additional testing on cycles 300 and 400 shows that the model retains good generalisation capability beyond the training data range. The analysis of the predicted hysteresis loops confirm that the model correctly reproduces the shape of the stress-strain relationship during both loading and unloading. Overall, the obtained results demonstrate the effectiveness of ensemble machine learning approaches for modelling the nonlinear behaviour of shape memory alloys and highlight their potential for predicting

mechanical characteristics of SMAs under cyclic loading conditions.

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