SMART FACTORY COMPETITIVENESS BASED ON REAL TIME MONITORING AND QUALITY PREDICTIVE MODEL APPLIED TO MULTI-STAGES PRODUCTION LINES

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Abstract
Industry 4.0 is the industrial revolution based on Cyber-Physical-Systems (CPS) in the context of Factory of Future. The digital innovation is not an exclusivity of new and advanced technology and production processes. The traditional production processes and plants are evolving following this digitalization combining the long experience and the new fast 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.
Overall Equipment Effectiveness is connected to Intelligent Manufacturing System based on data mining and predictive models.
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). 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 of the most "defect-generating" and "energy-consumption" processes in EU industry, 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 platform presented in this paper is the main outcome of EU FP7-MUSIC project (funded in the frame of the Call FoF-ICT-2011.7.1 Smart Factories: Energy-aware, agile manufacturing and Customization) giving a new age to the traditional multi-stages production. The digitalization of 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.

1. Introduction
The industrial digital transformation plays at different levels: the shop floor with monitoring based on PLC; the scheduling and monitoring of the production efficiency by Manufacturing Execution System (MES) and the integrated management of core business processes by Enterprise Resource Planning (ERP) including procurement, accounting and human resource, etc. There are various tools, protocols and platforms to manage the information in a collaborative way. The shop floor data are the basement for the business and for the evaluation of the production efficiency and cost in-line. The OEE (Overall Equipment Effectiveness) is the gold standard for measuring manufacturing productivity. In the language of OEE, the 100% Quality (only Good Parts), 100% Performance (as fast as possible), and 100% Availability (no Stop Time) are the KPI to be elaborated, as well as the estimation of cost impacts. In particular, the OEE indexes of performance are calculated with average measurement versus maximum reference value creating a percentage and statistical visualization of factory efficiency. In the new digital era, all data coming from the shop floor are available in real time to record the stop time and cycle time when the vent is happen or finalized, as well as, the number of good quality products if the predictive meta-model is available in-line.

The data flow and data quality are ingredient of Intelligent manufacturing system to capture the process stability and key performance indicators. The OPC UA (Unified Architecture) are industry standards applied to the multi-stages production to improve the communication.

The ultimate Knowledge Discovery from Data (KDD) goal is to extract high-level knowledge from low-level data. KDD includes multidisciplinary activities. This encompasses data storage and access, scaling algorithms to massive data sets and interpreting results. The data cleansing and data access process included in data warehousing facilitate the KDD process.
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.
The 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.

The Control and Cognitive platform has to be flexible, with high interoperability, data-centric combining tools of data mining, statistic model e Artificial Intelligence to support the decision making process by Operator (Quality oriented), Production manager (Efficiency oriented - OEE) and Business manager (Cost-oriented).

The Foundry case study starts from existing data from machine and some devices, but never used in a predictive quality model or real time efficiency elaboration.
European non-ferrous foundries are a group of about 2700 companies, with a production assessed at 4 million of tons of castings in 2015. Key players are Germany and Italy, with 60% of total production from Europe (1,220 and 0,900 Mio tons for Germany and Italy corresponding to a turnover of 5.743,5 and 4.460,0 Mio of euro) [source: CAEF]. The non-ferrous foundry production is mainly constituted by Al alloys, and at least 60% of Al alloy castings are produced by HPDC process. High Pressure Die Casting (HPDC) of light alloys is one of the most representative large-scale production-line in manufacturing fields, which are strategic for the EU-industry largely dominated by SMEs.
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. The Intelligent Manufacturing Approach (IMA) 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. The Intelligent Sensor Network to capture the process data

The data flow from heterogeneous devices and controllers in the same production line and the data communication from and to the MES/ERP are requiring a new flexible, centralized and interoperability platform.
The Intelligent Manufacturing System (IMS) components are the CPS application, the connectivity and cognitive platform and the Production decision support system (PDSS) to optimize the process and apply the retrofit in the right and efficient time. The centralized database is the first 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.

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. Production devices include sensors, instruments, PLCs, RTUs, DCSs, HMIs, historians, trending subsystems, alarm subsystems as used for example in process industry, manufacturing, building automation, traffic management, energy production and smart grids

Within this context, the *Control & Cognitive platform* (Fig. 1) developed in the frame of the MUSIC project predicts the quality, energy and cost of the injection process in real-time, covering the 100% of products, and suggests the appropriate re-actions to adjust the process set-up and/or mechanism. The client-server connection works in combination with the real time monitoring system (the Intelligent Sensor Network) 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 [2-3] and active sensors in the production line. This communication protocol was chosen since it meets all the requirements needed by the Control & Cognitive platform.
The System performs time-critical operation so the Performance Requirements must be absolutely achieved; High delay is a serious problem for the delivery and elaboration of data since the quality state of the good predicted is real-time.
The Time-Critical Responses Availability Requirements because the processes analyzed by the *Control & Cognitive platform* are continuous. Unexpected outages of systems that control such processes are not acceptable: they must be planned.
Automated response time or system response to human and machine interaction is also critical and the information flow must not be interrupted. The system was designed to be robust to the stress events with a high fault tolerance level.
The requirement about Risk Management and Architecture Security are take in consideration even if Data confidentiality and integrity aren't the primary concerns for such industrial process monitored by, but behind data exchanged and stored there is a big know-how and the intellectual property must be preserved. Also since the Control & Cognitive platform is connected to the HPDC machines, it must be prevented any adversely impact on the edge device, so the protection of the system is very important.
The Components Lifetime and Accessibility requirements for software and hardware modules must be kept in consideration since the *Control & Cognitive platform* is installed on a Factory floor. To achieve this, Operating system and software libraries with long term support and the hardware spare components have been chosen. Furthermore components must be isolated and it must ensure an extensive physical effort to gain access to them.

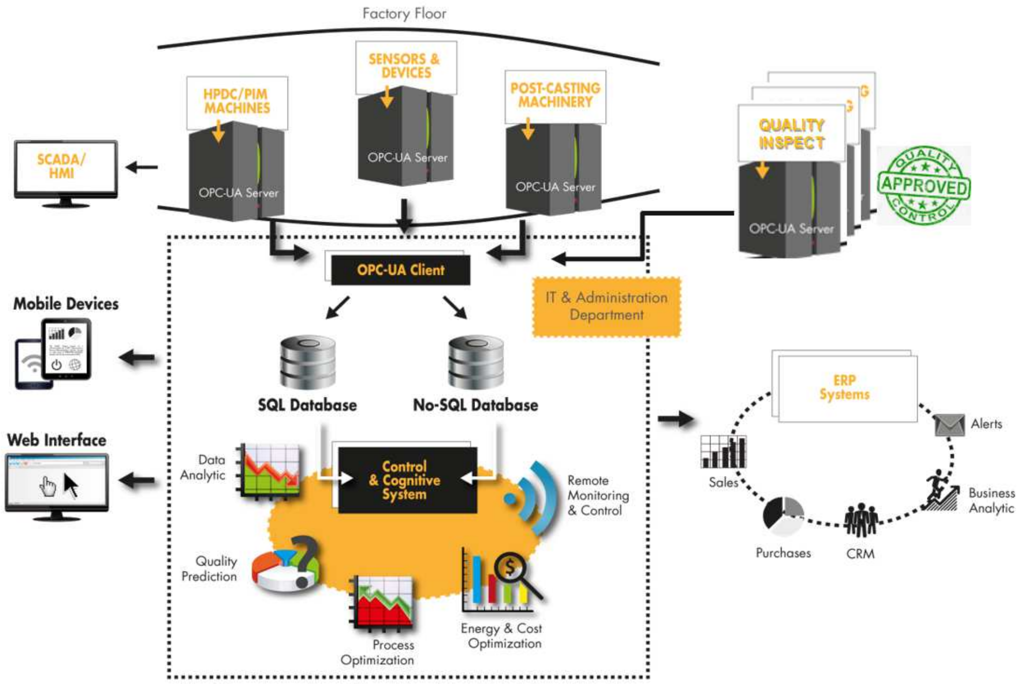

Fig. 1 – Introducing the *Control & Cognitive platform* with the OPC_UA client–server in the factory floor

A fundamental innovative characteristic of *Control & Cognitive platform, called Smart Prod ACTIVE,* is the predictive Quality model integrating multi-resolution and multi-variate process data.
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 Quality classification and investigation methods [4-5], 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 (retrofit) based on the captured signals from the process (Fig. 2).
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 …) 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. The training of the Quality predictive model

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 estimate 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 injection 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 (Santner et al., Fang et al. 2006). Several studies have shown the qualities of different types of experimental designs with respect to the

prediction capabilities of the meta-model (e.g. Simpson et al. 2001); 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 (Simpson et al. 2001, Fang et al. 2006).
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. For such models, modern statistical learning algorithms can show much better ability to build accurate models with strong predictive capabilities (Marrel et al.); the validation of the meta-model. In the field of classical experimental design, proper validation of a response surface is a crucial aspect and is considered with care.
However, in the field of numerical experiments, this issue has not been deeply studied. The usual practice is to estimate global criteria (RMSE, absolute error, etc.) on a test basis, via cross-validation or bootstrap (Kleijnen and Sargent, Fang et al.)
The idea is to build for every output variable more than one Radial basis Function (RBF) model and to choose the model with the lowest cross validation error.
In the field of mathematical modeling, a radial basis function network is an artificial neural network that uses radial basis functions as activation functions.

4. The High Pressure Die Casting Foundry case study

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.

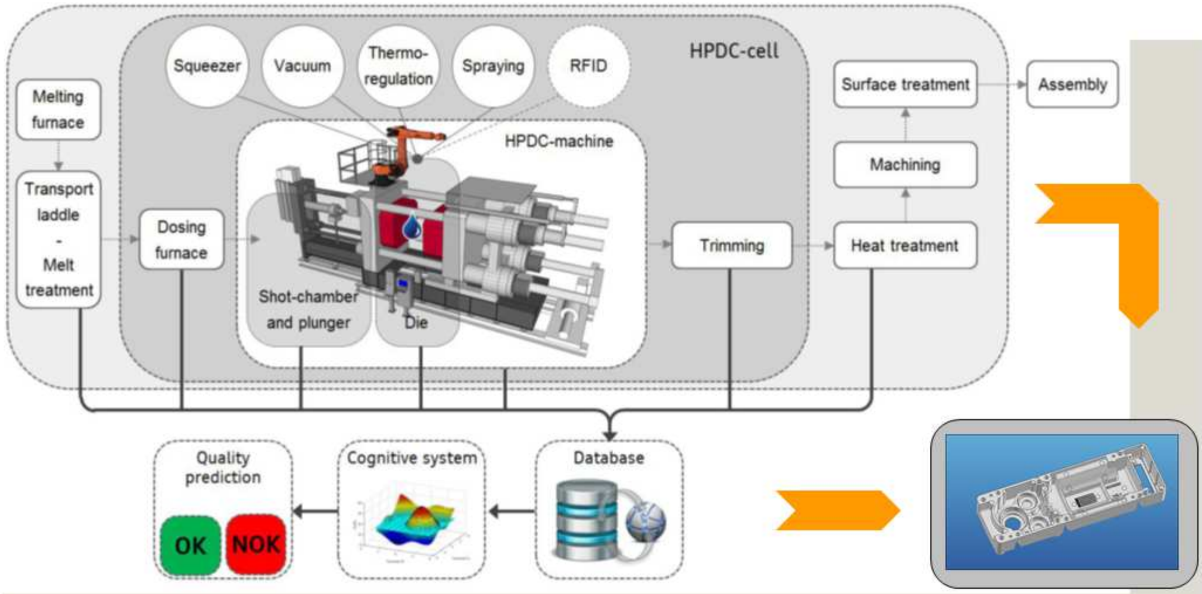

Fig. 2 – The application of *Smart Prod ACTIVE platform* in Foundry 4.0

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. The model needs to be trained with reference to a specific product and process, because the quantification of correlations are unique and not generalized.
Similar approach has been applied to train a model based on really produced and investigated castings. The same DOE has been performed, to validate the virtual meta-model generated by casting process simulator.

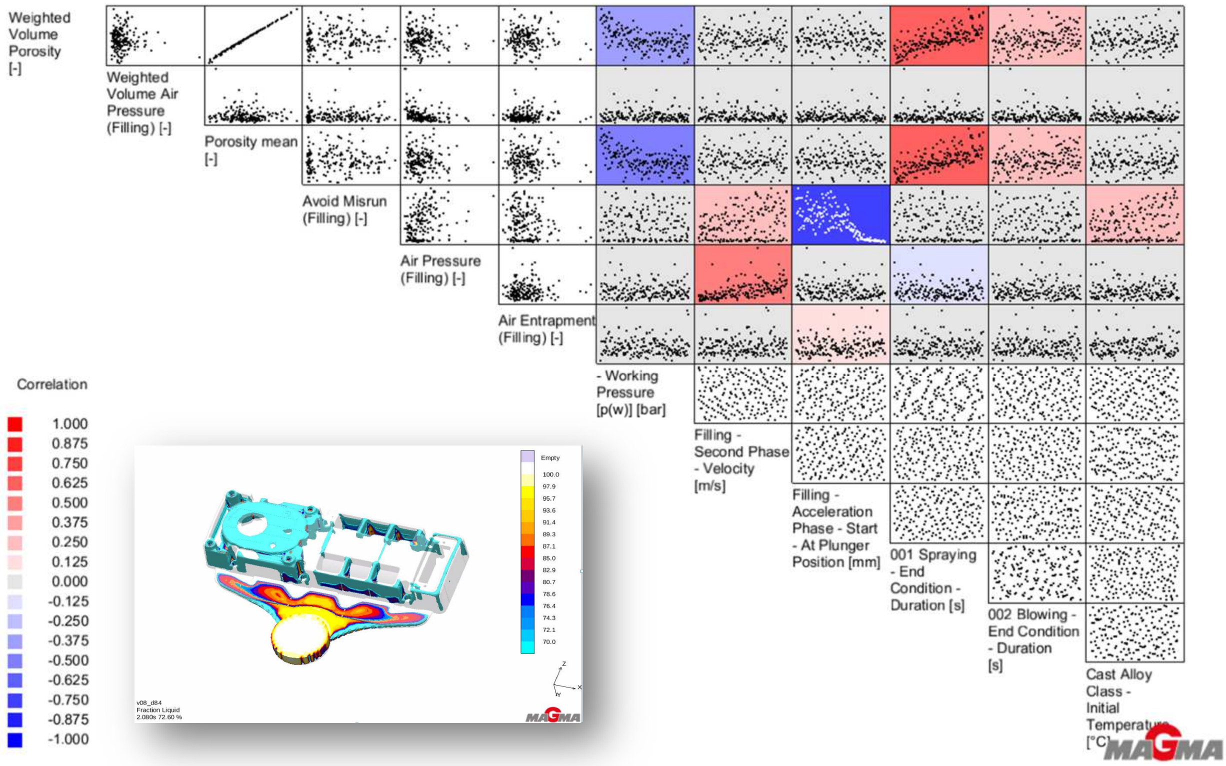

Fig. 3 - Correlation matrix based on 185 designs simulated by MAGMA5

The multi-stages HPDC production line at RDS Foundry has been the place to implement the innovative intelligent sensor network (ISN) [5] and the Cognitive system [6] from the design to the validation. As test-product on which evaluate the new technology, a diecast 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 [3].

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 has been validated in an industrial production context of Al-alloy gear box housings.
The production starts normally, 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.

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

5. Cost model and decision making

The Control and Cognitive platform includes a cost model, properly developed to consider and manage costs related to the whole multi-stages HPDC production process. 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 composting 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 Fig. 5.

Melting	• Labour cost, depreciation cost, cell maintenance cost: scheduled or extraordinary maintenance, resource cost, consumption material cost, liquid/waste disposal cost, set-up 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, set-up cost
Quality	• Costs for control activities allocated into the melting, the process and the post-processing

Fig. 5 – Specific cost voices for each cost center

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.

6. The expected impacts

The *Smart Prod ACTIVE system* is a solution to measure, analyze and act oriented to the maximization of the OEE improving the sustainability and profit of factory of future.

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.

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.

7. Conclusions and future developments

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, thermo units, etc.) lead to cost reduction [8-12].
The digitalization in foundry and in plastic injection factory 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 extension of application 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.

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