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Prediction of Gurson Damage Model Parameters Coupled with Hardening Law Identification of Steel X70 Pipeline Using Neural Network

by

Abdelmoumin Ouladbrahim¹, Idir Belaidi¹, Samir Khatir², Erica Magagnini³, Roberto Capozucca³,
Magd Abdel Wahab^{4,5}

ABSTRACT

The Gurson–Tvergaard–Needleman damage model (GTN) describes the three stages of ductile tearing of steel: nucleation, growth and coalescence of micro-voids. This work is divided into two main parts. In the first part, based on the inverse analysis and the comparison between the experimental and numerical data, the parameters of the GTN damage model in conjunction with the hardening law are determined. The identification is broadened to include a considerable number of experimental tests drawn from our previous works and other works done at ALFAPIPE Ghardaia laboratory. In the second part, an Artificial Neural Network model is developed to predict the parameters of the (GTN) model coupled with the hardening law that goes through the prediction of traction and impact properties of API X70 steel pipe depending on its chemical composition. The weight of the chemical elements in percentages is considered as the inputs and the GTN parameters are considered as the outputs. In order to validate the obtained ANNGTN parameters, traction and impact tests are simulated. The numerical results are compared with the experimental ones and revealed that the developed model is very precise and has the potential to capture the interaction of GTN parameters coupled with hardening law and chemical composition of steel pipelines.

Keywords: GTN model; Hardening law; Inverse analysis; Finite element modelling; Artificial neural network (ANN); API X70 Chemical composition.

¹ LEMI Laboratory, Department of Mechanical Engineering, University M'hamed Bougara Boumerdes, 35000 Boumerdes, Algeria

² Faculty of Civil Engineering, Ho Chi Minh City Open University, Ho Chi Minh City, Viet Nam
Samir.khatir@ou.edu.vn ; Khatir_samir@hotmail.fr

³ DICEA, Structural Section, Polytechnic University of Marche, Ancona, Italy

⁴ Institute of Research and Development, Duy Tan University, 03 Quang Trung, Da Nang 550000, Viet Nam

⁵ Soete Laboratory, Faculty of Engineering and Architecture, Ghent University, Technologiepark Zwijnaarde 903, B-9052 Zwijnaarde, Belgium

1. Introduction

The field of pipelines for the transportation of oil and gas has experienced remarkable development with increasing demand for energy. Many companies are working in the manufacture of high-pressure pipes below the minimum yield point, i.e. 60–80 ksi (60–80 MPa), due to the urgency of these characteristics where fracture accidents are inevitable. We have to rely on the high quality of these pipes to avoid fragile breakage. Pipe failure can occur due to ductile fracture, sometimes resulting from certain conditions that cause cracks to develop and lead to potential environmental and structural damage, economic losses and increased maintenance costs and repair. Control of elongated cracks and mechanical tests are used to determine deformation, but high cost and time are required. Therefore, the finite element method (FEM) has been developed in the analysis and simulation of many Charpy tests in recent years [1–5]. Impact testing techniques were put in place to verify the fracture characteristics of the materials. The Gurson–Tvergaard–Needleman (GTN) damage model [6] is well known, widely applied and used to simulate the dynamic propagation of ductility fractures. Due to the limited set of parameters in this model, it is often adopted in the industrial field. Throughout the development of laboratory-scale fracture toughness experiments, sample sizes continued to increase. In this paper, the application of the GTN damage model is presented in the simulation of tensile tests and for the dynamic propagation of fractures in the Charpy test case. The tensile and fracture toughness simulations are applied to a high strength pipe material, namely X70 steel. The results of the numerical model are used to construct a force–displacement curve in order to compare the experimental data with the numerical predictions to identify the parameters of GTN model and the law of coupling with the law of Ramberg–Osgood hardening. The identification has broadened to include a considerable number of experimental tests drawn from our previous works and other works done at ALFAPIPE Ghardaia laboratory. The approach based on micromechanical modelling of materials is an efficient method used in damage analysis. Many models consider a coupling between plasticity and damage, for example for the behaviour of a porous ductile material in the Gurson model [7]. The model was built using many

parameters [8, 9]. The description of the model goes through a general study on metallography [10]. Generally, the model is characterized by three mechanisms of evolution of voids, which represents the processes of ductile fracture in metallic materials. The hardening behaviour of the microstructure of the material results in different mechanical properties as a function of different process parameters [11, 12]. Therefore, due to the interaction of many variables in this case, the modelling of mechanical properties according to different process parameters remains complex and requires a lot of data although it is considered as a reasonable solution. Moreover, we can add to this the dependence on chemical composition and manufacturing process [13, 14]. For example, solid solution hardening and microstructure are dependent on the forming conditions and the chemical composition, which provide details of tensile and impact properties in a steel. Therefore, on the basis of a large amount of data, many researchers have studied the underlying relationships between mechanical properties and chemical composition. Moreover, in the second part ANN model is developed to predict the parameters of the Gurson-Tvergaard-Needleman model (GTN) coupled with hardening law through the prediction properties of traction and impact of API X70 steel pipe as a function of its chemical composition. The importance of each component in the structure is summarized based on recent relevant works. The method of precipitation the carbon (C) allows making a reinforcement of the structure matrices [15]. The higher content of Nickel (Ni), Silicon (Si) and Molybdenum (Mo) and Chromium (Cr) gives great resistance to the steel [16]. Minimization of the ductile–brittle transition temperature is due to the Manganese (Mn) component effect [17]. Niobium (Nb), Titanium (Ti) and Vanadium (V) components play a role in retarding recrystallization and limit the growth of austenite grains [18]. In the passes of rolling and manufacturing, Niobium (Nb) allows to reduce the temperature at the time of recrystallization [19], improvement of tensile strength and toughness by the components vanadium (V) and titanium (Ti) [20]. Furthermore, we can add the study of the influence of carbon (C) on stress corrosion cracking of API X80 steel by using a carburization treatment [21]. Experimental and numerical investigation of hydrogen embrittlement effect on microdamage evolution of advanced high-

strength dual-phase steel was presented in Ref [22]. Effect of accelerated cooling rate and rolling temperature on the occurrence of arrowhead markings in drop-weight tear test of API 5LX70 linepipe Nb–V–Ti Steel Plate was studied in Ref [23]. Artificial Neural Network was used for modeling the tensile properties of ferrite-pearlite steels [24]. Another application using ANN for vickers hardness of Sn-9Zn-Cu solder alloys was reported in Ref [25].

2. GTN Model Constitutive Equations

Plastic damage is the process of plastic deformation until fracture. The damage mechanism is the damage evolution process of the micro-hole formed by the internal inclusions or two-phase particles of the metal being nucleated, growing up and converging under the external force. In order to describe the mechanism of meso-damage of plastic materials and its evolution process, a suitable model should be established [26]. Gurson [6], based on McClintock, Rice and Tracey [26], assumed that plastic deformation of the material was mainly caused by micro-hole damage. Gurson did not use the assumption of the infinite matrix, but proposed a finite matrix with microporous cell model. Later, Tvergaard and Needleman [27] modified some parameters of the Gurson model, which greatly improved its prediction accuracy. The Gurson yield surface function corrected by Tvergaard and Needleman is as follows:

$$\Phi = \left(\frac{\sigma_{eq}}{\sigma_e} \right)^2 + 2q_1 f^* \cosh \left(\frac{3q_2 \sigma_m}{2\sigma_e} \right) - (1 + (q_1)^2 f^{*2}) = 0 \quad (1)$$

where σ_{eq} is the macroscopic von Mises equivalent stress; σ_e is the yield stress of the base metal in the element; σ_m is the macroscopic mean stress, and f is the pore volume fraction. q_1, q_2, q_3 are the correction parameters taking into account the micro-hole around the non-uniform stress field and the adjacent holes in the middle of the interaction, which are usually taken equal to $q_3=q_1^2, q_1=1.5, q_2=1.0, q_3=2.25$.

$$f^* = \begin{cases} f & f \leq f_c \\ f_c + \frac{f_u^* - f_c}{f_F - f_c} (f - f_c) & f_c < f < f_F \\ f_u^* & f \geq f_F \end{cases} \quad (2)$$

In the above formula, f^* is the equivalent void volume fraction, which explains the gradual decrease of the bearing capacity of the material due to the void coalescence; f_c is the void volume fraction at the time when the holes start to coalesce; f_F is the broken void volume fraction when the material is destroyed; f_u is the limit void volume fraction when the stress-bearing capacity is zero.

3. GTN Model and Hardening Parameters Identification

The objective of the first part of this study is to simultaneously identify the Gurson model parameters and the hardening law for API X70 steel. Thus, a numerical inverse analysis procedure based on the finite element method is used for the modelling, see Fig. 1. The numerical model outputs are coupled with an optimization tool in MATLAB.

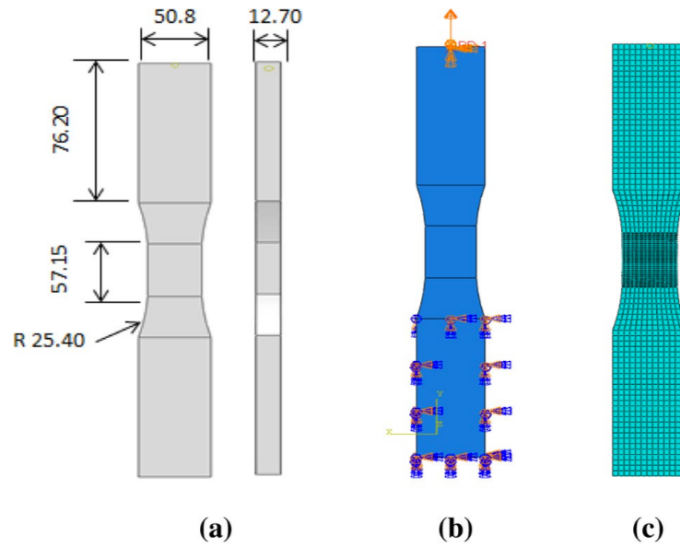


Figure 1 - Specimen geometry and finite element model of a notched tensile test.

3.1. Tensile Tests and FE Model of API X70

A tensile test on notched specimens is used in this study using API X70 steel. The initial shrinkage of these specimens usually occurs at the notch. In Fig. 1a, the experimental specimen with the

dimensions is shown, and in Fig. 1b and c the simulated model (FE) is illustrated. This model was constructed in the software Abaqus/Explicit with conditions similar to the experiment. After obtaining the results, the experimental values are matched with the numerical values for a considerable number of tests. An optimum mesh consisting of elements C3D8R are used (element with eight nodes of isoparametric type). Mesh refinement is applied at the critical region as shown in Fig. 1c, where the size of element is very important for damage analysis (GTN) [28]. In this application, we used 8226 elements in the FE mesh with the assumption of quasi-static state. The steel, API X70, is believed to have isotropic elastoplastic behaviour. The elastic model part is the Hooke model with Young's modulus of $E = 210$ GPa with Poisson's ratio of $\nu = 0.3$. The density of the material is 7850 kg/m³. In the plastic stage, the failure criterion of von Mises is used. It is added to the porous plastic part of the GTN parameters in the Abaqus/Dynamic Explicit software [29]. Several hardening laws exist in the literature to describe the hardening behaviours of metal. In this study, the law adopted in this reverse identification procedure is the Ramberg–Osgood law according to the following equation:

$$\varepsilon = \frac{\sigma}{E} + \left(\frac{\sigma}{H} \right)^{1/n} \quad (3)$$

where σ is the value of the stress, E is the modulus of elasticity of the material, H is the material constant and n is the strain hardening exponent of the material, which can be calculated from the known properties of the material.

3.2. Identification Strategy

Identification strategy based on the reverse procedure makes it possible to determine the work hardening law and Gurson parameters of the studied API X70 steel. Based on the numerical model described above and in order to minimize the difference between the experimental data and the numerical values, a program under MATLAB is used for the optimization of the results. The optimal GTN parameters are obtained by minimizing the cost function (Q) (see Eq. 4). To reduce

the number of numerical simulations, we propose a factorial design in the process of identification of GTN parameters and we study the numerical output sensitivity through comparison with the experimental design. The optimal GTN parameter value is taken at the minimum of the cost function value having less than 5% or close to this value as shown in Fig. 2. If all values are greater than 5%, we go to a new series of parameters proposed in a factorial way. We suggest less than 5% for the acceptable value of cost function to ensure the good performance of our simulation. In our previous research works, this tool was widely used [30, 31] in the characterization under static, dynamic, uniaxial and biaxial stress in metal alloys. The scheme and steps of the reverse procedure are shown in Fig. 3.

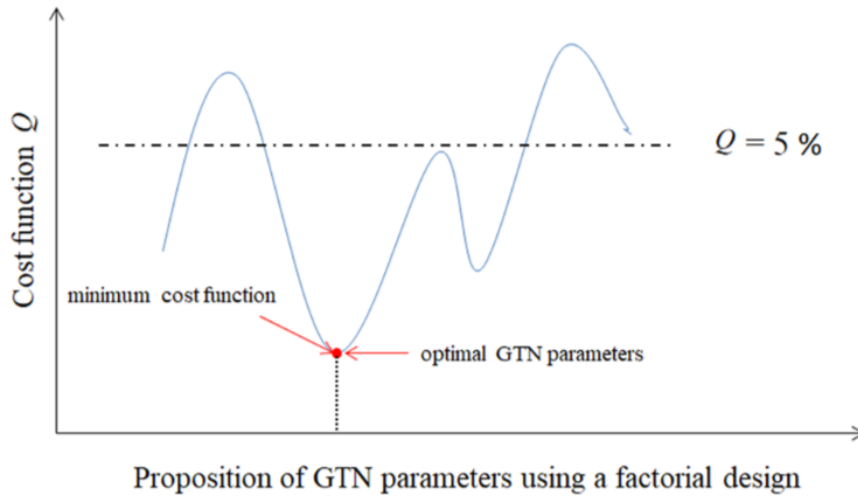


Figure 2 - The optimal GTN parameters.

The minimized function is represented by following formulation:

$$Q = \frac{\sum_{i=1}^N (\bar{F}_{i-\text{exp}} - \bar{F}_{i-\text{num}})^2}{\sum_{i=1}^N (\bar{F}_{i-\text{exp}})^2} \quad (4)$$

where $F_{i-\text{exp}}$ (or $F_{i-\text{num}}$) = (F_i) and $i=1, 2, \dots, N$, N is the total number of measured points in the numerical simulations and experimental results.

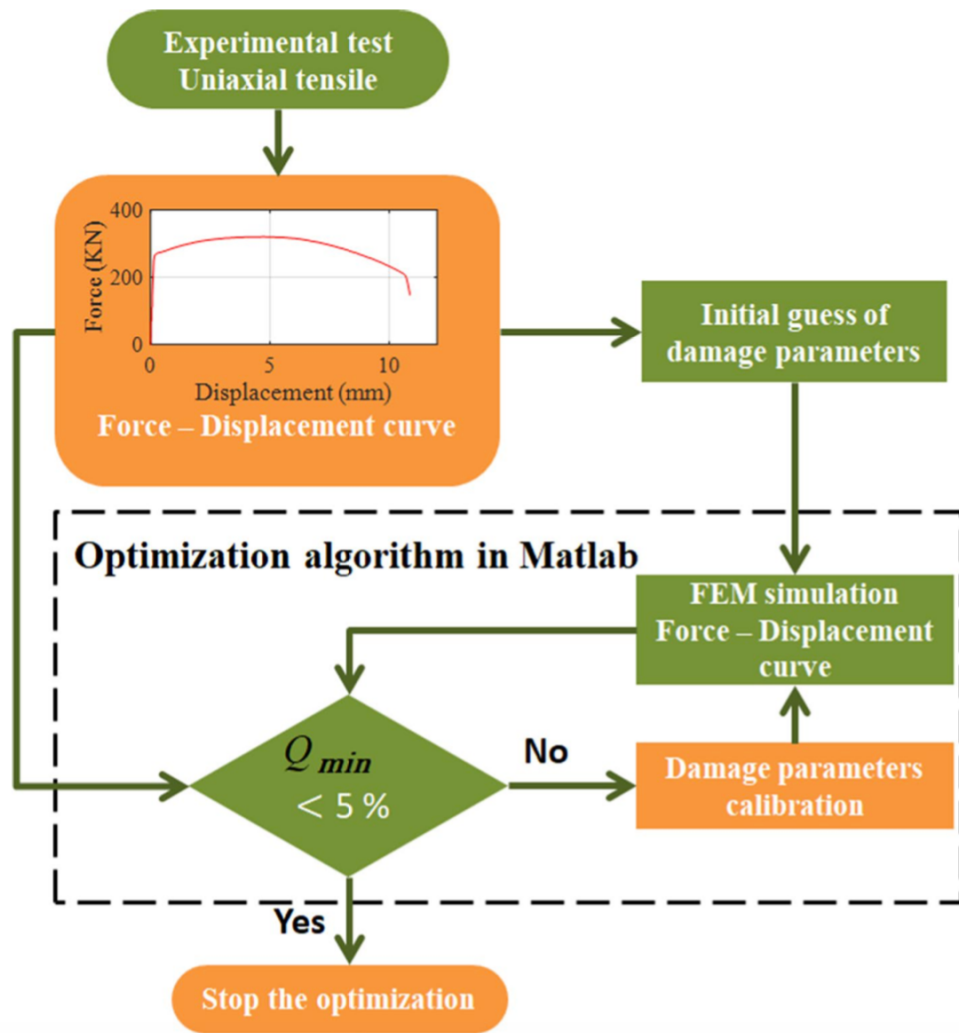


Figure 3 - Principle of the inverse analysis method used for the identification of parameters.

3.3. Procedure for Identifying Model Parameters

There are different methods for determining the damage parameters, one of which is the method of comparison between the experimental results and simulations, see for example some studies in which the damage parameters have been determined [32, 33]. In our study, we took two main parameters in the model (GTN), which greatly affect the behaviour of a ductile fracture, namely: critical void volume f_c and nucleation void size f_n with the application of the reverse method to determine their values. In the first step, by using a tensile test, the parameters of the Ramberg–Osgood hardening behaviour of direct scheduling are determined using ABAQUS software.

3.4. Results and Discussions

Figure 4 shows the displacement versus load curve for tested notched specimen and that obtained from simulation. The comparison is made for the GTN model coupled to the Ramberg–Osgood hardening law as presented in Fig. 4 and Table 1. We note that the identified GTN parameters are similar to those of the reference [23] and give a good approximation for the experimental fracture point. The plastic parameters ($H = 840$ MPa and $n = 0.04$) of hardening and the GTN parameters ($f_c = 0.022$ and $f_n = 0.0024$) are also used to describe the fracture point “P” (Fig. 4). A good agreement between the numerical and experimental curves can be seen. The results of the reverse identification used are summarized in Table 1.

Table 1 - Identified GTN and Osgood parameters.

	The initial values	Range of values	Identified parameters	Ref. [34]
n	0.02	0.02–0.06	0.040	–
H	650	650–980	840	–
f_n	0.0002	0.0002–0.008	0.0024	0.005
f_c	0.018	0.018–0.03	0.022	0.02
Fixed f_F	0.18	–	0.18	0.18
Cost function	10%	–	5.26%	–

Table 2 - Identified GTN and Osgood parameters for several tests.

	Parameters	Number of experimental test data (N)	Identified parameters			STDEVA
			Min	Max	Mean	
The strain hardening exponent	n	71	0.026	0.059	0.043	0.007
the constants H for the Ramberg–Osgood	H	71	694.989	973.583	828.050	63.807
nucleation micro-void volume fraction	f_n	71	0.0002	0.0074	0.0038	0.00233
Critical volume fraction	f_c	71	0.019	0.023	0.021	0.001
Void volume fraction (Fixed)	f_F	71	0.18	0.18	0.18	0

N is number of cases (tests), $STDEVA$ Standard Deviation

The study is expanded to include a considerable number of experimental tests made at ALFAPIPE Ghardaia laboratory to determine GTN parameters and the constants of Ramberg–Osgood. The results obtained are presented in Table 2.

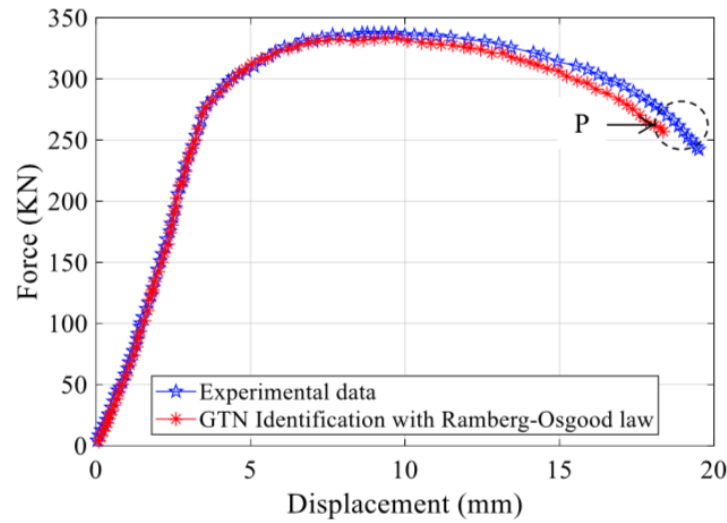


Figure 4 - The load vs. displacement numerical and experimental curve in the case of the coupled identification of GTN model and Osgood hardening law.

4. Experimental Methodology for the ANNGTN Model

In the standard case, the development of a good and reliable ANN application depends on a good selection of training data. In many research works, the design architecture of the experimental methodology has been used, for example see Ledoux et al. [35] to optimize the process of parameter formation based on this technique. ANN model has been developed to predict the parameters of the Gurson-Tver- gaard-Needleman Model (GTN) coupled with the hardening law that goes through the prediction of tensile and Charpy impact properties of steel of API X70 pipeline depending on its chemical composition. The percentage by weight of chemical elements was considered as the inputs and the tensile and impact properties of Charpy were considered as the outputs in the first step and the GTN parameters and the hardening law parameters in the second step as shown in Fig. 5

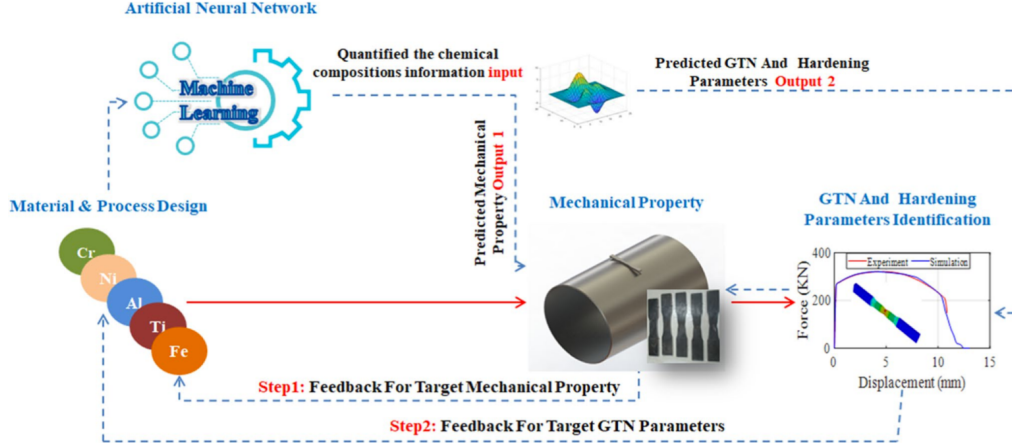


Figure 5 - ANN development steps to predict GTN parameters and Osgood constants.

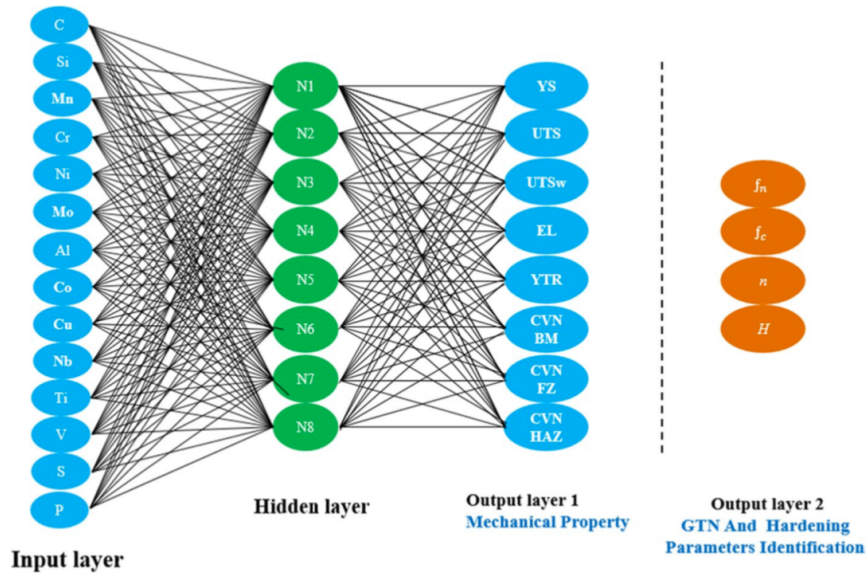


Figure 6 - Architecture of Neural Network.

ANNs have been widely used in several research studies to study the correlation between numerical input data and target orientations [36]. We try to use ANN to study the relationship between GTN parameters and chemical composition.

Thus, in our study, 80% of the data provided in Table 3 is used for training and 20% for testing and validation of neural networks for the prediction of mechanical properties and damage parameters. In MATLAB [37], the desired inputs and outputs or targets are imported into the workspace and the network "nntool" is created using inputs and targets. The ANN model has a multi-layered structure,

which is connected by nodes with three main layers, namely the input layer (14), the hidden layer (s) (8 neurons) and the output layer (step 1 = 8 neurons and step 2 = 4 neurons) as shown in Fig. 6.

Table 3 - Parameters of input data and targets data (1 and 2).

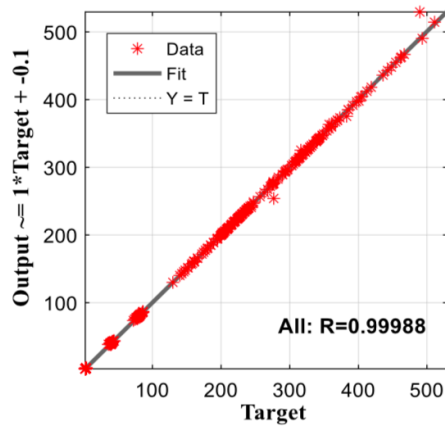
Variable	Symbol	N	Min	Max	Mean	STDEVA
<i>Input</i>						
Carbon (wt%)	C	71	0.025	0.174	0.075	0.025
Silicon (wt%)	Si	71	0.156	0.450	0.273	0.062
Manganese (wt%)	Mn	71	0.788	1.920	1.575	0.215
Chromium (wt%)	Cr	71	0.010	0.250	0.061	0.046
Nickel (wt%)	Ni	71	0.011	0.400	0.069	0.070
Molybdenum (wt%)	Mo	71	0.007	0.290	0.071	0.085
Aluminium (wt%)	Al	71	0.003	0.050	0.034	0.009
Cobalt (wt%)	Co	71	0.002	0.022	0.005	0.003
Copper (wt%)	Cu	71	0.006	0.310	0.056	0.063
Niobium (wt%)	Nb	71	0.010	0.081	0.051	0.015
Titanium (wt%)	Ti	71	0.001	0.033	0.014	0.008
Vanadium (wt%)	V	71	0.001	0.087	0.040	0.031
Sulfur (wt%)	S	71	0.001	0.015	0.008	0.003
Phosphorus (wt%)	P	71	0.008	0.040	0.020	0.006
<i>Output 1</i>						
Yield strength (MPa)	YS	71	486.70	555.21	524.64	12.03
Ultimate tensile strength (MPa)	UTS	71	592.07	696.96	632.19	24.74
Ultimate tensile strength weld (MPa)	UTSweld	71	641.42	761.97	690.14	20.77
Elongation (%)	EL	71	35.86	44.17	40.36	1.46
Yield to tensile ratio (%)	YTRatio	71	72.40	86.42	80.78	2.55
Charpy strength BM (J/cm ²)	KV (BM)	71	262.80	372.81	315.79	31.09
Charpy strength FZ (J/cm ²)	KV (FZ)	71	129.85	244.34	239.59	56.14
Charpy strength HAZ (J/cm ²)	KV (HAZ)	71	140.02	322.58	207.67	24.20
<i>Output 2</i>						
The strain hardening exponent	n	71	0.026	0.059	0.043	0.007
The constants H for the Ramberg–Osgood	H	71	694.989	973.583	828.050	63.807
Nucleation micro-void volume fraction	f_n	71	0.0002	0.0077	0.0039	0.0017
Critical volume fraction	f_c	71	0.019	0.023	0.021	0.001

The mass percentage values of API X70 elements are inputs: C, Si, Mn, Cr, Ni, Mo, Al, Co, Cu, Nb, S, P, Ti and V. The output layer (step1) represents the Charpy tensile test and impact resistance values: YS, UTS, UTS weld, EL, YT Ratio, CVN (BM-FZ- HAZ). And in step2, the parameters are: n , H , f_c , f_F .

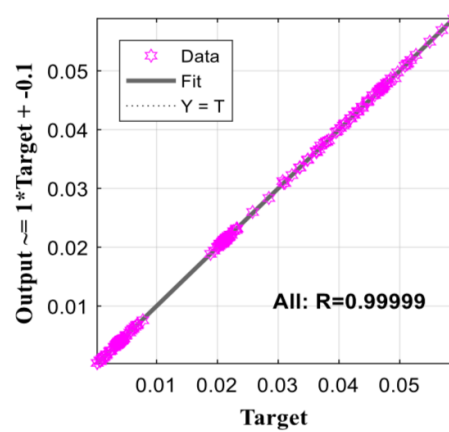
The chemical composition test input values taken by chemical analysis in a laboratory are shown in Table 4. The obtained results with the regression analysis (Fig. 7a and b) and performance analysis (Fig. 7c) for the prediction of GTN parameters coupled with the work hardening law and the prediction of mechanical properties of API X70 steel as a function of chemical composition are shown. The test input is considered (chemical compositions) to predict different parameters. The provided results are plotted in Fig. 8.

Table 4 - Chemical composition for test input.

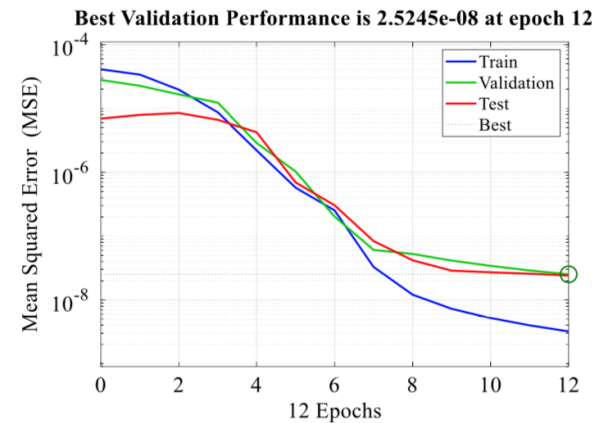
ANN-Test input														
	C	Si	Mn	Cr	Ni	Mo	Al	Co	Cu	Nb	Ti	V	S	P
MB	0.072	0.352	1.687	0.013	0.016	0.015	0.033	0.004	0.016	0.059	0.022	0.003	0.001	0.007



(a) Regression analysis with Mechanical properties- Experimental data output



(b) Regression analysis with GTN parameters and (n, H) - Numerical data output



(c) Performance analysis with GTN parameters and (n, H) -Numerical data output

Figure 7 - The results obtained for the prediction of GTN parameters and Osgood constants and mechanical properties.

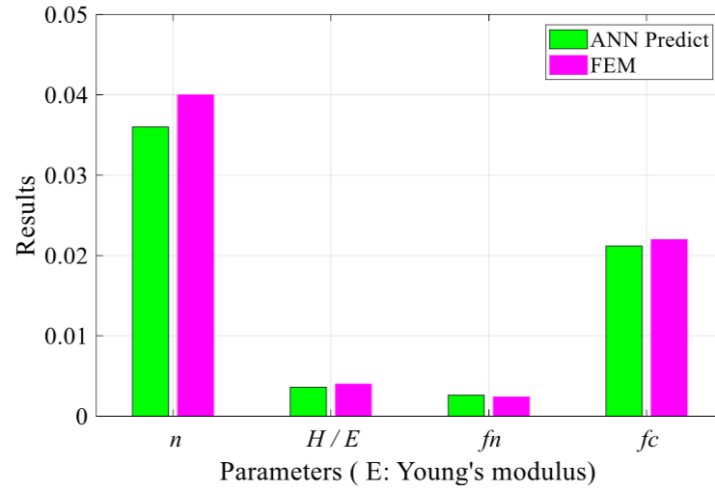


Figure 8 - Simulation by FEM versus predicted data.

5. Experimental and Numerical Analyses

5.1. Experimental Tensile test on a Steel Pipeline Specimen

The investigation of our study is concerned with manganese carbon steel pipes used for the transport of hydro- carbons under a working pressure of 70 bars with the commercial name APIX70. The material meets the specification imposed by the standard API5L [38].

In order to determine the load–displacement curves and the mechanical properties of X70 steel, flat specimens according to French standard NF EN 10,002–1 [39] were used. Uniaxial tensile tests were carried out on three specimens at room temperature using the Mohr machine (ZAWICK) at the ALFAPIPE laboratory (Fig. 9a). The initial material is presented in the form of coils of the same casting. The specimens were characterized by the geometrical dimensions shown in Fig. 9b. Tensile tests were carried out by increasing the tensile load applied at the specimen’s extremities. All tests were performed under displacement control.

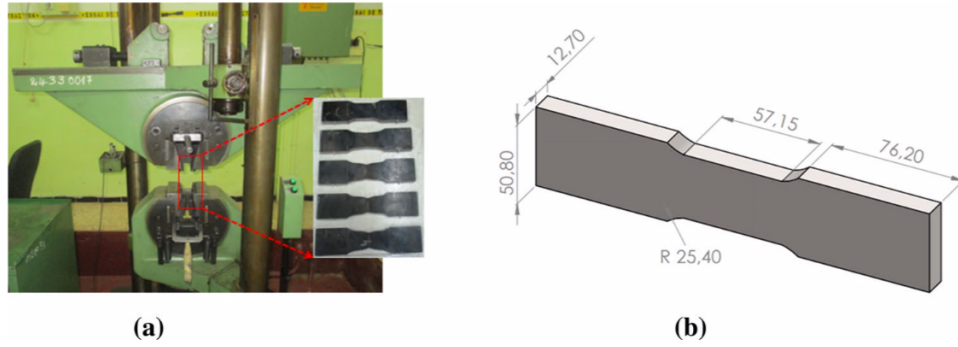


Figure 9 - Set up of uniaxial tensile tests with tensile extensometer (a); geometrical dimensions according to EN 10,002–1 standard (b).

From a tube, we cut a ferrule. Then, we took two plates from this ferrule, one transverse to the ferrule, which contains only the base metal, and the other transverse to the weld bead. The two plates obtained are illustrated in Figs. 10c and d. From the plates (c) and (d), we cut 3 test specimens having 50 mm wide each. The ultimate shape of a tensile test specimen is obtained by the milling process (Fig. 10a and b). The rest of the two plates were used for the other tests (impact test), see Fig. 10e. The obtained results for both cases are shown in Tables 5 and 6.

Table 5 - Results of tensile tests for the base metal.

Test number	Width	Thickness	YS (MPa)	UTS (MPa)	EL (%)
1	38.1	13.04	556	670	38
2	38.3	13.05	560	671	37.7
3	38.2	13.04	561	666	37

Table 6 - Results of tensile tests for the weld metal.

Test number	Width	Thickness	YS (MPa)	UTS (MPa)	EL (%)
1	38.4	12.89	645	713	27.32
2	38.2	12.96	620	714	29.0
3	38.4	12.95	638	716	29.6

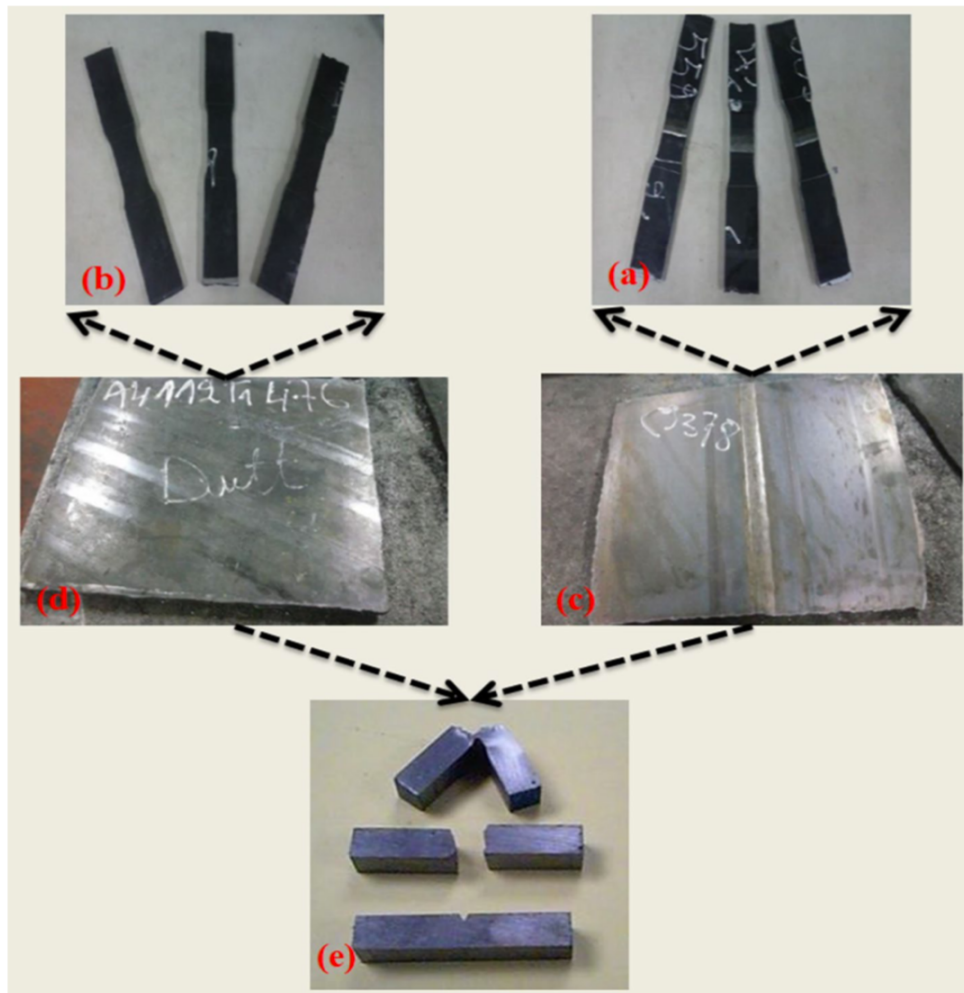


Figure 10 - Sample for tensile test (a, b), Butt joint of API X 70 steel using arc welding (c), Steel plate (d), sample for impact test (e).

5.2. Charpy Test

The mechanical characterizations deduced from the tensile test may be insufficient because failure may happen below the yield strength under special conditions rendering the material to a brittle state. The impact test is an essential complement to the tensile test. These tests were carried out on a Charpy V sheep (see Fig. 11), at a temperature of $-10\text{ }^{\circ}\text{C}$. The resilience test was carried out on standard CVN 10×10 test specimens, following the geometry proposed according to API 5L. The dimensions of the test specimen are given in Fig. 12. Nine specimens were prepared: three specimens machined from Base Metal (BM), three others were taken at the level of the Welded Metal (WM), and the remaining three for the Heat-Affected Zone (HAZ), i.e. transition zone.



Figure 11 – Resilience machine and cooler.

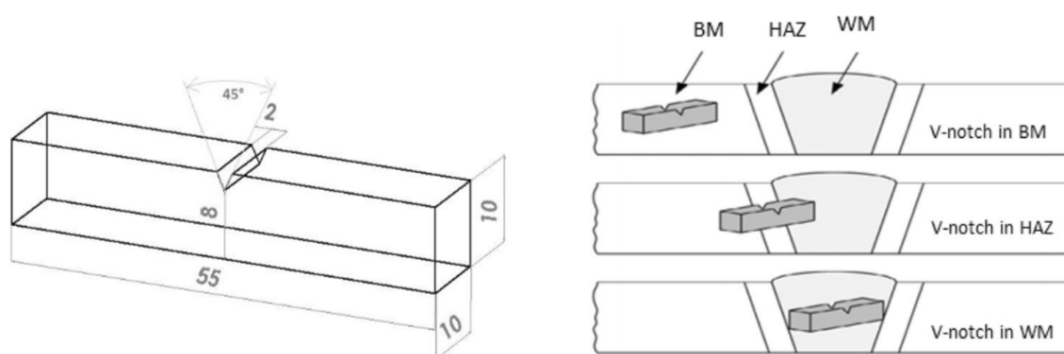


Figure 12 - Standardized test piece of the impact test.

The variation in fracture energy, i.e. energy absorbed by the specimen, in the three zones is very large and the experimental results of the impact tests at different positions (BM- HAZ-WM) for API X 70 steel are presented in Table 7. It is possible to notice that the energies of the test specimens with welding are low compared to the material test specimens, which represents the effect of the welding.

Table 7 - Macro-characteristics of Charpy specimens cut from X70 pipe steel tested for different impact position.

Base metal			Welding			Zone transition		
Energy (J)	J/cm ²	Average (J/cm ²)	Energy (J)	J/cm ²	Average (J/cm ²)	Energy (J)	J/cm ²	Average (J/cm ²)
231.8	289.8	286.1	205.8	257.2	210	205.6	257.0	234.7
237.8	297.3		152.6	190.8		176.6	220.7	
216.8	271.0		161.8	202.2		181.0	226.3	

Table 8 - ANN-GTN model parameters.

ANN-input														
	C	Si	Mn	Cr	Ni	Mo	Al	Co	Cu	Nb	Ti	V	S	P
MB	0.125	0.270	1.680	0.051	0.040	0.021	0.038	0.004	0.045	0.033	0.003	0.084	0.005	0.012
WM	0.06	0.41	1.24	0.032	0.56	0.008	0.003	0.046	0.027	0.003	0.032	0.013	0.010	0.007
ANN-Output														
	n				H				f_n				f_c	
	0.043				837.69				0.0024				0.0214	
	0.05				869.4				0.0002				0.022	

5.3. Finite Element Modelling

According to the results obtained by ANN, the parameters of Ramberg–Osgood and other parameters of the model of damage GTN are related to the reinforcement of the material of the matrix, taking as $q_1=1, 5$; $q_2=1.0$ and $q_3=2.25$. The mean equivalent plastic strain and the standard deviation of the nucleation strain are $\varepsilon_n = 0.3$ and $s_n = 0.1$, respectively. The load–displacement curve evaluated by FEM is compared with that obtained by experimental tests. Finally, the comparison between the experimental values and those obtained by simulation based on ANN-GTN parameters is presented in Table 8.

Finite element analysis of tensile test base metal and weld metal is performed using ABAQUS software. The tensile test and Charpy impact are modelled as deformable bodies. A 3D solid finite element model was implemented to reproduce the laboratory scale Charpy V-Notch experiment (CVN). The ABAQUS/Explicit solver permitted the application of the GTN damage model for the simulation of dynamic propagation of fractures. For this purpose, the model called "porous metal plasticity" was used. The geometry was created based on the standard dimensions of the specimen, as stated previously. In each model, the mesh was created using 8-node linear brick elements with reduced integration. The mesh size is of significant importance when the GTN damage model is implemented. In this study, an element size of 0.2 mm was used. The condition of zero penetration between the hammer and the test specimen has been implemented. In addition, friction has been taken into account using a penalty function with a coefficient of friction equal to 0.1. Due to the

impact load in the CVN, the acceleration and, as consequence, force measurements can show pronounced oscillations. Therefore, the velocity data was extracted and derived to obtain acceleration and force data. This method reduced the presence of oscillations and made it possible to construct the force–displacement curves for each respective simulation. The Charpy Impactor is modelled as a discrete rigid body in the simulation.

The proposed model is constrained on one side as follows: $U1=U2=U3=UR1=UR2=UR3=0$, and on the second side it is allowed to move in the direction of (Y), see Figs. 13a and b. In Fig. 10c, macrograph of the weld zone is shown, from which we take a reference length of the properties of the weld zone in the finite element model. In this study and the simulations of ABAQUS program, we consider the ZAT region as part of the weld region. From the experimental data, the weight of the impactor is 19.8 kg and its speed is 5.5 m/s in the Y direction only with the two ends of the part being fixed (Figs. 14a and b).

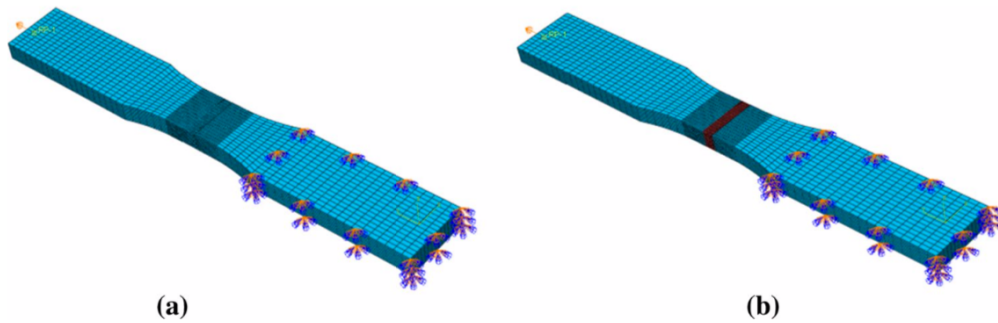


Figure 13 - Tensile test modelling with boundary conditions: a Base metal and b Welded metal.

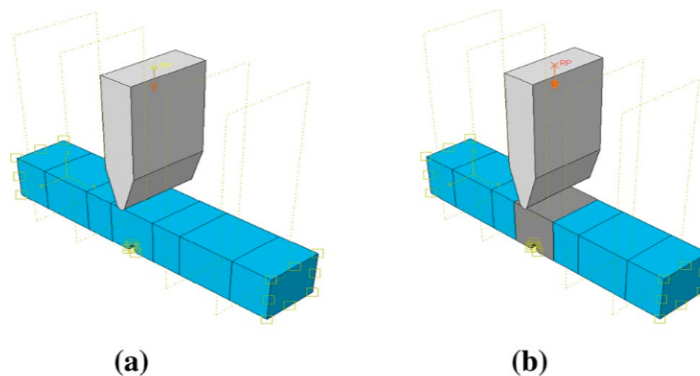


Figure 14 - Impact test modelling with boundary conditions: a Base metal and b Welded metal.

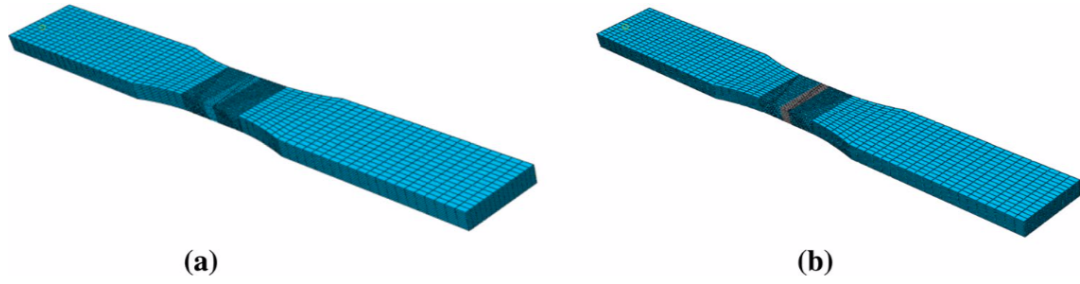


Figure 15 - FE model of tensile test specimens: a Base metal and b Welded metal.

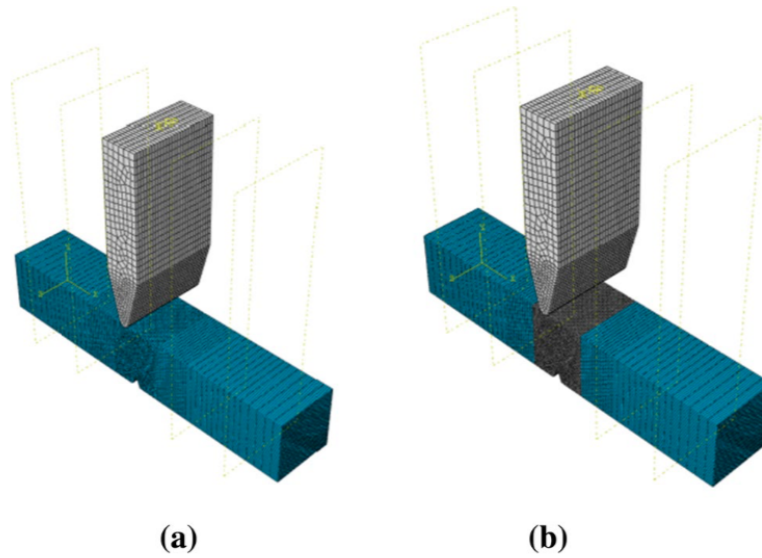


Figure 16 - FE model of impact test specimens: a Base metal and b Welded metal.

The mesh patterns of the base metal and welded metal traction and Charpy samples are shown in Figs. 15a and b and 16 a and b, respectively. The mesh element type for both tests is a hexagonal element shape, i.e. a C3D8R element type.

6. Results and Discussion

The results of the experimental uniaxial tensile test and FE analysis are shown in Fig. 17. At the centre of the tensile test specimen, the necking behaviour with successive shrinkage and fracture of the metal in the experiment is illustrated in Figs. 17a and c and in the FE analysis is shown in Figs. 17b and d, respectively.

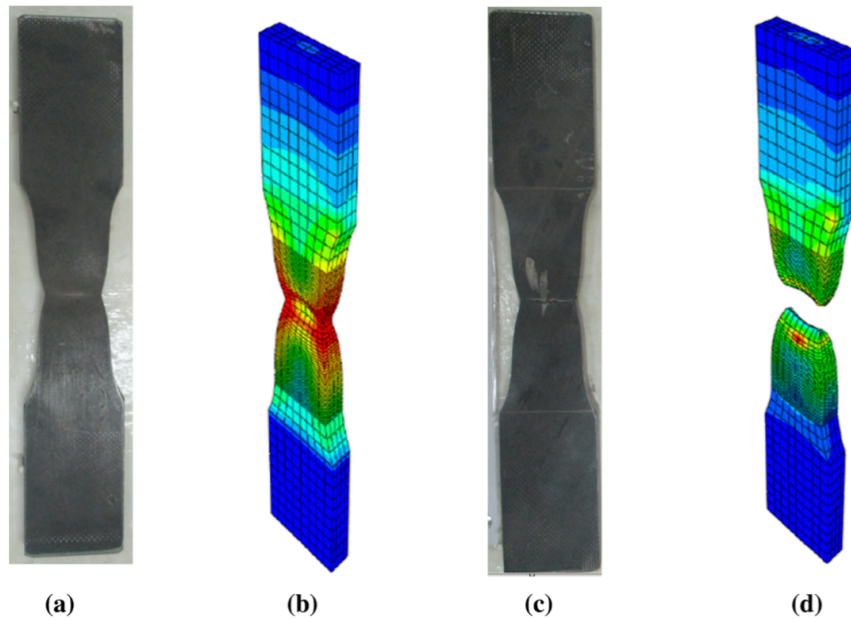


Figure 17 - The tensile test from experiment and FE analysis (a and b—necking, and c and d—fracture).

The experimental fracture area indicates a ductile failure mode and that the fracture is identical to the FE analysis as shown in Fig. 18. In addition, the narrowing and fracture location of the weld metal sample from an experimental analysis and FE is shown in Fig. 19. Experimental analysis and FE show good agreement for weld metal describing failure behaviour. The engineering stress versus engineering strain curves from the experimental and FE analyses are shown in Fig. 20.

The fractured specimens base metal and weld metal also exhibit a ductile type fracture. Figure 21 shows the graphical representation of the energy displacement graph obtained by the base metal and weld bead impact test simulation.

The graphical representation in Fig. 21 shows on the X axis displacement (mm) and on the Y axis impact energy absorbed by the base metal and weld seam (J/cm²). The experimental load displacement curve and the corresponding numerical prediction for the tests are shown in Fig. 22. By comparing FE and experimental results, one may notice that a good correlation with the experimental data is obtained.

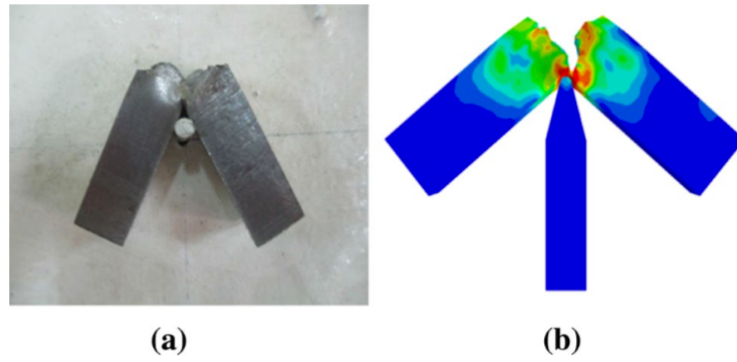


Figure 18 - Impact test in the experiment and FE analysis.

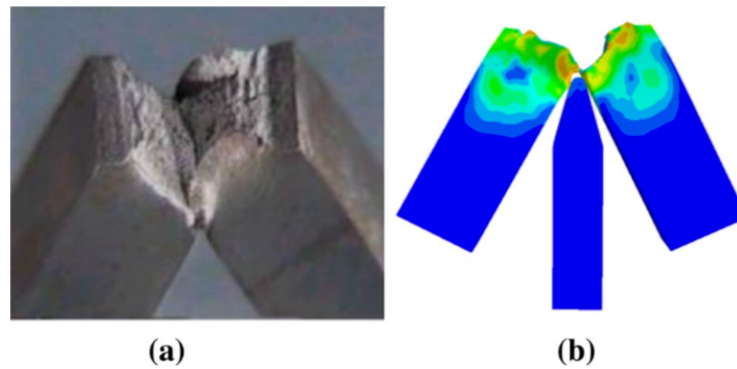


Figure 19 - Comparison of weld metal impact test between experimental and FE analysis.

From Table 9, we can see a comparison between the experimental results and the ANN prediction of the mechanical properties of API X70 steel. In addition, the simulation results obtained from ABAQUS based on the values of the original parameters of prediction ANNGTN torque with the law of hardening are also given in Table 9.

Table 9 - Comparison of mechanical properties for the three different sources.

Results		Experimental	Prediction ANN	Error (%)	Simulation based on ANNGTN parameters	Error (%)
Yield strength (MPa)	YS	559	526	5.90	545	2.50
Ultimate tensile strength (MPa)	UTS	669	628	6.13	663	0.90
Ultimate tensile strength (MPa)	UTSw	714	643	9.94	650	8.96
Elongation (%)	EL	37.5	39.51	5.09	33	12
Yield to tensile ratio (%)	YTR	84	88	4.76	80	4.76
Charpy strength BM (J/cm2)	KV (BM)	286.1	317	9.75	302	5.56
Charpy strength FZ (J/cm2)	KV (FZ)	210	180	14.29	191	9.01

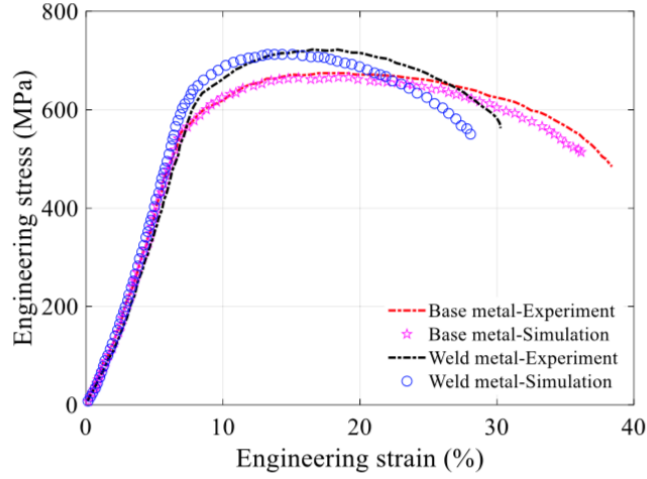


Figure 20 - Engineering stress versus engineering strain plot for base metal and weld metal.

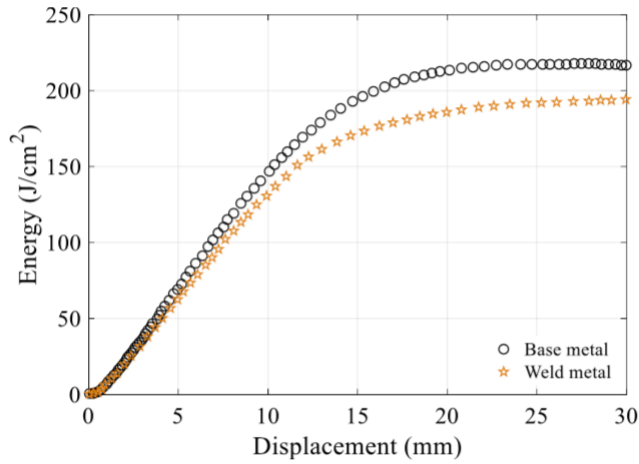


Figure 21 - Energy–Displacement graph (simulation-impact energy).

7. Conclusion

An artificial neural network model was developed in this work to predict the parameters of the GTN damage model and the constants of the Ramberg–Osgood hardening law of API X70 steel pipelines.

Based on the data obtained, the following conclusions can be drawn:

- Despite the high number of parameters and simulations, the approach applied in this study allowed them to be determined with minimal errors and good accuracy using a reverse identification procedure.

- The minimum difference between the numerical results in the case of coupled identification allows the identification to be broadened to include a considerable number of experimental tests from the previous results obtained at the ALFAPIPE Ghardaia laboratory.
- Subsequently, the identified GTN parameters are used to develop an ANN model to predict two principal parameters of the GTN damage model, namely f_n and f_c , coupled with hardening law.
- The developed model offers the basic metal chemical composition API X70 as an input because it directly influences the mechanical properties of this steel.
- The results obtained by the ANNGTN were used in the numerical model of the tensile test and of the Charpy test. Next, the numerical load–displacement curve was compared with the experimental results and provided good results.
- It can be said that the ANN has been used successfully to facilitate the prediction of GTN parameters and mechanical properties of steel, thanks to the good compatibility of the experimental and numerical analyses.
- The developed model has a great capacity to predict the results before making mechanical tests and determines the variation in mechanical properties by the simulation 17. according to the chemical compositions of steel.

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