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Framework of an experimental setup to enable an adaptive process control based on surrogate modelling

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Abstract
Numerical simulations can help to reduce the necessity of experimental studies. Nevertheless, these simulations are costly in terms of their computational effort resulting in significant expenditure of time and hence prevent a flexible adaption to continuously changing process conditions in real time. To address this shortcoming, the paper describes a framework for the application of surrogate models to enable an adaptive process control in real time. Following, an experimental setup to validate the general framework is designed for a laser metal deposition process. In particular, the component distortion shall be simulated and the results are then used to train the surrogate models. By measuring the final component distortion the quality of the surrogate models can be assessed.

Keywords: adaptive process control, additive manufacturing, in-situ, surrogate modelling

1. Introduction

The increase in available computing capacity is creating new possibilities for designing and optimising manufacturing processes. For example, the implementation of data-driven methods, like the usage of Machine Learning (ML) models, is gaining more and more interest for industrial processes [1]. These models can be trained from real recorded data, but also from the results of simulations, namely surrogate models (SM) [2]. Due to the time involved, simulations are usually carried out before the actual manufacturing process and optimal parameters are derived. Only little attention can be paid to changing production conditions as long as they are not already included in the simulation.

This study aims at developing a general framework to use the surrogate modeling approach to enable an adaptive process control (APC) facilitating an adjustment of machining parameters with regard to changing production conditions. Furthermore, an experimental setup is designed to validate the framework. The setup is created for a sample process in the field of additive manufacturing, precisely for a laser metal depositions (LMD) process.

2. Generic Framework

The core of this paper is to enhance adaptive process controls for existing machine tools for subtractive or additive manufacturing technologies. In order to address the aforementioned challenges that arise with this undertaking in an universal way, the authors of this paper see the need to introduce a generic framework that enables the users to implement the method of surrogate modelling into APCs.

The generic framework is shown in figure 1 and can be divided into two main components, namly the hardware and the software component. In the following two sections these components will be examined in more detail.

2.1. Hardware component

The focus of the hardware component mainly lies on the programmable logic controller (PLC) as well as the sensors of the machine tool of interest. The PLC is responsible for controlling the machine tool by ensuring that processes within the machine are executed in a correct way. For ensuring that programs are executed in a predefined way it can adapt relevant machining parameters. In order for the PLC to function accordingly within the proposed framework, it is required to be able to communicate with external software within the Digital Twin (DT).

The sensors' task on the other hand is it to accumulate data from the real production processes. The information that is produced can be used to ensure that certain process steps function in the intended way. In order to be able to choose the right sensors and hence acquire the right data, it is fundamental to know the cause-effect-relationships within the process to be monitored. The data builds the input for the SM.

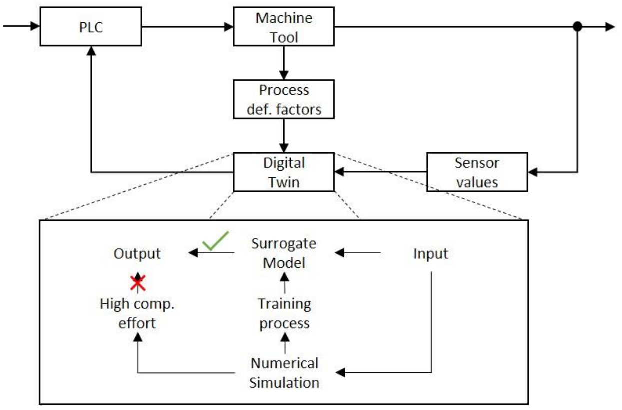

Figure 1. Generic framework for enabling adaptive process control based on surrogate modelling

2.2. Software component

The software component is represented by the Digital Twin which in the context of manufacturing has no unique definition. For this paper the DT will be defined as “digital representation of an active unique product“ [3]. As one major component, it comprises numerical simulations of the relevant manufacturing processes that enable a detailed knowledge about the processes and their optimal parameters. Nevertheless, due to their high computational effort, numerical simulations are not suitable for real-time applications and hence, cannot be used for APCs.

One possible method to address this shortcoming is the use of surrogate models which approximate computational expensive simulations through the use of sample data [4]. SMs can be build through a three step process consisting of a design of experiments (DoE) of the numerical simulation, surrogate model fitting as well as the model validation [5]. Within the DoE different machining parameters are generated which are then used as input data for the numerical simulation. The simulation itself leads to data points characterizing the manufacturing process which in the next step can be used to train the chosen SM type. Eventually, the SM has to be checked regarding its accuracy.

The validated SM receives the input data from the sensors and calculates an output which is then send back to the PLC.

3. Experimental Setup

The general framework, described above, can be used for various manufacturing processes enabling a faster and less complicated approach of predicting optimal manufacturing parameters without using time-consuming numerical simulations. The framework shall be tested in an experimental setup, which is designed for a LMD manufacturing process. The planned test construction is described in this chapter starting with the simulation and the derived SMs.

3.1. Simulation and Machine Learning model

The setup consists of a simulation of a LMD process, serving as a basis for the SM to be trained. Via simulating the built process, information can be provided about the final component distortion based on the part geometry and the temperature induced by the laser layer by layer. In order to reduce the complexity of this investigation, simple artefact types in the form of disks are simulated. A ML model is trained with the results of this simulation to approximate its statements. Therefore, a Gaussian Process (GP) model can be used since those models are well suited for non-linear regression problems and already provided promising results in similar trials [1, 2, 6, 7]. Those GP models shall enable a location-dependent quantification about the present distortion. The simulated process can then also be carried out on a manufacturing machine, receiving concrete information about the actual production process and the resulting component distortion.

3.2. Manufacturing machine and parameters

The experiments are carried out on the TRUMPF TruLaser Cell 7020 depicted in figure 2 which is used for repair and modification of components.

In order to investigate the functionality of the trained models, different manufacturing conditions are simulated and experimentally proven. Therefore, the conditions are varied regarding the injected laser power, the scan speed and the layer number of the built-up component. The combination of laser power and scan speed represents the energy per unit and has a significant impact on thermal strain [7]. As mentioned previously, continuously measured process parameters represent the input for the trained SM to enable a quantitave statement about quality relevant product characteristics. As a simplification for this experimental setup only the characteristics will be predicted, but no adjustment of process parameters via the PLC will be performed in this first step. The surface temperature of the current build-up layer is used for this purpose. Based on the measured layer temperatures the SM predicts the final distortion.

Figure 2. TRUMPF TruLaser Cell 7020 located at the FRAUNHOFER IPK

3.3 Validation based on component quality

The distortion predicted by the SM can then be compared with the distortion according to the simulation result as well as with the actual existing distortion of the manufactured components. For this, a 3D scan of the final part is taken, leading to a point cloud, which enables a quantification of the actual distortion along the whole part geometry. Relative errors of the predictions of the simulation and the SM can then be calculated and compared to each other to assess the quality of the SM.

4. Conclusion and Outlook

This paper introduces a framework for designing advanced APC through the use of SMs. Firstly, the framework is explained for the generally valid use in machine tools for additive and subtractive manufacturing. Secondly, an experimental setup for a LMD process is described that functions as use case for the application of the framework. However, the practical deployment of the framework in the LMD process has not been performed yet and will be subject of future works.

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