

MODELLING INFORMATION FOR THE BURNISHING PROCESS IN A CYBER–PHYSICAL PRODUCTION SYSTEM

JUSTYNA PATALAS-MALISZEWSKA ^{a,*}, MARCO POSDZICH ^b, KATARZYNA SKRZYPEK ^a

^aInstitute of Mechanical Engineering
University of Zielona Góra
ul. Licealna 9, 65-417 Zielona Góra, Poland
e-mail: {j.patalas-maliszewska, k.skrzypek}@iim.uz.zgora.pl

^bFaculty of Mechanical Engineering
Chemnitz University of Technology
Strasse der Nationen 62, 09111 Chemnitz, Germany
e-mail: marco.posdzich@mb.tu-chemnitz.de

Currently, the manufacturing management board applies technologies in line with the concept of Industry 4.0. Cyber-physical production systems (CPSs) mean integrating computational processes with the corresponding physical ones, i.e., allowing work at the operational level and at the strategic level to run side by side. This paper proposes a framework to collect data and information from a production process, namely, the burnishing one, in order to monitor real-time deviations from the correct course of the process and thus reduce the number of defective products within the manufacturing process. The proposed new solutions consist of (i) the data and information of the production process, acquired from sensors, (ii) a predictive model, based on the Hellwig method for errors in the production process, relying on indications of a machine status, and (iii) an information layer system, integrating the process data acquired in real time with the model for predicting errors within the production process in an enterprise resource planning (ERP) system, that is, the business intelligence module. The possibilities of using the results of research in managerial practice are demonstrated through the application of an actual burnishing process. This new framework can be treated as a solution which will help managers to monitor the production flow and respond, in real time, to interruptions.

Keywords: cyber-physical production system, production process, burnishing process, enterprise resource planning system.

1. Introduction

The digitisation and automation of information processing requires new solutions to be obtained in order to support the functioning of a manufacturing company in accordance with the concept of Industry 4.0 (I4.0). The I4.0 paradigm includes five approaches, namely, the Internet of things (IoT), the cyber physical system (CPS), information and communications technology (ICT), enterprise architecture (EA), and enterprise integration (EI) (Yli-Ojanpera *et al.*, 2019). The integration of such areas is made in order to increase the levels of automation and efficiency in manufacturing and further requires the creation of a CPS, which is one of the main tasks of I4.0 (Roldán *et al.*, 2019). Moreover, the significant increase

in data amounts needs to be processed in different activity fields of each manufacturing company (Jaworski, 2018). The analysis of the literature leads to the conclusion that, to be competitive, every modern and innovative manufacturing enterprise should implement the concept of Industry 4.0. Therefore, these enterprises cannot function without the use of CPSs (Alcácer, 2019; Mourtzis, 2020).

The CPS concept has been known for more than a decade now and is characterized, primarily, by its feature of integrating computational processes with the corresponding physical processes, i.e., synchronising the physical and cyber worlds (Krupitzer *et al.*, 2020), so-called cybernetic components, with physical processes (Wojnakowski *et al.*, 2021). CPSs require manufacturers to become increasingly flexible and adaptable in order to meet the challenges of the increasing process complexity.

*Corresponding author

Along with the dynamic technological progress, the problem is, also, the effective process of transferring and storing data as well as information and knowledge within an organization. Operators face a difficult challenge, namely the process of transferring knowledge about production processes to management boards. New types of intelligent interactions between managers and operators are sought via CPSs, which will support the decision-making process and the completion of tasks (DAT, 2016).

CPSs are based on a smart network which collects and manages data and information in order to make decisions at the strategic level within a company (Tonelli *et al.*, 2021). It is worth pointing out that CPSs can interact with all the hierarchical layers of the information system, applied in manufacturing (i.e., enterprise resource planning—ERP, manufacturing executing systems—MES, supervisory control and data acquisition—SCADA), ultimately resulting in a much improved process workflow (which is a characteristic feature of CPSs and I4.0 technologies in industrial use).

Therefore, this article attempts to develop a framework for modelling and transferring data and information from the operational level of the physical world, i.e., from machinery and production processes, to the strategic level, within a company's information system and hence, on to the so-called digital level. In summary, this paper addresses the following research question: 'How can data and information about production processes be transferred, in real time, to the information system, in support of the work of managers and how can managers monitor and analyze this process?'

The research in the article was conducted on an example of the burnishing process, which is a finishing procedure mainly used for rotationally symmetrical workpieces in the power-train industry (Chomienne *et al.*, 2016). The process uses a spherical or rotationally symmetrical tool to form the material in the area close to the surface, by means of selective surface pressure. The tips of the surfaces are thus depressed and at the same time the imperfections are filled. In the processing of materials that are difficult to grind, burnishing offers an especially viable alternative to producing surface qualities with a roughness R_a of $0.1 \mu\text{m}$ (Hassan and Maqableh, 2000) for ductile metals.

The research by de Lacalle *et al.* (2011) shows the potential to increase the level of automation in the finishing of moulds by substituting manual polishing processes. Although it is indicated that the implementation of CPSs is necessary for manufacturing companies, in order to maintain and achieve a competitive advantage, there is still a lack of solutions enabling the integration of data and information from the production process into the process supporting decision making, which means that solutions enabling connection of the

production company's layer information systems to the management's layer is being sought. Additionally, it is important to monitor the course of the production process and forecast possible errors therein; this requires implementation of a model based on a data-driven method.

Data-driven methods began to be core in the field of performance evaluation (Chen *et al.*, 2020). According to different data-processing modes, data-driven methods are divided into different categories. Quantitative methods include artificial intelligence methods, signal processing methods and statistical analysis methods (Wang *et al.*, 2020). Artificial intelligence methods include the artificial neural networks, fuzzy mathematics, genetic algorithms, etc. The signal processing methods mainly cover empirical mode decomposition. In addition, statistical analysis methods include principal component analysis (PCA), Bayesian techniques, etc.

This article, therefore, is looking for a solution to collect data and information from a production process, more specifically the burnishing one, in order to monitor deviations from the correct course of the process, in real time, so that the number of defective products within manufacturing can be reduced. Therefore, it is necessary to set forth an approach, within a company, that would allow the acquired data and information, i.e., the predictive model for production process errors, based on a statistical method, to be transferred from the production process, in real time, to the business intelligence (BI) module in the ERP system applied at the strategic level. The key role for BI in managing information effectively is to help the management to improve access to accurate information when needed (Farzaneh *et al.*, 2018). BI can provide the management board with the ability to make a faster, more accurate and more reliable decision (Alpar and Schulz, 2016).

The main contributions of the paper can, therefore, be summarized as follows:

- Hellwig's method, based on the predictive model for the production process error, further relying upon the indications of the status of the machine when it was built;
- the framework for a CPS is built, integrating the production layer, i.e., the predictive model for the production process error, with the management layer in ERP BI;
- the research is carried out during a live burnishing procedure.

2. Materials and methods

2.1. Overview of information modelling for cyber-physical production systems. Connectivity in CPSs

is realised over the Internet. Integration enables the exchange of data and information between different systems, smart devices and people (Broy, 2010; Rojas *et al.*, 2017; Meissner and Aurich, 2019). The connection within the company and through the network is done by integration in two different directions: horizontally and vertically (Meissner and Aurich, 2019). Horizontal integration connects different stages of production and business planning, processes and corresponding information systems (Meissner and Aurich, 2019). This integration enables an information exchange that can also be used within networked companies. In contrast, vertical integration describes the integration of different information systems that are used at separate, hierarchical levels, for example, ERP or MES (Meissner and Aurich, 2019). Consequently, this leads to an end-to-end solution (Kagermann *et al.*, 2013; Meissner and Aurich, 2019).

Our approach, presented in the form of a framework for a CPS, integrating the production layer with the management layer of manufacturing in BI ERP (Fig. 1), assumes that the data about the production process is collected from sensors placed on the machine; then, using statistical analysis methods, a predictive model for the production process error is developed. Next, thanks to the algorithms, it is possible to integrate the data collected in real time from the machine's operation with the predictive model, in the new BI ERP functionality (Fig. 1), and also to visualize the evaluation of deviations from the correct course of the process.

2.2. Collecting data about a production process. An essential element for recording data is based on a new type of sensory burnishing tool. It measures the process force in the tool axial direction and sends it, via WiFi, to an external PC. The PC then transmits the force values directly to the NC kernel (NCK) of the machine tool, using a Snap7 communications interface—this setup is shown in Fig. 2.

During the machining process, a trace function, integrated into the control system, records various machine parameters and sensor data in a single file. All machine data, including the sensor data are collected every 4 ms. In addition to the machine-related data, three other position sensors are included in the modelling. This process data is recorded, independently of the machine tool, by a separate PC. Thanks to I4.0 technology, it is possible to obtain a high volume of data from sensors and networking machines generated from the SINUMERIK Solution Line Trace (<http://www.siemens.com>).

2.3. Statistical analysis method. The selection of the appropriate statistical analysis method depends on the characteristics of the production process being investigated. The research experiments were, therefore,

carried out based on indications of the machine's status. In the beginning, the use of ordered logit models was taken into account for the construction of the predictive model for the production process error, based on indications of the status of the machine. However, after an experiment with calculations, it became apparent that this method over-simplifies the status quo and the resulting data do not represent the essence of the problem under analysis. Therefore, due to the type of data available and in order to estimate the individual parameters of the production process, it was decided to apply the following methods: the method of elimination of quasi-constant variables, the method of information capacity indices (Hellwig's method) and the linear regression method. To create a model, it is necessary to select predictors that are related to the response. The coefficient of variation is a measure of the level of variation (Borkowski *et al.*, 2017):

$$V_j = \frac{S_j}{\bar{x}_j}, \quad (1)$$

where S_j is the standard deviation of a given variable x_j , $\bar{x}_j$ is the arithmetic mean of x_j .

From the set of pre-selected explanatory variables, those are eliminated which, for a fixed critical value of the coefficient of variation V^* , satisfy the inequality $|V_j| \leq V^*$ (Borkowski *et al.*, 2017). Variables are called quasi-constant when they do not contribute significant information to the model (Borkowski *et al.*, 2017). Hellwig's method is one of the basic methods used in selecting explanatory variables for an econometric model (Kowalik, 2012). This method uses the idea of selecting variables that are strongly correlated with the explained variable and those which are weakly correlated among themselves (Borkowski *et al.*, 2017). The best combination of explanatory variables is considered to be the one for which the integral capacity of information carriers has the maximum value (Borkowski *et al.*, 2017). Linear regression is a statistical method that assesses the influence of many different characteristics; these are termed independent or explanatory variables, while characteristics of particular interest are termed dependent or response variables (Borkowski *et al.*, 2017).

2.4. Business intelligence. The main functionality of BI solutions is to provide decision makers with high quality information, obtained on the basis of ongoing analysis of large amounts of data. BI consists of the following elements (Tutunea and Rus, 2012): data warehouse (architecture, modelling, storage, management, processing); extracting, transforming, loading and integrating data (extract, transform, load—ETL), generating reports, data visualization, dashboards, multi-dimensional data analysis (online analytical processing—OLAP); statistical analysis and

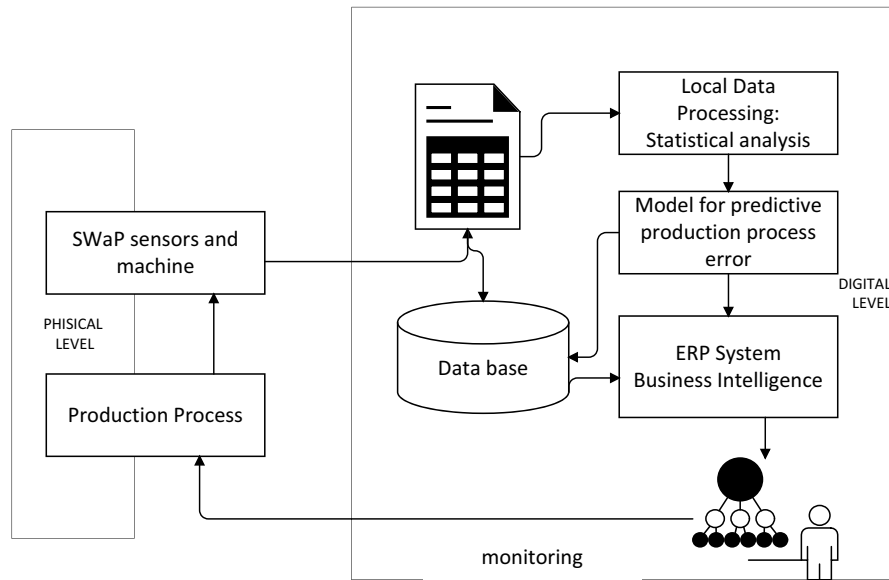


Fig. 1. Overview of the framework for the CPS, integrating the production layer with the management layer of manufacturing in BI ERP.

forecasting. BI enables access to business-critical data and information and facilitates their multi-dimensional analysis.

3. Experimentation settings

The experimental setup is based on a DMG Mori DMC 850V 3-axis milling machine. A similar setup has already been described by Posdlich *et al.* (2010). The workpiece material used consists of 7075 aluminium and is shown in its clamped position in Fig. 3.

The production process is performed in two steps. The upper surface of the workpiece was CNC-milled. A ball end mill with a diameter of 6 mm was used for this. The milled geometry is shown in Fig. 4 and describes a two-dimensional free-form surface. This surface is fundamentally based on sinuous basic geometry whose amplitude is only 0.1 mm. Three error geometries were overlaid on this. First, a faulty clamping is generated, which is described by a linear equation (Area 1). Next, a simulated tool breakage, erratic in its behaviour, was generated (Area 2), along with further increased tool wear (Area 3). Both the initial contour and the defects were described mathematically and then translated into a machine programme via a CAM system and completed by the milling process.

The burnishing process is then carried out in the same clamping. In this way, unknown defects were reduced. The burnishing process uses a new type of tool holder, which measures the burnishing force in the direction of the z -axis. The actual force is generated by the machine tool through the infeed, in the direction of the workpiece,

and was set to 200 N. The tool trajectory oscillates and slides parallel to the x -axis with a discrete research stroke of 0.1 mm in the y -axis at a speed of 600 mm/min. In completing the NC programme, the plane to be machined is flat. Thus, the free-form surface and the errors are not known to this machining process. The sensory tool must react independently to the changes in the surface, in co-operation with the machine tool and thus must also detect them. Building on the burnishing process, the final processing is now carried out and the sensor data are recorded in parallel. Table 1 lists all recorded sensor data in detail.

The burnishing process data were recorded and includes 507,790 measurements, taken over a period of 0.004000 to 2037.580000 ms (all 4 ms). The acquired .XML file, generated by SINUMERIK Solution Line Trace, Tracesession version = 01.00.03.02, contains the sensor readings and records any subsequent data, saving it to the specified network location. A dedicated website has been created on the server whose task is to monitor a given location. After starting the process, the path to the data file is retrieved (Algorithm 1 in Appendix). Next, the process of deserializing an object from an XML file must be provided (Algorithm 2 in Appendix). Finally, serialized data can be recorded in the base data (Algorithm 3 in Appendix). Research experiments were then carried out in order to develop the predictive model for the production process error, based on indications of the machine status. The value of the resulting geometry (IST) (response variable) was selected for modelling. Its value was calculated from the formula $IST = 0.1 \times \sin(\text{time} \times 0.06283) + 0.001 \text{ time}$. In the first step of

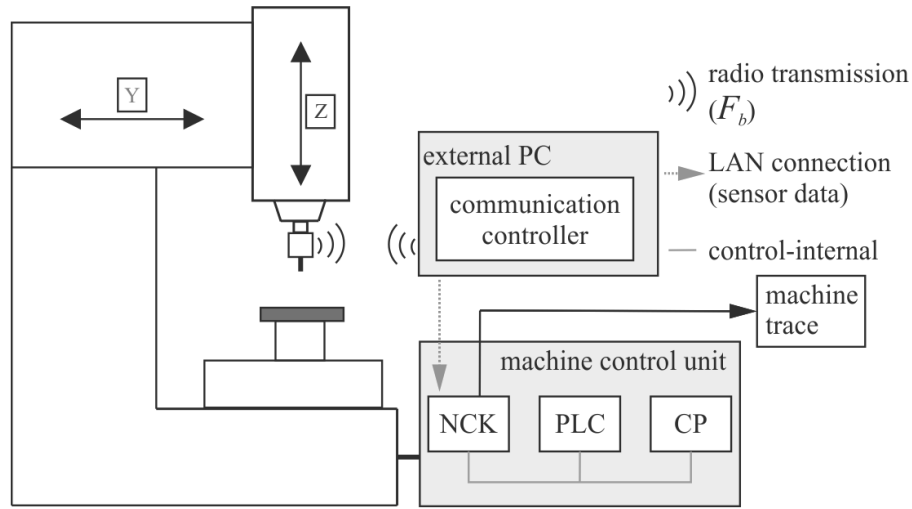


Fig. 2. Completion of sensor data transmission in connection with the machine control system.

Table 1. Overview of the recorded measurement data divided into machine-related and external data.

Machine-related measurement data (4 ms)	External measurement data
f_1 temperature compensation (x -axis) f_2 drive power (x -axis) f_3 drive power (y -axis) f_4 actual position value (x -axis) f_5 drive power (z -axis) f_6 actual position value (y -axis) f_7 temperature compensation (y -axis) f_8 temperature compensation (z -axis) f_9 force sensory data f_{10} actual position value (z -axis)	tool tilting in burnishing direction (x -axis) tool tilting in feed direction (y -axis) tilting of the clamping fixture

our research, data from 2529 measurements (10% of all measurements) were selected to define the model. Next, quasi-constant variables were eliminated. Variables are called quasi-constant if they have an insufficient level of variation. These variables do not provide meaningful information about the dependent variable. Using the procedure described in Section 2.3, predictors are eliminated from the set of explanatory variables, which for a fixed critical value of the coefficient of variation V^* satisfy $|V_j| \leq V^*$.

By applying the formula described in Section 2.3, the results presented in Table 2 were obtained. It was assumed that $V^* = 0,1$.

Based on the results obtained (Table 2), selected machine measurement data, i.e., variables f_2 , f_3 , f_4 , f_9 , f_{10} , were considered for model estimation. These variables affect the resulting geometry.

In the second step, the information capacity method (Hellwig's method) was applied. It was chosen due to the type of data available and in order to estimate the individual parameters of the burnishing process as well as the numerical criterion of the so-called integral

capacity. This criterion makes it possible to select the best combination of variables (with the highest total capacity) from among the potential combinations of the explanatory variables considered. The following were determined:

- the number of possible combinations,
- the combination matrix,
- the absolute values the correlation coefficients between the explained variable and the explanatory variables (Table 3).

Next, indices h_{sj} and H_j were determined. Based on these, the variable f_4 was selected for model construction. In the next step, the linear regression method was applied. The formula obtained was

$$\text{IST} = 0.003457773f_4 + 0.19382405, \quad (2)$$

where $R^2 = 0.999375222$. By using the model, the value of the resulting geometry (IST) can be approximated as a function of the parameter f_4 .

Table 2. Elimination of quasi-constant variables.

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}
Arithmetic mean	0.0016	0.5214	-0.6026	4.7388	-3.3293	35	-0.0111	-0.0087	-0.0105	0.0034
Standard deviation	0.0000	0.0910	0.0782	5.8355	0.2602	0	0	0.0000	0.0278	0.0419
V_j	0.0000	0.1746	-0.1297	1.2314	-0.0782	0	0	0.0000	-2.6433	12.4046

Table 3. Absolute values of the correlation coefficients between the variables.

	IST	f_2	f_3	f_4	f_9	f_{10}
IST	1	0.219490442	0.384725496	0.999687562	0.910488279	0.142125392
f_2	0.219490442	1	0.842261164	0.210032966	0.083867453	0.532734451
f_3	0.384725496	0.842261164	1	0.368679393	0.010509059	0.489088638
f_4	0.999687562	0.210032966	0.368679393	1	0.917561937	0.134590296
f_9	0.910488279	0.083867453	0.010509059	0.917561937	1	0.030540267
f_{10}	0.142125392	0.532734451	0.489088638	0.134590296	0.030540267	1

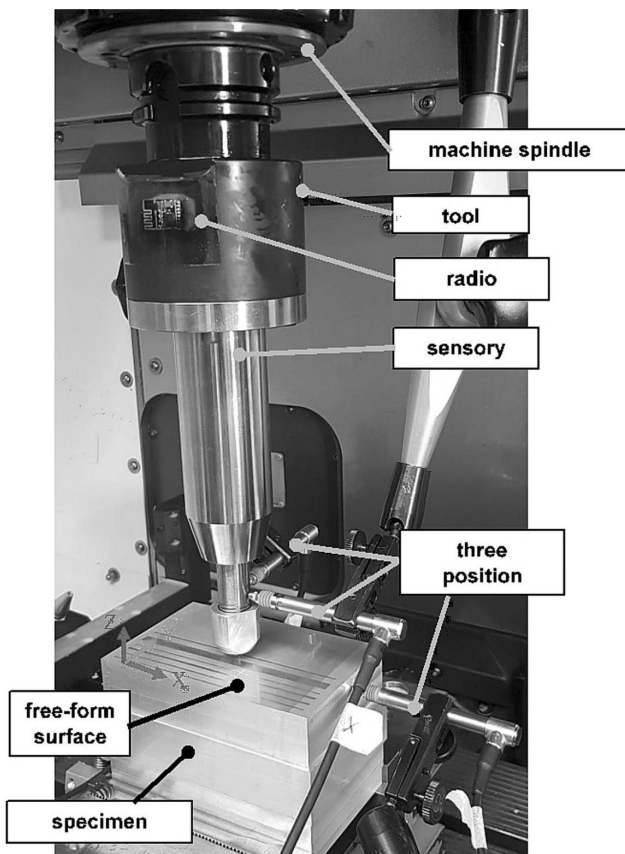


Fig. 3. Test setup with a sensoric tool holder and an external sensor.

The framework for the CPS integrates data from the production process, obtained in real time and the predictive model (2) in the ERP system database. Figure 5 presents the layer of an ERP system, i.e., the business intelligence (BI) module.

In the ERP system, in the BI module, it is possible to monitor the course of the production process on an ongoing basis and react to interruptions to the workflow, thus reducing the number of defective products within manufacturing. The monitoring process of interruptions to the production process is visualized in Fig. 6.

4. Discussion

The idea is based on the collection of data from the sensors of the burnishing tool, application of the statistical method, integration of the layer of information systems, the BI module and visualisation of the predictive model created. The literature describes models developed by various organizations that enable connectivity in CPSs (Rojas *et al.*, 2017). There is a ZVEI model, which places an MES at the centre of its communication platform and requires other systems (ERP, PLM, etc.) to be aligned with it (Dumitrescu *et al.*, 2015). Another model, i.e., SAP's HANA platform, provides the services necessary for business models and end-to-end processes. SOA is a software design concept providing services for the interaction of independent software solutions by working on defined communication protocols over a network (Trabesinger *et al.*, 2019). The use of 5G networks for wireless communication in CPPSs is also described (Jeehyeong *et al.*, 2019).

Our solution was applied in BI ERP, in order to support the management board in the ongoing monitoring of the production process. Our approach enables certain tasks to be independently controlled and interact with

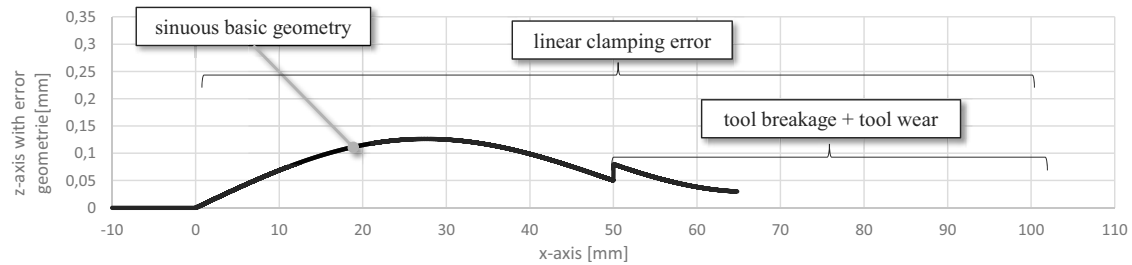


Fig. 4. Description of the surface to be machined consisting of the target geometry (sinuous) and superimposed errors.

the operator via an interface at the management layer of manufacturing in BI ERP. The ERP system is modular and the model (2) has been implemented in the BI ERP module, thanks to which it is possible to forecast the value of the resulting geometry (IST) as a function of the parameter f_4 . In addition, the solution is in line with the characteristics of an autonomous CPS because it accomplishes tasks from classification to control and forecasting.

Moreover, the proposed framework for CPSs, combines data about the actual burnishing process, statistical methods (Hellwig's method and linear regression) and the functionality of ERP systems, in order to design and provide self-adapting abilities at the strategic level more effectively. The limitation of our framework is that this solution focuses on the burnishing process. It should be emphasised that each completed production process has its own characteristics and the methods for building predictive models (useful for a given process) may not be appropriate for other production processes, that is, it would be unwise to generalize the findings too broadly to other production processes. Moreover, ERP BI predictions are currently made on an ongoing basis, but in the case of more advanced predictive models, the monitoring process will require more time. However, the advantage is that it is possible to automatically integrate the production layer with the management layer of manufacturing in ERP BI.

5. Conclusions

The main innovation presented in this paper relies on building the framework for a CPS, integrating the predictive model for production process error with the management layer in ERP BI. Moreover, this research was carried out based on the actual burnishing process implemented in industrial practice. The demonstration, based on an implementation of the system in a real-life environment, showed good results in the integration of data from the physical world into the digital level of manufacturing. Future work will be carried out in order to apply other categories of data-driven methods and build predictive models to detect production process errors

and apply new technologies for processing data, such as blockchain technology.

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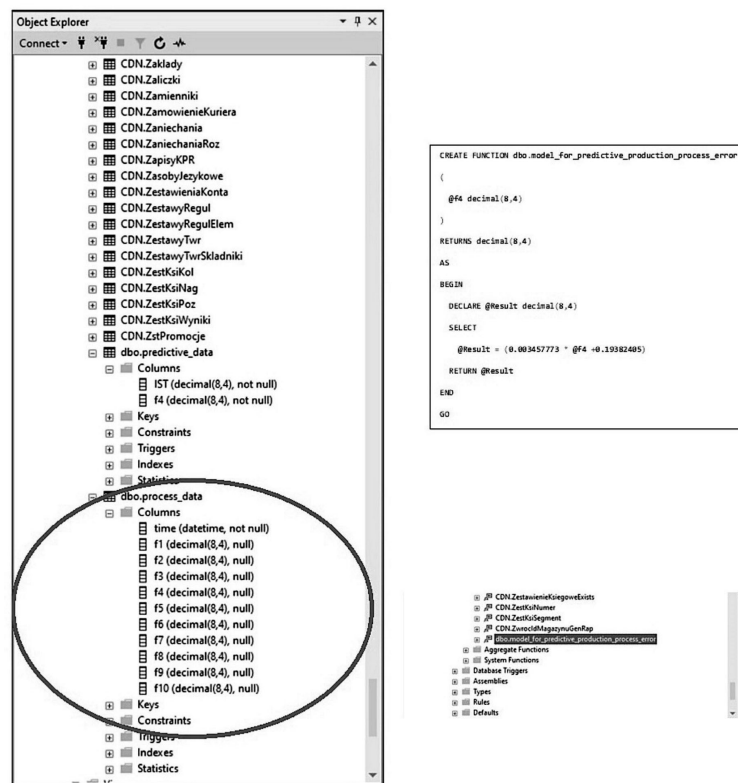


Fig. 5. Layer of an information system integrating the data acquired from the process, in real time, along with the model for predicting errors within the production process in the ERP system (business intelligence module).

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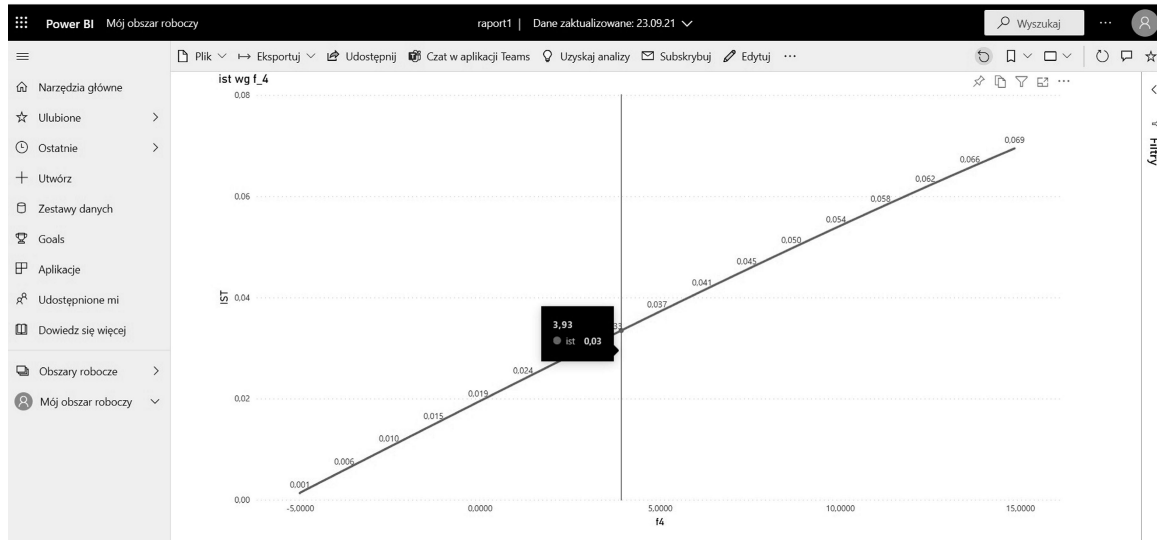


Fig. 6. Visualization of the monitor, in the course of the production process, on an ongoing basis in ERP BI.

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Justyna Patalas-Maliszewska is a professor at the Institute of Mechanical Engineering of the University of Zielona Góra. She focuses her research on computational intelligence in production, modelling and designing methods, as well as tools and solutions in support of manufacturing companies. She has been awarded a number of international scholarships. She is the author of over 200 scientific publications, including scientific monographs and articles in influential and impactful journals; she is also the author of numerous expert opinions and recommendations for enterprises at regional and national levels. She has carried out various international research projects concerning, e.g., information systems.



Marco Posdich is a research associate at the Chair of Production Systems and Processes at the Chemnitz University of Technology. He has been working on process combination of milling free-form surfaces and smooth-rolling to produce functional surfaces since 2016. His interest is also in the realization of a force control on CNC milling machines. Various CAM strategies are included. A special focus of his research is on individual post-processing of additively manufactured workpieces in cooperation with regional medium-sized companies and machine manufacturers.



Katarzyna Skrzypek has graduated in computer science and econometrics (information systems) from the Faculty of Mathematics, Computer Science and Econometrics, University of Zielona Góra. She now works as an assistant professor at the Institute of Mechanical Engineering there. In her scientific and research work she deals with production engineering, in particular with the application of information technologies and statistical analyses in production enterprises.

Appendix

Algorithm A1.

```
internal void ImportProcess()
{
    SensorData data = GetSensorData();
    SaveToDataBase(data);
}
private SensorData GetSensorData()
{
    string path = GetImportFilePath();
    return
    DataSerializer.DeserializeFromFile
    <SensorData>(path);
}
```

Algorithm A2.

```
class DataSerializer
{
    public static
    T Deserialize<T>(string input)
    where T : class
    {
        XmlSerializer serializer =
        new XmlSerializer(typeof(T));
        using (StringReader stringReader =
        new StringReader(input))
        {
            return
            (T)serializer.Deserialize(stringReader);
        }
    }
    public static
    T DeserializeFromFile<T>(string filePath)
    where T : class
    {
        XmlDocument xmlDocument =
        new XmlDocument();
        xmlDocument.Load(filePath);
        var xmlStr = xmlDocument.InnerXml;
        return
        Deserialize<T>(xmlStr);
    }
}
```

Algorithm A3.

```
private void SaveToDataBase(Sensor
Data data)
{
    using (var dbContext = new DbContext())
    {
        DeviceMeasurement measurement =
        MapDataToSQLObject(data);
        dbContext.DeviceMeasurements.
        InsertOnSubmit(measurement);
        try
        {
            dbContext.SubmitChanges();
        }
        catch (Exception expection)
        {
            HandleImportError(expection);
        }
    }
}
```

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