Toward the quality prognostic of an aircraft engine workpiece in Inconel Alloy 625: case study and proposed system architecture

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Manufacturing companies are under a constant pressure due to multiple factors: new competition, disruptive innovations, cost reduction, etc. To survive, they must strive to innovate and adapt their business model to improve their productivity. Recent developments based on the concept of Industry 4.0 such as big data, connectivity and artificial intelligence provide several new avenues to explore. In the specific context of machining, we are working toward the development and implementation of an automatic system capable of making the prognostic of the quality (in terms of dimensional conformance) of a workpiece in real time while it is being manufactured. The goal of this paper is to showcase a prototype of the data acquisition aspect of this system and a case study. This case study has been conducted at our industrial partner facility (Quebec, Canada) and is based on the manufacturing of an aircraft engine component made from Inconel alloy 625 (AMS5666). The proposed prototype is a data acquisition system installed on a 5 axis CNC machines (GROB model G352) used to acquire and to contextualize signals obtained from the CNC machine sensors. The contextualization of the data is a key component for future work regarding the development of a prognostic system based on supervised machine learning algorithms. In the end, this paper depicts the system architecture as well as its interactions between the multiple systems and software already in place at our industrial partner. This paper also shows preliminary results describing the relationship between the workpiece quality (in terms of respect toward the dimensional requirements) and the extracted features from the sensors signals. Future work regarding this project will include data acquisition from a wider range of products (i.e. different shapes, materials, processes, etc.), development and testing of a machine learning based prognostic model and the implementation and validation of this system at our industrial partner.

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