Machine Learning-Based Generalized Model for Finite Element Analysis of Roll Deflection During the Austenitic Stainless Steel 316L Strip Rolling

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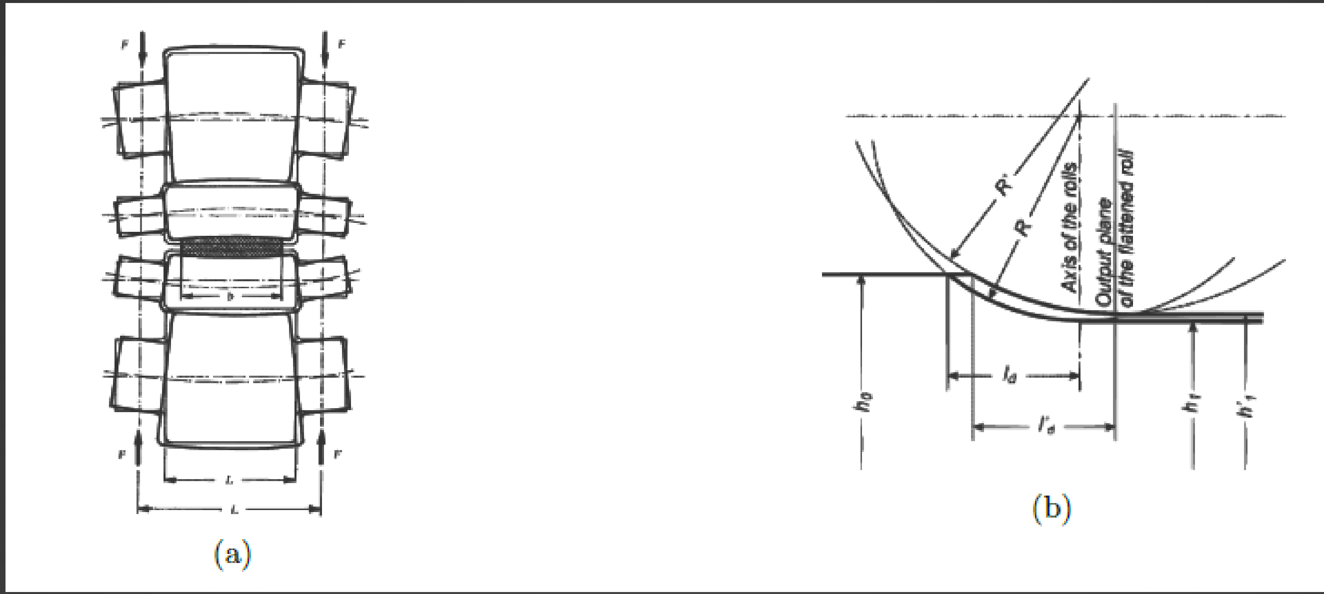
Overview

- Introduction
- Methodology and Model
- Deflection and Work-roll Characteristics
- Artificial Neural Network (ANN)
- Evaluation and Results
- Conclusion and Discussion

Introduction

- What is work-roll Deflection?

Forces acting within the roll gap, caused by the resistance of the metal deformation, result in the elastic deformation of the roll, which changes the roll dimensions.



(a) elastic deflection of the rolls *(b) Elastic flattening of the rolls*

Introduction

Which characteristic of Austenitic Stainless Steel 316L makes it to behave differently from other kind of steels?

The results of the X-Ray pattern diffraction of the deformed ASS 316L show three phases including ε-Martensite, Austenite, and α'-Martensite.

Cold plastic deformation

Strain-induced Martensite

Improve the mechanical properties

Methodology and Model

Following Orowan's Theorem and solve the Equilibrium Equation using an FD Approach → Mean Pressure which the Strip applies to the Roll → Utilizing Numerical FEA for One-Dimensional (1D) Cantilevered Beam to obtain the Roll Deflection.

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Mean Pressure which the Strip applies to the Roll

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Mechanical Tensile Tests;

- 0.001, 0.00052, 0.0052, 0.052 s^{-1}
- In a Room Temperature
- Annealed at 1030℃ for 30 minutes

→ Collect the strain and stress from tests to make a required Dataset.

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Inputs

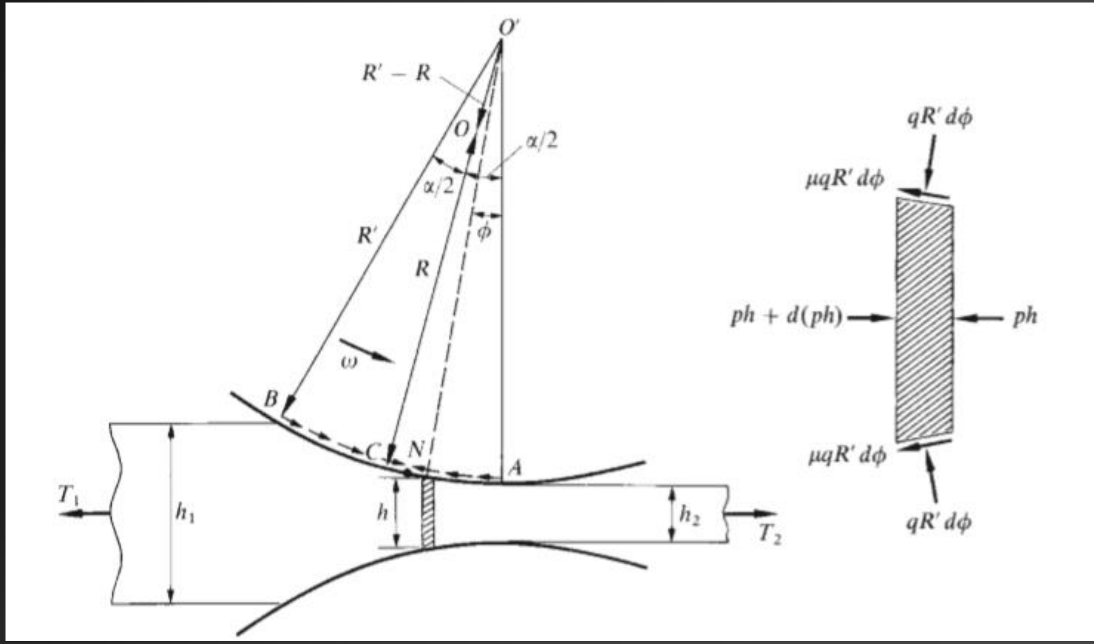
Strain & Strain rates

Outputs

Dynamic Flow Stress

Methodology and Model

Equation of Equilibrium



Yield Criterion

$$q - p = 2k$$

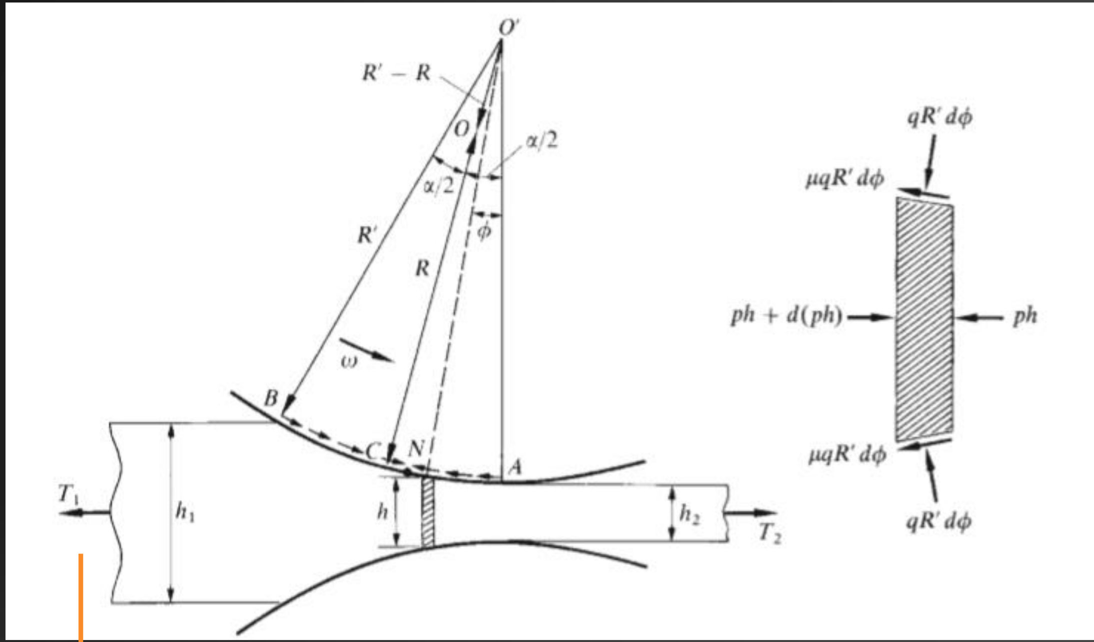
$$h = h_2 + 2R'(1\text{-}\cos\phi) \simeq h_2 + R^2\phi^2$$

$$\frac{d}{d\phi}(hp) = 2qR'(sin\phi \mp \mu cos\phi)$$

- **Forward Difference for both Sides**
- **Dynamic Flow Stress updates from ANN**

Methodology and Model

Equation of Equilibrium



$$\frac{h_i(q_{i+1} - 2k_{i+1} - q_i + 2k_i)}{\phi_{i+1} - \phi_i} + 2\mu R q_0 = 4kR\phi_i$$

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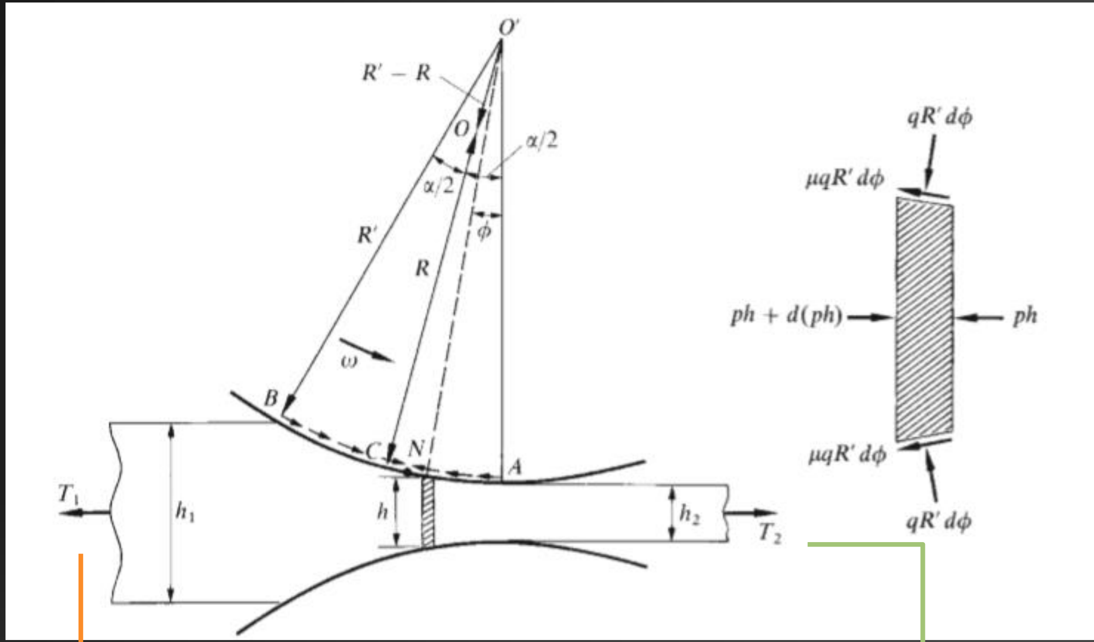

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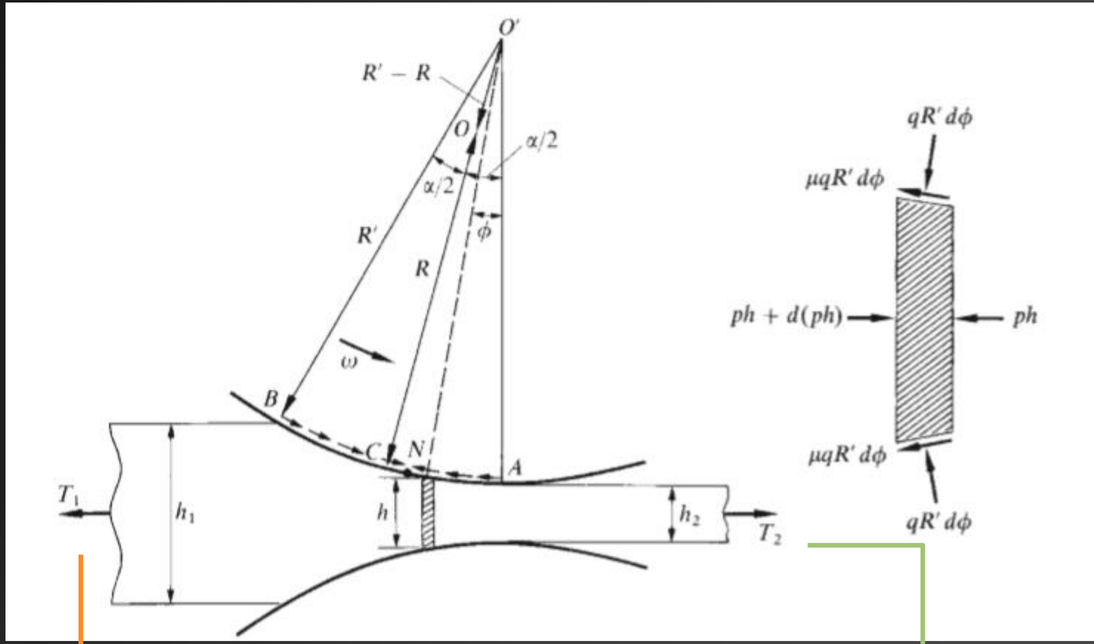

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$$\bar{P} = \frac{\int_{\alpha}^{0} q\, d\phi}{\Delta\phi}$$

Deflection and Work-roll Characteristics

Distributed Load

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w: Work-Roll Deflection
x: Length of the Roll

I: The Second Moment of Inertia

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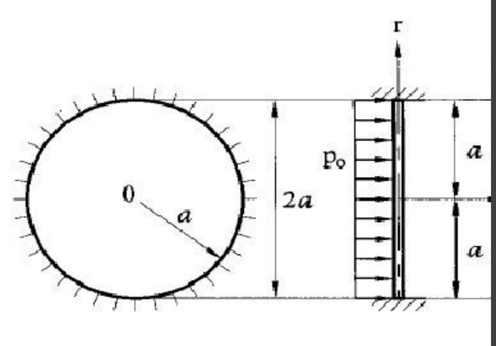
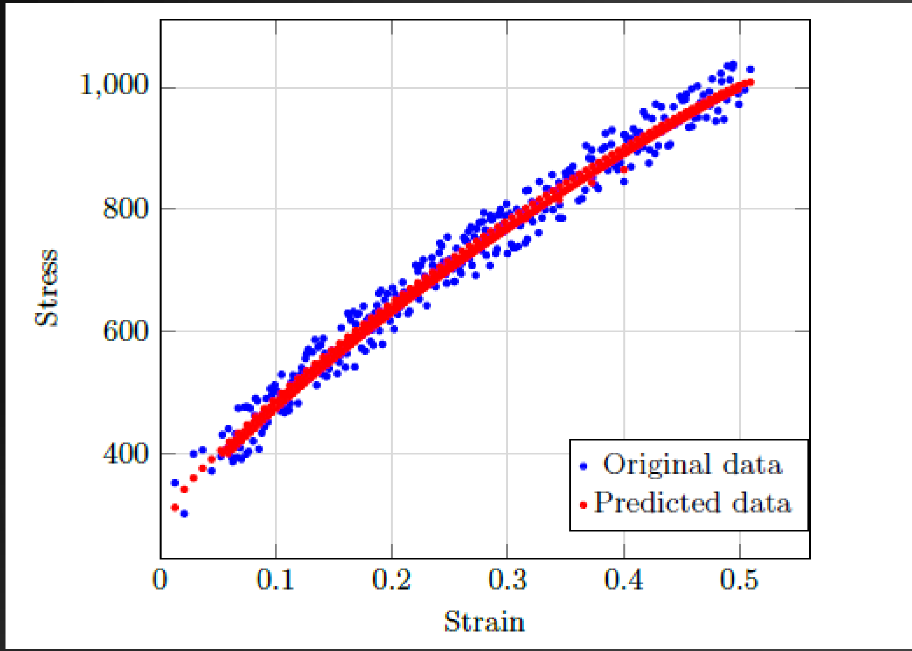


$$\begin{cases} Deflection\ (Max) = \dfrac{pa^2}{16\pi D} \quad at\ r = 0 \\ D = \dfrac{Et^3}{12(1-\nu)} \end{cases}$$

Calculate the Work-Roll Deflection using Analytical Analysis

Artificial Neural Network (ANN)

Linear Regression



$$y = X\beta + \epsilon$$

$$X = \begin{bmatrix} 1 & x_{11} & x_{12} \\ 1 & x_{21} & x_{22} \\ \vdots & \vdots & \vdots \\ 1 & x_{n1} & xn2 \end{bmatrix}$$

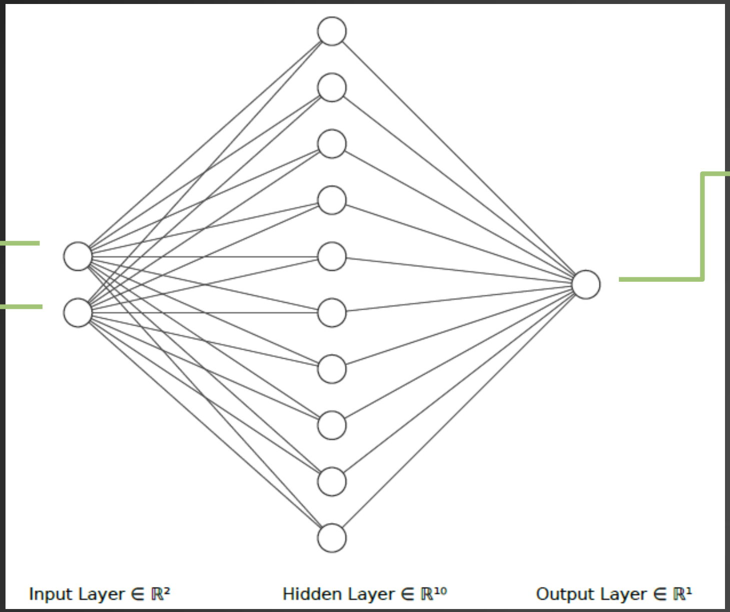
X: Feature vectors of our data
y: Output Prediction
n: Total Number of Data
β: Weights
ϵ: Biases

X: Strain and Strain rate values
y: Predicted Dynamic Flow Stress

Artificial Neural Network (ANN)

Strain

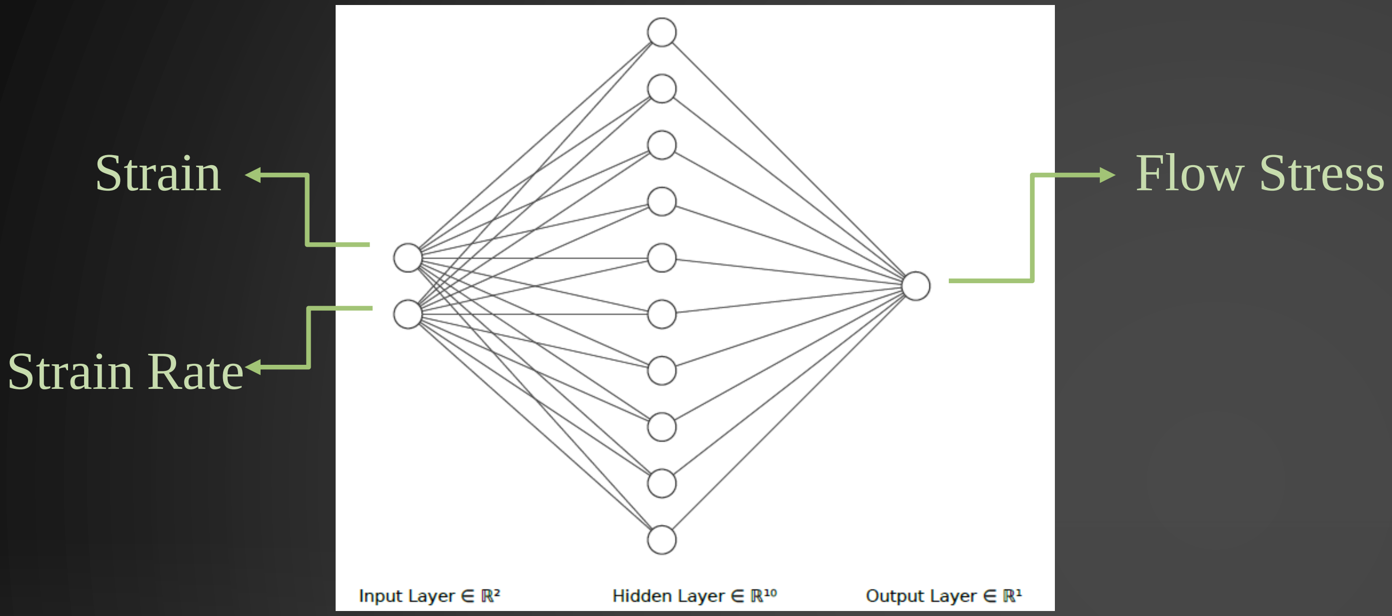
Strain Rate



Flow Stress

Model Architecture.

Artificial Neural Network (ANN)



Model Architecture.

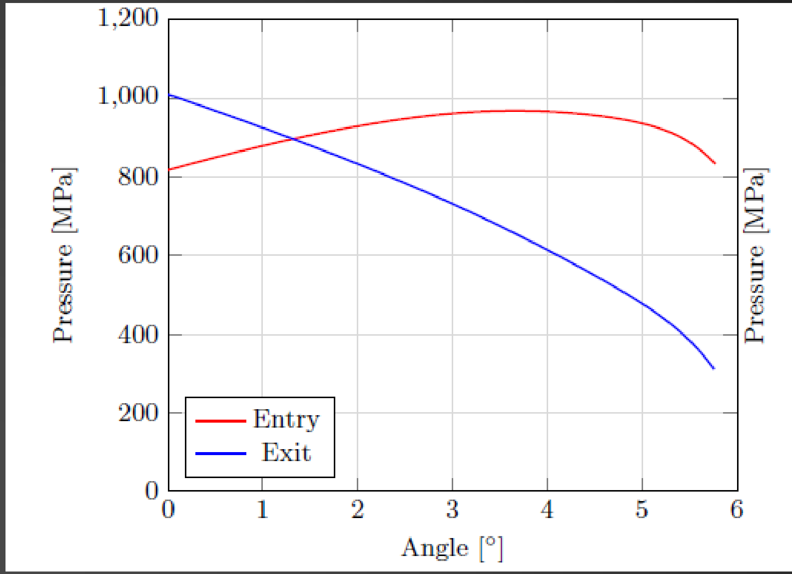
$$MSE = \frac{\sum_{i=1}^{n}(y_i - y_i')^2}{n}$$

- Training Data: 70%
- Test Data: 15%
- Validation Data:15%

Evaluation and Results

Final thicknesses of specimens after multi-pass rolling.

2-Pass	3-Pass	4-Pass	5-Pass	6-Pass	7-Pass
2.8	2.48	2.23	1.99	1.74	1.44



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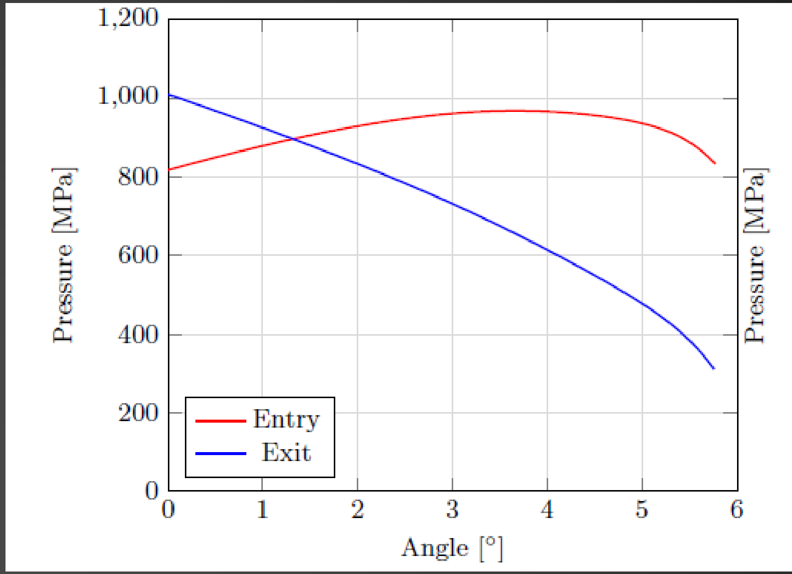

(1) The angle of the neutral point for 1-pass rolling, using proposed Finite Difference Method; **Is 1.31°**

(2) While using an analytical manner;

$$\sin\gamma_n = \frac{\sin\alpha}{2} + \frac{\cos\alpha - 1}{2\mu}$$

Is 1.42°

Evaluation and Results

Mean pressure values as distributed loads for multi-pass rolling.

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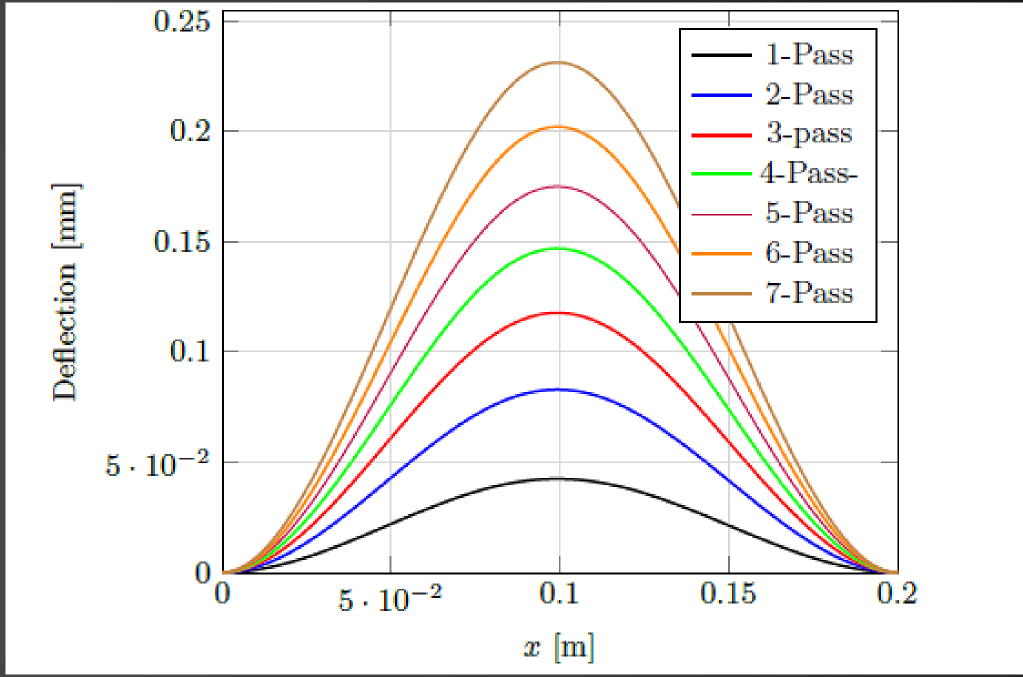

Comparing deflection values along the roll widths, which are caused by the multi-pass rolling of the ASS 316L in the room temperature.

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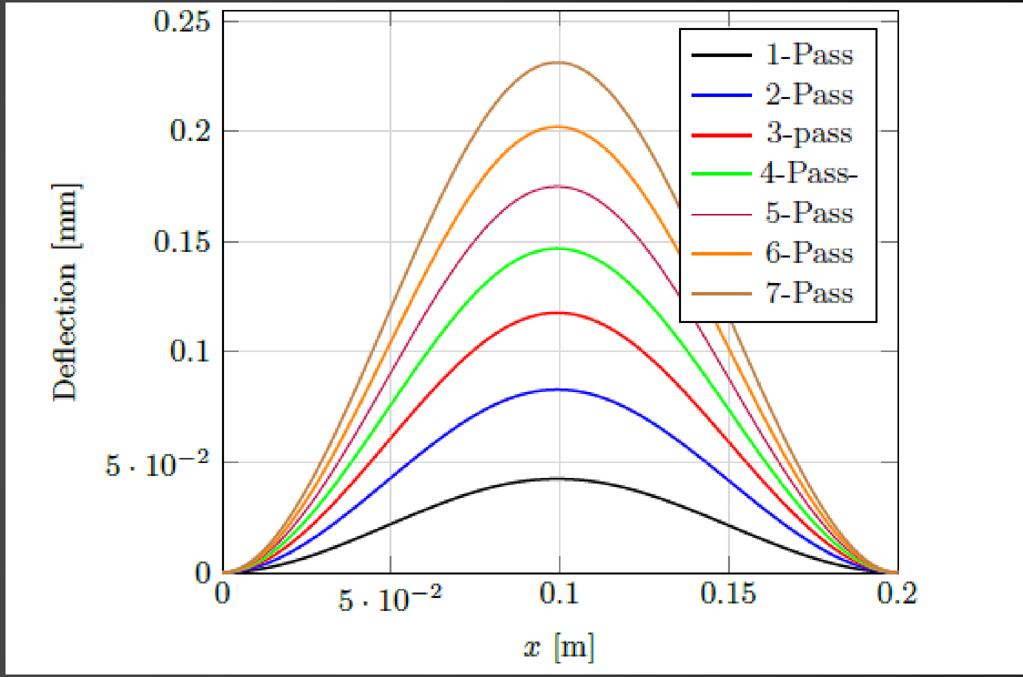
Plain-Strain condition

Deflection values vary according to the normal distribution along the width of the roll.



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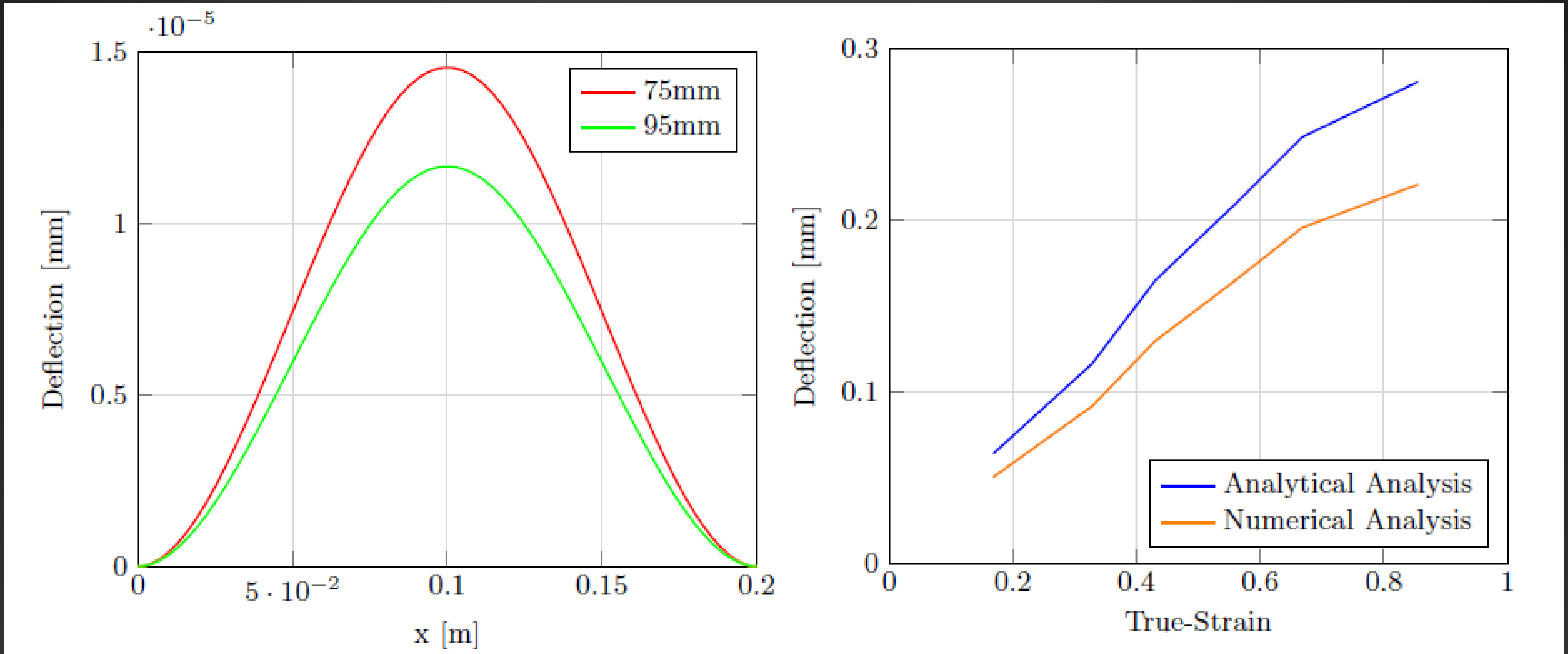

Evaluation results.

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- Additionally, we created Stress316L, the first public dataset for Strain-Stress values of ASS 316L during cold tension from real experiments.

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For future work,

- We will consider the temperature factor in the tensile tests by conducting different sub-zero temperatures tests in order to extend our Stress316L dataset.

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- With increasing the dimensionality of the feature vectors, we could utilize deeper networks. Training different networks and ensembling the resulting fits would also be beneficial.

Conclusion and Discussion

Thank you for listening!