



Development of an artificial neural network for predicting energy absorption capability of thermoplastic commingled composites

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ABSTRACT

Soft computing techniques including artificial neural networks (ANN) and machine learning reflect new possibilities to behavior prediction models of commingled composites. This study focuses on developing an artificial neural network capable of predicting the impact energy absorption capability of thermoplastic commingled composites, in the context of crashworthiness, based on a compilation of experimental results, multiple regression analytical model and factorial design method. Furthermore, the scientific approach of this project comprises the (i) development of intelligent models for designing and manufacturing of new composite components, (ii) application of computational methods to predict material performance and behavior, and (iii) optimization of manufacturing processes. The innovativeness of this proposal is to initiate the use of computational methods to describe mechanical and structural properties of thermoplastic commingled composite materials and the development of an artificial neural network able to predict the energy absorption capability of these materials, considering some properties of polymer matrix, thermal degradation kinetics model and consolidation parameters. The obtained results from impact testing indicate that the proposed approach can predict the impact energy with satisfactory accuracy. The use of an analytical model database as input for the ANN is an innovative methodology to increase the reliability and accuracy of the ANNs.

1. Introduction

Consolidation of thermoplastic composites involves a set of processing parameters that, combined with the thermal properties of the matrix, directly affect the impact energy absorption capability of the structure [1]. Understanding the material performance in an impact event associated with the level of thermo-oxidative thermoplastic matrix degradation during consolidation is a complex challenge that requires the development of methods and models to predict and optimize thermoplastic composites processing [2,3].

Interest in the use of structural composite materials in components for the automotive industry has been increasing considerably in recent years, driven by the manufacture of hybrid and electric vehicles [4,5]. For this reason, improvements on structural composites crashworthiness are directly related to the human safety in a possible automotive crash and it depends on the energy absorption capability of the composite components [6–8].

Part of the innovation of the proposed study is the incorporation of an analytical regression model derived from experimental results as input for training an artificial neural network (ANN). The use of analytical models as ANN input database is still largely unexplored in the area of structural composite materials and the literature does not contain well-defined research lines. Therefore, the development of an ANN based on an analytical model and computer simulations is a promising research topic and may assist in the accuracy and effectiveness of prediction models. Therefore, this work aims the development of an ANN trained by an analytical database to predict the impact energy absorption (IEA) capability of thermoplastic commingled composites.

Based on recent studies [1,9] a multiple regression model was used to generate the ANN input database. This multiple regression model is capable of predicting IEA of thermoplastic commingled composites as a function the low velocity impact test (LVI) responses. In addition, thermal degradation limits and consolidation parameters were

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provided by Friedman's isoconversional method [10] and the by the Darcy's law [11]. The developed model can predict IEA at different consolidation conditions. The equation generated by the regression model was used to provide the dataset ANN input.

A literature review points to recent studies [12–19] of computational modeling development applied to structural composite materials. Soft computing methods have been recently used [20] to improve the behavior of structural composite materials [21], including the design optimization of composite parts made of long fibers composites [22], recyclability of thermoplastics composites [23], structural behavior of natural fibers reinforced composite [24], and to improve the mechanical properties correlation of composite materials [25,26]. However, most of the research has been focused on the behavior of thermo-rigid composites, which reinforces the innovativeness of the present proposal in the development of an ANN applied in thermoplastic composites, especially commingled ones. The use of analytical models and artificial intelligence (AI) is still largely unexplored in the area of commingled composite materials and the literature does not contain well-defined research lines. Therefore, the development of an ANN based on analytical models is a promising research topic and may assist in the accuracy and effectiveness of the commingled composites manufacturing.

Although many studies have been reported on the use of artificial intelligence applied to composite structures [27–31], very few have been focused on the use of ANN as a technique to predict the IEA of thermoplastics composites. The work presented here assesses the potential of a long-term prediction of impact energy absorption based on manufacturing parameters. More specifically, the major contributions of this article are summarized as follows: (i) use of an analytical model database as ANN input; (ii) obtain accurate predictions of impact energy absorption as a function of the consolidation parameters, thermal degradation kinetics and matrix properties; and (iii) demonstrate the accuracy of the ANN developed.

2. Theoretical background

2.1. Impact energy absorption capability of composite materials

The evaluation of a composite material IEA capability is determined by the damage resistance of multidirectional polymer matrix composite laminated plates subjected to a drop-weight impact event (low velocity impact test). The damage resistance properties generated by this test method are highly dependent upon several factors, which include specimen geometry, layup, impactor geometry, impactor mass, impact force, impact energy, and boundary conditions. Thus, results are generally not scalable to other configurations, and are particular to the combination of geometric and physical conditions tested.

The dissipated energy (E_D) of the specimens on LVI test is calculated considering the impact velocity (v_i), impactor displacement (δ) and time during test (t), as shown in Eqs. (1)–(3) [32]. The E_D also represents the material IEA capability. The impact velocity is defined by:

$$v_i = \frac{w_{12}}{t_2 - t_1} + g \left(t_i - \frac{(t_1 - t_2)}{2} \right) \quad (1)$$

where, w_{12} is the distance between leading edges of the first (lower) and second (upper) flag prongs; t_1 , t_2 and t_i are, respectively, the time first (lower) flag prong passes detector, the time second (upper) flag prong passes detector, and the time of initial contact obtained from force versus time curve [33]. The impactor displacement is given by:

$$\delta(t) = \delta_i + v_i t + \frac{gt^2}{2} - \int_0^t \left(\int_0^t \frac{F(t)}{m} dt \right) dt, \quad (2)$$

where, δ_i is the impactor displacement from reference location (i) at $t_{\text{imet}} = 0$ s, g is the acceleration due to gravity, m is the impactor mass, and F is the measured impactor contact force at time t [31]. The dissipated energy is then defined by:

$$E_D = \frac{m(v_i^2 - v(t)^2)}{2} + mg\delta(t), \quad (3)$$

The total LVI energy (E_T) is related to E_D and the elastic energy (E_E) according the following relation:

$$E_T = E_D + E_E \quad (4)$$

2.2. Backpropagation artificial neural networks

Composite materials engineering needs systematic and interactive approaches, which should allow for achieving optimum material characteristics. This process requires the application of various methods and technologies aiming at (i) investigation of the physical and mechanical properties of each constituent, as well as of the composite material; (ii) optimization of the properties of the composite according to the specific working conditions; (iii) understanding the effects of manufacturing and composition on the properties of the composite material; and (iv) development of computational methods for characterization, analysis and prediction of the performance of materials under different working conditions. This appears especially important in the case of composite materials characterized by strongly inhomogeneous properties.

The integrated process of modelling, calculation, prediction and/or optimization of the properties of a composite material against different influencing factors is the most important part of materials engineering. That is why soft computing techniques, integrated with different numerical methods, could support that process.

An ANN is a system composed of many simple processing elements operating in parallel, whose function is determined by the network structure, the connection strengths, and the processing performed at computing elements or nodes. A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects: (i) knowledge is acquired by the network through a learning process, and (ii) the interneuron connection strengths, known as synaptic weights, are used to store this knowledge [34].

The Levenberg–Marquardt algorithm (LMA), also known as the Damped least-squares (DLS) method, is used to solve non-linear least squares problems. These minimization problems arise especially in least squares curve fitting. The LMA is used in many software applications for solving generic curve-fitting problems [35]. However, as with many fitting algorithms, the LMA finds local minima, which is not necessarily the global minimum. The LMA interpolates between the Gauss–Newton algorithm (GNA) and the method of gradient descent. The LMA is more robust than the GNA, which means that in many cases it finds a solution even if it starts very far off the final minimum. For well-behaved functions and reasonable starting parameters, the LMA tends to be a bit slower than the GNA. LMA can also be viewed as Gauss–Newton using a trust region approach [36,37].

The Hyperbolic tangent sigmoid transfer function (*Tansig*) is usually used in multilayer networks that are trained using the backpropagation algorithm [38]. *Tansig* is a neural transfer function that calculates a layer's output from its net input. ANN transfer functions are the way to simulate phenomena's reaction using input and output parameters. *Tansig* was used as the activation function in the ANN developed and it is related to a bipolar sigmoid which has an output in the range of -1 to $+1$, as shown in Fig. 1(a). The output n , often referred to as the net input, goes into a transfer function f , which pro-

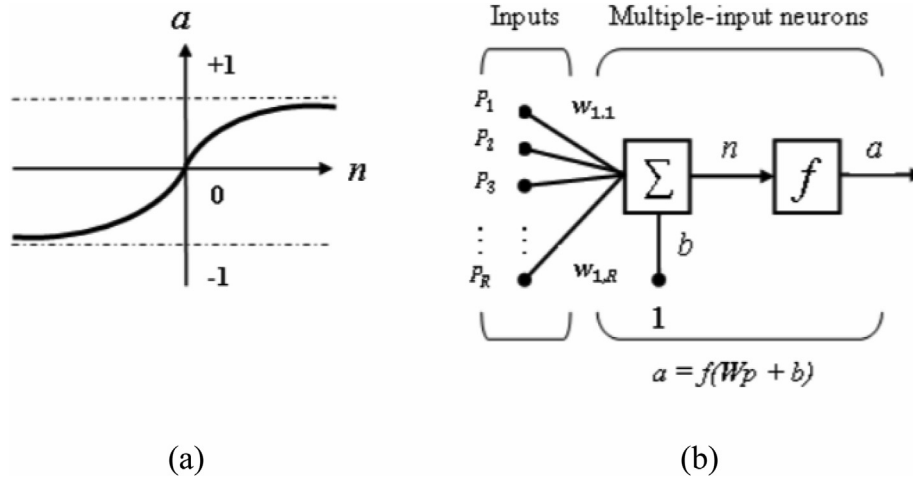


Fig. 1. Hyperbolic tangent sigmoid transfer function: (A) TANSIG function and (B) multiple-input neurons. Source: DOROFKI et al. (2012) [39].

duces the scalar neuron output a . A neuron with P inputs is shown in Fig. 1(b).

The *Tansig* function (α') can be calculate by using the following equation [39].

$$\alpha' = \text{Tansig}(n) = \frac{2}{1 + e^{-2n}} - 1 \quad (5)$$

Tansig function takes one input and optional function parameters and returns each element of n squashed between -1 and 1 . The multiple-input function is a good tradeoff for ANN, where data processing speed is more important than the exact shape of the transfer function.

3. Experimental background

3.1. Materials

The selected materials of this study have been used for crashworthiness application [1,9]. The reinforced fibers were manufactured by Toho Tenax® [40]. According to the supplier, the HTS40 carbon fiber (CF) is characterized by 4,240 MPa and 237GPa of tensile strength and elastic modulus, respectively. Concordia Manufacturing Co Inc. has supplied the polymers yarns to manufacture the commingled 12 k tows. The multifilament yarn polyamide 6 (PA6) has the specification of Nylon 6-900/72 [41]. Both the CF/PA6 and CF/PEEK 12 k commingled tows have the standard type of interlacing [42] which contributes to the wettability [43] of the reinforcing fibers during the thermal consolidation [44]. The polyether ether ketone (PEEK) has the specification PEEK-900/68 [41]. The CF/PEEK 12 k commingled tow presents the specification of AS4. Both materials have 59% of reinforcing fiber content. The response to low velocity impact test was used in the factorial design analysis based on the multiple regression model developed previously [9], which is able to predict IEA as a function of independent variables related to (i) consolidation parameters, (ii) thermal degradation kinetics and (iii) matrix properties.

3.2. Consolidation parameters

From the perspective of fluid dynamics, Darcy's law is given by a constructive equation that can be used to guarantee and predict whether a given viscous fluid is able to impregnate the reinforcing fibers in a composite material [11]. The flow rate of the viscous polymer u_p and the impregnation time t_{imp} can be described by the Darcy's law [11] (Eq. (6)) taking $\frac{dp}{dx}$ constant (Eq. (7)).

$$u_p = \frac{dx}{dt} = \frac{K}{\nu} \frac{dp}{dx} \quad (6)$$

$$t_{imp} = \frac{\nu D_p^2}{2KP} \quad (7)$$

where, ν is the polymer viscosity, K is the reinforcing fibers coefficient of permeability, $\frac{dp}{dx}$ is the pressure gradient, and D_p is the impregnation distance. D_p is directly associated with the homogeneity of the polymer yarns distribution throughout the commingled tow. Inhomogeneity of distribution causes increase of D_p . The consolidation pressure P range was determined empirically by previous studies, as well as the matrix viscosity as a function of temperature [1,9].

The quality of the commingled composites depends on the total and effective impregnation of the matrix within the reinforcing fibers during the consolidation process. The use of Darcy's law (Eq. (7)) accurately determines the impregnation time required for the manufacture of high-performance structural laminates.

3.3. Evaluation of thermal degradation kinetics

Friedman's isoconversional method was applied to both materials to identify how the degradation kinetics acts during consolidation and how does it affect the final mechanical properties of thermoplastic commingled composites. Crashworthiness is directly associated to the material structural performance after consolidation and the ANN considers this topic.

The kinetics of degradation can be calculated using Eq. (8) [45,46], where α is the degree of degradation, t is time, $k(T)$ is a temperature-dependent factor, and $f(\alpha)$ is the reaction model. Arrhenius's equation (Eq. (9)) determined the $k(T)$, where E_a represents the activation energy, R is the universal gas constant and A_a is the pre-exponential factor,

$$\frac{d\alpha}{dt} = k(T)f(\alpha) \quad (8)$$

$$\frac{d\alpha}{dt} = A_a e^{\left(\frac{-E_a}{RT}\right)} \quad (9)$$

Friedman's isoconversional method [10] allows the determination of E_a and A_a (Eq. (10)) considering the degradation degree rate $\frac{d\alpha}{dt}$ as a function of $\frac{1}{T}$, for each predetermined degree of degradation α :

$$\ln\left(\frac{d\alpha}{dt}\right) = \ln A_a - \frac{E_a}{RT} \quad (10)$$

For each temperature, Friedman's isoconversional method also allows for predicting α over time, according to Eq. (11),

$$\alpha = A_a \exp\left(\frac{-E_a}{RT}\right) t \quad (11)$$

The commingled composites manufacturing depends on the thermo-oxidative degradation limits provided by the Friedman's isoconversional method [47,48]. Thermogravimetric methods for the evaluation of degradation kinetics of thermoplastic composites deal with tests at different heating rates to plot the material limits of degradation, beyond the E_a determination as a function of α . The temperature of the peak T_{peak} represents the point at which the heat input is equal to the heat absorption ratio (Eqs. (12) and (13)):

$$\frac{m(\Delta H)}{gk} = \int_{T_1}^{T_2} \Delta T dT \quad (12)$$

$$\Delta T_{min} = \left(\frac{dH}{dt}\right)_{max} \frac{m}{gk} \quad (13)$$

where ΔH is the total enthalpy, m is the mass of the sample, ΔT is the temperature variation between the start T_1 and the final T_2 of the process, g and k are constants related to the sample, the sample port and the instrument used [48]. Consequently, the Friedman's isoconversional kinetic method was able to estimate the degradation time limits at each processing temperature, considering the α predetermined. The polymer melting point T_{melt} is associated with its time limit t_{melt} . Furthermore, T_{onset} can be determined by thermogravimetry and it is associated with the onset time limit t_{onset} .

3.4. Multiple regression model

The multiple regression model used to generate the ANN input database is described by Eq. (14) [9]:

$$IEA = \beta_0 + \beta_1 \left(\frac{-E_a}{\ln\left(\frac{\alpha}{A_a t}\right)} \right) + \beta_2 \left(\frac{\nu D_p^2}{2KP} \right) \quad (14)$$

The analytical model correlates the Friedman's isoconversional method degradation limits, the matrix properties, and the consolidation parameters provided by the Darcy's law. Theoretically, the regression model predicts the IEA capability of commingled composites.

The regression coefficients β_0 , β_1 , and β_2 indicate a change in the mean response to each unit of the independent variable [49,50]. The regression model was based on the method of least square to find the more appropriate fit for a set of data to minimize the maximum likelihood of the function L of the model [49–52]. Also, the stepwise method of variable selection determined a subset of independent variables that best explain the response, and the Akaike Information Criterion (AIC) was based on a sample fit to estimate the likelihood of a model to predict or estimate future values [53–54].

Previous work [1,3,9] supported the database acquisition related to the LVI test and to regression model development to predict the energy absorption capability and crashworthiness of composite materials.

3.5. Full factorial design

A recent study [20] developed a custom factorial design model based on multiple regression model analytical responses for understanding the effects and interactions of the independent variables related to processing, properties of the polymer matrix and thermal degradation kinetics on the impact energy absorption capability of thermoplastic commingled composites. The design of experiments (DOE) analysis indicated how the effects and interactions of the independent variables significantly affect the impact energy absorption capability of commingled composites.

Table 1
Model summary.

S	R-sq	R-sq (adj)	R-sq (pred)
1.54476	97.46%	97.46%	97.46%

Adjusted R-squared (R_{adj}^2) of 97.46% proved the efficiency of factorial design model. The factorial model summary is shown in Table 1.

The regression Eq. [20] in uncoded units (Eq. (15)) obtained by the DOE analysis is shown below:

$$\begin{aligned} IEA = & 116.81 - 0.1438P - 0.2427T - 49.99Dp \\ & + 0.01036\nu + 0.000344P * T + 0.2348 + P * Dp \\ & + 0.000038P * \nu + 0.0431T * Dp - 0.000057 T * \nu \\ & - 0.05718Dp * \nu - 0.000499P * T * Dp - 0.000005P * Dp * \nu \\ & + 0.000192T * Dp * \nu \end{aligned} \quad (15)$$

3.6. ANN development

In this study, Matlab® software was used for computational programming of the artificial neural network. It is important to mention that no rule was established for choosing the optimal number of hidden layers and neurons for each layer, therefore they were decided by trial and error, and the mean square error (MSE) was used to control the performance of the neural network. According to Zhang *et al.* (2013) [56], while the error on the training set is driven to a very small value due to the powerful ANN learning process, a problem called over-fitting may arise. This is when new data is presented to the network and the error is large. This is because the network has

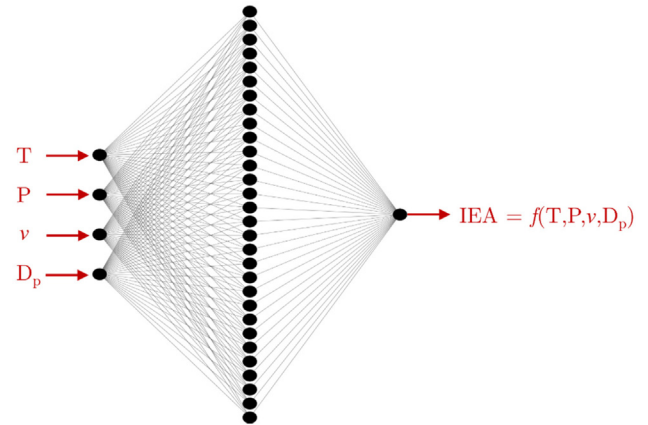
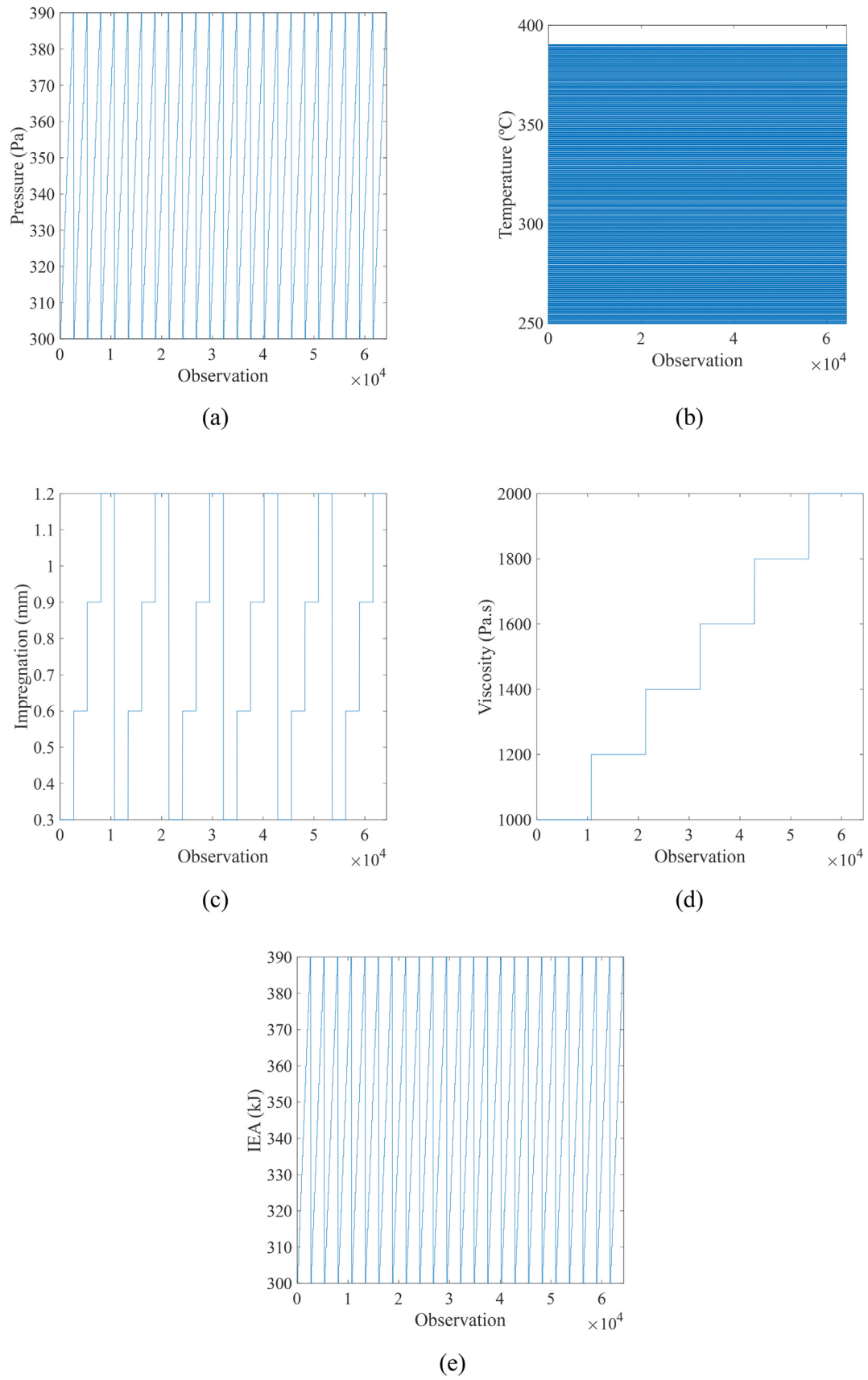


Fig. 2. ANN structure composed of 4 inputs, 1 hidden layer and 1 output.

Table 2
Neural network parameters setup.

Variable	Value
Training function	Levenberg-Marquardt
Activation function 1	Hyperbolic tangent sigmoid
Activation function 2	Linear transfer
Error (performance)	10^{-3}
Number of Neurons	50
Learning rate	0.02
Max. iterations	1000

**Fig. 3.** Data set used in ANN.

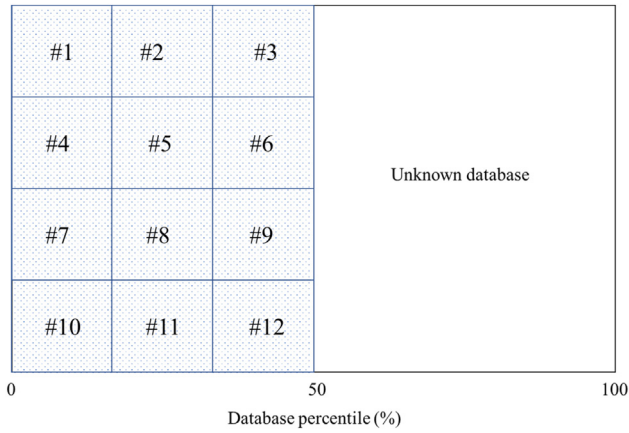


Fig. 4. Database percentile used to train and to verify the ANN.

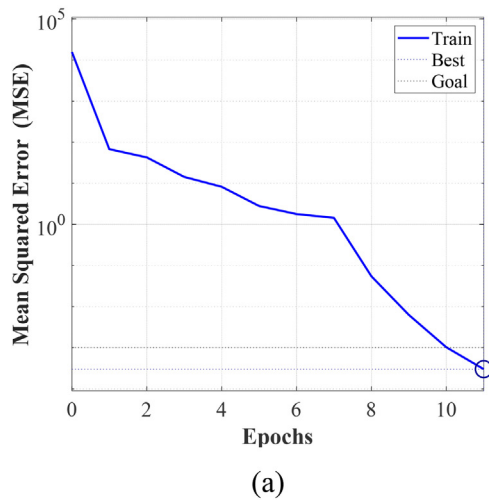
memorized the training examples, but it has not learned to generalize to new situations.

Artificial neural networks are computational systems, which simulate the microstructure (neurons) of a biological nervous system [55].

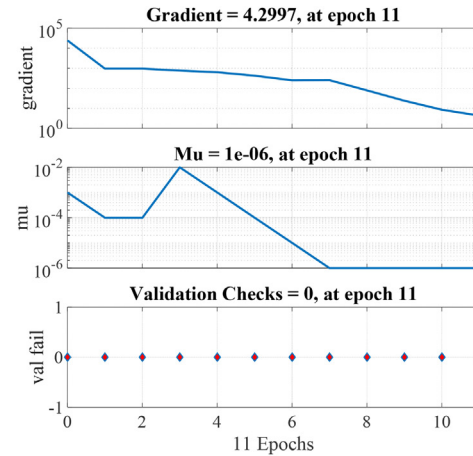
ANNs are composed of simple elements operating in parallel, i.e., ANNs are the simple clustering of the primitive artificial neurons. A neuron influences others behavior through a weight. Each neuron simply computes a non-linear weighted sum of its inputs and transmits the result over its outgoing connections to other neurons.

In the training phase, the ANN system learns by adjusting the weights of relative impact of inputs to outputs and trying many combinations of weights until a good fit to the training cases is obtained [56]. The network generally consists of several layers of neurons, namely input layer, hidden layer or layers, and output layer. The input layer takes the input data and distributes them to the hidden layer(s) which do all the necessary computation and transmit the final results to the output layer [57].

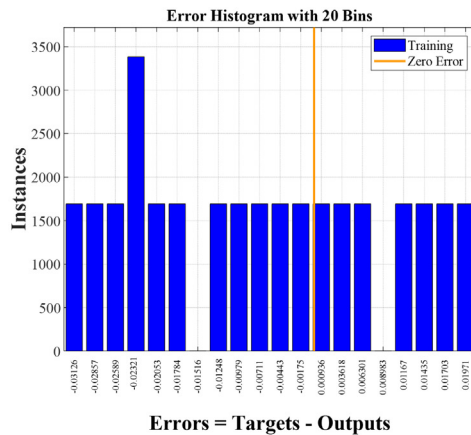
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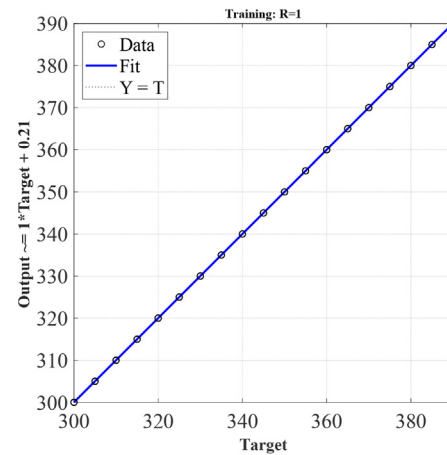
(a)



(b)



(c)



(d)

Fig. 5. ANN training results: (a) performance, (b) training state, (c) error histogram and (d) regression.

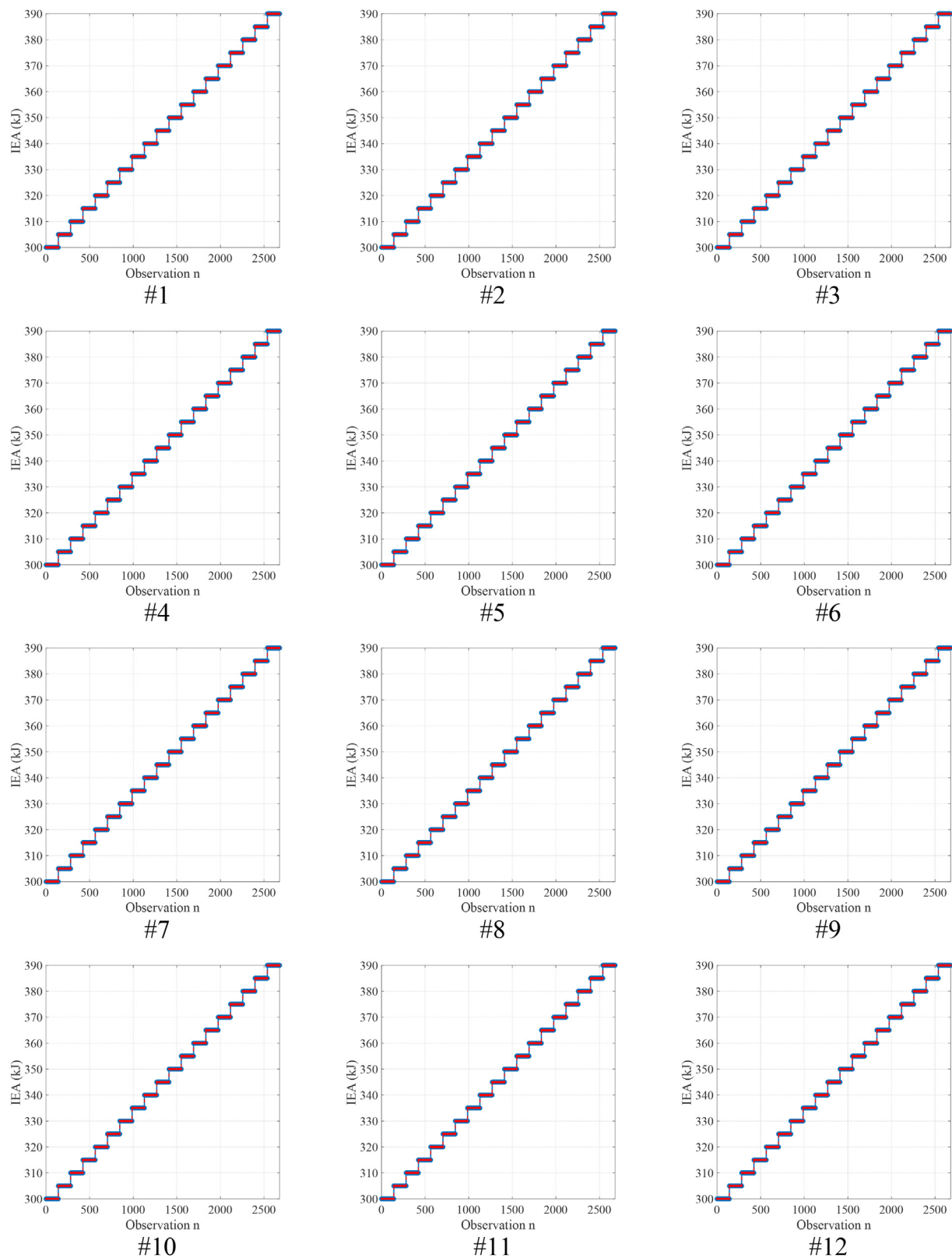


Fig. 6. Experimental and ANN trained output results (legend: ■ Experimental ■ ANN).

Then, after training sessions and ANN parameter modifications, the best configuration was found using 50 neurons in a single hidden layer. Fig. 2 shows the network architecture built for the IEA prediction problem addressed in this paper. As can be seen, the temperature,

pressure, viscosity and impregnation distance were chosen as input variables. The hidden layer has the interconnection of artificial neurons. The output layer then provides information about the impact energy absorption.

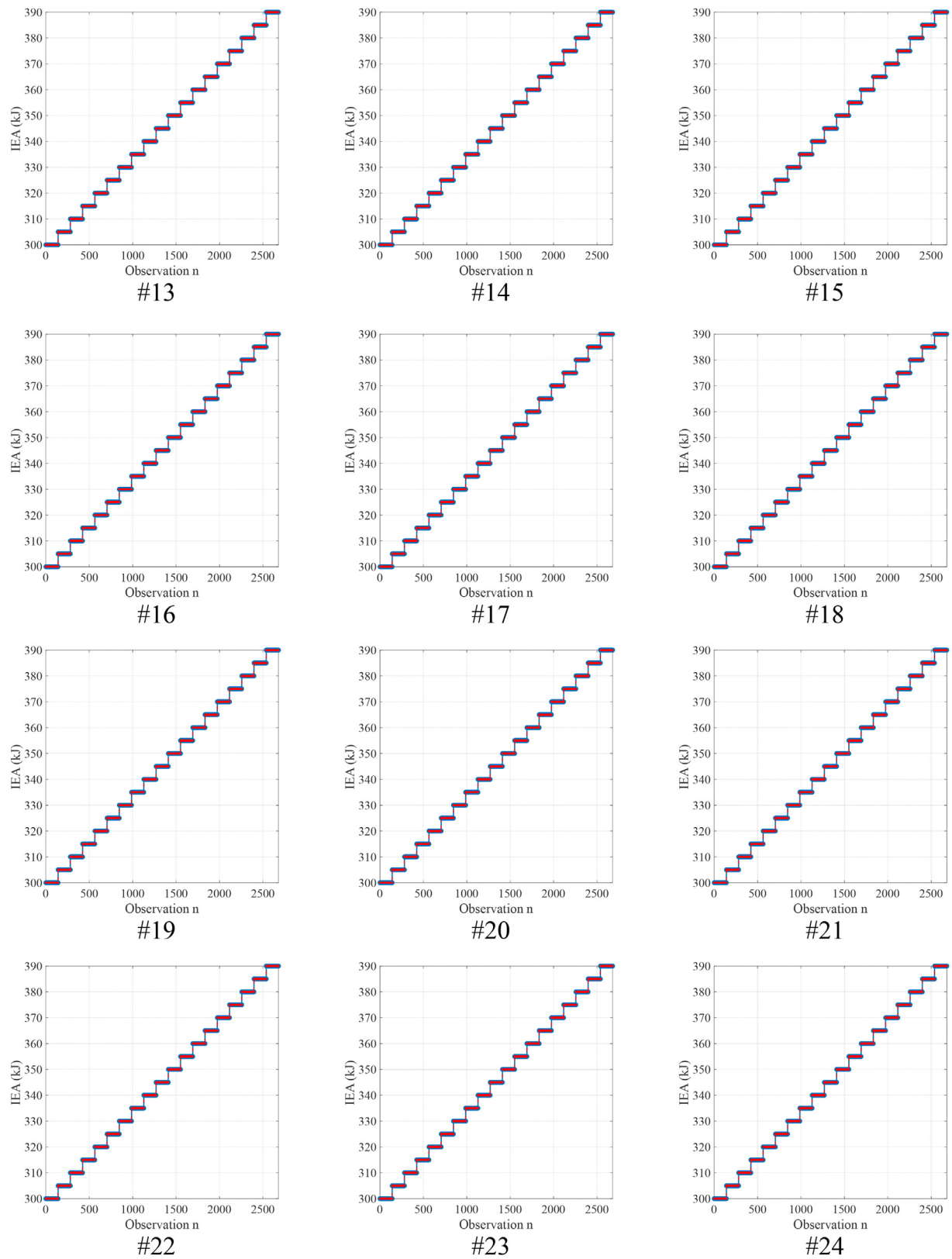


Fig. 7. Experimental and ANN output results for unknown data (legend: ■ Experimental ■ ANN).

Table 2 presents a summary of the neural network training and testing parameters. The learning rule employed was based on Levenberg-Marguardt algorithm, and the gradient descent transfer function was incorporated into the network.

The database generated by Eq. (14) provided $n = 64296$, considering all possible combinations by the allowable range of independent variables P , T , D_p and ν .

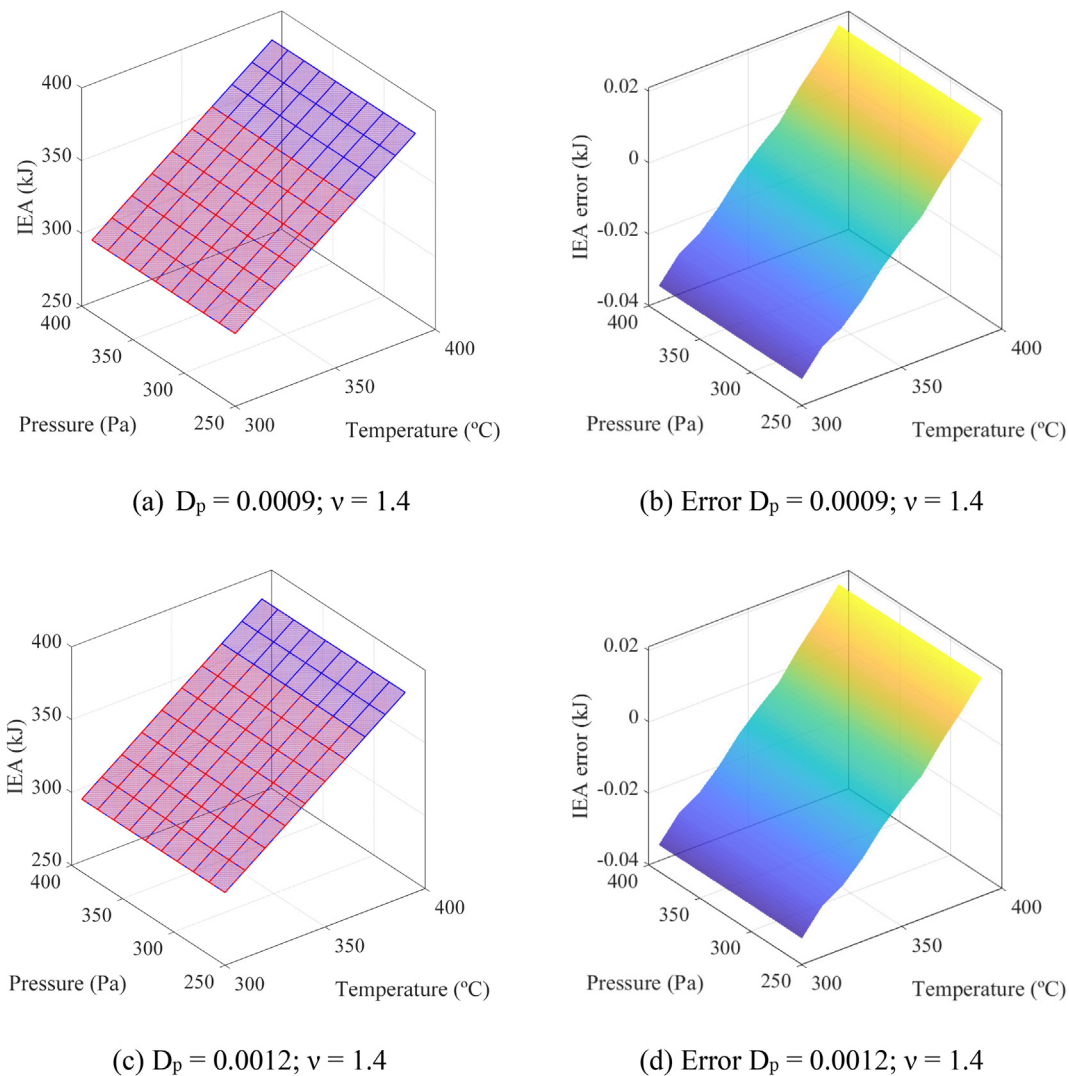


Fig. 8. Graphical results of the IEA standard for trained data known (legend: ■ Experimental ■ ANN).

Fig. 3 shows the data set according to decision variables (or inputs) pressure P (Fig. 3a), temperature T (Fig. 3b), impregnation distance D_p (Fig. 3c) and viscosity ν (Fig. 3d). The data set represents a total of 24 subsets (samples) that result in different IEA values (Fig. 3e).

The ANN was trained using 50% of the total observations, which was separated in 12 subsets according to Fig. 4. Each subset was trained separately, in order to later identify the accuracy of the ANN. The 50% of database remaining (unknown database) were used to check the forecasting capacity of the ANN.

4. Results

The artificial neural network developed in the present study was applied to Carbon Fiber/PA6 and Carbon Fiber/PEEK specimens subjected to LVI testing. In the training phase of the neural network, temperature, pressure, impregnation distance, and viscosity were selected as input variables. There was no need to preprocess the inputs, that is, normalize in the range 0 to 1. The output of the network is then targeted by obtaining the dynamic impact energy absorption property.

After performing the training phase, it can be verified that there was an excellent fit and regression results with experimental and trained data. The results showed that the application of the Levenberg-Marquardt/Hyperbolic tangent sigmoid/Linear transfer

algorithm leads to a high predictive quality for the global training results. In this situation, Fig. 5 shows the results for the training ANN phase considering a database corresponding to the subset of 12 specimens. The ANN showed a rapid rate of convergence (Fig. 5a) in the early stages considering the contour conditions and the methodology adopted. The gradient or gradient of the square of the error function (known target – ANN output) with respect to the unknown weights and biases is shown in Fig. 5(c). The training objective is to optimize the choice of weights and biases by minimizing the sum of the squared errors by using the method of steepest descent. In addition, Fig. 5(c) shows μ control parameter for the algorithm used to train the network. The choice of μ directly affects the error convergence. In case of LMS algorithm, μ is dependent on the maximum eigen value of the input correlation matrix. Equally important, the histogram of the errors (uniform) between target values and predicted values after training a feedforward neural network are presented in Fig. 5(c). These error values indicate how predicted values are differing from the target values. In terms of materials engineering, the characteristics of the data in question and the correct use of the network parameters reduces the time it takes to process the data and makes the analysis faster.

Equally important, Fig. 5(d) shows the regression results in relation to the experimental data and the ANN adjustment. The excellent

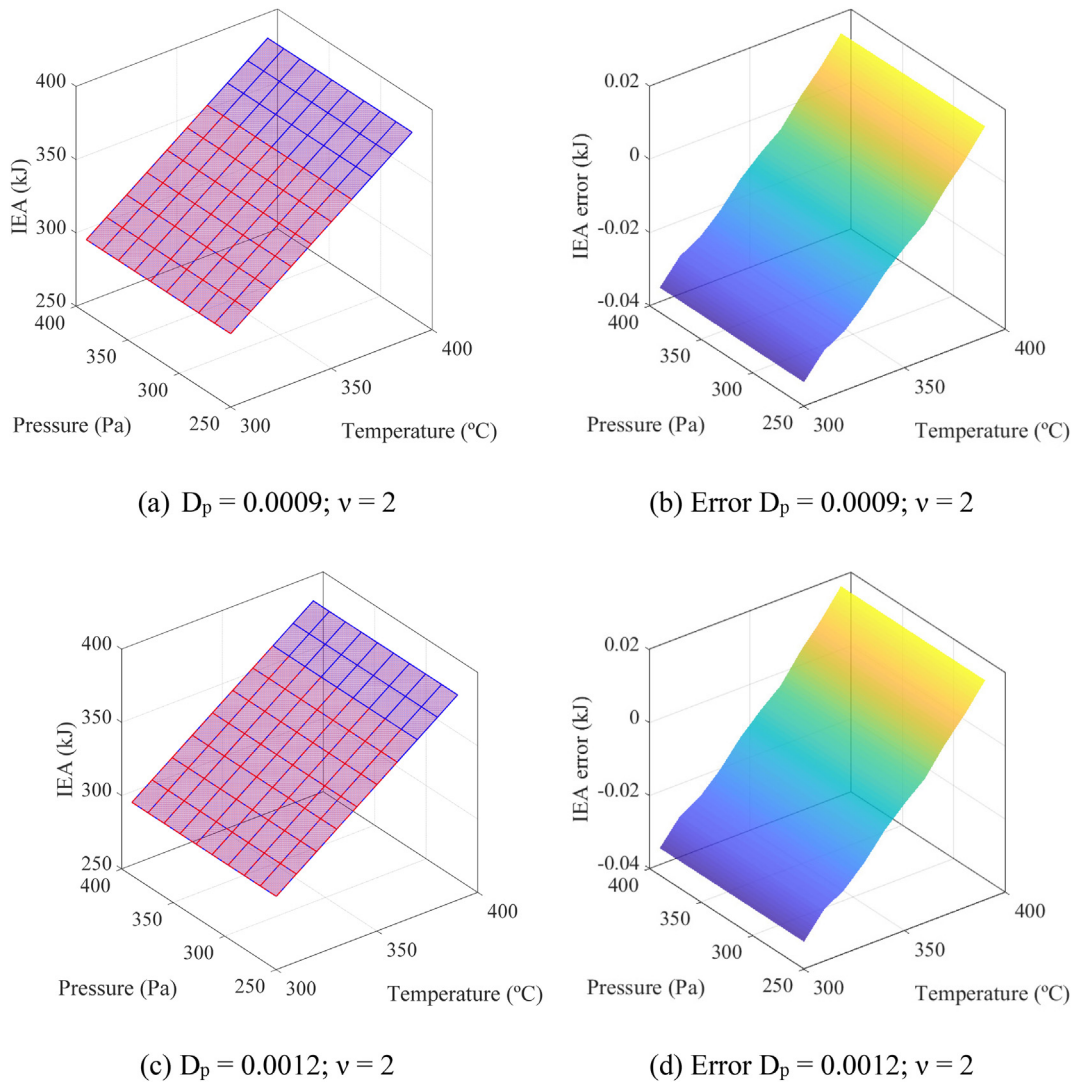


Fig. 9. Graphical results of the IEA standard for unknown trained data (legend: ■ Experimental ■ ANN).

adjustment by means of the coefficient R^2 is clear (~ 1.00). This shows a relation of the physical phenomenon between input–output data.

Fig. 6 shows the experimental and adjusted IEA values by training the network. Due to overlapping curves shown by the subsets (#1 to #12) IEA data has a very well-defined pattern which led to an excellent prediction result.

Then, the unknown database was tested by the RNA to verify its competence in predicting the IEA. Thereby, a new data set consisting of 12 subsets (#13 to #24) was selected to verify the ANN's efficiency. Fig. 7 shows the results for the 12 unknown data subsets of the neural network. ANN's validity and accuracy test proved that even with unknown data, the built architecture was able to efficiently predict the IEA. Comparing the ANN responses with experimental data, a high compatibility has been observed.

Furthermore, Fig. 8 shows the graphical results of the IEA standard as a function of pressure and temperature for fixed values of impregnation and viscosity. Fig. 8a and c show the overlapping experimental results and those obtained by ANN. It turns out that the planes are practically overlapping. Fig. 8b and 8d show the error obtained, that is, the difference between trained (IEA_{TR}) and experimental (IEA_{EXP}) data, so $IEA_E - IEA_{TR}$. The global difference for the known data from the neural network is of the order of 0.02 kJ ($< 1\%$).

Subsequently, Fig. 9 presents the prediction results considering the 12 subsets of data unknown of the neural network. The planes of experimental IEA and the IEA obtained by ANN are overlapping (Fig. 9a and c).

The errors observed are of the order of 0.02 kJ, as in the previous case. It is worth mentioning that this unknown data set has viscosity values of $\nu = 2.0$, which was not part of the network's training data. Therefore, the network can be considered robust in terms of IEA forecasting. This is due to the quality of the data obtained from the experimental tests and the good configuration of the neural network parameters.

5. Conclusions

ANN technique has been used to model the IEA dependence of manufacturing input variables pressure, temperature, impregnation distance and viscosity. Experimental IEA data obtained from impact testing and treated by a multiple regression model have been modeled by backpropagation ANN. An excellent agreement between the modeled and experimental data has been found. The predictive abilities of ANN models can also be used in the development of new thermoplastic composites with desired mechanical impact properties.

As a main result, it is found that the application of Backpropagation ANN is effective in the prediction of the Impact Energy Absorption in commingled composites due to the data linearity. Accurate results have been obtained in the testing and validation stages.

It could be also concluded that the ANN may be considered an alternative to traditional methods to determine the appropriate processing parameters for the manufacturing of commingled composites for impact purposes. Furthermore, the use of an analytical multiple regression model as a new approach of ANN architecture is a promising approach which, based on the results of this study, causes an increase of ANN's reliability.

The results from this study will be particularly useful for designers, manufacturers and engineers that wish to employ commingled composites for impact applications. Using the analytical-numerical-experimental results of this study, the IEA can be determined according to the ANN input variables temperature, pressure, impregnation distance and viscosity.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.compstruct.2020.113131>.

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