X. From Data to Insight: Neural Networks to Predict Grinding Residual Stresses –

Carla Cunha, M.Sc. (ITA)

Surface integrity, particularly the residual stresses induced by finishing operations such as grinding, plays a fundamental role in the performance of mechanical components, especially gears. However, measuring and controlling these stresses directly on the shop floor remains a major challenge, particularly in high-productivity environments. This scenario highlights the need for innovative and data-driven solutions that can be implemented in real time.

This work presents a neural network-based approach to predict residual stresses resulting from the gear profile grinding process. To support the model, an experimental database with 240 grinding conditions, covering a wide range of depth of cut, feed rate, and cutting speed combinations, was build to comprehensively represent process boundaries. Online acquisition of process force and spindle current was conducted without compromising the workpiece, supporting the feasibility of in-situ implementation.

Two top-performing models were identified, each achieving a Mean Absolute Error below 30 MPa. This represents only 3.8% of the average residual stress and is even lower than the experimental uncertainty of 38.3 MPa. Additionally, only 25% of the individual predictions exceeded this uncertainty, and even then, the maximum deviation was around 10% of the mean stress level.

These results demonstrate the accuracy and robustness of the proposed approach, showing great potential for its integration into intelligent, data-driven manufacturing systems focused on process optimization and quality control.

From Data to Insight:
Neural Networks to Predict Grinding Residual Stresses

Carla Cunha M.Sc. *(ITA)*

São José dos Campos, August 13th & 14th, 2025

Agenda

1. Residual Stress in Focus: Contributions and Challenges
2. A Neural Network Approach to Predict Grinding Residual Stresses
3. Residual Stress Predictions: Model Insights
4. Summary and Outlook

Residual Stress in Future Manufacturing

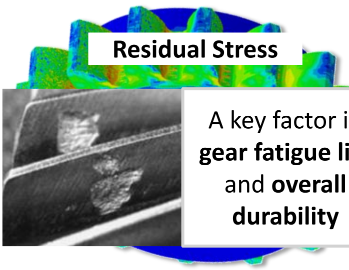
TECHNICAL REQUIREMENTS FOR **ENERGY TRANSITION**

Higher rotations | Lower dimensional tolerances | High productivity

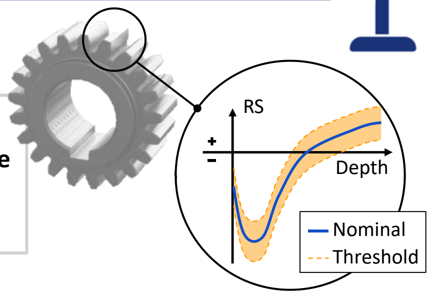
By 2030 30% of new vehicles will be **electric** [1]

By 2035 the **power capacity** of wind turbines will **increase** by 300% [2]

Tighter requirements on quality, durability, and process reliability for gears [3]



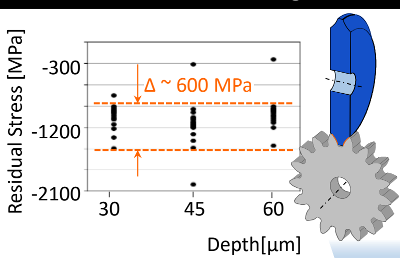
A key factor in **gear fatigue life** and **overall durability**



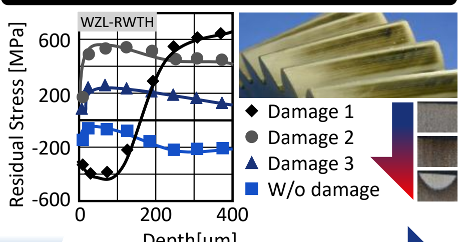
Source: [1] MCKI16, [2] WISE21, [3] MOSQ20

The Residual Stress Challenges in Manufacturing

Residual Stress Production Large Variability

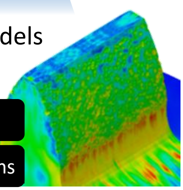


Grinding Burn



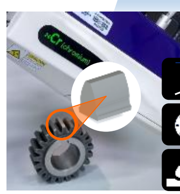
SIMULATION — **SETUP** — **INSPECTION**

Finite Element Models



- Time-consuming
- Limited Applications

X-Ray Diffraction



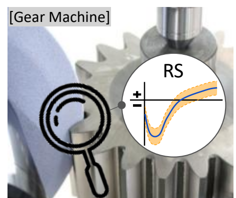
- Position-dependent
- Time-consuming
- Destructive Testing

Agenda

Objective & Approach

Scenario and State-of-the-art

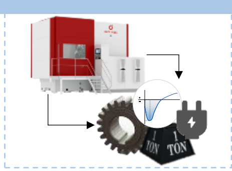
- High need for **surface integrity control** and **dimension accuracy**
- **Highly complex**: large number of input parameters & non-stationary
- **Lack of developments** for **in-situ monitoring** of the **residual stress state** in **grinding** processes



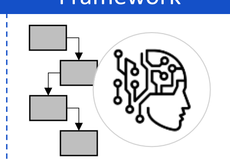
OBJECTIVE

Development of **neural networks** for **residual stress prediction** in gear profile **grinding**

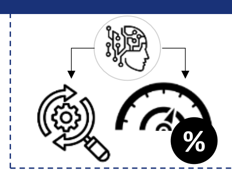
Grinding Dataset



ANN*-Based Predictive Framework



Performance Evaluation



ANN: Artificial Neural Networks

Grinding Dataset

Samples

Gear Data	
z = 21	β = 0°
m_n = 2.85 mm	d_a = 65.510 mm
α = 17.5°	b = 22 mm
AISI 5120 case hardened	

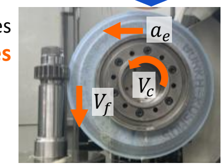
ITA Geometry

Design of Experiments

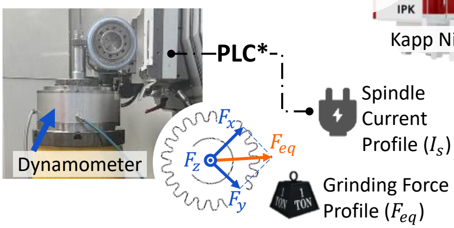
Sample Preparation → Grinding Pass 1 → Grinding Pass 2

240 comb. w/ 3 replicates

720 samples



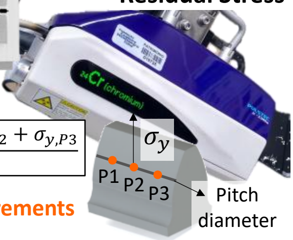
Instrumentation



Residual Stress

$$\overline{\sigma_y} = \frac{\sigma_{y,P1} + \sigma_{y,P2} + \sigma_{y,P3}}{3}$$

> 3000 measurements



PLC: Programmable Logic Controller

ANN-Based Predictive Framework

Data Preparation

Data

Cleaning

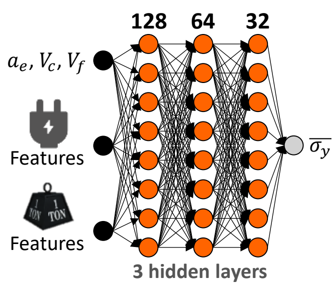
Features (8x)

Storage

Input data

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

ANN Architecture Design



- Activation function: *ReLU*
- L2 Regularization (λ = 0.001)
- Weights initializer *Glorot Uniform*
- Optimizer: Adam Learning Rate 0.001
- Dropout rates: 0.4 / 0.4 / 0.2
- Loss Function: Mean Squared Error
- Epochs: 200 | Batch size: 8

Optimization Pipeline

Feature Selection

- Feature Correlation Elimination
- Genetic Algorithm

Hyperparameter Tuning

Grid Search with Cross Validation

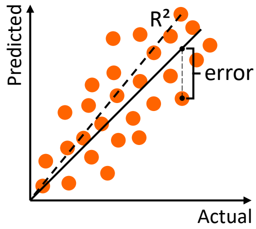
# Neuron	LR*
Dropout	Batch size

Model Selection

LR: Learning Rate

Performance Evaluation

Evaluation Metrics

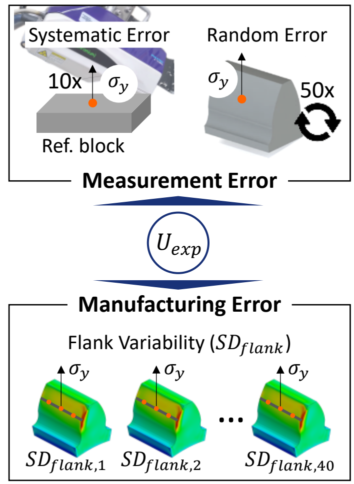


R^2 = Coefficient of determination

$$\text{MAE*} = \frac{\sum error_i}{n}$$

n: number of samples

Experimental Uncertainty (U_{exp})



Prediction Comparison

What is the ***actual accuracy*** *of the model?*

Error Uncertainty Ratio (EUR)

$$\text{EUR} = \frac{\text{MAE*}}{U_{exp}}$$

**MAE: Mean Absolute Error*

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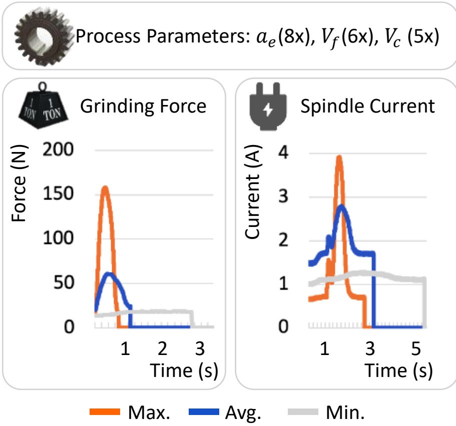
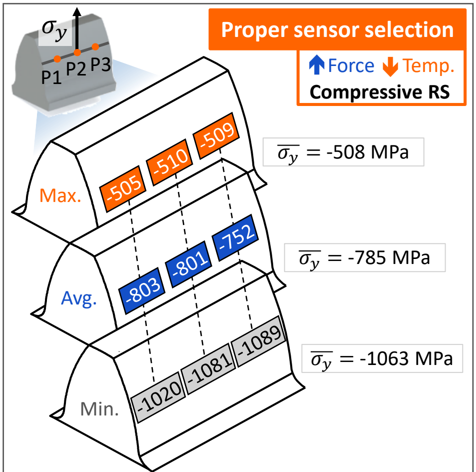
Dataset Overview: *Inputs and Target Outputs*



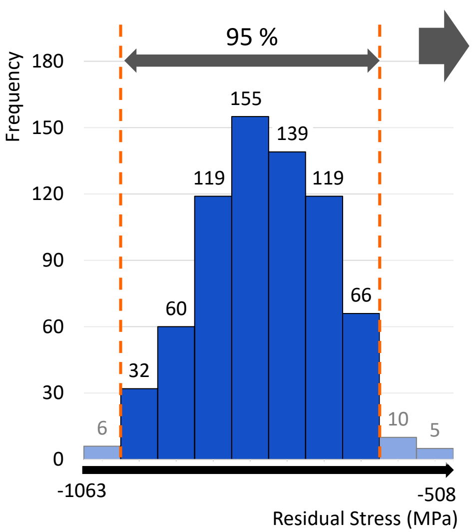
Force and spindle current acquired **without destructing workpieces**

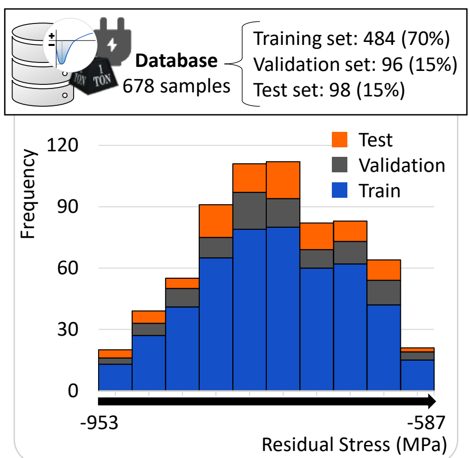
In-situ requirement



Interval within expected range for grinding: [-1063, -508]

Data Preparation: *Controlled Dataset Partitioning*

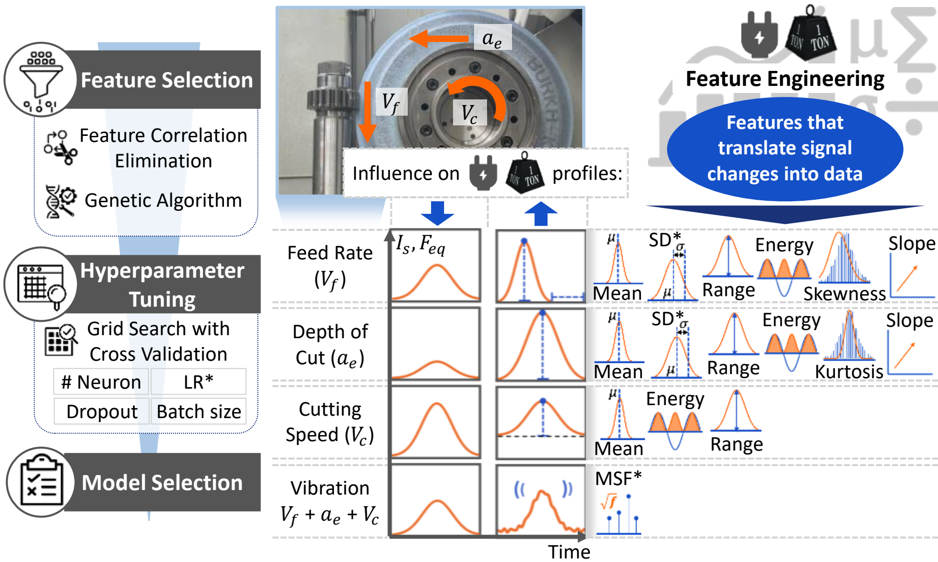




Same parameter combinations kept in the same set

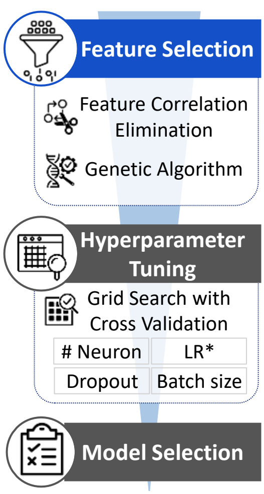
Data Leakage Prevention

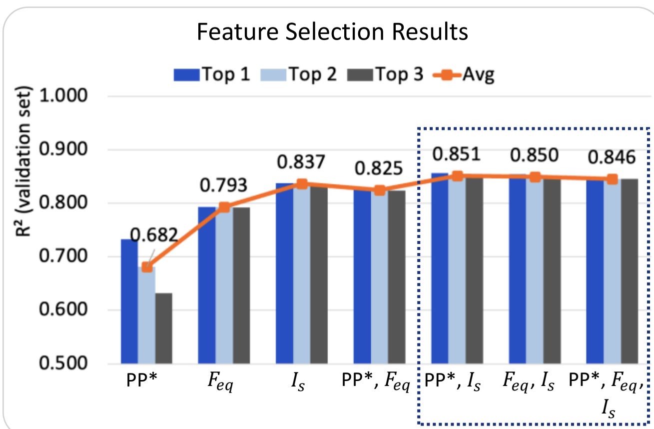
Data Preparation: *Feature Engineering*



*LR: Learning Rate, SD: Standard Deviation, MSF: Mean Square Frequency

Model Optimization: *Feature Selection*



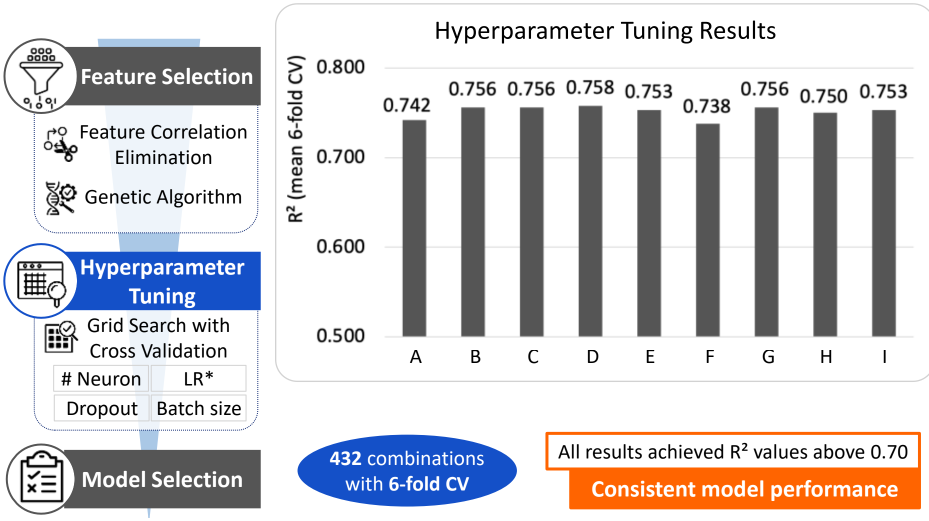


Spindle current appears consistently among the top results.

Input Significance Indicator

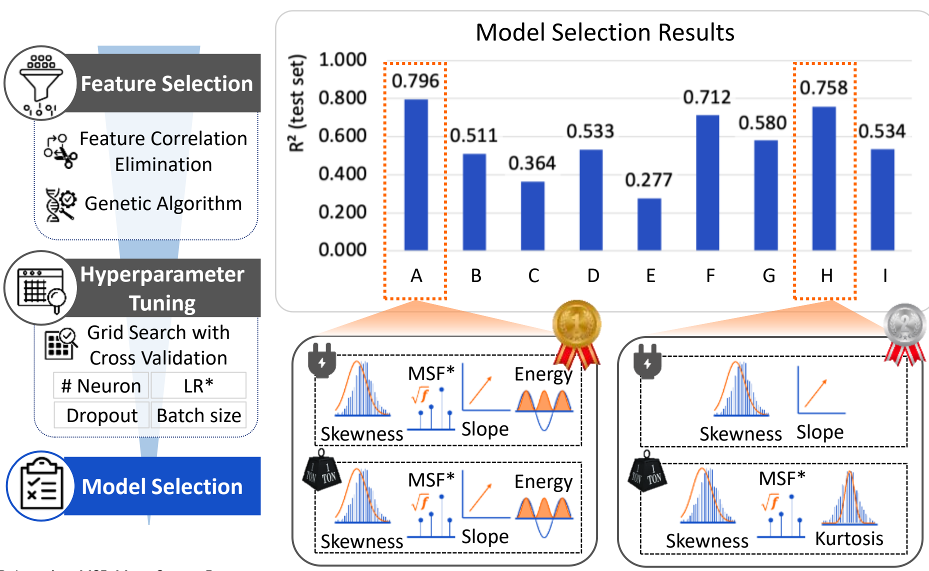
*LR: Learning Rate, PP: Process Parameters

Model Optimization: *Hyperparameter Tuning*



*LR: Learning Rate

Model Optimization: *Data Evaluation*



*LR: Learning, MSF: Mean Square Frequency

Performance Evaluation

Evaluation Metrics

Metrics	A	H
R^2	0.796	0.758
MAE (MPa)	29.2	29.6

MAE < 30 MPa (~3.8%)
Errors: 0.1 – 13.2%

Low prediction errors

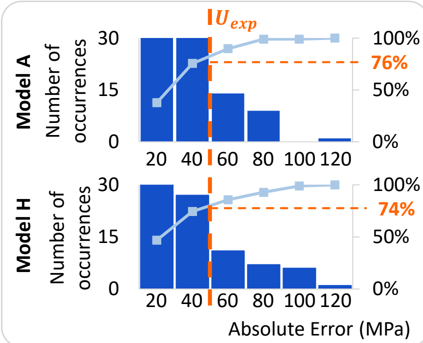
Experimental Uncertainty (U_{exp})

Systematic Error (MPa)	-2.1
Random Error (MPa)	20.2
SD_{flank} (MPa)	32.4
U_{exp} (MPa)	**38.3**

Error Uncertainty Ratio (EUR)

Model	EUR
A	0.76
H	0.77

EUR < 1



Only **~25%** of predictions exceed experimental error

Predictive performance is **compatible with current levels of measurement precision**

Strong Model Reliability

Industrial deployment:

Reducing experimental uncertainty and developing context-specific datasets

MAE: Mean Absolute Error, SD_{flank}: Flank Variability

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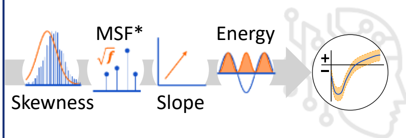
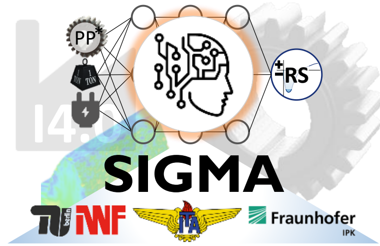
Key Insights

- Neural Networks effectively applied to **Residual Stress Prediction**:
  - ✔ Application focused on **Gear Profile Grinding**
  - ✔ Database built under **consistent** and **non-intrusive conditions**
  - ✔ Prediction errors **below** the level of **experimental uncertainty**
- Demonstrated **potential for industrial integration** in intelligent, data-driven manufacturing systems



PP: Learning, MSF: Mean Square Frequency

cornet



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