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Artificial intelligence-driven internet of things monitoring system towards industry 5.0 – a case study of mold manufacturing process

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ABSTRACT

Applying artificial intelligence (AI) into manufacturing in the context of Industry 5.0 (I5.0) provides for enhancing quality control of processes. This paper employed real life data of the mold manufacturing process with the objective of developing a tool for controlling and predicting the quality of a manufactured highly technically demanding product used for the air conditioning of high-end cars. Firstly, the parameters that affect the quality level of the manufactured end products, namely compressors, were defined. Next, the values of these parameters were collected and pre-processed from IoT-based sensors and the Enterprise Resource Planning (ERP) system during the execution of an order within one month. In total, 9919 real data relating to the die castings process for the selected product was received. Secondly, this study applied artificial neural network (ANN) to develop an AI-based classifier of the quality level of manufactured parts. Finally, an AI-driven data analytics model was developed and verified. The accuracy achieved in the training and testing phases amounted to 98.62% and 98.94%, respectively. Additionally, this study developed the approach to simulate of process parameter value changes for improving the quality level of manufactured parts. This is a universal AI-driven IoT monitoring system (AIMS) for industry supporting proactive management.

Keywords: mold manufacturing process, real life case study, IoT-based sensors, AI-based classifier, predictive model, monitoring the production quality.

INTRODUCTION

Nowadays, the manufacturing enterprises to be competitive in the market should be more adaptable to meet the customer individualized and rapidly changing needs. This means that production should be carried out according to mass customization (MC) strategy, one of the challenges within the Industry 5.0 (I5.0) concept. Currently, the activities provided within industry according to concept I5.0 are moved to highlight the importance of social aspect in usage Industry 4.0 technologies. The large volume of data acquired by sensors and using internet of things (IoT) during the machining process results in the need to apply artificial intelligence (AI) to enhance user interaction and safety [1, 2]. AI-driven IoT is transforming manufacturing enterprises into smart factories [3]. IoT sensors located on machines and devices are used to collect data and next AI-based algorithms are applied to develop the predictive models to monitor as well as improve the resource, quality and cost efficiency [4]. AI-based solutions applied to the systems supporting machining process managing and providing facilitate e.g. real-time monitoring, improve quality, transparency and flexibility of the process [5, 6].

According to the definition of the concept I5.0 provided by the European Commission, manufacturing processes should shift from smart manufacturing to human-centric technology development and adoption [7, 8]. Currently, solutions are being sought enabling collaboration between humans and smart machines to improve the capability of humans [9]. Examples of a channel of communication between the human and machine include sensors as well as computer vision to natural language processing (NLP) and GUI commands [10]. Therefore, combining the sensors usage and control with big data analysis and AI-based tools for improving the production efficiency is a need for manufacturing companies in the context of implementing the assumptions of I5.0 [11]. The literature analysis of applying AI to manufacturing process in the context of I5.0 indicates that effective exploration of the variable space in manufacturing systems guarantees the improvement of production planning and scheduling [12]. Next, precise modeling of process dynamics and optimization of production parameters through the use of the AI-based models to improve the quality of manufactured parts [13]. It solves also many challenges in sustainable production, such as optimizing energy resources, logistics, supply chain management and waste management [14, 15]. This trend provides a vision for the future of work in modeling AI-based solutions applied to the machining process in the light of I5.0. Early detection of faults and prediction of future machine operation ensure their reliability and effective maintenance [15]. Moreover, automation of repetitive, time-consuming tasks by robots, as well as a study of harmonious cooperation between humans and machines can enhance the production quality [16]. To summarize, the analysis of the scientific literature highlights, that the great challenges associated with AI adoption in manufacturing are issues related to data acquisition and management, human resources, infrastructure, security risks, trust, and implementation difficulties [15]. Moreover, the scientific literature research analysis provided in [17] confirms that it is crucial to provide father research on AI utilization within the domain of molding processes.

This paper offers a novel AI-driven IoT monitoring system (AIMS) for controlling and predicting quality of manufactured parts based on the example of the mold manufacturing process. It explains how to integrate IoT-based sensors, data from ERP systems and AI-based algorithms to achieve a higher level of the quality of manufactured parts. It employs real life case study and expert knowledge to develop AIMS for enhancing the sustainable production level and predicting forthcoming disruptions and proactive management. IoT-based sensors enable data acquisition, but the processing and understanding the collected data requires building new AI-based models [18] and applying to the production process. To the best of the author's knowledge, there is a limited research of real case studies exploring IoT-based sensors adoption within the mold manufacturing process, next big data analysis and applying AI as the majority of studies in this area tend to be theoretical.

Secondly, based on the empirical research results, this study proposes a recommendation for overarching Industry 5.0 priorities: creating a sustainable, human-centric, and resilient industry owing to the integration to the production process AIMS [19] This study pioneers by providing practical insights into how applying Industry 4.0 technologies into manufacturing process achieve the I5.0 priorities. The developed insights guide managers in decision-making processes regarding forthcoming disruptions.

Thus, there is still a research gap in the context of developing a generic tool for controlling and predicting quality of manufactured parts for the mold industry. The main objective of this study was to analyze the data concerning the quality level of manufactured highly technically demanding products used for the air conditioning of the high-end cars, with a focus on the method and tools for achieving the I5.0 priorities. The following research questions (RQ) are formulated thus:

- RQ1: What are key parameters and how is the concept of data acquisition for improving the quality level of manufactured parts for the mold industry?
- RQ2: How can the quality level of manufacturing of the die-casting mold be monitored and predicted?
- RQ3: What challenges can be defined in the context of moving from smart manufacturing and toward human-centric technology development?

The main contributions of this study in the context of introducing changes in the mold industry towards moving from smart manufacturing to raising an enterprise the I5.0 priorities are as follows:

- This study presents the AI-driven data analytics approach based on the 9919 real data of mold manufacturing process to predict and monitor quality of manufactured product.

- It applies first an artificial neural network (ANN) and next the set of unique feature values to determine the quality parameters of mold manufacturing process for enhancing quality of manufactured parts.
- It determines the tools supporting proactive quality management based on the case study from the mold industry.
- It highlights the main challenges for smart manufacturing enterprises to move toward human-centric technology development.

MATERIALS AND METHODS

Methodology

This paper introduces AIMS for manufacturing process and especially highlights the role of process data analytics in enhancing quality control in manufacturing based on a real-life case study. The proposed methodology combines a real-life case study, namely actual analysis of the physical process flow and I4.0 technologies, namely: IoT and neural networks for understanding I5.0 priorities.

In the first stage of the methodology (Figure 1), the research unit in the real-life manufacturing was constructed. According to the vision for next-generation I4.0 manufacturing machines, they should be equipped with external actuation and sensors [20] to develop the models for efficient monitoring of quality parameters in the industrial environment [21]. The tools were located on the Buhler Diecasting Machine (Figure 2) and were designed to acquire process data during the manufacturing process. As presented in Figure 2, 840T closing force Buhler Diecasting fully automated machine Cell, green arrow presents sensor for resetting the plunger position, red arrow: sensor for calculating the plunger position, blue arrows: pressure sensor positions. The switching points of speed and pressure and the three casting phases are read from the piston position sensor.

Next, the IoT sensors for measuring, real time actual pressure on the alloy, pressure on the hydraulic cylinder, actual switching points of the speed and pressure of the plunger of the three phases of casting, are installed on the die-casting machines. Piston position sensors to read the switching points are as explained below (Figure 3a, Figure 3b). In Figure 3a, the green arrow presents a sensor for resetting the plunger position, the red arrow represents the sensor for calculating the plunger position. There is a scale (ruler) on the piston, based on which the piston position is calculated using the above sensors. The switching points of speed and pressure and the three casting phases are read from the piston position sensor. In Figure 3b, pressure sensors are mounted on the compressed gas tanks. On the basis of the

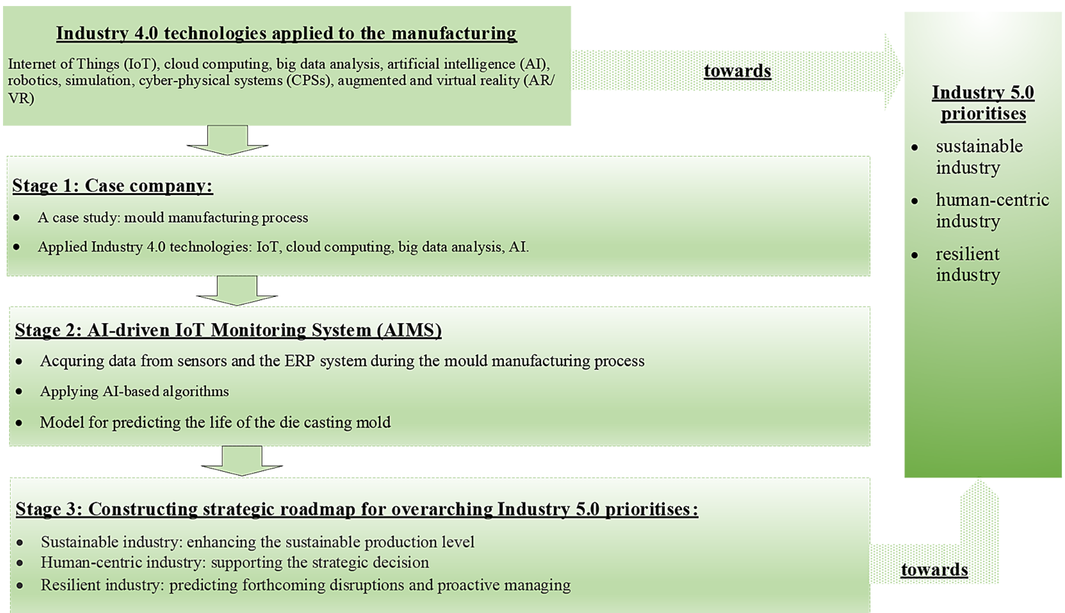

Figure 1. An approach to understanding the I5.0 priorities based on the example of the mold manufacturing process

Figure 2. Buhler Die-casting Machine – real photos within the factory

readings of these sensors, the machine calculates the actual pressure in the casting chamber.

On the CNC machines (Figure 3), the selected IoT sensors collect the power consumption on real time basis. In addition to this, the temperature field of the molds is collected manually using thermal cameras periodically during the diecasting process (the same can be extended to be done by IoT-enabled thermal camera to take images after each shot of the mold). Additionally, data are acquired from an Enterprises Resource Planning (ERP) system SAP HANA such as the weight of the part both gross and net, alloy type, and standard cycle times assumed at the beginning of the project by the technologists, manually. The information, such as production batch sizes, traceability data for raw materials, manpower and time (shift) of production etc. is entered in the ERP system manually, and shifted by shit by the planners and production employees. However, the number of total parts produced and the number of NG (not good) parts produced are collected in real time directly from the machine and such data is also integrated to be available in the ERP system.

In the second stage of our methodology, the data set is defined and analyzed based on the real case study. This case study uses realizing the mold manufacturing process of the compressor which is a highly technically demanding product and is used for the air conditioning of the high-end cars.

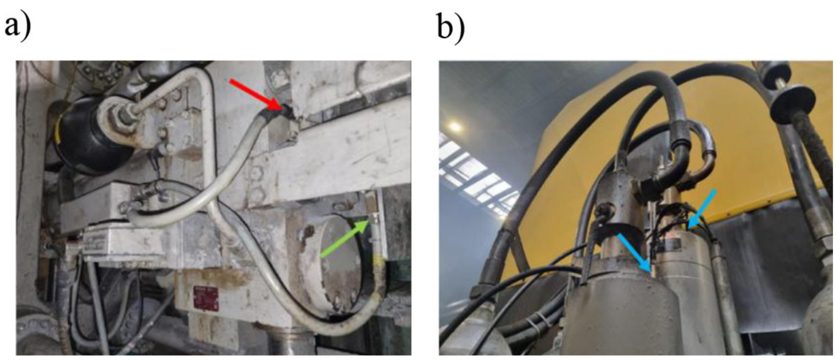

Figure 3. Plunger position measuring sensors: a) pressure measuring sensors, b) located on the Diecasting machine

Next (Stage 2, Figure 2) neural networks (NN) are applied to monitor the quality of the analyzed product by using processing parameters (Table 1) as input parameters. It is assumed that the analysis of the life of the die-casting mold is based on defined parameters that influence the formation of defects during the die-casting process. This study used the multilayer perceptron (MLP) due its ability to solve any classification tasks, regardless of the distribution, features and complexity of the data [22]. Optimal combinations of data based on the neural network were identified, and the effectiveness of the model was validated using its ability to generalize to new, unseen data that was not used during training. The input data was divided into three sets: training, validation, and test. The model was trained on the training set, and its performance was monitored on the validation set, which is not used during training itself. Validation consisted of comparing the validation data with the network predictions to calculate performance measures, such as accuracy, precision, and mean square error (MSE). On the basis of these results, the network is tuned to improve its performance (predictions). The final evaluation of the model is performed on the test set, which was also not used during training or validation.

Experiment design and data acquisition tools

The research was conducted on a real-life industrial case study of mold manufacturing process. Real-time data is collected for two orders from a similar family of compressor parts namely Valeo_Renault CH. Answering the first research question, the analysis of the quality of manufactured parts, based on the expert knowledge of the employees involved in dealing with the process is divided into four groups:

1) Design of the mold: type of steel – main forming elements, hardness – main forming elements (HRC), coating of forming elements (type] No/PVD/Nitr, stress relieving after mold test (y/n), stress relieving continuation (no of cycles), no of cavities (PCS), cooling system (oil, water – O/W), gate inlet area (mm^2), overflows inlets area (mm^2], venting channel area (mm^2), vacuum system included (y/n).
2) Design of the part/casting: average part wall thickness [mm], projected of the casting area onto the parting surface [mm^2], share of part weight in the entire injection (%), maximum speed of alloy during cav, filling (m/s), filling time (ms), leak test pressure requirements (Pa) if no N, plunger diameter [mm], whole cast weight (g), part complexity (according assumption from 1–5).
3) Parameter alloy preparation: alloy type [name], alloy temperature (melting C, deg), type of melting furnace (shaft, crucible – S/H), density index of alloy (number), number of shots per batch (PCS), scrap ratio in the alloy composition (%).
4) Process parameters: alloy temperature (casting C, deg), first phase speed (m/s), second phase speed (m/s), third phase pressure in the alloy (bar), tablet height (mm), closing force (kN), cycle time (s), shot sleeve filling factor (%), automatic process (y/n), casting machine number (No), solidification time (s), vacuum level (mbar), type of spraying (micro/emulsion – M/E) [23].

On the basis of the real-life case study, Table 1 illustrates the parameters of alloy preparation and Table 2 analyses process parameters.

Any leakage due to porosity in the part may result in leakage of the gases leading to potential

Table 1. The parameters alloy preparation in the real-life die casting process

Parameters of alloy preparation		
Parameter	Measure	Value
Alloy type	Numerical alloy designation	ADC12
	Chemical designation of the alloy	(AlSi9Cu3(Fe))
Alloy temperature (melting C deg)	Actual material temperature	815 °C
	Set material temperature	800 °C
Type of melting furnace	Shaft furnace	STRIKOMELTER MH II – T 2000 / 1500 G-eg
Density index of alloy	Percentage	89%
Number of shots per batch (PCS)	Per shift	500
Scrap ratio in the alloy composition	Percentage	max 40%

Table 2. The parameters of the real-life die casting process

Parameters of alloy preparation		
Parameter	Measure	Value
Alloy temperature (casting C, deg)	Actual material temperature	694 °C
First phase speed [m/s]	Temperature range; from the sensors as explained before (m/s)	680 ÷ 700 °C; 0.30
Parameters	Measure	Value
Alloy temperature (casting C, deg)	Actual material temperature	694 °C
Second phase speed [m/s]	From the sensors as explained before (m/s)	4.20
Third phase pressure in the alloy [bar]	From the sensors as explained before (bar)	730
Tablet high [mm]	mm	15
Closing force [kN]	kN	8330
Cycle time [s]	s	51.8
Shot sleeve filling factory [%]	Percentage	48%
Automatic process [y/n]	yes	
Casting machine number [No]	Description	PH156 - Buhler 84D Compact
Solidification time [s]	Sec	9.0
Vacuum level [mbar]	A	69
	B	295
Mold temperature fixed side [°C]	°C	Max 222.8–232.1 °C Min 115.6–123.5 °C
Mold temperature moving side [°C]	°C	Max 276.8–284.7 °C Min 168.2–184.3 °C
Delta of temperature fixed side [°C]	°C	101 ÷ 117 °C
Delta of temperature moving side [°C]	°C	100 ÷ 108 °C

fire hazards in the cars. Therefore, the tolerances are very tight for these parts after machining. One of the critical tolerances is +/- 3 µm on a diameter of about 100 mm for example. Therefore, the parts produced after diecasting are expected to have to be within the required tight physical dimensions and porosity levels. Every part undergoes a 100% leak test after machining. If the parts are not cast and machined within the required limits of tolerances the parts are scrapped. The quality of the parts coming out of the die casting machine is highly dependent on the quality of the mold itself and the defined quality parameters during the die casting manufacturing process. This is a two cavity mold produced on 840T Buhler machine and subsequently machined on an Okuma and Fanuc four-axis CNC machines.

Next, as presented, the data is acquired owing to the installed IoT-based sensors (Figure 3, Table 1, Table 2) and from the ERP system SAP HANA (Table 1, Table 2). The values of the thirty-nine specified parameters that affect the quality level of the manufactured end products concerned the execution of a precisely defined order executed in three shifts over the course of one month in 2024 with a deviation of one minute.

Dataset description and data pre-processing

As a sample to test the hypothesis, real time data is collected on the Valeo_Renault CH compressor parts for over 3000 parts over the above-mentioned parameters with 3 days of production. In total, 9919 items of data relating to the die castings process for the selected product was received. The data were imported directly into MATLAB. A matrix with dimensions of 9919×40 was created, representing the entire dataset from the spreadsheet. The information about the data categories was located in the last column, so the data was divided into an input set (a 9919 × 39 matrix) and an output set (a 9919 × 1 matrix containing the classification information). The data was divided into a part to be analyzed and a set containing categories for the analyzed data. Table 3 shows sample input data as the values of data for analysis the quality of the parts during the mold manufacturing process, where output data is quality attribute: 1 to BAD, 2 – LOK, 3 – LOT, 4 – OK, 5 – OUT.

Table 3. Sample input data

Quality atribute	OK	…
Type of spraying (Micro/emulsion) [M/E]	M	…
Vacuum level [mbar]	250	…
Solidification time [s]	8	…
Casting machine number [No]	ph156	…
Automatic process [y/n]	Y	…
Shot sleeve filling factor [%]	61	…
Cycle time [s]	47.1	…
Closing force [kN]	8444	…
Tablet hight (mm)	20	…
Third phase pressure in the alloy [bar]	875	…
Second phase speed [m/s]	4.32	…
First phase speed [m/s]	0.15	…
Alloy temparature (casting C deg)	690	…
% of scrap ratio in the alloy composition [%]	60	…
Number of shots per batch [pcs]	7218	…
Density index of alloy [number]	1	…
Type of melting furnace (shaft, crucible S/H)	S	…
Alloy temparature (melting C deg)	730	…
Alloy type [name]	ADC12	…
Part complexity (according assumption from 1-5)	3	…
Whole cast weight [g]	3165	…
Plunger Diammeter [mm]	80	…
Leak test preasure requirements [Pa] if no N	N	…
Filling time [ms]	44	…
Maximum speed of alloy during cav. Filling [m/s]	45	…
Share of part weight in the entire injection (%)	47.4	…
Projected of the casting area onto the parting surface [mm^2]	61946	…
Average part wall thickness [mm]	3.7	…
Vacumm system included [y/n]	Y	…
Ventings chanels area [mm2]	87.6	…
Overflows inlets area [mm2]	224	…
Gate inlet area [mm2]	390	…
Cooling system (oil, water) [O/W]	W	…
No of Cavities [pcs]	2	…
Stress relieving continuation (no of cycles)	0	…
Stress relieving after mold test [y/n]	Y	…
Coating of forming elements [type] No/PVD/Nitr	No	…
Hardness - main forming elements [Hrc]	46	…
Type of steel - main forming elements	Dievar	…

Both the data for analysis and the classification information contained columns of text, so they had to be appropriately transformed to be used by machine learning algorithms. Each column of data can have different data types, and the goal was to unify this data into a numerical form that is needed to train the model. This was converted into a format that can be used by the neural network.

Since the data for analysis, as well as the classification information, contained columns with text and mixed types, they had to be appropriately transformed to be utilized by machine learning algorithms. Each data column might have different data types, and the goal was to standardize these data into a numerical form, which is necessary for training the model. The data was converted into a format that can be used by the neural network. This conversion applied to both the input and output data (which is why there are 40 columns). The data in each column is checked. If a column contains numeric values (e.g., int or double), the code leaves them unchanged. If a column contains logical values (true/false), they are converted to numbers 0 (false) and 1 (true). If a column is already of the categorical type, the code converts it into numbers representing the individual categories. If a column contains text (e.g., string or cellstr), it is converted to a categorical variable and then encoded as integers representing the different categories. If a column contains dates/times, they are converted into numbers corresponding to, for example, the number of days from a starting point (in MATLAB, the epoch is January 0, 0000 in the Gregorian calendar, so the date is transformed into numbers representing the number of days since that day). If a column contains mixed values, such as ADC12, 46000, ADC13, 92000, each value will be assigned a unique number, e.g., 1, 2, 3, 4. In any other case, a message 'Unsupported column type' will be displayed. Preparing the output data additionally requires the use of the one-hot encoding technique. This encoding is widely used in machine learning and data processing, especially in the context of classification. Its purpose is to represent data categories in a numerical form that is easy for machine learning algorithms to process (e.g., for classification options (essentially classes) 1 represents BAD, 2 – LOK, 3 – LOT, 4 – OK, 5 – OUT). This was necessary for the network to classify correctly.

Applied neutral network

Multi-layer perceptron (MLP) is a type of neural network that is widely used as a classifier. MLP is one of the simplest and most versatile neural network architectures and is used for many tasks, including classification and regression. Various configurations of neural networks (in terms of the number of layers, the number of neurons) were analyzed, but the best results were obtained for the architecture with one input layer, one hidden layer (20 neurons) and one output layer [24].

The use of MLP instead of deep learning is due to several factors related to the characteristics of the data and the computational requirements. First, the data in this case is probably relatively simple and does not require advanced architectures that are characteristic of Deep Learning, such as convolutional neural networks (CNN) or recurrent neural networks (RNN). The program uses MLP with one hidden layer, which is sufficient to solve the classification task in this case, because the input data has a simple structure (data table). Deep Learning usually requires larger data sets to obtain an adequate model quality. For smaller data sets, such as those used in this program, MLP may be more effective, because a more complex model may lead to overfitting and not bring significant performance improvement.

RESEARCH RESULTS

Research experiments

According to RQ2 the experimental part of the research, based on the literature research results was provided. MLP classifier for predicting the life of the die casting mold is applied. The number of hidden layers was determined as a result of experiments, conducted in Matlab 2023b environment. The number of inputs results from the number of variables obtained in the preprocessing process, and the number of outputs corresponds to the parameters determined in Table 3. The training parameters of the network were as follows: net.trainParam.goal = 1e-9; net.trainParam.epochs = 1000; net.trainParam.min_grad = 1e-7; net.trainParam.max_fail = 6;

The study involved changing the number of layers in the network and the number of neurons in the network. The network effectiveness was calculated using the formula (1):

$$Efficiency = \frac{\sum_{i=1}^{N} predictedLabels_i == testLabels_i}{N} \times 100 \quad (1)$$

where: $\sum_{i=1}^{N} predictedLabels_i == testLabels_i$ – is the sum of cases where the predicted labels are equal to the test labels; N – is the total number of samples.

The script calculated accuracy, which measures how well the model predicted the correct labels relative to the number of test samples. Accuracy is not an error measure (like MSE or RMSE) but rather an indicator of classification correctness. The percentage of correctly classified samples out of all samples allows for an intuitive interpretation of the results. This method of calculating accuracy is commonly used in classification tasks. As for MSE and RMSE (in a retrained network, as I did not save the previous process), the results are as follows:

- Test MSE: 0.038992,
- Test RMSE: 0.19746.

Therefore, the results were as follows: 1layer with 5 neurons – 97.98%, 1 layer with 10 neurons – 96.30%, 1 layer with 20 neurons – 98.94%, 1layer with 25 neurons – 98.45%, 1 layer with 30 neurons – 97.89%, 2 layers with 5 neurons – 98.75%, 2 layers with 10 neurons – 98.52%, 2layers with 20 neurons – 98.37%, 2 layers with 25 neurons – 98.69% and 2 layers with 30 neurons – 98.79%.

For training data, the network (1 layer with 20 neurons) efficiency was ~98.62% (98.94% for the test data). The number of neurons in this input layer corresponds to the number of features in the input data (39). The number of neurons in the output layer depends on the number of classes

that can be obtained (in this case it is 5). The activation function for the hidden layer is 'tansig' (hyperbolic tangent) and for the output layer it is 'purelin' (linear function) – Figure 4, where:
- Input – this is the first layer (39 neurons) of the neural network that receives the input data,
- Hidden – this is the hidden layer,
- Output – this is the final layer (5 neurons) of the neural network that generates the model's results,
- W (weights) – these are the values assigned to the connections between neurons in different layers.
- b (bias) – this is an additional parameter added to the weighted sum of inputs before applying the activation function.

The prepared MLP network was implemented and run in the MATLAB R2023b environment using the Deep Learning Toolbox. The data to be processed (a 9919×39 matrix after import) was divided into training, validation, and test datasets in a 0.7/0.1/0.2 ratio. The training data formed a 6943×39 matrix, the validation data formed a 992×39 matrix, and the test data formed a 1984×39 matrix. The training data was used to train the network, and the test data was used to verify the classification accuracy of the network. The training process continued until the validation error failed to improve (decrease) for 6 consecutive epochs. At that point, the training process was terminated. The value of 0.003702 for MSE means that the model achieved its best performance in terms of mean square error on the validation set in the 139^{th} training epoch. This means that at this stage the model predicted values close to the true values with minimum mean square error (Figure 5). Classification errors are visualized in a confusion matrix, which is used to evaluate the model performance (Figure 6).

As it can be seen in the obtained results, the model performs well in most classes, with particularly high accuracy in classes 1, 4, and 5. For class 1, it achieves 99.6% accuracy, correctly classifying 454 instances with only 2 errors misclassified as class 3. Class 2 is also well classified with 96% accuracy, though it misclassifies 3 cases as class 1 and 5 cases as class 3, which accounts for 4% errors. The performance for class 3 is concerning, as the model fails to classify any instances correctly, with NaN values in the confusion matrix, possibly indicating a data issue or lack of training examples for this class. For class 4, the model performs excellently with 98.9% accuracy, correctly classifying 9129 instances, with 30 misclassified as class 1 and 69 misclassified as class 5. Similarly, class 5 has 98.9% accuracy, with 31 correctly classified instances and 2 misclassified instances. Overall, the model is highly accurate for most classes.

Next, the experiments were conducted to evaluate the performance of different activation functions applied to the last layer of a network. The activation functions tested include 'purelin', 'softmax', and 'logsig'. The results show that the purelin function generally provides the highest accuracy, with test accuracies ranging from 96.72% to 98.94%. 'Softmax' performs well, with test accuracies between 96.12% and 96.98%, while 'logsig' also delivers competitive results, with test accuracies ranging from 96.57% to 97.03%. These findings (Table 4) highlight the variation in performance across different activation functions when used in the last layer of an MLP model.

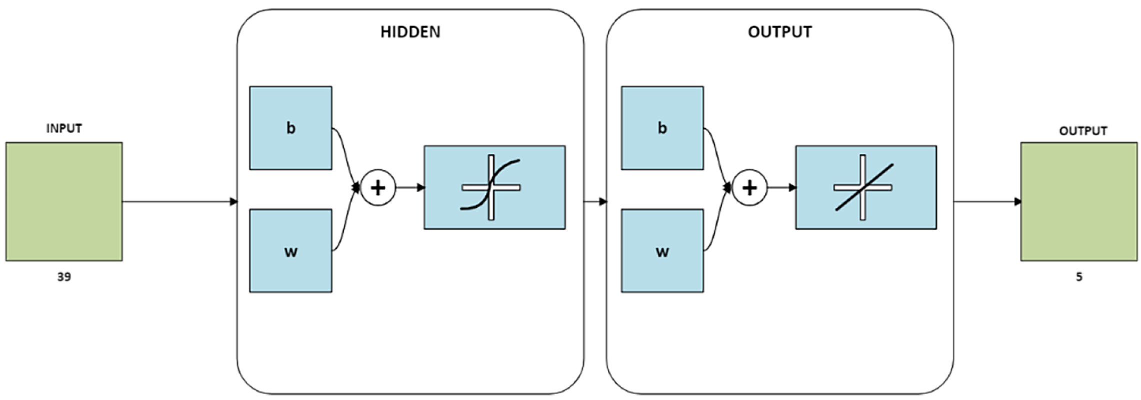

Figure 4. Architecture of the neural network

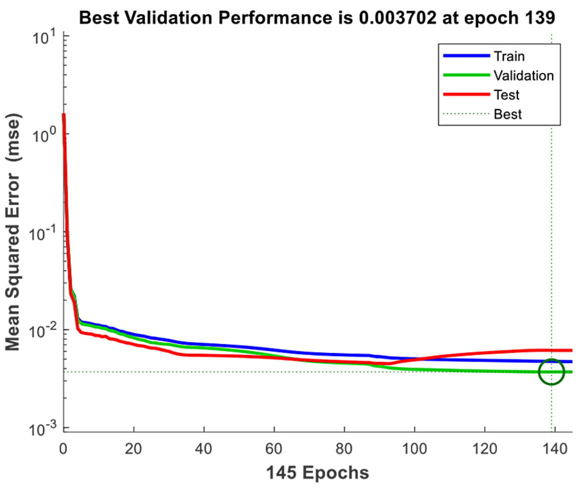

Figure 5. Best validation performance

Figure 6. Confusion matrix

Model for predicting the quality of manufactured parts

Answering RQ2, this study developed the approach to predict the expected values of parameters influencing the improvement of the quality level of manufactured parts.

The analysis of the sample features raised the question of whether it is possible to change the values of the sample features in such a way that the sample is correctly classified, i.e., assigned to class 4. Such an approach would enable the analysis of the impact of features on the classification process by iteratively changing feature values until the sample is correctly assigned to the appropriate category. The proposed approach is based on creating a set of unique feature values (uniqueValues) for the test samples, which includes all values actually occurring in the data for each feature. Instead of using aggregated measures such as averages or extreme values, which may not reflect actual characteristics (e.g., sensor readings), this set relies exclusively on actual data, ensuring a more accurate representation of the real behavior of the analyzed parameters. For each feature in the dataset, all unique values present in the test data are collected. This makes it possible to reference actual readings and parameters

Table 4. Performance of a network with different activation functions in the last layer of an MLP

Activation function	Test accuracy [%]	Train accuracy [%]	Validation accuracy [%]
PURELIN	98.94	98.62	98.59
	98.75	98.74	98.69
	98.59	98.88	98.79
	97.23	98.24	97.98
	96.72	97.82	97.68
SOFTMAX	96.97	96.40	96.97
	96.87	96.53	95.86
	96.72	96.57	96.27
	96.62	96.57	96.47
	96.12	96.64	96.57
LOGSIG	97.03	96.37	97.58
	96.77	96.49	97.17
	96.72	96.57	96.57
	96.67	96.46	97.48
	96.57	96.79	95.46

that have been measured, eliminating the risk of errors associated with improper data aggregation.

In the next stage of the process, the samples misclassified by the model are analyzed. In misclassified samples, the values of individual features are iteratively changed to all available options from the created uniqueValues set. After each change, a new class prediction is made for the sample. The process is repeated until the desired classification is achieved (e.g., assignment to class 4). However, if, after testing all values for a given feature, the correct classification is not obtained, the checking process continues with other features in the sample. The process ends when the correct classification for a given sample is achieved or after all features have been tested. In this way, each feature in the sample is analyzed for its impact on the classification result, and by changing its value to all possible options, the modification that leads to correct classification can be identified.

This approach allows for a more detailed identification of key features influencing the model's decisions, as it is based on actual data rather than theoretical average values. Testing all options for a given feature ensures a more accurate fit to real-world conditions, which in turn can lead to a better understanding of which feature values are important in the classification process and how they can be modified to achieve the desired outcome.

As a result of the conducted experiments, the classification of samples to class 4 was successively modified for 128 out of 130 samples. In this experiment, the following features were modified to achieve assignment to the correct class: feature 10 – 8 times, feature 17 – 7 times, feature 29 – 19 times, feature 3 – 13 times, feature 30 – 11 times, feature 31 – 8 times, feature 32 – 39 times, feature 8 – 23 times. Next, the following features were modified to achieve assignment to the correct class (132 out of 167 samples): feature 29: 40 times, feature 30: 36 times, feature 3: 23 times, feature 8: 16 times, feature 12: 9 times, feature 10: 2 times, feature 16: 2 times, feature 31: 2 times, feature 15: 1 time, feature 9: 1 time. The varying number of samples analyzed results from the different splitting of the dataset into training, validation, and test sets in MATLAB.

Therefore, the developed model enables the simulation of process parameter value changes in order to obtain the belonging of the output parameter to the best class. In practice, this means that it is possible to predict the quality of the manufactured product by changing the input parameters. Knowing that the data is obtained during the implementation of the process, it is possible to use the developed model as a tool supporting proactive product quality management.

DISCUSSION

As the results of the provided research experiments show, the applied approach allows for designing a classifier to determine the level of quality of manufactured product. Applying ANN AI-driven data analytics, the model was developed and verified. This developed approach enables the definition of a set of parameters describing the process at that quality level. This means that the characteristics of the new order can be classified into a specific group indicating the quality level (from 1 to 4 and 5 – OUT). Next, a novel methodology addresses misclassified samples, particularly those incorrectly excluded from Class 4 (OK), representing acceptable product quality. For such cases, systematic modifications of individual feature values were conducted using actual dataset values instead of statistical approximations. Iterative reclassification by ANN identified the feature adjustments that enabled proper classification into Class 4. This approach not only improved classification accuracy but also highlighted critical features influencing quality outcomes.

This is particularly important for supporting decision-making regarding the realization of the new order and understanding how I4.0 technologies can influence quality production level improvement and next can provide to achieve the I5.0 priorities.

Therefore, this study proposes a universal AIMS for industry supporting proactive management (Figure 7).

Therefore, to monitor the quality level of manufactured products in real time using AIMS (Figure 7), the parameters that affect the quality of manufactured products should be defined in the first stage. In our case, 39 features were defined based on expert knowledge, the values of which affect the quality level of manufactured elements. Then, the values of this data are obtained from sensors and the ERP system. IoT-based sensor for measuring, real time, actual pressure on the alloy, pressure on the hydraulic cylinder, actual switching points of the speed and pressure of the plunger at the three phases of casting and

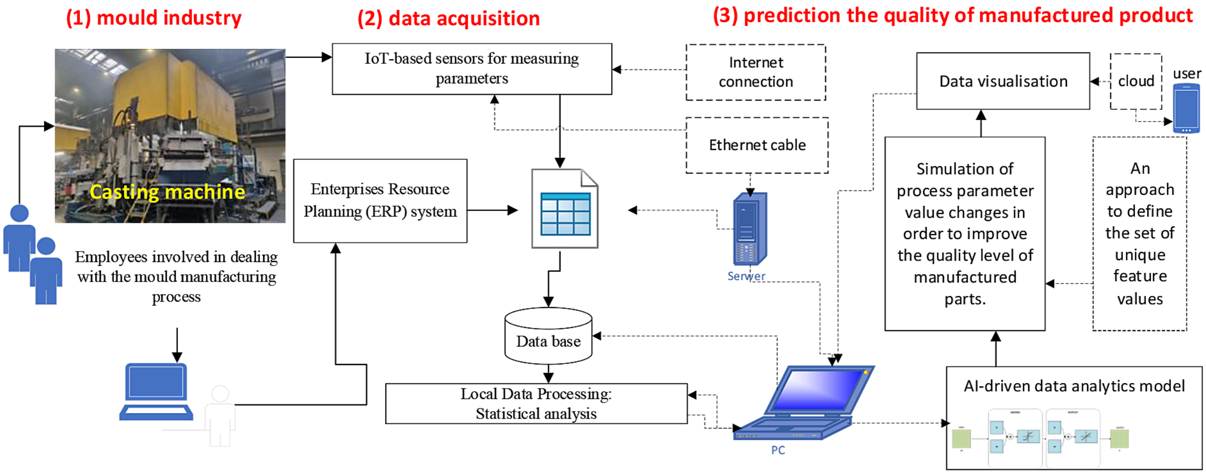

Figure 7. AIMS for mold industry supporting proactive management

are installed on the die casting machines. On the basis of the acquired data on the reference order, it is possible, using in this case the verified neural network architecture with the best efficiency (the accuracy was achieved in the training and testing phases 98.62% and 98.94% respectively), to predict the quality level of manufactured elements for the next order, with similar parameters to the reference. The advantage of this approach is that the knowledge base is constantly being expanded, and therefore it should be expected that the predictive model will, with the acquisition of further data, achieve even better efficiency. Moreover, in the proposed AIMS it is possible to simulate the values of parameters, the change of which will affect the quality level of manufactured products.

It was noticed there are examples of AI-driven IoT Monitoring Systems for industry, but no solutions were found working at mold industry and concerning modeling and forecasting the quality of manufactured highly technically demanding product used for the air conditioning of the high-end cars (Table 5).

Table 5 presents literature results in the space of AI-driven IoT monitoring systems for industries in research and summarizes the main features that distinguish proposed study from those related research already existing. It enriches with a rapid overview of the main outcome of the presented work with respect to the state of the art analyzed. Going into more detail, Table 5 reports information on the related works about: exploitation and achieved accuracy of the proposed AI-based model for AI-driven IoT monitoring system, applying the model in industry and usage of the system. To the best of knowledge- and as already highlighted in the state-of-the-art analysis (Table 5) this is a new approach in the area of supporting decisions regarding production, especially quality of manufactured highly technically demanding product used for the air conditioning of the high-end cars in the mold industry. Thus, this research proposed a new AIMS for mold industry supporting proactive management, which consists of: set of indicators of the quality of the parts during mold manufacturing process, real data: indicators values, acquired form IoT-based sensors located on the casting machine and form ERP system - based on empirical research results, applying AN. The strict collaboration between the Universities and company enabled to develop, verify and validate the proposed AIMS in a real industrial use case.

This practical model tested with one project and with one manufacturing process, is very generic. It concludes that the same can be used with any manufacturing process in which the real time data of critical process/quality parameters are monitored through IoT enabled sensors during manufacturing, layered over the set of important parameters specific to the project either established at the beginning of such manufacturing project (or process) by the technologist in the ERP system, manually. Empirical results demonstrate that AIMS improves quality control, minimizes waste, and supports sustainable manufacturing by optimizing energy use and supply chain efficiency. The steep machine learning and validation curve and its ability to predict the future performance in real time is of paramount use for manufacturing companies to avoid the production of scrap and ensure production of quality parts by either doing

Table 5. State-of-the-art analysis of SP in research

AI-driven IoT monitoring system	AI-based model accuracy	Industry/ manufacturing process	Application	Ref.
Real-time IoT-powered AI system for air quality monitoring	Long short-term memory (LSTM) model: 99 % R^2 and 0.33 MAE	Chrome plating industry	Supporting decision about improving air quality	[25]
(IoT)-based and cloud-assisted monitoring architecture	Autoencoders (AE) long short-term memory (LSTM) AE-LSTM: testing: 93.5% and recall 88.77%	Production of a solar thermal high-vacuum flat panel	Detect eventual anomalies occurring into the production	[26]
AI-Driven Intelligent IoT Systems	Convolutional Neural Network (CNN): 95.2%, recall 94.5%	Food supply chain	Monitor and analyze food quality	[27]
AIDA – a holistic AI-driven networking and processing framework	XGBoost: 61.70%, random forest (RF): 40.40%	Steel industry, which is a long-lasting process	Forecast the minimum pressure and detection of pumping issues	[28]
Approach to fault detection	Deep belief network	Manufacturing High Intensity Discharge (HID) car headlight module	Supporting multi-sites and multi-products manufacturing	[29]
Decision-making tool for the automotive industry	K-means, hierarchical clustering	Waterjet cutting	Continuous monitoring of machines in order to anticipate failures	[30]
IoT and ML-based decision support system for predictive maintenance	Random forest: MAE: 0.089; MSE: 0.018, R2:0.868	Advanced processing and measuring machines	Solving the machining quality and predictive maintenance task in a real industrial use case	[31]
predictive maintenance system for manufacturing production lines	Random forest: Xgboost:	A consumer goods manufacturing plant	Predictions of potential failures for production line	[32]
AI-driven IoT Monitoring System (AIMS)	Multi-Layer Perceptron (MLP): in the training and testing phases 98.62% and 98.94% respectively	Mold industry	Forecasting the quality of manufactured highly technically demanding product used for the air conditioning of the high-end cars	This paper

course correction of the production process parameters manually or even by adjusting them through a closed loop directly to the manufacturing machines. This will help the industries to increase the OEE (Overall Equipment Efficiency), quality of production, longer life of the production machinery by avoiding production of bad quality parts. This is possible by knowing and correcting such events before occurrence of them.

However, the main limitation of the research is that the data was acquired from the limited case study. This approach made it possible to build a universal approach to support proactive quality management in production. In the further work, data from other orders realized within a company from each cluster, will be acquired from sensors and ERP systems implemented within a company. In addition to this, data collection process during the die-casting process can be extended to be done by an IoT-enabled thermal camera to take images after each shot of the mold. This research will allow for the verification of the proposed approach and the extension of the database. The next limitation is related to the changes in the parameters of the features of individual samples. Here, the correlation of data, the combination of feature changes (group change of features and their influence on classification) can be analyzed.

In order to expand the scope of this research, the following further study has to be carried out to determine, how the additional parameters defined for monitoring product quality will have influence on the different sets of parts with different numbers of cavities, different alloys, different materials treatment of mold forming elements (machining / coating, etc). Furthermore, the interactions with experts revealed that the thermal shocks (variations in temperature from ~600 degrees to ~200 degrees) when the Aluminum changes from liquid form to solid within t~ 40 s has a great influence on the life of the mold. Therefore, to further refine the research on this subject, it was decided to have the IOT-enabled sensors (thermal cameras to take the images) installed to measure temperature of the molds on various points of the mold, after every cycle to record the real time data to carry out deep learning and build AI to accurately predict the life of the mold.

Overarching industry 5.0 priorities

According to RQ3, the first challenge is finding the balance between providing (1) sustainable industry, (2) human-centric industry and (3) resilient industry. The close relationship between human-centric technology development and sustainable production (SP) is clearly visible. The idea behind SP is to reduce energy and resource consumption, improve the well-being of communities and employees as well as maintain safety. SP plays an important role in the context of ensuring the economic properties of products, improving the production system, promoting innovation, and creating new space for economic growth. Industry needs to be sustainable [33] as well as flexible, adaptable, agile and resilient [34]. The industry should adapt its production in an agile way to the forthcoming disruptions. Therefore, it is a need to build the data-based approach as a universal framework but also highly tailored to meet industrial requirements [1]. However, further research is needed to explore the relationship between the implementation of I4.0 technologies in the mold industry and the increase in the level of SP, the level of human-centric technologies implementation and the level of the solutions adaptation, that enable the industry to operate even under the conditions of unexpected disruptions and to respond very quickly to emerging changes. In that context, the proposed AIMS can be expanded with parameters related to monitoring the SP level (e.g. SDGs) and extended to HRC workstation in the mold manufacturing process. HRC plays a key role in increasing employee productivity, which is the main goal of any company in terms of creating a production system. The second major challenge is related to the competence and knowledge of employees within the production company. Employees need to enhance their skills focused on the cooperation with the smart devices. Further research should be undertaken to develop solutions that facilitate employee adaptation to working conditions with I4.0/I5.0 technologies in manufacturing and to create better worker safety and well-being.

Finally, the third challenge concerns the adoption of generative artificial intelligence (GAI) into production. The usage of GAI enables enhancing the efficiency of manufacturing processes and improving the SP level [35]. Therefore, the research question that remains open is modeling the effects of implementing I4.0 and I5.0 technologies, especially the adaptation of AI-based tools in the context of increasing the quality level of manufactured highly technically demanding product. This is particularly important for further research focused on finding a model that supports decision-making regarding proactive management in the mold industry.

CONCLUSIONS

This study examines a universal tool to support supporting proactive quality management based on the case study from for the mold industry. Using the 9919 real data of mold manufacturing process the AI-driven data analytics model to predict and monitor quality of manufactured products was developed. The AIMS is designed for mold manufacturing, showcasing its application in producing high-end automotive air conditioning compressor molds. By leveraging IoT sensors, ERP data, and MLP models, AIMS ensures real-time monitoring, defect prediction, and mold life estimation, thereby enhancing process transparency, flexibility, and sustainability. Furthermore, the main challenges are identified in shifting from smart manufacturing enterprises toward human-centric technology development. The findings emphasize the potential of integrating IoT, AI, and machine learning in driving Industry 5.0 principles for production excellence.

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