Validation of a digital twin: part distortion in heat treatment

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Abstract. This paper presents a study on multi-process manufacturing optimisation, employing a sophisticated data analytic model based on Gaussian Processes. Through strategically designed aluminium trials and rigorous model evaluation using leave-one-out cross-validation, the efficacy of the model in identifying optimal parameters is demonstrated. An interactive dashboard, powered by the Anaconda Panel(c) library, enables real-time insights into the impact of varying parameters on outcomes. Experimental validation showcases the model's ability to reduce distortions yet highlights the dynamic nature of manufacturing processes. The iterative refinement of optimal parameters based on real-world observations underscores the adaptability of the model. This study emphasises the importance of combining advanced data analytics with practical experimentation for enhanced precision in modern manufacturing, paving the way for further advancements in the field. Real-world validation of predicted optimal parameters reveals unexpected distortions, highlighting the dynamic nature of manufacturing processes and the necessity for continuous refinement. Further analysis uncovers a discrepancy in distortion outcomes, emphasising the need for vigilant investigation and iterative refinement. By incorporating the latest experimental findings, the data analytic model has generated updated optimal parameters, effectively minimising part distortion. This study underscores the significance of data-driven decision-making and the continuous integration of new experimental results in the pursuit of optimal manufacturing parameters, paving the way for further advancements in manufacturing optimisation.

1 Introduction

In the realm of advanced manufacturing, the pursuit of optimal process parameters is an ongoing challenge, essential for achieving unprecedented efficiencies and precision. This paper explores the paradigm of multi-process manufacturing optimisation, validating a sophisticated data analytic model grounded in Gaussian Processes, a non-parametric methodology highly regarded in machine learning.

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The research conducted by Aurrekoetxea et al. [1] offers an exhaustive examination of advanced prediction and control methods for machining distortion. The study underscores the significance of key factors including cutting load, clamping loads, and residual stresses in accurately forecasting machining distortions. Through their paper, the authors shed light on the critical role these factors play in understanding and mitigating the challenges associated with machining processes. Nonetheless, an area that remains unexplored in their research is the impact of heat-treatment on part distortion. DANTE^{TM} [2], which is a software package for addressing heat treat distortion challenges emerged as a top tier solution for this unexplored area of research. Following its acquisition for testing purposes, example calculations conducted with DANTE^{TM} unveiled its highly sophisticated features. Notably, according to R.A. Hardin et al. [3] its predictive capabilities aligned relatively well with certain prior measurements of heat treatment distortion. However, the documentation of such experiments in the literature is incomplete which makes it difficult to replicate these results.

Our approach synthesises the precision inherent in Gaussian Processes, leveraging different Python libraries to craft a bespoke data analytic model. Uniquely tailored, this model addresses the intricacies of multi-process manufacturing data. For more information regarding the model please refer to [4]. The study unfolded through a series of aluminium trials, strategically designed as integral components within a multi-step manufacturing value chain. Far from standalone experiments, these trials formed the basis for a data-driven exploration, aiming to uncover optimal process parameters that transcend conventional empirical approaches.

To rigorously evaluate the model's efficacy, we employed leave-one-out cross-validation [5], a strategy finely attuned to iterative model refinement through training and validation on diverse sets of experimental data. The ultimate objective was to identify optimal soak time, quench temperature, and quench orientation to minimise distortion in the manufactured parts. Further enriching our study, we introduce an interactive dashboard powered by the Anaconda Panel(c) library [6]. This dynamic interface empowers users to interact with the model's predictions, offering real-time insights into the impact of varying parameters on outcomes. This not only enhances interpretability but also equips decision-makers with valuable tools in the ongoing optimisation journey. Upon unveiling the computed optimal parameters, we transition to the crucial phase of real-world validation. The recent experiment, executed with the predicted optimal parameters, serves as the litmus test, exposing the model to the practical nuances of the manufacturing shop floor.

A fascinating revelation emerges as certain probing locations exhibit unexpected distortions even under anticipated optimal conditions. This finding prompts a deeper exploration, underscoring the dynamic nature of manufacturing processes and the necessity for continuous refinement.

2 Data analytical model testing

2.1 Experimental procedure

The experiment investigated the impact of varying heat treatment conditions, particularly quenching in water, on distortion and residual stresses in AA7075 aluminium alloy parts. By recording quench temperature, orientation, and furnace time, alongside machining parameters and distortion measurements, the study aimed to understand how different heat treatment scenarios affect part behaviour. Utilising a combination of horizontal and vertical heat treatment configurations, alongside precise machining using a Sandvik face milling cutter and DMG MORI HSC 75 milling machine, the experiment meticulously controlled variables to gather comprehensive data. The analysis sought to uncover signatures of the heat treatment process, contributing to the optimisation of manufacturing processes and the enhancement of product quality in aluminium alloy components. For more details see [4].

Table 1 provides a detailed breakdown of the experimental parameters. The gathered data will serve as inputs for an analytics model, enabling the discovery of distinctive signatures characterising the heat treatment processes. This model integrates machining and metrology data, offering a comprehensive understanding of the intricate interactions between heat treatment conditions, machining operations, and part characteristics.

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

Experiment No.	Soak time (mins)	Quench temp. (°C)	Quench orientation
1_3.5HRS_20 DEG_V	210	10-20	Vertical
2_3.5HRS_50 DEG_V	210	50-60	Vertical
3_1.75HRS_20 DEG_H	105	10-20	Horizontal
4_3.5HRS_50 DEG_H	210	50-60	Horizontal
5_1.75HRS_20 DEG_V	105	10-20	Vertical
6_3.3HRS_20 DEG_H	210	50-60	Horizontal
7_1.75HRS_35 DEG_V	105	35	Vertical

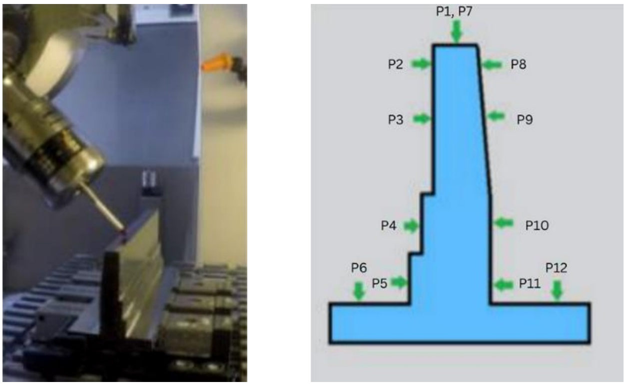


Fig. 1. (a) On-machine probing; (b) Probing locations (numbered from 1-12) along the length (200 x 65 x 75 mm, l x w x h)

Throughout the machining process, each part underwent probing using MSPTM software to assess in-process distortion, as illustrated in Fig.1a and 1b. The probing cycles were consistently conducted at identical locations for every part, including the one produced with optimal parameters. This approach ensured a standardised and thorough evaluation of the model's predictions in real-world manufacturing conditions. The shape of the part on the two sides were machined differently to observe the effect of the shape in distortion.

2.2 Data analytical model

The data analytics model at the core of our study was thoughtfully constructed using Gaussian Processes, a robust methodology renowned in machine learning practice [7, 8]. Noteworthy for its non-parametric nature, this method relies solely on observed data, making it well-suited for approximating and interpolating unknown non-linear relationships within datasets [7, 8]. Additionally, it provides a means to quantify uncertainty in model predictions, with accuracy typically improving as the volume of available data increases.

The development of the data analytics model involved the creation of custom software in Python, leveraging the powerful Numpy/Scipy libraries. This tailored approach was chosen specifically to accommodate the intricate structure of multi-process manufacturing data, with a keen focus on in-process probing of the part during machining. Our exploration encompassed aluminium trials, comprising six deliberately designed experiments aimed at observing the intricacies of a multi-process manufacturing value chain, as opposed to merely seeking standalone empirical results.

To assess the model's efficacy, we employed a leave-one-out cross-validation strategy. This involved training the model on (N-1) experiments and validating it on a single experiment, iterated N times. This rigorous evaluation enabled us to fine-tune the model and extract valuable insights from the wealth of initially collected data, with the primary goal of identifying optimal parameters crucial for the manufacturing process.

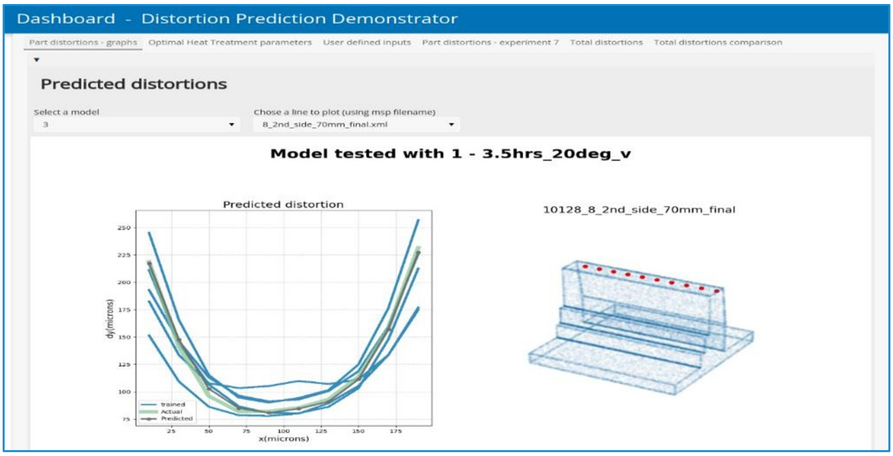
The model successfully facilitated the identification of optimal soak time, quench temperature, and quench orientation based on the initially gathered data. Specifically, the computed optimal values were 105 minutes for soak time, 34.7 °C for quench temperature, and a vertical orientation for quenching. To validate these predictions, a new experiment (referred to as Experiment 7) was conducted using the predicted optimal parameters.

An interactive dashboard was also developed utilising the Anaconda Panel(c) library, providing users with a dynamic interface to engage with the visualised outcomes of the data analytic model (see Fig.2a and 2b). This interface allowed users to seamlessly navigate and manipulate the data, enabling the flexibility to switch between different sets of training data. Specifically, the data analytic model was trained with various subsets, each comprising N-1 experimental results, providing users the ability to explore how alterations in training data influenced the model's predictions.

2.3 Results and discussion

With the developed dashboard, we are able to customise the probing location within the dashboard, facilitating a comprehensive exploration of predicted outcomes versus actual distortions. The dashboard, exemplified in Fig.2a, offers an intuitive and user-friendly experience, presenting a comparative view of predicted and actual distortions, thereby enhancing the interpretability of the model's performance.

The optimal parameter conditions, crucial for minimising distortions, were distinctly highlighted. For added clarity and insight, the dashboard incorporated 3D plots as depicted in Fig.2b. These plots not only illustrated the predicted total distortions for the suggested optimal conditions but also included expected uncertainties, offering a nuanced understanding of the model's confidence in its predictions. This feature empowered users to make informed decisions by visually identifying the parameter configurations associated with optimal outcomes, thereby streamlining the decision-making process in the manufacturing optimisation journey.



Select a model: 3

Chose a line to plot (using msp filename): 8_2nd_side_70mm_final.xml

Fig. 2a. Panel$^{(c)}$ dashboard visualising on-machine probing and prediction results. The red points indicate the points along the line of probe location 8.

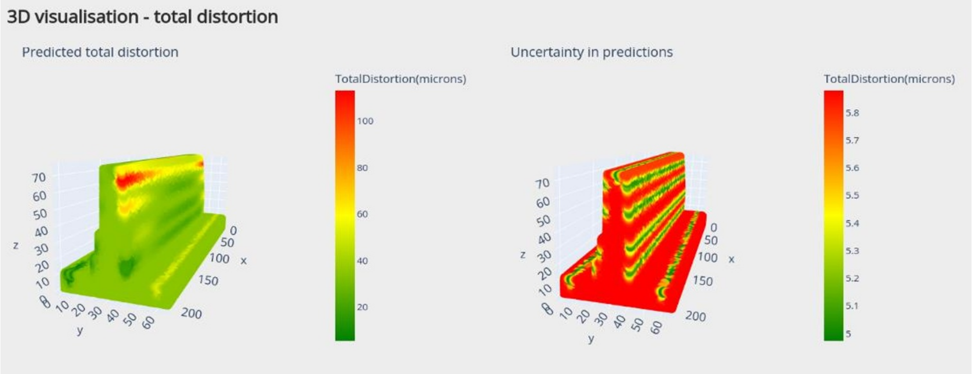


Fig. 2b. Panel$^{(c)}$ dashboard for interactive distortion predictions

As depicted in Fig.3, the analysis of Experiment 6 highlights that the greatest distortion occurred along the line of probe location 8, surpassing distortions at other probing locations. A similar behaviour was observed for all the other experiments where the highest distortion was observed along the line of probe location 8. In accordance with Figure 4, which consolidates results from experiments 1 through 6, it is evident that the distortion along the line of probe location 8 reached a maximum distortion of 256μm and minimum of 74μm.

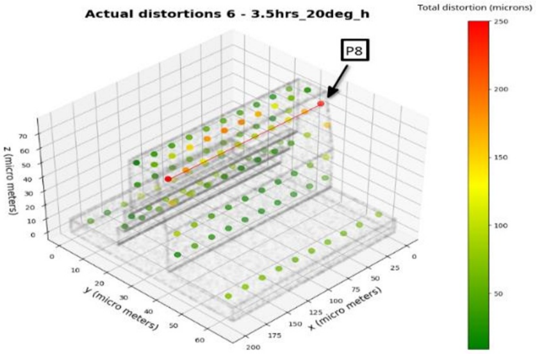


Fig. 3. Distortions observed in Experiment 6 across the part on all the probed locations. The red line highlights the measurements collected along the line of probe location 8.

Upon conducting Experiment 7, a distinct improvement in distortion outcomes along the line of probe 8 was identified (shown in Fig.4). The maximum distortion reduced to 196µm, and the minimum distortion decreased to 11µm, underscoring the effectiveness of the optimised parameters. This reduction in distortion signifies a tangible enhancement in the manufacturing process, validating the impact of the fine-tuned parameters on mitigating undesired effects along the probed locations.

Despite the anticipated optimal conditions, where the model forecasted a maximum distortion of 21µm along the line of probe location 2, a closer examination of the actual results presented in Fig.5a reveals a significant deviation. Experiment 7 demonstrates a substantial increase in distortion along probe location 2, reaching 442µm. This observation starkly contrasts with distortions observed in all other experiments. While the predicted results align closely with the trained experimental results as expected, we attribute the notable contrast in outcomes to the geometry of the machined part.

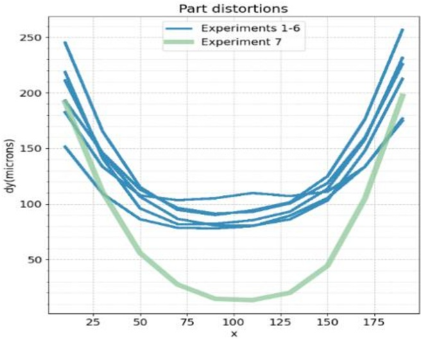
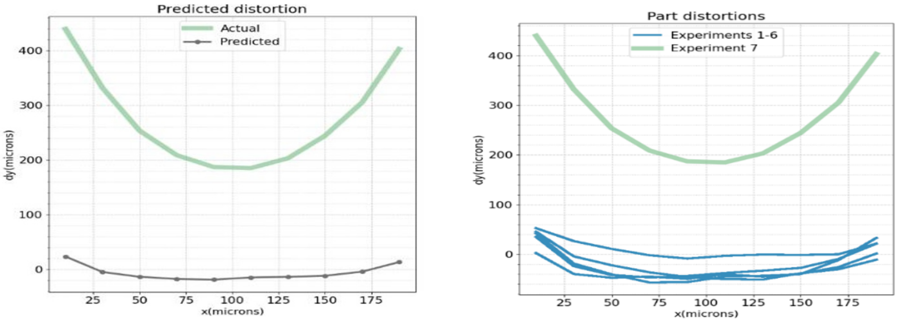


Fig. 4. Distortion along the line of probe location 8 for all the experiments conducted through 1-7

Surprisingly, while the optimal parameters effectively mitigate distortion along the slightly slanted surface, they unexpectedly exacerbate issues on the straight surface. Despite not expecting a higher distortion along probe location 2, as even higher temperatures like 50°C resulted in much lower distortion when soaked for 210 minutes, it appears that lower soak times at higher temperatures could lead to increased distortions on straight surfaces. This unexpected finding sheds light on the complex interplay between temperature, soak time, and surface geometry in influencing distortion during machining and heat treatment processes.

This discrepancy underscores the importance of vigilant analysis and continuous improvement in the manufacturing process. The significant increase in distortion along probe location 2 in Experiment 7 suggests a potential area that requires further refinement. The deviation from the predicted values emphasises the dynamic and intricate nature of manufacturing processes, urging a closer investigation into the factors contributing to the observed distortion. Addressing and refining the conditions specific to probe location 2 could lead to a more comprehensive and accurate optimisation of the manufacturing process, aligning the predicted outcomes more closely with the actual results. This highlights the iterative and adaptive nature of the optimisation journey, necessitating ongoing adjustments based on real-world observations and data.



(a) (b)

Fig. 5. (a) Experiment 7 predictions in comparison to actual distortions for probe location 2 (b) Actual distortion along the line of probe location 2 for all the experiments conducted through 1-7

By incorporating the latest experimental findings into the training dataset, the data analytic model has generated updated optimal values for soak time, quench temperature, and quench orientation. As per the model's computations, the recommended optimal parameters are now a vertical orientation, 105 minutes for soak time, and a quench temperature of 20°C. This refinement underscores the model's capacity to adapt to new data, offering enhanced insights into the dynamics of the manufacturing process based on the most recent experimental observations. Of particular interest is our experiment conducted with these parameters, wherein upon comparing all available experimental results, Experiment 5 exhibited the least distortion (refer to Fig.5). This finding underscores the efficacy of the model's updated recommendations and highlights the potential for practical application in optimising manufacturing processes to minimise part distortion effectively.

3 Conclusions

In conclusion, our study delved into the optimisation of multi-process manufacturing through the utilisation of a sophisticated data analytic model, particularly leveraging Gaussian Processes. The literature reveals a notable gap in the development of predictive models specifically tailored to anticipate part distortion resulting from the combination of machining and subsequent heat treatment processes. This gap underscores a crucial need within the field for comprehensive understanding and predictive tools capable of addressing the intricate interplay between these two fundamental manufacturing processes. By bridging this void, researchers can offer invaluable insights into optimising both machining and heat treatment protocols, ultimately enhancing the overall quality and reliability of manufactured parts.

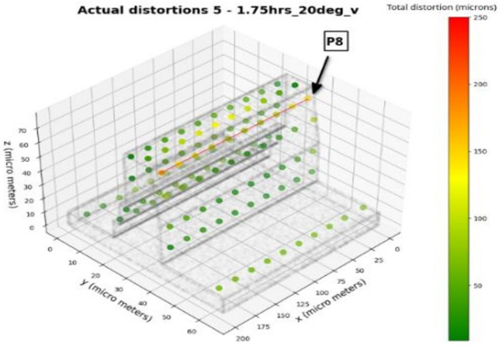


Fig. 6. Distortions observed in Experiment 5 across the part on all the probed locations. The red line highlights the measurements collected along the line of probe location 8

Experiment 7, conducted with the predicted optimal parameters, served as a practical validation, aligning the model's predictions with the intricacies of the manufacturing floor. However, the notable increase in distortion along probe location 2 in Experiment 7 prompts further investigation and emphasises the ongoing need for refinement and adaptability in the manufacturing process.

Our findings underscore the significance of a holistic approach to manufacturing optimisation, combining advanced data analytics with practical experimentation through digital twinning. The journey toward optimal parameters is iterative, demanding continuous refinement based on real-world observations. The adaptability of our model, as demonstrated through the updated predictions, positions it as a valuable tool for navigating the complexities of modern multi-process manufacturing.

As we move forward, the insights gained from this study pave the way for further advancements in manufacturing optimisation, emphasising the importance of data-driven decision-making and the continuous integration of new experimental results for enhanced precision in the pursuit of optimal manufacturing parameters.

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