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Prescriptive Analytics - A Smart Manufacturing System for First-Time-Right Printing in Wire Arc Additive Manufacturing using a Digital Twin

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Abstract

First-time-right printing is needed for extensive industrialization of Wire Arc Additive Manufacturing. However, due to process instabilities defects can occur even if suitable process parameter were chosen, resulting in production scrap due to an insufficient part quality. In this paper, we propose a smart manufacturing system which enables the compensation of previously created defects by means of a Digital Twin. We predict the future position of the welding torch, analyze its spatial context and adapt the process parameter if needed accordingly to compensate defects. Using this approach, a fault-tolerant manufacturing process is enabled, resulting in a first-time-right process.

Keywords: Digital Twin; Wire Arc Additive Manufacturing; Smart Manufacturing; Prescriptive Analytics; Process Control; First-Time-Right Printing

1. Introduction

In aerospace industry, large-scale metal parts are commonly manufactured by milling, resulting in a buy-to-fly-ratio of up to 10 and thus in a waste of resources. By means of additive manufacturing (AM), this ratio can be decreased and near net shape parts can be produced. Wire Arc Additive Manufacturing (WAAM) is an AM technology which is capable of printing such large-scale metal parts while at the same time being cost effective. The process is based on a wire as feedstock and an electric arc as heat source. The material is deposited along a multi-axes toolpath to create the final part.

To industrialize Wire Arc Additive Manufacturing (WAAM), first-time-right printing must be achieved. However, currently, it is needed to optimize process parameters in a trial-and-error approach for every part [1]. If a new part with complex geometry is printed, several iterations are needed first. Additionally, along the process, uncertainties are present. Due to changing environmental and thermal conditions or pollutions in the feedstock material, the substrate or the inert gas flow, a defect could occur, resulting in production scrap and high costs.

To handle these defects, a fault-tolerant process must be created. Therefore, the system must be aware of the manufacturing context to adapt process parameters accordingly in an autonomous fashion.

In this paper such a smart manufacturing system is presented. It is capable of predicting future steps in the manufacturing process, of analyzing the spatial context of the predicted positions and of adapting process parameters accordingly to compensate already existing defects or to avoid follow-up defects. Hereby, a fault-tolerant process is created, enabling first-time-right printing even in case of uncertainties.

The remainder of the paper is structured as follows. In chapter 2, the background and related work is presented. Chapter 3 is dedicated to the methods and the setup of the system. The smart manufacturing system is presented and the use of the digital twin for the prescriptive analytics is shown. In chapter 4, the results are presented and discussed. Finally, chapter 5 concludes the paper and proposes future directions of research.

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2. Related Work and Background

WAAM is a manufacturing process which is based on arc welding. Thus, common defects in WAAM can also be found in welding, such as porosity, cracks, lack of fusion, burn trough, discontinuity, slag inclusions, humping effect and oxidation [2, 3, 4, 5].

These defects can be detected by using a process monitoring setup to analyze the current process state. For instance, Xu et al. proposed a monitoring setup based on several sensors to obtain information about the process quality [6]. Chen et al. investigated multisensory information fusion in welding [7]. Zhao et al used a combination of spectrum and vision to monitor the WAAM process [8].

In WAAM, the creation of defects depends not only on the current choice of process parameters but also on the surrounding. Certain defects can propagate over several layers [9]. For instance, oxidation defects result in slag and lack of fusion in the subsequent layer. Lack of fusion causes an interruption in the heat transfer which could result in a burn through due to a heat accumulation in the following layer. Discontinuities might be created due to a humping effect and could propagate over several layers.

In order to analyze the surrounding, Reisch et al. proposed a method for providing spatial context [10]. It's using an Octree in order to create a digital representation of the part. According to the definition of Kritzinger et al. [11] this can be regarded as a Digital Shadow as the digital representation mirrors the physical world but doesn't interact with it. A Digital Twin instead uses a bidirectional communication channel to adapt the real world according to the optimization objective. A Digital Twin is usually focusing on models and data, while the cyber physical system provides actors and sensors as backbone to interact with the real world [12, 13]. By combining both, a smart manufacturing system can be created which is one of the main objectives of Industry 4.0 [14].

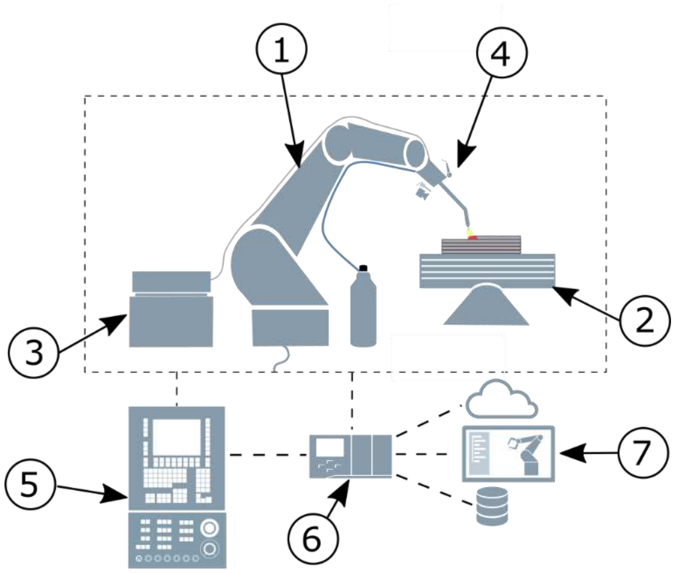

Figure 1 Scheme of the smart manufacturing system for WAAM. It includes a robot (1), a tilt-turn table (2), a welding source (3), a sensor setup for monitoring (4), a control unit (5), an edge device (6) and a human-machine-interface (7)

Based on such a smart manufacturing system, prescriptive analytics can be achieved [15]. Instead of analyzing only what happened (descriptive) and why it happened (diagnostic), prescriptive analytics builds on top of the question what will happen (predictive) to decide on what to do (prescriptive).

3. Methods

In the following, first the smart manufacturing system which was used for the prescriptive analytics is presented. Afterwards the steps to conduct the process parameter adaptions are described. Finally, a test methodology is presented.

3.1. Smart Manufacturing system for WAAM

The smart manufacturing system consists of seven parts as shown in Figure 1. The kinematic setup is based on a six-axes robot (1) with a two-axes tilt-turntable (2). The welding process is enabled by a welding source (3). The WAAM process is monitored by a sensor setup (4) including voltage and current sensor, welding camera, spectrometer, structural acoustic sensor, microphone, and gas flow sensor. For further details on the monitoring setup, the reader is referred to a previous publication of the authors [4]. The kinematic as well as the welding equipment is controlled by a numerical controller (5), which is connected to an edge device (6). The edge device is handling the data from the sensors and analyzes them. Additionally, it provides a live stream enriched with information about the process to the machine operator or the quality engineer via a human-machine-interface (HMI) (7). The edge-device is connected to the control, the sensors and the HMI using OPC UA and industrial ethernet protocols. Additionally, a data bus based on MQTT is set up in order to enable 1-to-n connections within a micro service software architecture. A connection to the internet is enabled to allow remote access to the machine and to a digital twin which is created on the edge device in process.

The digital twin consists of five main modules:

1. System adaptors enable the data exchange with external entities such as sensors, actuators, other edge devices or controls.
2. Process monitoring services analyze the incoming data and the current digital representation to enrich the data with semantic information about the process and the part. For instance, anomalies are detected, and defects are classified.
3. The Digital Shadow obtains a digital representation of the part and the process. The part representation is based on an Octree as introduced in the background chapter. It enables the search for spatial context.
4. The process adaption services decide on when and how to adapt the manufacturing system in order to ensure a secure manufacturing process which results in high quality of the final part.

5. Visualization services provide the machine operator and quality engineer with relevant information about the process to enable human-machine interactions.

The Digital Twin is based on a bidirectional communication with the physical manufacturing system.

3.2. Prescriptive Analytics

Using the Digital Twin, a prescriptive analytics approach is followed in order to adapt the process parameters if necessary. Hereby, defects can be compensated, and follow-up defects can be avoided.

Along the manufacturing process, the sensor data is analyzed and synchronized with the tool center point (TCP) position. The obtained information is stored in the part representation of the Digital Shadow using spatial indexing. In this study, especially the defect type and the anomaly score are of interest. The latter one is computed using the neural network for anomaly detection proposed in [10] and will be referred to as Anomaly Score (AS). The AS is normalized between 0 for 0% and 1 for 100% defect probability respectively. In our study, the defect classification is conducted based on the AS. If the AS exceeds a certain threshold T_D, the datapoint is marked as defect.

During an active print, a look-ahead method predicts the TCP position which will be reached within a certain prediction time. Using the predicted TCP position, its spatial context is analyzed to obtain information about defective areas in the proximity. In case of adjacent defects, a countermeasure is initiated.

A detailed view on the TCP position prediction, the spatial context analysis and the data driven decision making is presented below.

3.2.1. Prediction of TCP position

The prediction of the TCP position enables the system to evaluate what comes next in the process as shown in Figure 2. Based on the current TCP position x_0 in the process, the current welding velocity vector v_{TCP} and the prediction time $t_{prediction}$, an approximation of the future TCP position x_{pred} is computed using interpolation:

$$x_{pred} = x_0 + v_{TCP} \cdot t_{prediction} \tag{1}$$

In case of short prediction times and straight tool paths, this results in a sufficient positional accuracy of the prediction. However, in case of complex path patterns and dynamic TCP movements, it would result in severely wrong approximations of the future TCP position. For that reason, the machine code is considered during the prediction. Based on the current position, the closest point in the machine code is selected. This can be done for instance by comparing the real toolpath to the planned one using dynamic time warping which is an algorithm to compare sequences of values with different length [16]. It is recommended to interpolate between the single points in the machine code toolpath beforehand to obtain a higher positional accuracy in finding the correct point in the machine code.

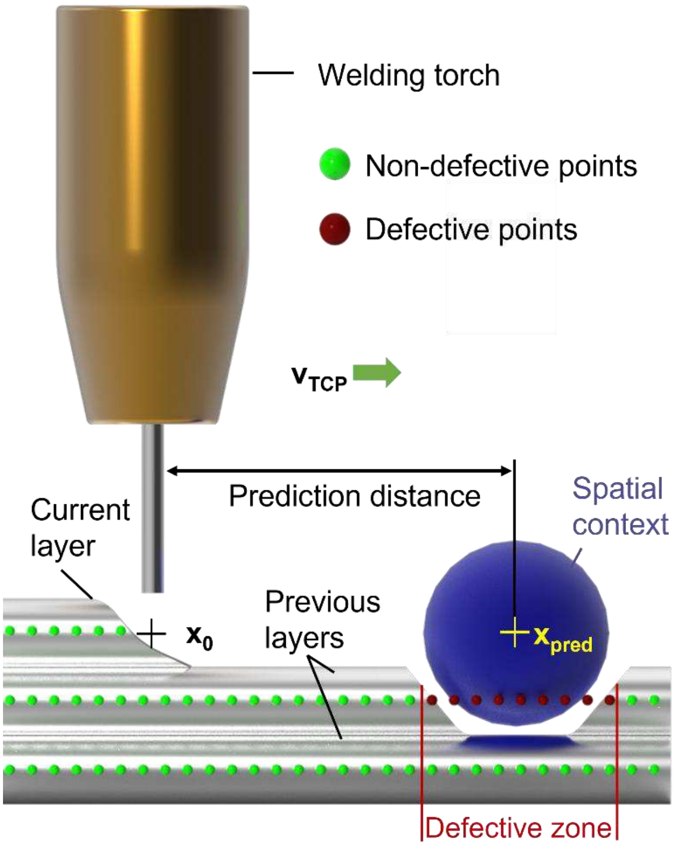

Figure 2 Scenario for the prescriptive process parameter adaption. Around the predicted TCP position x_{pred}, the spatial context is analyzed to obtain information whether a process adaption must take place.

Using this point, the subsequent machine code lines are evaluated in order to predict the future TCP position based on the prediction time. The prediction time must cover the latencies for data processing and transfer as well as the reaction time t_{System} of the system.

3.2.2. Spatial context query

In WAAM, the process is not only affected by the point below the current TCP but also by the surrounding. Thus, the spatial context of the predicted TCP position x_{pred} is evaluated in order to detect defective points in the proximity as visualized in Figure 2. The Digital Shadow is queried using a geometrical form which defines the spatial relevancy. This geometrical form can be for instance a double-ellipsoid to model the weld bead geometry or - in a simpler version - a sphere.

To ensure that all datapoints of the underlying layer are included in the spatial context, the dimension of the geometrical form must extend over the layer height h which is defined in the tool path. Additionally, to take the discretization of the positional data into account, the sample rate f and the welding velocity must be considered. The size of a sphere as spatially relevant context is defined by the radius R, which is calculated by means of the following equation:

$$R = k \cdot \sqrt{h^2 + \left(\frac{v_{CTP}}{2f}\right)^2} \tag{2}$$

The factor k depicts a security factor in the order of 1.05 which ensures a slightly bigger radius than the minimum usable value. For the use of double-ellipsoids in the scope of spatial context queries, the interested reader is referred to [10].

As result of the spatial context query, all datapoints located within the spatially relevant area around x_{pred} are retrieved. Every datapoint includes not only the positions of the voxel but also information about corresponding anomaly scores or defect types.

3.2.3. Data-driven decision making

The system decides on a suitable process parameter to adapt and to which extent the adaption should take place. To ensure an informed decision making, the obtained datapoints are analyzed as the adaption depends on information about the severity of the defect, the relative location of defective voxels to the future TCP position and the defect type. The sample implementation tested in this study focuses on the compensation of discontinuities in the weld track as shown in Figure 4.

If no defect is apparent, no parameter adaption takes place, and the process goes on as planned. If there is a defect, the datapoints are analyzed more in detail. On the one hand, a low T_D value increases the controller's sensitivity, in the worst case resulting in undesired compensations due to false positives. On the other hand, a desensitized controller is not capable of recognizing defects thus allowing discontinuities to propagate over several layers.

Defective datapoints can be located either directly below the future TCP position (directly affected) or with an offset (indirectly affected) as shown in Figure 3. According to the position of the defective datapoint, we can derive two compensation strategies. Underlying discontinuities are to be remedied through the variation of welding velocity. By reducing this parameter, a higher deposition rate can be achieved locally thus closing the gap formed in the work piece. Similarly, a wider weld track aims for the compensation of discontinuities parallel to the current tool path. This can be accomplished by increasing the wire-feed rate during the process.

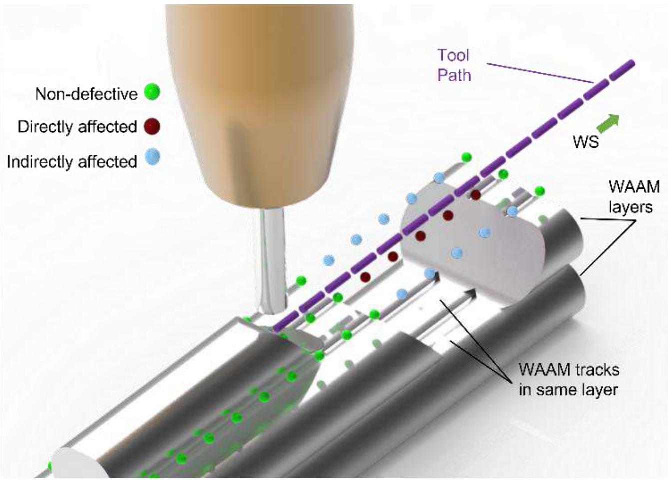

Figure 3 Positions of defective datapoints. They could be located below the tool path (directly affected) or not below the tool path (indirectly affected) within the relevant spatial context.

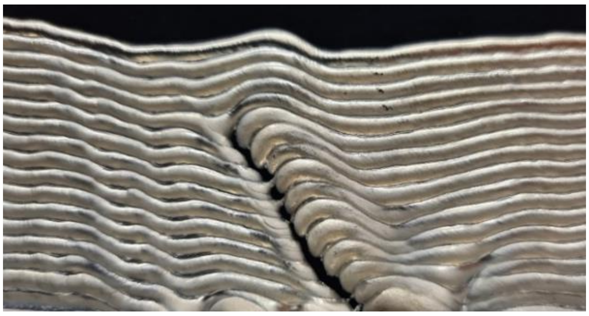

Figure 4 Sample of a discontinuity which propagated over several subsequent layers. The defect was compensated in the 14th layer.

The severity of the defect is obtained by computing the mean AS of the directly affected and the indirectly affected datapoints. Depending on the obtained value, the parameter is adjusted proportionally.

The chosen parameter adaption is initiated in the correct moment. It is important to consider the latencies and the reaction time t_{System} of the system. Ideally, the parameters are adapted at the beginning of the defective zone in order to fill the material gap of the discontinuity.

3.3. Test methodology

The proposed methodology for prescriptive analytics is tested by evaluating the compensation success in case of discontinuities.

In total 85 thin walls with 10 layers each were built. In every experiment, in the first two layers, a discontinuity was artificially induced by severely reducing the wire feed rate in the middle of the wall. This resulted in a propagating discontinuity as shown in Figure 4.

Starting from the third layer, the prescriptive controller was activated. Hence, defects could only be compensated starting from this layer. The effectiveness of the parameters set was measured by the number of the layer, in which the discontinuity was compensated. This will be referred to as layer of success (LoS). The earlier the defect was detected and compensated, the higher was the controller's effectiveness. For proper tuning of the controller, ten combinations of T_D and t_{System} were tested. Based on preliminary tests, T_D was oscillating within a range of 0.30 to 0.35 and t_{System} did not exceed 1.5 s. For each parameter set, six test geometries were built. For validation purposes, 25 walls without prescriptive controller were built.

4. Results and Discussion

The results of the tests can be seen in Table 1. Experiments, in which the discontinuity was not closed until the 10^{th} layer were marked with an LoS of >10, implying total failure in compensating the defect.

The median value for the LoS of each parameter set is listed on the right column of the table and is used to rank the overall performance of the controllers.

Table 1 Results of the prescriptive analytics to compensate discontinuity defects for potential process control parameter

Adaption parameter		Layer of success (LoS)										
T_D	t_{System}	3	4	5	6	7	8	9	10	>10	Σ	Median
-/-	-/-	-	-	-	-	-	1	3	3	18	25	>10
0.35	0.3	-	-	-	-	1	2	1	1	1	6	8.5
0.35	0.8	-	-	1	1	1	1	-	2	-	6	7.5
0.35	1.0	-	-	-	-	1	-	2	1	2	6	9.5
0.325	1.0	-	-	2	-	2	1	1	-	-	6	7.0
0.325	1.2	-	-	2	-	-	1	-	2	1	6	9.0
0.31	1.0	-	2	1	3	-	-	-	-	-	6	5.5
0.31	1.2	-	-	-	2	-	4	-	-	-	6	8.0
0.31	1.5	-	1	1	-	-	4	-	-	-	6	8.0
0.30	1.0	1	3	1	1	-	-	-	-	-	6	4.0
0.30	1.2	-	1	2	2	1	-	-	-	-	6	5.5

First, the robustness of the defect creation is evaluated. In 72.0% of all experiments without prescriptive process parameter adaption, the discontinuity was propagating to a layer greater than 10. In 96.0% of all cases, the defect propagated at least until the 8th layer. Thus, the defect creation can be regarded as robust.

Using the prescriptive process parameter adaption, the defect propagated to the 10th layer and above in only 6.7% of all experiments. In 76.7% of the experiments, the defect was compensated in or before the 8th layer.

When comparing the different control parameter combinations, a high value of T_D resulted in a worse compensation capability. In these cases, the sensitivity of the defect detection was reduced, resulting in false negatives in the defect detection. Thus, the prescriptive process parameter adaption was not initiated, resulting in the high median LoS. Instead, a lower T_D increased the sensitivity of the defect detection, resulting in fewer false negatives. The prescriptive controller was compensating the defects accordingly. However, in case of a value of T_D lower than 0.3, a high number of false positives was present. The system was not stable anymore as the prescriptive controller interacted with the WAAM system permanently.

In regard to t_{System}, it is all about the right timing. If t_{System} is set too low, e.g. 0.3 s, the system adapted the velocity too late, resulting in a low compensation capability as the material gap could not be filled sufficiently. On the contrary, long reaction times over 1.5 s resulted in premature parameter adaptions resulting in a failure of compensating the defect. As the WAAM process is commonly using a welding velocity between 300 mm/min and 800 mm/min, a t_{System} of 1.0 s results in a positional offset of 5.0 mm to 13.3 mm. In case of Titanium as feedstock material, the positional offset could be even higher due to the higher welding velocities.

Condensed, the best results were seen with $T_D = 0.30$ and $t_{System} = 1.0$ s for the discontinuity defect. The median LoS was at 4 and the system was able to compensate a defect even in the first possible layer.

5. Conclusion

In this paper, a fault-tolerant Wire Arc Additive Manufacturing process is enabled by proposing a smart manufacturing system which uses a digital twin to avoid and compensate defects. The method for prescriptive process parameter adaption predicts the future tool center point position and analyzes its spatial context. In case of a defect in the proximity of the predicted position, the system initiates a countermeasure. In 93.4% of all cases, the prescriptive process parameter adaption was successful in compensating a discontinuity defect. Further research should be conducted about several aspects of the present work. For instance, precision of the process parameter adaption could be optimized, e.g. by including additional sensor values and such as a wire stick-out measurement [1]. Furthermore, the method could be transferred to additional defect types such as pores, oxidation, and form deviation.

Acknowledgements

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