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Machine Learning Surrogate Model for Sensitivity Analysis in Hot Stamping

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Abstract

The role of simulation in the sensitivity analysis studies is crucial due to the need of exploring the parameter space without perturbing the real manufacturing system. In hot stamping, the initial conditions, the setup parameters and the materials properties form a wide domain. The configurations within the domain have a direct impact in the thermomechanical phenomena and the material phase transformations occurring during hot stamping. Therefore, many simulations are required for extensive sensitivity analysis and optimization studies during the design stage to ensure the desired mechanical properties in the final parts. However, the elevated cost in time and computational resources of these simulations and the high dimensionality of the domain is an important limitation. The aim of this work is to present a pipeline to overcome this drawback, with a Machine Learning based surrogate model of the simulation of the hot stamping of a hat-shaped part of boron steel. Moreover, a comparison between a Latin Hypercube Sampling and a Forward Selection method is implemented to show the sampling importance in surrogate modeling. The introduced methodology is an enabler to boost the sensitivity analysis and optimization procedures, due to the fast response of the surrogate model estimations. The proof-of-concept results show high potential in the soft-real time prediction of unseen configurations within the domain, focusing on important variables regarding the mechanical properties and the quality of the final part, such as the temperature and the martensite content.

1 Introduction

Simulations in hot stamping play a fundamental role in the design stage and prototype testing, where they offer an effective way for the product development, decreasing the waste of materials, the wear of the tools and the overall costs. Commonly, finite element (FE) method has been employed to model the mechanical, thermal and microstructural phase transformation phenomena taking place during the hot stamping process [1]. Despite the increase in computing resources, the high-fidelity simulation models have also increased their complexity. This still supposes a high time expense, being unfeasible to apply these models during the real-time production.

In recent years, the paradigm of Industry 4.0 has enabled a digitalization process of the industrial plants and a concept of data-driven manufacturing with the introduction of Artificial Intelligence (AI) in the industrial framework has emerged [2]. Machine Learning (ML) is one of the AI-based tools that has been extensively used in different manufacturing processes and scenarios [3]. Focusing on the process of hot stamping, some recent works have also employed ML approaches to tackle problems of interest of this topic. For instance, supervised ML algorithms have been used for the prediction of the thickness of the formed parts [4] or to classify the microstructure of after the forming [5], and Reinforcement Learning (RL) have been applied to control and optimize the hot stamping cycle time [6]. An important contribution of ML techniques is their application in building surrogate models (SMods). SMods are metamodels that have arisen to overcome time limitations of high-fidelity simulations. The main objective of SMods is to provide a faster response than the simulation model, approximating the function that relates the inputs with the outputs. SMod plays the same role than the simulation model, but providing a simpler representation of the system, achieving a reasonable accuracy but boosting a lot the response time [7]. ML-based SMods have proved their potential in manufacturing in optimization, sensitivity analysis and uncertainty quantification.