Graph Neural Network-Based Surrogate Model of Hot Stamping Finite-Element Simulations

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Continuous material monitoring during manufacturing processes is of upmost importance for both process control and materials design. The objective of this work is to create a Graph Neural Network-based Surrogate Model to predict the behavior of the materials during the manufacturing process of hot stamping. The proposed approach provides a faster and more sustainable way to generate data in soft-real time, which is unfeasible with Finite-Element simulations and supposes a high cost in real industrial plants.

The establishment of Industry 4.0 (I4.0) has contributed to identify *data* as one of the most important assets in manufacturing. In fact, among the changes driven by the paradigm shift of I4.0, we can remark the transition to a data-driven manufacturing thanks to the exploitation of data and the introduction of Artificial Intelligence-based solutions [1].

However, the data acquisition from manufacturing systems is not an easy task. On the one hand, an investment is required to deploy sensors and software in industrial plants. Furthermore, performing tests supposes an expense in human resources, raw material, time and the use of the production plant to non-fruitful operations. On the other hand, high-fidelity Finite-Element (FE) simulations overcome the drawbacks of the industrial plants but imply a high time and computational cost.

Some of the most innovative technologies of I4.0 demand fast and sustainable data generation in manufacturing, such as the Reinforcement Learning (RL) application in autonomous control agents [2] and Digital Twins (DTs) for a complete virtual representation of a manufacturing system [3]. The feasibility of these technologies is subjected to a fast response model, able to produce large volumes of data in a reduced time.

To address this challenge, data-driven Surrogate Models (SMods) have shown remarkable results in boosting the response of a complex simulation model [4]. They are metamodels that describe the system in a simpler but representative way. Recently, the application of Machine Learning (ML) techniques in this field have lead to the popularization of ML-based SMods. Several studies have tackled the most common challenges and have identified the main categories of problems where SMods are employed [4, 5].

Despite a lot of algorithms have been used in surrogate modeling, one of the latest innovations in the introduction of Graph Neural Networks (GNNs) [7] to create SMods. GNNs can capture dependencies thanks to message passing between neighbors. The main advantage of GNNs lies in that they do not have limitations regarding structure, since the modeling and the learning is based on the graph nodes and edges. GNNs have been successfully implemented for the prediction of complex physical phenomena [8]. Focusing on FE simulations, GNNs for surrogate modeling is a hot topic to model different problems [9,10].

In the context of hot stamping, this process is of crucial importance for the automotive industry, being commonly used to manufacture high-responsibility automotive parts. Historically, FE simulations have been fundamental in the modeling of hot stamping. However, nowadays there is a high interest in implementing digital solutions such as RL agents and DTs to improve the process, due to the need of reducing the economic and environmental impact testing new lightweight materials, increasing of efficiency of the process and ensuring the production quality and traceability. Therefore, the creation of SMods in hot stamping to enhance the response time FE models is needed. In [11], a Convolutional Neural Network (CNN) approach is presented for the prediction of geometrical features of the final part such the thinning field. Another example is presented in [12], where the phase fraction of the final hat-shaped part is obtained training to a Fully Connected Neural Network (FCNN) as SMod, using the element histories of simulations to extract the input features of the FCNN, allowing to avoid the phase content calculations in the simulation reducing the computational time and cost. In [13], a ML-based SMod predicts the final temperatures in specific points of the sheet and the die during the different batch cycles of a steel sheet hot stamping line.

The mentioned works focus on the prediction of properties of the material or variables of the process, and the SMods perform a prediction of the final output variables of interest given some inputs. Nevertheless, the mechanical, thermal and microstructural phase transformation phenomena happening during the forming and quenching are not modeled although they play an important role to determine the final state of the material. Therefore, the aim is to create a GNN-based SMod of the hot stamping process able to model the heat transfer problem that occurs during the hot stamping cycle. Concretely, in the studied use case, the SMod predicts the temperature evolution of a DIN 1.2344 die and an austenized 22MnB5 blank in time. The training and test set are generated with ABAQUS FE simulations. The results show that the SMod can be used as a more efficient simulator than ABAQUS FE simulations, since it generalizes under different initial conditions and predicts the whole temporal evolution in a fast and accurate way, enabling the development of DTs or RL control in hot stamping.

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Figures

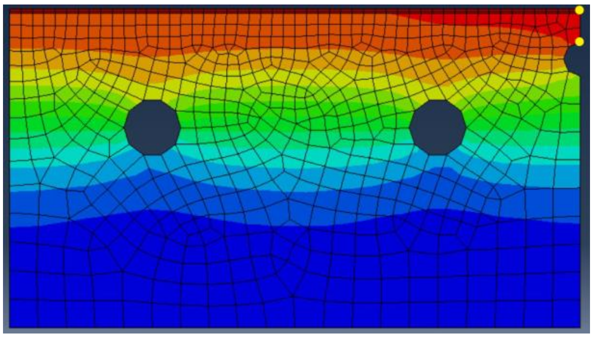

Figure 1. ABAQUS Finite-Element Mesh representing temperature distribution for a given time step of a hot stamping simulation.

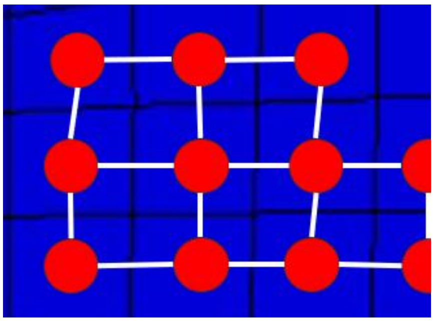

Figure 2. Construction of the graph from FE mesh. Elements of the simulation are established as nodes of the graph and the edges of the graph relate neighboring elements.

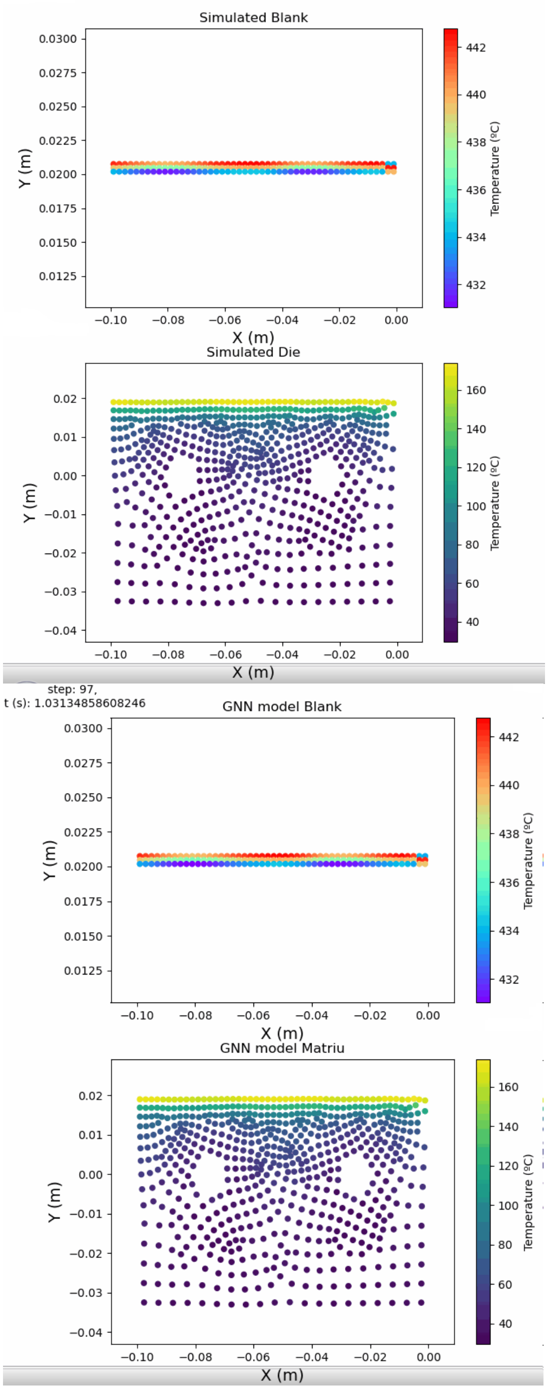

Figure 3. Upper figure: Temperature distribution in the elements of the blank and the die in t = 1.03 s with ABAQUS FE simulations. Lower figure: Temperature distribution in the elements of the blank and the die in t = 1.03 s predicted by the GNN-based SMod.