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# OPTIMIZATION APPROACH TO PREDICT DAMAGE MODEL PARAMETERS FOR DUCTILE FRACTURE OF PIPELINE USED IN NUCLEAR REACTOR

Booklet of Ph.D. Theses

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# 1. INTRODUCTION

The Titanic was thought to be unsinkable, the dream ship, until it hit a large iceberg on April 14, 1912, and sunk in less than three hours. The Titanic carried about 2200 passengers and staff on her first journey to America. Only 705 people made it out alive.

The main question following the Titanic disaster was, "What caused this accident ?" Many analyses were conducted to provide rational solutions to the world's curiosity about why the massive Titanic sank.

The main reason behind the Titanic sinking was the material failure at low temperatures, the material had to behave in ductile mode, but unfortunately, brittle failure took place !!!!

After this accident, the researchers decided to study the fracture of the materials deeply and give more importance to the mechanical phenomenon near the crack tip, which gave birth to the new science field of Fracture mechanics [1]

Fracture mechanics is mainly based on studying the crack initiation and propagation in the steels.

It is important to study how steel fails and how the Crack behaves in the material; in other words, we need to be able to predict its failure, especially in nuclear power plants.

The leakage problem in the pipelines is one of the critical issues that's might affect the performance of the Nuclear Power Plants [2-4], and ferritic steel is the primary type of material from which the pipelines usually constructed. The majority of ferritic steels deformed plastically before failure [5].

Over the last five decades, deep research has been undertaken to explore the ductile failure of pipelines using mechanical damage models such as the Gurson Tveegard Needelman model. [6–12].

Even so, there has been no detailed investigation into predicting GTN parameters in the nuclear field using optimization models such as artificial neural networks. Most studies have only focused on direct methods to predict the GTN parameters.

As a result, there is a clear gap in the literature for an optimization model based on an artificial neural network that accurately determine the GTN parameters which will lead us to predict the failure of the pipeline in the nuclear field. In this booklet, I present a summary of the main results found during the Ph.D. studies

## 1.1. Aims and scope

My research interest is focused on the damage to engineering materials and on analysing industrial degradation to develop a recommendation for mitigating actions to avoid future degradation.

When researching the damage to engineering materials, one of the most important questions is how to extend the component's lifetime while avoiding damage to those components.

Preventing catastrophes is possible by gaining a deep understanding of material properties, degradation processes, and external factors such as temperature and radiation, and by developing new methods to extend the lifespan of critical components, particularly in the nuclear energy sector

Ensuring the nuclear safety of nuclear power plants means keeping all the parts working correctly and with high performance, the pipeline is one of these parts.

The leakage problem in the pipes is a critical issue that might affect the performance of the nuclear power plant if it is not detected from the beginning. The prediction of the failure of pipelines is an important topic because it helps during the design the nuclear power plant parts and prevents problems that might occur due to the leakage of the pipelines.

The European Union is financing many R and D projects [13] dealing with nuclear safety.

From my point of view, the prediction of GTN model can be made smart and optimized using ANN tools. The concept is based on training a neural network with data found from simulations done with MARC MENTAT software [14]. After training the network, I can quickly get GTN parameters for the pipeline, and the model can do the same task with other specimens with different geometries.

The experiments mentioned in this study were done by the project partners, EDF France and Framatome Germany.

The main objectives of this study are to validate the applicability of the GTN model and determine the GTN parameters by using ANN for predicting the ductile failure of ferritic steel material based on different geometries.

Various sub-objectives or activities can be identified and conducted to achieve these objectives.

The first sub-objective is to validate the usability of the GTN model: to reach the first goal, an experiment and simulations were conducted using the Marc mentat model to determine the GTN parameters required to predict the failure of the SENT specimen based on the CT specimen, In addition, the research delved into the mysterious phenomena of the convergence of GTN parameters and evaluated their sensitivity based on hundreds of simulations. The most sensitive GTN parameters were identified through this study, which can help other researchers working with the GTN model to determine the correct set of GTN parameters with greater precision.

The second sub-objective is to apply the direct method using GTN parameters to predict the failure of a large component, which in this case is the pipeline, and analyse the time consumed during the process.

As a third sub-objective, the study aims to optimize the time consumed when determining GTN parameters and include the backpropagation approach to reduce it; this study will be based on an NT specimen.

Lastly, the fourth sub-objective investigates subsidized specimens as an alternative to normal-sized specimens and determines the J-R Curves.

These sub-objectives will be conducted in a way that supports the main objective of validating the applicability of the GTN model and the GTN parameters determination through ANN for predicting the ductile failure of ferritic steel material for different geometries.

## 2. METHODOLOGY

To provide an overview of the main topics, in the first chapter of our thesis, I provided a state-of-the-art review of the GTN model and its significance; additionally, the Artificial neural network was included, as it is the primary optimization method used in this work.

The experimental section described the various experiments conducted as part of the European projects ATLAS+ and STYLE.

In the second part, I define the core of the dissertation by describing the research and innovation done during the Ph.D. study period, where the main dissertation target is divided into several theses completing each other to achieve the final target, which the elaboration of an optimization approach to predict the failure of the pipeline in a short time based on the determination of GTN parameters, Or the method of defining the GTN model is divided into two main processes:

First Process: Present the direct method of determining GTN parameters which is the combination of the experimental data and the results found using finite elements methods, so I had to repeat the simulation many times based on different sets of GTN parameters until finding the correct set which predicts exactly the experimental data, this process is time-consuming, and it needs to be done by choosing values of GTN parameters that have physical meaning and not arbitrary numbers.

Second Process: Presents the introduction of the ANN during the determination of GTN parameters, so the advantage of this approach is that the time consumed during the determination of GTN parameters is short, and it leads us to find parameters with physical meaning and not just arbitrary number, so, in other words, using this approach I build a neural network that could do the simulations instead of Marc Mentat software and predict the correct set of GTN parameters.

As mentioned above, there are two main processes for the determination of GTN parameters, but in order to use the model in this work, I had to prove that it could be included, so I started by predicting the failure of the SENT specimen (Figure 2) using a direct method based on CT specimen (Figure 1)

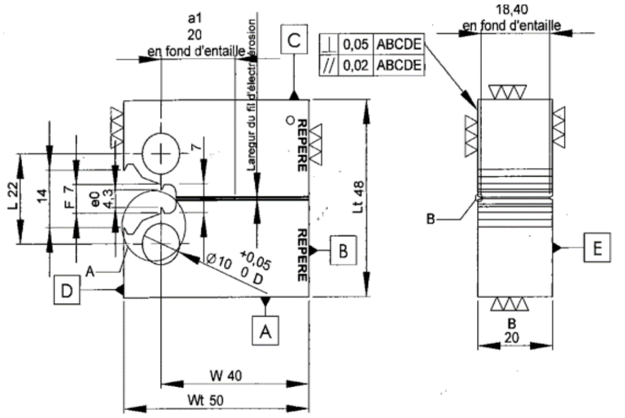


Figure 1. CT specimen geometry

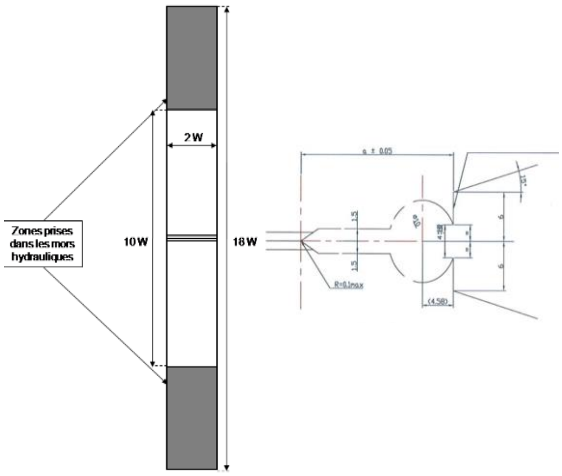


Figure 2. SENT specimen geometry

The results found (Figure 3) from our first study show that the GTN model can be used in this work, and I can go further with our study.

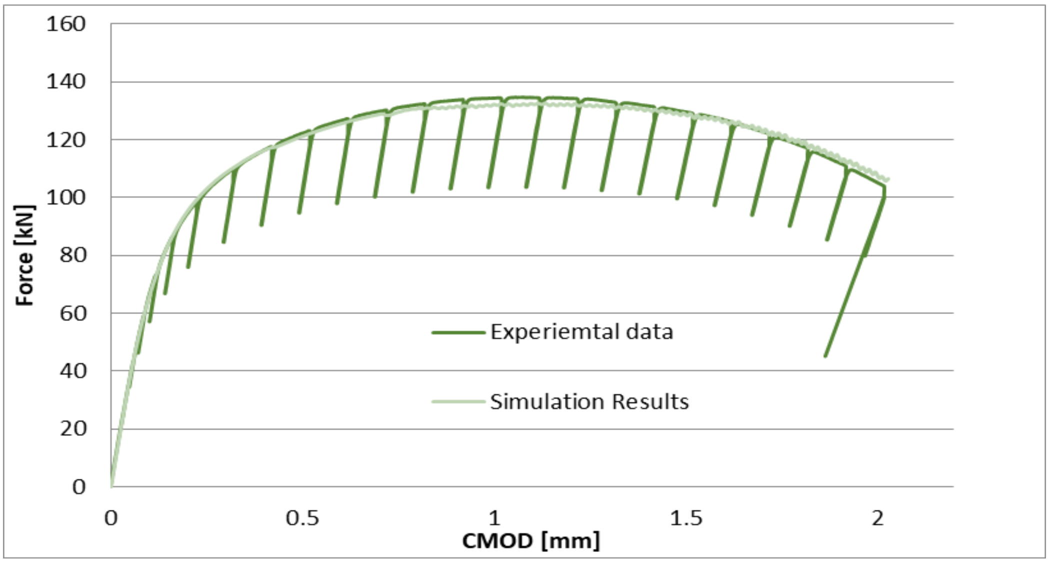


Figure 3. Force-COD curve using the direct method

After demonstrating that the direct method using the GTN model leads to correct predictions, I decided to use a combination of ANN and GTN model to predict the failure of the SENT specimen.

The next step is to demonstrate whether the backpropagation approach can be included in the process and to be able to compare it with the direct method (Figure 4).

Figure 5 presents the results.

To apply the ANN approach, I proceed as below:

- Conduct small-scale experiments (CT, SENT) to collect experimental data.
- Conduct 3D Numerical Simulations and create a database for neural networks.
- Using a mix of experimental and FEM data and an Artificial Neural Network, estimate the GTN parameters.
- The software used during the optimization approach is MATLAB 2019

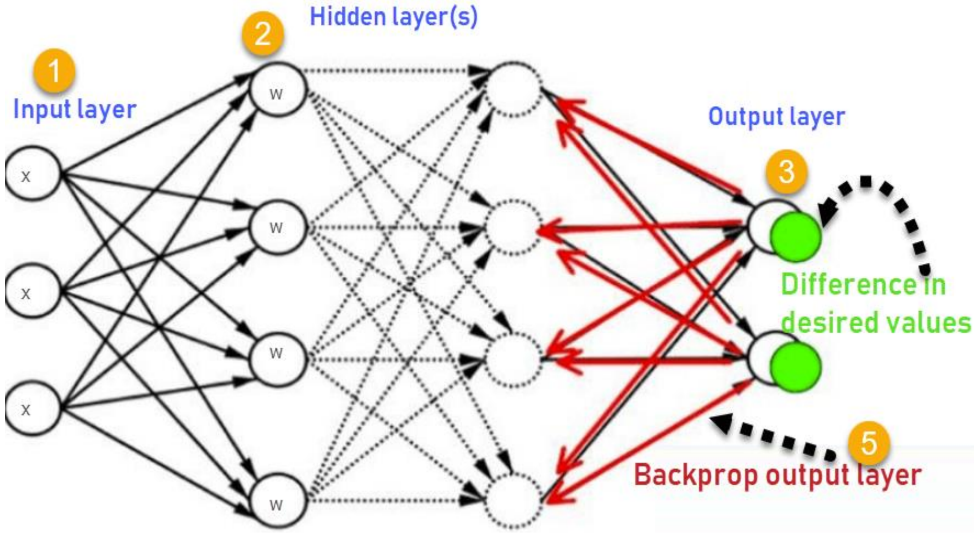


Figure 4. Backpropagation algorithm

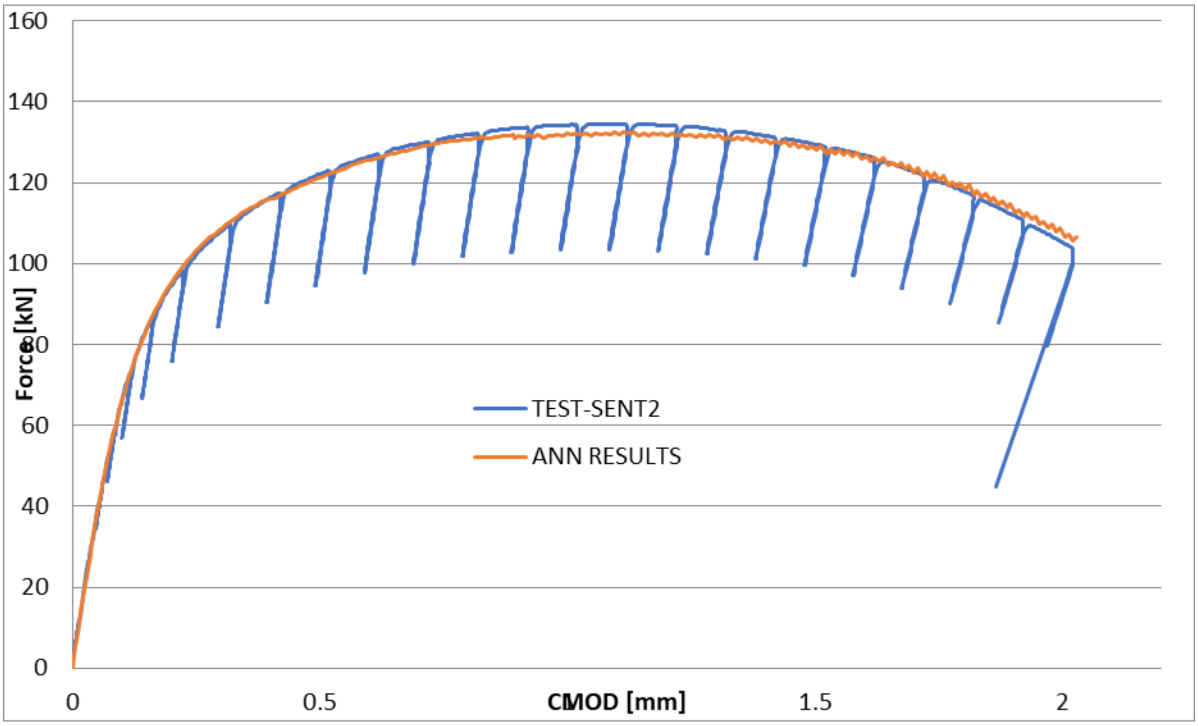


Figure 5. Force-COD curve using the ANN method

During the analysis of the GTN model, I noticed that the parameters are quite sensitive to small changes, so I decided to determine the most sensitive parameters; I ran 120 simulations in total, with 20 runs for each parameter.

- $f_0$ = 0.003 (I made the variation of the parameter by this value ±0.0003)

- $f_n$=0.3 ( I made the variation of the parameter by this value ±0.03)
- $f_c$=0.007 (I made the variation of the parameter by this value ±0.0007)
- $f_f$ =0.35 ( I made the variation of the parameter by this value ±0.035)
- $S_N$ =0.005 (I made the variation of the parameter by this value ±0.0005)
- $\varepsilon_n$ =0.065 ( I made the variation of the parameter by this value ±0.0065)

I was able to find an interesting result:

- The main sensitive parameters are $f_0$, $\varepsilon_{n,}$ and $S_n$
- The exact value of $f_0$ must be more precise and have physical significance.
- The difference in the stress-strain curve is quite small for $f_c$, $f_f$ and $f_n$,
- Changing the values of the $f_c$, $f_f$ and $f_n$, values has no macroscopical effect on failure prediction.
- When the value of $f_f$ is less than the value of $f_c$, no simulation may be started.

Based on the information mentioned above, I tested the GTN model using both the direct model and artificial neural network and identified the most sensitive parameters.
The subsequent step entails using the obtained results to estimate GTN parameters for the pipeline through both the direct method and artificial neural network approach.
I used the direct method, combining the experiment and finite element results-
I perform a FEM simulation using the GTN parameters only on the crack propagation area, which is the most sensitive part of the model (Figure 6)

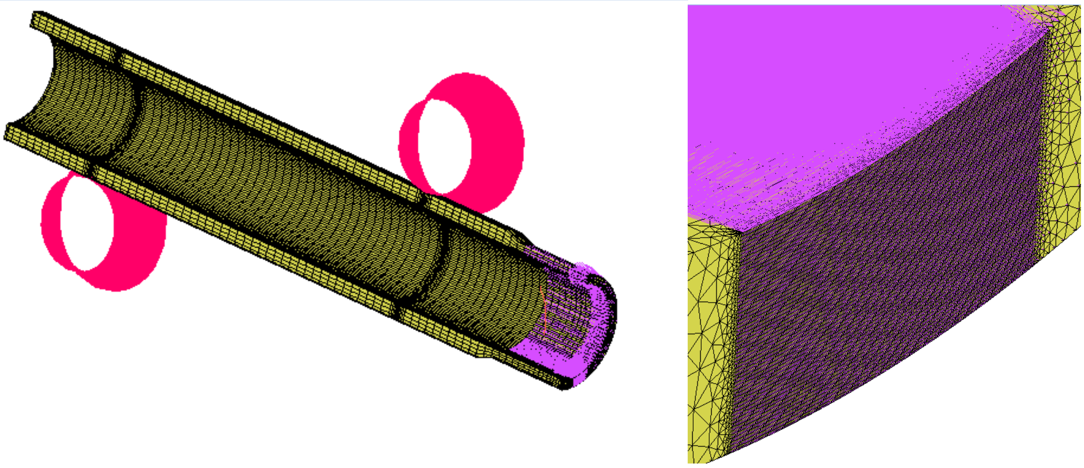

Figure 6. mesh near the crack tip

Due to the huge number of elements in the model, it took around two days of computing for one simulation.

So, to get the correct set of GTN parameters, I had to do around 15 simulations, which means around 30 days of computation (Figure 7)

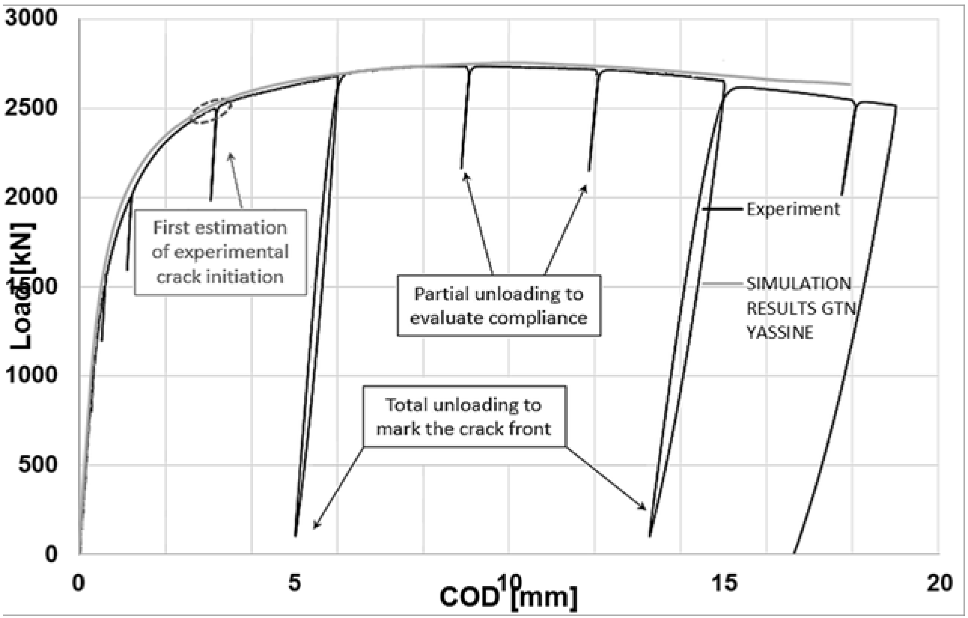


Figure 7. Force vs. Crack opening displacement using the direct method

The results lead me to a correct determination of the highest load and crack propagation of the pipeline using the direct method, but it is time-consuming; therefore, it is important to reduce the time and elaborate an optimization approach to predict the failure of the pipeline in a short time using combination between GTN model and backpropagation algorithm (Figure 8)

The next step is to predict the GTN parameters using ANN for the PIPELINE.

- Conduct small-scale experiments (NT) (Figure 9) to collect experimental data.
- Make the Finite Element Simulations of the Notch specimen; the reason behind choosing Notch tensile specimens is that the simulation will take just 5 to 10 min and I can simulate just a quarter of the specimen due to the axisymmetry
- Conduct 3D Numerical Simulations and create a database for neural networks.

Using a mix of experimental and FEM data and an Artificial Neural Network I could estimate the GTN parameters.

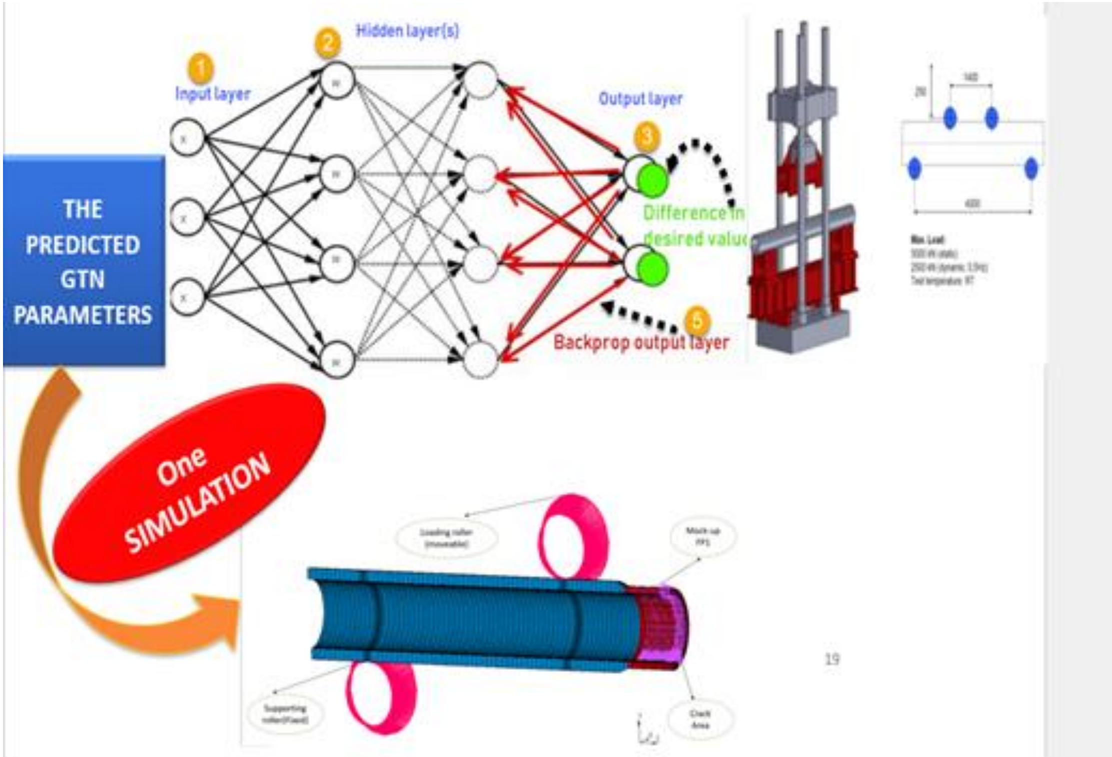


Figure 8. Backpropagation approach for pipeline failure prediction

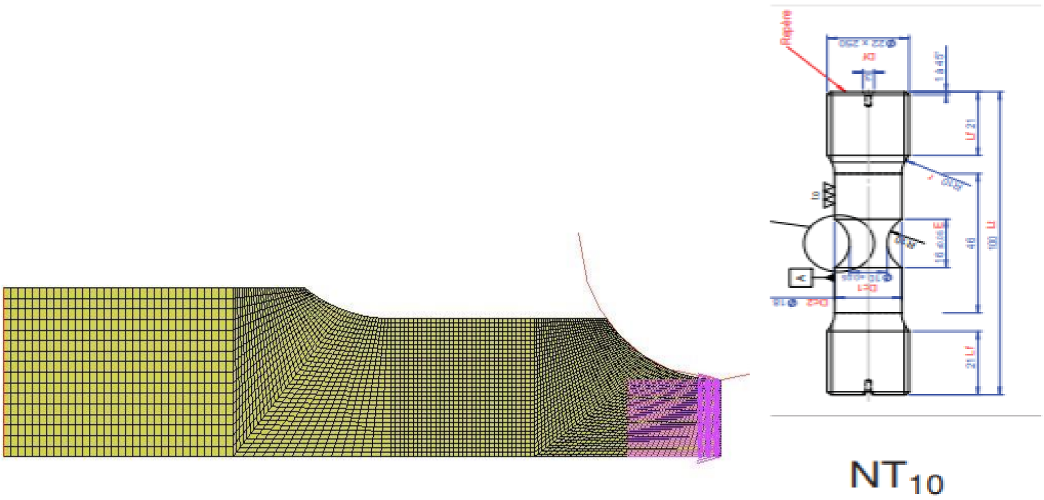


Figure 9. Notch specimen and simulation

The introduction of the backpropagation approach led to important results that were not expected; I could reduce the time consumed for predicting the GTN parameters from 30 days (direct method) to 6 hours (ANN method).

The results shown below (Figure 10) prove that the prediction of the pipeline's crack propagation and load behaviour is possible using a combination between ANN and GTN model.

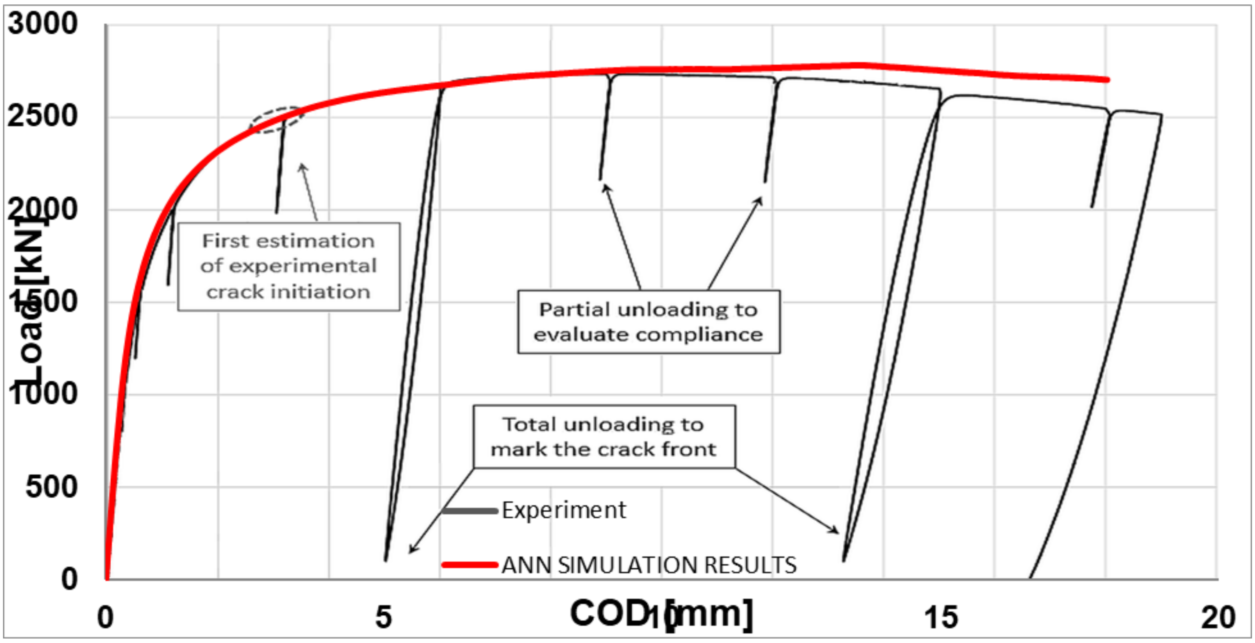


Figure 10. experimental and simulation results

I decide to run a Statical comparison between the ANN and direct method for the first mockup FP1.

1. Descriptive statistics: The mean, median, standard deviation and range for the load force results obtained from the direct method and the artificial neural network method are shown in the table below:

| Method | Mean | Median | Standard Deviation | Range |
|---|---|---|---|---|
| Direct | 50.82 | 51.29 | 3.01 | 14.55 |
| ANN | 50.50 | 50.44 | 3.19 | 13.91 |

2. Normality testing: I performed The Shapiro-Wilk test to check the normality of the data. The results indicate that the load force results obtained from both methods are normally distributed ($p > 0.05$).

Before doing the Shapiro-Wilk test, I first computed the load force results for the direct and ANN techniques.
The Shapiro-Wilk test was employed in this study to check the normality of the load force data produced using the direct technique and the ANN approach. I concluded that the data were normally distributed, and I found that the p-value is higher than 0.05.
In the next step, I decided to study the accuracy of the ANN direct method with the experimental data by using MAE, RMSE, and R2.
- Mean Absolute Error (MAE): The metric assesses the standard deviation between expected and observed values. It is derived by averaging the absolute disparities between the values that were anticipated and those that occurred. The model performs better in terms of prediction when the MAE is lower.
- Root Mean Squared Error (RMSE): The RMSE is a metric that assesses the average squared variation between the expected and actual values. The average of the squared discrepancies between the expected and actual values is considered in its calculation. The model performs better in terms of prediction, the smaller the RMSE.
- the R2 value (s) indicates how much of the variance in the dependent variable can be predicted by the independent variable. Higher values indicate stronger prediction skill; it ranges from 0 to 1. The R2 value of 1 indicates that the model perfectly fits the data, while an R2 value of 0 indicates that the model does not explain any of the variability in the data.
Ultimately, I found that the Artificial Neural Network (ANN) technique outperformed the Direct method in forecasting the GTN results. Compared to the Direct approach, the ANN model had significantly lower Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared values. Compared to 12.958 and 16.128 for the Direct technique, the MAE and RMSE values for the ANN method were 6.853 and 8.195, respectively. With the ANN and Direct approaches, the R-squared values were 0.962 and 0.855, respectively. Therefore, the ANN method is recommended for future GTN parameter predictions.

Based on these results, it can be concluded that there is no significant difference between the load force results obtained from the direct method and the artificial neural network method.

To confirm the results that I found, I decided to proceed with the same concept and predict the failure of another mock-up FP2 (Figure 12) but with a different crack shape (the Crack introduced through-wall FP1, but for the second mock-up, the initial defect was in surface fractures, the Crack is introduced in all cases using EDM and fatigue pre-cracking.) ( Figure 11)

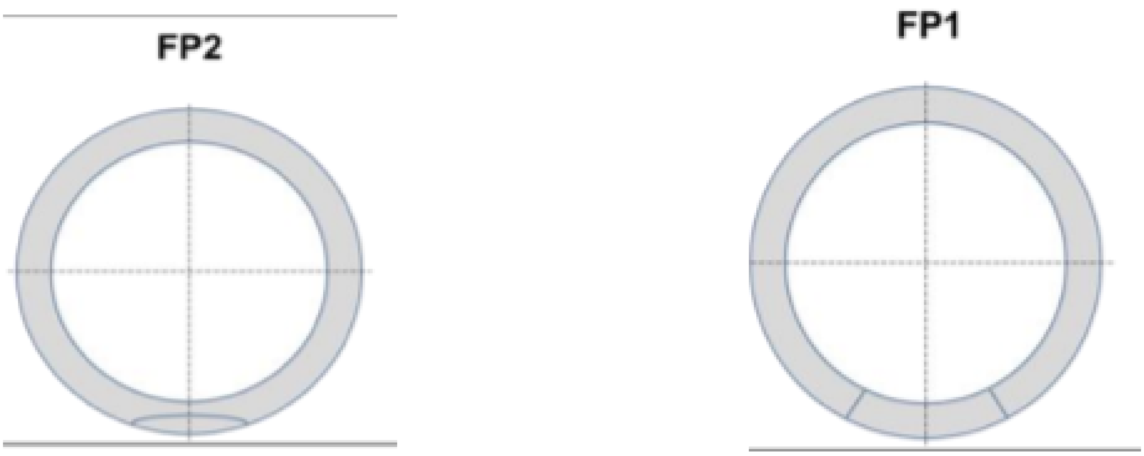


Figure 11. FP1, FP2 crack defect shapes

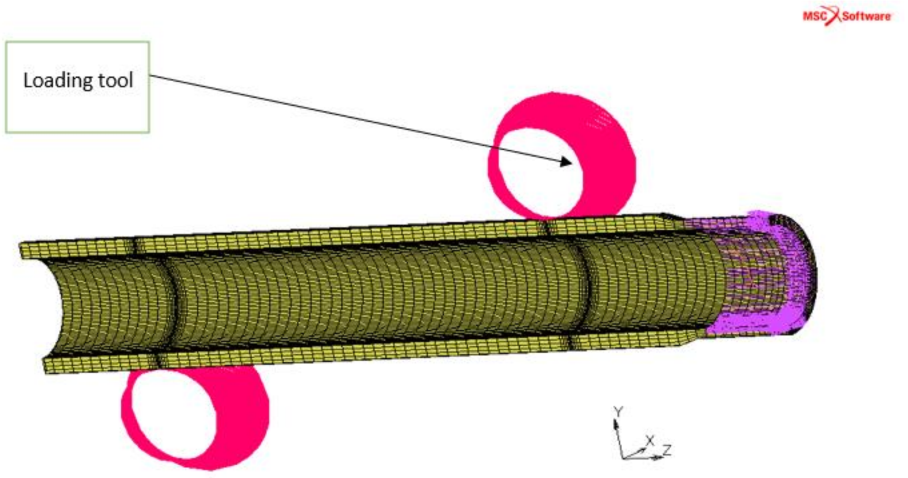


Figure 12 Simulation of the second mock-up

As I have done for the first mock-up of FP1, I was able to predict the failure of FP2 using the backpropagation algorithm; the results are shown in (Figure 13).

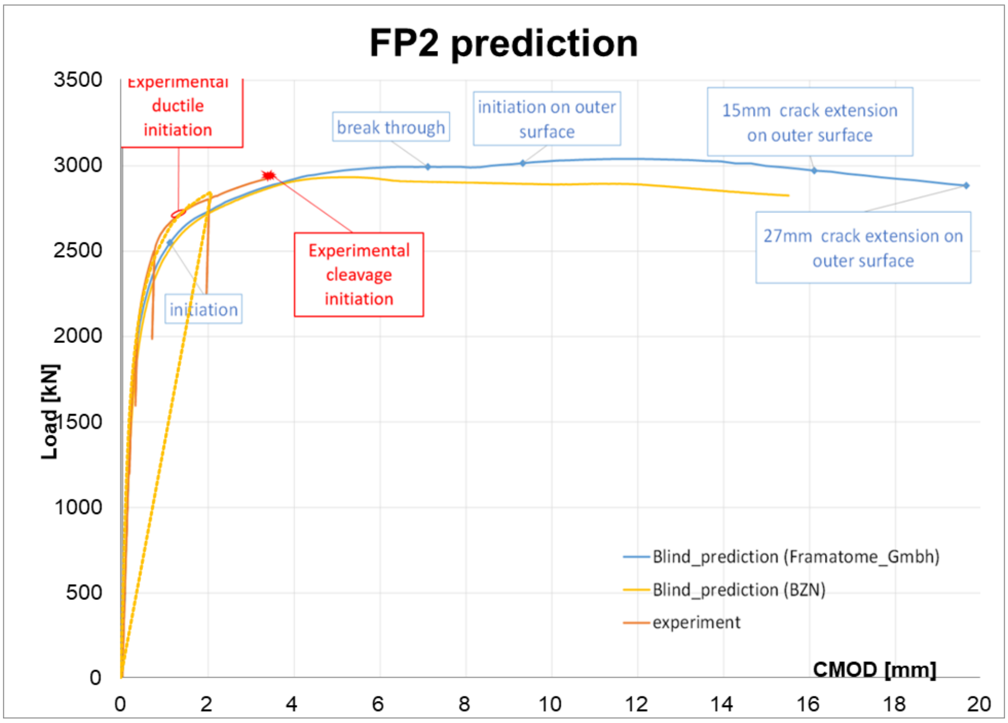


Figure 13 Load vs. Crack opening displacement of fp2

It is important to highlight that the initiation and maximum load are well predicted.

By analysing the curves above (Figures 10 and 13), it is obvious that ANN estimates the correct values of GTN parameters used to predict the failure of the SENT specimen.

It is noticeable that the curve found by ANN is not fully fitting the experimental data, especially at the end of the curve; this phenomenon is related to the database used to train the network.

I cannot control the database used in the neural network, but it is possible to use other geometries as a database, such as CT and SENT specimens. Still, this approach will take more time compared to the NT specimen.

**REMARKS AND INTERPRETATION :**

- The GTN model is a practical tool that can be used in the nuclear industry to improve safety.
- The backpropagation algorithm was a powerful optimization tool that reduced prediction time from 30 days to six hours.
- Increasing the amount of training data is necessary to address the convergence issue and improve the accuracy of predictions.

- Due to the critical area from which I obtained the specimens for fracture toughness tests, specimen size is a significant obstacle. Subsidized specimens can be used instead of normal-sized specimens to overcome this issue.
- One of the main challenges of the GTN model is the number of parameters that must be determined, which depend on the type of material and load conditions. It is critical to find the correct set of GTN parameters.
- Predicting the pipeline's maximum load and crack propagation is essential for avoiding pipeline failure.

The main goal of this thesis was to predict pipeline failure using a combination of the ANN and GTN models. To open avenues for future research, I provided a general overview of subsidized specimens, which could potentially reduce prediction times even further.

From what was mentioned above, I could reach this thesis's main goal, which was predicting the failure of PIPELINE using the combination between the ANN and GTN model

Standardized specimens are currently rather large because they were created primarily to evaluate massive structures against brittle failure,

However, these standard specimens are impractical in many circumstances due to the size constraints imposed by the experimental material or the component under consideration.

As a result, new techniques utilizing much smaller specimens must be developed, and processes utilizing smaller specimens must be offered, with their validity limitations and relationship to standardly acquired results, to provide a solution for a wide range of applications.

Mechanical properties, such as fracture toughness for brittle fractures, are determined using standard standards (ASTM E1820, E399). These standards state that specimen size restrictions are required for testing. The conditions cannot be met in rare circumstances, such as irradiated specimens or restricted material sources.

It is important to highlight that the sub-size specimens do not meet the size criteria of the standard ASTM E1820 (2011).

Employing small-size or even miniature mechanical specimens is becoming increasingly common due to the potential to optimize material usage, particularly where material availability is a concern or space inside irradiation facilities is restricted.

On the other hand, the utilization of subsidized specimens raises many obstacles. These difficulties are related to adequate consideration for structural parameters and the transferability of tiny specimen data to the actual structures of interest. The most often used sample shape in surveillance programs is the Charpy V-notch specimen.

Any fracture toughness specimen made from the broken standard Charpy specimens may be used to evaluate reactor pressure vessels.

The most frequent specimen shape used in nuclear safety programs is the Charpy V-notch specimen.

The Mini-CT specimen approach has the benefit of having the same cross-section (10x10 mm) as a regular Charpy specimen, allowing it to be created from a simple slice of a damaged Charpy specimen.

Further studies must be done to validate the Prediction of the SENT, CT, and PIPELINE based on the Subsidized specimen, overcoming many constraints and resolving the transferability issue.

## NEW SCIENTIFIC RESULTS – THESES

T1- The validation of the GTN model was crucial to its use in this work. Using the direct method, I achieved a perfect fit between the predicted results and experimental data using the GTN model. However, I had to deal with the issue of sensitivity, which required a detailed study of the variation in the effect of the parameters to slight changes in their values. To address this, I conducted 120 simulations and demonstrated how the parameters behave, which will be valuable for future researchers in this field, as a new result based on this study I concluded that the main sensitive parameters are $f_0$, $\varepsilon_n$, and $S_n$ [P1] [P2] [P3] [P4]

T2- This study presents a novel optimization approach for determining GTN parameters based on backpropagation, which was found to significantly reduce the calculation time from 30 days to just 6 hours. The results of this approach provide accurate values of GTN parameters and enable accurate predictions of crack behaviour in pipelines, which is of paramount importance for improving nuclear safety guidelines in the industry. Overall, our study contributes to the development of more efficient and accurate methods for predicting GTN parameters and crack behaviour, with potential applications in various industries.[P5] [P6]

T3- The ANN method is found to have outperformed the Direct method with significantly lower MAE, RMSE, and higher R-squared values. Therefore, the ANN method is recommended for future GTN parameters predictions.

## LIST OF PUBLICATIONS RELATED TO THE TOPIC OF THE RESEARCH FIELD


**1.** Chahboub Yassine & Dr. Szabolcs Szavai Determination of GTN parameters for SENT specimen during ductile fracture PROCEDIA STRUCTURAL INTEGRITY (2452-3216) : 16 pp 81-88 (2019)

**2.** Chahboub Yassine et al, Determination of GTN parameters of sent specimen during ductile fracture Tendon : Tamás Kékesi (Metallurgy of non-ferrous metals Tamás Kékesi) ME / FMME / Energy and Quality Institute (eds.) MultiScience - XXXIII. MicroCAD International Multidisciplinary Scientific Conference : Miskolc, Hungary 23.05.2019. - 24/05/2019 Miskolc-University City : ME, pp 1-10 Paper B-10. (2019)

**3.** Chahboub Yassine & Dr. Szabolcs Szavai The Study of the Sensitivity of GTN Parameters PROCEDIA STRUCTURAL INTEGRITY (2452-3216) : 28 pp 1930-1940 (2020)

**4.** Chanboub, Yassine & Dr. Szabolcs Szavai (2021) A Back Propagation módszer alkalmazása a GTN paraméterek meghatározásában - The Application of Back Propagation Approach in the Determination of GTN Parameters. GÉP, 72 (1-2). pp. 80-82. ISSN 0016-8572

**5.** Chahboub Yassine & Dr. Szabolcs Szavai Determination of GTN Model Parameters Based on Artificial Neutral Network for a Ductile Failure Journal of Mechanical, Civil and Industrial Engineering : 2 1 pp 1-5 (2021)

**6.** Chahboub Yassine & Dr. Szavai Szabolcs Damage Prediction of Ferritic Pipeline Using Artificial Neural Network Procedia Structural Integrity Volume 42, 2022, Pages 1025-1032

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