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Procedia CIRP 00 (2019) 000–000

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9th CIRP Conference on High Performance Cutting

A statistics based Digital Twin for the combined consideration of heat treatment and machining for predicting distortion

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Abstract

This paper introduces a novel concept of Digital Twinning of heat treatment and machining for predicting distortion. A set of physical experiments were conducted, and statistical models based on these trials were created. The experiments involved heat-treating AA7075 billets with multiple input conditions and measuring distortion during machining trials. This trained a Gaussian Process machining model to reproduce the real-life behaviour of a part, and to predict distortions. These predictions matched the shape and magnitude of data points of the trials. The paper suggests further refinements of the model. The developed statistical tool enables distortion prediction to produce right-first-time parts.

Keywords: Predictive Model; Distortion correction; Machining

1. Introduction

Manufacturing process modelling tools are already having significant impact on the optimal design of advanced manufacturing processes, such as the use of forming models that allow residual stress distributions to be optimised, or machining models that simulate part machinability, distortion and dynamic stability [1-5]. However, these models assume a constant operating condition of the process. In reality, processes have variation of input conditions and environmental and operational disturbances such as material properties or equipment condition, changing the behaviour of machining processes. This means that existing models cannot take the next step of in-process control without dynamically, adapting to the specific conditions of each part.

This article discusses the investigation of a statistics based dynamic process model for digital twinning of heat treatment and machining processes. For this article, the authors refer to the term digital twin as a digital copy of the physical system to perform real-time optimisation [6]. Every part that passes through the manufacturing process carries its own unique set of model parameters. This work focuses on part machinability and in-process distortions. Data was monitored from the heat treatment and machining processes of AA7075 to help to understand distortions occurring through bulk residual stresses. The material, aluminium AA7075, was selected due to its susceptibility to distort sufficiently under typical machining conditions. The data informs models which can run in real time and drive predictions, which in turn drive heat treatment and machining parameters (toolpath). This study provides a strong case for further research into in-process dynamic models that apply active automatic learning, to optimise multi-stage manufacturing processes.

2. Experimental Procedure

A refined experiment was conducted using water quench medium. Quenching in water, induces high thermal gradients, through rapid quenching [7]. Subsequently, this creates large distortions. It was decided to carry out the aluminium heat treatment, varying conditions from high to low while keeping the quench medium constant. To build a full story behind the water quench method, the quench temperature, orientation of quenching, and the time in the furnace was recorded. AA7075 aluminium alloy was selected to be used for the full experiment, due to its susceptibility to distort sufficiently under typical machining conditions [8]. The high thermal gradients produced after quenching, produces distortion and residual stresses within the part. When initially quenched, the part surface rapidly cools, creating a hard outer shell, which constrains the inner contracting region, and undergoes tensile plastic deformation. After further cooling, the surface is subjected to compressive stresses, and the inner region is in tension [9].

Typical heat treatment conditions for this material include, soaking in a furnace at a solution temperature of 466 °C, and then quenching in water [10]. The soaking is required to bring all the alloying elements into solid solution at the respective temperature, to homogenise the material. Warm water is recommended for quenching aluminium parts, to reduce residual stresses. Depending on the orientation of the parts, the residual stress magnitudes and distribution may be altered for parts with higher aspect ratios. Due to the quenching sensitivity of the material, the quench delay was kept below 5 seconds. Table 1 details the experiments. The data collected would be input into the analytics model, and a signature of the heat treatment processes, along with a combination of machining and metrology data can be discovered.

Table 1. Experimental plan for aluminium trials which were heated in a furnace at 466 °C.

Experiment No.	Soak Time (minutes)	Quench Temperature (ºC)	Quench / heating Orientation
1_3.5HRS_10DEG_V	210	10 – 20	Vertical
2_3.5HRS_50DEG_V	210	50 – 60	Vertical
3_1.75HRS_10DEG_H	105	10 – 20	Horizontal
4_3.5HRS_50DEG_H	210	50 – 60	Horizontal
5_1.75HRS_10DEG_V	105	10 – 20	Vertical
6_3.3HRS_10DEG_H	210	10 – 20	Horizontal

The parts were heat treated at the AFRC in a Carbolite furnace GPC 12/131. The chamber dimensions are 500 x 350 x 750 mm (W x H x D) with a volume of 131 Litres.

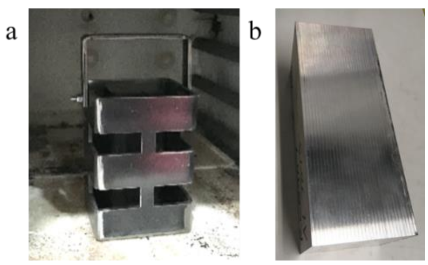

Fig. 1. (a) AFRC heat treatment basket; (b) Material prior to machining

For the horizontal heat treatment, the parts were placed on blocks within the furnace. To allow the parts to be heat treated vertically, a basket (Fig. 1 (a)) was designed and used to place these parts into the furnace, where it was held at a temperature of 466 °C. At this stage of the project, the parts were 200 x 75 x 75 mm.

After being heated in the furnace, the part was quenched in water, which was agitated. The water quench tank used has a capacity of 1000 Litres.

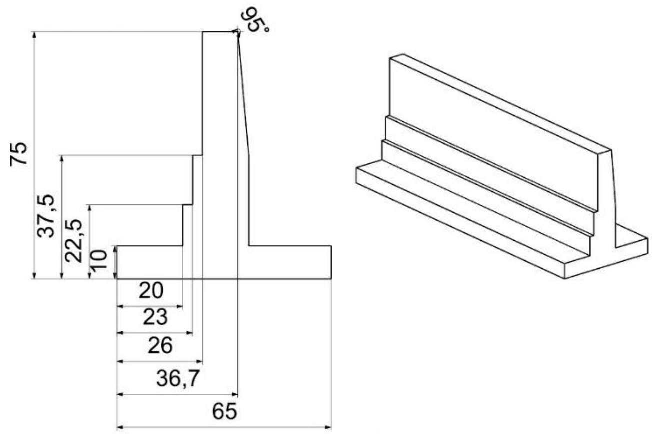

Fig. 2. Cross section of the geometry selected

Each part was then machined to the drawing shown in Fig. 2, using a 44 mm diameter Sandvik face milling cutter. All parts were machined using HOCUT 4260 coolant. A surface speed of 600 m/min and feed rate of 0.15 mm/tooth was selected to machine the parts. Each toolpath was a straight cut from one end of the part to the other (see Fig. 3) with a radial depth of cut of 60% of the tool diameter, and an axial depth of cut of 2.5 mm. The left-hand side from Fig. 2 was machined first, and then the right hand side was machined. This was the strategy for all parts in the experiment.

The machine tool used was the DMG MORI HSC 75, which is a 5-axis milling machine using linear drives in all directions allowing increased speed, accuracy and accelerations of up to 2 kg. This is suited for high-speed machining.

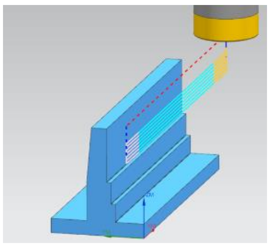

Fig. 3 Cutting strategy

The CAM program was created in Siemens NX® manufacturing suite and was then verified with the machining simulation package Vericut®, to eliminate any risk of collisions during machining.

During the machining, each part was probed using MSP software, to check in-process distortion (Figs. 4a and 4b). The probing cycles were carried out in the same locations for each part. Areas of particular interest were the top faces, and the top of the walls, as these are known areas of high distortion. The probing cycle was created using the G54 which was located at the bottom right corner, which can be seen in Fig. 3. The probe points were then compared to the G54 location, which was selected as the reference for the part.

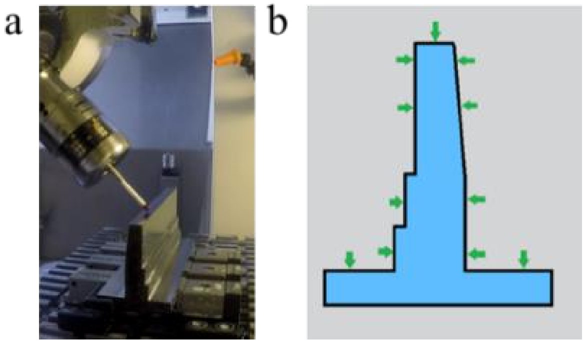

Fig. 4. (a) On-machine probing; (b) Probing locations along the length

The data analytics model was created using Gaussian Processes to represent the manufacturing process. This method is suited for the practice of machine learning models [11]. It is a non-parametric process, and the model relies on the observed data only. This method is efficient and well-tested for approximating and interpolating unknown non-linear relationships within data [11], and quantifies uncertainty in the model predictions. Accuracy improves typically with the number of data available.

Learned models to predict post process observations, from process factors, were implemented using MSP probing data. The predictions span the entire 3D surface of the machined part.

For efficiency reasons of the project, the following assumptions were made for the model:

- No control/baseline experiment without treatment
- No replicates to determine experimental noise
- No intermediate factor settings to detect curvature in relationship
- No probe measurements at the left or right side of the part

3. Results and Discussions

3.1. Data Analytics Model

The data analytics model was created using bespoke software written in Python, using the Numpy/Scipy libraries. It was written in this way due to the rich structure of the multi-process manufacturing data. It was based on the in-process probing of the part during machining. Aluminium trials were carried out. Five of the experiments detailed in Table 2, were machined to produce observations of a multi-process manufacturing value chain for the analytical model, rather than for empirical results of their own. The data was used to evaluate the model using leave-one-out cross-validation. It was trained on (N-1) experiments and validated on 1 experiment a total of N times. The model served two purposes: firstly, the model helps with the identification of optimal parameters based on the initially collected data. The model helped in identifying the optimal time for soaking, the best quench temperature and quench orientation, to reduce the predicted distortion across the part. The optimal soak time, quench temperature and quench orientation computed through from the model was 105 minutes, 34.7 ºC. This was quenched in a vertical orientation. Fig. 5 illustrates this for optimal calibration, where the most distortion occurs along the darkest red region.

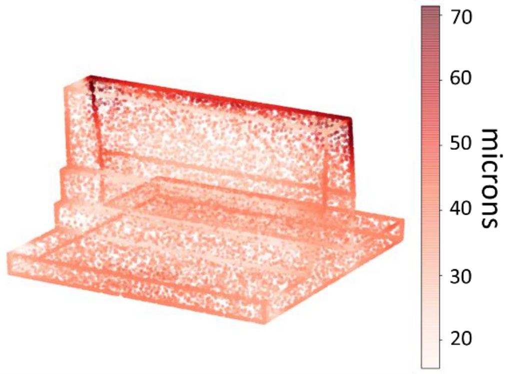

Fig. 5. Calibrate model using input data and machine learning to output optimised parameters

Secondly, the model can be used to predict the post-machining distortion. This can be extremely beneficial in industry that seeks to produce products "right-first-time" under varying input conditions. The model helps the manufacturing engineer to understand how the part will distort before any physical machining. On a regular modern laptop computer, the evaluation of a trained model takes only milliseconds. The model helps to avoid the long and costly trial-and-error cycles practiced currently in industry. The rapid evaluation of the model outperforms time-consuming Finite Element Modelling simulations. This aspect of the project illustrates the feasibility of adapting tool paths (or modifying machines) real-time prior to machining. Traditionally, the concepts behind adaptive machining would be to modify toolpaths on the machine during machining, as the part distortion would be illustrated after each cutting tool path. This project shows that the model can predict part distortion using the data analytics tool prior to machining. Parts do not have to undergo any physical metal removal, and a slow and risky probing iterative tool path adaptation – the tool paths can now be adapted before the part is physically machined, thus following the goal of digital twinning of heat treatment and machining.

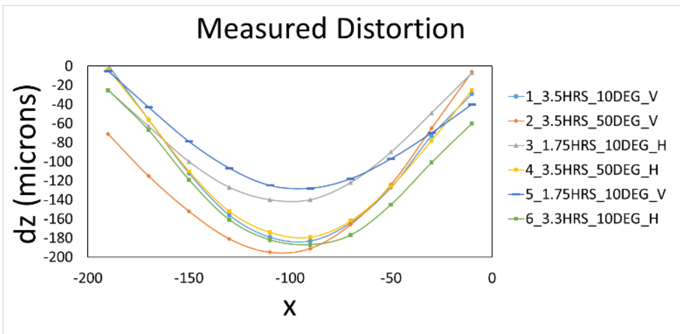

Fig. 6. Measured distortion for all machining trials

Fig. 7 illustrates the output of the data analytics model for experiment 1_3.5HRS_10DEG_V across the length of the top face. Here the measured distortion (black), against the predicted distortion (red), follows a similar shape and magnitude. A comparison of this same probe location for the other experiments can be seen in Fig. 6. The light grey lines in Fig. 7 represent the training data which were completed multiple times to update the model to perform optimally. This data would be used in understanding the shape of the toolpath needed to produce a part with a lower part distortion. This graph shows that the maximum part distortion was measured to be 175 µm.

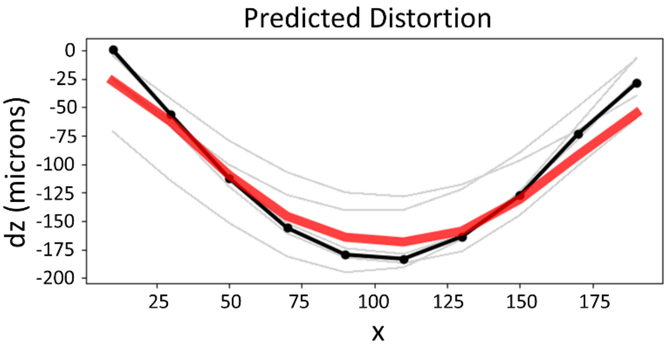

Fig. 7. Measured distortion (black) vs Model Predicted distortion (red) vs Training data (grey) for experiment 1_3.5HRS_10DEG_V

If the toolpath was adapted, or the machine was modified using model prediction, a maximum distortion of 40 µm would be found as shown in Fig. 8. This assumes no other distortion would be introduced by changing the toolpath. Fig. 8 is an interpolation based on observed attributes.

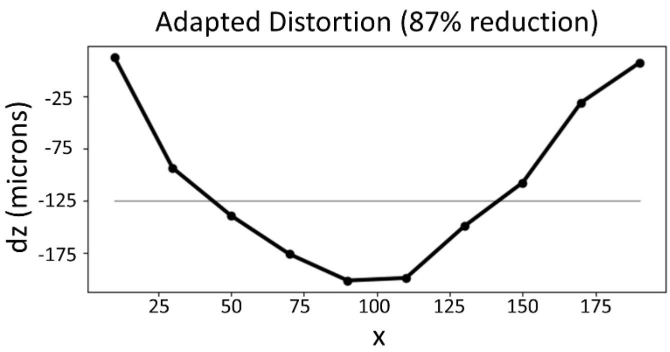

Fig. 8. Distortion if toolpath had been adapted using model prediction

Figures 7 and 8 illustrate the errors from the ground truth for a particular 1D row of MSP probes (such graphs exist for all probes across the surface of the part). X is the position along the x-axis with respect to part positioning in the machine.

The model essentially interpolates from data it has seen. Although it benefits from more data, it can still do so from very little data, albeit with a corresponding increased level of uncertainty. Analytical performance is largely dependent on the complexity of the underlying function being approximated. Given the physical constraints on part distortion in these experiments, it seems reasonable that this underlying function is not intractably complex, and can be well approximated even with few data points.

3.2. Discussion

The project produced an effective statistical model for the integrated modelling of the heat treatment and milling processes on AA7075. By reducing the distortion to <50 µm using the analytics model, this has demonstrated a feasibility of this approach. It is a fundamental first step towards a more advanced digital twin model that integrates the various complex manufacturing steps that require costly and time-consuming trial-and-error loops.

The principle of distortion after heat treatment applies to all types of metal, however, the effect is expressed on short samples, statistically more significant on aluminium rather than steel. Hence, the usefulness of the model would also apply to other materials with aluminium showing the largest effect in the experiments.

The choice of the parameter-free statistical Gaussian Process (GP) model, proved to be the feasible option for accurately describing the distortion behaviour of the aluminium samples. The number of sample data locations and points, were sufficient to train the process model. The process model is fast and accurate enough for its integration into a real-time digital twin in the future.

Gaussian Processes are data-driven, and not based on any underlying model of the physical processes. In manufacturing, they can be used empirically, by just collecting data, and are fast to train and evaluate − unlike traditional mechanistic partial differential equation models. Further, GPs are grounded in traditional mathematical statistics, and do not require the voluminous data required by many modern computational AI techniques.

Ultimately, GP are a sophisticated non-linear interpolation technique, which makes them flexible and expressive, but unlikely to work in all cases for all manufacturers. However, the work has demonstrated a first use-case where they work admirably − under modest data collection and analysis requirements.

Due to time/cost constraints it was not possible to further assess the model against held-out test data. This is an omission, but arguably not a critical one since the technical risk of overfitting is addressed by cross validation with data that is not observed by the model.

Due to time/budget constraints the predicted optimal process parameters were not experimentally verified. The supposed optimality of these parameters is not a claim of this work or, indeed, the purpose of the study. Nevertheless, the possibility to perform such an analysis is a valuable aspect of the approach and worth demonstrating explicitly.

The project shows that it is possible to consider jointly the process of heat treatment and machining in one single hybrid process model to minimise machining time and maximise accuracy through overarching joint process parameter optimisation. This approach could reduce waste and could save a significant amount of energy, as fewer scrapped parts are anticipated.

4. Conclusions

The aim of this project was to investigate a new dynamic process of digital twinning of heat treatment conditions and machining processes, using a Gaussian Process data analytics model. This work focused on part machinability and in-process distortions of aluminium alloy AA7075 to understand distortions occurring through bulk residual stresses. As the selected material was susceptible to distort sufficiently under typical machining conditions, it was ideal in applying the data analytics model. This model was designed to provide predictions on part distortions, which in turn can select heat treatment and machining parameters. Key observations of the study are detailed below:

- Parts were heat treated at different parameter sets, and subsequently machined.
- Different levels of distortion were observed in each of the experiments, using in process probing techniques
- The probing points were used to train the Gaussian Process data analytics model – the digital twin
- Measured and predicted distortion provided good correlation
- An adapted parameter (toolpath) scenario was described which produced smaller distortions
- The optimal soak time, quench temperature and quench orientation was found to be 105 minutes, 34.7 °C, and at a vertical orientation

The integration of the statistical model into a larger digital twin, that also considers digital twinning of the machining process, is now possible. This allows the testing and optimisation of a complete digitally twinned factory production run, before investing in, and machining of costly parts. In addition, digital twinning using the demonstrated approach can reduce waste, and could save a significant amount of energy.

This study provides a strong case for further research into dynamic models, that apply active automatic learning to optimise multi-stage manufacturing processes. Future work can investigate replications of the tested parameters to validate the model, and validation of the adapted toolpath. Furthermore, additional variables and multistage processes can be added to the model, to provide more robust manufacturing process data.

Future work

- Carry out replications
- Carry out validation trials on updated model

Acknowledgements

We would like to thank the EPSRC Future Metrology Hub for supporting this feasibility study project CRAD_1057Metrology Hub Feasibility- Digital Twin of Machining Processes.

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