



Undergraduate Thesis

Lucas Manassés Pinheiro de Souza

IMPLEMENTATION OF A DEEP NEURAL NETWORK FOR THE CORRECTION OF PLASTICITY EFFECTS IN THE HOLE DRILLING METHOD FOR MEASURING HIGH LEVELS OF RESIDUAL STRESS IN FLEXIBLE RISERS

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Advisor: Prof. Armando Albertazzi Gonçalves Júnior, Dr. Eng.

Co-advisor: Matias Roberto Viotti, Dr. Ing.

Unofficial co-advisor: Thiago Wilvert, Me. Eng.



Structure of the Presentation

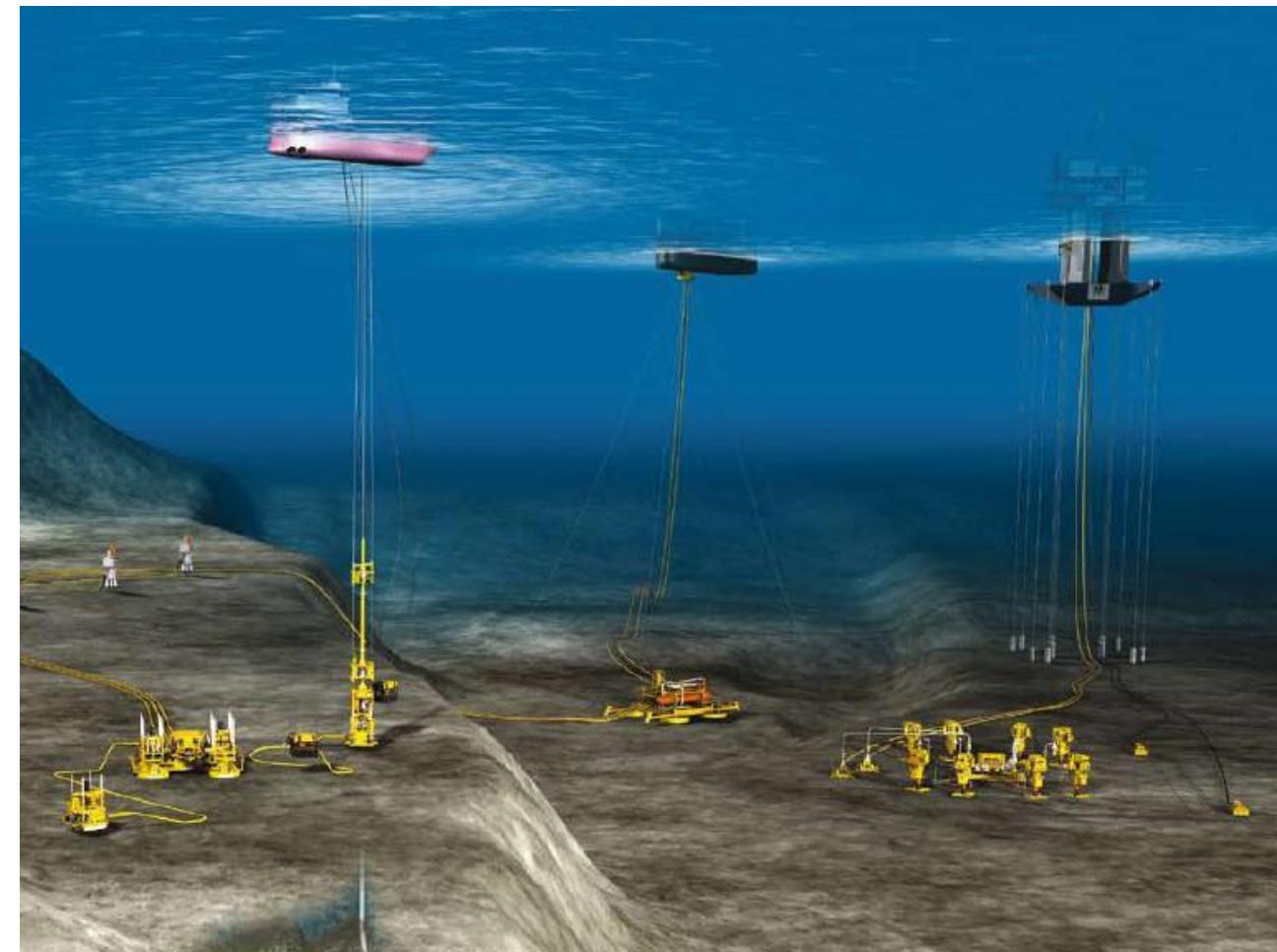
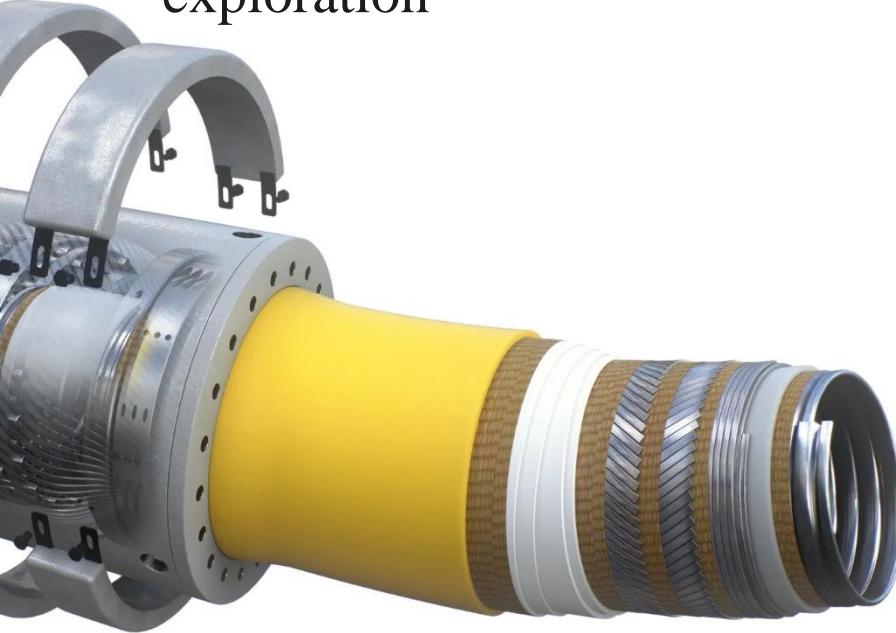
1. Introduction
2. State of the Art
3. Methodology
4. Results and Discussions
5. Conclusions and Suggestions for Future Works



Summary

1. Introduction
2. State of the Art
3. Methodology
4. Results and Discussions
5. Conclusions and Suggestions for Future Works

- What are Flexible Risers ?
- Flexible risers connect the **seabed** to the **floating platform**
- They are essential for **deep water** exploration



Source: MPCNEWS (2010) [2]



Introduction

Source: adapted from NOV Inc. (2022) [4]

Carbon steel pressure armour

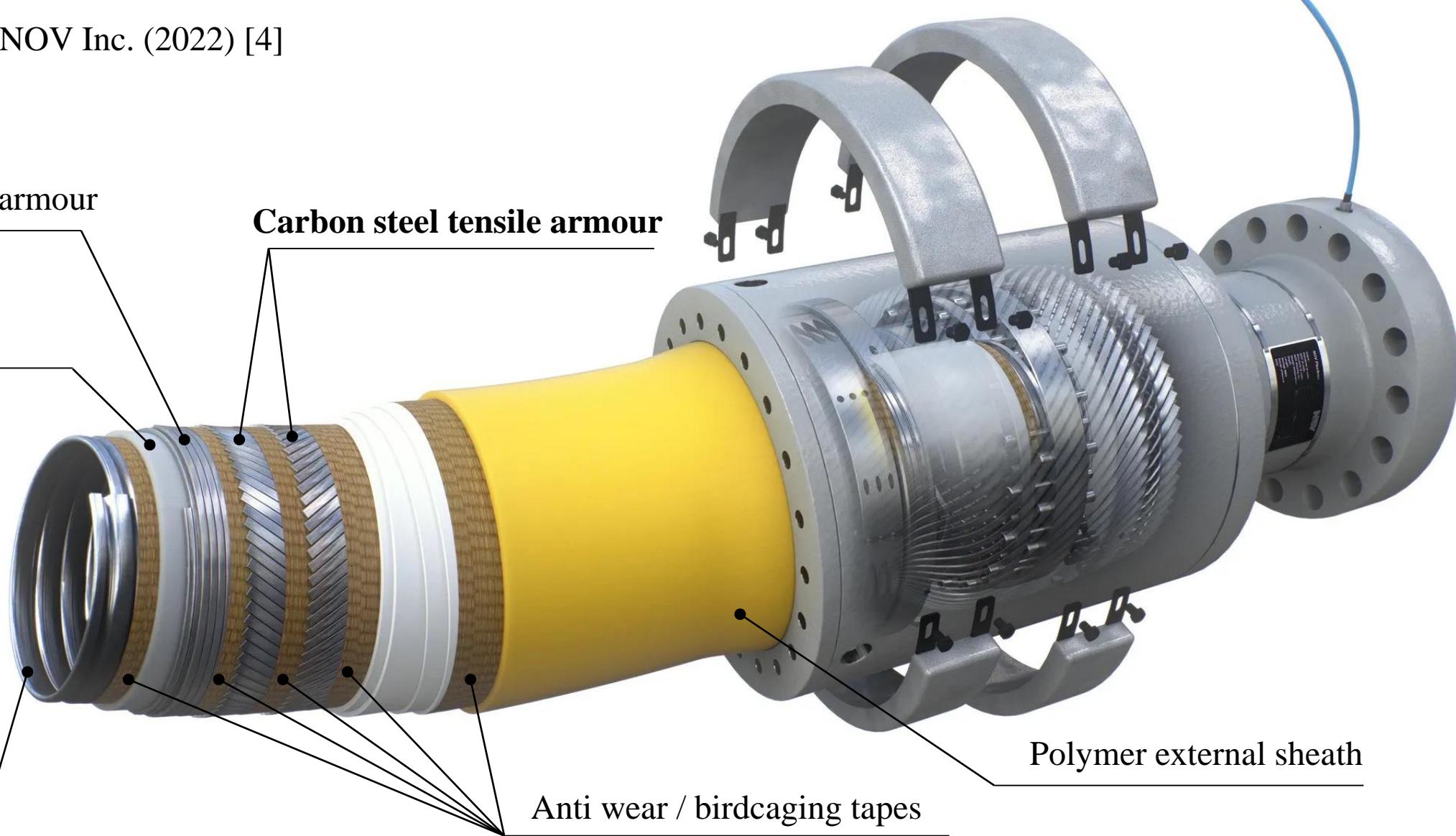
Polymer fluid barrier

Carbon steel tensile armour

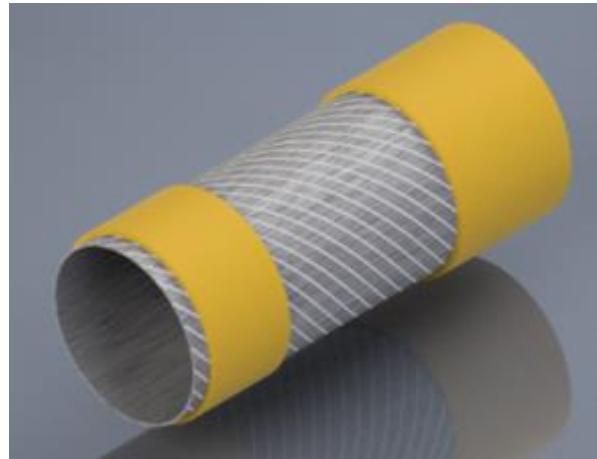
Stainless steel carcass

Polymer external sheath

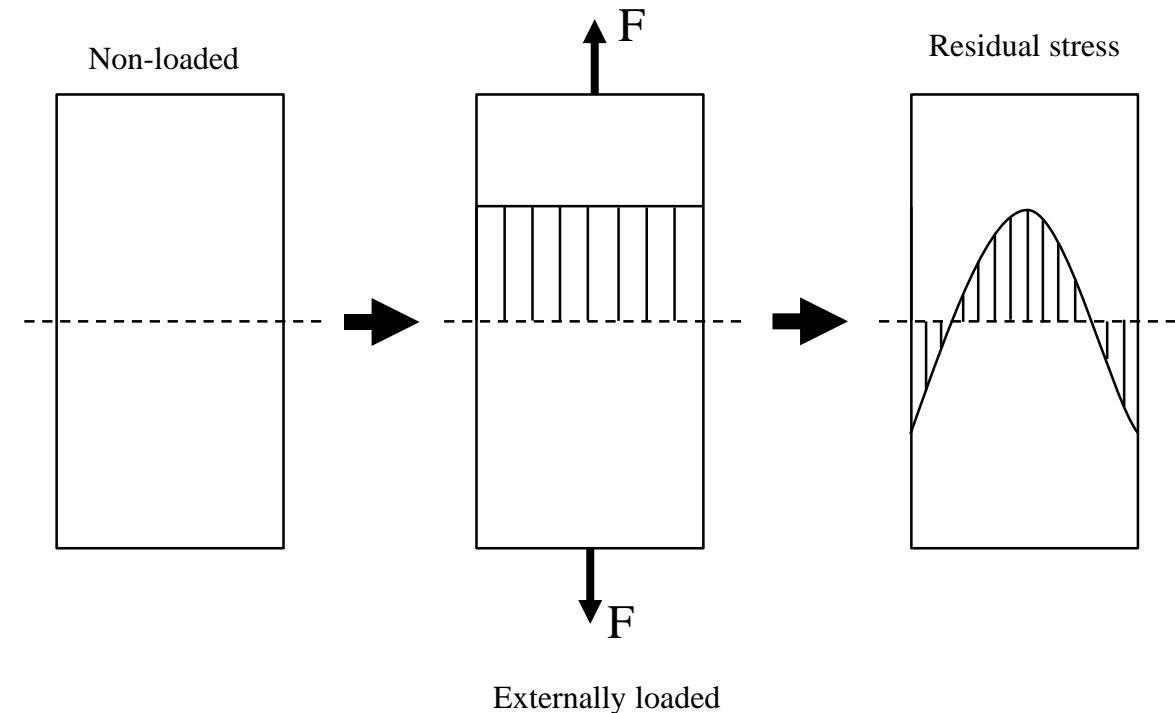
Anti wear / birdcaging tapes



- Risers are exposed to cyclic loads, such as tensile, bending, and internal stress variation.
- Wires undergo different manufacturing processes and are **helically wound**.

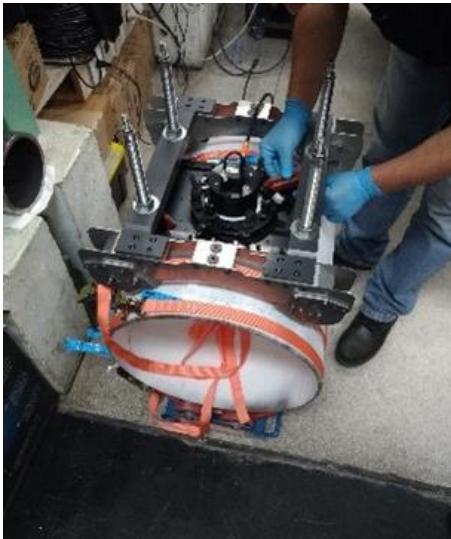
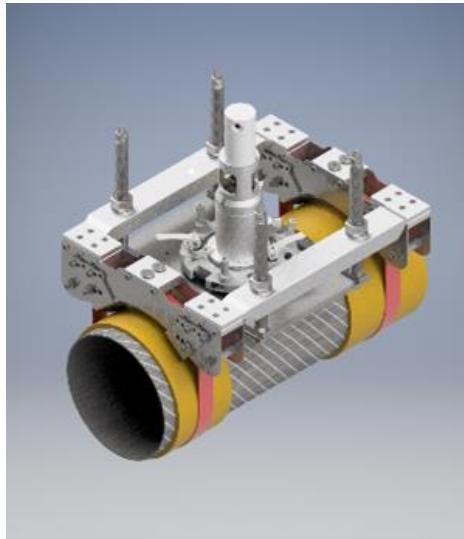
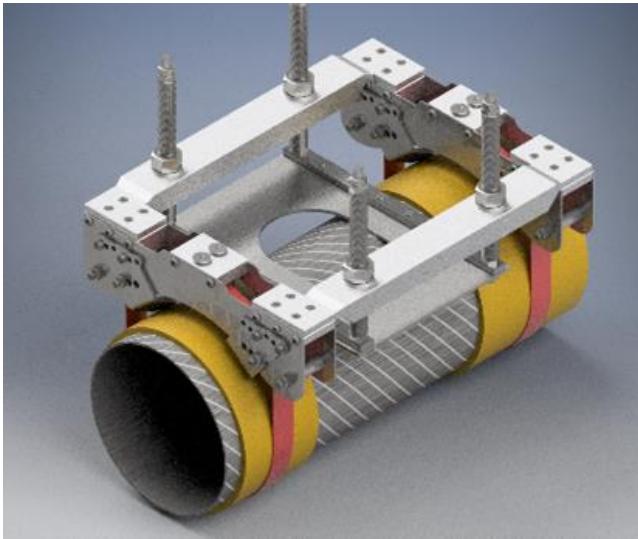


Source: TRRiFlex project (2019) [1]





Introduction



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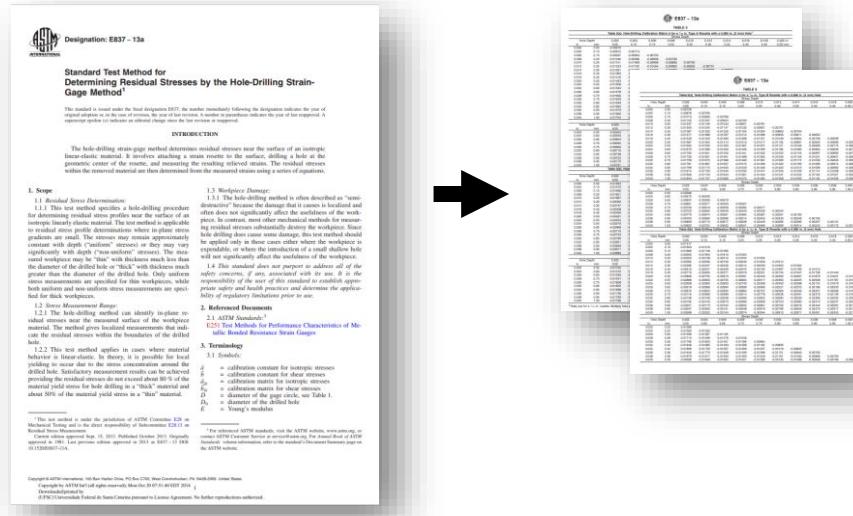
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- HDM is employed in the **oil and gas industry**, specially for **transportation** (LABMETRO)
- New cooperation → identify failure of flexible risers

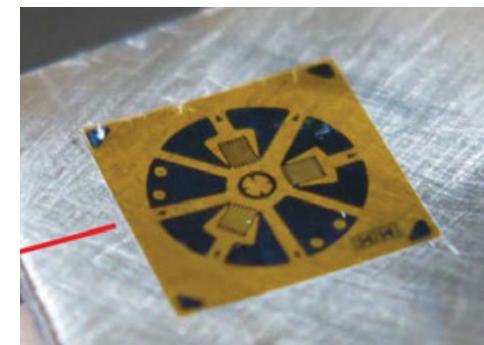
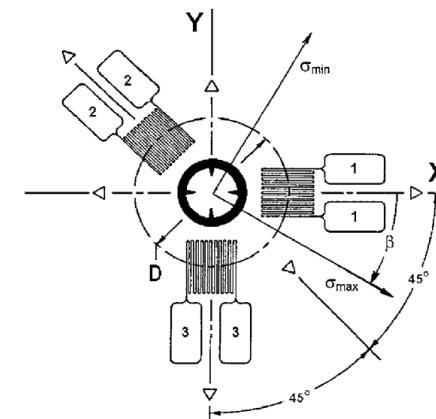
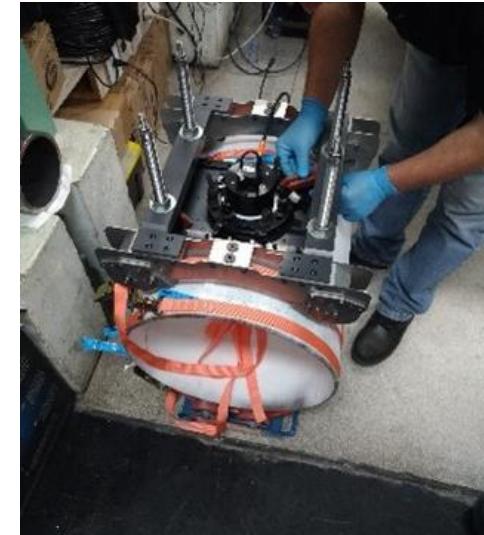
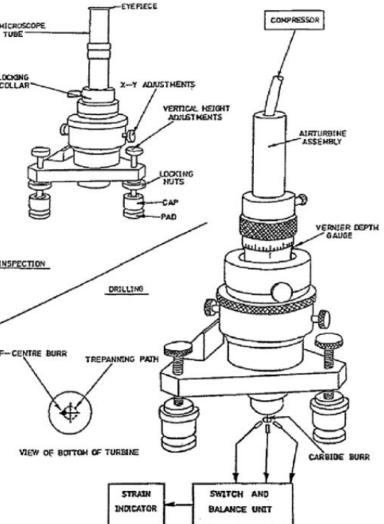
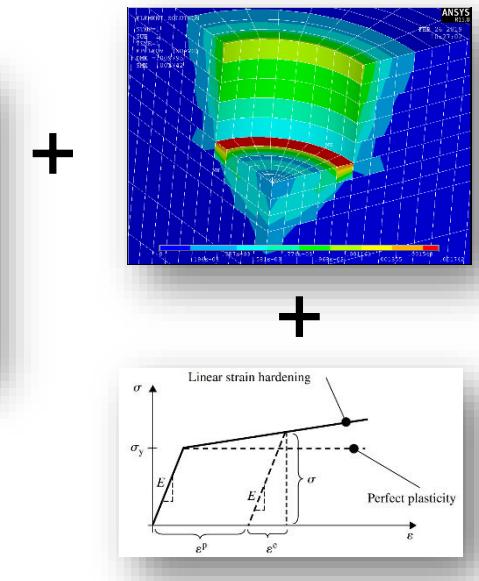
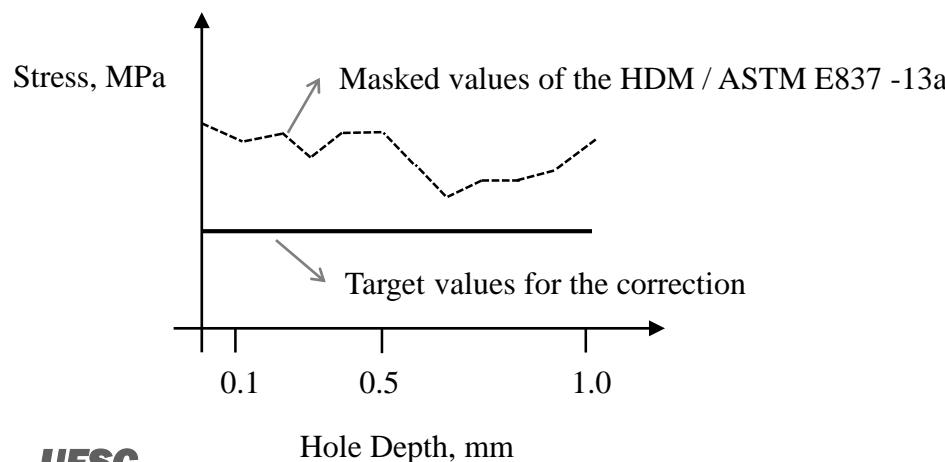
TRRiFlex



Introduction

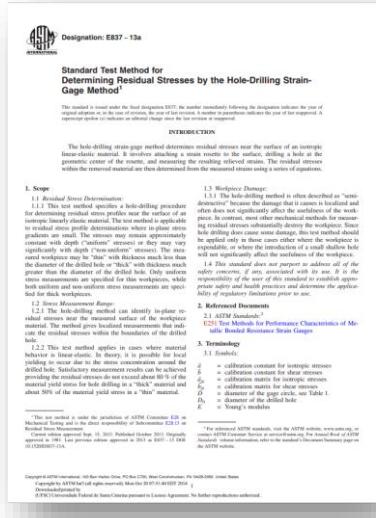


HDM / ASTM E837 -13a [6]

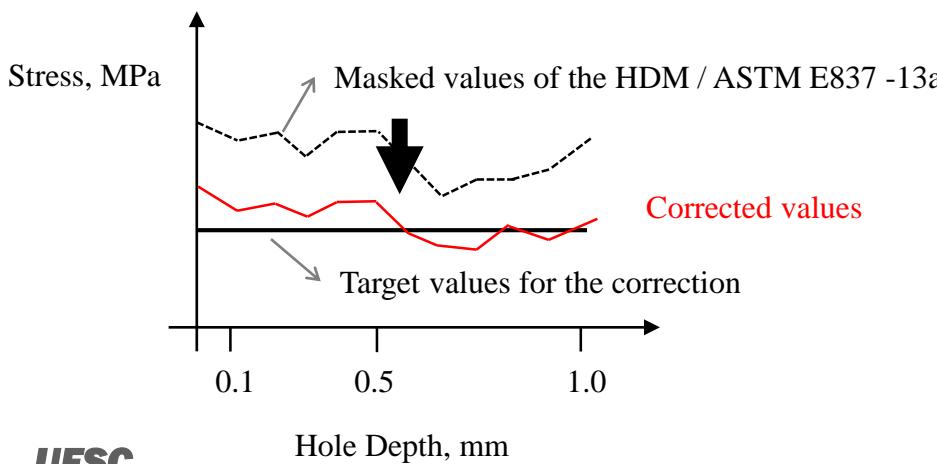




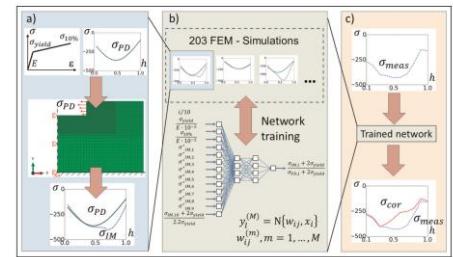
Introduction



HDM / ASTM E837 -13a [6]



- There are a few methodologies available to **correct the residual stress** in HDM measurements taking into account the **plasticity effect** in the uniform method (limited for the nonuniform method) and for equibiaxial loaded cases.

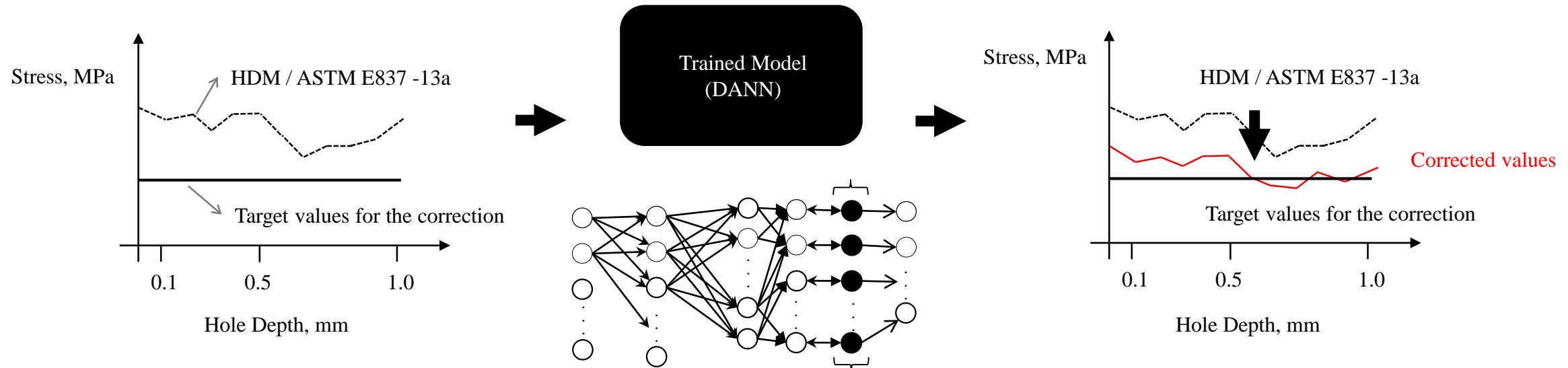


CHUPAKHIN, S., et al. (2017) [7]

- In this context, **given the limitations** of the ASTM E837 – 13a [6] in the plastic regime, there **is the need for a developed model** (trained on data resulting from several elastoplastic numerical simulations) that seeks to **correct the plasticity effects** in the residual stress values presented in uniaxial loaded **flexible risers**.

General Objective:

- The objective of this undergraduate thesis is to develop and implement a Deep Artificial Neural Network (DANN) model, based on numerical simulations data, for the correction of plasticity effects in the HDM, that is, the Standard Test Method for Determining Residual Stresses by the Hole-Drilling Strain-Gage Method (ASTM E837 – 13a), used for measuring high levels of residual stress in flexible risers.





Introduction

Specific Objectives:

- Deepen the study of the ASTM E837 – 13a [6] and its limitations regarding the effects of plasticity through a Literature review, as well as a reproduction of similar models found in the literature.
- Develop a Finite Element (FE) model in Ansys Mechanical APDL for the execution of the needed numerical simulations, considering the most appropriate boundary conditions for working with elastoplastic analysis available in the literature.
- Execute several numerical simulations with the developed FE model and compute the summarized numerical results values via the IM.
- Analyze, filter, and establish different datasets from the summarized results in order to build the Deep ANN model.
- Train, validate, test, and implement the Deep ANN model for the correction of plasticity effects in the HDM.
- Analyze the model correction performance by means of comparison with a classic multivariate linear regression model and implement the necessary changes to the final model.

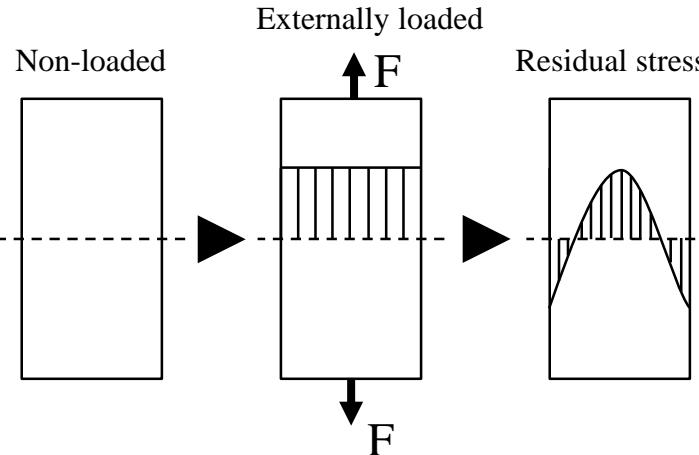


Summary

1. Introduction
2. State of the Art
3. Methodology
4. Results and Discussions
5. Conclusions and Suggestions for Future Works

Residual stresses

- The stress that **remains inside** a component or structure after all **applied forces** have been **removed**.
- The residual stresses are **formed** when a material **reaches equilibrium** following plastic deformation induced by applied **mechanical loads, thermal loads, or phase transitions**.
- The total stress experienced by the material at a given location within a component is equal to the residual stress plus the applied stress.



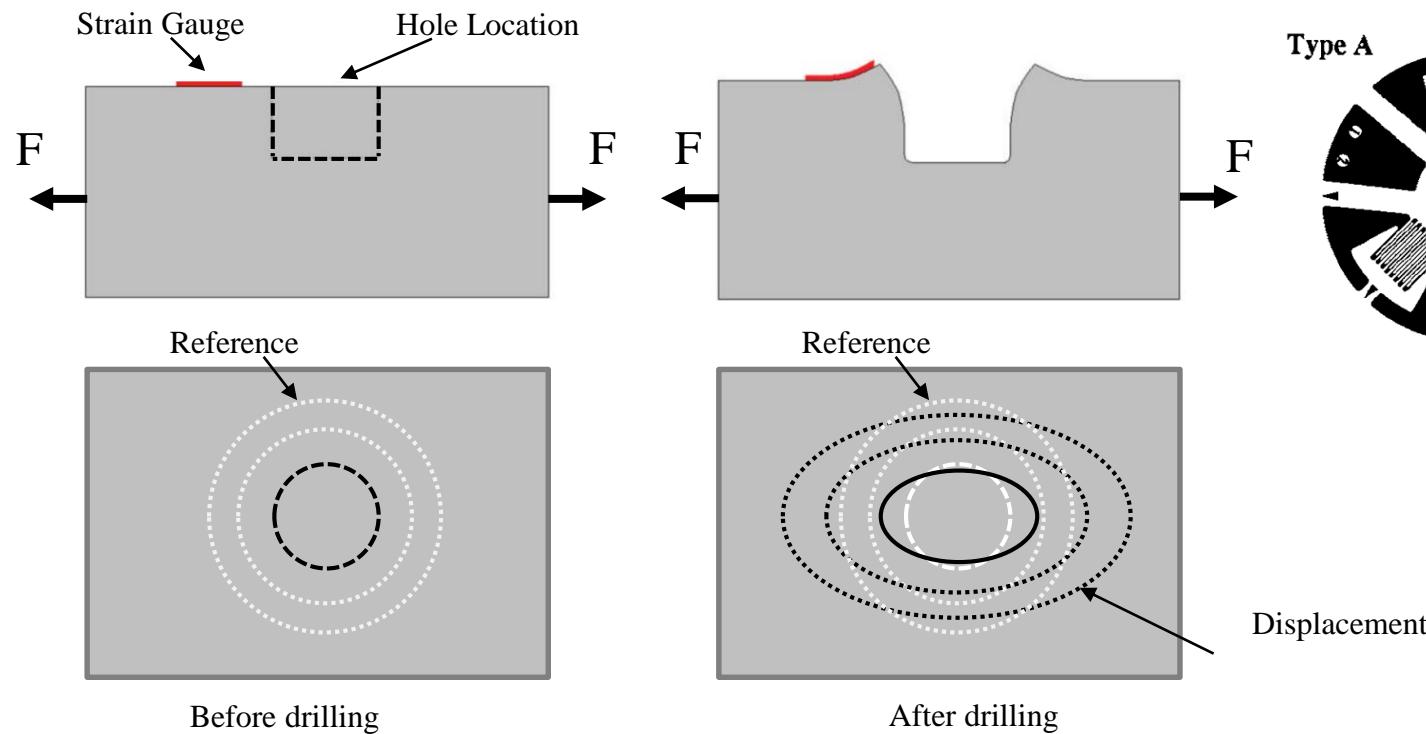
$$\text{TOTAL STRESS} = \text{RESIDUAL STRESS} + \text{APPLIED STRESS}$$

- **Measuring** residual stress has several **advantages**, such as **reducing catastrophic failures** by **ensuring safety**, extend the **life of a component** or structure by ensuring that sufficient compressive residual stress exists. Tracking residual stress degradation allows for more accurate replacement requirements.



The Hole Drilling Method

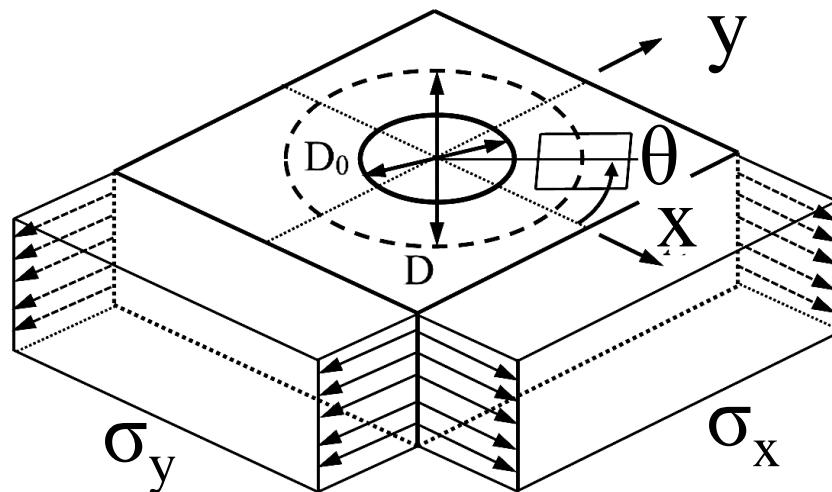
- The Hole-Drilling Method is a semi-destructive technique with normalized procedures described in the standard ASTM E837-20 (experimental procedure, computation steps)
- Incremental drilling leading to a localized stress relief that induces strains around the hole



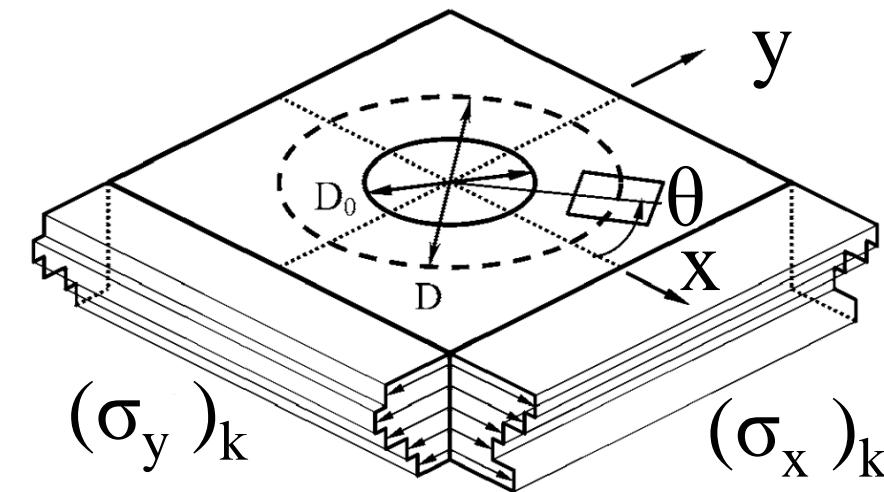
Source: ASTM E837 – 13a, 2013.

Stress Computation

- Two computation methods: the uniform and the non-uniform method
- The **uniform** method provides an **average**
- An improvement in the computation procedure resulted in the non-uniform method
- Mathematical relations → FEM



Uniform Stresses

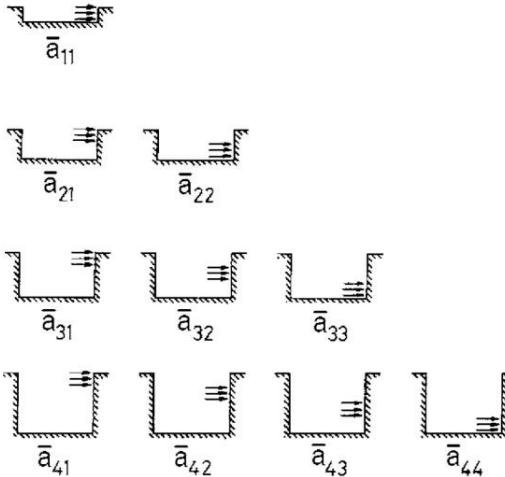


Non-uniform Stresses

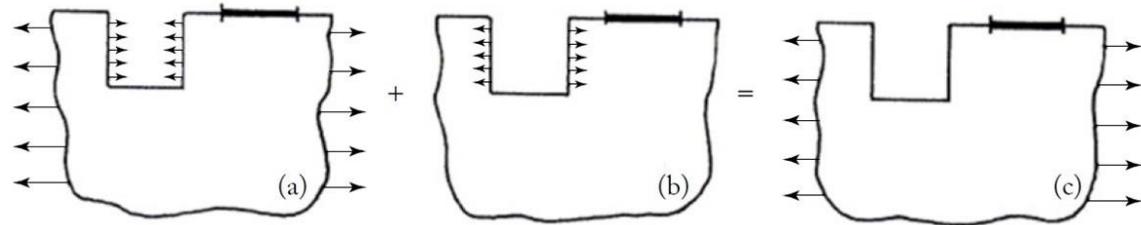


Acquisition of calibration coefficients

- Loads at the boundaries (uniform) or at the hole wall
 - Superposition principle



Source: ASTM E837 13a [6].

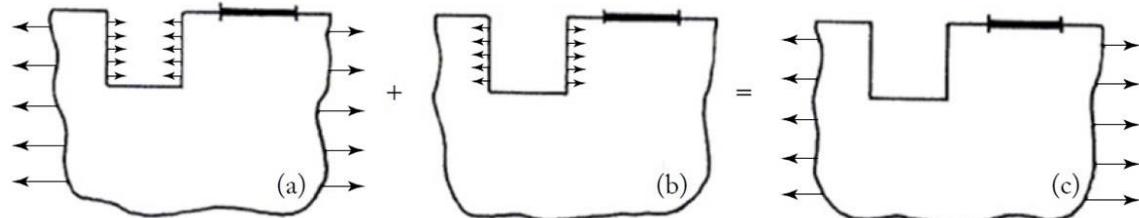
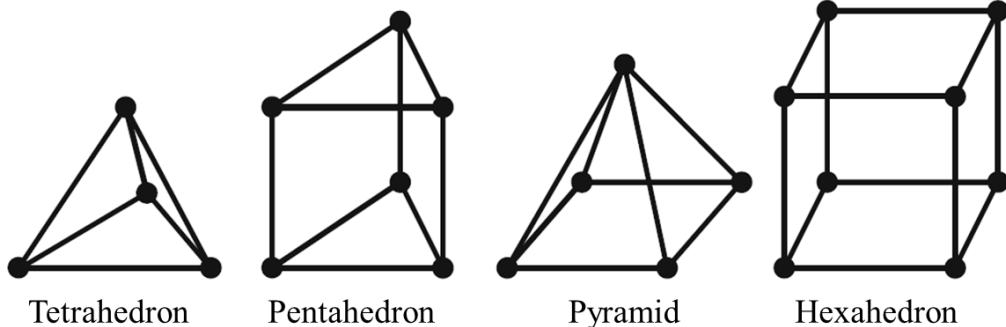


Superposition principle

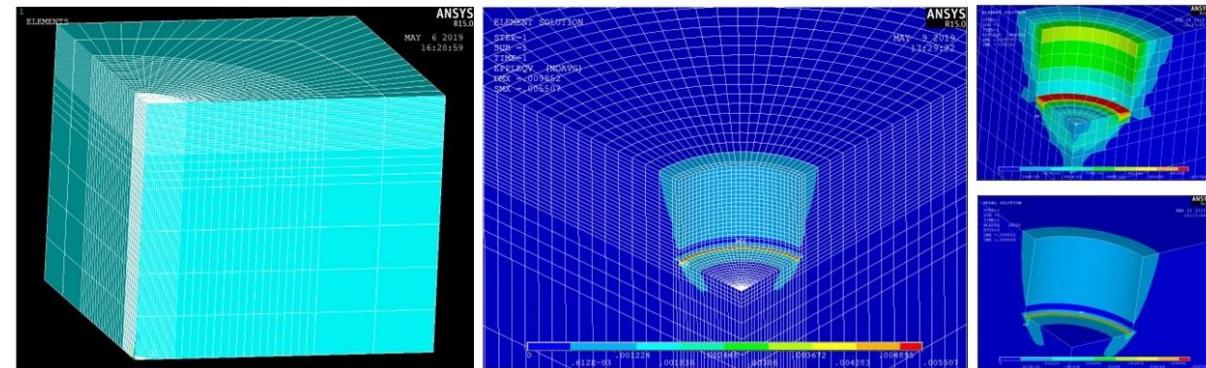
HDM / ASTM E837 -13a [6]

Finite Element Method

- Useful tool in different fields of study
- Elements with 1, 2 or 3 dimensions – meshing test.
- Symmetry conditions
- HDM: Large number of geometries and loads
- Collecting displacements.



Superposition principle



Source: ALBERTAZZI and VIOTTI (2020) [14]

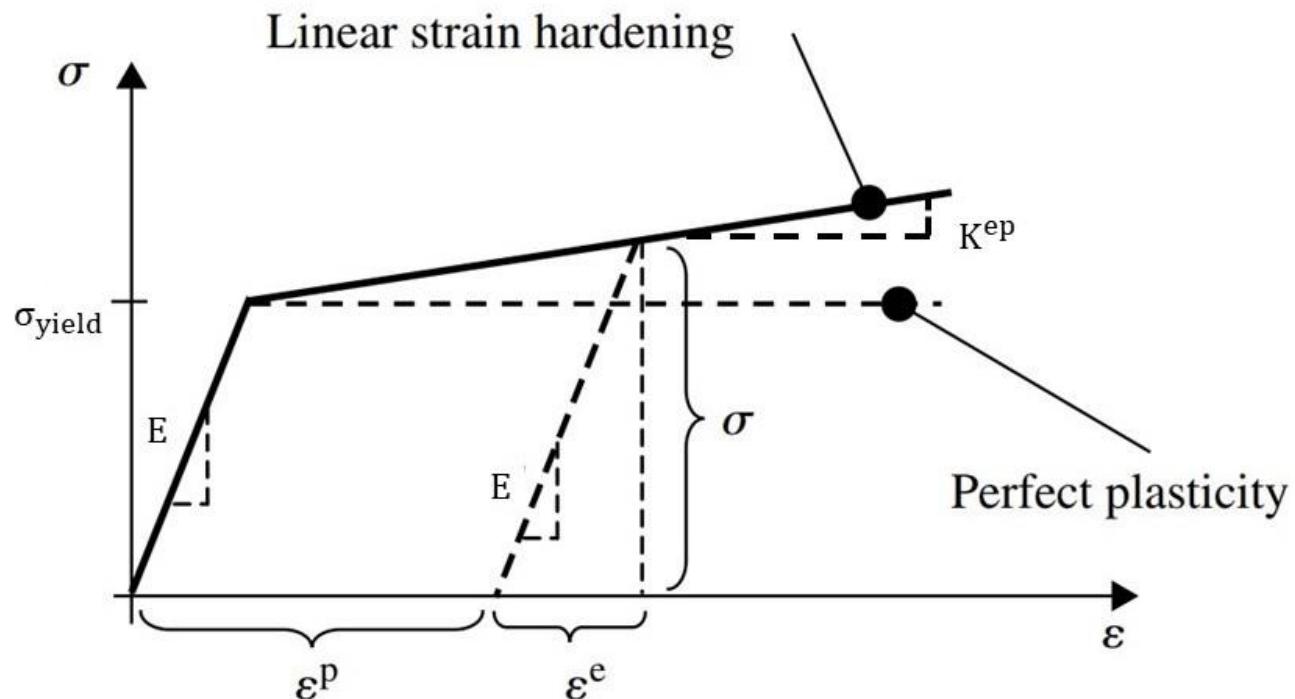
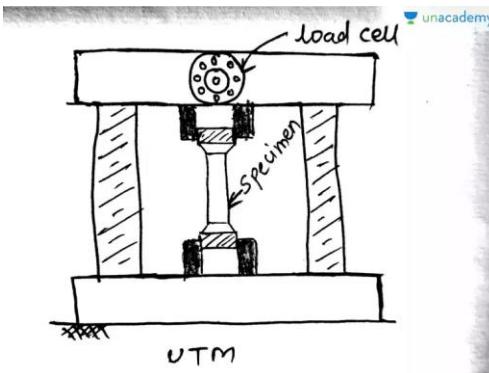
Plasticity

- Nonlinear relationship
- Uniaxial tensile test

$$\varepsilon = \varepsilon^e + \varepsilon^p$$

$$\sigma = E \varepsilon^e = E (\varepsilon - \varepsilon^p)$$

- Bilinear isotropic hardening





Measuring high levels of residual stresses

- The dimensionless plasticity factor f
- Correction factor for uniform measurements (Beghini *et al.*, 1994)

$$f = \frac{\sigma_{eq} - \sigma_{eq,i}}{\sigma_{yield} - \sigma_{eq,i}}$$

$$\sigma_{eq,i} = \sigma_{yield} \frac{\sqrt{1 - \Omega + \Omega^2}}{3 - \Omega}$$

$$\Omega = \frac{\sigma_y}{\sigma_x}$$

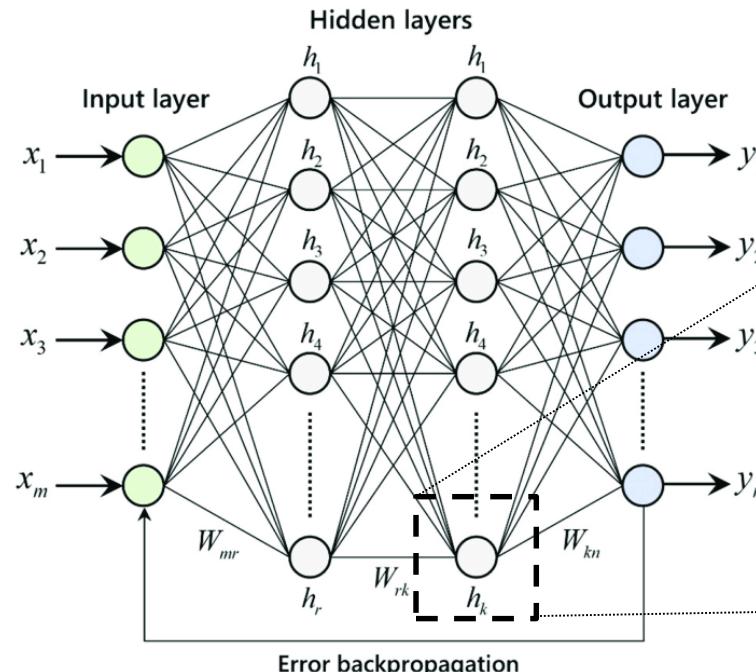
- For an equibiaxial stress condition, where $\sigma = \sigma_y = \sigma_x$, $\Omega = 1$, $\sigma_{eq,i} = 0.5 \sigma_{yield}$ and $\sigma_{eq} = \sigma$, the Equations reduce to

$$f = 2 \left(\frac{\sigma}{\sigma_{yield}} \right) - 1$$

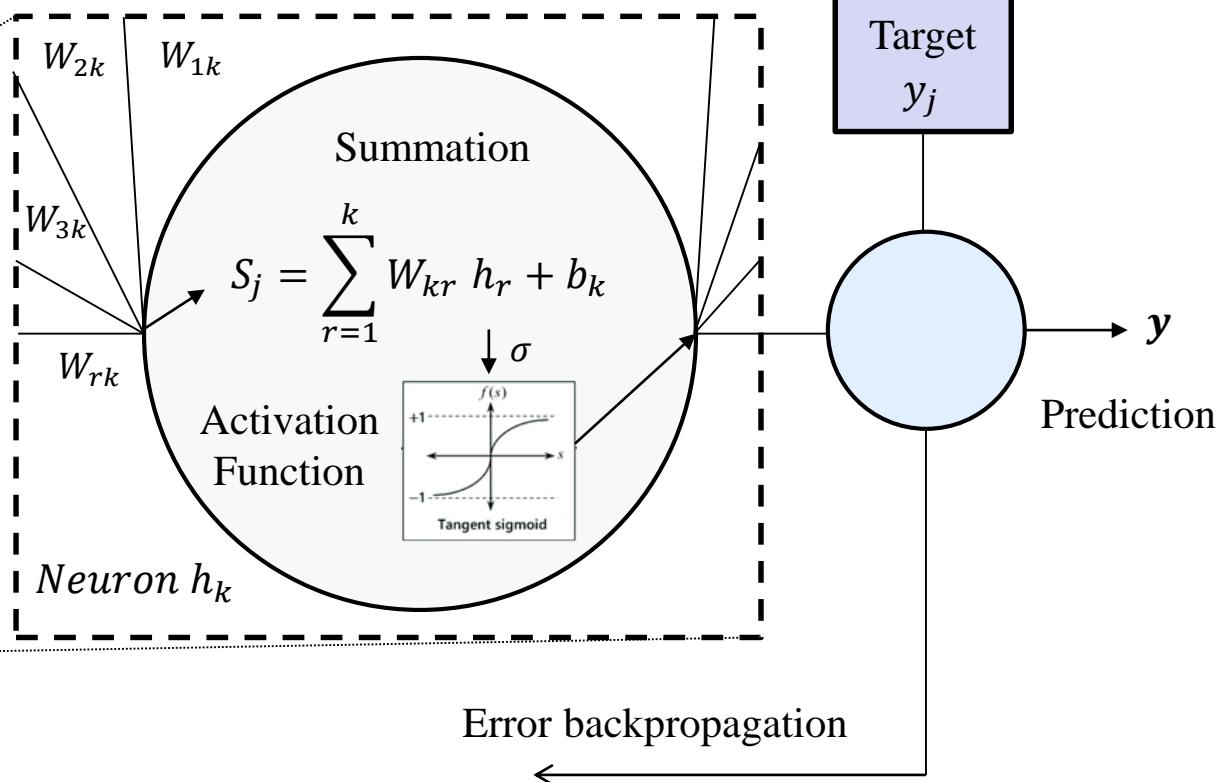


Artificial Deep Neural Networks - ADNN

- Computational models inspired by the human brain' architecture
- Use of ANN in many processes to predict residual stresses or identify its generating parameters
- The architecture of ANNs.



Activation propagation



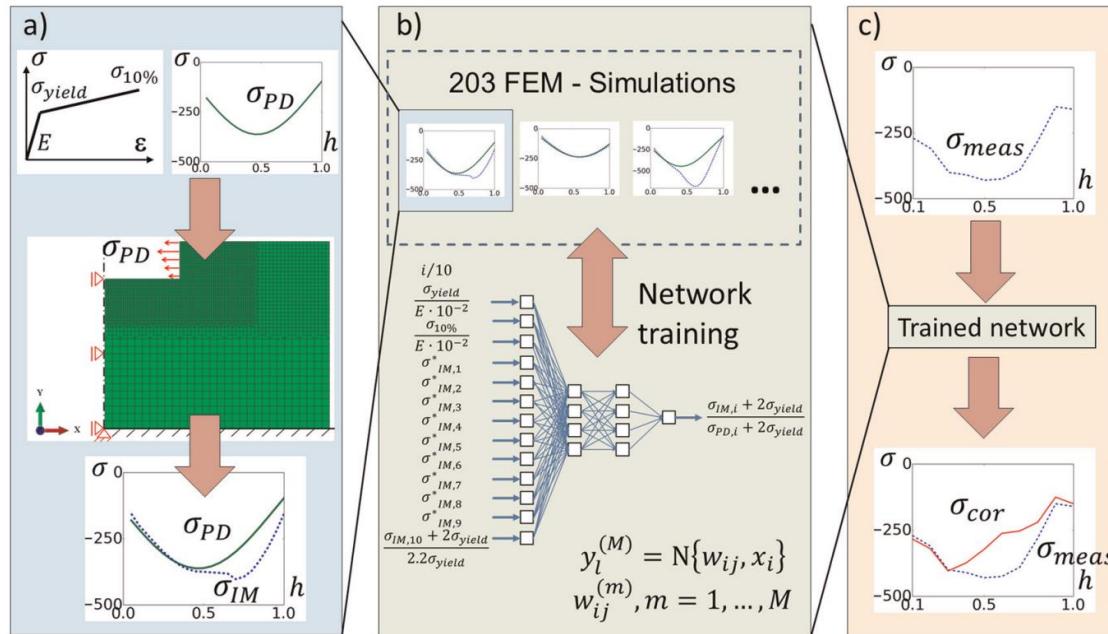
Artificial Neural Networks implemented in the HDM

- Use in the HDM
- Chupakhin et al. [7]

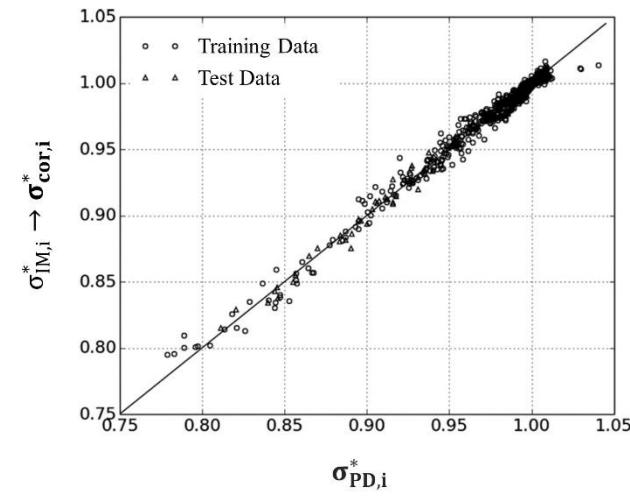
$$X := \left\{ \sigma_{IM,1}^*, \sigma_{IM,2}^*, \dots, \sigma_{IM,9}^*, \frac{\sigma_{IM,10} + 2 \sigma_{yield}}{2.2 \sigma_{yield}}, \frac{\sigma_{yield}}{E \cdot 10^{-2}}, \frac{\sigma_{10\%}}{E \cdot 10^{-2}}, \frac{i}{10} \right\}$$

$$Y := \left\{ \frac{\sigma_{IM,i} + 2 \sigma_{yield}}{\sigma_{PD,i} + 2 \sigma_{yield}} \right\}$$

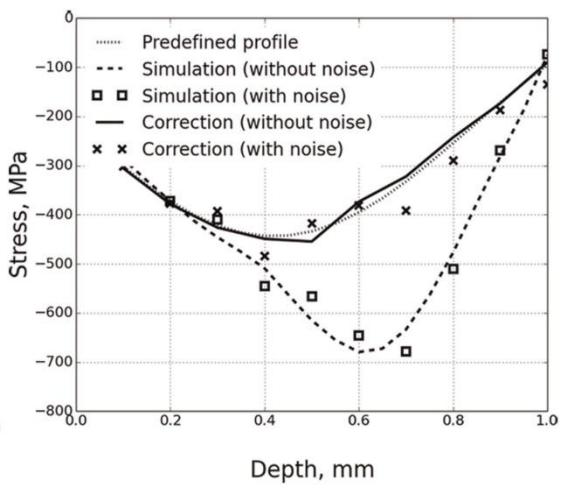
$$\sigma_{IM,i}^* := \frac{\sigma_{IM,i} + 2 \sigma_{yield}}{\sigma_{IM,10} + 2 \sigma_{yield}}$$



Evaluation of the ANN model:



a)



b)

Source: Chupakhin *et al.*, 2017.



Summary

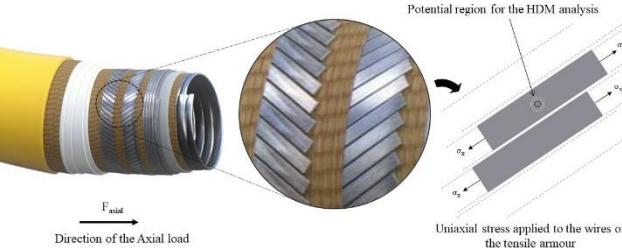
1. Introduction
2. State of the Art
3. **Methodology**
4. Results and Discussions
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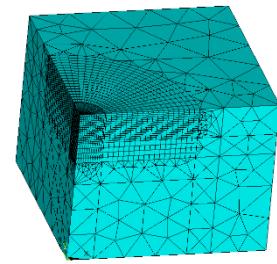
Methodology

Summary of the work flow of the undergraduate thesis

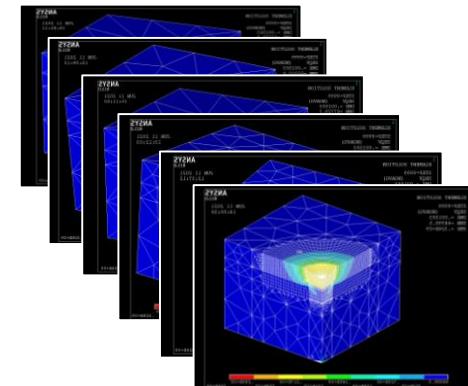
Armour wires of the Flexible Riser



Ansys APDL
Script



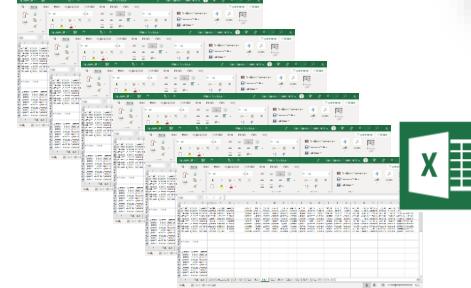
Development
of a FE model



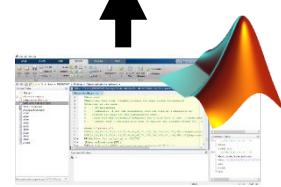
Execution of 420
simulations



Preprocessing Data
Python Script

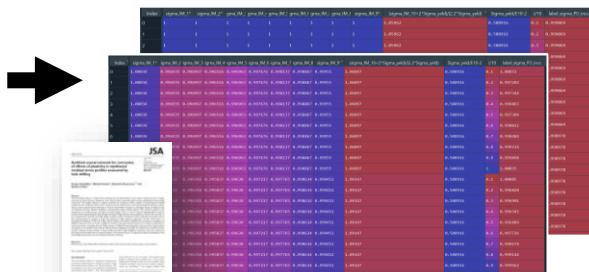


Stress Data files for diff.
 f values

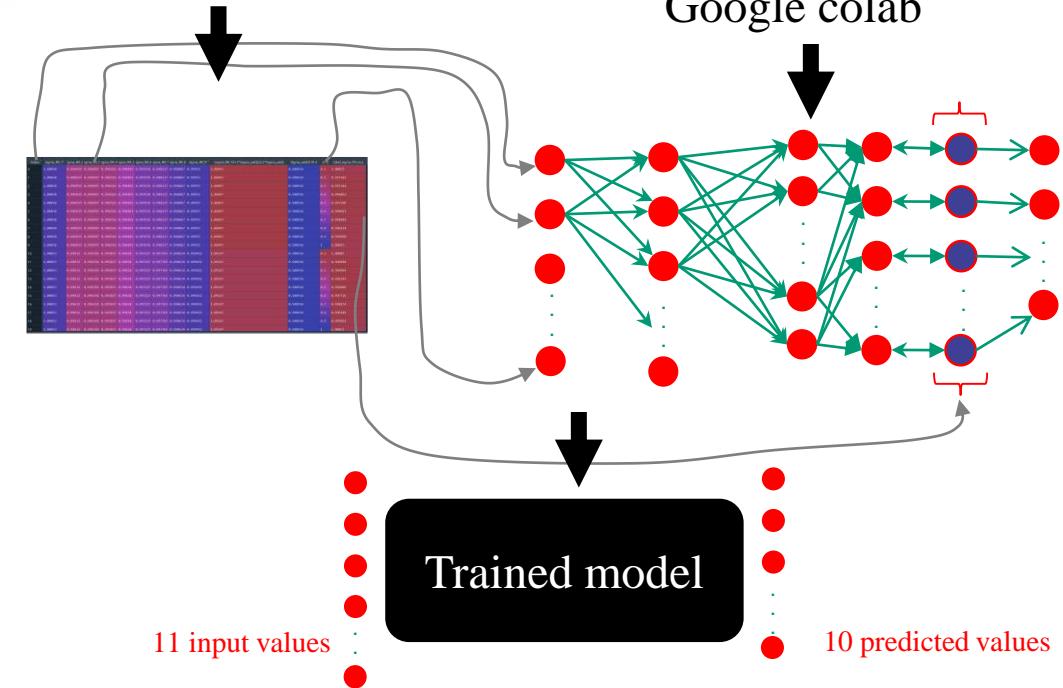


Stress Computation
MATLAB Script

Datasets based in Chupakhin [7]



Datasets for Test 1 & 2



Training and Testing of
the Deep ANN model



TensorFlow + Keras

Python Script in
Google colab

Residual stress in Flexible Risers

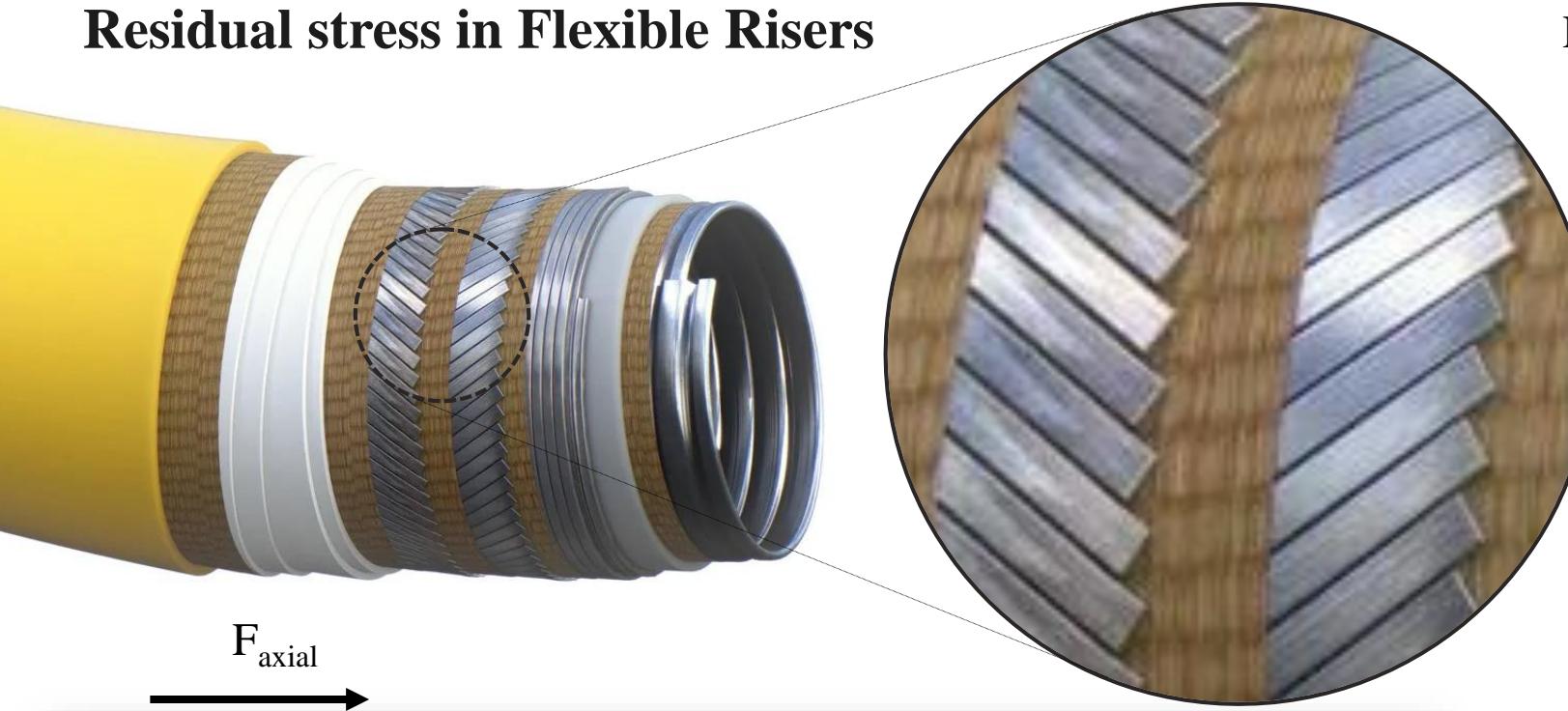
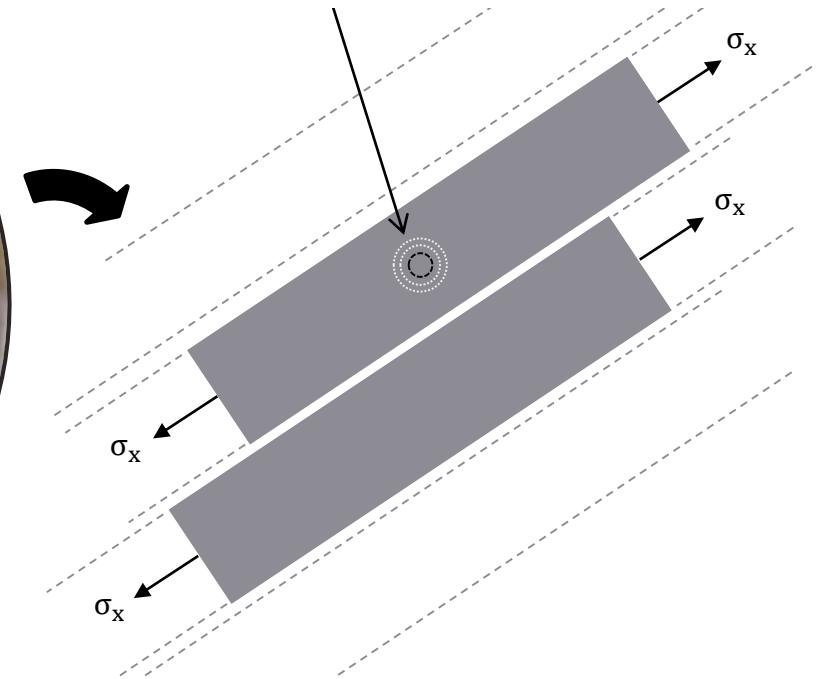


Table 3.1 - Material properties of the armour wires of flexible risers.

Material	Yield stress	Young's modulus	Poisson's ratio
	σ_{yield} (MPa)	E (GPa)	ν_{poisson}
High-Carbon Steel			
Alloy*	1056	207.5	0.3

Source: elaborated by the author. Data provided by LABMETRO.

Potential region for the HDM analysis



Uniaxial stress applied to the wires of the tensile armour

- Chupakhin et al. [7], $\Omega = 1$ (equibiaxial case).
- This thesis, $\Omega = 0$ (uniaxial case).



Methodology

Developing a FE Model for Numerical Simulations

/PREP7 (processor)

1. Definition of the Solid Model Geometry
2. Selection of the Element Types
3. Definition of the Material Properties
4. Meshing

/SOLUTION (processor)

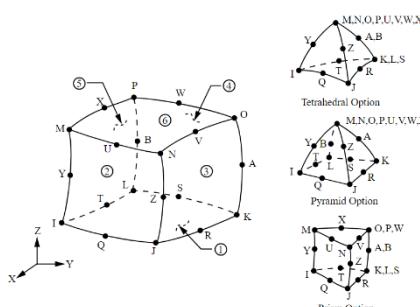
5. Definition of the Boundary Conditions
6. Definition of the Load Conditions
7. Setting of the Solution Options
8. Solving

/POST1 or /POST26 (processors)

9. Plotting, Viewing, and Exporting the Results
10. Comparison and Verification of the Results



Ansys APDL Script



Element SOLID186

Development of a FE model

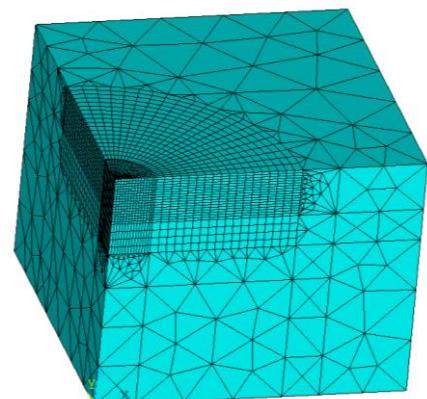
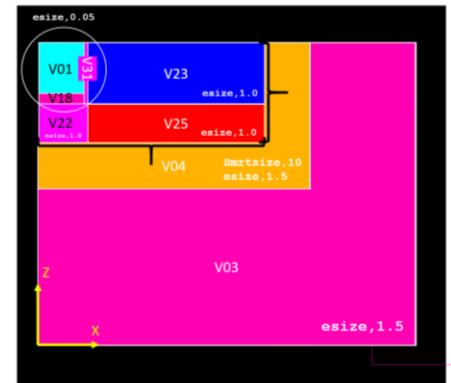
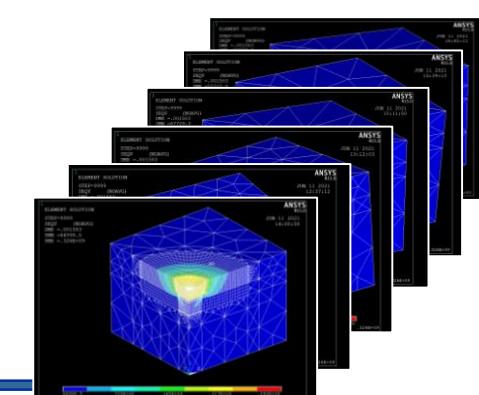


Chart 3.1 - Tests of mesh refinement values. Variation of the *esize* command

Test nº	Solution time (hh:mm:ss)	APDL	Solver iteration	Load (MPa)	<i>esize</i> of V01, V18, V31 (mm)	Intermediate Mesh <i>esize</i> of V04 (smartsiz,10) (mm)	Coarse Mesh <i>esize</i> of V03 (mm)
00	00:20:30			237.5	0.05	1.5	1.5
01	00:26:30			237.5	0.05	1.5	2.0
02	00:20:20			237.5	0.05	2.0	2.0
03	00:29:10			237.5	0.05	2.0	2.5
04	00:19:00			237.5	0.05	2.5	2.5
05	00:20:50			237.5	0.05	3.0	3.0

Source: elaborated by the author.

Execution of 420 simulations





Methodology

Developing a FE Model for Numerical Simulations

- Execution of the numerical simulations

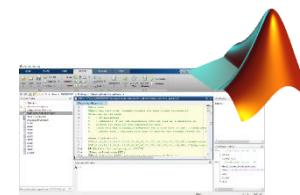
$$\sigma_x = \sigma_{eq} = f \times (\sigma_{yield} - \sigma_{eq,i}) + \sigma_{eq,i}$$

$$\sigma_y = 0 \quad \sigma_{eq,i} = \frac{1}{3} \sigma_{yield} = 352$$

- Stress computation using the calibration coefficients



A black right-pointing arrow icon.



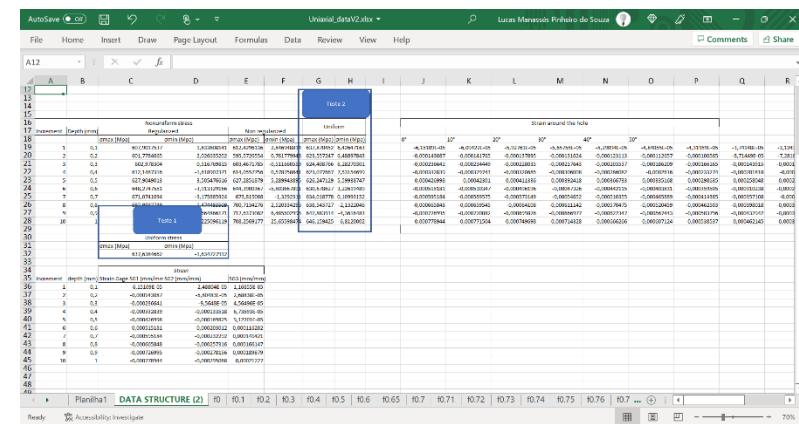
Stress Computation MATLAB Script

HDM / ASTM E837 -13a [6]

Table 3.2 - Values of Plasticity factor (or Beghini's factor) with the corresponded applied load value.

Plasticity factor	Applied Load	
f	$\sigma_x (= \sigma_{eq})$ (MPa)	σ_y (MPa)
0	352	0
0,1	422,4	0
0,2	492,8	0
0,3	563,2	0
0,4	633,6	0
0,5	704	0
0,6	774,4	0
0,65	809,6	0
...
1,1	1126,4	0
1,25	1232	0
1,3	1267,2	0

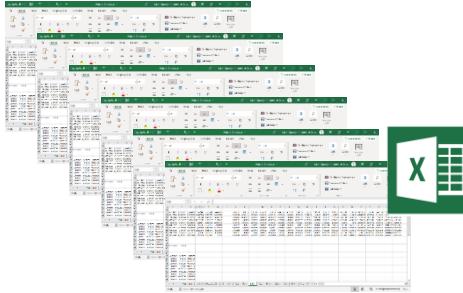
Source: elaborated by the author.



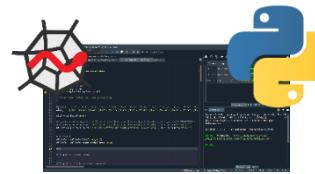


Methodology

Establishment of the ANN Database



Stress Data files for diff.
 f values

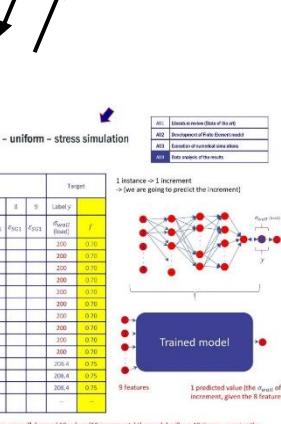


Preprocessing Data
Python Script



Datasets based in Chupakhin [7]

	Age	σ _{IM,1}	σ _{IM,2}	σ _{IM,3}	σ _{IM,4}	σ _{IM,5}	σ _{IM,6}	σ _{IM,7}	σ _{IM,8}	σ _{IM,9}	σ _{PD,10}	σ _{PD,11}	σ _{PD,12}	σ _{PD,13}	σ _{PD,14}	σ _{PD,15}	σ _{PD,16}	σ _{PD,17}	σ _{PD,18}	σ _{PD,19}	σ _{PD,20}
1	1	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557
2	2	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557
3	3	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.1	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557
4	4	0.4	0.5	0.6	0.7	0.8	0.9	1.0	1.1	1.2	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557
5	5	0.5	0.6	0.7	0.8	0.9	1.0	1.1	1.2	1.3	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557
6	6	0.6	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557
7	7	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557
8	8	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5	1.6	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557
9	9	0.9	1.0	1.1	1.2	1.3	1.4	1.5	1.6	1.7	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557
10	10	1.0	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557
11	11	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557	210.557
12	12	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811
13	13	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0	2.1	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811
14	14	1.4	1.5	1.6	1.7	1.8	1.9	2.0	2.1	2.2	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811
15	15	1.5	1.6	1.7	1.8	1.9	2.0	2.1	2.2	2.3	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811
16	16	1.6	1.7	1.8	1.9	2.0	2.1	2.2	2.3	2.4	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811
17	17	1.7	1.8	1.9	2.0	2.1	2.2	2.3	2.4	2.5	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811
18	18	1.8	1.9	2.0	2.1	2.2	2.3	2.4	2.5	2.6	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811
19	19	1.9	2.0	2.1	2.2	2.3	2.4	2.5	2.6	2.7	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811
20	20	2.0	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811	222.811



Based on Chupakhin's model:

$$\mathbf{X} := \left\{ \sigma_{IM,1}^*, \sigma_{IM,2}^*, \dots, \sigma_{IM,9}^*, \frac{\sigma_{IM,10} + 2 \sigma_{yield}}{2.2 \sigma_{yield}}, \frac{\sigma_{yield}}{E \cdot 10^{-2}}, \frac{i}{10} \right\}$$

$$\left(\frac{\sigma_{IM,i} + 2 \sigma_{yield}}{\sigma_{PD,i} + 2 \sigma_{yield}} \right) = f \left(\sigma_{IM,1}^*, \sigma_{IM,2}^*, \dots, \sigma_{IM,9}^*, \frac{\sigma_{IM,10} + 2 \sigma_{yield}}{2.2 \sigma_{yield}}, \frac{\sigma_{yield}}{E \cdot 10^{-2}}, \frac{i}{10} \right)$$

DANN model

Sketch of the dataset considering some engineering features



Methodology

Establishment of the ANN Database

1. Database with **uniform** stress values - Test 1

Index	sigma_IM_1*	sigma_IM_2*	gma_IM_1	gma_IM_2	gma_IM_3	gma_IM_4	gma_IM_5	gma_IM_6	gma_IM_7	gma_IM_8	gma_IM_9*	(sigma_IM_10+2*Sigma_yield)/(2.2*Sigma_yield)	Sigma_yield/E10-2	I/10	label_sigma_PD_incs
0	1	1	1	1	1	1	1	1	1	1	1	1.05962	0.508916	0.1	0.999069
1	1	1	1	1	1	1	1	1	1	1	1	1.05962	0.508916	0.2	0.999069
2	1	1	1	1	1	1	1	1	1	1	1	1.05962	0.508916	0.3	0.999069
3	1	1	1	1	1	1	1	1	1	1	1	1.05962	0.508916	0.4	0.999069
4	1	1	1	1	1	1	1	1	1	1	1	1.05962	0.508916	0.5	0.999069
5	1	1	1	1	1	1	1	1	1	1	1	1.05962	0.508916	0.6	0.999069
6	1	1	1	1	1	1	1	1	1	1	1	1.05962	0.508916	0.7	0.999069
7	1	1	1	1	1	1	1	1	1	1	1	1.05962	0.508916	0.8	0.999069
8	1	1	1	1	1	1	1	1	1	1	1	1.05962	0.508916	0.9	0.999069
9	1	1	1	1	1	1	1	1	1	1	1	1.05962	0.508916	1	0.999069
10	1	1	1	1	1	1	1	1	1	1	1	1.08979	0.508916	0.1	0.998978
11	1	1	1	1	1	1	1	1	1	1	1	1.08979	0.508916	0.2	0.998978
12	1	1	1	1	1	1	1	1	1	1	1	1.08979	0.508916	0.3	0.998978
13	1	1	1	1	1	1	1	1	1	1	1	1.08979	0.508916	0.4	0.998978
14	1	1	1	1	1	1	1	1	1	1	1	1.08979	0.508916	0.5	0.998978
15	1	1	1	1	1	1	1	1	1	1	1	1.08979	0.508916	0.6	0.998978
16	1	1	1	1	1	1	1	1	1	1	1	1.08979	0.508916	0.7	0.998978
17	1	1	1	1	1	1	1	1	1	1	1	1.08979	0.508916	0.8	0.998978
18	1	1	1	1	1	1	1	1	1	1	1	1.08979	0.508916	0.9	0.998978

$$\sigma_{IM,i}^* := \frac{\sigma_{IM,i} + 2 \sigma_{yield}}{\sigma_{IM,10} + 2 \sigma_{yield}}$$

$$\sigma_{IM,1}^*, \sigma_{IM,2}^*, \dots, \sigma_{IM,9}^* \text{ and } \left(\frac{\sigma_{IM,10} + 2 \sigma_{yield}}{2.2 \sigma_{yield}} \right)$$

2. Database with **non-uniform** stress values - Test 2

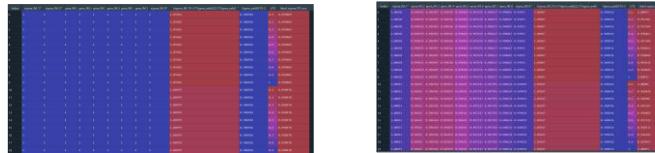
Index	sigma_IM_1*	sigma_IM_2	gma_IM_3	gma_IM_4	gma_IM_5	gma_IM_6	gma_IM_7	gma_IM_8	gma_IM_9	(sigma_IM_10+2*Sigma_yield)/(2.2*Sigma_yield)	Sigma_yield/E10-2	I/10	label_sigma_PD_incs
0	1.00038	0.996935	0.996997	0.996516	0.996963	0.997676	0.998137	0.998867	0.99955	1.06097	0.508916	0.1	1.00072
1	1.00038	0.996935	0.996997	0.996516	0.996963	0.997676	0.998137	0.998867	0.99955	1.06097	0.508916	0.2	0.997282
2	1.00038	0.996935	0.996997	0.996516	0.996963	0.997676	0.998137	0.998867	0.99955	1.06097	0.508916	0.3	0.997344
3	1.00038	0.996935	0.996997	0.996516	0.996963	0.997676	0.998137	0.998867	0.99955	1.06097	0.508916	0.4	0.996863
4	1.00038	0.996935	0.996997	0.996516	0.996963	0.997676	0.998137	0.998867	0.99955	1.06097	0.508916	0.5	0.997309
5	1.00038	0.996935	0.996997	0.996516	0.996963	0.997676	0.998137	0.998867	0.99955	1.06097	0.508916	0.6	0.998022
6	1.00038	0.996935	0.996997	0.996516	0.996963	0.997676	0.998137	0.998867	0.99955	1.06097	0.508916	0.7	0.998484
7	1.00038	0.996935	0.996997	0.996516	0.996963	0.997676	0.998137	0.998867	0.99955	1.06097	0.508916	0.8	0.999214
8	1.00038	0.996935	0.996997	0.996516	0.996963	0.997676	0.998137	0.998867	0.99955	1.06097	0.508916	0.9	0.999898
9	1.00038	0.996935	0.996997	0.996516	0.996963	0.997676	0.998137	0.998867	0.99955	1.06097	0.508916	1	1.00035
10	1.00033	0.99632	0.996392	0.995837	0.99638	0.997217	0.997765	0.998634	0.999452	1.09147	0.508916	0.1	1.00085
11	1.00033	0.99632	0.996392	0.995837	0.99638	0.997217	0.997765	0.998634	0.999452	1.09147	0.508916	0.2	0.996828
12	1.00033	0.99632	0.996392	0.995837	0.99638	0.997217	0.997765	0.998634	0.999452	1.09147	0.508916	0.3	0.996901
13	1.00033	0.99632	0.996392	0.995837	0.99638	0.997217	0.997765	0.998634	0.999452	1.09147	0.508916	0.4	0.996345
14	1.00033	0.99632	0.996392	0.995837	0.99638	0.997217	0.997765	0.998634	0.999452	1.09147	0.508916	0.5	0.996889
15	1.00033	0.99632	0.996392	0.995837	0.99638	0.997217	0.997765	0.998634	0.999452	1.09147	0.508916	0.6	0.997726
16	1.00033	0.99632	0.996392	0.995837	0.99638	0.997217	0.997765	0.998634	0.999452	1.09147	0.508916	0.7	0.998274
17	1.00033	0.99632	0.996392	0.995837	0.99638	0.997217	0.997765	0.998634	0.999452	1.09147	0.508916	0.8	0.999144
18	1.00033	0.99632	0.996392	0.995837	0.99638	0.997217	0.997765	0.998634	0.999452	1.09147	0.508916	0.9	0.999962
19	1.00033	0.99632	0.996392	0.995837	0.99638	0.997217	0.997765	0.998634	0.999452	1.09147	0.508916	1	1.00051



Methodology

Building and Implementing the ANN Model

Datasets based in Chupakhin [7]

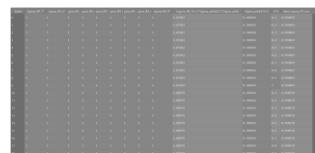


Test 1 Test 2

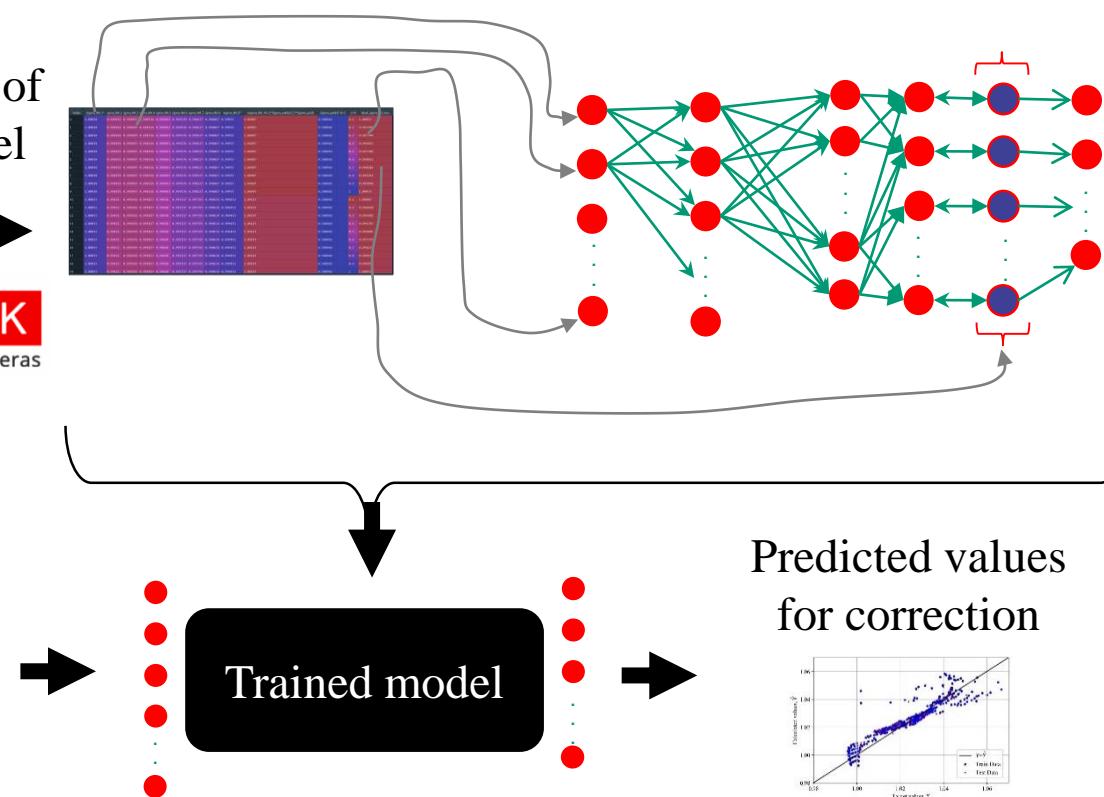
Training and Testing of
the Deep ANN model



Python Script in
Google Colab



Experimental or
validation Data



Parameters of the training of the DNN model.

Values based on Chupakhin's model.

Parameters	Test 1	Test 2
Nº of layers	5	5
1º hidden layer		
Nº of neurons	4	4
Activation function	Relu	Relu
2º hidden layer		
Nº of neurons	4	4
Activation function	Relu	Relu
3º hidden layer		
Nº of neurons	1	1
Activation function	Linear	Linear
Optimizer	Adam	Adam
Loss function	MSE	MSE
Nº of Epochs	5000	5000
Split ratio (testing/training)	10/90	10/90
Values Approach	Uniform	Non-uniform

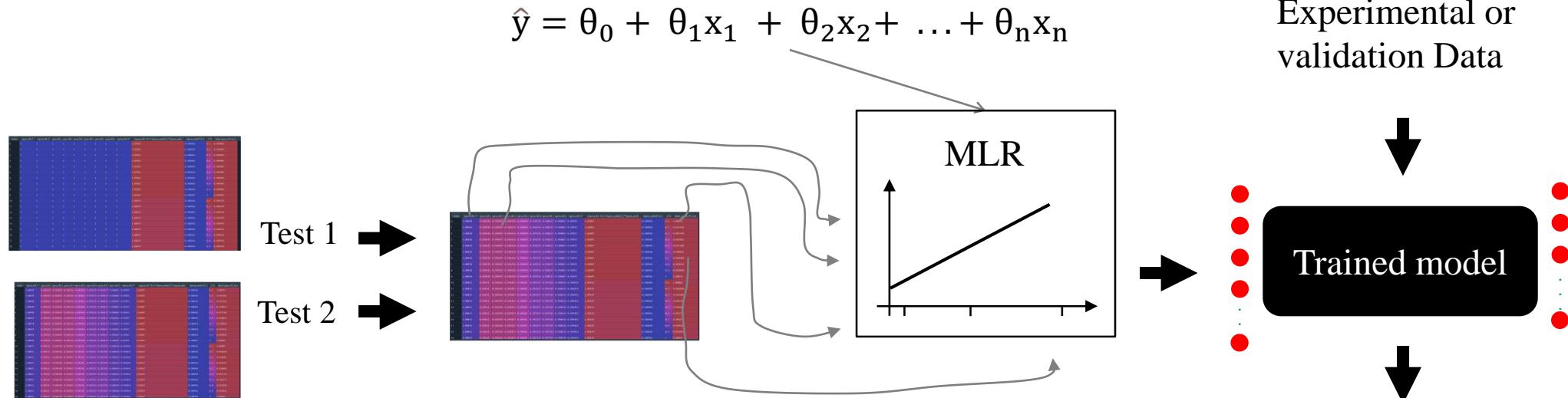
Source: elaborated by the author.



Methodology

Building and Implementing the ANN Model

- Evaluation performance of the DANN model by classical comparison.



Datasets based in Chupakhin [7]

Training and Testing of the Deep ANN model

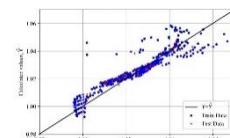
Experimental or validation Data

Trained model

Predicted values for correction



Python Script in Google Colab





Summary

1. Introduction
2. State of the Art
3. Methodology
- 4. Results and Discussions**
5. Conclusions and Suggestions for Future Works



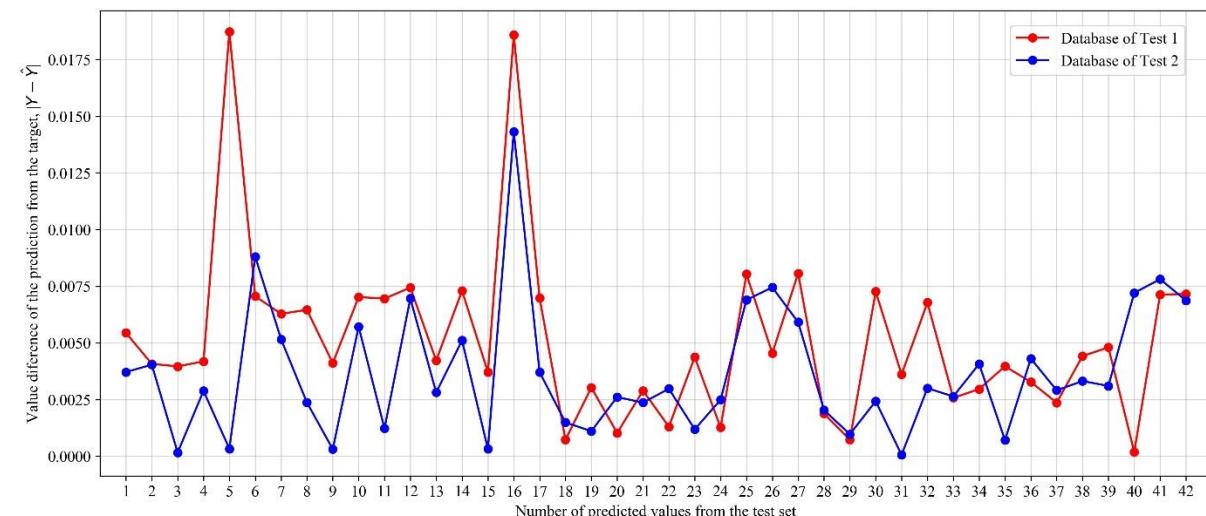
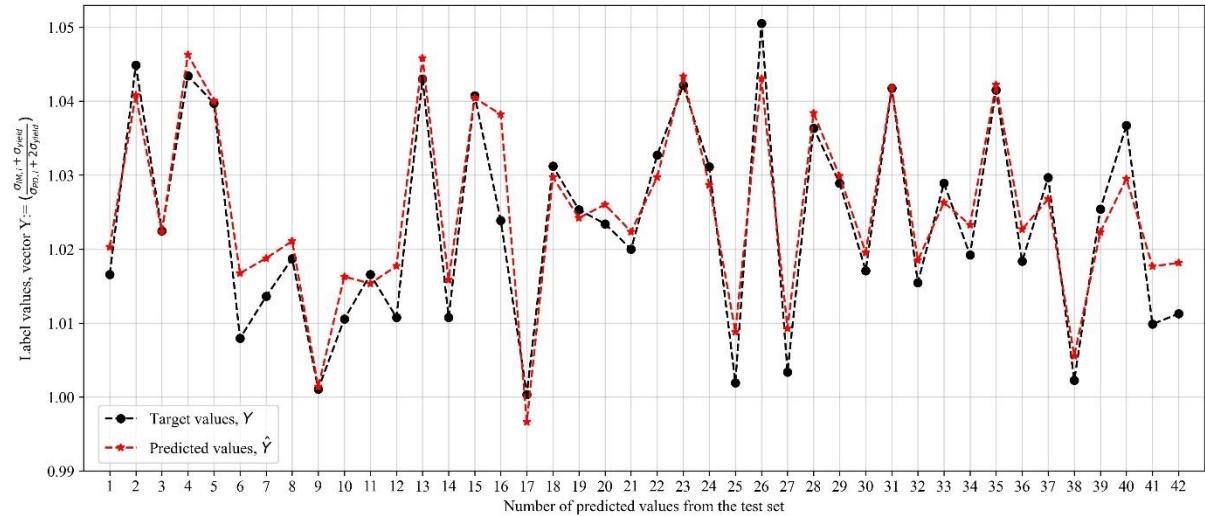
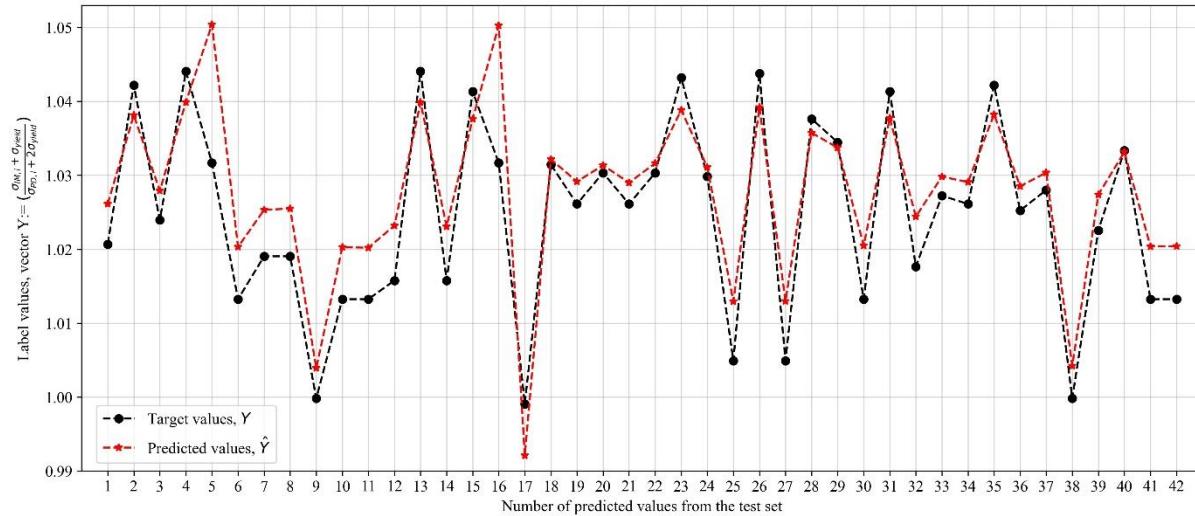
Analyses

1. Validation of the Test Set
2. Predictions of the Trained Model for the Entire Set
3. Evaluation Performance of the DANN Model
4. Selected Profiles from the Set of Data



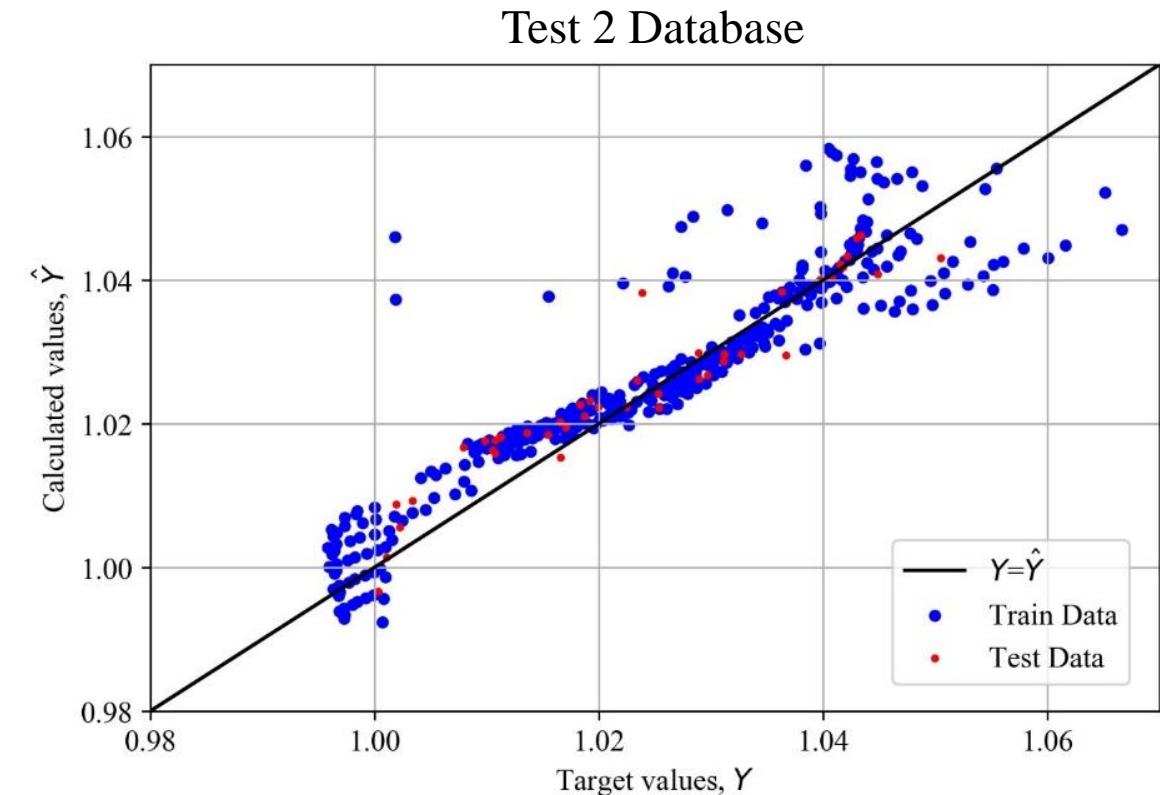
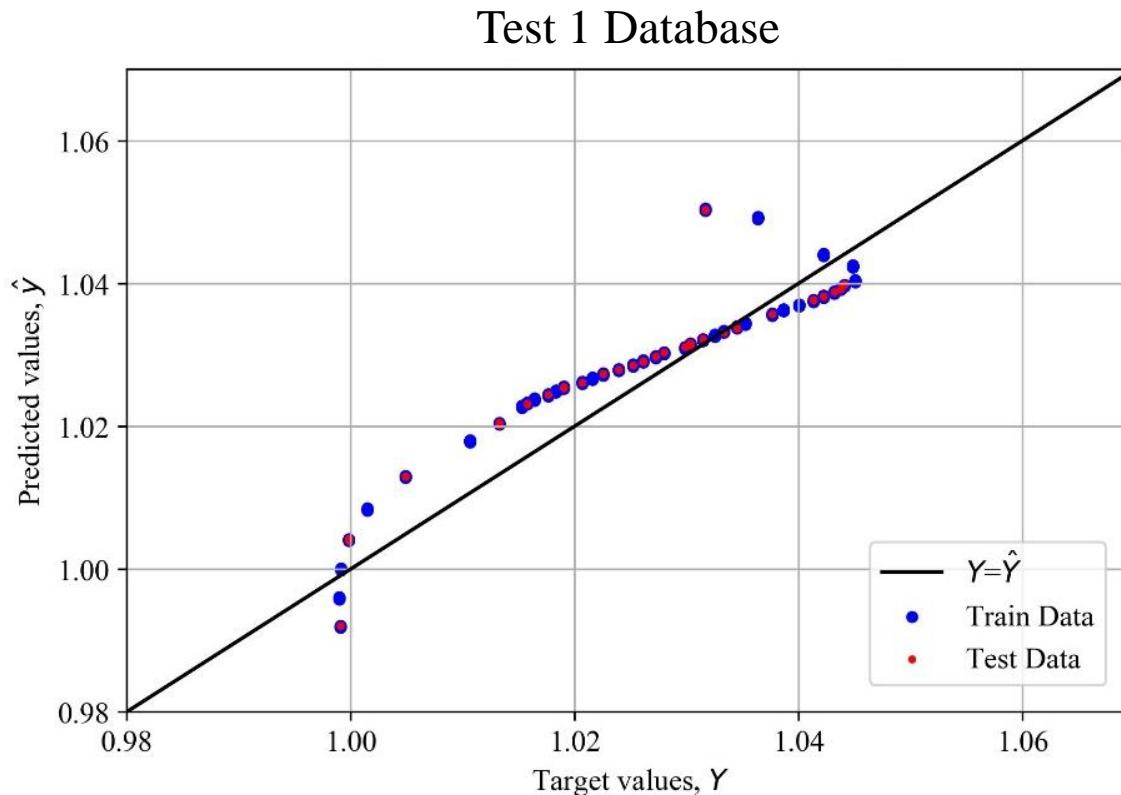
Results and Discussions

1. Validation of the Test Set



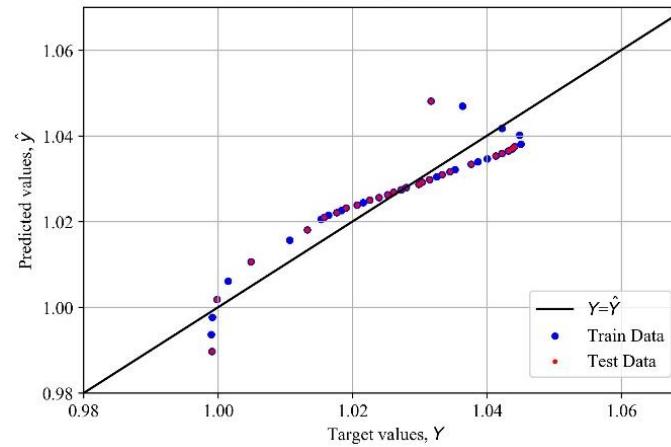
2. Predictions of the Trained Model for the Entire Set

Predictions of the DANN model vs. the target values of Test 1 and Test 2 Database.

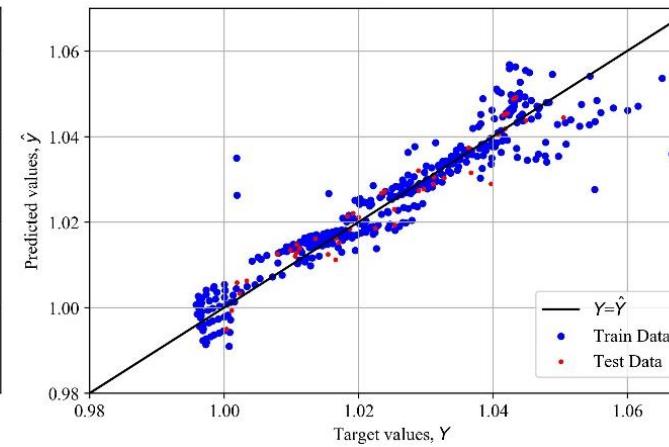


3. Evaluation Performance of the DANN Model

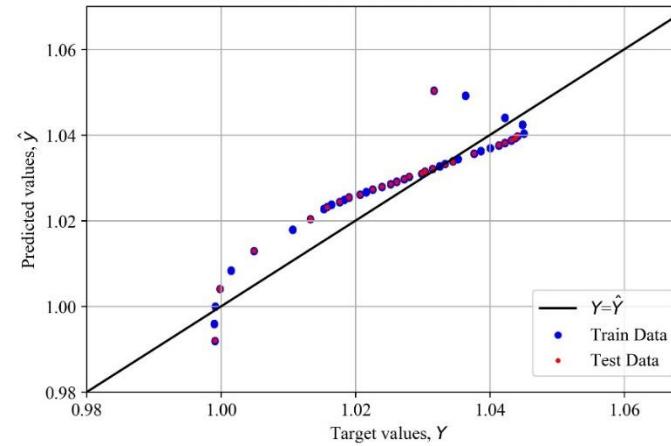
MLR - Database of Test 1



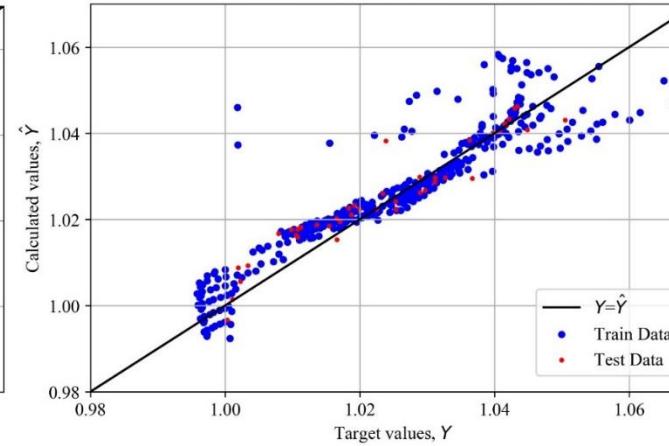
MLR - Database of Test 2



DANN – Database of Test 1



DANN – Database of Test 2

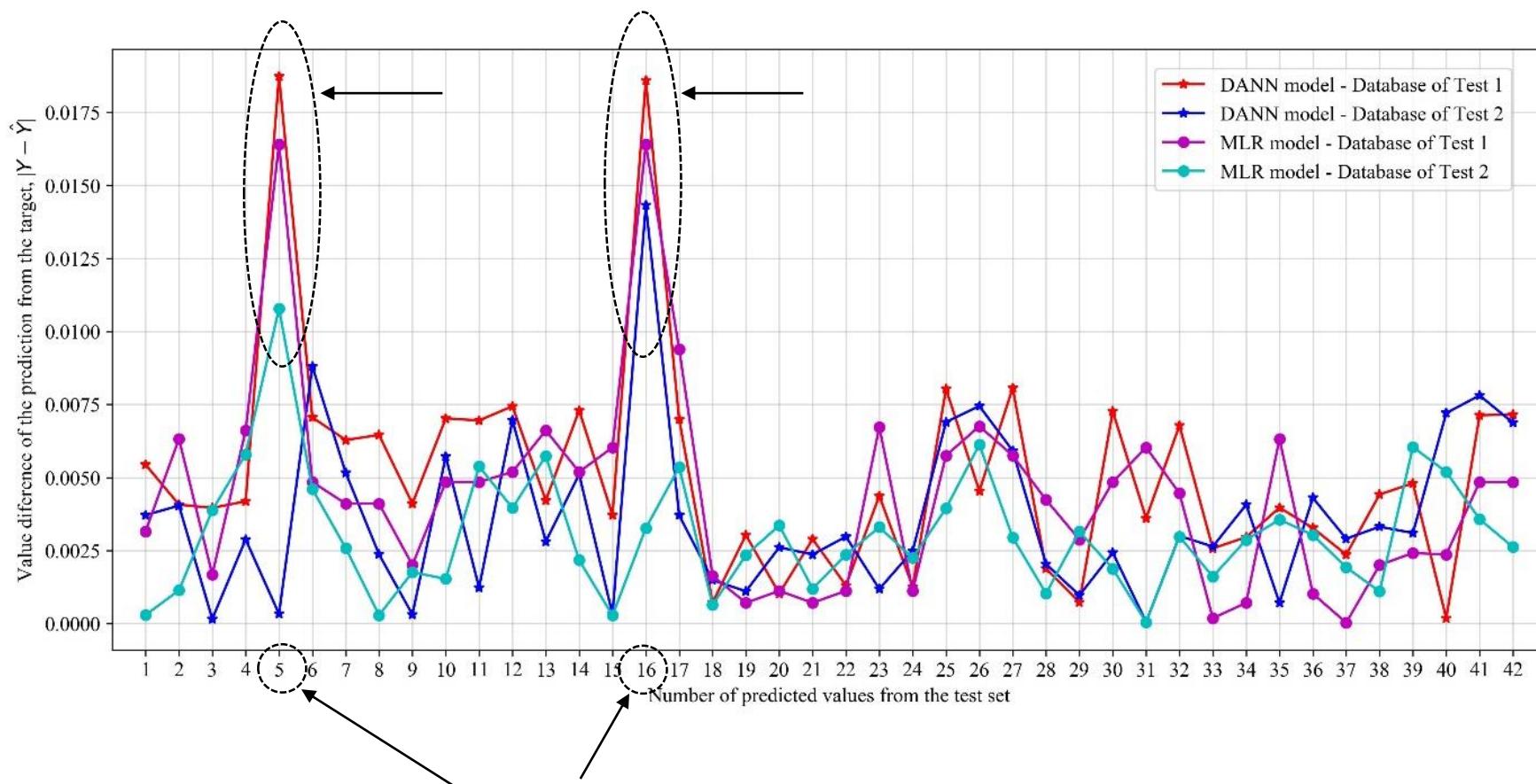


Predictions of the MLR model vs. the target values.

- Test 1: from 42 values (Test set), 28 less errors with MLR, 14 less errors with DANN.
- Test 2: from 42 values (Test set), 29 less errors with MLR, 13 less errors with DANN.
- It was expected more instances diversion (decreasing errors) with Test 2 Database, but errors increased.
- **Is DANN efficient for this problem?**

3. Evaluation Performance of the DANN Model

Errors values of the models for the test set.



Plasticity Factor f values corresponding to the indexes of the test set

Index	f								
1	0.76	11	0.65	21	0.81	31	0.95	41	0.65
2	0.96	12	0.71	22	0.85	32	0.73	42	0.65
3	0.79	13	0.99	23	0.97	33	0.82		
4	0.99	14	0.71	24	0.84	34	0.81		
5	1.30	15	0.95	25	0.50	35	0.96		
6	0.65	16	1.30	26	0.98	36	0.80		
7	0.75	17	0.00	27	0.50	37	0.83		
8	0.75	18	0.86	28	0.92	38	0.30		
9	0.30	19	0.81	29	0.89	39	0.78		
10	0.65	20	0.85	30	0.65	40	0.88		

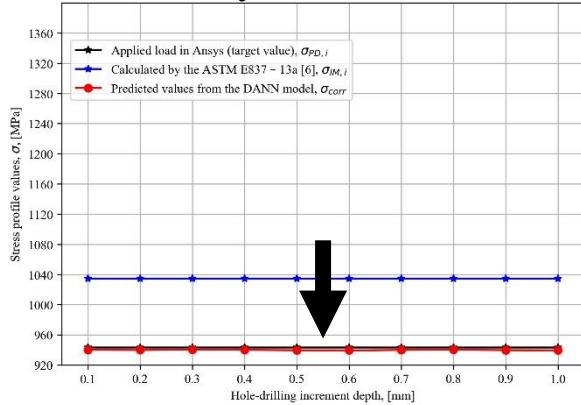


Results and Discussions

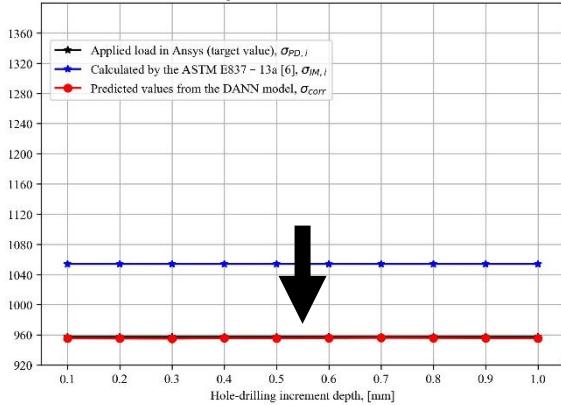
4. Selected Profiles from the Set of Data

Correction of the Stress profile values for a given Plasticity factor value

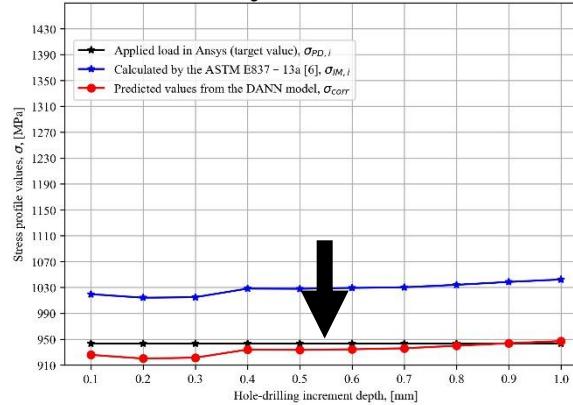
Plasticity factor $f = 0.84$



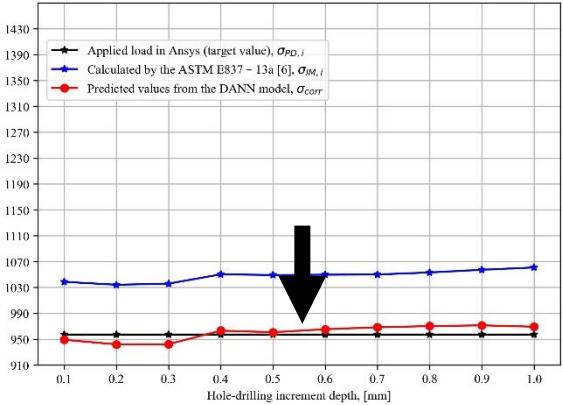
Plasticity factor $f = 0.8$



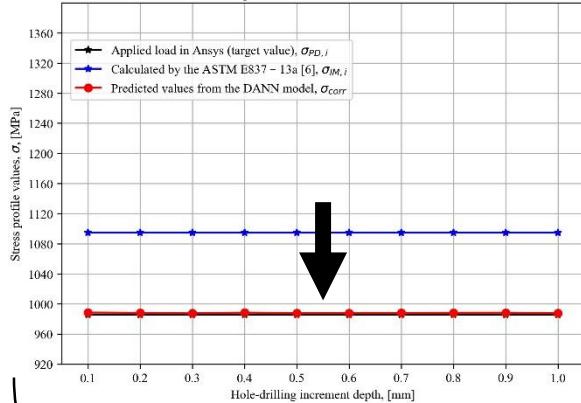
Plasticity factor $f = 0.84$



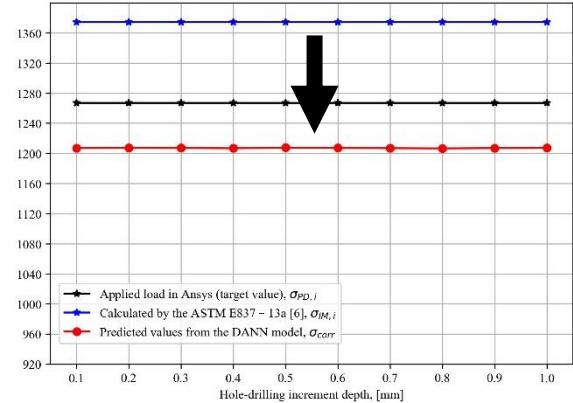
Plasticity factor $f = 0.8$



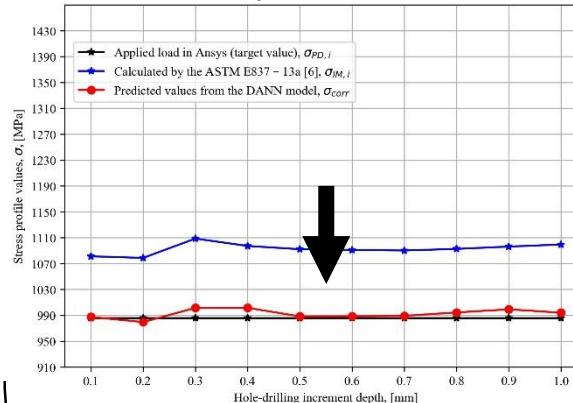
Plasticity factor $f = 0.90$



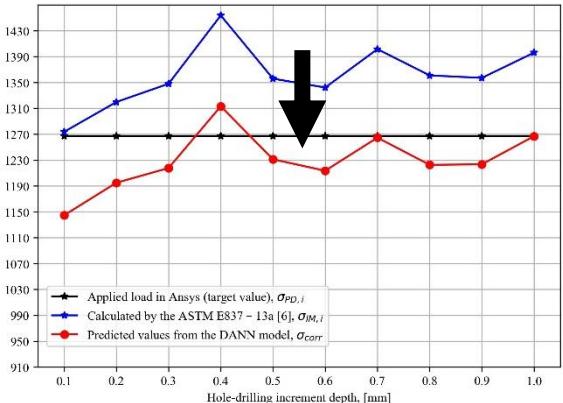
Plasticity factor $f = 1.30$



Plasticity factor $f = 0.90$

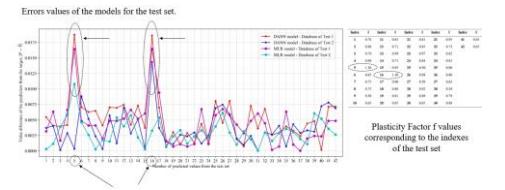


Plasticity factor $f = 1.30$



Database of Test 1

Database of Test 2





Summary

1. Introduction
2. State of the Art
3. Methodology
4. Results and Discussions
- 5. Conclusions and Suggestions for Future Works**



Conclusions and Suggestions for Future Works

- Given the limitation of the ASTM E837-13a, DANN trained models on numerical simulation data were **implemented** for the **correction** of plasticity effect in HDM. A FEM model was **developed** for the numerical simulations.
- **Two** different model based on two different databases **Test 1** (uniform stress profile) and **Test 2** (non-uniform stress profile). Both DANN models **performed relatively accurately** (in the test validation). Errors on the order of **4.4×10^{-3} for Test 1 and 3.8×10^{-3} for Test 2**.
- The **pre-process of features** was based on the work of Chupakhin *et al.* [7].
- A classical **MLR model** was also **implemented** to compare the **performance** and **errors** of the DANN model.
 - The prediction error from MLR model **was lower** than the DANN model.
 - The result **questioned the computational efficiency** of implementing a DANN model.
- Plasticity Factors **f values** in the testing set **were investigated**. The largest errors were simulated with the same value of **f = 1.30**.
- **Four profiles** (with different values of f) were taken from the total set of data from each database and used as **input** for the **correction**.



- The trained model **relies heavily on numerical results** from controlled simulations under very **specific conditions and parameters**, which may make the trained model **not perform well in generalization**.
- A **validation** via **experimental** data by means of comparison would be **needed**.
 - Extension of the work - experiments and measurements – comparison
- **Low sampling** of data for model training, both databases were considered **poor datasets** of **12 features for 420 instances**. Fairly standard recommended in Data Science is in the proportion of **10 (features) to 20'000 (instances)** [18] - **Generality of the model ?**
- Calculated **features** were **based** on the **equations** established by **Chupakhin et al. [7]** – **suggestion**: larger exploration of statistical features.
- Exploring other **ML models** - great way to investigate better corrections.
 - Example of ML regressor models that could be implemented are the **Radom Forest** regressor, the **Decision Tree** regressor and the **PCA** regressor.



Conclusions and Suggestions for Future Works

- Exploring the variation of the parameters of the training of the DANN model. Variate from Chupakhin's model values.
- Deeply **investigate the relationship** between the values of the **Pasticity Factor f** and the **predicted values** from the models.
 - Literature points to the **beginning of plastic effects for $f > 0.6$** , an investigation of this **upper range** with **separate databases** for testing could be carried out.

Parameters of the training of the DNN model.
Values based on Chupakhin's model.

Parameters	Test 1	Test 2
Nº of layers	5	5
1º hidden layer		
Nº of neurons	4	4
Activation function	Relu	Relu
2º hidden layer		
Nº of neurons	4	4
Activation function	Relu	Relu
3º hidden layer		
Nº of neurons	1	1
Activation function	Linear	Linear
Optimizer	Adam	Adam
Loss function	MSE	MSE
Nº of Epochs	5000	5000
Split ratio (testing/training)	10/90	10/90
Values Approach	Uniform	Non-uniform

Source: elaborated by the author.



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