QUALITY CONTROL OF ADDITIVE MANUFACTURING USING STATISTICAL PREDICTION METHODS

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Abstract

Additive Manufacturing (AM) is increasingly used to design new products. This is possible due to the further development of the AM-processes and materials. The lack of quality assurance of AM built parts is a key technological barrier that prevents manufacturers from adopting. The quality of an additive manufactured part is influenced by more than 50 parameters, which make process control difficult. Current research deals with using real time monitoring of the melt pool as feedback control for laser power.

This paper illustrates challenges and opportunities of applying statistical predictive modeling and unsupervised learning to control additive manufacturing. In particular, an approach how to build a feedforward controller will be discussed.

Keywords:

Additive manufacturing, Process control, Predictive modeling, Predictive control

1 INTRODUCTION

Additive Manufacturing (AM) is increasingly used to design new products. This is possible due to the further development of the AM-Processes and materials. The less of assurance of quality of AM built part is a key technological barrier that prevents manufacturers from adopting Am technologies especially for high-value applications where component failure cannot be tolerated [1]. The lack of quality implies inadequate dimensional tolerances, surface roughness, embedded material discontinuities, and defects. Part quality issues may be attributed to AM process parameter settings. The settings are typically chosen by a trial and error process, which is time-consuming. More and more modeling is used to get a deeper understanding of the physics of AM process. Significant effort has been dedicated to the search of predetermined optimal processing conditions which result in desired mechanical properties for a given part. This optimization can be done with commercial modeling packages, mostly based on finite element methods. However, this approach is not economical nor robust enough to deal with perturbations. Uncertainty in the simulation inputs and simplification of physical phenomena lead to uncertainty in the process parameters and thus the optimization is less beneficial. [2] [3]

Process control in general can limit the lack of quality assurance of AM built parts and the lack of the known variance of optimized process parameter from physical models.

This paper will discuss a new approach to using metamodel technologies to enable process optimization, to improve the AM part quality and to reduce the number of insufficient AM parts. The main goal is to reduce the waste of time and money by either detecting major errors of the AM part in a very early stage and stop the building job or fixing an expected defect during the build process by changing process parameters.

2 STATE OF THE ART

Using additive manufacturing to build a part with certain desired properties such as dimensional accuracy, part density, mechanical properties or microstructures can be challenging for several reasons. First, the number of parameters that have to be determined in an AM process is large. Second, some parameter can vary during the build process. For example, the porosity of powder bed may change depending on the distribution of the powder size particles in a layer. Third, some parameter could vary across builds, for example, if the lens focusing the laser beam gets polluted. Finally some material properties such as the absorptivity cannot be known precisely. In conclusion, these factors introduce uncertainties that influence the repeatability of the process and create uncertainties in the properties of the AM parts [4].

2.1 Process parameters correlation

The view on process parameter correlation follows the ideas of Mani et al. [5]. In an AM process there exist correlations between the process parameters, process signatures and product qualities. The AM process parameters are the inputs, which sometimes determine with uncertainties. The process parameters can be categorized either in controllable such as laser power and scan speed or predefined parameters. For example, material properties are predefined for every build job. The process signatures are dynamic characteristics of the powder heating, melting and solidification processes as they occur during the AM process. They are categorized into either observable that means measurable signatures or derived and determined from analytical modeling or simulation. The product qualities are also grouped in geometric, mechanical and physical qualities. Figure 1 identifies the correlation between the three categories which should facilitate the development of in process sensing and real-time control of AM process.

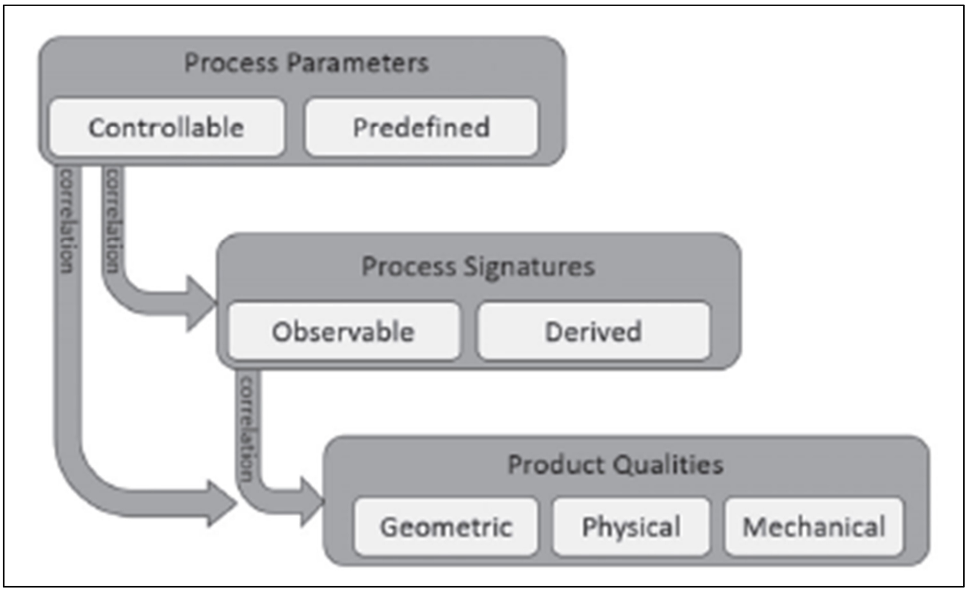

Figure 1: Correlation between process parameters, process signatures and product qualities [5].

Mani et al. identified a large number of process signatures which may potentially be monitored to identify irregularities that might result in poor product quality [5].

The basic idea as given in Figure 1 is categorizing the parameters and identification of their general relationship. This is used as foundation for the described models in chapter 3.

2.2 Computational models

Process signatures that cannot be measured during production, need simulation models for derived parameters like melt pool deep or residual stress. A number of scientific investigations were devoted to the numerical analysis of the thermal processes during laser beam melting. One of the studies was conducted by Ilin et al. [6]. This study focuses on the numerical analysis of the temperature distribution in the vicinity of the melt pool during laser beam melting process depending on the local geometry of the generated part. They use a simulation model to optimize the laser beam melting technique towards a stable formation of the melt pool during the entire generating process.

Commercial simulation tools allow predictions of the temperature during the build process and can therefore be used to forecast the distortion and residual stresses in the AM part. Normally these predictions take not into account the uncertainty of the input parameters or the variability in the process itself.

Running these simulation tools is a preliminary work for the optimization of process parameters like laser power or laser scan speed. It is possible to calculate with these simulations tools several controllable process parameters like the needed laser power, laser scan speed etc. These values can be calculated for every position on every layer. Because of the long computing times, it is not possible to use this kind of technology during the build process to control the process parameter.

2.3 Current control schemes in AM

Process control has been identified as an important tool to overcome the lack of quality and reliability in AM processes. Feedback control allows the intelligent modulation of process parameters following measurements of process signatures. Feedback control approaches for AM are often utilized in directed energy deposition processes. Most approaches are based on thermal signals gathered with cameras and photodetectors. The typically used algorithms are based on proportional-integral derivative (PID) controllers [3] [7]. Sometimes more advanced approaches, like model predictive control (MPC), are used. The feedback control is used with process signatures which are measurable or with derived signatures. A feedforward control is used for tuning the laser cladding melt pool shape online [8]. Adopting feedback control methods in AM is constrained by significant barriers. One is the lack of appropriate models for online estimation and control as well as the high sampling rates required to capture fast solidification dynamics in metal based AM.

3 RESEARCH APPROACH

The use of statistical methods will be useful to handle the process control in AM systems. Normally an AM process, for example, the selective laser melting (SLM) process, depends on about 50 parameters [9]. Some parameters are precisely known, other parameters have a higher variance. To manage the process control with predictive modeling two hypotheses must be valid. First, an effective direction must be existent in the process. This means small defects in layer n lead to errors in future layers n+y. Every AM part is sliced in layers. y is the number of layers that have been built until the known defect at layer n becomes a crucial defect at layer n+y, which in turn damages the AM part (see Figure 2). The second hypothesis implies a different significance of the layers. Not every layer has the same importance for future layers. The previous layer is most important for the following one. Former layers are less important.

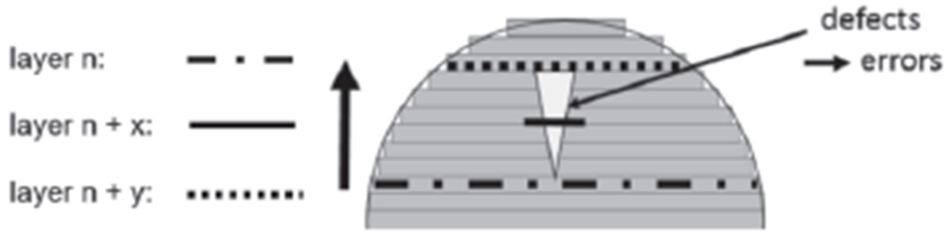

Figure 2: Hypothesis error spread.

A single layer is generated during one laser scan. A layer itself is divided in cubes. Every cube has the height of the layer thickness and the area is the square of the track distance + variance. A cube as defined here may contain more than one voxel. It is important that all dimensions of the cube relate directly to process parameters as illustrated in Figure 3.

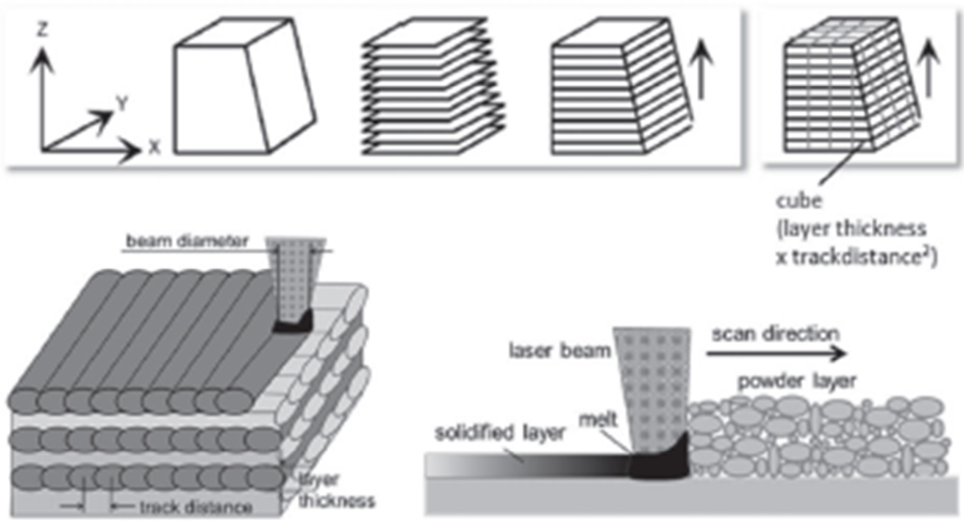

Figure 3: Geometry with cubes, voxel and laser beam.

The basic idea is to detect a situation that will lead to a potential low-quality piece, before the situation itself happens. Practically this means small deviations in layer n lead in summary to a relevant error in layer n+y. After detection of small defects, the parameters might be adjusted in layer n+x to avoid the error in n+y, assuming x is smaller than y. Therefore it is important that calculation time for forecasting errors from the data volume must be shorter than the time for production from layer n until layer n+x.

3.1 Predictive models in general

Predictive modeling is used to estimate an unknown dependency from known input-output data. Input variables might include quantities of different process parameters by a cube. Output variables might include an indication of the level of a cube of whether a defect happens or not. Output variables are also known as targets in predictive modeling.

In deployment, there is likely to be a time gap between using the model that has been developed and carrying out the activity. The analysis period consists of the base period (for the input variables) and the aim or target period (for the target or output variables). The base period always comes before the target period and reflects the time gap between running a model and using the results of the model (Figure 4) [10].

Figure 4: Development of models learning phase.

To visualize how the general set up can be used for AM processes the model learnings phases are added to the research approach.

Depending on former activities, an anticipation of the deployment time gap (y) can be made. Then a temporal mismatch can be added into the modeling data. This is crucial, because input variables such as geometry, laser power or melt pool temperature are generated for every layer until layer n and target variables generated e.g. out of the melt pool temperature are from a later period, say layer n+y. Note that the time period (y) may differ depending on the type of the AM process, AM machine or material.

This temporal mismatch of variables is a major difference to other statistical models and to the above-described state of the art solutions. It is possible that the measurement of some parameter until layer n is used as input variables and adding the measurements at layer n+y to define the target variable. Besides the temporal shift in the data, the availability of the data also needs to be considered.

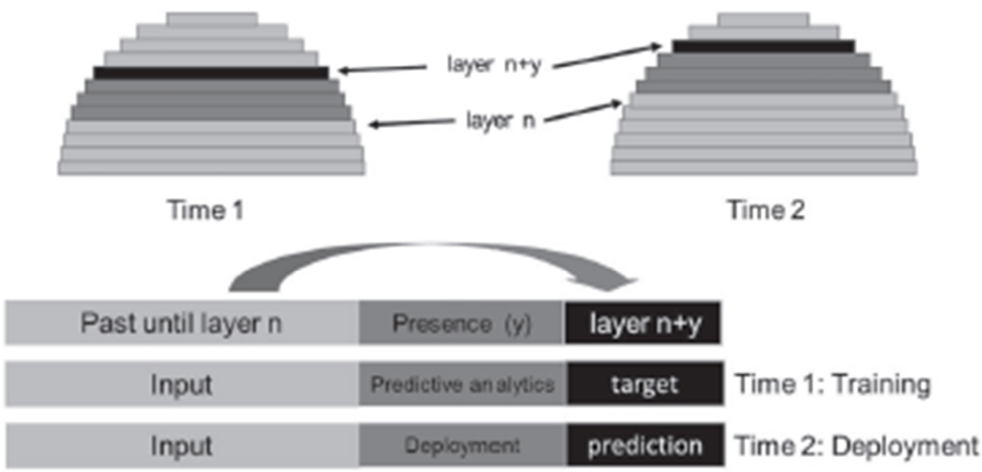

Figure 5: Phases in AM process.

It is to consider that at one point in time (Time 1) the model has to be built, at that time the target must be known. The whole input and target data are given from the past. After the model is validated it will be deployed at time 2 when only input variables are assessable. Within this deployment, a prediction of the target is generated. The prediction in turn gives an answer on the question whether the target is leading to a potential defect or the quality of the AM part is fine. Once the model is validated and established it can be also used for time 3, time 4 and so on.

4 PRAGMATIC WORKFLOW

To incorporate this knowledge and technology to a solution, which provides the opportunity to control and react on upcoming defects in any AM-process, the following workflow is defined. In general the Finite Element Modeling (FEM) and two metamodels (I and II) will be employed. The Finite Element Modeling is used to generate data for an ideal situation. This data will be used to build a simplified metamodel (I) that can be used to regulate the process to avoid potential future defects. Afterwards the likelihood of having a potential future defect is calculated by metamodel (I).

For phase time 1 following pre work has to be done.

- Define measurable outcome parameters, which show the optimum scope for results.
- Development and usage of relevant design of experiments (DOE).
- Data generation by DOE. Data that leads to good AM parts and data represent bad or defected parts are generated.
- Identification of potential standard parameters for a simplified metamodel (II) for deviation correction.
- Computer simulation (FEM) to identify the ideal outcome parameter per cube/per layer.
- Build a second metamodel (I) based on the data generated in the simulation. The aim of the model is to find a simplified and fast equation to estimate the outcome parameters as good as possible.
- As input parameters only machine parameters and known physical equations are accepted.

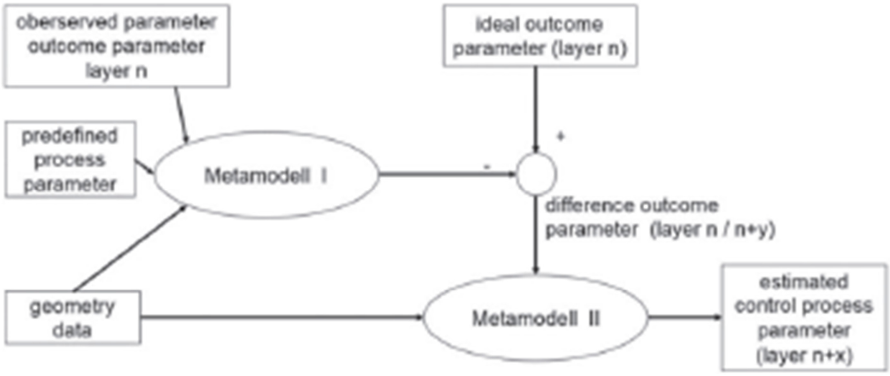

Figure 6: Deployment predictive control process.

Based on the workflow the following predictive control process can be developed.

Figure 6 shows the control process:

- Step 1: Start with calculating the ideal outcome parameter (p_{ideal}) for every layer and cube with use of metamodel (I). Can be done before starting the building process itself in the preparation phase.
- Step 2: With metamodel (I) outcome parameters ($p_{(n+\text{y})}$) of layer n+y based on the actual measured data until layer n are estimated.
- Step 3: Compare the ideal outcome parameter (p_{ideal}) with estimated outcome parameter ($p_{(n+\text{y})}$).
- Step 4: Calculate differences and correct some process parameter at layer n+x with the help of metamodel (II).
- Step 5: Use the corrected process parameter at layer n+x

The amount of layer x depends on the time for calculation and adjustment of the process parameter. This time must be less or equal compared to the time needed for production from layer n to n+x.

5 CONCLUSION AND OUTLOOK

The development of metamodels can be used to implement simple calculation rules for AM-process. Ideal outcome parameters $p(n+\text{y})$ for every cube in a layer can be estimated easily for different forms and geometries. The measured data until layer n and estimation of outcome parameters $p(n+\text{y})$ lead to a change in process parameter at layer n+x. This in turn leads to a better part quality and therefore to enormous time savings.

Based on this approach a controlling of the production process will be possible. A next step will be to evaluate the applicability of the theoretical concept described in this paper. The concept must be proven in an industry environment together with industrial partners.

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