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Inclusion scraps control in aerospace blades production through cognitive paradigms

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Abstract

The reduction of the scraps is fundamental to achieve goals of competitiveness. Some key parameters have a direct influence on any process and they need to be predicted and taken under control.
This paper present an approach) is to develop a robust monitoring solution of the ceramic shell manufacture that will be able to determine a significant reduction of the inclusion scraps (due the ceramic shell) of the superalloy components. The control will be obtained by processing data coming both from sensors and laboratory measured values. The sensor data come from the new equipment of the Europea Microfusioni Aerospaziali SpA (EMA) and have been tested and used to develop the EMA demonstrator within the EC FP7 Project on "Intelligent Fault Correction and self-Optimizing Manufacturing systems - IFaCOM". The sensor data will merge the data measured in the EMA laboratories and both the values will concur to create the sensor fusion pattern vector, which will be used to feed an automatic system for the prediction of the process parameters. The automatic system will be implemented using cognitive paradigms, in particular Artificial Neural Networks, that will combine both data.
The first testing phase will predict the number of blades with inclusions. It will provide a first idea of the correlation between the input, as a matrix composed by the sensor fusion pattern vectors per each worked blade, and the outputs, as a vector of rejected blades on the total. Moreover, this work will be the basis to implement a predictive system to estimate which is the reference range of each working parameter.

Keywords: Neural Network; Decision Making; Zero-defect Manufacturing

1. Introduction

Sensors are devices used to obtain information from the environment in which they operate. Information from a single sensor can be very limited; i.e., a radar information would be more complete if a vehicle could be identified and it would be more valuable if the shape of objects detected by the sonar could be elucidated.

Measurements taken using single sources are not fully reliable and are very often incomplete due to the operating range and limitations, which characterize each sensor.

The use of multiple sensors has numerous advantages over single sensor instruments. Because of the technical features which characterize each sensor, redundant and/or complementary observations about a measure can be made. The combination of this information can be used to generate a more complete picture of the environment than is currently obtainable with a single sensor. A multiple sensor device can include any instrument with several sensors of identical or similar types used to measure a physical quantity.

The simultaneous use of similar sensors can be very advantageous when large areas need to be covered in a short time, or to assess the accuracy of a reading by comparing multiple outputs.

The following benefits can be identified in the use of multiple sensor devices:

- a downtime reduction and an increase in reliability;
- complementary information;
- a higher signal-to-noise ratio;
- a reduction in measurement uncertainty;
- a more complete picture of the environment.

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All of these results in an overall increase in system performance. Information from multiple sources needs to be effectively combined in a coherent and efficient manner in order to compensate for their limitations and deficiencies. The disadvantages in the use of multiple sensor devices can be found in the increase of the system cost and the difficulties in managing a large amount of data.

As the terminologies data fusion, data integration, multisensor integration, become more widely used in day-to-day scientific publications, their meaning needs to be clarified. Waltz and Llinas [1], Hall [2], and Rothman and Denton [3] gave their views and definitions of what data fusion really is. In 1990, the US Department of Defense defined data fusion as a technology which involves the acquisition, integration, filtering, correlation and synthesis of useful data from diverse sources for the purposes of situation/environment assessment, planning, detecting, verifying, diagnosing problems, aiding tactical and strategic decisions, and improving systems performance and utility. This is a very complex definition oriented towards military applications rather than a general explanation of data fusion. In simple terms it can be summarized as the processing, interpretation and use of data from multiple sources. Data fusion is used in an important variety of topics and technologies. A general data fusion system model capable of handling various applications is very difficult, if not impossible, to design. As a consequence, various data fusion models can be found in the literature. General reviews on data fusion were presented in 1988 by Blackman [4], Schoes and Castore [5] and Luo and Kay [6] in 1990 by Hackett and Shah [7] and in 1991 by Rothman and Denton [3] where different fusion technologies were described.

1.1. EMA demo: user case expectations overview

The main goal of the Europea Microfusioni Aerospaziali S.p.A. (EMA) is to develop a robust monitoring solution of the ceramic shell manufacture able to determine a significant reduction of the inclusion scraps (due the ceramic shell) of the superalloy components.

The EMA demo is based on monitoring parameters to obtain the minimum number of scrapped blades. Such parameters are related to the liquid slurry and are monitored by means of traditional and new IFaCOM equipments. Specific interest is paid to some characteristic, such as slurry viscosity and temperature values, plate weight and slurry silica content: these measurement data are recorded, for further analysis [8].

To achieve some tangible results, consistent with the resources available within the EC FP7 Project on "Intelligent Fault Correction and self-Optimizing Manufacturing systems - IFaCOM", the investigation was restricted to the development of novel methods for robust control and analysis of the primary slurry and the development of specific control methods for the ceramic shell.

The final goal of EMA-Demonstrator (DEMO) research is to optimize the process of ceramic shell manufacturing by means of a more robust control and data acquisition of the primary slurry parameters and quality characteristics of the shell, in order to reach a significant reduction of the components inclusion scraps. The DEMO was designed as an iteration process, which will lead to the end of the three iterations provided, to understand the robust range of the key parameters to use in order to minimize the content of inclusions in the superalloy components, using the new methods of measurement and control introduced during the project.

The DEMO activity developed in the frame of the first production iteration was carried out by means of:

- robust control of the industrial manufacturing of the ceramic shells of one aeronautical vane component on the company's production line, using a focused monitoring of the primary slurry parameters and additional control of the ceramic shell quality that are not normally actuated during standard production cycles;
- in-line and off-line data process acquisition (primary shell parameters, shell mechanical characteristics and inclusion scrap rate of the components) and storage in a dedicated database (DB) using specifically developed software (SW);
- cognitive systems - Neural Networks (NNs) data analysis with the aim to find the correlations between the measured Key Process Variables and the Target Variable (output quality parameter) - inclusion scrap rate.

1.2. EMA use case description

During the dipping of the wax assembly models for the solid shell fabrication a better control of the properties and the behavior of the slurry is required, with respect to the pre-IFaCOM situation. The purpose is to improve such control and to prevent the damaging influence on the occurrence of ceramic inclusions in the superalloy turbine vanes (final product).

Furthermore, the activities will validate the developed feature vectors paying attention to the identification of defective products – scrap components due to ceramic inclusions. The assessment of the sensor fusion pattern vector will be carried out in terms of success rate in the identification of such defects. Cognitive systems, such as NN, will be used to understand, estimate, and predict the correlation between input features (vital characteristics of the primary slurry and mechanical properties of the developed ceramic shells) and output quality parameters (ceramic inclusions in the manufactured superalloy components) [9]. Practically, the sensor fusion feature vectors represent the input, while the output is the end-user given quality parameters identifying the final product quality in terms of number of inclusions per component and/or number of scrap components per ceramic inclusion.

To establish a thorough control of the primary shell fabrication, the following vital parameters were monitored with the new IFaCOM equipments, as well as in the standard way (pre-IFaCOM) [10]:

- Silica Content (wt%) measured with the new IFaCOM equipment XRF analyzer – primary slurry characteristic;