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Experimental investigation of Notched Identification based on Maximum Resistance Force in Steel Specimens using an Artificial Neural Network

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Abstract

In this paper, a robust methodology is presented to identify the notch depth value in X70 steel specimens based on the maximum resistance force using an artificial neural network (ANN). The mechanical characterizations of fracture behavior of the X70 steel specimens are simulated using XFEM. The main goal is to obtain the best identification of notch depths as a function of various maximum resistances. The collected data are used as inputs and outputs for the proposed ANN using optimal parameters to identify the notch depths in different steel specimen designs based on different maximum resistance force values. The provided results showed the effectiveness of the ANN based on the convergence study of the obtained results and the accuracy of notch depth identification.

Keywords: Steel specimens; Charpy V- Notch (CVN); Maximum resistance force; XFEM; ANN.

1. Introduction

The use of X70 steel for long-distance high-pressure pipes has been covered in many studies, with a focus on structural integrity and the importance of exceptional low temperature toughness. It is emphasized that the Drop Weight Tear Test (DWTT) is a better technique for determining the fracture resistance and transition temperature of

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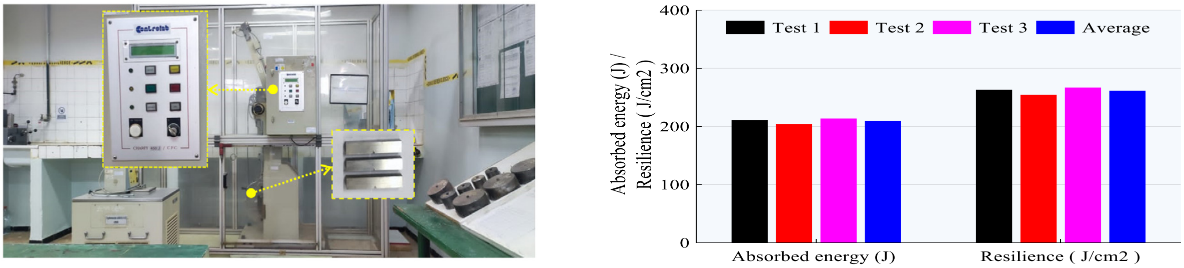
pipeline steels than the Charpy test. Many approaches for modeling and forecasting the behavior of steels, composite materials, fracture identification, and structural damage assessment have been investigated. These approaches were used Artificial .Neural Networks (ANN) combined with different optimization algorithms to improve the accuracy of the prediction as presented in Refs (Nasiri, Khosravani et al. 2017, Liu, Athanasiou et al. 2020, Khatir, Oulad Brahim et al. 2024, Zara, Belaidi et al. 2024). Furthermore, the effectiveness was provided in designing composite structures because they reduce the need for experimental data and the testing expense. The study modeled fractures in high-strength steel using XFEM and other optimization techniques, concentrating on peak loads and absorbed energy for various crack lengths. This paper is organized into sections covering experimental presentation, numerical simulations, and optimized ANN models to improve the identification and results. The toughness of a material and its temperature-independent ductile-brittle transition are examined using the quantity of energy absorbed during the testing procedure (Kim, Kim et al. 2020, Cauwels, Depraetere et al. 2022). The structural reliability can be evaluated by calculating the amount of energy that the model material absorbs during the impact test and understanding how the model material deforms and fails by using a specific data collection system and strain gauges to conduct tests to obtain the impact response (Paermentier, Debruyne et al. 2021).

Numerous investigations across several domains, particularly in fracture mechanics, have applied XFEM (Lin 2021, Jiang, Ma et al. 2022). Samir et al. (Khatir and Abdel Wahab 2019, Khatir, Boutchicha et al. 2020) employed PSO and Jaya algorithms for crack identification. Dadrasi et al. (Dadrasi, Farzi et al. 2020) reported on the study conducted on the fracture energy and fracture toughness of epoxy-based nanocomposites. Benaissa et al. (Benaissa, Hocine et al. 2021) developed a unique optimization method named YUKI, and the proposed optimization was evaluated for the purpose of identifying cracked plate using several scenarios. In general, metaheuristic algorithms (Khatir, Capozucca et al. 2022, Seguini, Khatir et al. 2024) have been shown to be effective techniques for optimization of the main parameters of ANN. In this study, impact testing with different steel specimen designs is used to determine the notch depths at these loads in fractures using XFEM. Data inputs and outputs based on various notch depths are numerically created using the maximum resistance values. These data are then gathered and trained using the ANN model. The notch depths of the initial steel specimen designs for a variety of maximum resistance forces are identified. The aim of this study is to use high-quality data to obtain improved outcomes. This study is divided into four parts. Section 1 provides a detailed description of the experimental results. Section 2 contains numerical simulations of the CVN impact. Section 3: ANN was used to identify the notch depths. The obtained results and a short discussion are presented in Section 4. Finally, Section 5 lists remarks and conclusion.

2. Experimental model presentation

The ASTM E23 standard was followed for the preparation of the CVN specimens, which had dimensions of 10 (width)×10 (thickness)×55 (length) mm (see Fig. 1) (Dagostini, Moura et al. 2021). For the CVN tests, a hammer, two anvils, a CVN specimen, a mass of 19.8 kg and an initial velocity of 5.5 m/s were utilized. Fig. 1.a shows the three specimens that were created and tested at ambient temperatures in the base metal (BM). According to the experimental findings of the X 70 steel tests carried out in three tests, there are notable approximation values in the energy absorbed by the specimen, between the three proposed tests. The CVN utilizing the Charpy Impact Testing Machine was performed using a Zwick Roell machine (refer to Fig. 1. a).



a b

Fig. 1. (a) Steel X70 impact machine and specimens used for CVN; (b) Results of impact Charpy in steel specimens.

For the tested steel specimens, the analysis employed the real mechanical properties, and the values are listed in Table 1 along with the average mechanical properties of X70 steel, which were derived from the test data. (Ouladbrahim, Belaidi et al. 2021).

Table 1. Mechanical characterizations of X70 steel (Ouladbrahim, Belaidi et al. 2022)

Material	Steel	Yield Strength - *YS* [MPa]	558
Elastic modulus - *E* [GPa]	210	Ultimate tensile strength - *UTS* [MPa]	672
Poisson's ratio - ν [-]	0.3	Elongation *EL* - [%]	38
Hollomon parameters	K= 850; n= 0.095		

Fig. 1. b shows the absorbed energy and resilience data for each number of test. It is noted that the resilience value is calculated by dividing the energy absorbed by the specimen section (S= 0.08 cm^2). The resilience machine has a built in digital display that clearly shows the energy absorbed (J) and ascension angle (°). Three types of specimens are fabricated (Fig. 1. a).

A notch is made completely from the base metal at the center of the X70 steel specimen. The collected results are presented in Fig. 1. b, it is logical to note that the tests provided impressive results with less error for each sample, explaining the influence of the homogeneity of the material and good sample preparation. Interesting, the steel is ductile.

3. Numerical simulations of CVN impact

To determine the approximation parameters and output values, a numerical simulation of CVN impact tests using XFEM is carried out, and employed in the construction of a database for various notch depth scenarios and specimen designs. The goal is to obtain the best identification of notch depths as a function of various maximum resistance forces.

A CVN specimen impact test model is created using the FE software. The prototype consists of three components: a CVN specimen, two anvils, and a hammer. The rendered view and FE mesh are shown in Fig. 2.

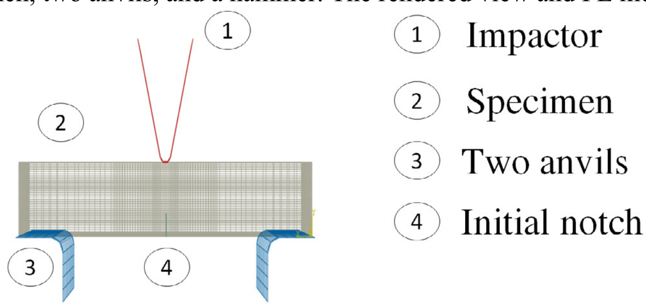


Fig. 2. CVN specimen with an initial notch and 3D meshing with applied velocity.

An eight-node linear brick, hourglass control, and reduced integration (C3D8R) is used to model the simulation environment. Each fixed, rigid parts (the anvils and hammer) are used. The standard specimen is positioned between two parts of rigid anvils and the impactor in the probable fracture propagation regions. A fixed mesh size of 0.3 is utilized in the critical area, which progressively improved in the specimen's center (see Fig. 2). The interactions between the specimen and anvils, as well as between the impactor and specimen, were modeled with a friction coefficient of 0.1. The surface of the specimen is defined as the master surface, whereas the impactor and support surfaces are set as the slave surfaces. The impactor, weighing 19.8 kg, moved vertically at 5.5 m/s while the supports are fixed. The explicit system records the system's response over time. Since the ABAQUS Dynamic/Explicit solver doesn't support XFEM, the Dynamic/Implicit solution was used to overcome this limitation. (Talemi 2016)

The example of the distribution of Von Mises force and reaction force in the model during notch propagation (Initial notch depth equal to 2.7 mm) are illustrated in Figs. 3 and 4.

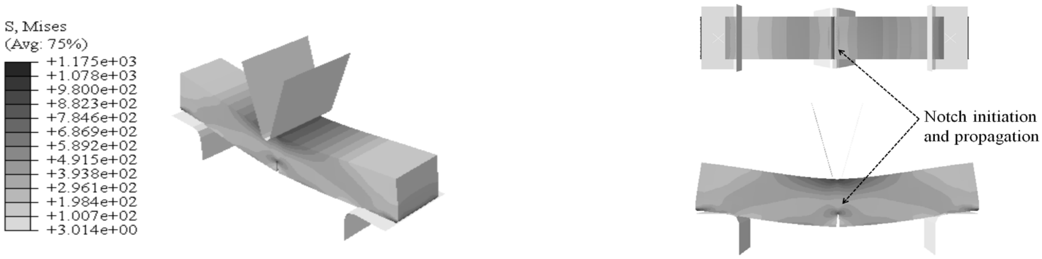


Fig. 3. Von Mises distribution during fracture initiation and growth in the model.

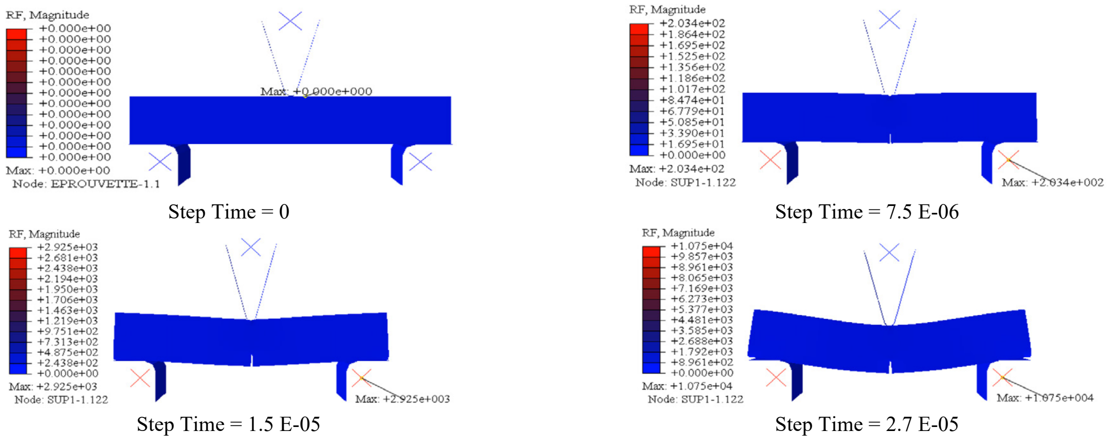


Fig. 4. Reaction force magnitude for different step times.

Based on the results, the parameters of the numerical model for the X70 steel specimens are selected, accounting for the influence of the type and quantity of mesh elements utilized in the study, as presented in Fig. 5, the maximum reaction force (peak load) as the notch initiating commencement for different steel specimen designs. The initial notch depth (a=2.7 mm) is assumed to be equal to the first notch depth (a_0).

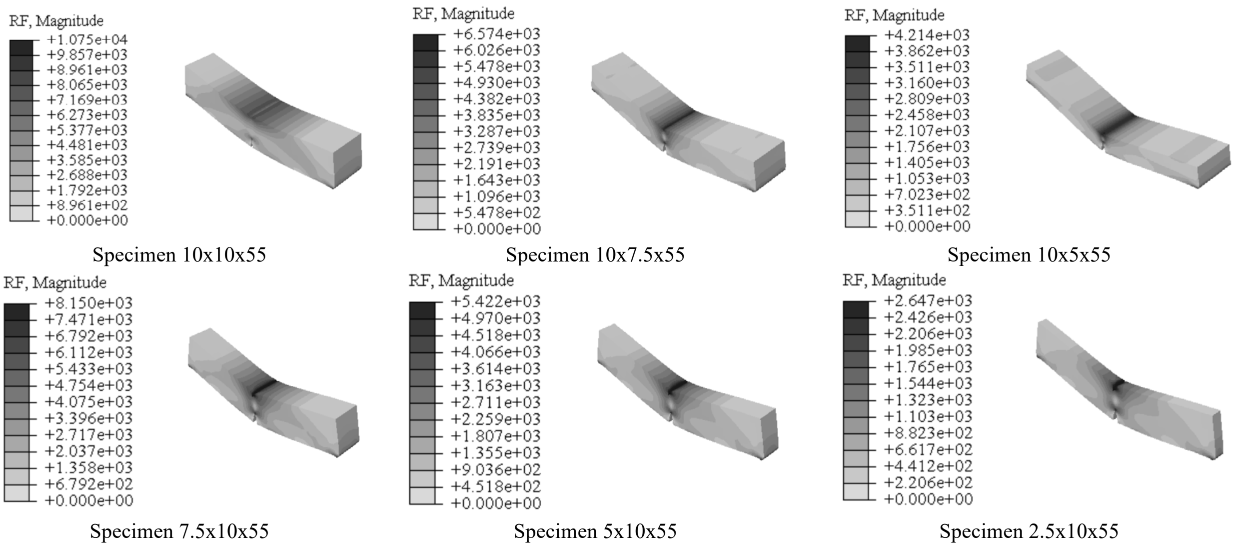


Fig. 5. Maximum reaction force in specimens for a proposal dimension cases

The resistance of the structures decreases with increasing notch depth, and they will not be able to withstand additional loading. In our study, the thickness of each specimen decreased as the notch depth increased and the notch tip experienced increased stress intensity. This will cause the resistance force to decrease using a numerical model based on the cohesive segment in XFEM method.

4. Artificial Neural Network

The neural network is trained as a proposed model, in addition the model use to identify the notch depth in steel specimens under loading. Based on the obtained results of the numerical parameter used, the application can identify the tested notch depth based on the maximum resistance forces for several specimen designs. A single design parameter (notch depths, specimen designs, and maximum resistance forces) and total datasets are created for each sample design scenario, allowing the creation of a dataset with a number of instances, which is then used to train the identification ANN model. A number of recommendations and parameters have been collected as shown in Fig. 6.

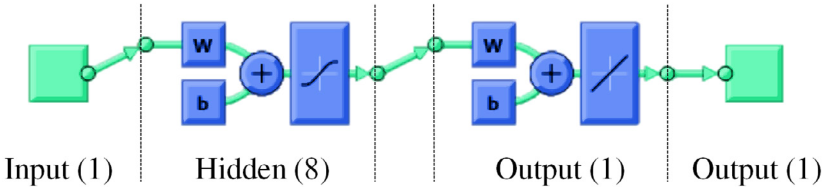


Fig. 6. ANN architecture for each study cases

Table 2 contains the data that is utilized in the artificial neural network model, 20 percent of this data is used for network testing and validation, while the other 80 percent is used for training.

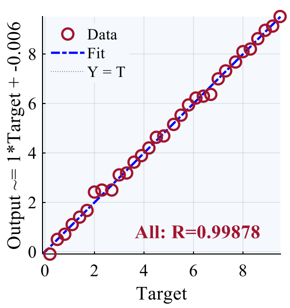
Table 2.The range of notch depth and maximum resistance force values for different specimen designs.

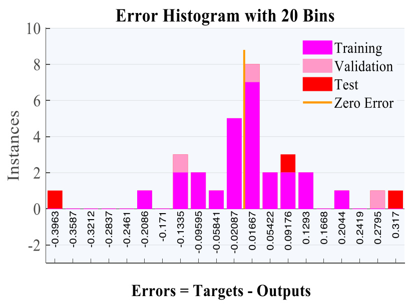
		Max resistance forces (N)			
	Notch depth (mm)	Specimen 10x10x55	Specimen 7.5x10x55	Specimen 5x10x55	Specimen 2.5x10x55
Max value	9.5	11090	7702	5134	2538
Min value	0.2	5216	3622	2415	1194
Average value	4.8	7772	5397	3598	1779
STDEV	2.8	2023	1405	937	463

The hidden layer number in this investigation is suggested to be eight (8) based on the behavior and performance of the neurons, which produces favorable outcomes. The multi-layered structure of the ANN model is constructed from up of nodes which connect the three essential dimensions. For every investigation, maximum resistance forces are regarded as the output parameters, while the notch depths, specimen designs, are suggested as input parameters.

5. Results and discussion

To identify the notch depths based on maximum resistance force values using number of collected data cases, the regression, and the error histogram are presented. Figs. 7 and 8 present the most effective validation performance using different training model databases.





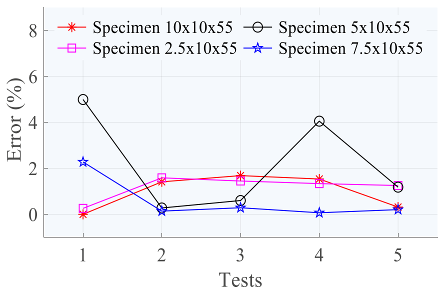


Fig. 7. Regrission analysis and error percentage results using ANN model output.

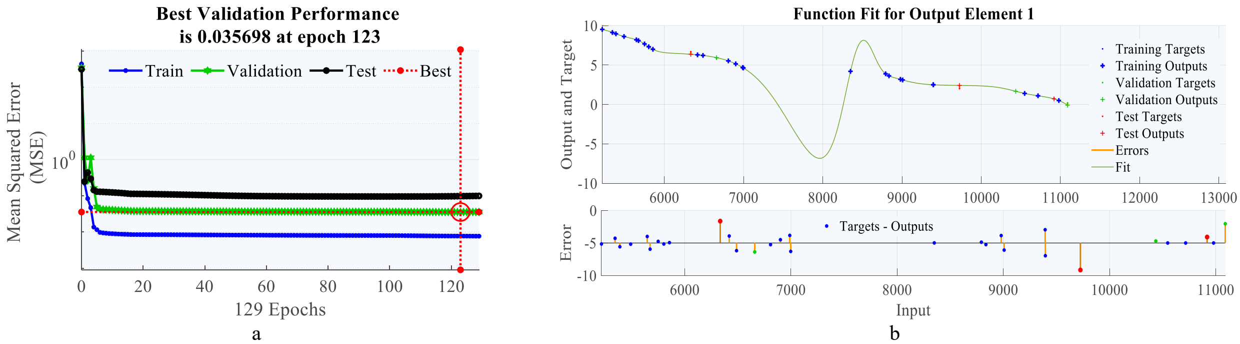


Fig. 8. (a) Performance analysis from ANN model output; (b) Actual and test ouput using ANN model output.

The study considers several notch depths and steel specimen designs, as well as different maximum resistance forces. The work is to collected a number of dataset and identify the values of the notch depths based on forces and collected data cases, for the four steel specimen designs (10x10x55 mm, 7.5x10x55 mm, 5x10x55 mm, and 2.5x10x55 mm).

Various inputs are given distinct notch depths. Fig. 9 presents the results using the ANN on different steel specimen designs.

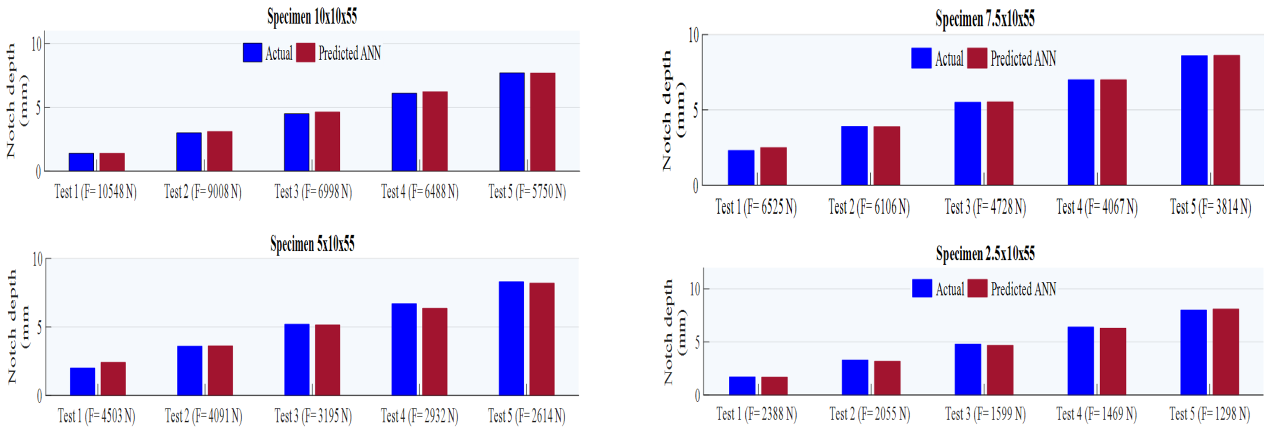


Fig. 9. Frequency values based on different tests

After considering maximum resistance forces and designs, which are displayed in Figs. 7, 8 and 9, it is visible that shows the best accuracy and good performance in identifying all notch depth values in the various specimen designs.

6. Conclusion

By taking into account the maximum resistance forces across various specimen designs, the artificial neural network (ANN) shows to be a very useful tool for determining the notch depth values in X70 steel specimens. Using ideal settings, the ANN successfully achieves accurate notch depth predictions, having been trained with input data from XFEM simulations of fracture behavior. As can be seen in Figs. 7, 8 and 9, the findings indicate how the ANN can handle a variety of design situations and reliably identify notch depth based on maximum resistance forces. The resilience of the ANN in producing exact and consistent outcomes is highlighted by these results. This highlights the promise of the ANN as an effective technique for resolving challenging material and mechanical property prediction problems.

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