

# Optimization of Rolls-Royce gas turbine components machining using artificial intelligence

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**Abstract.** Industry 4.0 has changed the ways in which Small to Medium (SME's) and Large Enterprise (LE's) manufacturers and businesses operate. Artificial Intelligence (AI), Bigdata, Edge Computing, Cloud Computing, Internet of Everything (IoE), Fifth Generation (5G) and Information Communication Technology (ICT) allow processes to be optimized, controlled, and monitored in close real-time. These enabling technologies allow manufacturing facilities to collect enormous amounts of data from process lines, such as real-time measurement data, machinery state of health, and cycle time, to accurately plan and report the state of both processes, machinery, and final products. In this work, the research programme focuses on the collected data from process input variables that can be monitored to ensure process outputs and final components conform to design specifications. Current methods of analyzing data, especially in aerospace manufacturing environments, require engineers or process operators with a precise and high skill set to be able to map the results into the appropriate chart and interpret these results. Furthermore, the quantity of data analysis required to monitor process inputs in real-time renders conventional analysis techniques unfeasible. Current development using AI has shown the potential and the capability to detect trends in large data sets using machine and deep learning. It also enables a more precise and automated analysis without human intervention. This paper focuses on determining the feasibility of using a deep neural network (i.e., deep neural networks - DNN) to predict process outputs based on process inputs. A simplified example is presented using data collected from firing a 'statapult' with varied configurations, training a deep neural network and predicting future results based on process inputs. Initial results are presented, and the results show promising estimating and prediction capabilities.

**Keywords:** Deep Neural Network, Artificial Intelligence, Process Capability, CNC Machining, Statistical Process Control.

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## 1 Introduction

AI is revolutionizing the way the manufacturing industry solves problems and processes data. The history of AI dates back over two centuries [1]; however, the term “Artificial Intelligence” was first coined by John McCarthy in 1956 [2], [3]. AI technology is increasingly being utilized in manufacturing environments to reduce human error and improve product quality and cost. One of the transformational workflows in the Rolls-Royce business plan deployment for 2024 onwards is to embrace and invest in new digital technologies such as AI, big data, edge computing, cloud computing, and the internet of everything. Turbine component machining, such as the grinding of turbine blades and Nozzle Guide Vanes (NGVs), is a data-rich process. Many features and process inputs & outputs are measured, making the use of AI feasible to optimize and monitor the process, allowing operators to make essential adjustments before non-conformance is generated, resulting in scrap product. Due to the hostile environment in which turbine components operate, the materials and castings are complex and expensive. Investment casting is used, and single crystal casting technology is utilized when manufacturing high-pressure section components, resulting in an expensive casting of raw material and high initial investment. Moreover, the machining of turbine components is highly complex with tight dimensional tolerances. Complex machining processes result in high scrap rates of expensive castings. Statistical Process Control (SPC) of machining is a well-known and proven technique that can significantly improve product yield. One downside of SPC is the human aspect of spotting trends in the measurement data and acting accordingly – this is another aspect where Artificial Intelligence (AI) could be beneficial. One of the potential AI solutions is explored in this ongoing research programme.

## 2 State-of-the-art of technology

AI technology is increasingly utilized in manufacturing environments to reduce human error and improve product quality and cost. The use of sensors and AI to improve surface roughness in milling, turning, drilling, and grinding operations by automation of the parameter setting, with a focus on neural networks, image recognition, fuzzy logic, adaptive neuro-fuzzy inference systems, Bayesian networks, support vector machine, ensembles, decision and regression trees, k-nearest neighbours, artificial neural network (ANN), Markov model, singular spectrum analysis and genetic algorithms have been discussed [4]. It concluded that ANNs are the most popular AI model although use in an industrial environment is rare due to extensive tuning requirements and the broad range of types of ANN requiring expert input. Furthermore, it stated that the requirement for robust sensors and data collection systems is challenging to implement. A similar study experimented with AI in milling to optimize parameters to improve surface finish and reduce re-processing [5]. The study used spindle speed and feed rate monitoring sensors and an AI supervision controller to adjust speed and feed in real-time to ensure surface finish requirements were achieved. A fuzzy neural network (FNN) was trained using a design of experiments (DoE) and used as the supervision controller. Findings of the paper through a case study showed that the technology can improve the difference between required and predicted surface finish from  $3.6\mu\text{m}$  to  $0.12\mu\text{m}$ , however, other variables are required to be taken into account to ensure the robustness of the controller such as tool wear and vibration prediction.

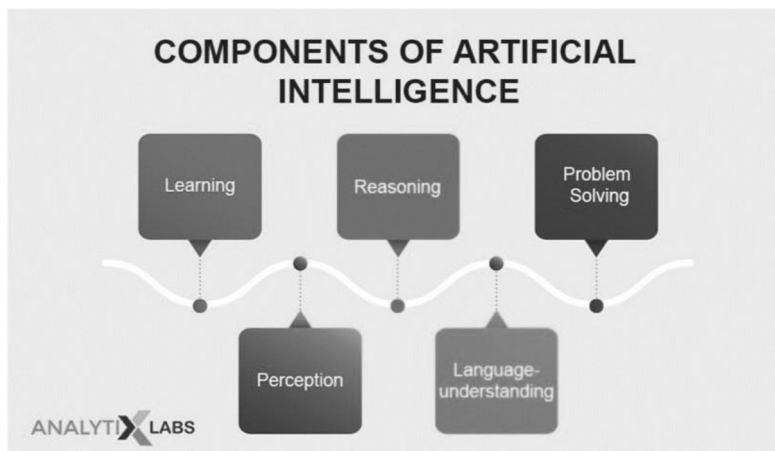
When considering the current development of AI in manufacturing in terms of a technology s-curve, it's evident that AI is still in the innovation, and development phase. [6] discusses the opportunities and challenges with AI technology in this nascent phase. It discussed the opportunities related to embedding sensors in machine tools to capture data for analysis. Opportunities such as error measurement and compensation by techniques such as

thermal compensation, process optimization by tool path optimization and parameters optimization, chatter vibrations management using vibration sensing and predicting technology, tool condition monitoring using sensors to detect breakages and AI to predict tool life are also discussed. Further to the opportunities, the authors also explore challenges such as poor data quality in industrial sites and transferability between work centres and tools due to the retraining requirements of the algorithm.

Modelling and monitoring of abrasive finishing processes such as grinding using AI techniques is investigated, and examined [7]. The work suggests types of algorithms that could be best suited for different combinations of abrasive processes and monitoring objectives. One area of further research from this study is to test and validate the findings. It also advised that the monitoring and modelling of abrasive finishing processes using AI algorithms is not fully exploited.

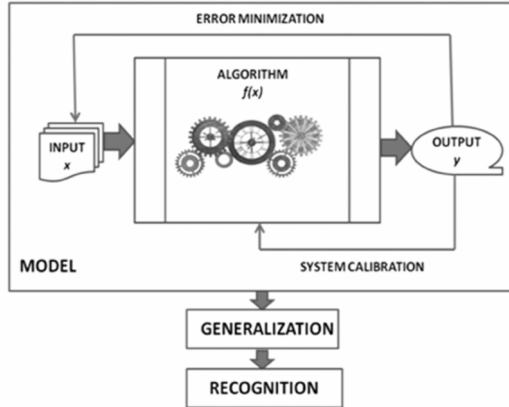
### 3 Analysis and optimization system architecture using AI

AI has many applications, such as speech recognition, vision systems, natural language processing, gaming, robotics and problem-solving [2]. For AI to work across such a diverse range of applications, the way in which AI is configured to work must be bespoke to each. To understand the ways in which AI can be tailored to applications, first it is important to understand the constituent components of an AI system. Gupta and Mangla introduced AI system as primarily consisting of the following components: Learning, AI programming languages, knowledge representation, problem-solving, and AI hardware [2]. Fig. 1 shows a slightly simpler representation of AI components and can be summarised as learning, reasoning, problem-solving and perception and understanding [8 - 9].



**Fig. 1.** Components of analysis and optimization system using AI [8]

Consensus is that for an AI to operate, it must be able to learn. The term learning implies that an action is taking place whereby the AI is improving its performance to complete a task. The simple mathematical function  $y = f(x)$  can adequately describe a basic AI model, where  $y$  is the output,  $x$  are the inputs and  $f(x)$  is the AI model which maps the inputs to the outputs. A diagrammatic version of this is shown in Fig. 2, in which a system with a feedback loop is shown. Chen and Chen describe how AI systems learn using supervised learning, where the AI matches the output data to the training input data and minimizes the error through many iterations [3]. This relies on the training data set being representative of the data which the AI is designed to work with.

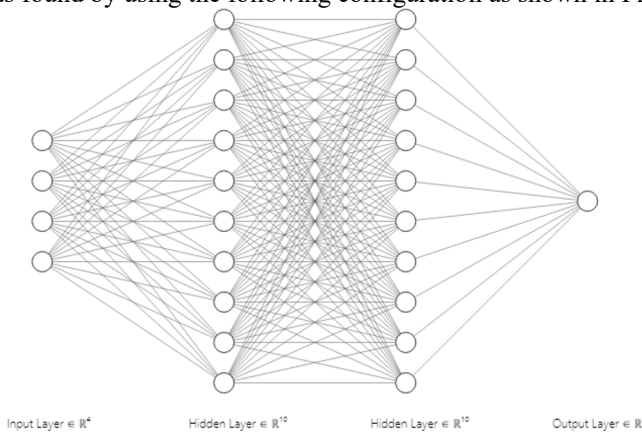


**Fig. 2.** A simple analysis and optimization system architecture using AI [3]

### 4 CAD model of deep neural network

Data was collected by firing a ‘stapult’ while varying four different firing configurations; firing angle, stop position, cup position and hook position, and measuring the distance at which the fired ball lands. A stapult is a statistical catapult which is commonly used in six sigma training for statistical process control, design of experiments and cause and effects training [10].

An AI model was developed using a distribution of the Python programming language called Anaconda. Anaconda comes with an open-source web-based interactive development environment (IDE) application named JupyterLab which was used for the creation of this AI model. TensorFlow – a deep learning Application Programming Interface (API) developed by Google was used in Python to develop the DNN. This model was then trained using 80% of the data which had been segregated for training and tested against the remaining 20%. Many iterations of altering the quantity of hidden layers and nodes were trialed. The best performance was found by using the following configuration as shown in Fig. 3.

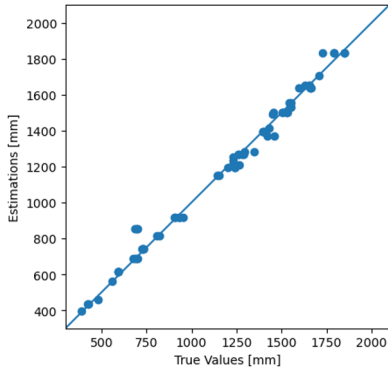
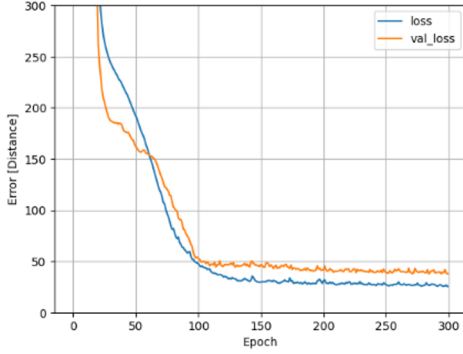


**Fig. 3.** DNN layer architecture

### 5 Model test and validation

The performance of the model can be determined using loss functions. While loss functions are useful for determining the performance of a model, they can be difficult for humans to

comprehend [11]. To make the loss more straightforward to comprehend, the mean absolute error (MAE) is calculated and plotted for each epoch as shown in Figure 4. The model was then tested against the validation data set to determine how well the DNN could estimate the process output, i.e. the distance the ball would travel, based on the varying process inputs. Results showed a good correlation between the AI estimated distances and the actual distances fired, measured and recorded in the data set as shown in Figure 5 and Table 1.



**Fig. 4.** Model Training error vs validation error

**Fig. 5.** AI model estimated values mapped against true values from validation data

**Table 1.** A sample of values showing the AI estimated distances against the actual distances

True Value (mm)	Estimation (mm)
592	628.665
618	628.665
588	628.665
560	539.874
1420	1379.211
1405	1379.211
730	719.546
1280	1269.331
1230	1269.331
1250	1269.331
867	812.637
810	812.637
1530	1515.047
1510	1515.047
1520	1515.047

## 6 Conclusion

This ongoing research programme is focused on determining the feasibility of using a deep neural network to predict process outputs based on process inputs. The intention is to use such potential technology to optimize Rolls Royce gas turbine components machining using AI (machine, deep and cognitive) learning. The CAD model of DNN and data collection approach of a simple example of firing a 'statapult' have been developed. The model has demonstrated promising capabilities in estimating and predicting process outputs based on process inputs through rigorous testing and validation. These initial results highlight the promising potential of this approach for enhancing manufacturing efficiency and precision within the manufacturing industry. It also indicates potential use to enhance the machining optimization of gas turbine components.

## References

1. Grzybowski, K. Pawlikowska-Łagód, and W. C. Lambert, *A History of Artificial Intelligence*, Clin. Dermatol., p. S0738081X23002687, Jan. (2024), doi: 10.1016/j.clindermatol.2023.12.016.
2. N. Gupta and R. Mangla, *Artificial intelligence basics: a self-teaching introduction*. Dulles, Va: Mercury Learning & Information, (2020).
3. R. H. Chen and C. C. Chen, *Artificial intelligence: an introduction for the inquisitive reader*, First edition. Place of publication not identified: Chapman and Hall/CRC, (2022).
4. D. Y. Pimenov, A. Bustillo, S. Wojciechowski, V. S. Sharma, M. K. Gupta, and M. Kuntoğlu, *Artificial intelligence systems for tool condition monitoring in machining: analysis and critical review*, J. Intell. Manuf., vol. 34, no. 5, pp. 2079–2121, Jun. (2023), doi: 10.1007/s10845-022-01923-2.
5. L. C. Moreira, W. D. Li, X. Lu, and M. E. Fitzpatrick, *Supervision controller for real-time surface quality assurance in CNC machining using artificial intelligence*, Comput. Ind. Eng., vol. 127, pp. 158–168, Jan. (2019), doi: 10.1016/j.cie.2018.12.016.
6. Y. S. Chuo et al., *Artificial intelligence enabled smart machining and machine tools*, J. Mech. Sci. Technol., vol. 36, no. 1, pp. 1–23, Jan. (2022), doi: 10.1007/s12206-021-1201-0.
7. V. Pandiyan, S. Shevchik, K. Wasmer, S. Castagne, and T. Tjahjowidodo, *Modelling and monitoring of abrasive finishing processes using artificial intelligence techniques: A review*, J. Manuf. Process., vol. 57, pp. 114–135, Sep. (2020), doi: 10.1016/j.jmapro.2020.06.013.
8. S. Bansal, *Components Of Artificial Intelligence - How It Works?* Accessed: Apr. 22, 2024. [Online]. Available: <https://www.analytixlabs.co.in/blog/components-of-artificial-intelligence/>
9. SOCI, *The Basic Components and Branches of Artificial Intelligence : SOCI*. Accessed: Apr. 22, 2024. [Online]. Available: <https://www.meetsoci.com/resources/knowledge/localized-marketing/branches-of-artificial-intelligence/>
10. Aircad, *Official Statapult® Catapult for Lean Six Sigma Training | Air Academy Associates*. Accessed: Apr. 25, 2024. [Online]. Available: <https://airacad.com/statapult/>
11. Z. M. Chng, *Loss Functions in TensorFlow - MachineLearningMastery.com*. Accessed: Apr. 25, 2024. [Online]. Available: <https://machinelearningmastery.com/loss-functions-in-tensorflow/>