The International Journal of Advanced Manufacturing Technology (2024) 134:5481–5492
https://doi.org/10.1007/s00170-024-14472-0

ORIGINAL ARTICLE

Machine learning applied to predict the flow curve of steel alloys

André Rosiak[1] · Murilo Schmeling[1] · Roderval Marcelino[2] · Lirio Schaeffer[1]

Received: 6 May 2024 / Accepted: 11 September 2024 / Published online: 20 September 2024

Abstract
This study aims to employ machine learning, specifically artificial neural networks (ANNs), to predict the flow curve of hot-deformed steel alloys. The method involved creating a dense ANN with two hidden layers, trained with data from 70 steel classes, including information on chemical composition, temperature, and strain rate. The results indicate robustness and good generalization capability, with a mean absolute error of 11.4 MPa and a mean squared error of 10.3 MPa. The model demonstrates an R^2 value of 0.98, highlighting its effectiveness in explaining variability in the data. The conclusions underscore the feasibility of ANNs in describing the mechanical behavior of steel alloys, providing an efficient and rapid tool for metal forming projects, with potential for future research and innovations in this field.

Keywords Artificial neural networks · Flow curve · Machine learning · Steel alloys

1 Introduction

The development of successful metal forming technologies requires reliable information about the material's mechanical behavior during plastic deformation. The flow curve is crucial information in the design of mechanical forming processes, outlining the relationship between the flow stress (k_f) and true strain (φ) [1]. This curve plays a fundamental role in quantifying the main variables of forming processes [2].

The plastic deformation of a metal can be envisioned as a large number of irreversible microscopic processes. The flow curve is the macroscopic representation of the microscopic effects described during metal forming. The flow stress (k_f) can be defined as the stress value acting on a metal capable of inducing flow or plastic deformation. This stress value is influenced by various factors associated with the deformation process, such as strain (φ), strain rate ($\dot{\varphi}$), and temperature (ϑ), as well as material-related factors such as chemical composition, microstructure, segregation, and deformation history [3]. Thus, the flow stress can be expressed as follows:

$$k_f = f(\varphi, \dot{\varphi}, \vartheta, material) \tag{1}$$

The knowledge of the relationship presented in Eq. (1) is a basic prerequisite for the application of analytical and numerical calculation methods in forming technology [3]. Currently, the flow curve is an essential input parameter in finite element software, being indispensable for obtaining accurate solutions.

In cold work, the flow stress depends fundamentally on the material characteristics and the imposed degree of strain. In this condition, the material's mechanical behavior is governed by work hardening or the increase in material strength due to plastic deformation. In hot work, in addition to work hardening, various simultaneous microstructural changes occur, such as dynamic recovery and recrystallization [4]. In this condition, the flow stress becomes highly sensitive to temperature and strain rate. These parameters influence the recovery mechanisms that occur in the material. The increase in temperature favors the migration of linear defects. Consequently, the material's flow stress decreases with the temperature increase. The concomitant change in the arrangement of dislocations leads to material softening. However, this process requires time, which is reduced as the strain rate increases. This means that as $\dot{\varphi}$ increases, there is progressively less time available for recovery and recrystallization processes. Therefore, the flow stress increases with the material's velocity during hot forming [3].

André Rosiak
andre.rosiak@ufrgs.br

[1] Metal Forming Innovation Center (CBCM), Federal University of Rio Grande do Sul, Porto Alegre, Brazil

[2] Federal University of Santa Catarina, Araranguá, Brazil

Flow curves are commonly determined experimentally on a laboratory scale. Compression, tension, or torsion tests are standardized and widely used for this purpose [5–7]. In these tests, the relationship between flow stress and true strain can be determined from experimental force data and the change in the sample's cross-sectional area. The experimental procedure is relatively simple when the material is deformed at room temperature. However, the analysis of hot forming processes requires more complex and expensive procedures. In this condition, it is essential to know how the material responds to deformation at the temperatures and deformation velocities imposed by the specific forming operation. This requires a series of tests. Additionally, the flow curve must be determined from tests conducted at constant strain rate, under well-controlled temperature conditions, with continuous measurement of stress, strain, and temperature during deformation [6]. These procedures require a substantial amount of time, highly trained personnel, and expensive equipment. These aspects limit the accessibility of this technology to only a few companies.

An alternative approach is found in literature research and databases. However, the available information is limited to traditional materials conventionally used in metal forming processes. The current trend of companies using modern materials recently developed by the steel industry generates the need for characterization of these new materials.

Currently, a frequently used approach in the literature [8–15] to determine flow curves is inverse modeling. This iterative approach is based on simulation models that minimize the deviation between simulated and experimentally measured forces [8]. This methodology reduces experimental effort but requires high knowledge in numerical modeling, which can be a barrier to industrial application.

It is essential to explore alternatives that enable the characterization of the mechanical behavior of materials in a fast, simple, and cost-effective manner. In this context, artificial intelligence emerges as a promising approach, garnering increasing interest for its innovative capabilities.

To broaden access to the mechanical behavior of materials in an agile and reliable manner, this study proposes the application of machine learning to predict the flow curve of steel alloys. The methodology uses flow curves and chemical compositions of a wide variety of steels to train an artificial neural network (ANN) model and define an optimized data architecture. The central objective is to evaluate the effectiveness of ANNs in predicting the mechanical behavior of steels during hot plastic deformation. This approach represents an innovative and highly promising initiative to assist in metal forming projects. To provide a better understanding of the proposal, a brief introduction to the principles of artificial neural networks is presented below.

2 Artificial neural networks

Machine learning can be conceptualized in three fundamental elements: performance, task, and experience. In this context, a computer program learns from experience regarding a specific class of tasks. The essence of this learning lies in the continuous improvement of the program's performance in assigned tasks as it accumulates experience over time [16]. These machine learning systems can be succinctly represented by the following equation [17]:

$$Objective + Sample + Algorithm = Model \tag{2}$$

The "Objective" represents the problem to be addressed, often expressed as an objective function. The "Sample" is a subset of the population selected for study, often obtained through data preprocessing. This includes data cleaning, where incomplete, incorrect, inaccurate, or irrelevant parts are identified and addressed [18]. Feature engineering is also part of this process, involving the extraction, selection, construction, and learning of features to optimize the application of machine learning algorithms. The "Algorithm" component covers the machine learning algorithm and the model optimization algorithm. Among the most common machine learning algorithms are support vector machine (SVM), decision tree (DT), and artificial neural network (ANN). The "Model" is the resulting mathematical description of the process, reflecting the learned algorithm based on the Sample [17].

In this study, artificial neural networks (ANN) were chosen over other techniques due to the specific objective and the complex nature of the data involved. ANN is particularly suited for problems that involve complex, nonlinear relationships between variables, as is the case with predicting the mechanical behavior of materials under different thermomechanical conditions, where multiple factors, such as chemical composition, temperature, and strain rate, interact in a highly intricate manner.

An artificial neural network (ANN) is a versatile model for nonlinear statistical analysis, capable of performing both data classification and regression calculation tasks. This approach establishes a connection between input and output data through a set of nonlinear functions, allowing the representation of complex relationships and patterns in datasets. This flexibility makes ANNs valuable tools in a variety of applications, from pattern recognition to numerical predictions, providing a powerful capacity for learning and adaptation to diverse data [19]. In recent decades, this technology has found application in manufacturing processes for various purposes. In metal forming, the use of ANNs began in the late 1990s [20]. The technique has been used to predict forces [21], design tools [22], minimize springback [23–26], estimate processing costs [27, 28], identify material properties [29, 30], predict defects [31–34], define parameters [35–38], and optimize maintenance [39].

ANNs seek to emulate the functioning of the human brain, drawing inspiration from how neurons communicate. Artificial neural networks are composed of nodes, also known as artificial neurons, organized in interconnected layers, as illustrated in Fig. 1. The first layer receives and summarizes input information, the last provides target values, and intermediate layers are referred to as hidden layers. Each node in a hidden layer is characterized by the following mathematical expression [37]:

$$z_i = \varnothing\left(\sum_j w_{ij} z_j + d_i\right) \tag{3}$$

where z_i is the output of the node in layer i, z_j is the output of the node in the previous layer j, w_{ij} is the weight associated with z_j, d_i is a bias term, and $\varnothing$ is a non-linear activation function.

Once an input layer is established, weights are assigned to assist in defining the importance of each provided variable. Larger weights have a more significant impact on the output compared to other inputs. Each input is multiplied by its respective weight, and the results are summed. Then, the output goes through an activation function, thus determining the result. If this output surpasses a certain threshold, the node is "activated," transmitting data to the next layer in the network. This process, where the output of one node becomes the input for the next, characterizes the neural network as a feedforward network [38, 40].

In the context of regression problems, nodes in the output layer follow a similar formulation but without the application of an activation function. The learning process of a neural network is termed training, mathematically grounded in the concept of gradient descent, which seeks to minimize the associated error function [41]. The process involves iteratively adjusting the weights to improve the model fit. This is achieved through backpropagation of errors, where weights are adjusted to minimize the discrepancy between the model's predictions and the actual values. This iterative process aims to achieve a minimal estimate of prediction error.

3 Materials and methods

This study aims to develop an artificial neural network capable of making reliable predictions of the flow curve of steel alloys. Figure 2 schematically illustrates the methodology employed. The work is carried out in two main phases, consisting of the dataset creation phase and the prediction and analysis phase, respectively. This working scheme has been successfully applied by other researchers in using AI to predict material properties [42, 43].

3.1 Database

The input dataset used in this study was obtained from the material library of the Qform UK finite element software. The database provides information on a wide range of materials commonly used in metal forming processes, including various steel alloys. The flow curve for each material can be accessed at different strain rates and temperatures. Additionally, the chemical compositions of the materials are available. All this information can be downloaded as an Excel document. Since it is not possible to retrieve information for multiple materials simultaneously, it was necessary to download data for each material individually.

Raw data for 70 steels were obtained. The set encompasses the main steel classes used in hot forming: carbon steels, C-Cr, Cr-V, Cr–Mo, structural steels, Mn steels, Mn-Cr, Mo-Cr, Ni–Cr, and stainless steels. For each alloy, flow curves were recorded at five different temperatures and six deformation rates. That is, for each material, a set of 30 flow curves was obtained, covering deformation rates ranging from 0.01 to 500 s^{-1} and temperatures from 700 to

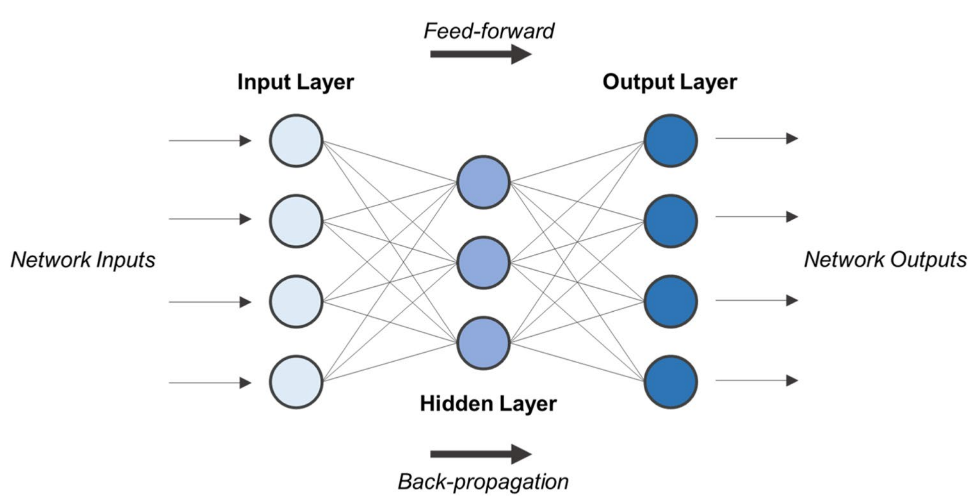

Fig. 1 Example of artificial neural network architecture

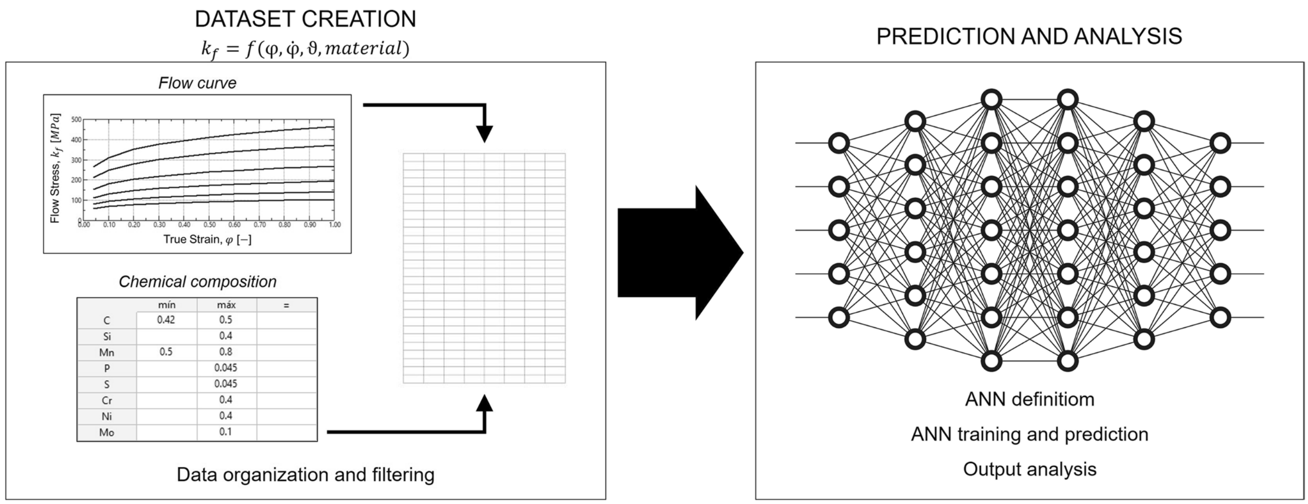

Fig. 2 Applied methodology

1250 °C. Each curve included between 8 and 10 points representing different relationships between k_f and φ. The fixed strain values ranged from 0.02 to 1.5. The chemical composition was defined by recording carbon and 14 other chemical elements: C, Si, Mn, P, S, Al, Cr, Ni, Mo, Ti, V, Be, N, and Cu. Once the data for all materials were downloaded, the information contained in all these files was sequentially read and interpreted.

This dataset was carefully selected so that the ANN could capture and understand the mutual interactions between the chemical elements and their influence on flow stress, considering the synergistic effects under various thermomechanical conditions. Thus, the model is capable of accurately reflecting phase changes and recrystallization phenomena in its predictions, which play a crucial role in the mechanical behavior of steels at high temperatures.

3.2 Data preprocessing

In-depth understanding and careful preprocessing of data, including the application of appropriate normalization techniques, are crucial steps in the effective conduct of data mining [44]. Input data often have multiple dimensions, and each variable has distinct interval scales. Therefore, it becomes essential to normalize each variable to a standardized range from 0 to 1 [45].

To ensure that all features contribute equally to the network training, regardless of their original scales, data normalization was performed. The process involves adjusting the values of input variables to a standardized scale. The Z-score normalization technique was used. This technique uses Eq. (4) to generate a distribution with a mean of zero and a standard deviation of one:

$$z = \frac{x - u}{s} \tag{4}$$

where x corresponds to the training sample value, u is the mean, and s is the standard deviation of the training samples.

3.3 ANN design

The next step involves selecting the architecture of the artificial neural network (ANN). This task plays a crucial role in the performance and generalization ability of the model and is inherently linked to the characteristics of the training data. After defining the architecture, the model development process takes place, where different topologies are tested and adjusted.

Once the data has been filtered and transformed into a CSV file, it was imported into Google Colab. This tool allows for quick tests and implementations of libraries that minimize the work of the solution developer in defining the artificial neural network project.

To enhance the performance of the artificial intelligence model, it is necessary to find the optimal combination of parameters that best fits the data and the problem at hand. In this process, an iterative approach involving trial and error is adopted. Initially, the training set was divided into two parts (Fig. 3): a temporary training set containing 80% of the data and a validation set encompassing the remaining 20%. This division was done randomly and repeated. For each model trained with the temporary training set, predictions were made on the validation set, followed by evaluations of predictive performance [37].

This is a widely adopted practice in machine learning. The model is trained with 80% of the data, while its performance is evaluated on the remaining 20%, reserved for

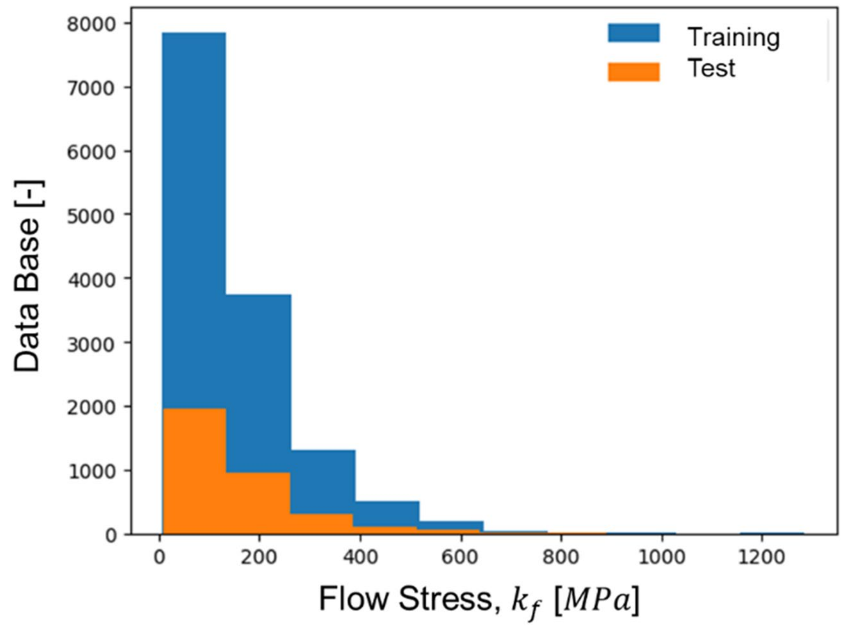

Fig. 3 Distribution between training and testing data

Table 1 Input variables used in this research

Feature	Variable	Range	Feature	Variable	Range
1	C	0,03–1,15	9	Mo	0,0–3,5
2	Si	0,05–3,3	10	Ti	0,0–2,0
3	Mn	0,1–10,0	11	V	0,0–1,15
4	P	0,01–0,11	12	Be	0,0–0,5
5	S	0,008–0,33	13	N	0,0–0,55
6	Al	0,0–1,2	14	$\dot{\varphi}$	0,01–1000
7	Cr	0,0–23,0	15	φ	0,002–1,6
8	Ni	0,0–37,0	16	ϑ	675–1250

testing. It is crucial to emphasize that, to avoid any bias, the same data is not used for both training and predictions. This approach aims to prevent overfitting, a phenomenon in which the model becomes overly tailored to the training data, compromising its ability to generalize to new data. By adopting this strategy, the goal is to ensure the acquisition of accurate and meaningful metrics to assess the model's effectiveness and its generalization capability in scenarios not covered during training [46]. The difference between training and testing errors, especially in the initial iterations, is an expected occurrence that decreases as the model adjusts and improves its performance. This data division plays a crucial role in ensuring that the ANN can accurately predict the behavior of new steel alloys, reliably replicating the technological parameters and thermomechanical conditions involved in industrial processes. Sixteen input variables were selected (Table 1) for the model, including the chemical elements that make up the composition of the steel alloys, values of true strain (φ), strain rate ($\dot{\varphi}$), and temperature (ϑ). Other material-related features were not considered in this study due to the absence of data or lower correlation with the yield stress. The value of k_f was chosen as the output. Thus, the model development process was responsible for defining the ideal number of hidden layers and the optimal number of neurons in each hidden layer.

A maximum limit of 5000 training iterations was established to prevent potential infinite loops. This approach aims to ensure computational efficiency and avoid overfitting the model to the training data.

3.4 ANN performance assessment

After completing all training and prediction iterations, the subsequent phase involves a comprehensive analysis. An extensive battery of statistical metrics is computed, and various graphs are generated to summarize the training and prediction steps, providing a solid foundation for discussing the results [47].

The evaluation of the model's performance was based on three metrics. The first one is the mean squared error (MSE) defined by the following:

$$MSE = \sqrt{\frac{1}{j} \sum_{i=1}^{j} \left(\frac{y_i - y_i^*}{y_i} \right)^2} \tag{5}$$

where j is the number of sets that include input and output data and y_i and y_i^* are, respectively, the measured and predicted response values for the output variables. MSE is a common metric in regression problems. It measures the average of the squares of the differences between the model predictions and the actual values. The lower the MSE, the better the model's performance.

The second metric is the mean absolute error (MAE), which is given by the following:

$$MAE = \frac{1}{j}\sum_{i=1}^{j}\left|y_j - y_i^*\right| \tag{6}$$

The R^2 value was also calculated, given by the following:

$$R^2 = 1 - \frac{\sum_{i=1}^{j}\left(y_j - y_i^*\right)^2}{\sum_{i=1}^{j}\left(y_j - \overline{y}\right)^2} \tag{7}$$

where $\overline{y}$ corresponds to the mean of the measured response values of the output variables. R^2 is a regression metric that measures the proportion of variability in the data explained by the model. A higher R^2 indicates a better fit of the model to the data and a higher likelihood of the model making good predictions for unseen data [37].

4 Results and discussion

4.1 Artificial neural network (ANN) design

The architecture of the ANN is directly dependent on the characteristics of the training data. To explore the nature of the database, graphs were plotted that relate the flow stress to the alloying element content. Figure 4 illustrates this relationship for the elements C, Si, Mn, Cr, Mo, and Ni. The recorded k_f values correspond to the flow stress required to generate a deformation $\varphi = 1.5$ at a strain rate of $\dot{\varphi} = 1s^{-1}$ and a temperature $\vartheta = 1000°C$.

It can be observed that the data exhibit intricate and nonlinear relationships. For instance, when analyzing the graph related to carbon content, the expectation would be a continuous increase in flow stress with the increase in %C. However, Fig. 4 reveals that the k_f values do not follow a linear relationship with carbon content. This observation holds true for the other elements as well. From a metallurgical perspective, this highlights the complexity involved in hot work, making it challenging to quantify the individual effect of each alloying element on the mechanical strength of steels. In contrast to cold work, where strain is primarily associated with material work hardening, hot work encompasses a series of metallurgical phenomena. In this context, the flow stress value not only reflects the impact of a specific element on the magnitude of recovery and dynamic recrystallization but also influences the kinetics of these phenomena. This added complexity makes the analysis considerably more challenging.

In the perspective of data analysis, it becomes evident that the selected data architecture for the artificial neural network (ANN) model must be capable of handling data with complex relationships. The characteristics of the data play a crucial role in defining the architecture of the artificial neural network (ANN) to be employed. Given the evident complexity in the relationships between variables, it is essential to choose an architecture that can capture and learn these nuances. To meet the objectives of this work, which aims to predict the yield curve of steel alloys effectively and accurately, an architecture of a dense neural network (DNN) was modeled [48]. This class of networks has the capacity to learn more abstract hierarchical representations, suitable for complex data with non-linear relationships and intricate patterns.

By selecting this architecture, the goal is to strengthen the propagation of resources and maximize the recognition of network connections between nodes. In a DNN, each neuron receives a weighted sum of the outputs of the neurons connected to them, making quicker calculations to learn estimates about the training sets [49].

The model was adapted with an input layer, two hidden layers, and an output layer, as shown in Fig. 5. The input layer has 14 neurons that include the chemical elements composing the steel alloys, true strain (φ), strain rate ($\dot{\varphi}$), and temperature (ϑ). The hidden layers consist of 20 neurons each, and the output layer has one neuron. The output of the neural network corresponds to the yield stress value (k_f) obtained when the material, defined by a specific chemical composition, is subjected to a specific value of φ, at a specific $\dot{\varphi}$ and ϑ. In total, the network has 801 parameters to be trained.

The hidden layers enable the network to learn more abstract and complex data representations, which is crucial when the relationships between variables are not simply linear. The ability of DNNs to act as universal approximators, combined with the flexibility provided by the hidden layers, facilitates modeling more complex and nonlinear relationships present in the data [50]. This topology resulted from a series of optimization steps aimed at balancing learning capacity with the resources needed for training [51].

In this context, it is worth highlighting that the complexity of the topology plays a crucial role. More complex topologies have the ability to learn more intricate functions compared to simpler topologies but require additional resources during training, such as additional time, computational power, and more extensive volumes of input data [43]. Throughout the process, a careful balance was achieved between the depth and width of the network, aiming to optimize performance without excessively compromising the required resources. This approach aims to maximize the efficiency of the model, providing robust and effective learning.

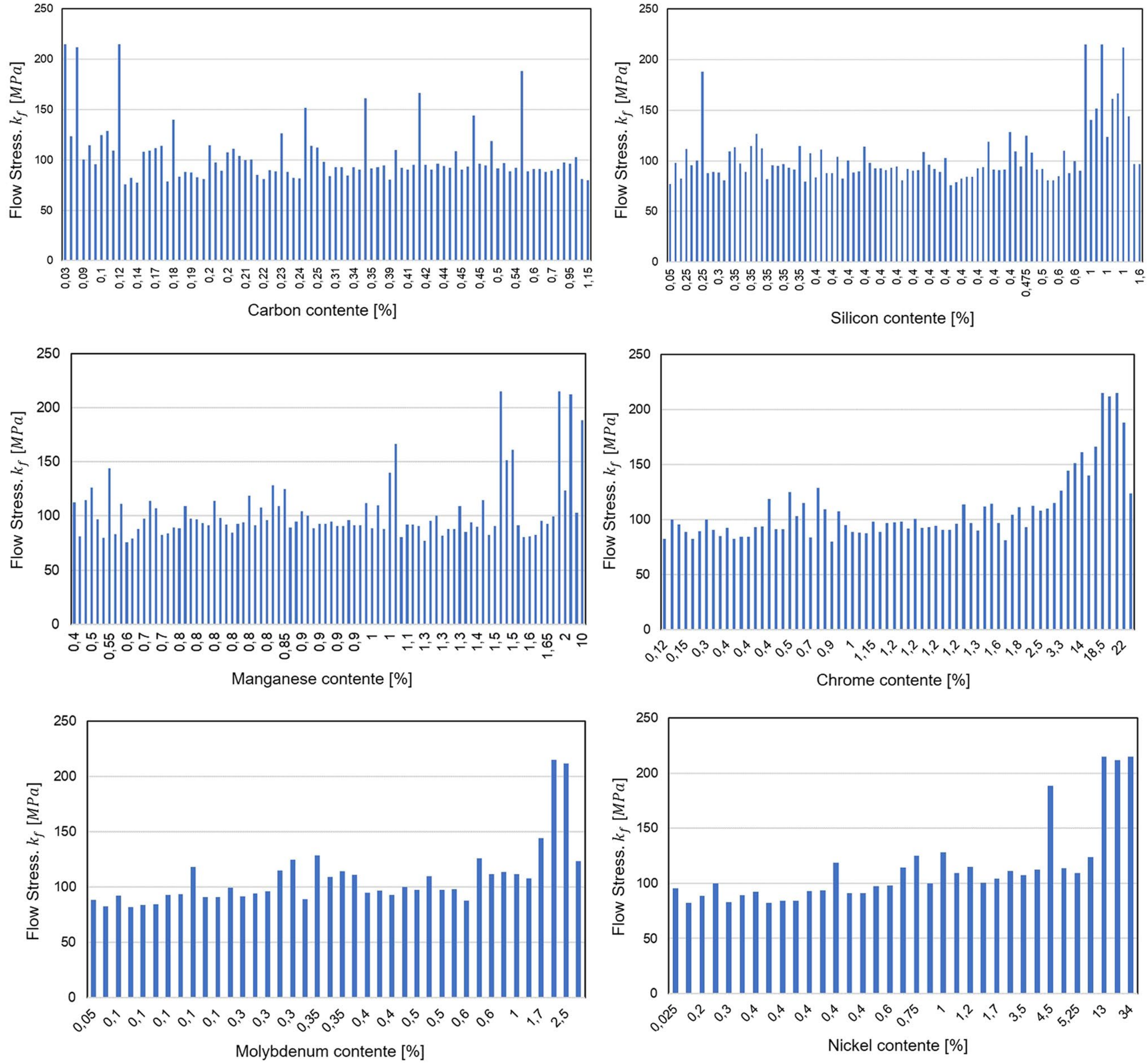

Fig. 4 Relationship between flow stress and the content of elements C, Si, Mn, Cr, Mo, and Ni. The recorded k_f values correspond to the yield strength required to generate a strain $\varphi = 1.5$ at a strain rate of $\dot{\varphi} = 1s^{-1}$ and a temperature $\vartheta = 1000°C$

4.2 Performance evaluation

Figures 6 and 7 present, respectively, the evolution of mean squared error (MSE) and mean absolute error (MAE) as a function of the number of iterations during model training. These graphs are valuable tools to understand the performance and convergence of the model over time. They provide insights into how the training algorithm is adjusting the network weights to minimize errors.

Initially, both MAE and MSE decrease as the model adjusts to the training data. This reflects the learning process of the network to reduce discrepancies between predictions and actual values. As training progresses, convergence of errors to relatively low values is observed, indicating that the artificial neural network (ANN) is learning effectively and approaching an optimal solution. Subsequently, the graphs show stability with minimal variations in error values, indicating that the model has reached a point where additional adjustments do not provide significant improvements.

Both graphs demonstrate that the training algorithm is consistently working to minimize errors. In other words, the error curve continues to move towards zero, indicating an active search for a solution that closely approximates the training data.

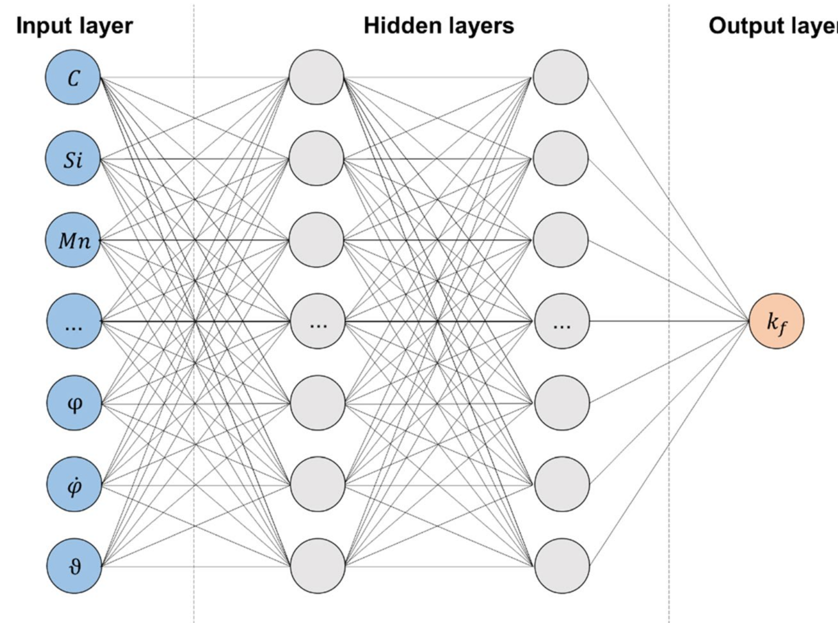

Fig. 5 Architecture of the proposed dense artificial neural network

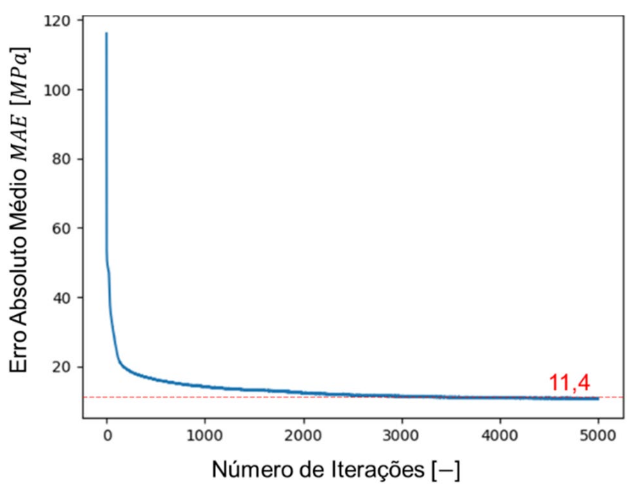

Fig. 6 Evolution of the mean absolute error as a function of the number of iterations for model training

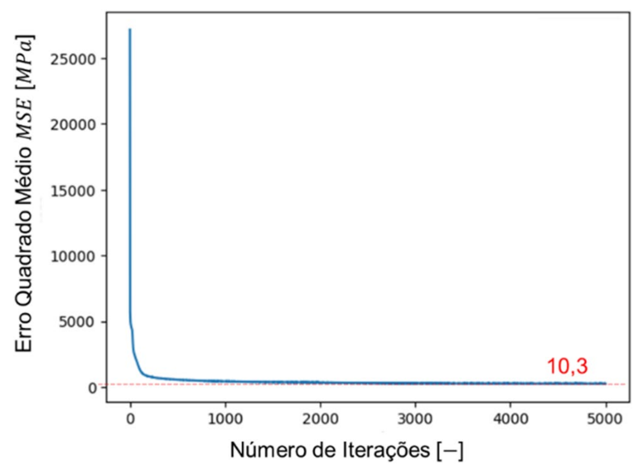

Fig. 7 Evolution of the mean squared error as a function of the number of iterations for model training

After 5000 iterations, the mean absolute error is 11.4 MPa, while the mean squared error is 10.3 MPa. MAE represents the average of the absolute differences between actual and predicted values. Therefore, an MAE of 11.4 MPa indicates that, on average, predictions of yield strength deviate by 11.4 MPa from actual values. MSE represents the average of the squared differences between actual and predicted values. An MSE of 10.3 MPa indicates that, on average, the mean squared deviations of predictions from actual values are 10.3 MPa.

The interpretation of results regarding MAE and MSE depends on the specific application domain and the characteristics of the output variable. It is always useful to compare these metrics with other approaches to assess whether the model meets the required accuracy for the particular application. In the experimental construction of the flow curve of a material, deviations in flow stress values are common. The dispersion of mechanical properties is often observed in samples cut from the same bar. This phenomenon has been documented in the literature and industrial applications and is likely caused by the lack of homogeneity characteristic of metallic materials [52, 53].

Additionally, industrial mechanical forming processes induce severe strain in metals. Therefore, the flow stress typically varies on a scale of hundreds of MPa. According to ALTAN (2005), the closed-die forging process of steel alloys, for example, typically involves stresses between 415 and 690 MPa [1]. In this scenario, an MAE of 11.4 MPa can be considered acceptable, indicating that the predictions, on average, deviate by about 2% of the total scale.

Figure 8 presents the model prediction graph. This graph is a powerful tool for intuitively and visually assessing the quality of predictions made by an ANN. If the points on the graph are approximately aligned along a straight line, it suggests that the model is effectively capturing linear relationships in the data. A linear distribution indicates a good match between predictions and actual values.

From the graph, the value of R^2 can be extracted. This performance metric shows the proportion of data variability explained by the model. The proposed model has an R^2 value of 0.98. A coefficient of determination of 0.98 indicates that the ANN model is highly effective in explaining data variability. In this case, the value of 0.98 suggests that approximately 98% of the variability in the model output is explained by the provided inputs. In simple terms, this means that the model has an excellent ability to fit the training data and capture underlying patterns.

It can be observed that the points on the graph in Fig. 8 are close to the diagonal line, and there are no discernible deviation patterns. Moreover, no significantly scattered points are identified far from the diagonal line (outliers). Based on these results, it is expected that the model predictions are very close to the actual values.

Although the obtained results have been promising, it is crucial to highlight that the limited size of the input dataset used in this study represents a constraint on the learning capacity of the neural network [41, 47]. Another critical aspect for the predictive ability of the model is associated with the presence of input data with zero values. During training, the weights of the neural network are adjusted to minimize error. If a specific input has a zero value, the weights corresponding to that input may not be updated effectively, as multiplication by zero does not contribute to weight updates. Furthermore, if the relationship between the zero-value input and the network output is nonlinear, the network's inability to adjust the corresponding weights may result in an inadequate representation of this relationship.

Figure 9 visually represents the difference between predicted and actual values for different data points. The graph indicates that the model's predictions are very close or nearly identical to the actual values. Effective convergence shows that the model is adjusting its parameters to minimize discrepancies for all levels of flow stress.

4.3 Inference tests

After creating the model, inference tests were conducted to further evaluate the predictive capability of the model. Inference tests refer to the ability to make predictions on unseen data based on the trained model. This inference phase is crucial to understand how the model performs in real-world situations and how its predictions can be applied. The tests include applying the model to new datasets that were not used during training, allowing an assessment of the model's generalization capability.

The ability of a model to correctly predict new examples different from those used for training is known as generalization [54]. This property of the model depends on the quality of the data, the size of the database, and the training

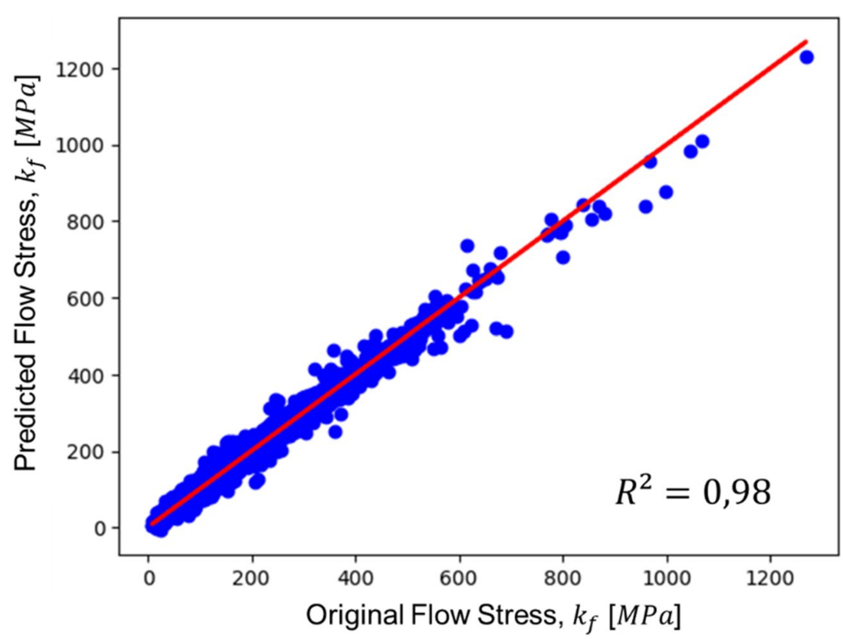

Fig. 8 Prediction of flow stress as a function of its original value

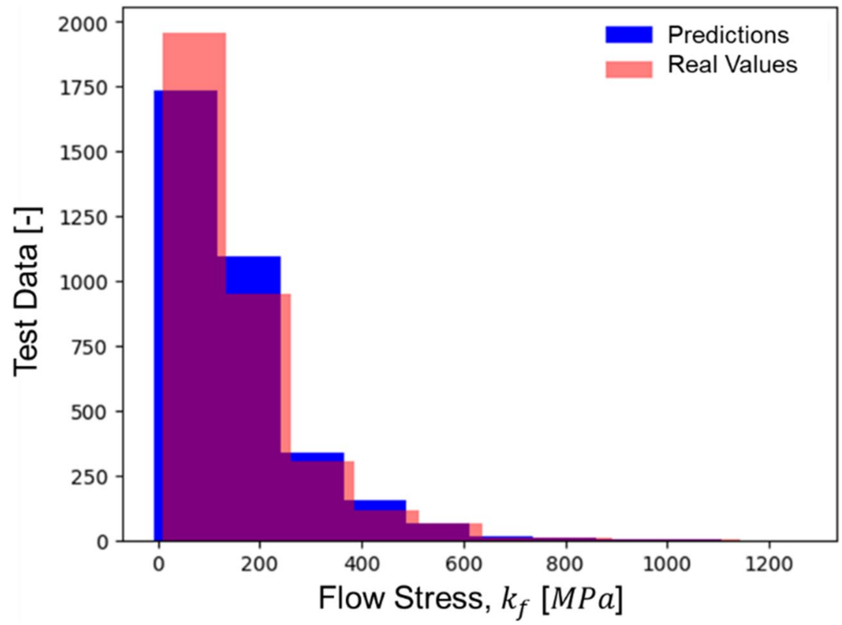

Fig. 9 Convergence of training data with real data

algorithm [11]. Improving this competence, minimizing the model's error, is the universal goal of machine learning [16].

For the tests, three steel alloys that were not included in the neural network's database were selected. These alloys are vanadium microalloyed steel DIN 38MnVS6 and the chromium-molybdenum steels DIN 9CrMo4-5 and DIN 22CrMo4-4. Table 2 shows the chemical composition of the steels used in the inference tests.

Figure 10 displays the actual and predicted flow curves by the model developed in this study for the steels DIN 38MnVS6, DIN 9CrMo4-5, and DIN 22CrMo4-4. It can be observed that the predicted curves align well with the real curves. The neural network demonstrated the ability to satisfactorily predict the actual behavior of the materials.

The discrepancy between the real and predicted curves can be quantified by calculating the area bounded by both curves [42, 55, 56]. The area between the two curves corresponds to 2.0%, 4.5%, and 3.7% of the area of the real curve for DIN 22CrMo4-4, DIN 9CrMo4-5, and DIN 38MnVS6, respectively. This deviation can be used as an indicator of the error incurred when using the approximation instead of the real curve [42].

The model's responses to different conditions and scenarios demonstrate its robustness and practical utility in various real-world situations. Moreover, an error of less than 5%, as achieved in the inference tests, implies performance comparable to other artificial intelligence models applied in materials science [42, 57, 58].

5 Conclusions

This study investigated the applicability of artificial neural networks (ANNs) in predicting the flow curve of hot-deformed steel alloys. The results indicate significant advancements. It was demonstrated that ANNs are effective in predicting the mechanical behavior of these alloys, considering factors such as chemical composition and forming conditions ($\varphi, \dot{\varphi}, \vartheta$). A dense neural network, with two hidden layers containing 20 neurons each, proved capable of learning complex relationships, resulting in robust performance, as evidenced by a mean absolute error (MAE) of 11.4 MPa and a mean squared error (MSE) of 10.3 MPa. The MAE and MSE values are considered acceptable, given that in industrial mechanical forming processes, the yield strength typically varies on the scale of hundreds of MPa.

The model demonstrated excellent predictive capacity, indicated by $R^2 = 0.98$ and validated by inference tests involving steel alloys not present in the training data. Consistent responses in different conditions and scenarios

Table 2 Chemical composition of DIN 38MnVS6, DIN 9CrMo4-5, and DIN 22CrMo4-4 steels

Steel	C	Si	Mn	P	S	Al	Cr	Ni	Mo	Ti	V	Cu
9CrMo4-5	0,9	0,15	0,7	0,01	0,01	-	1,15	-	0,5	-	-	0,1
22CrMo4-4	0,26	0,4	0,8	0,035	0,035	-	1,2	0,6	0,5	-	-	-
38MnVS6	0,4	0,6	1,45	0,015	0,03	0,017	0,19	-	-	0,01	0,11	-

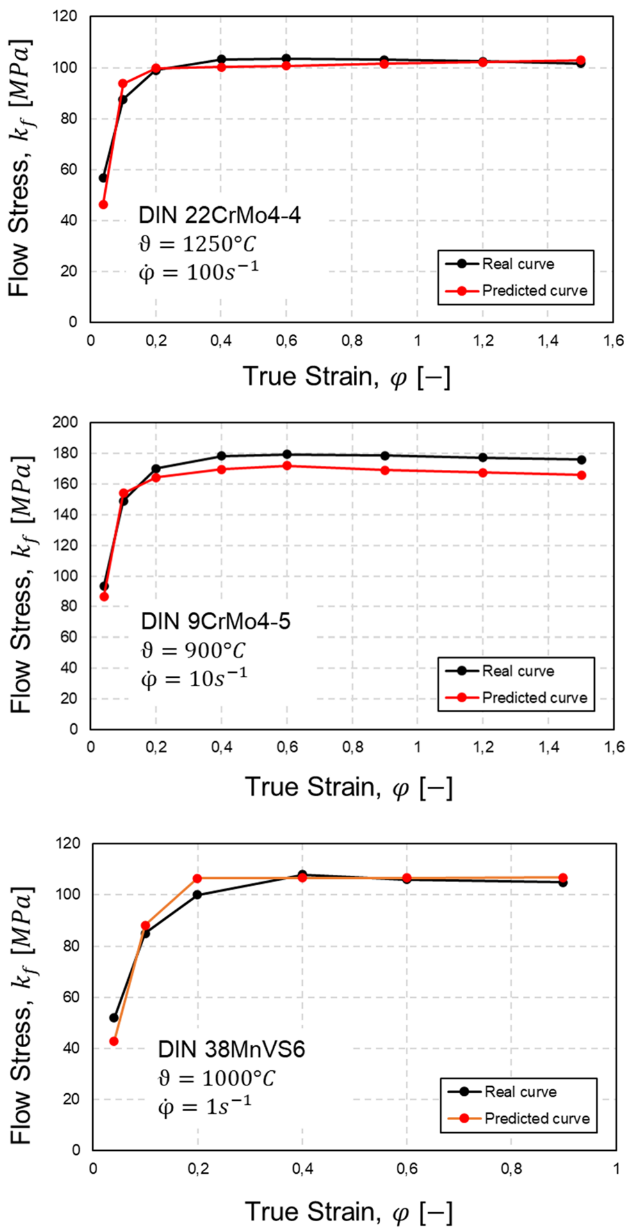

Fig. 10 Actual flow curves and approximations predicted by the proposed model

highlighted the robustness and practical utility of the proposed model.

This work contributes to the development of mechanical forming processes, providing an effective tool based on artificial intelligence. Furthermore, it opens possibilities for similar research in other metals. The ANN proved suitable for describing the plastic behavior of industrial materials without the need for costly tests. Moreover, expanding the database and exploring more advanced network architectures offer potential for future improvements.

Funding The authors thank CNPq (National Council for Scientific and Technological Development) and Capes (Coordination for the Improvement of Higher Education Personnel) for financial support.

Declarations

Ethical approval Not applicable.

Conflict of interest The authors declare no competing interests.

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