Digital twins and predictive AI-based inspections for quality control

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Abstract

As of today, limited transparency concerning the quality characteristics of components manufactured at suppliers' sites results in costs and inefficiencies for focal firms. This paper analyses a possible scenario in which digital twins of each produced component are created and the potential of Artificial intelligence (AI) is leveraged for predictive inspections. Here a possible use-case is presented, where the assembly cost between stator units and a designed cooling jacket is predicted in real-time via an inverse FEM-based Deep Learning framework to provide a possible evaluation criterion for the inspection, allowing to detect pairing fails at early stages and leading to potential savings.

Keywords

Quality control, Digital twins, FEM-based Deep Learning

1. Introduction

Quality control is a critical function in manufacturing industries to ensure that the final products meet the required quality standards. It involves a systematic process of monitoring, testing, and verifying the quality of raw materials, production processes, and finished products to identify defects and prevent their occurrence. Furthermore, accurately estimating quality characteristics can facilitate transparent data-sharing between suppliers and customers, mitigating potential drawbacks such as customer dissatisfaction, complaints, and pseudo-scraps. One of the most common methods of quality control in manufacturing industries is inspection, which involves visually examining the final product to identify any defects or deviations from the required quality standards. Inspection can be performed manually or using automated systems, and it is essential to ensure that the final product meets the required quality standards. However, inspection has limitations in detecting hidden defects and doesn't provide a direct evaluation of the final functionality of the product.

The objective of this paper is to propose a solution to achieve an exhaustive data-sharing with digital twins of product units while providing functional inspections to predict mechanical behaviours in real-time, leveraging AI methods such as FEM-based Deep Learning (DL) approaches.

A digital twin is a virtual representation of a physical system that mutually exchanges information with it [1]. The representation of the digital twin is strictly related to the application, and in the context of quality control, it must contain all the necessary information for the inspection, relying on measurements gathered by real sensors. Furthermore, the digital twin is updated many times along the production line to comprise measurements and production parameters at different phases, allowing for potential inference on quality characteristics.

On the other hand, FEM-based Deep Learning approaches are data-driven methods that allow to efficiently perform Finite Element Analysis in real-time by training Deep Neural Networks (DNNs). The neural networks will undergo training using a dataset generated with FEM simulations, in which each sample is related to a specific experiment on a pre-defined task where input data represents the applied boundary conditions and output data constitute the resulting outcome. The deep learning model is trained to exhibit the capability of predicting simulation outcomes for unexplored experiments, i.e., generalizing beyond the training set of the dataset. Once the model has been trained, it could be exploited to make real-time predictions in inference, contributing to the

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evaluation of quality inspection.

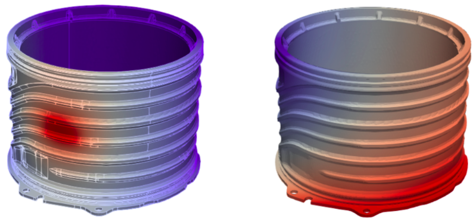
2. Related works

One popular class of FEM-based Deep Learning approaches relies on Physics Informed Neural Networks (PINNs) [2],[3],[4], that include both the data and the assumed governing Partial Differential Equations (PDEs) during training. This approach confers a potential advantage in that a reduced volume of data may suffice for the purposes of training, an attribute of considerable significance for numerous data-driven applications. It is worth noting that despite the lack of explicit imposition of physics during the training phase (non-PINN scenario), it remains possible to recover said physics in the trained model through implicit adherence to an extensive corpus of training data. For example, [5] trained different regression models with FEM data to predict the deformation of the human soft tissue, [6] proposed a data-driven method based on a U-Net architecture that approximates the non-linear relation between a contact force and the displacement field computed by an FEM algorithm, [7] developed a Bayesian multiscale CNN framework to predict local stress fields in structures with microscale features. [8] provides a probabilistic U-Net framework that is able to capture all the uncertainties present in the data and the model.

3. Use-case

Here a possible use-case of predictive quality inspection in the context of e-motor mounting is presented. The aim is to inspect stator units and determine their compatibility for assembly with a designed cooling jacket, detecting stators that would lead to pairing fails and predicting optimal heating patterns to apply on the cooling jacket to achieve the assembly.

The assembly process involves expanding the cooling jacket via heat treatment and consequently inserting the stator inside. This means that the cooling jacket should be thermally expanded according to the shape of the stator to fit the insertion, and the heat treatment has to be predicted to check feasibility and find the optimal heat pattern to minimize the energy cost. To this end, we could directly predict the assembly cost in terms of energy needed to pair the two components in real-time, relying on the geometry estimation of the stator coming from its associated digital twin and exploiting an FEM-based Deep Learning model trained on the designed cooling jacket. Thus, the DL model will learn an approximated function that maps the displacement and the temperature distribution on the cooling jacket that characterise the thermal expansion. Furthermore, by just swapping inputs with labels we can easily learn the inverse function, namely the one that maps a displacement field with the temperature distribution that causes it. This implication will associate the simulation with the class of inverse FEM problems. Making some assumptions on the heating treatment that could depend also on physical hardware, we can restrict the domain of all possible boundary conditions that can be applied, generating a distribution from which to sample dataset instances. Just to give visual feedback, figure 1 reports a qualitative result of an FEM experiment computing the temperature and the displacement distribution assuming a localized heat pattern. A Deep Learning model like the one proposed by *A. Mendizabal et al.* [6] can be used for the purpose of this application, adapting the task to the thermo-mechanical case. As the geometry of the cooling jacket yields in the three-dimensional space, to tackle the inefficiency coming from the 3D convolutions of the U-Net, the input could be also represented as a graph, extrapolating the volumetric mesh of the cooling jacket already used for the FEM simulation. This could simply involve replacing the U-Net architecture with its counterpart designed to handle graphs: the Graph U-Net proposed by *H. Gao and S. Ji* [9].



a) Temperature distribution b) Displacement (magnitude) distribution

Figure 1: Resulting temperature (a) and magnitude of displacement (b) distribution on the cooling jacket coming from a single FEM simulation assuming local heating patterns.

4. Conclusion

This essay has investigated the potential of leveraging AI to make advanced inspections for quality control. A possible scenario forecasts an exhaustive data-sharing between customers and suppliers about quality characteristics of product units in the context of the manufacturing industry, leading to potential savings coming from pseudo-scraps detections at early stages. As a use case, an inverse FEM-based Deep Learning model has been hypothesized to predict assembly feasibility between cooling jackets and stators for the production of e-motors, saving costs associated with inefficient assembly procedures and potential pairing failures.

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