Prediction of the Stress-Strain State of a Workpiece Using a CAE System and an Artificial Neural Network

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Abstract

The software complex for predicting changes in the stress-strain state (SSS) of a workpiece in the CAE system has been developed. The artificial neural network (ANN) in this package operates in parallel with the CAE system, analyzes the calculation results, and predicts changes in the SSS of the workpiece during deformation modeling. ANN monitors changes in a given number of elements in the workpiece body. The article considers the modeling of two new plastic deformation processes that implement the reverse shear scheme. The ANN training time is less than 60 seconds. The prediction accuracy obtained when using SSS in four workpiece elements was 89%-98%, depending on the size of the training sample and the number of training epochs. This approach allows the effective use of ANN to predict changes in SSS simultaneously with the calculation process in the CAE system. If negative trends in the change of the workpiece SSS are observed, then the modeling in the CAE system is stopped, and the geometry of the die is changed. Thus, the combined use of the CAE system and ANN reduces the time needed to select rational parameters for the deformation process by predicting the state of the workpiece.

Keywords

CAE, finite element method, artificial neural network, forecasting, stress-strain state

1. Introduction

The development of mathematical modeling methods leads to an expansion of the area of their successful use. The finite element method (FEM) is commonly used for modeling to reduce the complexity of physical experiments [1, 2]. The use of computer-aided engineering (CAE) systems has, in many cases, replaced physical research methods through the application of FEM [3, 4]. Thanks to parallel computing methods and numerous calculation models, it is possible to study the influence of various technological conditions on the initial result of workpiece processing in detail [5, 6].

Performing the analysis of the deformation process in a CAE system is characterized by the high accuracy of the results obtained based on the calculation of the influence of a large number of parameters on the workpiece. The use of classical calculation methods requires performing a large number of calculations, and therefore, when using this type of software, high requirements are placed on the computer's hardware. First of all, the speed of performing elementary operations (requirements for the processor) and the speed of data transfer for it (speed of RAM) are important. Depending on the characteristics of these components, the time required to calculate the analysis area can vary significantly.

Calculations using FEM require significant time to obtain the needed solution. This is especially evident when performing cyclic optimization procedures. Therefore, this study solves the problem of predicting changes in the values of workpiece parameters during plastic deformation using artificial neural networks (ANN) based on a model created for use in a CAE system.

Prediction of a workpiece stress-strain state (SSS) using CAE and ANN involves using machine learning models to effectively predict its mechanical behavior during plastic deformation. Connecting ANN to the CAE system can significantly speed up the prediction of the workpiece's SSS. At the same time, the use of machine learning models will reduce the computational time and costs associated with numerical methods such as FEM.

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Researchers consider different approaches to the use of ANN. Thus, works [7–9] prove that convolutional neural networks (CNN) effectively predict stress and strain fields from material microstructures. They provide faster predictions than traditional modeling using FEM. It is emphasized that CNNs effectively handle multidimensional problems and sparse data scenarios. In works [7, 9], unique architectures such as U-Net and Convolutional Autoencoders were used to predict stress fields. These NNs showed high accuracy in mapping input microstructures onto the stress-strain curve.

It has been pointed out in [10, 11] that high-density training data is crucial for accurate predictions. For example, a fully connected feedforward network with sufficient training data can effectively model the stress-strain relationship. However, it should also be noted that ANNs can generalize well to unseen data and are capable of zero-shot generalization, predicting stress and strain fields for new workpiece geometries without additional training [12–15].

Another advantage of using ANNs is that they can model complex material behavior, such as temperature- and rate-dependent reactions, without explicit mathematical formulations of yield functions or hardening laws [16, 17]. These models are scalable and can be adapted to different classes of materials, providing a universal approach to material modeling [16, 18].

The purpose of this work is to increase the efficiency of the modeling process in the CAE system for processing a workpiece using plastic deformation methods and machine learning methods to predict changes in the parameters of the workpiece's SSS over time. Compared to performing a complete calculation in the CAE system, the reduction in analysis time is achieved by deciding to stop the calculations when undesirable trends in SSS changes are detected.

2. Case study

Performing the analysis of the deformation process in a CAE system is characterized by the high accuracy of the results obtained based on the calculation of the influence of a large number of parameters on the workpiece. The use of classical calculation methods requires the performance of a large number of calculations; therefore, when using this type of software, requirements are primarily placed on such components of the hardware as the speed of elementary operations (processor requirements) and the speed of data transfer for it (RAM speed). Depending on the characteristics of these components, the calculation time of the analysis area may vary.

As an optimization of the process of performing engineering calculations, alternative methods of finding the parameter's value at a specific point in time of workpiece processing were considered. The object of analysis was the process of the workpiece deformation distributed in time and observation of the parameters characterizing its state; therefore, changes in these parameters were presented in the form of a time series.

The process model allows for determining the changes in the deformed state in a given direction, section, or volume of the workpiece over time. It is also possible to analyze other parameters (restrictions) of the process obtained as a result of numerical modeling based on the physical model of the process. In addition, quality criteria are required for the development of the process over time. These criteria will allow us to determine the changes in the deformed state in the calculation process and evaluate the quality of the process. If changes in the parameters affect the quality criteria in such a way that the efficiency of the process decreases, then it will allow the calculation process to stop. This will allow the creation of a decision-making model in the calculation process.

As an alternative to the numerical solution of the deformation process modeling problem, we used time series element prediction using machine learning methods. This approach allowed us to replace many long-term calculations with the analysis of a short time interval based on the trends of changes in the parameters monitored during the analysis.

The designed ANN should combine two stages of execution. First, the training time series (x_t, y_t) is analyzed, with a step $Y(t) = 1/n$, where x_t is the vector of input values, y_t is the time series under study, and n is the number of recorded values per unit of time.

Based on the analysis of this series, we use ANN to estimate how system parameters change over time. In the second stage, we apply the constructed network to make a direct forecast and evaluate its accuracy.

At the same time, to reduce costs in performing the analysis of calculation data in the CAE system, this software module can combine the specified stages into a single execution algorithm. It trains the network on existing data and proceeds to predict a given number of steps, calculating the deformation of the workpiece at given points. It should be noted immediately that the larger the gap to be predicted, the more input steps the network requires to maintain the accuracy of the result.

The developed software module employs a convolutional neural network (CNN) architecture. The input data is a package of multivariate time series $X \in \{B, T, F\}$, where: B – batch size (it is not specified in our case), T = 3 – number of time steps, and F = 5 – number of parameters at each time step. Each input instance is $x_t = (x^{(1)}{}_t, x^{(2)}{}_t, x^{(3)}{}_t)$.

A 1D convolutional layer is applied across the temporal dimension T with 256 filters, Kernel size = 3, and step = 1.

The convolution for each filter j is:

$$z_j = \sum_{t=1}^{3} w_{j,t} \cdot x_t + b_j.$$

The Softplus activation function $f(x) = \log(1 + \exp(x))$, is applied within the convolutional layer to ensure smooth non-linearity.

A fully connected (dense) layer maps the 256-dimensional activation to 5 outputs. The output layer is the final forecast vector y_t.

Training minimizes the mean square error $MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$. The following metrics are also used: mean absolute error (MAE) and root mean square error (RMSE). Training stops prematurely if RMSE does not improve, and the model reverts to the last best weights.

The main structure of the model is presented in Table 1.

Table 1
The main structure of the model

Layer Type	Shape	Parameters	Description
Input Layer	(None, 3, 5)	–	Accepts batches of input data (3 time steps × 5 parameters)
Convolutional Layer	(None, 1, 256)	4096	256 filters used to process the input; 1D convolutions for time series
Fully Connected (Dense) Layer	(None, 1, 5)	1285	Connects the flattened output of the CNN to the output layer
Output Layer	(None, 1, 5)	–	Predicts 5 parameters at the next time step

Training specifics include:

- Initial training with 400 epochs, achieving up to 98% accuracy in about 3 minutes
- Optimized training with 60–100 epochs, reducing training time to about 1 minute with 89–98% accuracy
- Early stopping is based on the RMSE minimum to avoid overfitting.

In addition, the possibility of premature termination of model training when reaching the extremum point for losses, which are also calculated using the root mean square error formula, is implemented. In this case, a return to the last successful coefficients is performed. This is done to avoid oversaturation of the model with data and the increased influence of individual parts of the series, which can lead to a severe loss of forecast accuracy.

Since the software module for forecasting is implemented as a library, its execution requires the presence in the software environment of the current version of the Python interpreter, the TensorFlow and Keras frameworks, and libraries whose functions are used in the neural network training process and the forecasting process itself. The issue of the availability of these tools is resolved by a separate command file that searches the software system for the necessary software and, if required, installs what is missing for the software to work.

The work cycle of the developed software complex involves close interaction with the CAE system Abaqus, which is used as a modeling tool and the main data source. For their preparation and transfer, the possibility of integrating ANN into the analysis script by connecting it as an additional library, selecting parameters for analysis, and calling the model training function has been implemented.

The process of integrating the software module should occur before analyzing a small part of the workpiece processing process to obtain training and test data, which will be used to train the ANN model and build a forecast of further changes in the system parameters selected by the user.

It is also possible to create a model based on previously saved analysis results, presented as an MS Excel table with the distribution of monitored parameters in columns and their values in time intervals in rows.

3. Results and discussion

To check the speed of the developed software package and the predicted accuracy results, we performed a partial analysis of the simulated workpiece processing, indicating material properties and the form of influence.
After that, it is possible to query the CAE system to obtain analysis data and implement a prediction of changes in the state of the workpiece on its basis.

During experimental tests to study the accuracy of the obtained model, we used the forecast of changes in values at the points of the workpiece with previously calculated data and determined the error of the obtained result.

The general functionality of the system is shown in Fig. 1 as a use case diagram. The system generates a task of workpiece deformation for implementation in the CAE system. For this, the geometry of the workpiece and tool is designed, and the material's mechanical characteristics and the nature of the loading are determined (use case - Selection/construction of the process model). These parameters are used to create a calculation project in the CAE system using FEM (Construction of the design model). For this, the type of finite elements is selected, grids are formed, the tool and workpiece are divided into a set of finite elements, and the boundary and initial conditions for process modeling are set. The results of step-by-step calculations of the parameters of the workpiece SSS are written to an Excel file, which serves as a means of data exchange (use case - Export data to an Excel file). Using the accumulated data, arrays are formed for training and using ANN.

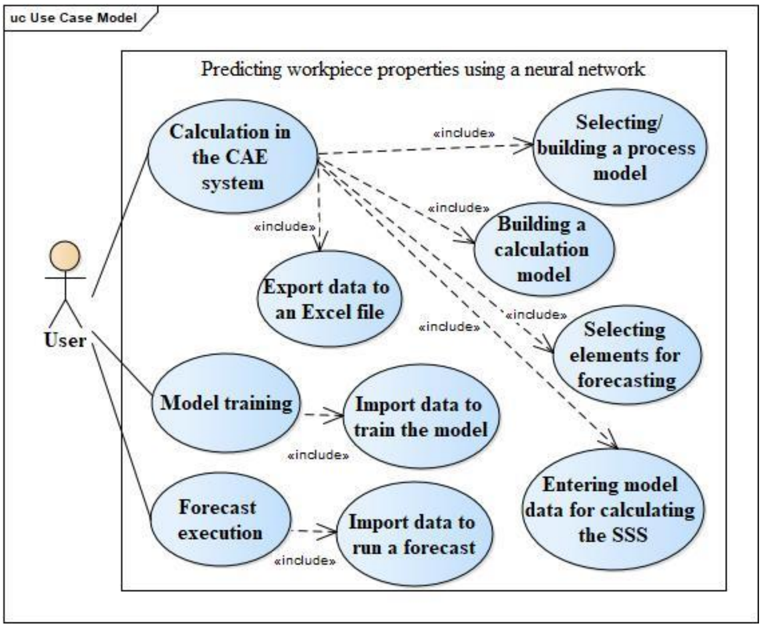


Figure 1: Use case diagram for predicting the values of workpiece SSS parameters during CAE modeling

To analyze the process, characteristic elements in the workpiece volume that characterise the workpiece SSS are selected (Selection of elements for forecasting). The efficiency of the deformation process can be assessed by changing the SSS of the workpiece over a given period of time. To ensure the system's operation, a mechanism for creating and configuring models by the user (operator) was developed. An operator provides the flexibility of the program's operation with different datasets and to adjust the forecast to different possible conditions of the studied process. For this purpose, the "Model Training" use case was defined. The values of the process flow generated by the CAE system, the model of which requires forecasting, were used as the data source.

The selected business process entities are presented in the class diagram (Fig. 2). The main task of the software and methodical complex is to predict the parameters of the stressed-deformed state of workpieces during pressure processing.

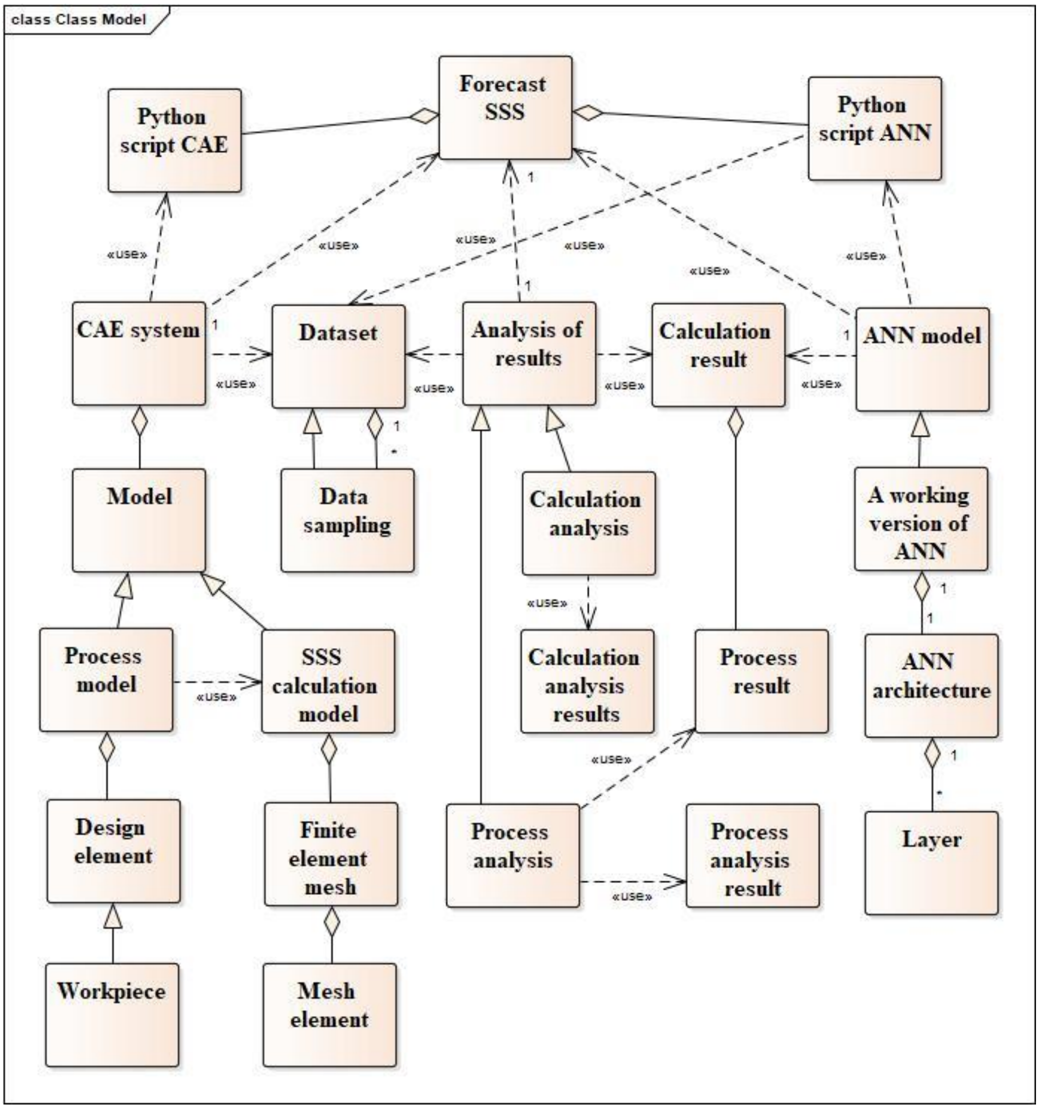


Figure 2: Class diagram of the software and methodological complex for predicting parameter values during modeling in CAE systems using ANN

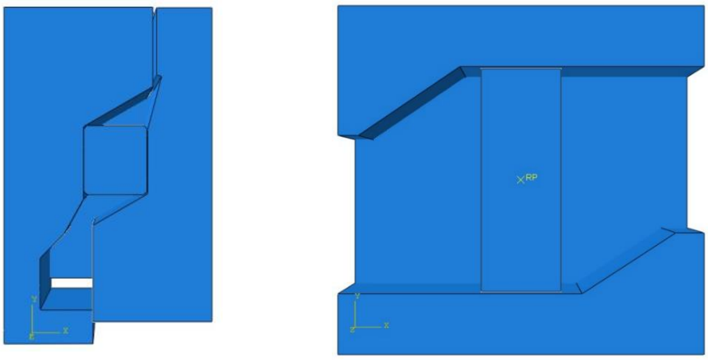
In the "Forecast SSS " class, the choice of the sequence of working with models for designing the deformation process and further forming a calculation model in the CAE system is determined. At the same time, the geometry of the design elements of the die set and workpiece are determined, too. Besides, the mechanical characteristics of the materials and the deformation conditions are specified (Process Model). For calculations, the software is integrated with the CAE system. Automation of the task formulation for the CAE system is performed for typical processes using a Python script. The script determines the model parameters for calculations. At the same time, a geometric model of the process is formed, including models of the die set and workpiece elements, the workpiece's mechanical characteristics, and the specified deformation conditions. A calculation model is also developed, which includes a finite element model, generation of a mesh that divides the part for study, and which is represented by the nodes of this mesh. The conditions for implementing the modeling process are specified (class - SSS Calculation Model). Then, a step-by-step modeling process is performed in the CAE system, accumulates calculation results, and a dataset is formed for further use (Dataset class).

The resulting dataset is used to form arrays necessary for training and monitoring the correct neural network operation (Data Sampling class). A neural network with a predefined architecture is used to analyze the received information (Dataset class). Work with the neural network model is automated using a Python script (Script class). As a result of the neural network (Neural Network class) work, calculation results are formed for the finite elements selected at the previous stage (Calculation Results class). The modeling process results are also determined (Process Results class).

In the next stage, the obtained results are analyzed, as well as the results of the modeling process (the Results Analysis and Process Analysis classes). For this purpose, various types of analysis are used: the obtained data are compared with experimental data, with the results of calculations in the CAE system. The results of different kinds of data analysis are recorded in separate files for further consideration (the Analysis Results class). In case of deviations from the adequacy of the results when using the neural network, its architecture is changed, or the process of its training is improved (the Working Version of the Neural Network, Architecture classes). The "Architecture" class includes the "Layer" classes and reflects the logical component of the neural network. The representation of the structure in this project is used to analyze the activity of the neural network and control its parameters, such as the error value depending on the epoch and the time spent passing the epoch during training.

A dataset was formed to test the operation of the software module and train the neural network. The test data were the results of calculating the accumulated equivalent plastic strain (PEEQ) for four elements according to the deformation scheme of reverse shear (RS) (Fig. 3a) [20] and multi-directional reverse shear (MDRS) (Fig. 3b) [21]. The calculations of the workpiece SSS for the RS and MDRS processes were performed in CAE Abaqus. The projects were prepared using three-dimensional graphics. Each project for calculation in CAE Abaqus included steps (stages) for performing four deformation operations and auxiliary steps that are necessary for unfolding the workpiece before the next deformation operation. Thus, each of the calculations consisted of 13 steps.

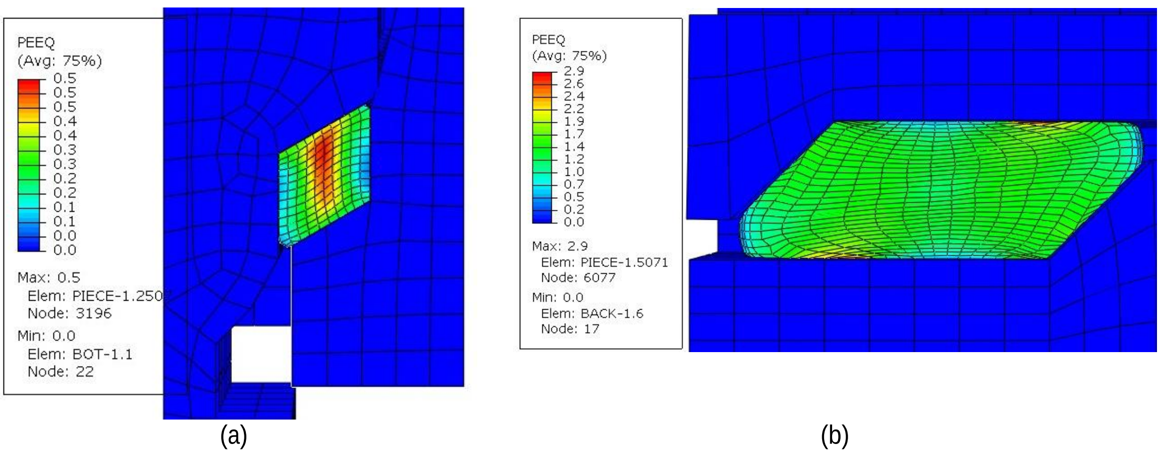
CAE Abaqus saves the calculation results in the internal *.odb* format, which can be accessed by connecting a Python script to the CAE Abaqus post processor and importing data. Data can be imported in full or selectively for individual parts of the model and individual steps of the calculation. Data can also be exported from CAE Abaqus using the built-in tool.



(a) (b)

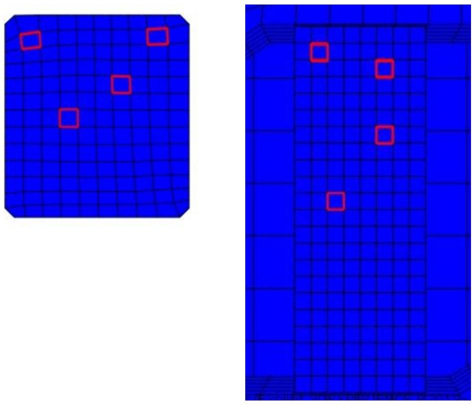
Figure 3: Process model in CAE Abaqus: (a) according to the RS scheme, (b) according to the MDRS scheme

As a result of the calculations, deformed workpieces were obtained (Fig. 4a, 4b), and four elements were selected for the analysis of the change in the equivalent deformation PEEQ (Fig. 5a, 5b).



(a) (b)

Figure 4: Deformed workpieces: (a) according to the RS scheme, (b) according to the MDRS scheme

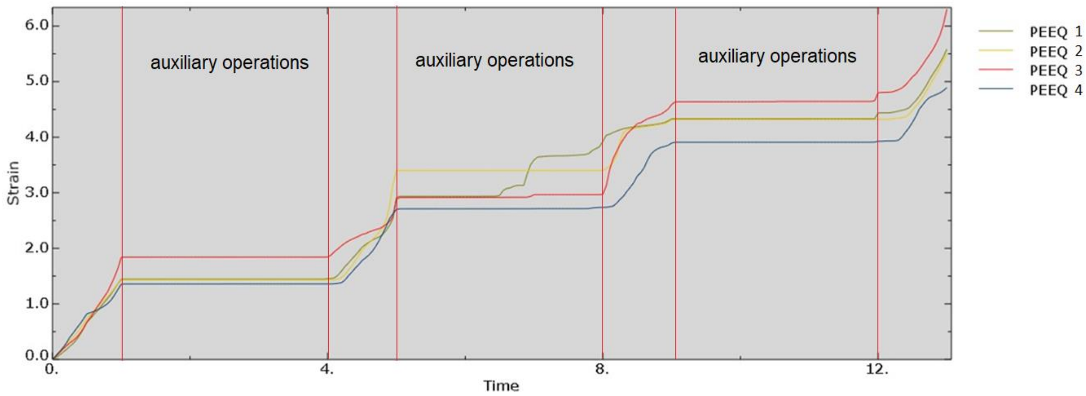


(a) (b)

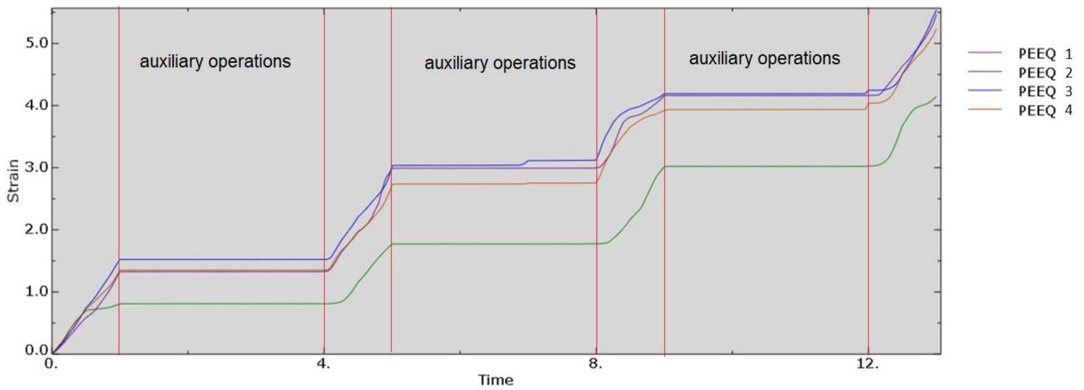
Figure 5: Selection of elements for equivalent deformation analysis PEEQ: (a) according to the RS scheme, (b) according to the MDRS scheme

The elements were selected for analysis in the state before deformation, in the corners and the middle part of the workpiece. Considering the symmetry of the deformation scheme, the selected elements are sufficient for evaluating the key areas of the workpiece cross-section.

CAE Abaqus tools were used to plot the equivalent strain PEEQ during deformation for selected workpiece elements (Fig. 6a, 6b). The plot includes areas with increasing equivalent strain PEEQ, corresponding to the steps in which the workpiece is deformed, and horizontal areas corresponding to the steps for performing auxiliary operations (rotations of the workpiece in space). The horizontal areas of the plot do not carry useful information for training the neural network and are removed during dataset preparation. Export of the results of the calculation of the equivalent deformation PEEQ for selected workpiece elements was performed using the built-in CAE tool Abaqus (Fig. 7).



(a)



(b)

Figure 6: Graph of the growth of the equivalent strain PEEQ with deformation time: (a) according to the RS scheme, (b) according to the MDRS scheme

The next step was to prepare the obtained data in an MS Excel table, including deleting the calculation data for the auxiliary stages and the deformation time for each given element of the workpiece. The prepared data in the MS Excel table included five columns: change in deformation time in the range from 0 to 3 seconds with intervals of 0.05 s; calculated values of the equivalent deformation PEEQ for four elements corresponding to the calculation stage. For this study, a limited dataset was selected, which allowed us to prepare the data quickly and develop a neural network model for training and predicting the equivalent deformation PEEQ for the chosen workpiece elements.

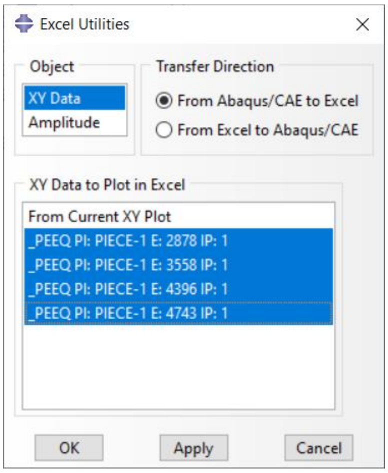
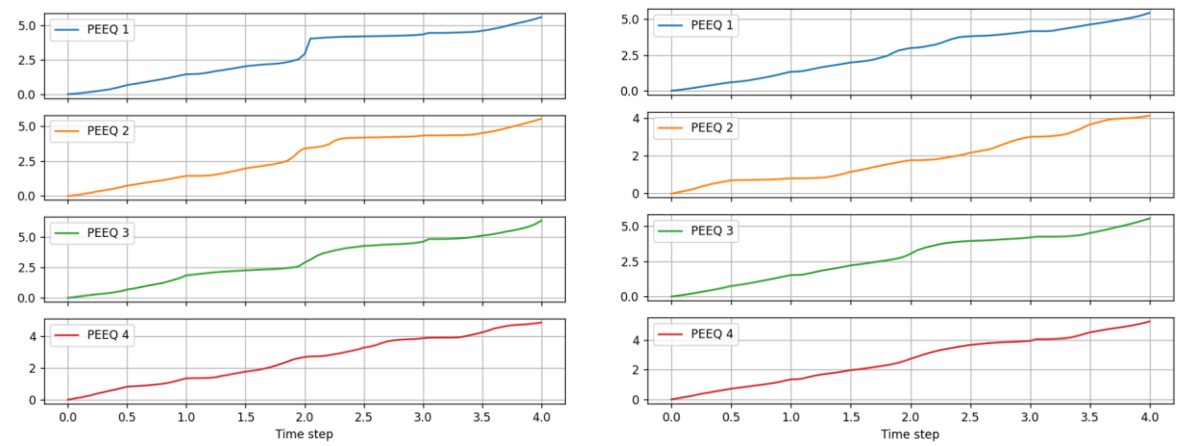


Figure 7: Built-in CAE Abaqus tool for exporting simulation results to MS Excel

For each of the processes of RS and MDRS, MS Excel tables were prepared, which were used during the training of the neural network and for predicting the values of the equivalent deformation PEEQ. During the training process, the neural network reads a dataset and forms a time series for training the model, subsequently performing a forecast of individual values of this series.

The neural network program was launched in the Anaconda 3 environment with the Tensorflow and Keras frameworks configured with Cuda technology support. During the operation of the neural network script, a dataset is read from the MS Excel table. A graph of the change in the equivalent deformation PEEQ of four elements labelled PEEQ 1 – PEEQ 4 is displayed to evaluate the initial data. The graph (Fig. 8a) shows the change in the equivalent deformation PEEQ for the workpiece elements deformed by the RS process. The graph shows that for elements PEEQ 1 and PEEQ 2, there are areas with an uneven increase in the equivalent deformation PEEQ, which is explained by the location of the element in the workpiece zone, which intensively moves along the tool by the process scheme. The presence of such areas creates random situations with the general nature of the change in the equivalent deformation PEEQ. Additional research on the neural network model and the volume of data for training is required. For elements PEEQ 3 and PEEQ 4, the nature of the change in the equivalent strain PEEQ is relatively uniform. The graph (Fig. 8b) shows the change in the equivalent strain PEEQ for the workpiece elements deformed by the MDRS process. All elements PEEQ 1 – PEEQ 4 have a uniform nature of the change in the equivalent strain PEEQ.



(a)

(b)

Figure 8: Dependence of equivalent strain PEEQ on deformation time: (a) according to the RS scheme, (b) according to the MDRS scheme

To train and predict the values of the equivalent deformation PEEQ, a neural network model was used, which included an input layer for processing data with values (None, 3, 5), a convolutional layer with values (None, 1, 256) using 256 filters for input data and the number of parameters 4096; a fully connected layer with values (None, 1, 5) and the number of parameters 1285; an output layer with values (None, 1, 5). The selected topology of the neural network is sufficient for processing a small dataset and predicting values.

The neural network operation was studied with a change in the number of epochs to evaluate the neural network training process and analyze the loss function (Fig. 9a, 9b).

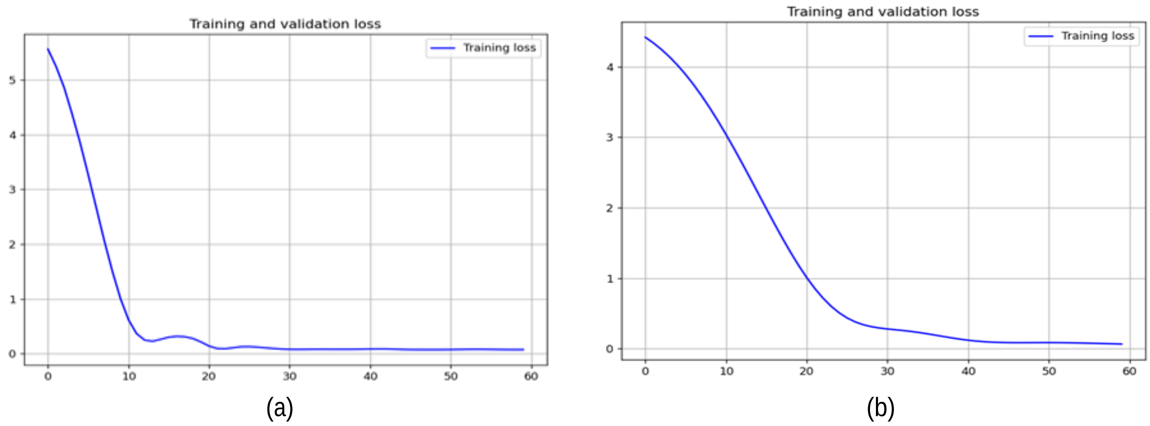


Figure 9: Dependence of the loss function on the number of training epochs: (a) according to the RS scheme, (b) according to the MDRS scheme

In the first attempts to train the neural network, 400 epochs were set, showing a maximum training accuracy of about 98%. The training time was about 3 minutes. In subsequent studies, the number of epochs was reduced to 100 and 60, which allowed us to reduce the training time to 1 minute and achieve a training accuracy of 89%.

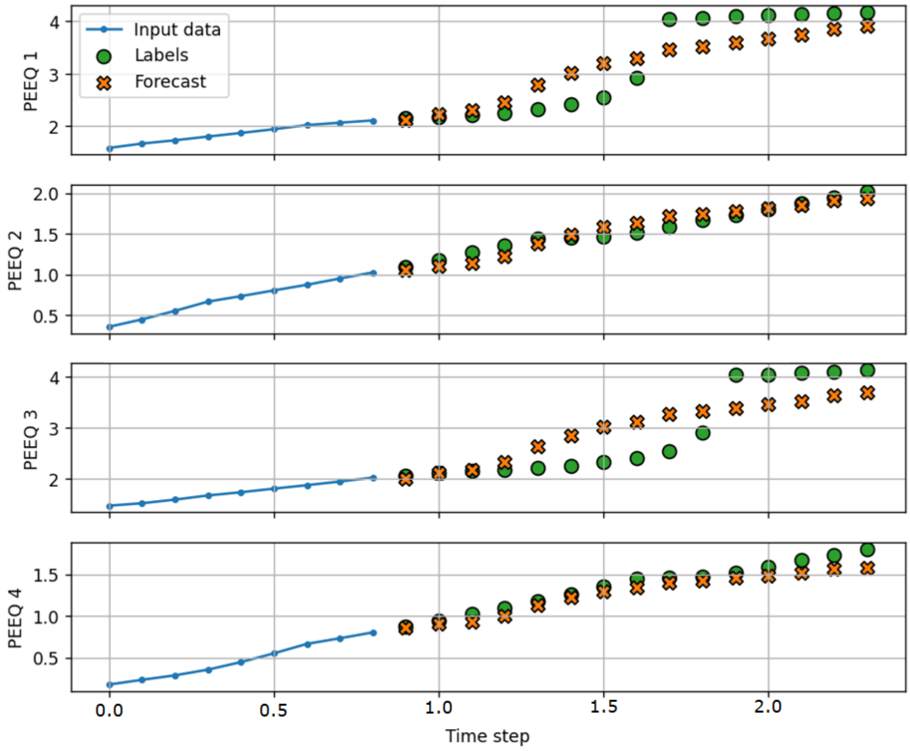
To predict the values of the equivalent deformation PEEQ, the data window size was set to 15 points; the prediction range was 5, 10, and 15 points. To monitor the correctness of the neural network, a prediction was performed within the known values; the results are presented in Tables 2 and 3, and in the form of graphs (Fig. 10a, 10b). As a result of 60 epochs of CNN training on the given data (Fig. 10a, 10b), we obtain a prediction with an average error of the predicted steps of 0.01 – 0.25, which, given the range of the studied values, corresponds to an accuracy of 75%– 98%.

Analysis of the loss function graphs shows a significant decrease in losses after 10 epochs of training for the RS scheme and stabilization of the learning process after 30 epochs. For the MDRS scheme, there is a gradual decrease in training losses after 40 epochs and stabilization of the training process after 50 epochs.

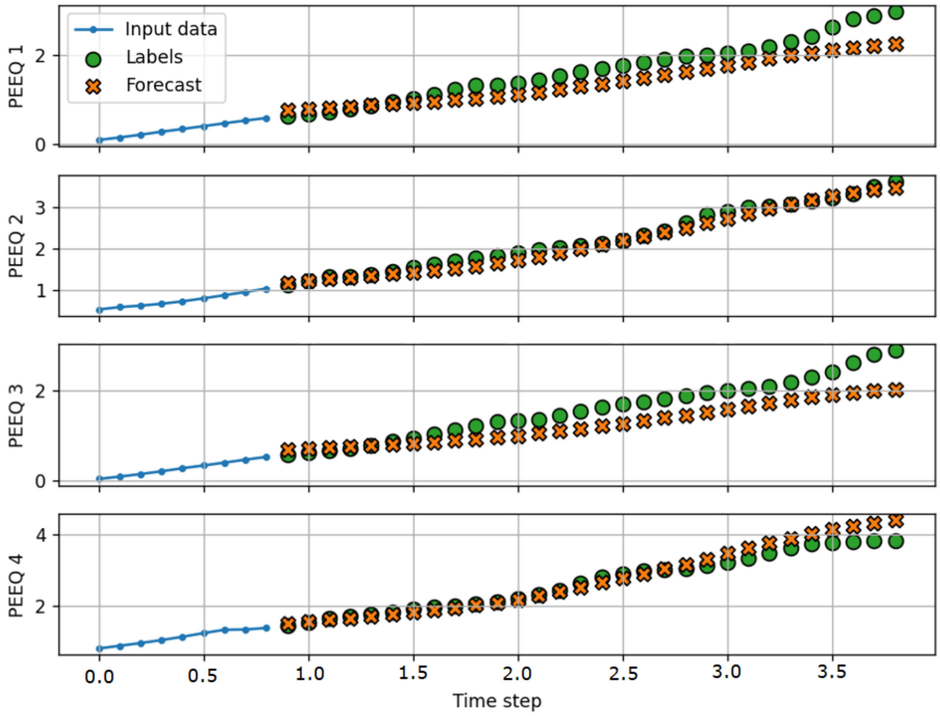
Table 2
Forecast data according to the RS scheme

N	PEEQ 1		PEEQ 2		PEEQ 3		PEEQ 4	
	Value	Forecast	Value	Forecast	Value	Forecast	Value	Forecast
1	2.15	2.13	1.09	1.05	2.07	2.01	0.87	0.86
2	2.18	2.24	1.17	1.11	2.11	2.12	0.95	0.91
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
14	4.15	3.85	1.94	1.91	4.11	3.64	1.73	1.56
15	4.17	3.9	2.02	1.93	4.13	3.69	1.80	1.58
MSE=		0.174		0.01		0.25		0.01

The conducted studies have shown that the selected topology of the neural network and the prepared datasets for prediction give correct values in the workpiece elements with a uniform growth of the equivalent strain PEEQ, while high prediction accuracy is observed. For elements with an uneven growth of the equivalent strain PEEQ, deviations in the prediction of up to 16% are observed, which does not reflect the real changes in the equivalent strain during the deformation process. Thus, to increase the accuracy of the prediction of elements with an uneven growth of the equivalent strain PEEQ, it is necessary to use a larger dataset for training the neural network, which will allow it to cover a larger number of elements with uneven growth of the strain. Another way to improve the result is to complicate the topology of the neural network for a more sensitive response to data heterogeneity.



(a)



(b)

Figure 10: Predicted values of equivalent strain at selected points (PEEQ 1...4) compared with the results of calculations in the CAE system: (a) according to the RS scheme, (b) according to the MDRS scheme.

Table 3
Forecast data according to the MDRS scheme

N	PEEQ 1		PEEQ 2		PEEQ 3		PEEQ 4	
	Value	Forecast	Value	Forecast	Value	Forecast	Value	Forecast
1	0.62	0.77	1.13	1.19	0.59	0.69	1.46	1.51
2	0.67	0.80	1.23	1.23	0.62	0.72	1.54	1.56
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
29	2.90	2.22	3.48	3.41	2.82	2.00	3.83	4.33
30	2.99	2.26	3.62	3.47	2.90	2.04	3.84	4.41
MSE=		0.11		0.013		0.161		0.047

4. Conclusions

Neural networks, particularly deep learning models such as CNN, provide a powerful alternative to traditional numerical methods for predicting the stress-strain state in materials. These models offer high computational efficiency and accuracy, which makes them suitable for high-performance design and analysis of the plastic deformation of parts made of different materials.

A software package has been developed to predict the change in the values of the SSS at given points of the workpiece based on an artificial neural network, which is based on the results of modeling in the CAE system and works in parallel with it. The accuracy of the prediction of the equivalent deformation obtained as a result of the experiment varied from 89% - to 98%. The execution time for data preparation, analysis, and prediction of values by the neural network did not exceed 60 s with 60 epochs of neural network training. At the same time, a usable result is observed already at 50 epochs with a training time of about 60 s.

As a result of the modeling, it was found that the information processing cycle and forecast formation are significantly shorter than the time for a complete analysis of the SSS in a CAE system. The software package and the CAE system accelerate the verification of many options for the metal forming process during its optimisation.

The developed neural network model and the methodology for preparing the dataset demonstrate the possibilities of using numerical calculations and ANN together.

Integrating neural networks with CAE systems offers a powerful approach to accelerating stress and strain prediction.

Using the improved architecture of neural networks and sufficient training data, these models can effectively process complex material behavior and geometry, providing a scalable and flexible alternative to traditional calculation methods.

The proposed methodology requires improving the topology of the neural network and expanding the dataset, which will allow using this development to predict the values of the equivalent strain PEEQ for various deformation schemes with a more heterogeneous distribution of strain over the volume or cross-section of the workpiece.

A further improvement of the software package is adapting the neural network for various deformation processes, allowing for the semi-automatic creation of different model topologies for each calculation or dataset.

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Declaration on Generative AI

While preparing this work, the authors used Grammarly to edit the text. After using this tool, the authors reviewed and edited the content and are fully responsible for the publication's content.

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