European Research Studies Journal
Volume XXV, Issue 2B, 2022

pp. 45-58

Application of the Digital Twin Concept in Assessing the Readiness of Production Systems

Submitted 01/06/22, 1st revision 13/06/22, 2nd revision 12/07/22, accepted 30/07/22

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Abstract:

Purpose: *This paper is devoted to evaluating the efficiency of production systems using classification methods. These methods are not popular in application to manufacturing companies, therefore the possibility of their use in the process of system improvement and enhancement of business models is presented.*
Design/methodology/approach: *The article uses classification methods, emphasizing their practical significance in assessing the performance of production processes. They allow the construction of a model for classifying new objects based on the relationships found in the collected empirical observations. Such data mining methods may find application primarily in non-computerized systems with limited information processing capabilities.*
Findings: *The result of the publication is the presentation of a comprehensive method for assessing the efficiency of the production system. As a result, this solution will allow for more effective planning of processes and tasks, their ongoing correction, adequate to the available human, material and equipment resources, and reducing the risk of the system not being ready to perform the activities for which it is intended.*
Practical implications: *The presented method is primarily used to assess the impact of selected factors on the efficiency of production processes as well as to support decisions in the area of production planning.*
Originality value: *The presented model is built on the basis of archival data, but allows the transfer of the solution to cloud computing and obtaining readings in real time (online), which will allow for ongoing assessment and support of the operation of the investigated system in terms of monitoring and ongoing analysis of the implemented processes in real time, but also through the creation of simulation scenarios, considering decision-making options.*

Keywords: *Classification methods, production process efficiency, manufacturing, logistics process,*

JEL codes: *D2, D24, C3, C38.*

Paper type: *Research article.*

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1. Introduction

The activities of manufacturing companies are profit-driven through the effective implementation of their objectives. An important term in this area is efficiency. The term efficiency is used when referring to how effectively an organization uses its resources. According to Statistics Poland (2021), labor efficiency in industry is understood as the amount of production effects that are obtained as a result of human labor per unit of that labor. The concept of production process efficiency is also understood as the comparison of potential maximum output with actual observed output (de la Fuente-Mella *et al*., 2020). The concept of efficiency can also be described as the effort put in by the management of a company in activities to reduce costs, allowing additional profit to be generated (Osazefua, 2019).

A high level of company-wide efficiency can only be achieved if the individual processes and the employees involved are efficient enough. To measure efficiency, it is necessary to consider each element of the process in question individually. The efficiency of resource use per unit of output, as well as the rates of resource use, affect the efficiency of the process (Prokopenko *et al*., 2020). Process efficiency is higher when resources are used optimally (Ostapko, 2018). The introduction of automation and the creation of performance-oriented teams also improve efficiency (Kiełtyka and Charciarek, 2019).

Companies can measure the level of efficiency of the production process in a variety of ways. A useful tool in this area are Key Performance Indicators (KPIs) (Aleš *et al*., 2019), which are a set of measures useful for assessing the level of performance of a company (Grabowska, 2017). These indicators are used to measure economically, organizationally and technically relevant parameters (Pacana and Czerwińska, 2020). A composite of KPIs is Overall Equipment Effectiveness (OEE). This indicator is used to examine the total efficiency of the equipment used during the production process. Its value is the product of availability, machine productivity and quality of the produced assortment (Bartecki *et al*., 2018). Additionally, there are metrics to help measure reliability: Mean Time to Repair (MTTR), which determines the average time to repair a machine or set of machines, and Mean Time Between Failures (MTBT), which determines the average time between machine failures or micro downtimes (Michlowicz and Smolińska, 2017). Monitoring productivity and increasing its level is furthermore an important element of the idea of Industry 4.0 (Kozłowski *et al*., 2021; Gola *et al*., 2021).

In his publication, Cellary (2019) points out that the transformation of production in a cyber-physical environment can take place by performing operations on datasets that result in improved efficiency, innovation, productivity and personalization. Zarychta (2018) highlights the use of the augmented reality technology in industry. By digitally mapping a device or set of devices, information about the solution being implemented and its potential impact can be obtained. The use of modern technology in the production process is also considered by Ma *et al*. (2020) who address the problem of integrating digital twin technology with simulation platforms. Soderberg *et al*. (2017) in their publication focused on the appropriate use of data for simulation combined additionally with the quality control process as part of production optimization. In (Jasiulewicz-Kaczmarek *et al*., 2021, Agostino *et al*., 2020), attention is given to the concept of digital production twin in terms of process planning and control. The use of appropriate technology or software to support innovative manufacturing requires data collection and processing (Jasiulewicz-Kaczmarek and Antosz, 2021).

They are used to reflect the physical world. Models allow settings to be tested and optimized to achieve a satisfactory solution, thereby significantly reducing the time required to configure the machine while improving the quality of its performance (Sobaszek *et al*., 2020, Uhlemann *et al*., 2017). Support for activities such as selecting new equipment is also provided through Augmented Reality. Various methods and mathematical tools are used as part of process modeling. Among them are, among others naive Bayes classifier (Deng *et al*., 2021), decision trees (Matuszny, 2020), random forests (Grzelak and Rykała, 2021) and logistic regression (Borucka and Grzelak, 2019), which are also used in this paper. Therefore, this paper proposes the creation of a digital twin model by which the efficiency of a process involving the described variables can be predicted.

2. Materials and Methods

The research covered the efficiency of the production process. The company under study is from the medical industry and it specializes in the production of laboratory tips. The company runs its own distribution organization and sells on a global scale (28 countries). The described company has a modern machine park and uses an automated goods packaging system. Due to the business profile, the company's production facilities meet the requirements of medical standards.

The collected observations were divided into training observations, which make up for 3/4 of the set, and test observations, which constitute the remaining 1/4 of the set. Observations include variables such as machine manufacturer, service company (team), spare parts supplier, shift, and calendar month.

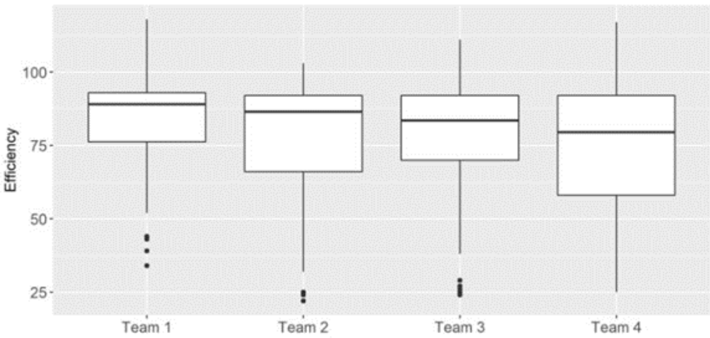
Machines are inspected on a weekly basis. Necessary components are replaced as needed. The time allowed for inspection is not included in the performance indicator.

It was assumed that the selected factors significantly affect efficiency, which was verified using statistical tests. The research began with calculating basic descriptive statistics of the variables in the groups. Box plots of efficiency versus variable were made. A normality of distribution analysis was then performed using the Shapiro-Wilk test. The working hypothesis was verified at the accepted significance level of $\alpha=0.05$. The next step of the research was to check if the variables were significantly different between the groups. The Kruskal-Wallis test was used for this, verifying the working hypothesis at a significance level of α=0.05. Based on the research, a decision was made whether the variables would be taken for further data mining using classification methods. Naive Bayes classifier, Decision trees, Random forests and Logistic regression were selected.

3. Analysis and Evaluation of Potential Predictors

In the first stage of the research, the effect of the selected variables on the process efficiency, expressed as a percentage, was evaluated. The following were selected: team, month, machine manufacturer, spare parts supplier, and shift. There are 4 categories for the variable group "service team". These are teams - companies that perform maintenance and inspection work on machines. A box plot of efficiency in each category of the variable "service team" is presented in Figure 1.

Figure 1. *Efficiency chart depending on the service team*



Source: *Authors' calculations.*

The differences by service team do not appear to be significant. To confirm this with a statistical test, the normality of the group distributions was first verified using the Shapiro-Wilk test. The test results are shown in Table 1.

Table 1. *The results of the Shapiro-Wilk test for the variable "team"*

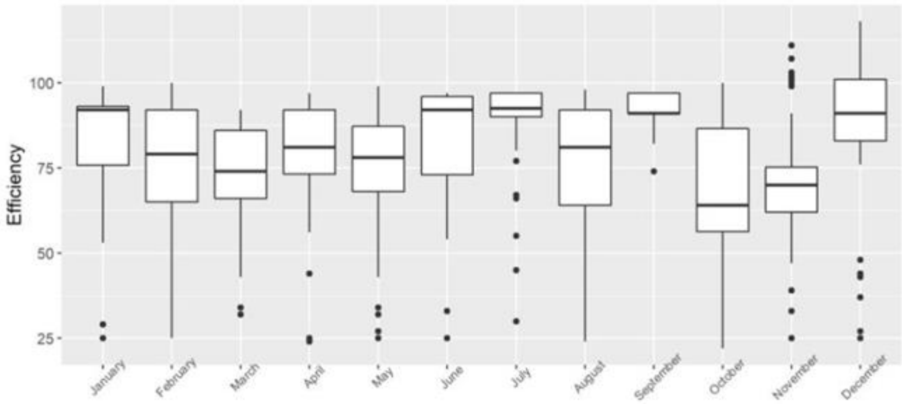
Team	Value of S-W test statistics	*p*-value
Team 1	0.92	$7{,}70 \cdot 10^{-11}$
Team 2	0.87	$1{,}65 \cdot 10^{-13}$
Team 3	0.89	$4{,}49 \cdot 10^{-12}$
Team 4	0.91	$6{,}43 \cdot 10^{-11}$

Source: *Authors' calculations.*

For all teams, the distributions were found not to follow a normal distribution, so the Kruskal-Wallis test was used to assess differences in the group. Its results (chi-square = 31,039 p-value = $8{,}34 \cdot 10^{-7}$) showed that the differences between the different service teams were statistically significant.

The variable "month" was then tested. Efficiency chart depending on the month is shown in Figure 2.

Figure 2. *Efficiency chart depending on the month*



Source: *Authors' calculations.*

Similarly, a normality test was first performed before evaluating differences. The test results are shown in Table 2.

Table 2. *The results of the Shapiro-Wilk test for the variable "month"*

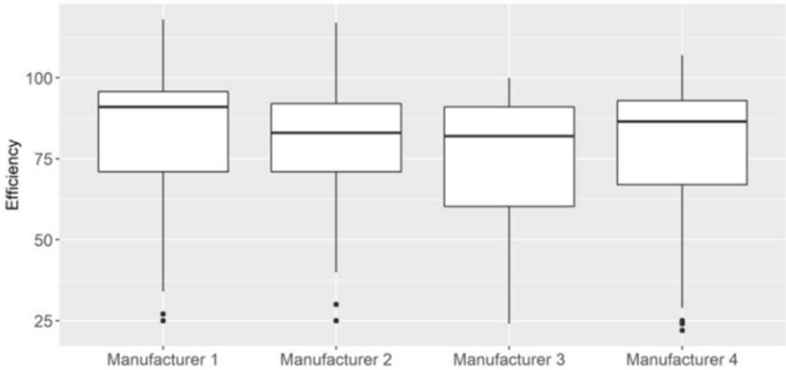
Month	Value of S-W test statistics	*p*-value
January	0.78	$6{,}39 \cdot 10^{-11}$
February	0.92	$2{,}16 \cdot 10^{-5}$
March	0.93	0.00
April	0.84	$2{,}50 \cdot 10^{-7}$
May	0.84	$1{,}45 \cdot 10^{-7}$
June	0.77	0.00
July	0.61	$1{,}21 \cdot 10^{-14}$
August	0.87	$6{,}17 \cdot 10^{-8}$
September	0.81	$5{,}36 \cdot 10^{-10}$
October	0.94	0.00
November	0.93	0.00
December	0.83	$4{,}98 \cdot 10^{-8}$

Source: *Authors' calculations.*

The lack of compliance with the normal distribution again determined the use of the Kruskal-Wallis test. The test statistic values of chi-square = 221,7 and p-value < $2,2 \cdot 10^{-16}$ were obtained, which means that at least two groups are significantly different from each other.

The next variable examined was the "manufacturer" variable. In this group, 4 manufacturers of machines that are used in the production process in question can be distinguished. Efficiency chart depending on the machine manufacturer is shown in Figure 3.

Figure 3. *Efficiency chart depending on the machine manufacturer*



Source: *Authors' calculations.*

Again, the lack of normality of the distribution of the variable in the groups (Table 3.) determined the performance of the Kruskal-Wallis test, confirming the differences in the groups of chi-square = 32,36 p-value < $2,2 \cdot 10^{-16}$.

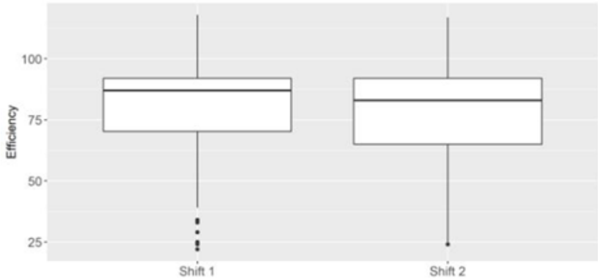
Table 3. *The results of the Shapiro-Wilk test for the variable "manufacturer"*

Manufacturer	Value of S-W test statistics	*p*-value
Manufacturer 1	0.88	$5,74 \cdot 10^{-13}$
Manufacturer 2	0.96	$2,03 \cdot 10^{-6}$
Manufacturer 3	0.86	$3,61 \cdot 10^{-14}$
Manufacturer 4	0.87	$6,95 \cdot 10^{-14}$

Source: *Authors' calculations.*

In the next step, the variable "shift" was tested. Work at the company is done in 2 shifts. Figure 4 shows the dependence of efficiency on shift.

Figure 4*. Efficiency chart depending on the shift*



Source: *Authors' calculations.*

The distributions within groups also do not follow a normal distribution (Table 4).

Table 4. *The results of the Shapiro-Wilk test for the variable "shift"*

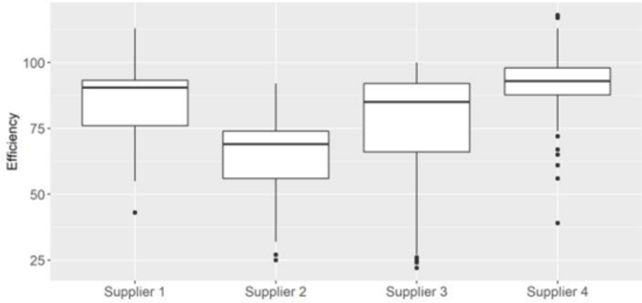
Shift	Value of S-W test statistics	*p*-value
First	0.89	$< 2,2 \cdot 10^{-16}$
Second	0.89	$< 2,2 \cdot 10^{-16}$

Source: *Authors' calculations.*

Therefore, the Kruskal-Wallis test was conducted in the next step. The obtained value of chi-square test statistic = 4,74 and *p*-value = 0,03 means that there are differences between the process efficiency obtained in each shift.

The last variable examined was the "supplier" variable. Figure 5 shows the dependence of efficiency on the supplier of spare parts used to repair and service machines.

Figure 5. *Efficiency chart depending on the spare parts supplier*



Source: *Authors' calculations.*

Table 5. *The results of the Shapiro-Wilk test for the variable "supplier"*

Supplier	Value of S-W test statistics	*p*-value
Supplier 1	0.88	0.00

Supplier 2	0.93	0.00
Supplier 3	0.86	$< 2{,}2 \cdot 10^{-16}$
Supplier 4	0.92	$1{,}82 \cdot 10^{-7}$

Source: *Authors' calculations.*

The results of the S-W test (Table 5) indicate that the distributions obtained do not follow a normal distribution.

The Kruskal-Wallis test conducted showed that there were statistically significant differences between suppliers (chi-square = 152,8 p-value $< 2{,}2 \cdot 10^{-16}$).

Based on the results obtained for all variables, a general conclusion was made that the variables differed among the groups and therefore will be used in further analysis.

3. Using Classification Methods to Evaluate Process Efficiency

For the purpose of the analysis performed and in accordance with the expectations of the company in question, the desired level of efficiency was assumed to be greater than 90%. Reaching a lower value indicates an undesirable situation. An analysis was then performed to assess the impact of each category of a variable on the probability of achieving a satisfactory process efficiency value. Selected machine learning methods, i.e., naive Bayes classifier, decision trees, random forests and logistic regression, were used for this purpose. A confusion matrix was calculated for each model. The confusion matrix allows us to determine what proportion of observations from a given class are correctly classified by the model (true positive cases) and what proportion of observations not belonging to a given class are misclassified observations (false positive) (Kozłowski *et al.*, 2021). Based on this, it is possible to calculate:

1. Sensitivity (True Positive Rate - TPR) - indicating the extent to which a true positive class was classified as positive:

$$TPR = \frac{TP}{TP+FN} \tag{1}$$

2. Specificity (True-Negative Rate - TRN) indicating the extent to which a true negative class was classified as negative:

$$TNR = \frac{TN}{TN+FP} \tag{2}$$

3. Positive Predictive Value (PPV), indicating with how much confidence we can trust positive predictions, i.e., what percentage of positive predictions are confirmed by the true positive state:

$$PPV = \frac{TP}{TP+FP} \tag{3}$$

4. Negative Predictive Value (NPV), which indicates with how much confidence we can trust negative predictions, i.e. what percentage of negative predictions are confirmed by the true negative state:

$$NPV = \frac{TN}{TN+FN} \tag{4}$$

5. Accuracy (ACC) expressing the ratio of correctly classified observations to all observations:

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

Kappa statistics were also used to evaluate the classifiers. It refers to the overall relevance of the model, as expressed by the compliance between the proposed allocation and the actual state. It assumes values from the set $\langle -1, 1 \rangle$. An absolute value greater than 0.5 indicates correct classification.

$$kappa = \frac{ACC-k}{1-k},\ k = \frac{1}{|D|^2}(O_1P_1 + O_2P_2) \tag{6}$$

where:

$O_1 = TP + FP$

$O_2 = TN + FN$

$P_1 = TP + FN$

$P_2 = TN + TN$

The calculated confusion matrices for each model are presented in Table 6 - 9.

Table 6. *Confusion matrix - naive Bayes classifier*

Act. / Pred.	TRUE	FALSE
TRUE	138	46
FALSE	39	79

Source: *Authors' calculations.*

Table 7. *Confusion matrix - decision trees*

Act. / Pred.	TRUE	FALSE
TRUE	152	54
FALSE	25	71

Source: *Authors' calculations.*

Table 8. *Confusion matrix - random forests*

Table 9. *Confusion matrix - logistic regression*

Act. / Pred.	TRUE	FALSE
TRUE	148	41
FALSE	29	84

Source: *Authors' calculations.*

Act. / Pred.	TRUE	FALSE
TRUE	146	45
FALSE	31	80

Source: *Authors' calculations.*

The results obtained are similar for all models. The decision tree model has the highest number of true positive predictions. The decision tree model also has the lowest number of false positive as well as negative predictions. The smallest number of true positive predictions occurs for the naive Bayes classifier. This model also has the highest number of false negative events. The largest number of cases of true negative predictions occurs in the random forest model.

Other measures of classifier evaluation are shown in Table 10.

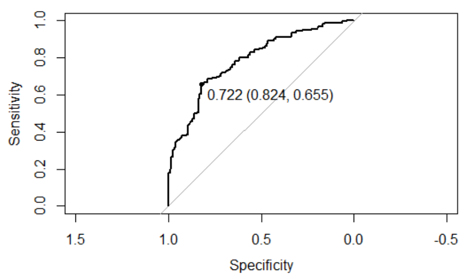
Table 10. *Selected measures of classifier evaluation*

	Naive Bayes classifier	Decision trees	Random forests	Logistic regression
Accuracy	0.72	0.74	0.77	0.75
No Information rate	0.59	0.59	0.59	0.59
Kappa	0.42	0.44	0.52	0.47
Sensitivity	0.78	0.86	0.84	0.82
Specificity	0.63	0.57	0.67	0.64
Pos Pred Value	0.75	0.74	0.78	0.76
Neg Pred Value	0.67	0.74	0.74	0.72
Prevalence	0.59	0.59	0.59	0.59
Detection Rate	0.46	0.50	0.49	0.48
Detection Prevalence	0.61	0.68	0.63	0.63
Balanced Accuracy	0.71	0.71	0.75	0.73

Source: *Authors' calculations.*

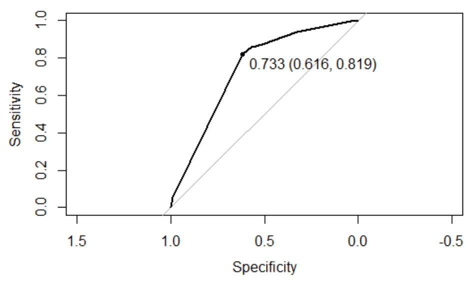
The best results for most measures were obtained for the random forest model. This can also be seen in the ROC curve plots presented for each model in Figure 6-9.

Figure 6. *ROC curve plot - naive Bayes classifier*



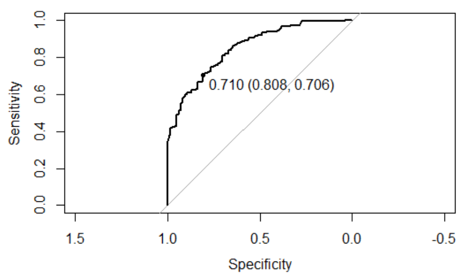
Source: *Authors' calculations.*

Figure 7. *ROC curve plot - decision trees*



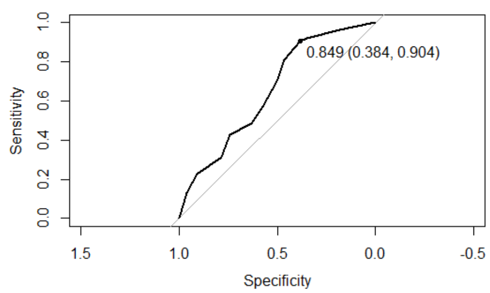
Source: *Authors' calculations.*

Figure 8. *ROC curve plot - random forests*



Source: *Authors' calculations.*

Figure 9. *ROC curve plot - logistic regression*



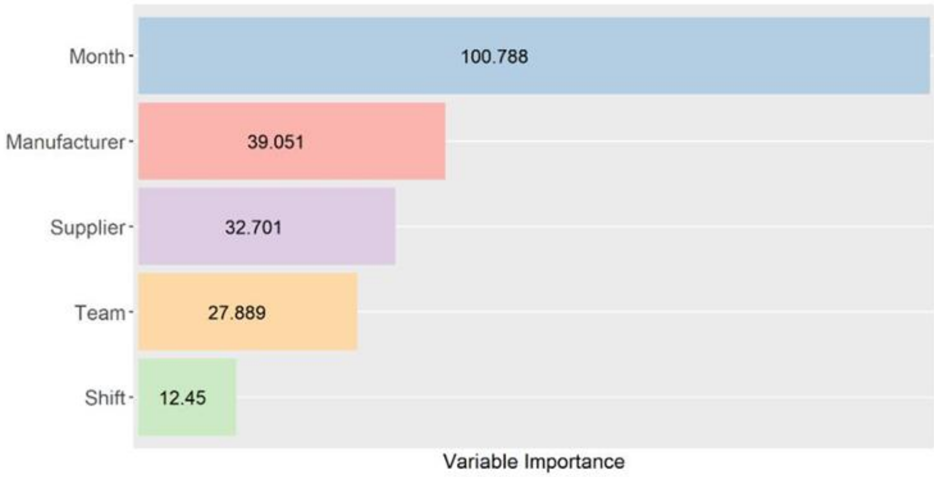
Source: *Authors' calculations..*

4. Conclusions

Using a random forest classifier, the discriminating variables for achieving the desired level of efficiency were identified and ranked. These are presented in Figure 10, in order of importance.

As can be seen, satisfactory performance is most affected by the month in which production takes place. The calculated conditional probabilities show that months such as January, June, July, September, December are conducive to achieving a satisfactory result (0.67). The analysis also showed the significant impact of external sources such as spare parts suppliers, showing that supplier one and supplier four strongly (0.75) favor efficiency greater than 90%. Next in importance was the influence of the machine manufacturer and the service team, as well as the shift during which the production processes are carried out. As a result, improvement activities should be implemented to identify the causes of reduced efficiency for specific suppliers, manufacturers and maintenance teams. Shift has the least impact on efficiency. The company should consider the problem of effective personnel management to eliminate situations where a shift adversely affects the efficiency level.

Figure 10. *Variables that discriminate achievement of desired efficiency level in order of importance*



Source: *Authors'calculations.*

Classification allows new observations to be assigned to the class to which they are most likely to belong, based on a classification model built using collected empirical data. In the case under review, it allows us to answer the question of whether production efficiency will be satisfactory given a particular set of known factors that affect it. In case of an undesirable result, it is possible to modify and adjust them to achieve the correct result. In the example analyzed, the set of factors was not large, but the method can be freely extended to include additional variables as well. The presented method finds its application mainly in non-computerized and non-automated systems, where simple methods allowing to evaluate and shape processes are extremely important.

The research presented here achieved two objectives. First of all, a method for evaluating the efficiency of production processes was identified, as well as the factors that affect it the most. In the company in question, the indication of the month suggests some deficiencies in the organization. These may be due to vacation periods or holidays. It is also worth considering other factors and choosing , for example, from among the suppliers the one whose products have the highest quality and reliability. In further research, the proposed method will be developed by creating an application to keep track of the values of the selected independent variables and the classifier results, following the idea of digital twin and development in accordance with the Industry 4.0 paradigm.

References:

Agostino, Í.R.S., Broda, E., Frazzon, E.M., Freitag, M. 2020. Using a Digital Twin for Production Planning and Control in Industry 4.0. In: Sokolov, B., Ivanov, D., Dolgui, A. (eds) Scheduling in Industry 4.0 and Cloud Manufacturing. International Series in Operations Research & Management Science, 289. Springer, Cham. DOI:10.1007/978-3-030- 43177-8_3.

Bartecki, K., Król, D., Skowroński, J. 2018. Determining key performance indicators of the production process - part I: theoretical research. Measurement Automation Robotics, 22.

Cellary, W. 2019. Non-Technical Challenges of Industry 4.0. In: Camarinha-Matos, L.M., Afsarmanech, H., Antonelli, D. (ed.), Collaborative Networks and Digital Transformation, IFIP Advances in Information and Communication Technology, vol. 568, IFIP-Springer, DOI:10.1007/978-3-030-28464-0.

de la Fuente-Mella, H., Fuentes, J.L.R., Leiva, V. 2020. Econometric modeling of productivity and technical efficiency in the Chilean manufacturing industry. Computers & Industrial Engineering, 139, 105793. DOI:10.1016/j.cie.2019.04.006.

Central Statistical Office, Concepts used in public statistics - Labor efficiency in industry. https://stat.gov.pl/metainformacje/slownik-pojec/pojecia-stosowane-w-statystyce-publicznej/599,pojecie.html.

Gola, A., Pastuszak, Z., Relich, M., Sobaszeka, L., Szwarc, E. 2021. Scalability analysis of selected structures of a reconfigurable manufacturing system taking into account a reduction in machine tools reliability. Eksploatacja I Niezawodnosc - Maintenance and Reliability, 23(2), 242-252. DOI:10.17531/ein.2021.2.4.

Grabowska, S. 2017. Key performance indicators-case study. Research Papers. Organization and Management/Silesian University of Technology, 105-111.

Jasiulewicz-Kaczmarek, M., Antosz, K. 2021. The Concept of Sustainable Maintenance Criteria Assessment. In: IFIP International Conference on Advances in Production Management Systems, 427-436. Springer, Cham. DOI:10.17531/ein.2018.4.16.

Jasiulewicz-Kaczmarek, M., Żywica, P., Gola, A. 2021. Fuzzy set theory driven maintenance sustainability performance assessment model: A multiple criteria approach. Journal of Intelligent Manufacturing, 32(5), 1497-1515. DOI:10.1007/s10845-020-01734-3.

Kiełtyka, L., Charciarek, K. 2019. Process management model using modern tools of Industry 4.0. Organization Review, 8, 5-12. DOI:10.33141/po.2019.08.01.

Kozłowski, E., Borucka, A., Świderski, A., Skoczyński, P. 2021. Classification Trees in the Assessment of the Road–Railway Accidents Mortality. Energies. 14(12), 3462. DOI:10.3390/en14123462.

Kozłowski, E., Mazurkiewicz, D., Sęp J., Żabiński, T. 2021. The Use of Principal Component Analysis and Logistic Regression for Cutter State Identification. In: International Conference Innovation in Engineering, 396-405. Springer, Cham. DOI:10.1007/978-3-030-78170-5_34.

Ma, J., Chen, H., Zhang, Y., et al. 2020. A digital twin-driven production management system for production workshop. Int J Adv Manuf Technol, 110, 1385-1397. DOI: 10.1007/s00170-020-05977-5.

Michlowicz, E., Smolińska, K. 2017. TPM indicators as performance measures of an upgraded manufacturing process. Research Papers of the Poznań University of Technology. Organization and Management, 189-199.

Osazefua, I.J. 2019. Operational efficiency and financial sustainability of listed manufacturing companies in Nigeria. Journal of Accounting and Taxation, 11(1), 17-31. DOI:10.5897/JAT2018.0329.

Ostapko, B. 2018. Methods of increasing productivity in a manufacturing plant - a case study. Research Papers. Organization and Management/Silesian University of Technology, 118, 434-444. DOI:10.29119/1641-3466.2018.118.32.

Pacana, A., Czerwińska, K., 2020. Key performance indicators - KPIs. Management and Quality. Scientific Society of Organization and Management Branch in Katowice. Katowice: TNOiK.

Prokopenko, O., Shmorgun, L., Kushniruk, V., Prokopenko, M., Slatvinska, M., Huliaieva L. 2020. Business process efficiency in a digital economy. International Journal of Management (IJM), 11(3).

Sobaszek, Ł., Gola, A., Kozłowski, E. 2020. Predictive Scheduling with Markov Chains and ARIMA Models. Applied Sciences, 10(17), 6121. DOI:10.3390/app10176121.

Söderberg, R., Wärmefjord, K., Carlson, J.S., Lindkvist, L. 2017. Toward a Digital Twin for real-time geometry assurance in individualized production. CIRP Annals, 66(1), 137-140. DOI: 10.1016/j.cirp.2017.04.038.

Zarychta, J. 2018. The impact of new technologies on management - a Microsoft Poland perspective. Part. 1 - Industry 4.0. Organization Review 4, 62-64.