Abstract

The growing complexity of modern engineering problems has increased the demand for accurate and reliable numerical simulation tools. In the context of Finite Element (FE) methods, 3D formulations can provide highly detailed results, but computational costs emerge as a significant limitation, especially for large-scale or more refined analyses. In contrast, reduced-order structural models, such as 1D and 2D formulations, offer a computationally efficient alternative, but restrictive assumptions often limit their ability to capture more advanced phenomena. Their accuracy strongly depends on a proper selection of the used theory. Despite their efficiency in terms of computational overhead, the lack of general selection criteria, combined with the need for problem-specific adjustments, have significantly hindered their widespread adoption beyond classical formulations.

This thesis explores the integration of Machine Learning (ML) techniques to improve the selection and optimization of reduced models, aiming to fully exploit their computational efficiency without compromising predictive accuracy. In particular, the study focuses on the Axiomatic/Asymptotic Method (AAM), a methodology designed to compare and evaluate the performances of structural theories formulated using different numerical approximations. The AAM traces its origins to historical developments in structural modeling, which have led to the definition of a wide range of 1D and 2D formulations over the past decades. The outcome of the AAM is the definition of optimal numerical formulations, referred to as Best Theories, that can provide the best accuracy for a fixed number of unknown variables involved. Although effective, the AAM becomes computationally prohibitive due to the exponential growth in the number of formulations that can be defined, especially when dealing with descriptions based on high-order series expansions.

This work proposes an ML-based approach, leveraging Convolutional Neural Networks (CNN) to drastically reduce the computational costs of the AAM. Using the Carrera Unified Formulation (CUF) as the theoretical framework, the proposed work systematically evaluates the generalization capabilities of CNNs in predicting optimal model formulations across a wide range of structural configurations and types of analyses. The crucial role of problem-dependent parameters on the importance of individual terms adopted in the formulation is investigated thoroughly, with the objective of laying the foundations for a versatile and reliable ML-based tool that can guide the design process of numerical simulations.

The study focuses on 1D and 2D structural models, specifically beam, plate, and shell formulations. The proposed methodology is assessed through static, free-vibration, and dynamic response analyses, considering multiple evaluation criteria. The objective is to establish a broad validation framework that ensures the effectiveness and adaptability of the proposed approach across different structural behaviors and applications.

A further contribution of this research is the extension of ML-assisted optimization to more advanced modeling techniques, such as those involving variable kinematic descriptions across the FE mesh. In the context of Node-Dependent Kinematics (NDK), the selection of distinct structural

theories for different elements or nodes introduces a new layer of optimization, allowing for enhanced accuracy in critical regions while avoiding unnecessary computational overhead. However, the high dimensionality of possible distributions and theories to adopt makes traditional brute-force optimization infeasible, further motivating the use of ML techniques.

The research findings demonstrate that ML-driven theory selection and optimization of reduced models offer a viable and scalable alternative. By training CNNs on a small subset of the total theory space, it is possible to predict optimal formulations with high reliability, significantly reducing the burden of procedures like the AAM. The obtained results can be used to lay the groundwork for a new paradigm in FE modeling, with ML facilitating the use of advanced yet computationally efficient reduced 1D and 2D models.