Modeling of Foundry Processes in the Era of Industry 4.0

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Abstract. The paper presents main areas of Industry 4.0 concept with regard to specificity and complexity of foundry processes. Data mining tools are discussed in terms of the possibilities and limitations of their application in Smart Factories. Data acquisition methods are described and the potential areas of restrictions in Internet implementation of things are identified on the example of foundry processes. The methodology of data preparation is also presented, including key tasks and actions to be taken, so that the collected production data are valuable from the point of view of Data Mining tools. As a result, the concept of CPS (Cyber-Physical Systems)/CPPS (Cyber-Physical Production Systems) tool allowing effective implementation of Data Mining tools in complex production processes is presented.

Keywords: Industry 4.0 · Data acquisition · Data mining · Foundry processes

1 Introduction

The idea of the fourth industrial revolution is technology development and, as a result, manufacturing processes based on automation, robotization, communication between machines and digitally supported product management processes. The result of these activities is the creation of Intelligent Factories, where the entire process of producing of an End-to-End product, from prototype due to technology development, production planning and production to control and service, will be digitally integrated in accordance with the principles of horizontal and vertical integration of value stream. In consequence, it will be possible to switch from mass production to individualized production, taking into account individual requirements of customers [1], while maintaining low production costs – this approach is known as mass customization [2].

2 Literature Review

The concept of Industry 4.0 assumes full, digital integration of humans with production machines [3]. In a smart factory, so-called smart manufacturing environment should be created, in which machines communicate with each other in an automated way, transferring a part of key information to a human operator.

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The methodology of Industry 4.0 includes several key components i.e.: CPPS – Cyber-Physical (Production) Systems, IoT – Internet of Things, IoS – Internet of Services and finally Smart Factories. Smart Factories are equipped with Social Machines, communicating with each other and with an operator, who is much more capable than a traditional operator, due to the use of digital technologies, such as Augmented Reality (AR) [4]. Some key components of Industry 4.0 are presented in Fig. 1.

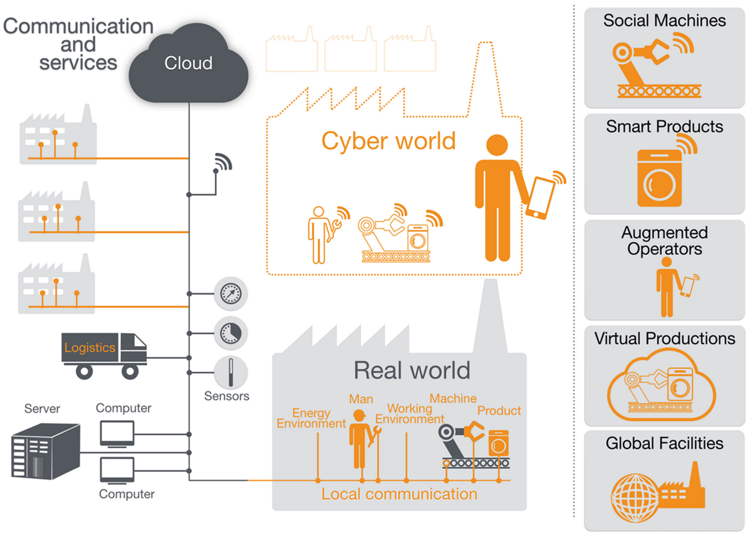

Fig. 1. Main components of Industry 4.0 [5].

An important element of Industry 4.0 concept is virtualization process, which is essential not only for simulation, but also for training. Here, it is worth to mention such concepts as Big Data (management of large data sets) or Cloud Computing (distributed computations), which are helpful for efficient implementation of calculations necessary for decision making, especially in the aspect of predicting possible defects of manufactured products. They are also listed as the key features of Industry 4.0 concept.

IoT is called IIoT in reference to industry (Industrial Internet of Things) and focuses on physical identification and communication between the elements of structural network of the whole process, such as objects, system and server platforms and other applications supporting the process. In the scope of IoT, the significant limitations in implementing of Industry 4.0 concept can be observed in foundry and other processes, in which difficult and demanding conditions occur, e.g. high temperature, high dustiness, manual control, electro-magnetic interference, vibrations or difficult connection and identification between a particular piece of finished product and process parameters.

IoS is the work methodology of service support systems (e.g. delivery of components from different suppliers), which helps analyze their availability at any time on demand. This includes standardization, which allows building and configuring an offers network for internal and interorganizational services, based on shared resources for all the participants of the value stream.

Smart Factories are treated as a target effect of factory transformation. In the structure of the intelligent factories, physical processes are monitored by CPPS. This digital image is processed on-line into a language understandable for the decision-making systems on subsequent levels. IoT enables and supports communication between CPSs, as well as between CPSs and humans and other parts of system, presented in Fig. 1. This transformed information triggers the decision chains, supported by Internet of Services, finally resulting processes or services, going to the customers along with the whole internal and external value stream.

It is important to emphasize here, that key concepts of Industry 4.0 focus not only on the manufacturing process itself, but also on the planning, design and transport processes [6]. They should all be digitally integrated to allow seamless communication between a client, a producer and a supporter. Some parts of communication can be automated, for example clients can use digital product configurators to create their own variants of products, output from such a system can be then automatically sent further to create a new design and place it to production. This helps realize mass customization concept [2].

Thus, the main factors enabling the development of Industry 4.0 are: mobile communication and digital channels of access for customers, as well as available enough data sets and tools for data analysis, which will be the scope of this paper.

It should be remembered that the concept of Industry 4.0 also has a place for a human operator (especially in case of foundry processes). The concept of so called Operator 4.0 assumes supporting physical and mental work performed by the operator due to various techniques, such as Virtual Reality (for training and CPPS simulations [7]), Augmented Reality (for training directly on production line [4], displaying data on the state of machines, production, resources or hints about decision making directly on production site). Within the concept of Operator 4.0, several functions can be distinguished, namely super-strength operator, augmented operator, virtual operator, healthy operator, smarter operator, collaborative operator, social operator and analytical operator. It also assumes the operator's work directly in the vicinity of automated production machines and his physical cooperation with robots [8]. It can be particularly valuable in processes difficult to be fully automated and requiring current analysis and interpretation of large amounts of data, such as in foundry.

In relation to the above mentioned, foundries and foundry processes seem to be a particular challenge while implementing Industry 4.0 solutions. Complex and difficult process conditions for machines, people and measurement devices, and a wide range of activities realized or controlled by humans can significantly disturb the implementation of even basic IoT solutions. The complexity of foundry processes, the number of input parameters related to the number and type of output parameters (properties of final product) as well as the number and type of casting defects (quality parameters), issues in linking and mathematical description of several process stages significantly limit the implementation of CPPS solutions.

The previous experience indicates that the foundries are at the initial stage of implementing Industry 4.0 concept, hence in this paper, the authors suggest solutions, which allow taking practical steps to implement this concept.

3 Research Methodology

3.1 Data Mining in Foundry Industry 4.0

CPPS implementation requires replacing the existing methods of manual control by a human with automated decision systems, which carry out, lead and control tasks in a repetitive manner and no worse than a human [9]. Recently, it has been particularly noticeable in foundry engineering [10]. In case of processes, where the human factor is an integral part (e.g. in foundry processes), it also requires methods supporting the decision-making processes and other activities physically implemented by humans. In production processes, including foundry ones, it usually boils down to analysis of dependencies between process parameters derived from sensors or DAQ tools (treated as inputs) and other process parameters used for control or product parameters (treated as outputs) [11, 12]. Among the many mathematical models used in Data Mining, two main groups can be distinguished. They are HARD mathematical models, i.e. equations and inequalities describing the analyzed process, phenomenon or object, and SOFT mathematical models, construction and operation of which is based on the data collected in the past. With respect to Industry 4.0 and foundry processes, hard models can only be used at the pre-processing stage for modeling of the selected process steps, e.g. pouring and solidifying of metal in a mold, to determine the initial parameters of the process. At present, there are no known methods allowing a comprehensive mathematical description of all the foundry processes. This raises a need for alternative solutions.

Unfortunately, in relation to Industry 4.0, complex production processes usually require more sophisticated techniques of process state analysis, especially when applying assumptions of mass customization in practice [13]. In such cases, Data Mining methodology and soft mathematical modeling are used. There are 3 main types of soft mathematical models, depending on the complexity of process and knowledge of laws governing it, as well as the complexity of models. Three models are statistical models, artificial intelligence and computational intelligence.

Statistical models are most often used during the first modeling phase. As a result, regression equation is created, enabling prediction of the output variable (e.g. a control variable value or quality characteristics of a finished product) depending on the input variables (e.g. signals from sensors) [14]. Their basic advantage in Industry 4.0 is the speed of their implementation and operation, which can be important when using them on-line. Simplicity of these models allows quick creation of new models, adapted to the changing process conditions, both at the level of augmented operators and social machines.

Artificial Intelligence (AI) models are expert systems, where the knowledge of the process comes from experts and other traditional sources (standards, guides, books, publications) and is intelligently processed by a computer system. They can significantly support the decision-making processes in foundry, at the augmented operators' level.

Computational intelligence (CI) models are the most complex ones used, where there are large data amounts of different nature for complex processes. This group includes among others: Artificial Neural Networks, Decision Trees and others. In CPPS range, these models can be used anywhere, where a human has decided about the process so far, using his experience, perceptiveness, daytime disposition, as well as where other modeling methods were insufficient as tools directly controlling the process or supporting decisions of augmented operators [15, 16].

For the proper use of soft mathematical models, an appropriate amount of data is needed, prepared in a way allowing its use in the modeling process, with the least interference. Methods of data acquisition and preparation in a specific environment of foundry processes will be presented in the further part of the paper.

3.2 Data Acquisition in Foundry Processes

Almost all diagrams showing Industry 4.0 concepts contain symbols of wireless data transmission, as well as cloud data storage and processing. This assumption is correct for highly automated processes with high IT equipment and high technical capabilities. It is different in foundry processes, where, despite continuous improvement in the methods and tools of quality control at particular stages of processes, quality and availability of production data, as well as continuous technical and IT development, data acquisition in this type of technologically complex processes are still difficult. Although the share of automatic and computer methods of data acquisition is increasing, many production, technical and administrative departments still use various types of paper documents. An especially important source of information is informal documentation, such as entries in personal notebooks, kept by process engineers, quality controllers and other foundry workers. Such data, often valuable and relevant information about the process, are in principle available only to a specific employee. The access to data should be common and quick for authorized persons. However, when they are only at the disposal of the above-mentioned persons, they are unfortunately not available to other departments.

In the era of Industry 4.0, it is necessary to collect data that are used not only for the ongoing monitoring and control of processes, but also for the knowledge capitalization. Production problems cannot always be explained directly with the help of knowledge and experience of an engineer. What is then necessary is production parameters analysis (of the collected historical data) using statistical methods or mathematical models of data mining (Data Mining) [12].

The first requirement, however, is a well-developed and implemented process of data acquisition [8], especially concerning the aspects of data acquisition related to the technical side of casting and associated with complex processes in foundry. Data acquisition in foundries is currently carried out in three ways [17]:

- manually – e.g. parameters of molding sand, such as moisture M [%], permeability p^m [m^2/Pa * s * 10^{-8}] and compressive strength R_c^w [MPa] (in moisture state), which are taken from different places of foundry molding line;

– automatically – e.g. non-contact measurement of pouring temperature of liquid alloy into molds using a pyrometer, non-contact measurement of mold pouring time by means of optical, ultrasound or microwave sensors;
– semi-automatically – occurs most often in case of combining automatic sources and derived from manual entries, e.g. automatic data recording from the Zwick – tensile strength R_m and manual addition of hardness measurement HB to the generated file; such a collective database can be further exported to CAx/ERP computer systems.

In a Smart Factory, guidelines on the frequency of data acquisition should be worked out for each type of data and the means of their acquisition. At further stages of their use in CPPS, this directly translates into efficiency of data processing systems, especially in online mode. Currently, the following data logging modes can be distinguished:

- cyclic mode – changing parameter values are collected in a constant time interval (e.g. every second),
- event mode (delta) – parameter values are collected only when their values change,
- forced mode – parameter values are collected in accordance with the method of data delivery to server (at specified times of the day or with means of extortion – e.g. device failure).

Considering the above mentioned, it seems reasonable that in a Smart Factory it is necessary to collect as much data as possible in electronic form, i.e. in IT databases. It is also important to develop procedures and methods facilitating their issuing "on demand" whenever the necessity of their use arises.

The specificity of foundry processes, the differentiation in the range of data sources and the complexity of this process and the difficult measurement conditions make it difficult to find valuable solutions dedicated to foundry in the marketplace. When implementing original methods and tools for data acquisition in the foundry, it is important to remember often overlooked aspects, such as appropriate supervisory procedures, especially where significant share of data is saved or rewritten manually to database systems. Methods supporting data validation of the collected information will be described below.

3.3 Methodology of Data Preparation for Modeling

Modeling of production processes should be based on reliable data. This requires designing appropriate acquisition system architecture and algorithms including assessment of information sources, data structuring concepts (depending on the type of data) and measurement procedures (from manuscripts to automated measurement systems). The type and class of measuring apparatus, the method of data recording, algorithms for their processing and classification, as well as all disturbances known at the time of measurement should also be taken into account [18].

The methodology of data preparation for modeling consists in the analysis and implementation of selected activities, including 4 main tasks, i.e. cleaning, merging, converging and reducing data [19, 20].

Data cleaning – it aims at elimination of inaccuracies or contradictions in the collected data. The key activities of this task are: deleting outliers and topping up missing data.

Data merging – it aims at combining data from different sources into a single, two-dimensional table. The key activities in this area are: identifying attributes in various databases, removing repetitions and analyzing formats or units compatibility.

Data reduction – it aims at reduction of a database dimensionality, in order to reduce data mining time. The main activities of this task are: analysis of significance and removal of non-essential attributes, deletion of similar records, aggregation, discretization.

Data conversion – it aims at enabling creation of a model and improvement of its accuracy and speed of operation. The main activities related to this are: smoothing, aggregation and normalization.

Apparently, the methodology of preparing data for modeling is a complex process. In the context of Industry 4.0 implementation, it should be mostly automated. Traditional methods, based on paper, should be replaced with digital database systems, including data validation procedures at the time of entering. Therefore, the conscious approach to the quality of data is crucial as early as at the acquisition stage, in order to limit the above-mentioned activities to a minimum.

4 Results

The example of application of the approach presented in this paper within the scope of Industry 4.0 concept, was a feasibility study of the use of Data Mining tools for foundry in ADI production process. The used approach and obtained results were described by the authors in other publications [21, 22].

The methodology and assumptions can be referred to operation of a cyber-physical system shown in Fig. 2.

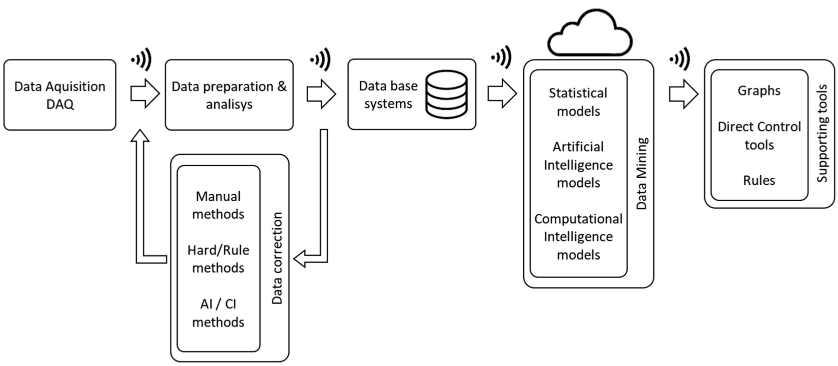

Fig. 2. Exemplary model of a cyber-physical system in foundry Industry 4.0.

The main goal of the analysis of ADI properties modeling was to build a mathematical model predicting mechanical properties such as: tensile strength Rm [MPa] and elongation A5 [%]. In the scope of social machines, it allowed to directly control the process and properly serve as an expert supporting decisions at augmented operators' level to select quasi-optimal process parameters. The effect described above was obtained based on special proprietary procedures for querying of Artificial Neural Networks models learned, taking into account the effect of synergy or competitive influence of process parameters. It is allowed to determine the most important groups of signals to control the process parameters and determination the reverse task, i.e. to search for ranges (intervals) of process parameters, allowing to obtain the values set of the output variables. The research involved the use of MLP Neural Networks with one layer of hidden neurons with the number of hidden neurons equal to the number of input neurons with a logistic activation function. In consequence, this allowed to obtain cast iron with given properties and process parameters control within defined limits. In the research, various mathematical models were used and their analysis was performed in terms of usability as to quality and performance.

The collected ADI database, derived from own research and data available in literature, encompassing over 1,400 records, was analyzed and prepared, taking into account the relevant methodology [20]. This required checking the possibility of implementing automated systems for correctness and data replenishment in on-line process.

Within CPPS in foundry industry, such predictions and suggestions for setting process parameters can be automated, provided that the model is supplied at the right time, along with the right data about the current state of process. In typical foundry processes, it will usually be a set of guidelines, instructions or rules addressed in an appropriate way to Operator 4.0.

5 Conclusions

The paper outlined the main areas of Industry 4.0 concept, taking into account the specific conditions of foundry processes. The implementation of Cyber-Physical (Production) Systems is also possible in these complex processes, however, it is necessary to switch to automatic control systems. Today, more and more often advanced systems supporting the work of operators are installed, such as, for instance, SCADA system (Supervisory Control and Data Acquisition). The example of this is FoMaSys system from Michenfelder which supports selected molding sand parameters control.

The paper shortly presents the stages of production data preparation and includes steps necessary for the data collection from the point of view of Data Mining tools (data cleaning, merging, reducing and transforming). Despite the fact that this paper presents only the concept related to the production process of ADI cast iron, the specific solutions are currently being implemented as a part of the test and development works in another selected foundry, in high-pressure die-casting processes.

It should be noted, that presently, fully automated foundry in accordance with Smart Factory concept is practically unlikely. It should be remembered, however, that quite a lot of production processes have recently been automated in a way that somewhat reduces operator's participation. In case of foundry processes, a human is still an integral part, although increasingly supplied with methods supporting the decision making processes. The experience gained by the authors, indicates that the implementation of IoT measurement methods and tools may be a significant limitation on the subsequent stages of their connection within CPPS, in relation to various stages of casting production.

The stage of production data acquisition is important, as only on the basis of the data completeness and awareness of the collection frequency, useful knowledge necessary to develop mathematical models can be built.

References

1. Trojanowska, J., Varela, M.L.R., Machado, J.: The tool supporting decision making process in area of job-shop scheduling. In: Rocha, A., Correia, A., Adeli, H., Reis, L., Costanzo, S. (eds.) Recent Advances in Information Systems and Technologies. WorldCIST. Advances in Intelligent Systems and Computing, vol. 571, pp. 490–498. Springer, Cham (2017)
2. Górski, F., Zawadzki, P., Hamrol, A.: Knowledge based engineering as a condition of effective mass production of configurable products by design automation. J. Mach. Eng. **16**(4), 5–30 (2016)
3. Gorecky, D., Schmitt, M., Loskyll M., Zuhlke D.: Human – machine – interaction in the Industry 4.0 ERA. In: 12th IEEE International Conference on Industrial Informatics (INDIN), pp. 289–294 (2014)
4. Górski, F., Wichniarek, R., Kuczko, W., Bun, P., Erkoyuncu, J.A.: Augmented reality in training of fused deposition modelling process. In: Advances in Manufacturing, pp. 565–574. Springer (2018)
5. Ottomotors: Defining the next industrial evolution. https://www.ottomotors.com/blog/understanding-industry-4-0. Accessed 25 Dec 2018
6. Ivanov, V., Vashchenko, S., Rong, Y.: Information support of the computer-aided fixture design system. In: Proceedings of 12th International Conference ICTERI' 2016, vol. 1614, pp. 73–86, CEUR-WS (2016). CEUR-WS.org
7. Żywicki, K., Zawadzki, P., Górski, F.: Virtual reality production training system in the scope of intelligent factory, intelligent systems in production engineering and maintenance. In: Burduk, A., Mazurkiewicz, D. (eds.) Intelligent Systems in Production Engineering and Maintenance – ISPEM 2017. ISPEM 2017. Advances in Intelligent Systems and Computing, vol. 637, pp. 450–458. Springer, Cham (2017)
8. Romero, D., Stahre, J., Wuest, T., Gorecky, D.: Towards an operator 4.0 typology: a human-centric perspective on the fourth industrial revolution technologies. In: International Conference on Computers & Industrial Engineering (CIE46), Tianjin, China, pp. 1–11 (2016)
9. Gramegna, N.: Smart casting process control and real time quality prediction The digitalization of foundry plays a key role in competitiveness introducing new integrated platform to control the process and predict in real-time the quality and the cost of the casting. In: 9th VDI Conference with Specialist Exhibition on Casting Technology in Engine Construction: Potential for the Next generation of Vehicle Propulsion, vol. 2304, pp. 227–234 (2017)
10. Industry 4.0 and what it means to the Foundry Industry. http://www.foundrytradejournal.com. Accessed 20 Dec 2017

11. Perzyk, M., Kochański, A., Kozłowski, J.: Comparison of data mining tools for significance analysis of process parameters in applications to process fault diagnosis. Inf. Sci. **259**, 380–392 (2014)
12. Rogalewicz, M., Sika, R.: Methodologies of knowledge discovery from data and data mining methods in mechanical engineering. Manag. Prod. Eng. Rev. **7**(4), 97–108 (2016)
13. Pavlenko, I.V., Simonovskiy, V.I., Demianenko, M.M.: Dynamic analysis of centrifugal machines rotor supported on ball bearings by combined application of 3D and beam finite element models. In: IOP Conference Series: Materials Science and Engineering, vol. 233, pp. 1–8. IOP Publishing (2017)
14. Andrzejczak, K., Selech, J.: Quantile analysis of the operating costs of the public transport fleet. Transp. Prob. **12**(3), 103–111 (2017)
15. Harding, J.A., Shahbaz, M., Srinivas, M., Kusiak, A.: Data mining in manufacturing: a review. J. Manuf. Sci. Eng. **128**(4), 969–976 (2006)
16. Köksal, G., Batmaz, I., Testik, M.C.: A review of data mining applications for quality improvement in manufacturing industry. Expert Syst. Appl. **38**(10), 13448–13467 (2011)
17. Sika, R., Popielarski, P.: Methodology supporting production control in a foundry applying modern DISAMATIC molding line. In: 13th International Conference on Modern Technologies in Manufacturing, Cluj-Napoca and AMaTUC, MATEC Web of Conference, vol. 137, p. 05007 (2017)
18. Sika, R., Ignaszak, Z.: SCADA systems and theirs connection with statistical process control in foundry. Arch. Foundry Eng. **15**(1), 145–153 (2015)
19. Kochański, A.: Data preparation. Comput. Methods Mater. Sci. **10**(1), 25–29 (2010)
20. Kochański, A., Perzyk, M., Kłębczyk, M.: Knowledge in imperfect data. Advances in Knowledge Representation. InTech (2012)
21. Perzyk, M., Kochański, A., Kozłowski, J.: Control of ductile iron austempering process by advanced data driven modeling. In: Cooper, D., Prat, J., Petzchmann, U. (eds.) Proceedings of 71st World Foundry Congress, pp. 1–11. World Foundry Organization Ltd (2014)
22. Perzyk, M., Kozłowski, J.: Methodology of fault diagnosis in ductile iron melting process. Arch. Foundry Eng. **16**(4), 101–108 (2016)