école doctorale **sciences pour l'ingénieur et microtechniques** SPIM

UNIVERSITÉ BOURGOGNE EUROPE

ImViA

Titre de la thèse/Thesis title : From multimodal magnetic and ultrasonic measurements to mechanical and physical properties of steels: Modeling, uncertainty quantification, and optimization for non-destructive evaluation

Laboratoire d'accueil / Host Laboratory : ImViA

Spécialité du doctorat préparé/Speciality : Instrumentation , Signal processing

Mots-clefs / Keywords : Non-destructive testing, multimodal measurements, magnetic signals, ultrasonic signals, mechanical properties, uncertainty quantification, machine learning, Bayesian modeling, inverse problems

Descriptif détaillé de la thèse / Job description

This research takes place in a collaborative project between a small-size industrial company (CMPHy) and a Vision and Artificial Intelligence academic research laboratory ImViA at Université Bourgogne Europe.

CMPhy is a company located in Chalon-sur-Saone, which specialized itself in developing advanced Non-Destructive Testing (NDT) machines based on (but not limited to) electromagnetic field effect. ImViA is based in Dijon and Le Creusot and is developing academic research on non-conventional imaging and image processing associated (ML and IA models).

The OCEA/OPTEND project aims to develop a non-destructive testing (NDT) tool (a hardware and a software) capable of predicting mechanical and physical properties of high-value steels (e.g., hardness, residual stress, carbon profile, magnetic permeability) from multimodal magnetic and ultrasonic measurements. This PhD is a collaboration between ImViA (academic laboratory) and CMPhy (industrial partner), with access to a pre-existing database of multimodal measurements (Barkhausen noise, Eddy currents, harmonic analysis of tangential magnetic field, incremental permeability, ultrasonic signals) collected on steel samples with various surface treatments (e.g., shot peening, nitriding, grinding) or applied mechanical constraints.

The challenge is to bridge the gap between raw sensor data and mechanical properties while accounting for uncertainties, noise, and variability in industrial environments. The PhD will focus on modelling, optimization, and uncertainty quantification, with the goal of delivering a robust and transferable solution for industrial applications.

The PhD will focus on:

- Developing predictive models (AI-based, Bayesian, or hybrid) to correlate magnetic/ultrasonic signals with mechanical properties.
- Optimizing input acquisition (signal types, parameters) to minimize uncertainty.
- Quantifying uncertainties in predictions, accounting for measurement noise, material variability, and model limitations.

A preliminary dataset will be built before the beginning of the PhD, and will be updated during the project using CMPhy's 4-methods probe (BN, EC, IP, HA), an ultrasound sensor and tensile testing machines. The candidate will collaborate with industrial partners to design experiments and validate models on real-world steel samples.

Missions principales / Main Tasks:

1 Development of Predictive Models:

Objective: Design and implement models to predict mechanical properties (e.g., hardness, residual stress) from multimodal magnetic and ultrasonic signals. First, applied strain will be studied as mechanical properties, then mechanical hardness will be estimated.

Approach:

Explore a range of modelling techniques, including:

- AI-based models (e.g., neural networks, transformer architectures).
- Physics-informed models (e.g., hybrid models combining domain knowledge with machine learning).
- Bayesian models (e.g., Gaussian processes for uncertainty-aware predictions).

Use the pre-existing database of calibrated measurements to train and validate models.

Collaborate with CMPhy to refine the understanding of signal-property relationships.

2 Optimization of Input Acquisition:

Objective: Identify the most informative signals and acquisition parameters to minimize uncertainty in predictions.

Approach:

- Perform sensitivity analysis (e.g., Sobol indices, Morris method) to determine which signals (e.g., Barkhausen noise, incremental permeability, Eddy current, harmonic analysis of tangential magnetic field and ultrasound) and parameters (e.g., frequency, amplitude) contribute most to prediction accuracy.
- Validate the protocol through experiments on steel samples with known properties.

3 Quantification of input signals Impact on Model Accuracy

Objective: Establish a quantitative link between input signals (type, number, acquisition parameters) and the accuracy of model predictions (precision, robustness, uncertainty). The goal is to develop a methodology for selecting which signals to acquire based on a desired prediction accuracy, while optimizing cost and acquisition complexity.

Approach: Sensitivity Analysis of Input Signals: Assess the impact of each type of signal (e.g., Barkhausen Noise, Eddy Currents, Incremental Permeability, Ultrasonic Signals) on prediction accuracy.

Use sensitivity analysis methods to quantify the contribution of each signal to model accuracy.

Evaluate the influence of acquisition parameters (e.g., frequency, magnetic field amplitude, probe orientation) on prediction quality.

Estimate prediction uncertainty based on the signals used: Use Bayesian methods or Monte Carlo simulations to propagate uncertainties related to input signals (e.g., measurement noise, material variability).

Map uncertainty as a function of signal combinations and their acquisition parameters.

Example: If only Barkhausen Noise is used, the uncertainty in hardness prediction is ±10%. By adding Incremental Permeability, this uncertainty drops to ±4%.

Timeline for the 3-year PhD:

Year 1
- **Literature review** (state-of-the-art in multimodal NDT, uncertainty quantification, and predictive modeling).
- **Preliminary modeling**: Test simple models to establish baselines. First, for applied stress estimation then for mechanical hardeness estimation

Year 2
- **Advanced model development**: Implement and compare AI-based (e.g., neural networks), Bayesian, or hybrid models.
- **Uncertainty analysis**: Begin integrating uncertainty quantification (e.g., Monte Carlo, Bayesian inference).

Year 3
- **Uncertainty quantification**: Finalize framework for estimating prediction confidence intervals.
- **Optimization**: Select optimal input signals/parameters to minimize uncertainty.
- **Validation**: Test models on industrial steel samples and compare with ground truth (e.g., tensile tests, hardness measurements).

Preliminary state-of-the-art

Song et al. [1] have shown how to predict mechanical properties from microstructure and material composition, using a multimodal (2 inputs: image and tabular) deep-learning model, applied to composite material only. Transformer based approach are developed in [2] to estimate missing properties (elastic tensor, bulk modulus) from multimodal information (charge density, crystallography and text information). Also, Bayesian based methods are used in [3] to estimate strength from multimodal information (composition, grain size, etc.) and takes care of uncertainties. Papers [4,5] demonstrate the use of deep-learning approach to estimate mechanical steel properties.

Références bibliographiques / Bibliography

[1] S. Lei, W. Donglei, L. Xuwang, Y. Aijun and L. Zhendong. 2023. « Prediction of mechanical properties of composite materials using multimodal fusion learning ». Sensors and Actuators A: Physical 358:114433. https://doi.org/10.1016/j.sna.2023.114433.

[2] V. Moro, C. Loh, R. Dangovski, A. Ghorashi, A. Ma, Z. Chen, S. Kim, P. Y. Lu, T. Christensen and M. Soljačić. 2025. « Multimodal Foundation Models for Material Property Prediction and Discovery ». Newton 1 (1): 100016. https://doi.org/10.1016/j.newton.2025.100016.

[3] J. Chen, D. Ersoy and Y. Liu. 2020. « Probabilistic bulk property estimation using multimodality surface non-destructive measurements for vintage pipes ». Structural Safety 87:101995. https://doi.org/10.1016/j.strusafe.2020.101995.

[4] L. R. Botvina , M. R. Tyutin, V. P. Levin, A. V. Ioffe, Y. S. Perminova and D. V. Prosvirnin. 2021. « Mechanical and Physical Properties, Fracture Mechanisms, and Residual Strength of 15Kh2GMF Steel for Oil Sucker Rods ». Russian Metallurgy (Metally) 2021 (4): 546-58. https://doi.org/10.1134/S0036029521040066.

[5] D. Ren, W. Chenchong, W. Xiaolu, L. Qingquan and X. Wei. 2023. « Building a quantitative composition-microstructure-property relationship of dual-phase steels via multimodal data mining ». Acta Materialia 252:118954. https://doi.org/10.1016/j.actamat.2023.118954.

Profil demandé / Applicant profile

The ideal candidate has a Master degree and/or an Engineering degree in Physics, Signal processing or Materials. Candidates with majors in AI are welcome to apply.

The candidate must have:

- Good understanding of materials and instrumentation.
- Good understanding of Modelization techniques, Machine-Learning and Deep-Learning
- Knowledge in NDT techniques.

Required skills:

- Background in data analysis, modeling, or NDT techniques.
- Proficiency in Python.
- Good written and oral English.

Preferred skills:

- Knowledge of machine learning, Bayesian methods, or optimization.
- Experience with experimental design or instrumentation.
- Familiarity with uncertainty quantification.
- Knowledge in: Experimental design, Design of Experiment

Personal qualities:

- Autonomous, rigorous, and team-oriented.
- High motivation for applied research and industrial collaboration.
- Enthusiasm for experimentation, instrumentation, teamwork, and capability of independent problem-solving.
- Eager to disseminate research results through publications and presentations at both academic and industrial international conferences.

Funding: ANR (Project LabCom OPTEND) Applications before 15/06/2026 Position start: 1er Octobre 2026 Salary (gross): **2200€ per month**
Direction de la thèse:/ **Thesis Supervisor** Patrick Marquié Stéphanie Bricq
Encadrement de la thèse : **Technical supervisors** Hermine Chatoux Baumeyer Julien
Please send the following documents by email to Hermine Chatoux (Hermine.chatoux@ube.fr) by June 15th: - CV - Cover letter - Academic transcripts - At least 1 reference letter or reference contact