Artificial Intelligence Research and Development
A. Cortés et al. (Eds.)

doi:10.3233/FAIA220331

Efficiency and Reliability Enhancement of High Pressure Die Casting Process Through a Digital Twin

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Abstract. Several factors can contribute to the final part quality in a High Pressure Die Casting process, in terms of roughness, porosity and strength. The injection velocity, the cooling of the die and aluminium's inlet temperature are some of the factors that can have a higher effect on the part quality. The new advances on process digitalization, sensortization and simulation tools, combined with artificial intelligence techniques allow developing a functional Digital Twin aimed to monitor in near real time the evolution of the temperature and pressure during the production cycle to detect possible anomalies and predict the final part properties, reducing the required quality control.

Keywords. Digital Twin, Artificial Intelligence, Machine Learning, Numerical simulation.

1. Introduction

The concept of Digital Twin (DT) appeared for the first time in 2002 in the context of product lifecycle management [1]. A DT is defined as a digital mirror of a physical system created from real data which includes algorithms and decision making [2]. In this sense, a Digital Twin must involve three main features: real system, virtual modelling of the system (including visualization tools and algorithms), and bidirectional communication between the real system and the virtual model.

The use of solutions based on artificial intelligence (AI) is increasing due to the need to solve complex problems that are too difficult to address with conventional analytic tools. A DT, which can combine complex AI-based algorithms, together with analytic and visualization tools, can be applied in several environments. For instance, DTs are being applied to jet engines in the aeronautic sector to ensure an optimal predictive maintenance strategy and to evaluate the behaviour of the monitored asset in front of unexpected events and different climate conditions [3]. In the automotive sector a DT

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can be applied to crash tests and to improve autonomous driving [4]. In logistics and value chain control, a full production plant can be represented by a DT used to optimize the productivity [5], check the process quality, improve energy efficiency, and do demand prediction including several external variables such as natural disasters, pandemics, and political conflicts. More recently, the use of DT is being applied to control and improve the efficiency of electric batteries [6] and could be also very useful to control smart cities as they can analyse and predict the traffic state, the weather, and the electric demand on buildings through machine learning algorithms among other features [7].

This paper explains the ongoing work on the design and development of a Digital Twin for the High Pressure Die Casting process (HPDC) with $AlSi_8Cu_3$ performed in the Eurecat premises.

2. Methods

To set up the Digital Twin of the HPDC process it is required to obtain experimental data from the manufacturing process (machine, die, sensors) and send this data to a digital platform, where simulations-based and AI-based models can be applied, show visual information for supporting decision making, and return information/commands to the shopfloor. The data acquisition of the process is done by three sensors (two pressure sensors and one temperature sensor) placed in the inner side of the die where the part is casted. The plunger position and velocity, which control the injection process, are also registered. The sensors placed in the die and in the injection machine (Bühler Evolution 53D) send the information to an industrial PC via OPC, to be then ingested by the DT platform.

The near real time data visualization in this DT is done in 4D, showing the surface evolution of the temperature/pressure as function of time. To obtain a 4D representation of the process it is required to calculate previously a set of similar configurations by numerical simulation in InspireCAST. Considering the geometry of the part the injection process is simulated. Matching the real temperature and pressure from the sensors with the simulated ones, a data driven calibration can be established to generate all the simulated sample grid. The simulations provide relevant information of the injection process, such as temperature and pressure as function of time and the final porosity of the sample (part quality indicator). Despite the expensive computational time of these simulations, AI algorithms can be combined with simulations and experimental tests to provide accurate results in a very reduced time window.

To create the DT of the HPDC process, four AI-driven models are considered: anomaly detection, virtual sensors, quality prediction and process configuration prediction. The anomaly detection is performed by means of an unsupervised Isolation Forest model considering a 3% of outlier factor, which checks the goodness of each new cycle data. A Virtual Sensor (VS) is able to reproduce the trend of a real sensor (temperature or pressure in this case) through correlations with other parameters, and then reduces the need (and the cost) of using real sensors. Extra Trees Regressor [8], Random-Forest Regressor [9], and Support Vector Machine Regressor [10] algorithms with different combinations of hyperparameters have been tested. For quality and process configuration prediction multi-class classification algorithms are used. The aim of the quality prediction is to determine the quality of the sample, which is tagged by visual inspection of the expert operator from 1 to 4, being 4 the best quality. The process configuration algorithm is developed to predict the configuration of the process (injection velocities v_1 and v_2, and aluminum inlet temperature) from the sensor's information. Extra Trees Classifier, Random Forest Classifier and Gradient Boosting Classifier [11] algorithms have been tested in both cases. For all the models 80% of samples are used for training and 20% for test.

3. Results and discussion

The DT of the HPDC process is created with the AI-based algorithms showing a lower root mean squared error (RMSE) and higher accuracy score. Considering all the features extracted from the sensor's information, the Maximum Information Coefficient (MIC) is calculated, which expresses the correlation of the different parameters with the target. Table 1 shows the MIC for the sample quality and process configuration.

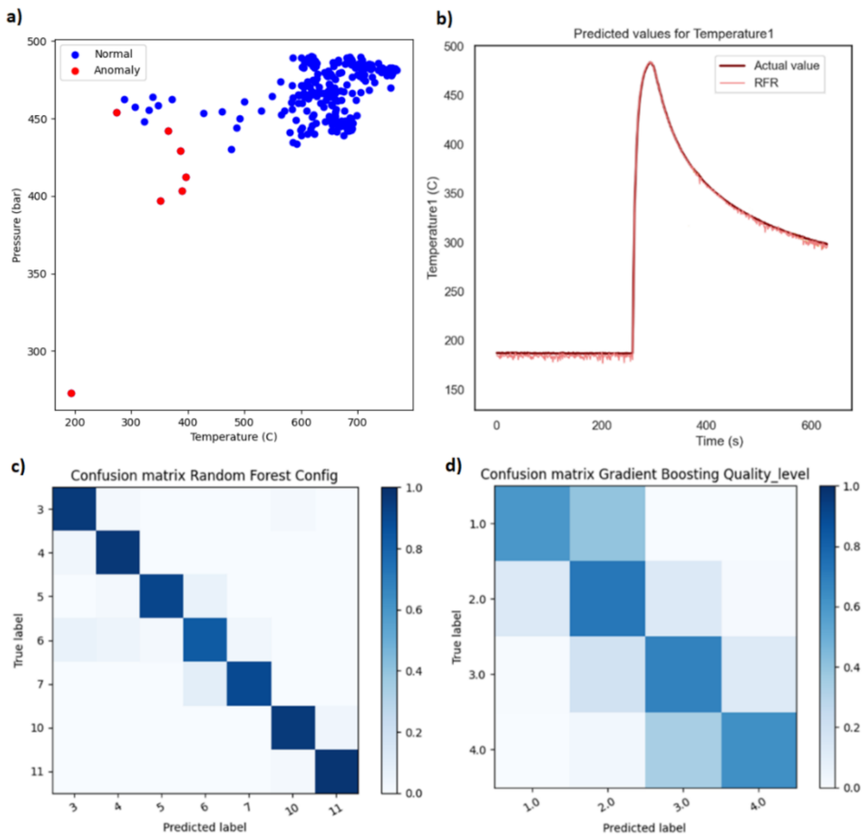

Figure 1. a) Anomaly detection prediction. **b)** Virtual sensor of Temperature. Confusion matrix for configuration prediction **(c)** and quality level (**d).**

For anomaly detection, the current developed algorithm has a score of 84%. As it can be observed in Figure 1a, there is a big cluster in the top right side that corresponds to the parts without die refrigeration and with a quality of 3 and 4. The other spread samples correspond to samples with die refrigeration, which have a quality of 1 and 2. Although the samples are spared, a small cluster is observed and therefore the algorithm does not detect them as anomaly.

For the part temperature VS, the most relevant parameters are the pressure of sensor 1 (MIC = 0.92), the injection velocity (MIC = 0.84), and the plunger position (MIC = 0.79). Using these variables as input, the predictions with lowest RMSE (6ºC) are found for the Random Forest Regressor. Figure 1b shows the prediction of the RFR compared with the real experimental data, where it can be observed that although there is some noise in the initial flat zone and during the cooling, the overall prediction reproduces the sensor's data.

Table 1. Higher correlations of the sample quality process configuration

Quality		Configuration	
Variable	**MIC**	**Variable**	**MIC**
Temperature increase	0.81	Initial Temperature	0.87
Max. Temperature	0.76	Max. Pressure 1	0.84
Initial Temperature	0.74	Pressure 1 increase	0.83
Cooling exponent	0.66	Max. Temperature	0.74

To predict the sample quality, the temperature increase experienced by the matrix is the most important parameter, while to predict the configuration of the sample the initial temperature, the maximum pressure and the pressure increase (at sensor 1) are the key factors. Based on Table 1, Figure 1c and Figure 1d show the results obtained for configuration and quality prediction, showing a score of 89.5% for the configuration (Figure 1c) and 68% for the quality (Figure 1d). Notice that although the score for quality prediction is lower, the error is limited to adjacent values (similar qualities).

4. Conclusions

In this work the preliminary results of the ongoing DT development of the HPCS process implemented at Eurecat's Laboratory facilities are presented. The methodology developed in this project is done in a way that can be extended to other industrial processes with minor modifications of the pipeline. The results show that the AI-based models can predict with high accuracy some process features like the produced part quality and estimate the process configuration parameters from few sensor's information. In addition, a temperature virtual sensor can be obtained from training regressors with the information of pressure of the die, injection velocity and plunger position. In the same way, the pressure of the die can be obtained from the temperature and the other two parameters.

The next steps will focus on improving of the prediction models to enable predictive maintenance solutions, and to extend the testing of the algorithms with different sample geometries and other aluminium alloys.

Acknowledgements

This work was financially supported by the Catalan Government through the funding grant ACCIÓ-Eurecat (Project PRIV DIGITS)". Albert Abio acknowledges the financial support of Eurecat's "Vicente López" PhD grant program.

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