Identification and identifiability analysis of material parameters using hybrid optimization algorithms and optimized artificial neural networks

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Abstract. Accurate data sets for material behavior model simulation are necessary for realistic numerical simulation. The true material parameter's identification is still a difficult task. When the optimization process is combined with a finite element simulation, this is typically constrained by the computational time. In this study, a procedure for the identification of material parameters based on a hybrid approach is described. This methodology suggests a strategy for decreasing the computing cost by substituting the FEM simulations by an artificial neural network (ANN) model in the optimization loop. For this reason, a parametric study of the FE simulation is carried out to generate an ANN training database. A high-predictive-performance ANN model is also created by optimizing the hyperparameters. To quantify the conditioning of the inverse problem and to justify the replacement of the FE model with an ANN model, an identifiability analysis based on an identifiability indicator (I-index) is also proposed. The classical characterization tensile test is used to apply this optimization approach. Finally, numerical and experimental stress-strain tensile curves are compared to evaluate the effectiveness of this methodology.

Keywords: Numerical simulation, Artificial Neural Networks, Parametric identification, Identifiability.

1 Introduction

Material parameter identification plays a crucial role in the field of engineering and science, allowing to analyze and predict the behavior of materials under various loading conditions, which in turn leads to improved designs. Additionally, the material parameters identification can present various challenges that may affect accuracy and

efficacy. Therefore, the correct parameter identification is critical for producing reliable numerical simulations that can impact real-life applications and decision-making.
Finite element model updating (FEMU) is one of the most important techniques for improving and refining numerical models based on experimental data [1, 2]. Although FEMU has proven its effectiveness in various engineering applications, some limitations exist, particularly regarding the computational cost for material parameter identification [3].
Artificial neural networks (ANNs) have revolutionized the field of material science, opening up new possibilities for material parameter identification thanks to their ability to model nonlinear relationships [4-6]. This innovative approach presents a significant reduction in computational cost compared to traditional methods. ANNs have demonstrated remarkable capabilities for solving complex problems and provide efficient solutions by mimicking the processes within biological neural systems. ANNs can then replace computationally costly Finite Element Method (FEM) simulations in optimization loops.
In the current study, the parameters of plastic behavior are determined from uniaxial tensile test using inverse analysis based on a hybrid optimization algorithm, combining genetic algorithms and LM algorithms. In the optimization loops, the ANN model is employed instead of finite element computations. To reflect the stability of the inverse problem solution and to justify the replacement of the FE model with an ANN model, an identifiability analysis is then carried out.
Finally, the experimental stress-strain curve is compared with the numerical counterpart as well as to the ANN model prediction in order to validate the identification methodology.

2 Experimental setup

Uniaxial tensile tests were carried out on flat copper alloy specimens annealed at 450°C for 30min. The tests were conducted on an MTS testing machine with a crosshead speed of 0.03 mm/s. The measurement of the specimen's elongation ΔL was performed by a laser extensometer and the reaction force F is measured by the way of load cell of 1 kN. The used specimens have a rectangular section (0.21mm x 5mm) with an initial gage length equal to 15 mm. The specimens were elongated up to fracture and the true stress–true strain curves were obtained.

3 Numerical modelling of tensile test

A finite element parametric model, programmed in MATLAB language, has been developed to numerically simulate the tensile tests. The LS-DYNA software with the explicit integration method is used to the numerical simulation. The specimen is meshed by 4-nodes quadrilateral shell element to decrease the computational time. For this test, the left boundary is fixed while the right boundary is moved in the x-direction, as shown in Fig. 1. The total reaction force is calculated by summing all nodal forces in X-direction at the fixed end.

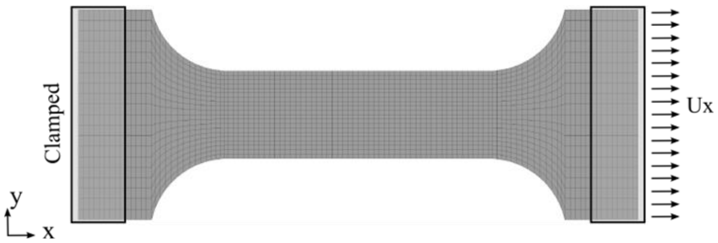

Fig. 1. Finite element modeling of the tensile test.

The mechanical behavior of the copper alloy is considered through an elastic–plastic law with isotropic hardening. The generalized Hooke's law is used to describe the elastic behavior of the material. Here, the isotropic yield criterion of von Mises is used, and the plastic behavior is modelled by the isotropic hardening law (Voce's law), as follows:

$$\dot{R} = b(Q - R)\dot{p} \tag{1}$$

R and p indicate respectively the isotropic hardening variable and the equivalent plastic strain. The parameters Q and b designate the asymptotic value and the exponent of the isotropic Voce's law, respectively [7].

For this material, the elastic parameters were obtained from ultrasonic characterization. Finally, three parameters characterizing the plasticity mechanism should be identified.

4 Artificial Neural Network model

In this section, the artificial neural network (ANN) is used to predict the relationship between the material parameters and the true stress-strain curve. In particular, the inputs are the material parameters, and the outputs are the true stress-strain curves associated with these values. To achieved that, a set of numerical tensile tests obtained from the FE parametric modeling is performed to generate an ANN training database. The feed forward neural network model (FFNN), which belongs to the class of multi-layer perceptron (MLP), is employed in this study. In the FFNN model, the neurons are completely interconnected and arranged in successive layers, mainly input, hidden and output layers. In this ANN model, the sets of the weights and biases are adjusted by a scaled conjugate gradient backpropagation algorithm, where the error between the output values and the target responses is minimized during training phase.

To obtain an ANN model with high predictive performance, it is necessary to optimize some hyperparameters defining the architecture design of the model, namely the number of hidden layers, the number of neurons per hidden layer and the learning algorithm. Hence, the Bayesian optimization method (BOA) was used to tune the hyperparameters, which saves time and enhances the training model's performance [8]. Hyperparameters are extracted by minimising the objective function, which is the difference between the predicted and trained responses. Convergence occurs when the objective function reaches a predetermined value or reaches its maximum number of iterations. The flowchart of optimization hyperparameters is shown in Fig. 2.

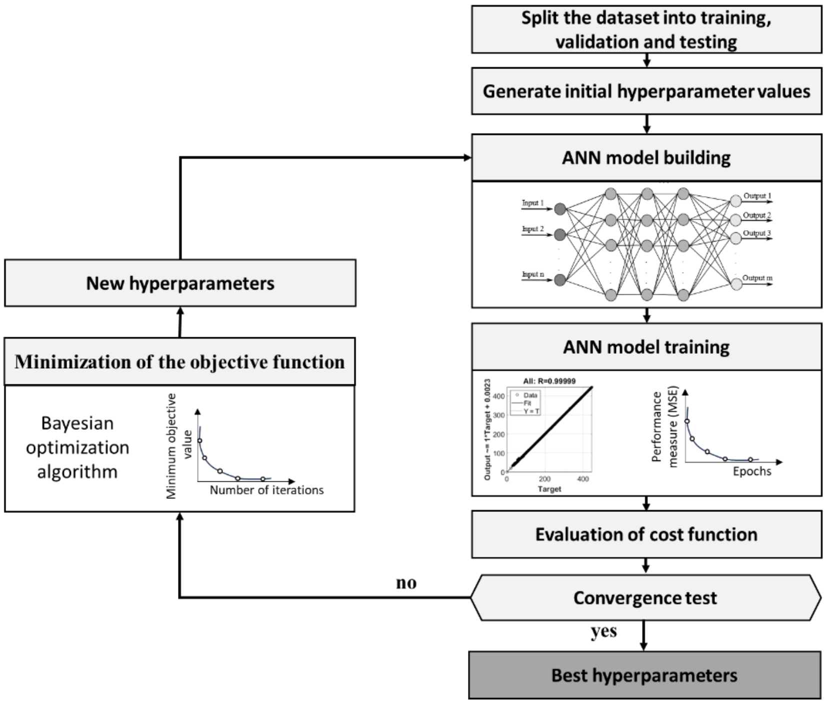

Fig. 2. Hyperparameters optimization procedure.

To validate the deep learning approach used to accurately predict the true stress strain tensile curves, a set of 324 simulations is performed to generate the database for ANN training according to the Taguchi orthogonal array approach (L=18), as described in [9].

Note that ANN performance analysis is evaluated using the correlation coefficient R and the mean square error (MSE). During the training period (Epoch), the MSE of training, validation, and testing data decrease continuously until a value of 0.08 without any significant traces of overfitting, as shown in Fig 2. A good correlation, with a regression coefficient R close to one (R≈1), between target and predicted stress strain-curves is demonstrated, as shown in Fig 4. The results show that the ANN model is well-generalized, indicating that it can be utilized as a substitute method for accurately predicting true tensile stresses.

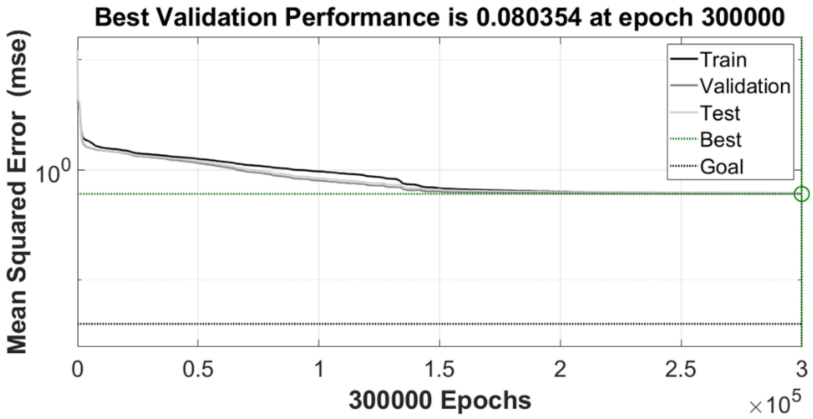

Fig. 3. Performance plot of the ANN model.

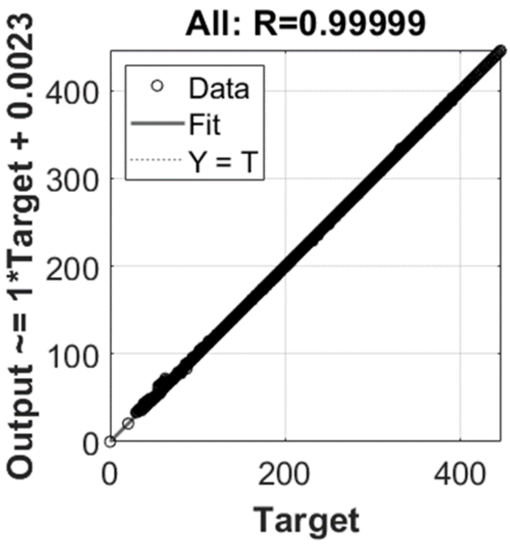

Fig. 4. ANN model regression plot.

5 Identification methodology and Identifiability analysis

In this section, the identification methodology and identifiability analysis of the material parameters will be presented. An inverse problem is used for the parameter's identification. The purpose of this inverse formulation is to find the material parameters that minimize the gap between the numerical and experimental stress-strain curves of the tensile test. During the identification process, the material parameters are adjusted using a hybrid optimization algorithm that combines genetic and Levenberg-Marquardt (LM) optimization methods. The LM algorithm starts by using the best set of parameters provided by the genetic algorithm in order to achieve an opti-

mal result. The numerical stress-strain curves used in the present identification method are predicted using the ANN model mentioned above since the ANN model response is almost instantaneous, which considerably reduces the computational cost.
In this study, the genetic algorithm uses 100 successive generations to find an initial solution, requiring 3030 simulations. This computation will take approximately 757.5 hours, if the FE model is applied using a massively parallel processing (MPP) version of LS-DYNA with 8 processors. By using the ANN model to predict the numerical stress-strain curves, the online computation time is achieved in only 30 mn. Furthermore, the offline computation time, corresponding to the dataset preparation, takes 81 hours.
The proposed methodology was implemented in MIC2M developed by Richard [10]. The current identification procedure is presented in the flowchart given in Fig.5.

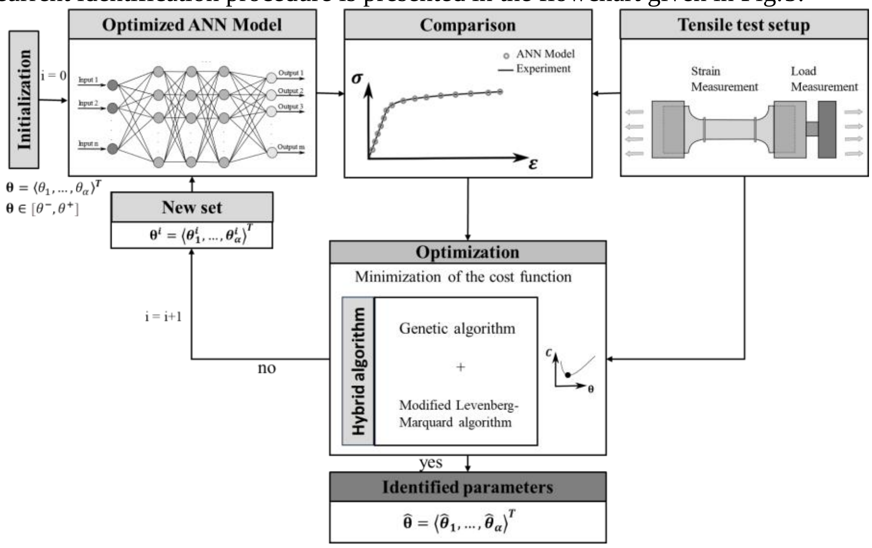

Fig. 5. Flowchart of the identification procedure.

The numerical stress predicted by FE and ANN models, using the identified plastic parameters, is compared in order to evaluate the ANN model robustness and validate the proposed identification approach, as given in Fig 6.

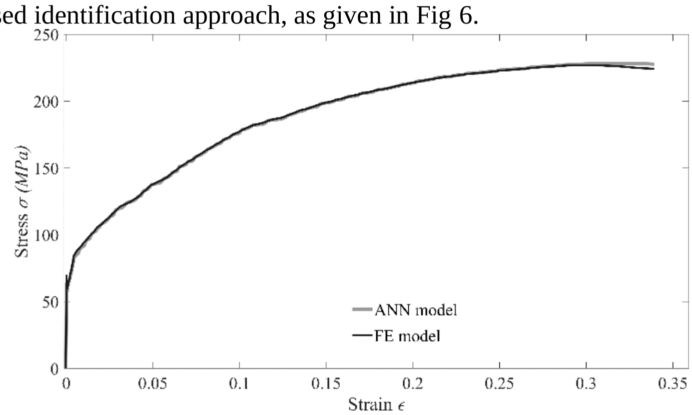

Fig. 6. Comparison of true stress-strain curves obtained by ANN and FE models.

The maximum error is around 2.1% at the beginning of the tensile test then it decreases when the plastic strain accrues. Overall, the mean absolute percentage error (MAPE) is equal to 0.56%. Therefore, the optimized ANN model accurately forecasts the numerical stress, which confirms the ANN model's replacement of the FE model.

The identifiability analysis based on an indicator is applied to quantify the conditioning of the inverse problem and to justify the substitution of the FEM by an ANN model for true-stress curve prediction. The present analysis reflects the stability of the inverse problem solution. As reported by Richard et al. [11], the measure of multicollinearity of the sensitivity functions of a set of parameters is a function of the ratio $\lambda_{max}/\lambda_{min}$. λ_{max} and λ_{min} are, respectively, the largest and smallest eigenvalue of the pseudo-Hessian matrix $\boldsymbol{H}$, defined from the sensitivity matrix. More details of the identifiability indicator can be found in [12]. An identifiability index of set of k parameters can be written as follows:

$$I_k = \log_{10}\left(\frac{\lambda_{max}}{\lambda_{min}}\right) \tag{2}$$

Fig. 7 shows the measurement of identifiability index with respect to the tensile test strain using FE and ANN models. The identifiability indicator decreases to a value less than 3 when the tensile strain increases, revealing that the problem is well-posed. After the tensile test, the identifiability index stabilizes at a value less than 3 for FE and ANN models, confirming the ability to identify the set of parameters using the tensile test.

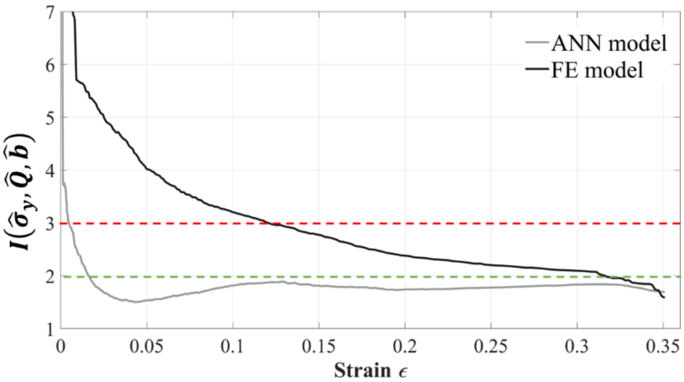

Fig. 7. Identifiability index measurement during the tensile test.

Fig. 8 shows a comparison between the experimental and the numerical true stress-strain curves. A good agreement is observed between the stress-strain identified and the experimental one.

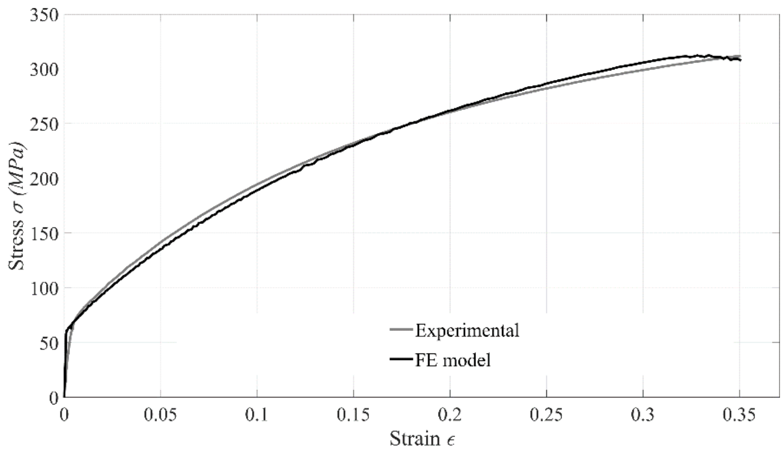

Fig. 8. Comparison of true stress-strain curves between EF modeling and experimentation.

6 Conclusion

In this work, a methodology for identifying material parameters based on a hybrid optimization algorithm, combining the genetic and the Levenberg-Marquardt algorithms, and an ANN model is developed.

The identifiability analysis, based on an indicator of multicollinearity, was conducted to estimate the reliability of the identified material parameters and to validate the conditioning of the inverse problem. This confirms that the artificial neural networks can then be used as an alternative way for stress-strain curve prediction with good accuracy. To validate the proposed identification strategy, the numerical simulation finding of the tensile test using the identified parameters and given in terms of stress-strain curve is compared with the same results predicted by ANN model and measured experimentally. The parameters identified by inverse analysis showed good agreement compared with the experimental measurements. The proposed methodology allows to reduce the computational cost of the optimization procedure. Future studies will focus on the extension of this method to try the identification of more complex constitutive models from more complex experimental tests.

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