Development of a neural network to predict the final geometry of forged rings after cooling

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ABSTRACT: The paper deals with an application of Artificial Neural Networks (ANNs) to predict the geometry of hot forged pieces after cooling. Different ANNs have been considered and evaluated; then a network with two hidden layers has been set up. Training and testing data have been obtained through calibrated numerical simulations of the cooling phase carried out with a finite element (F.E.) code. The good agreement between predicted and numerical results confirms the possibility of using well-trained neural network to foresee final dimensions of pieces after hot forging operations.

Key words: forging, cooling, artificial neural network, numerical simulation

1 INTRODUCTION

Distortions can affect steel-made components during the cooling phase that follows hot forging operations determining deformations that can induce permanent damage with the consequence that the effective geometry at room temperature can substantially differ from the nominal one. This is due to phenomena occurring during this step of the productive process and, mainly, to phase transformations and non-homogeneous boundary conditions [1].

Nowadays, only few pieces in a batch are measured at room temperature: in such a way, anomalies occurred during the forging process can be detected only after a large number of components have been produced. From this stand-point, if final dimensions could be known from the forming stage, it would be possible to eventually have a retroactive control on the process itself.

The possibility to reach this aim is strictly linked to the capability to accurately model the cooling phase after deformation taking into account all the phenomena occurring during it [2]. However, this task turns out to be quite difficult, mainly due to the coupling effects between phenomena that are not easy to be identified and quantified.

Neural networks can represent the most suitable tool to reach the proposed aim, as they are able to infer the complex relationships existing between parameters, the knowledge of whose effects is not known a priori.

The objective of the paper is to prove the possibility to utilise a well-trained neural network to predict the final geometry of rectangular section rings at room temperature after ring rolling operations.

A large number of ANNs characterized by different topologies have been considered and evaluated in terms of accuracy in predicting final dimensions of rings, identifying the most suitable network; the training phase has been performed on a database of different geometries obtained through a calibrated numerical model of the cooling phase. In particular, data about material behaviour (42CD4 steel) during cooling have been introduced in the numerical model so that it could accurately reproduce the industrial reference process. Then, the testing phase of the neural model has been conducted on a set of geometries that hasn't been used for training.

Finally the neural network-based model has been industrially validated.

2 THE APPROACH

The setting up of a model capable to predict final geometry of hot rolled rings after the cooling phase requires the complete understanding of all the phenomena occurring during this step of the production process. In particular, the modelling of micro-structural changes is needed to correctly evaluate the evolution of geometrical features during cooling. The numerical model of the cooling process then requires a suitable calibration in terms of boundary conditions and material data concerning the transformation phase. The reference component is a rectangular section ring whose productive process is schematically represented in Figure 1. Just after the exit of the rolling mill, the ring geometry as well as its surface thermal field is measured through a laser measuring system integrated with optical pyrometers.

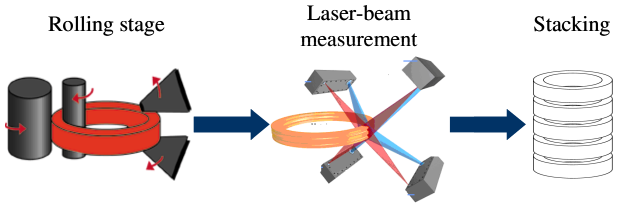


Fig. 1. Scheme of the rings manufacturing route .

To develop the numerical model of the cooling phase, the following assumptions have been done:

· the thermal field at the cooling starting is considered uniform in the section

· the geometry of the rings coming out from the rolling mill is set equal to the nominal one (no distortions due to ring rolling are considered)

· the previous thermal and mechanical histories due to ring rolling are considered as negligible.

Then, the model calibration has been extended to those parameters that have shown to significantly affect the behaviour during cooling. These data include thermo-physical characteristics as well as elasto-plastic properties of all the phases of the reference steel, which have been recognized to significantly influence plastic deformation during cooling [1]. Some of these data have been found in literature; while the others have been experimentally determined through physical simulation experiments carried out on the thermo-mechanical simulator Gleeble 3800™. More details about these tests and their relevant results can be found in [3].

2D axisymmetric simulations of the cooling phase have then been carried out with the calibrated numerical model implemented in the F.E. code Lagamine™ developed by the University of Liège [4].

3 NEURAL NETWORK MODEL

An artificial neural network is a model based on the neural structure of human brain capable to learn on the basis of experience. The general architecture of an ANN is schematically represented in Figure 2.

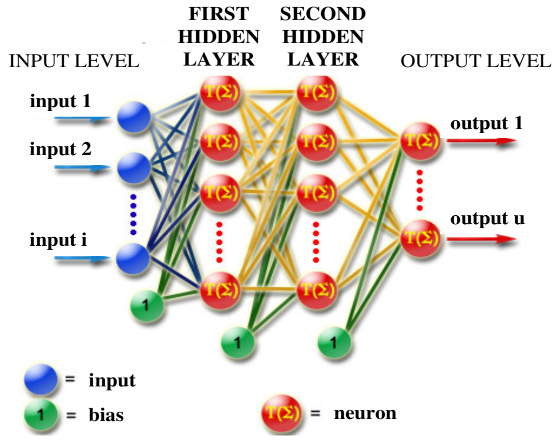


Fig. 2. Neural network general architecture.

The network consists of neurones disposed on layers; the human brain behaviour is reproduced through connections between neurons. In this way, the capability of the network to find a solution for a given problem is strictly linked to the flow of information through the layers.

The setting up of an ANN consists of two subsequent phases, called training and testing. During the first step, a set of examples is presented to the network to understand the relationships existing between inputs and outputs. The knowledge resulting from the training step is stored into the connections between layers called weights and biases. Then, during testing, another set of examples, different from the ones used during training, is presented to the network in order to evaluate the capability of the ANN to generalize and give a solution for the considered problem.

The network capability of predicting is measured through the so-called performance factor:

$$Performance = \sum_{i=1}^{E} \frac{1}{E} \sum_{j=1}^{U} \frac{1}{U} \left(p_{ji} - e_{ji}\right)^2 \qquad (1)$$

where E represents the number of examples, U the number of outputs, p_{ji} the prediction of the neural-based model and e_{ji} the expected output. The most suitable network should minimize errors both in training and testing [5-7].

3.1 Design of the training database

The reliability of an ANN in predicting is strictly linked to the effectiveness of the training phase.
In this work, a numerical training database has been generated: the cooling phase of rings with different dimensions and section shapes, all belonging to industrial production, has been numerically simulated using the calibrated model [1].
In particular, numerical simulations of the cooling phase have been carried out on rings with:

- different rectangular section shapes (plate, square or tubular);
- different dimensions (ratio between external diameter and height and between internal diameter and height);
- different thermal fields in the section at the cooling starting.

From these simulations, surface thermal field and geometry at the beginning and as well as geometry at the end of cooling have been recorded. These data constitute, respectively, the inputs and the outputs nodes of the neural network.
For the training phase, a set of about 1000 examples has been finally chosen. Rings geometries are represented in Figure 3.

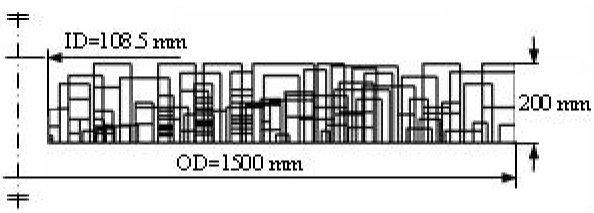


Fig. 3. Training set geometries.

3.2 Design of the ANN

A multi–layer feed-forward back-propagation neural network [6] has been utilized: the choice of its architecture for this application has required some trials.
Firstly, inputs and outputs have been identified. Input nodes are 20 and they correspond to the (x,y) coordinates of the 7 points represented in Figure 4 and their temperature, except for the y coordinate of point 1 that has been fixed to 0 in the numerical model. In Figure 4 heat transfer coefficients utilized in the numerical model of the cooling phase for each face of the ring, obtained from on-field experiments, are also reported [3]. The corresponding outputs are: x_1, x_4, y_4, x_5, y_5, x_6, y_6, x_{90}, x_{111}.

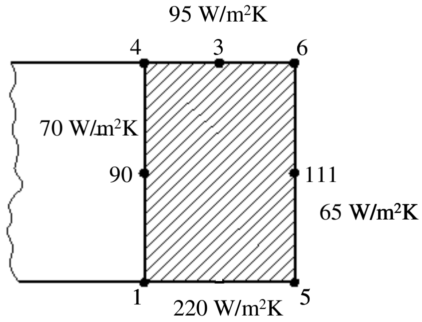


Fig 4. Points chosen as inputs of the network model.

The number and the position of the output nodes have been chosen in order to have, at room temperature, a satisfactory description of the ring section shape without excessively enlarging the dimensions of the network.
An ANN with two hidden layers has shown to give the best performances. Figure 5 shows the mean squared error (MSE) performances both in training and testing, changing the number of hidden neurons in each hidden layer of the network.

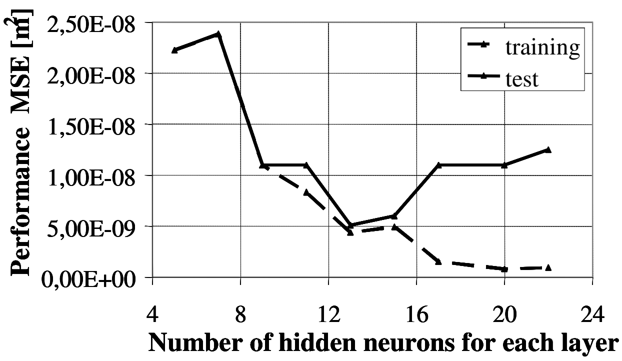


Fig. 5. Network performances as a function of the number of hidden neurons.

As it can be observed, the performance exhibits its minimum for a total number of neurons between 12 and 14 both for both training and testing. Finally, a two hidden layers network with 13 hidden neurons in each hidden layer has been chosen.
The network sensitivity to learning parameters has been also investigated; particular attention has been paid to model response to different transfer functions between the different layers and to the number of training epochs.
Network topology and relevant training parameters are presented in detail in Table 1.

Table 1. Network topology and training parameters.

Number of input nodes	20
Number of output nodes	9
Number of hidden layers	2
Number of hidden nodes for the each hidden layer	13
Activation function input-first hidden layer	logsig
Activation function first-second hidden layer	logsig
Activation function second hidden-output layer	purelin
Number of epochs	3000
Momentum, μ	10^{-3}
μ_{dec}	0.1
μ_{inc}	10
μ_{max}	10^{10}

4 NEURAL MODEL PREDICTIONS

In order to evaluate the accuracy of the network predictions, the testing phase has been first carried out on a data set of geometries coming from numerical simulations and, later, on industrial rings geometries, thus representing the industrial validation of the developed approach. The fitting between expected results and forecasting is really good; in fact, the network seems able to reproduce, through its connections, all the effects due to phenomena occurring during cooling and, also, the coupling between them.
Tables 2 and 3 report the network predictions on two industrial rings characterized by tubular and square sections, respectively.

Table 2. Testing results on industrial rings.

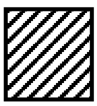
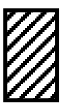
Hot nominal geometry [m]	**Output nodes**	**Predicted *(ANN)* [m]**	**Measured *(T_{room})* [m]**	**Deviation [m]**
OD=0.9580	X_1	0.4278	0.4278	-
ID=0.8680	X_4	0.4281	0.4281	-
H=0.0400	Y_4	0.0394	0.0395	10^{-4}
	X_5	0.4722	0.4722	-
	Y_5	-0.0003	-0.0002	10^{-4}
	X_6	0.4726	0.4725	10^{-4}
	Y_6	0.0392	0.0392	-
	X_{90}	0.4280	0.4280	-
	X_{111}	0.4724	0.4724	-

Table 3. Testing results on industrial rings.

Hot nominal geometry [m]	**Output nodes**	**Predicted *(ANN)* [m]**	**Measured *(T_{room})* [m]**	**Deviation [m]**
OD=0.9580	X_1	0.4279	0.4279	-
ID=0.8680	X_4	0.4285	0.4284	10^{-4}
H=0.0900	Y_4	0.0889	0.0889	-
	X_5	0.4723	0.4723	-
	Y_5	-0.0003	-0.0003	-
	X_6	0.4729	0.4728	10^{-4}
	Y_6	0.0886	0.0886	-
	X_{90}	0.4282	0.4281	10^{-4}
	X_{111}	0.4726	0.4726	-

As it can be noticed from Tables 2 and 3, the deviations of predictions from the expected values are lower than 1 mm for both rings; this value has been previously fixed as threshold for accuracy in forecasting.

5 CONCLUSIONS

In this paper, a new application of artificial neural network has been presented and results obtained in terms of prediction of rings geometry at room temperature have been evaluated. It has been demonstrated that ANN can represent a suitable tool to infer the complex relationships existing between phenomena occurring during cooling and influencing the final geometry of forged pieces. The use of artificial intelligence techniques in the prevision of geometrical distortions seems then encouraging and the developed procedure can be considered general enough to be applied to the geometry prediction of profiled section rings.

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