



HAL
open science

Smart Factory Competitiveness Based on Real Time Monitoring and Quality Predictive Model Applied to Multi-stages Production Lines

Nicola Gramegna, Fabrizio Greggio, Franco Bonollo

► **To cite this version:**

Nicola Gramegna, Fabrizio Greggio, Franco Bonollo. Smart Factory Competitiveness Based on Real Time Monitoring and Quality Predictive Model Applied to Multi-stages Production Lines. IFIP International Conference on Advances in Production Management Systems (APMS), Aug 2020, Novi Sad, Serbia. pp.185-196, 10.1007/978-3-030-57997-5_22 . hal-03635668

HAL Id: hal-03635668

<https://inria.hal.science/hal-03635668v1>

Submitted on 30 Jun 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

Smart Factory Competitiveness based on real time Monitoring and Quality predictive model applied to multi-stages Production lines.

Nicola Gramegna¹ and Fabrizio Greggio¹,
Prof. Franco Bonollo²

¹ EnginSoft SpA, Padova, Italy
n.gramegna@enginsoft.com

² Università di Padova – DTG, Italy,
bonollo@gest.unipd.it

Key words:

Industry 4.0, Digital Twin, Overall Efficiency, Zero defect Manufacturing, Data mining, Predictive modeling, Cost model

Special session: Data-Driven Applications in Smart Manufacturing and Logistics Systems

Abstract

Smart Factories are complex manufacturing ecosystems where the converging of ICT and operational technologies and competences drive the digital transformation. Smart manufacturing operations planning and control program, as defined by NIST, implement advances in measurement science that enable performance, quality, interoperability, wireless and cybersecurity standards for real-time prognostics and health monitoring, control, and optimization of smart manufacturing systems.

The traditional production processes and plants are evolving following this digitalization combining the long experience and the AI-driven methods to improve the production efficiency, to accelerate the fine-tuning and real-time adjustment of the process parameters oriented to the zero defect quality. The digitalization of multi-stages production processes (e.g. foundry) plays a key role in competitiveness introducing new integrated platform to monitor the process through an intelligent sensors network and predict quality and cost of castings in real-time.

The application presented in this paper is the main outcome of EU FP7-MUSIC project giving a new age to the traditional multi-stages production. The actual regional project PreMANI (POR FESR 2014-2020) is a new extended application of AI-driven digital twin in manufacturing process and quality control. This paper demonstrates the applicability of data-driven digital twins to small and medium-sized enterprises (SME) and to complex manufacturing sectors integrating the process monitoring with advance data mining and cognitive approach to predict the quality, the efficiency vs cost and react in real-time with the support of decision support system.

1. Introduction

Industry 4.0 is the industrial revolution based on Cyber-Physical-Systems (CPS) in the context of Factory of Future. The digital investment grow is estimated of 1,7% in digital economy, +40% of smart factory in the next 5 years, if technology potential is released thanks to an appropriate governance and soft skills and data-driven culture. In the new digital era, a Manufacturing Execution System (MES) is a first form of Digital Twin (DT), the evolution of the Internet of Things (IoT) and Industry 4.0 manufacturing concepts have opened new possibilities regarding how real-time data can be used to better control and optimize production [1]. Recent data-driven Digital Twin is enabling the advanced real-time data mining and the machine learning technologies to support the prediction of failures, defects and the impact on production key performance indicators (KPIs).

Today, however, there are three main categories in which a digital twin can be utilized: product design, process planning and validation, and execution. The product design, is more associated with product lifecycle management (PLM) and is probably the area of application for the digital twin that is most familiar in manufacturing industries; MES helps with planning and testing manufacturing models, including planning processes and resources; the DT in manufacturing execution, which this paper is referring, is the least explored of the three categories and it offers huge potential in helping drive production efficiency, especially in the manufacture of sophisticated technological products.

In this paper the definition of DT is the digital modelling representing of assets and processes to understand, predict and optimize performance of a process, product or service. DT consists of three components: a system model, the

data gathering with intelligent monitoring and the real-time data knowledge extraction and response prediction connecting the virtual and real worlds. The system model of Digital Twin, based on reference architecture us RAMI, has to be flexible, with high interoperability, data-centric combining tools of data mining and Artificial Intelligence (AI) to support the decision making process in a collaborative way [2].

In the context of data gathering with intelligent monitoring, the large data management and data quality are ingredients to capture the process stability, to elaborate the KPIs and to improve fast and proper decision making supported by A.I. The data standardization (e.g. defects classification) and the right communication protocol (e.g. OPC-UA) are pre-requisite applied to the multi-stages production to improve the communication [3].

Meta-modeling for manufacturing processes describes a procedure to create reduced numeric surrogates that describe cause-effect relationships between setting parameters and sensors as input and product quality variables as output for manufacturing processes. In-process, such advanced models can be used to determine the operating point and to search for alternative setting parameters in order to optimize the objectives of the manufacturing process, the product quality[4].

In agreement with this definition, the implemented cognitive meta-model, or Artificial Intelligence (AI) model, is defined and customized to the specific set of variables and output in order to assure reliability and maximum accuracy. The automatic learning process is applied to improve the meta-model by re-training approach including new data from production.

Data-Driven Digital Twin for manufacturing has to be flexible, with high interoperability, data-centric combining tools of data mining, statistic model e cognitive met-model to support the decision making process by Operator (Quality oriented), Production manager (Efficiency oriented - OEE) and Business manager (Cost-oriented).

In the context of multi-stages production processes, metal and polymer manufacturing current trends show an improvement in demand for light products considering the material substitution for complex structural parts, the design and technology innovation as well as the evolution in smart production (e.g. smart foundry). The foundry case study of this paper starts from existing data from machine and some devices, but never used in a predictive quality model or real time efficiency elaboration. Due to the high number of process variables involved and to the non-synchronisation of all process parameters in a unique and integrated process control unit, High Pressure Die Casting (HPDC), as well as Plastic Injection Molding (PIM), is one example of the most "defect-generating" and "energy-consumption" processes in EU industry [5, 6], showing less flexibility to any changes in products and in process evolution. In both, sustainability issue imposes that the production cells are able to efficiently and ecologically support the production with higher quality, faster delivery times, and shorter times between successive generations of products.

The development and integration of a completely new ICT platform, based on innovative Control and Cognitive system linked to real time monitoring, allows an active control of quality, minimizing the presence of defects or over-cost by directly acting on the process machine variables optimisation or equipment boundary conditions [7, 8]. The AI-driven manufacturing approach works at machine-die level to optimise the production line starting from the management of manufacturing information. An Intelligent Sensor Network (ISN) monitors the real-time production acquiring the multi-layers data from different devices and an extended meta-model (the Cognitive model) correlates the input and sensors data with the quality indexes, energy consumption cost function. Data homogenization, centralization and synchronization are the key aspects of control system to collect information in a structured, modular and flexible database. Process simulation, data management and training of the meta-model are key factors to generate an innovative Cognitive system to improve the manufacturing efficiency.

2. Multi-source data flow in production line

The multi-source data flow from heterogeneous devices and controllers in the same production is requiring a new flexible, secure and interoperability platform in agreement with RAMI4.0 architecture [1].

The essential elements that characterize a Digital Twin (DT) are: *Connectivity* based on appropriate ICT architecture (e.g. RAMI) and communication protocol (e.g. OPC-UA); Traceability of data that flows towards a structured and secure repository by storing setup information and sensors together with classified quality values; *Data Mining* which ensures the reliability of the data and the processing of the stability of real and virtual sensors where the latter can rely on mathematical applications also useful for the management of alerts; *Cognitive* model which has its roots in the programming of the instructive DOE suitable for the construction of predictive models with advanced self-learning and cross-validation algorithms; *Interoperability* offers a collaborative platform for different and multi-site users where the key performance indicators (KPIs) and cost index useful for a decision making process to optimize the process and apply the retrofit in the right and efficient time.

The structured and secure database is the ingredient to acquire all sensor signals by server-client connection. Remote real time visualization of the pure sensor measurements, as well as the preliminary data elaboration (e.g. velocity curve form movement in time and its relevant points), are the key metrics of process stability and alerting. The reliability of data is evaluated in terms of *Validity*, *Accuracy*, *Consistency*, *Integrity*, *Timeliness*, *Completeness*. Data *Accuracy* can be defined as the degree to which data correctly reflects the real world object or an event being described. On fast changing processes like HPDC and PIM, data must be accurately and quickly collected and aggregated to represent the interesting process transactions. Data *Timeliness* must be grant within the Control & Cognitive platform and can be measured as the time between when data is expected, from the Intelligent sensor Network, and when it is available by the Cognitive System and the user. Data *Completeness* is the extent to which the expected attributes of data are provided. So the Data Completeness means the expected completeness from the user or application requirements, but has strong impact on future elaborations. Data *Consistency* means that data across the system should be in synch with each other. Data is inconsistent, when it is in synch in the narrow domain of a system, but not in synch across the system. On the Factory 4.0 it must be trusted that all data coming from different production plants must be available and aligned each other. Data *Auditability* means that any transaction or statement of the identities represented can be tracked to its original state, that contextualized in the Digital manufacturing process means that all product quality and traceability data must be available for each process state. Data *Integrity* signify that data collected and stored is intact and unchanged, and in the Factory 4.0 this is achieved using correct saving, backup and security technologies and policies.

Standardization in communication and data mining is mandatory for future statistical model and KPI elaborations. Any production line is configured for the specific product and any volume of production, so the database has to be dynamic flexible to be connected with all possible sensors from various equipment as well as to archive the predicted output by Artificial Intelligence (AI) model. OPC and OPC UA (Unified Architecture) are industry standards that enable software to connect devices, machines and systems from different manufacturers using same interface. OPC servers add value for any device, machine or system, as it reduces any integration or application software development costs. Similarly OPC clients and application software utilizing OPC client features can be connected to any OPC server in a standard way without customization. OPC Foundation is dedicated to ensuring interoperability in automation by creating and maintaining open specifications that standardize the communication of acquired process data, alarm and event records, historical data, and batch data to multi-vendor enterprise systems and between production devices [3]

Within this context, the cognitive approach of data-driven digital twin (Fig. 1) predicts the quality, energy and cost in near real-time, covering the 100% of products, and suggests the appropriate re-actions to adjust the process set-up and/or mechanism.

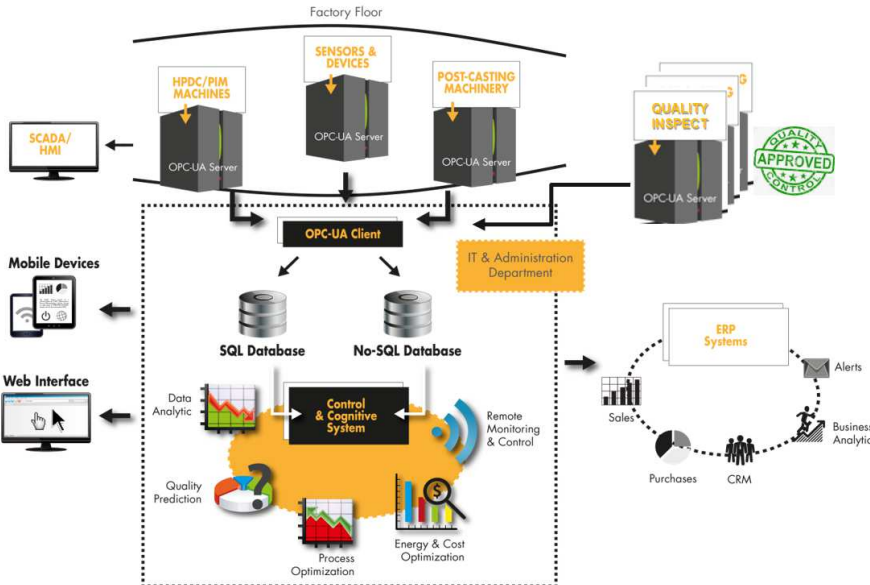


Fig. 1 – Introducing the *Data-Driven Digital Twin* with the OPC-UA client–server in the production line

The client-server connection works in combination with the real time monitoring system to elaborate instantaneously the production data set with respect to quality/energy/cost prognosis.

The database is collecting all process data, via OPC UA protocol, coming from all existing devices and active sensors in the production line. This communication protocol was chosen since it meets all the requirements needed by the ICT platform.

A fundamental innovative characteristic of digital twin platform, called *Smart Prod ACTIVE*, is the predictive Quality model integrating multi-resolution and multi-variate process data in a collaborative way to support the decision making process by Operator (Quality oriented), Production manager (Efficiency oriented - OEE) and Business manager (Cost-oriented).

The real-time visualization of elaborated data, including warning and safety messages and statistic production diagrams, can be customized for multiple users' interfaces as machine operator, production manager and plant director. The standardization of quality classification and investigation methods [5, 6], as well as the traceability, are fundamental to train the quality model guiding the minimization of relevant indexes affecting the scrap rate. The current version of the *Smart Prod ACTIVE* platform has a smart web application to visualize, share and communicate the significant data and to support the decision making with proper reactions in real-time based on the captured signals from the process.

To achieve this goal, the latency of data is always kept under control and the main delays trusted by the *Smart Prod ACTIVE* system are due to transmission, propagation, routing and data alignment.

The sampling delay is the delay of sampling data by the sensor at the given frequency. The transmission delay consist in having data sampled sent one after another, in the communication line. The propagation delay is given by the amount of time required to transmit data over the transmission line (e.g. wifi, ethernet cable, optical fiber). The routing delay is the time required for data to be sent through a Hardware or Software network node (e.g. router, switch, firewall, proxy, etc.) filtered analyzed and then addressed to another location. The data alignment delay is the amount of time that a input buffer actively waits for data with the intended number of shots or time-stamp to arrive.

3. HPDC foundry case study and quality prediction model

3.1 The HPDC cell

The multi-stages HPDC production line, represented here by RDS Foundry, has been the place to implement the innovative intelligent sensor network (ISN) [7] and the Cognitive system [8] from the design to the validation. As test-product on which evaluate the new technology, a diecasting Gear Box Housing has been individuated, as well as the priority list of defects/imperfections to be minimized/avoided: lamination, cold shots, flash, blister and incomplete casting.

In the foundry case study, a new die has been designed and built introducing various advanced sensors and in-line thermo-camera. All process parameters possibly affecting the quality of Gear Box Housing have been taken into account (Fig. 2), and used in the training stage of a meta-model, both virtual and real, correlating input process variables and data from sensors with quality indexes in the areas of interest, based on CEN Standard on defects classification in Aluminium foundry products [6].

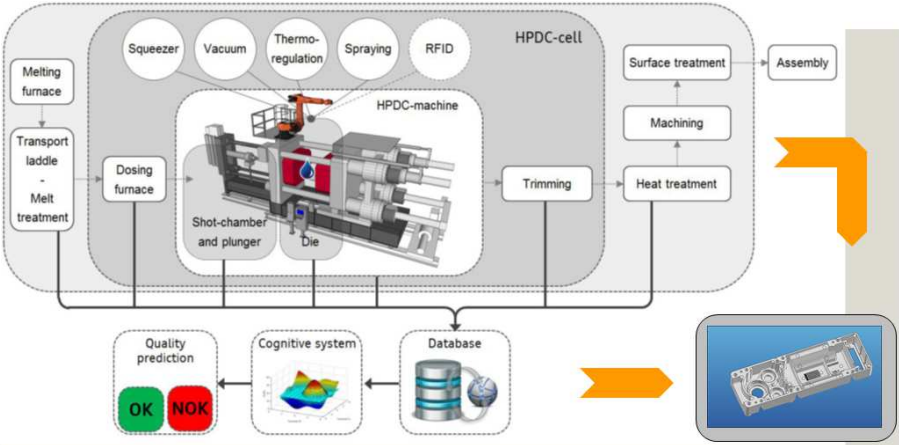


Fig. 2 – The application of *Data-Driven Digital Twin* in Foundry 4.0

The correlation matrix, based on 185 evaluated designs (Fig. 3), is one method to visualize the dependency of quality indexes from process parameters and virtual sensor measurements (e.g. temperature, pressure, velocity). As expected, defects such as misruns are strongly affected by the plunger position, when switching from first phase velocity to second fast velocity – the quantitative correlation is now available – but there are small opposite effects due to second phase velocity of the plunger and initial temperature of the alloy. Similar comments are possible for shrinkage porosities depending from overpressure and spray time, or blister correlated with second phase velocity.

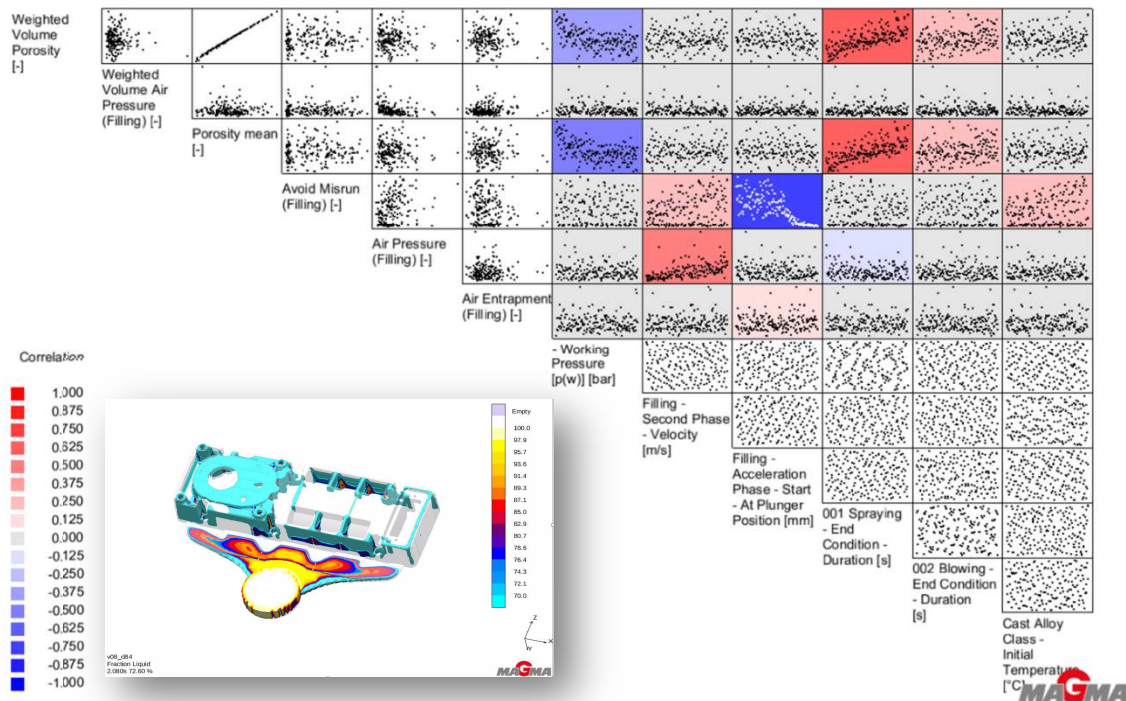


Fig. 3 - Correlation matrix based on simulated design of experiments

3.2 Quality prediction model

The prediction model needs to be trained with reference to a specific product and process, because the quantification of correlations are unique and not generalized. Typically, a meta-model is constructed based on data generated from a complex deterministic simulation of the system in which the random variation that exists in the real system is not represented. Design decisions, then, are based on system analysis and evaluation by approximating the system performance using the constructed meta-model. The primary objectives of metamodeling are to obtain an accurate estimation of the response and to minimize the required computational effort. This includes minimizing the necessary number of sample points and utilizing a computationally efficient modeling method valid for multi-layer and non-linear correlations like those found in the manufacturing processes. In addition, an important item underlying both tasks is the issue of performance evaluation and optimization of the system.

The main quality requirements for an experimental design are: the robustness (ability to analyze different models), the effectiveness (optimization of a criterion), the goodness of points repartition (space filling property) and the low cost for its construction. Several studies have shown the qualities of different types of experimental designs with respect to the prediction capabilities of the meta-model [9]; the choice of the meta-model that can be derived from any linear regression model, nonlinear parametric or non-parametric. The most used meta-models include polynomials splines, generalized linear models, generalized additive models, Kriging, neural networks, SVM, boosting regression trees.

Linear and quadratic functions are commonly considered as a first iteration. Knowledge on some input interaction types may be also introduced in polynomials. However, these kinds of models are not always efficient, especially in simulation of complex and nonlinear phenomena like those found in the injection manufacturing processes.

The usual practice is to estimate global criteria (RMSE, absolute error, etc.) on a test basis, via cross-validation or bootstrap [10]. The idea is to build for every output variable (e.g. single quality index of casting) more than one Radial basis Function (RBF) model and to choose the model with the lowest cross validation error.

The dataset of virtual and real experiments introduce the innovative data fusion to train the quality prediction model.

Application in production. The preliminary model, integrated in the digital twin, has been applied starting the casting production and the re-training method is applied any time new data are available to improve the accuracy of the model. The production starts normally, under the monitoring system, using the best process setup. The stability and repeatability of the best shot are monitored with real time comparison of reference curves. The example shown in Fig. 4 is the results of the optimization procedure applied during the production: the scraps were expected during the warm-up of the die and good quality achieved at thermal steady state; a 30 minutes break generated some scraps at re-start (e.g. casting number 157) and good production after 5 castings (e.g. casting number 162) has been recovered and automatically identified.

At the end, the introduction of the *Smart ProdACTIVE platform* in the factory floor needs a simple installation of LAN network connecting all devices of the production line, and it has been validated in an industrial production context of Al-alloy gear box housings.

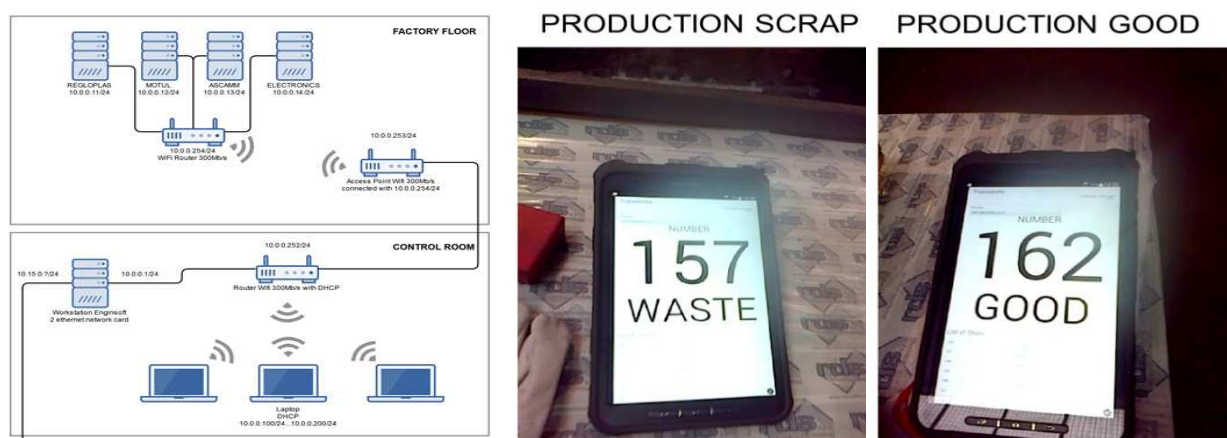


Fig. 4 – LAN network connection and real time prediction of Waste and Good castings shown on tablet

4. Cost model and decision making

The Data-Driven Digital Twin includes a cost model, properly developed to consider and manage costs related to the whole multi-stages HPDC production process [11]. This model is characterized by the presence of both real-time measurements, thanks to the positioning of an intelligent sensor network within the production process, which will guarantee a real-time quality and cost management as and a comparison of company’s past production data. The structure of the HPDC cost model has been developed based on the main units that are composing the entire process: the melting, the process, the post-processing and the quality. Four cost centers were thus identified for each the cited units. In particular the melting, the process and the post-processing centers reflect the real production process and are considered to be different cells characterized by different equipment. The melting cell is composed of all the activities starting from the arrival of raw materials till the movement of the cast material in the holding furnace; the die-casting cell includes all the activities starting from the holding furnace till the trimming activity that is the last activity realized close to the die-casting machine; the post-processing centre is composed by different cells that include heat treatment, machining and finishing before the final assembly. The fourth cost center is dedicated to the quality control activities to check how quality costs can influence the final product cost. The control of quality in different moments of the production could increase production efficiency thanks to the possibility to avoid waste and reworks within the production and accordingly to these considerations, the quality center aims to monitor all the quality control costs during the melting, the process and the post-processing activities. Specific cost voices are collected in Tab.1.

Table 1. Cost voices for each cost center.

Cost Center	Cost voices
Melting	Labour cost, depreciation cost, cell maintenance cost: scheduled or extraordinary maintenance, resource cost, consumption material cost, liquid/waste disposal cost, setup cost
Process	Labour cost, depreciation cost, cell maintenance cost: scheduled or extraordinary maintenance, resource cost, consumption material cost, liquid/waste disposal cost, warm-up cost, permanent mould cost, trim cost
Post-processing	Labour cost, depreciation cost, cell maintenance cost: scheduled or extraordinary maintenance, resource cost, consumption material cost, liquid/waste disposal cost, setup cost
Quality	Cost for control activities allocated into the melting, the process and the post-processing

The developed cost model is applicable at preliminary estimation of die-casting cost, but also during the real time monitoring of the production since it is connected in real-time with sensors and the database of the process parameters to estimate the cost impacts. The reduction of scrap is instantaneously translated in cost minimization, as well as the reduction of cycle time or alloy temperature and/or of energy consumption within the thermoregulation channel. As result any variations introduced to optimize the process or to satisfy the customer is tracked and optimized in terms of quality and cost.

With reference to the current production of the HPDC case study, the cost of material is predominant with 52% of the total cost per single piece, the melting process is 18%, the HPDC transformation process accounts for 19% while post-processing impacts for 10%. Quality affects 1% of total cost.

The cost model can provide projections in different scenarios: in case of two cavities per die, the estimation of industrial cost reduction is 19%. The potential reduction of 10 seconds per cycle impacts of -4.6% industrial cost and 13% reduction of energy.

5. The expected Impacts and Conclusions

The *data-driven digital twin* in production line is a solution to measure, analyze and react oriented to zero defect manufacturing and to the maximization of the OEE improving the sustainability and profit of factory of future.

With reference to the foundry application, the expected benefits are summarized as follow:

- 40% reduction in scrap rate for the involved HPDC foundry,
- -3% in no-quality costs for the involved automotive company,
- up to 40% decrease in the cost of quality control, to be applied only to specifically individuated products,
- 5-10% reduction in energy consumption, due to scrap reduction and increased production efficiency,
- better knowledge and control of the process, resulting in time to market reduction and minimization of trial & error approaches.

The application of *Smart Prod ACTIVE* system has been demonstrated and validated at foundry level. In the frame of HPDC production process, Operator and Process manager take advantage by adopting a centralized remote control system supporting process monitoring and quality prediction in real time. The decision is supported by cause-effect correlations, and proper reactions suggested by a continuously updated meta-model. Re-usability and flexibility of the *Smart Prod ACTIVE* system also allow agile re-start in case of small batches production.

The “zero defect” target is always the first priority of the approach, to minimize the defects with real-time retrofit suggested by the tool. The scrap rate reduction is focused on those defect factors mainly contributing the overall quality requirements of the product. Being the energy consumption connected to the production rate, the cycle time optimization (more pieces per hour) and the improved management of energy-demanding devices (furnace, thermal units, etc.) lead to cost reduction.

The digitalization of manufacturing plays a key role in competitiveness introducing new integrated platform to Control the process and predicting in real-time quality and cost of castings.

The new ICT technologies at manufacturing plant introduces significant potential impacts: (i) strengthened global position of EU manufacturing industry; (ii) larger EU market for advanced technologies such as electronic devices, control systems, new assistive automation and robots; (iii) intelligent management of manufacturing information for customization and environmental friendliness.

The application of data-driven digital twin has the natural extension to further multi-stages and multi-disciplinary production lines (e.g. sheet metal forming, forging, rolling, thermoforming, machining, welding, trimming, or the innovative additive manufacturing) is planned to exploit the same methodology in different industrial contexts.

Acknowledgments

The authors would like to thank the kind and professional technical support of RDS Moulding Technology staff involved in the industrial case study. The supports from EU FP7-MUSIC project (multi-stages production) and from PreMANI (POR FESR 2014-2020) project (new extended application of AI-driven digital twin in manufacturing process and quality control) are gratefully acknowledged.

References

1. Weber C., Konigsberger J., Kassner L., Mitschanga B.: A Maturity Model for Data-Driven Manufacturing. *Procedia CIRP* 63 (2017) 173 – 178
2. Lu Y., Liub C., I-Kai Wang K., Huang H., Xua X.: Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robotics and Computer Integrated Manufacturing* 61 (2020) 101837
3. OPC Foundation, OPC Unified Architecture Interoperability for Industrie 4.0 and the Internet of Things, version 10, November 2019
4. Auerbach T. et al.: Meta-modeling for Manufacturing Processes. *International Conference on Intelligent Robotics and Applications, ICIRA 2011: Intelligent Robotics and Applications* pp 199-209
5. Bonollo F., Gramegna N., Timelli G.: High-Pressure Die-Casting: Contradictions and Challenges. *JOM: the journal of the Minerals, Metals Society; Materials Society* 05/2015
6. CEN T/R 16749: Aluminium and aluminium alloys — Classification of Defects and Imperfections in High Pressure, Low Pressure and Gravity Die Cast Products, CEN, Brussels (2014).
7. Bonollo F., Gramegna N.: *The MUSIC guide to the key-parameters in High Pressure Die Casting*. Assomet servizi srl, Enginsoft SpA, ISBN 978-8887786-10-1, 2014
8. Bonollo F., Gramegna N.: *Smart Control and Cognitive System applied to the HPDC Foundry 4.0*. Assomet servizi srl, Enginsoft SpA, ISBN 978-8887786-11-8, 2016
9. Simpson T., Poplinski J., Koch P. et al.: *Metamodels for Computer-based Engineering Design: Survey and recommendations*. *EWC* 17, 129–150 (2001)
10. Kleijnen J. P. C.: *Regression Metamodels for Simulation with Common Random Numbers: Comparison of Validation Tests and Confidence Intervals*. *Management Science*, Vol. 38, No. 8. (Aug., 1992), pp. 1164-1185
11. Macchion L., Kral G., Bonollo F., Gramegna N.: *Application of Cost Model approach in HPDC contexts*. HTDC 22-23 June 2016, Venice (Italy)