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Significance of Manufacturing Process Parameters in a Glassworks

Łukasz Paśko*

Faculty of Mechanical Engineering and Aeronautics, Department of Computer Science, Rzeszów University of Technology, Powstańców Warszawy 12, 35-959 Rzeszów, Poland

Abstract

The article presents the use of artificial neural networks (multilayer perceptrons) to examine the significance of production process parameters. The considered problem relates to the occurrence of production periods with an increased number of defective products. The research aims to determine which of the 69 parameters of the manufacturing process most affect the number of defects. Two ways of expressing the parameters significance were used: using the sensitivity analysis and exploring the weights of connections between neurons. The results were determined using both single neural networks and a set of networks. The outcome from the research is the rankings of significance of the manufacturing process parameters. The analyzed data were obtained from a glassworks producing glass packaging.

Keywords

neural networks, glass industry, glass packaging, significance of variables, sensitivity analysis, machine learning

1. Introduction

Nowadays, in the era of the Internet of Things, manufacturing companies are increasingly using devices that generate and record data, for example, machines that perform operations in the manufacturing process or systems that monitor the manufacturing processes. Over time, recorded data create huge collections that potentially may contain valuable knowledge. The knowledge acquired by the decision-maker could facilitate making the right decisions and improve the functioning of the company.

Some important decisions made around the manufacturing process relate to problems with the quality of manufactured products. Product quality assurance is a key element in the strategy of modern manufacturing companies. Data collected during monitoring of the manufacturing process can be used, among others, in the problem of quality assurance of manufactured products. Many examples described in the literature confirm this statement.

In [1], the authors search for probable causes of defects during the production of steel castings using the techniques to examine the significance of process parameters. To check which of the examined variables significantly affect the quality of products, two tools were used: artificial neural network (ANN) and one-way analysis of variance. In [2], the properties of ductile iron products were predicted based on the analysis of physical and chemical phenomena occurring during the melting process. ANNs were used to solve that task. Thanks to ANNs, it was possible to determine the most important input variables affecting the mentioned properties of products. Research covering the metallurgical industry is also the subject of the work [3], where ANNs were used to predict the temperature of liquid metal in the metallurgical furnace and the silicon content that affect the quality of pig iron. Monitoring cutting operations also provide data that can predict tool wear or breakdown (e.g., breakage). The paper [4] shows that such data can also be used to monitor the quality of manufactured products using an ANN. In turn, the paper [5] deals with milling operations and its impact on surface roughness. The authors of the work use ANN and multiple regression method to create a model predicting surface quality. ANNs were also used for grinding operations, and their results were compared with the nonlinear regression method in [6]. An attempt to model the grinding process using a multilayer ANN with the back propagation algorithm is described in [7]. Predicting inadequate roughness was also the subject of the study [8]. This was done using ANN and response surface methodology (RSM). Although the ANN model is more computationally complex, its predictions were more accurate than RSM.

In summary, quality assurance using data mining methods is widely described in the scientific literature, especially in the case of the production of fabricated metal products, computer, electronic and optical products, as well as rubber and plastics products [9].

*Corresponding author: Łukasz Paśko

E-mail: lpasko@prz.edu.pl

In this article, an example of using data mining for quality assurance in the glass industry is presented. Modern glassworks monitor the manufacturing process. Thanks to this, all the most important parameters of the process and the number of defective products are recorded. Then, the saved data can be converted into information used, among others, to support the process of quality assurance. In the scientific literature, it is difficult to find similar applications in the glass industry. The exception may be papers [10, 11], in which the concept of such application is outlined and the first results obtained using random forests are presented.

This article is aimed to analyze the possibility of using ANNs to determine the impact of manufacturing process parameters on the number of defective glass packaging (bottles). The desirable results are rankings of significance of the manufacturing process parameters. The rankings show which parameters have the greatest impact on the predicted number of defective products.

2. Measures of Input Variables Significance

To achieve the described purpose of the article, methods for testing the significance of variables were used. The examination of variables significance is widely used in problems related to production engineering, as shown in the examples mentioned in Section 1. It can also be an appropriate approach to identify the causes of defects in products. If the input (explanatory) variables are the parameters of the manufacturing process, and the output (explained) variable is information about the number of defective product, then the examination of variables significance can be treated as the identification of key parameters that most significantly affect the manufacture of products with defects. As a consequence, the identified key parameters become the main candidates for the cause of defects in products. To confirm them as the causes of the increased number of defects, the insights should be confronted with domain knowledge and experience about the examined manufacturing process.

The authors of [12] distinguish three general ways of searching for information on the input variables significance using data-driven models:

- using the appropriate procedure to query the previously prepared model, which is treated as the so-called "black box" (which means the model stores the acquired knowledge in a hidden manner, which is difficult to interpret by the user);
- examination of model parameters, whose values are carrying information on the significance of input variables used to prepare it;
- comparing the predictive ability of a model created based on all input variables with the predictive ability of a model generated based on a reduced number of input variables.

Some of these methods can be used only with the quantitative explained variable, others can be used for a qualitative explained variable, but there are also techniques for determining the variables significance that are used regardless of the type of the explained variable [13]. The significance of input variables can be determined by many techniques, from simple, statistical data analysis procedures to advanced artificial intelligence methods, including machine learning and deep learning. Examples of techniques that can be the basis for generating a ranking of variable significance are decision trees [14], random forests [15], ANNs [16], rough sets [17], and hybrid approaches [18]. To examine the significance of variables, creation of a suitable model is needed. The model maps the dependence of the data placed at its output on the input data.

The review of techniques used to solve regression tasks that allow generating information about the significance of input variables is contained in the article [19]. In the case of classification models, it is necessary to apply different approaches to determining the significance of variables than in regression models [13]. The review of such approaches is included in the article [12]. The same article describes the method of reducing variables, which is an approach independent of the type of model—it can be used both for classification and regression tasks. In this method, the prediction accuracy $pa_{X_{in}}$ of the model created based on all input variables X_{in} is compared with the prediction accuracy $pa_{X_{in}\setminus\{X_i\}}$ of the model created for reduced data $X_{in}\setminus\{X_i\}$, which means the data without some input variable X_i. The Sig_{X_i} measure that expresses the significance of the variable X_i is the difference between the above-mentioned prediction accuracies:

$$Sig_{X_i} = pa_{X_{in}} - pa_{X_{in}\setminus\{X_i\}} \tag{1}$$

The procedure of variable reduction can be repeated for each input variable separately. The results obtained in this way will show the impact of removing individual input variables on the deterioration of the predictive ability of the model. This allows to create a ranking of input variables significance, in which the variable with the highest value of Sig_{X_i} will be the most significant. Sig_{X_i} may have positive and negative values. A negative value indicates that deleting the given input variable from the data set has improved the prediction accuracy.

The literature review shows that the most commonly used ways to express the input variables significance are:

- sensitivity analysis—shows what values will be taken by the output variable under the influence of changes in the values of the input variable [20];
- calculation for each input variable a coefficient expressing the overall effect of this variable on the value of the output variable [12].

Both ways make it possible to determine the ranking of input variables significance.

3. Description of the Experiment and its Results

The experiment concerns the analysis of the impact of manufacturing process parameters on the number of defective products in the glass industry. The analyzed data were obtained from a glassworks producing, among others, glass bottles. The data can be divided into two groups:

- parameters of the manufacturing process treated as explanatory variables: glass temperature in the furnace and forehearth, operating parameters of the furnace and forehearth, and parameters affecting the cooling of glass molds;
- the number of products with an Empty Bottle Inspector (EBI) defect—explained variable.

The considered EBI defect is revealed by the occurrence of air bubbles in the upper part of the product. The increase in the number of EBI defects above the assumed acceptable level is critical. The reason of that increase is usually difficult to determine due to high complexity of the manufacturing process. It can be caused by many factors related to the manufacturing process. Determining these factors is often problematic even for glassworks employees. Because the glassworks collects the values of hundreds of the manufacturing process parameters, it was decided to find reasons of increased number of defective products by using methods of analyzing these data.

The amount and dynamics of data collected in the glassworks favor the application of methods related to artificial intelligence and above all machine learning. Therefore, ANNs were used to solve the described problem. ANNs are information-processing systems that can map even very complex nonlinear relationships, learning them based on the supplied training data set. The basics of ANNs are described in [21-25]. ANNs differ primarily in the arrangement of neurons and the activation functions in the neurons. In the experiment, the universal and most commonly used type of ANN is considered—multilayer perceptron (MLP). The MLP network has three layers of neurons: input, hidden, and output layers. The signals flow only in one direction, from the input layer, through hidden, to the output. The number of input neurons is equal to the number of explanatory variables N in the training data set. The number of hidden neurons during the research was determined experimentally based on the Statistica Data Miner software (“Automated Neural Networks” module). The output layer in the MLP for regression task contains one neuron that calculates the final regression result (the number of defective products). Neurons in the hidden and output layers process signals using the appropriate activation functions. In that research, four activation functions were taken into account: linear, logistic, hyperbolic tangent, and exponential.

In this study, ANNs have been used to rank the variables significance in two ways:

- examining the weights of connections between neurons and
- using sensitivity analysis.

The examination of weights assumes that the knowledge extracted from training data is stored in the form of weights of the connections between neurons. The higher the weight in a given connection (in absolute terms), the more important signals pass through this connection. To determine the significance of the explanatory variables, the connections between input and hidden neurons were considered. The significance of the explanatory variable X_i is equal to the sum of the absolute values of connections weights $w_{Ii\to Hj}$ from the input neuron I_i representing the variable X_i to each of the K hidden neurons (designation H). It is expressed by the formula:

$$Sig_{X_i} = \sum_{j=1}^{K} \left| w_{Ii\to Hj} \right|. \tag{2}$$

Sensitivity analysis uses already described concept of variable reduction. The procedure for performing sensitivity analysis is to present the data N times for ANN. In each repetition, one of the X_i input variables is treated as missing variable. The ANN’s error $Err_{X_{in}\setminus\{X_i\}}$ is then calculated, analogously to the error $Err_{X_{in}}$ for the complete set of input variables X_{in}. Finally, the significance Sig_{X_i} of the variable X_i is determined as the quotient of the two mentioned errors according to the formula:

$$Sig_{X_i} = \frac{Err_{X_{in}\setminus\{X_i\}}}{Err_{X_{in}}}. \tag{3}$$

Owing to the rejection of one of the variables, a network error without one input is usually greater than the error $Err_{X_{in}}$. The larger it is, than the network is more sensitive to remove this variable from the input set. The smallest possible value of Sig_{X_i} is 1. Variables for which this value has been determined are considered as the least significant.

The following procedures were used in the research for creating ANNs:

1. Random division of the data set into three subsets: training, validation, and test in the proportions 70, 15, 15% of cases from the data set, respectively. Cases were allocated to the subsets randomly. The training subset is used to modify the weights of connections properly between neurons, the validation subset is used for ongoing control of learning outcomes during network training, and the test subset is used to finally check the quality of the network after training.
2. Creation of 50 ANNs, assuming for each of them different sizes of hidden layer and different activation functions in hidden and output neurons. A tool called “Automated neural networks” implemented in the Statistica Data Miner software realized network generation and selection of activation functions. The learning algorithm called

Broyden-Fletcher-Goldfarb-Shanno (BFGS) was used to train the ANNs.

3. Selection of the best ANN among created ANNs. The ANN with the smallest error made on the test subset was considered as the best ANN. In the case of obtaining several networks with very similar error on the test subset, the next criterion was the smallest error on the validation and training subsets.
4. Creation of 10 ANNs, assuming the same activation functions in the hidden and output layers as found for the best of the 50 ANNs.
5. Selection of the best ANN from 10 created ANNs using the criterion from the third step.

In the third step, it was determined that the ANN with the smallest error on the test subset contains the logistic activation function in hidden neurons and the linear activation function in the output neuron. Then, in the fourth step, 10 ANNs were created differing in the size of the hidden layer. The number of neurons in this layer is determined by the module "Automated neural networks".

The 10 ANNs created in the fourth step were treated as a set of ANNs. During prediction, each network in the set generates an output value for a certain input values. As a result of the entire ANNs set, the average output values of all networks included in the set are taken. The root of the mean squared error (RMSE) calculated for prediction using ANNs set is 18.66.

In the fifth step, it was determined that the best of the 10 ANNs contains 69 input neurons, 54 hidden neurons, and 1 output neuron (MLP 69-54-1). The RMSE for this network is 17.97. Comparing the RMSEs of the best network with the ANNs set, it can be observed that the differences are insignificant. Despite the fact that RMSEs are not close to zero, the developed regression models map the basic features of the output variable in an appropriate manner. This can be seen in the time series graph of the explained variable, on which the output (regression result) of the best ANN and the average result calculated for the ANNs set have been imposed (Figure 1).

The ANNs can map changes in the average EBI level and the variability of EBI in time. Comparing the MLP 69-54-1 output with the ANNs set output, it is noted that the plot for the ANNs set is smoother and the MLP 69-54-1 plot has a better match to the actual values. This is due to the averaged nature of the ANNs set results, which considers the output values of 10 models. The ANNs set was used in the sensitivity analysis of explanatory variables. The result of the sensitivity analysis for a given variable is the arithmetic mean of its results obtained through all 10 ANNs.

Figure 2 shows the created rankings of explanatory variables significance. The values in the column "Sensitivity analysis for MLP 69-54-1" were obtained for the best ANN using formula (2). For the same ANN, the examination of connection weights between neurons according to formula (3) was carried out. The results of this action are collected by the column "Total weight in MLP 69-54-1". Moreover, the average coefficients from the sensitivity analysis using 10 ANNs are contained in the column "Sensitivity analysis for set of ANNs" (the results were sorted in descending order by the value of this column). The observations resulting from the comparison of variable significance rankings are as follows:

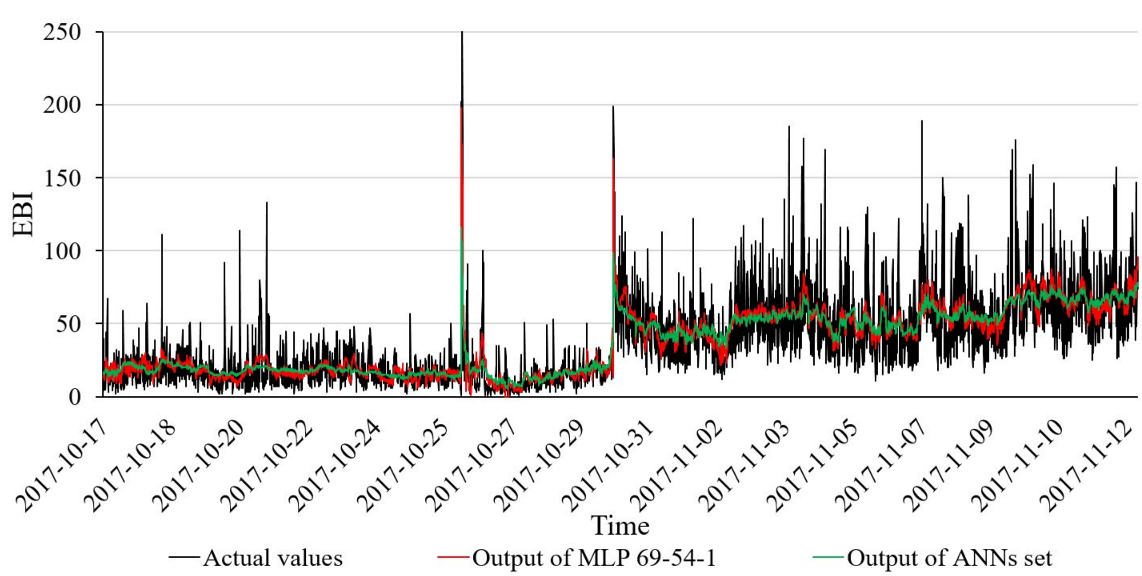

Figure 1. Actual values of the explained variable (EBI) and the values estimated using ANNs.

Sensitivity analysis based on the ANNs set indicates the glass temperature in the lower right of the forehearth's front section as the most significant variable. The same variable also comes first in the other two rankings. The plot of this variable (Figure 3) shows that its course is characterized by variation in value levels similar to the EBI. Level changes occur at the same times in which changes in the number of defective products can be observed. This is particularly well seen around October 26 and October 30, when the change in variable levels is most visible.

The highest places in the rankings are mainly occupied by variables related to the glass temperature in the following sections of the forehearth: the lower part of Refiner2, the upper part of Alcove, the upper part of Middle, and the left and right side of Back. This suggests that the glass temperature in the forehearth may have the greatest impact on the number of EBI defects. However, as mentioned earlier, this requires confirmation using alternative data mining techniques and confrontation with domain knowledge.

Ranking of variables based on sensitivity analysis for the best ANN gives similar results (especially in leading positions) to the ranking obtained on the basis of neuron weights in this ANN. However, there are also variables whose position in the neuron weight ranking is much higher than in the sensitivity analysis ranking (TC.FH1_FL.MID.TP.TC.PTC and TC.FH1_FR.MID.TP.TC.PV). To determine what affects these differences, an in-depth analysis should be carried out. In particular, the significance ranking can be determined based on the weights of the neurons of each ANN from the set, and then weights obtained can be summed to create a separate ranking.

In both rankings established based on sensitivity analysis, similar values are recorded in the last positions of the ranking. However, in the top positions, higher differences can be seen in the order of variables. When planning future studies using a set of models (not just ANNs), an additional study can be performed to determine the optimal number of models in the set because this number affects the results of the sensitivity analysis. The RMSE can be used as a criterion for choosing the optimal number of models. In addition, the obtained

Input variable	Sensitivity analysis for MLP 69-54-1	Sensitivity analysis for set of ANNs	Total weight in MLP 69-54-1	Input variable	Sensitivity analysis for MLP 69-54-1	Sensitivity analysis for set of ANNs	Total weight in MLP 69-54-1
J21.FR.BTM.TP.TC.PV	8,838	3,847	65,958	J21.FC.TOP.TP.TC.PV	1,153	1,107	23,366
J21.A1C.TOP.TP.TC.PV	3,712	3,591	32,631	J21.BL.CB.PR.PV	1,197	1,106	11,035
J21.FL.BTM.TP.TC.PV	5,560	2,850	58,980	J21.R1.CW.PV	1,241	1,104	20,687
J21.R2C.BTM.TP.TC.PV	4,010	2,510	44,977	J21.BR.CB.PR.PV	1,357	1,098	14,212
J21.FL.CV.PV	2,400	2,457	38,803	J2F.TUBEHT.AI.PV	1,175	1,088	13,392
J21.FC.BTM.TP.TC.PV	2,316	2,282	31,089	J2F.FONT.TP.TC.PV	1,211	1,078	9,671
J21.R1R.CV.PV	5,038	2,236	19,609	AI.FH1_R1.INT.PR.AI.PV	1,276	1,078	16,232
TC.FH1_FL.MID.TP.TC.PV	2,181	2,077	63,996	FN_TH.SW.TP.TC.PV	1,057	1,077	25,183
J21.R1R.CB.PR.PV	2,997	2,006	16,715	J21.BL.CV.PV	1,057	1,077	13,565
J21.MC.TOP.TP.TC.PV	2,729	1,800	16,449	J21.FC.TOP.TP.SP	1,112	1,072	6,334
J21.FR.CB.PR.PV	1,509	1,517	17,696	J21.R2.CW.PV	1,112	1,069	8,641
J21.ML.CV.PV	2,101	1,512	15,524	J21.M.CW.PV	1,062	1,062	11,123
J21.R1L.CB.PR.PV	1,835	1,489	14,147	Z3.KW	1,080	1,049	15,530
J21.BC.TOP.TP.TC.PV	1,271	1,453	22,241	TC.FH1_FC.MID.TP.TC.PV	1,137	1,040	10,737
J21.BC.BTM.TP.TC.PV	2,115	1,403	8,996	J21.FR.TOP.TP.TC.PV	1,145	1,033	18,843
TC.FH1_FR.MID.TP.TC.PV	1,555	1,311	53,260	J21.ML.CB.PR.PV	1,059	1,028	15,762
J21.BC.TOP.TP.SP	2,098	1,261	7,482	J21.R2R.CV.PV	1,181	1,028	4,663
J21.A1C.TOP.TP.SP	2,063	1,254	7,400	AI.FH1_R2.INT.PR.AI.PV	1,072	1,028	12,147
J21.R2L.CV.PV	2,119	1,244	8,649	FN_BTM.TP3.TC.PV	1,050	1,023	7,252
FN_STK.CV.PV	1,408	1,234	11,266	J21.FR.CV.PV	1,050	1,023	8,122
PULL	1,576	1,225	8,391	AI.FH1_M.INT.PR.AI.PV	1,111	1,023	6,858
J21.MR.CV.PV	1,444	1,207	10,369	J21.M1.CW.PR.PV	1,060	1,022	9,216
J21.M1.CW.TP.PV	1,302	1,198	29,313	J21.R2L.CB.PR.PV	1,072	1,022	5,208
J21.R2C.TOP.TP.TC.PV	2,117	1,190	13,367	Z2.KW	1,045	1,021	14,367
J21.A1Z.CV.PV	1,465	1,189	15,414	J21.MR.CB.PR.PV	1,075	1,019	6,351
J21.MC.TOP.TP.SP	1,160	1,151	10,964	J21.BR.CV.PV	1,025	1,015	13,714
J21.A1C.BTM.TP.TC.PV	1,026	1,142	4,473	Humidity	1,013	1,014	9,718
J21.MC.BTM.TP.TC.PV	1,404	1,133	22,208	J21.M1.CW.CV.PV	1,018	1,012	6,896
J21.R1L.CV.PV	1,377	1,132	7,581	Pressure	1,032	1,010	8,230
J21.R2C.TOP.TP.SP	1,490	1,132	10,251	AI.FH1_B.INT.PR.AI.PV	1,028	1,009	12,747
J21.A1Z.CB.PR.PV	1,138	1,125	15,208	Temperature	1,020	1,009	8,120
J21.FL.TOP.TP.TC.PV	1,161	1,120	21,941	FN_CH2.SPD.PV	1,013	1,005	10,928
J21.FL.CB.PR.PV	1,060	1,117	10,801	J2F.FN.PR.PV	1,009	1,004	7,307
J21.R2R.CB.PR.PV	1,165	1,117	7,239	J2F.GL.LEV.PV	1,001	1,000	5,690
J21.B.CW.PV	1,325	1,113	13,556				

Figure 2. Rankings of variables significance created on the basis of ANNs.

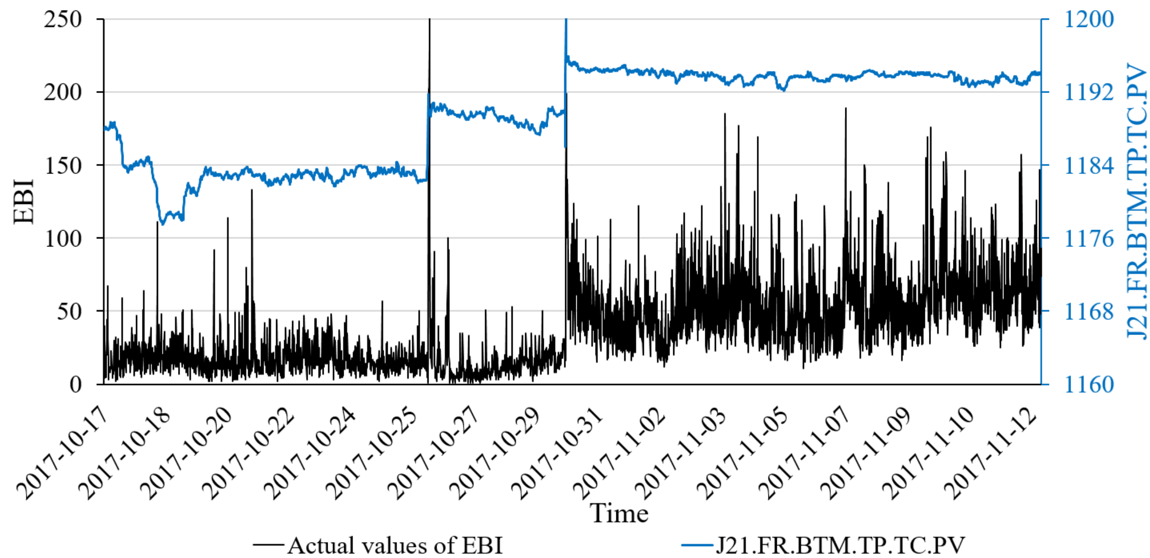

Figure 3. Comparison of time series plot for two variables: J21.FR.BTM.TP.TC.PV and EBI.

significance rankings can also be compared with the rankings created for another division of the data set. For this purpose: the data set should be divided *k* times into training, validation, and test subsets; for each division ANNs should be generated according to the approach described earlier; for each of *k* divisions, the rankings should be prepared. In that approach, the coefficients included in final ranking are averaged based on each of the *k* rankings.

4. Conclusions

In the conducted research, an attempt was made to combine industrial data on the number of defective products with the values of manufacturing process parameters at a glassworks. The research meets expectations of the modern industry. This is evidenced by the constantly growing amount of industrial data, not only in the glass industry. It is caused by, among others, a significant increase in the number of devices that generate data, which are engaged in the manufacturing processes.

The analyzed data were recorded in the period in which the number of defects increased for unknown reasons. Completed research shows that ANNs help to determine the parameters of the manufacturing process that can significantly affect the increase in the number of defective products. Two methods of examining the significance of parameters were used in the study: using the sensitivity analysis and analyzing the weights of connections between neurons. Examination of variables significance can also be used to select process parameters that are not likely to affect the number of defects. After rejecting that parameters from the data set, further analysis using quantitative or qualitative methods can be carried out.

It should also be noted that the results obtained should not be regarded as the definitive indicator of which parameters affect the number of defects. The final assessment of such impact should be based on several independent methods of examining the parameters significance. As a result, it is possible to find repeated relevant and irrelevant variables in each method of assessment used. Those variables that show high significance in several ways of assessing are more likely to be considered as key parameters in the problem being considered.

Future research will include the use of other types of ANNs in the considered problem. In particular, convolutional neural networks based on deep learning will be used. These types of networks, thanks to more than one layer of hidden neurons, can map more complex relationships than the MLP network with one hidden layer.

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