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Simulation Modeling in Production Effectiveness Improvement – Case Study

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Abstract
The paper deals with the problem of production material flow management. The proper way of logistic tasks management has an impact on the production process effectiveness and the cycle time, which is a very important factor in manufacturing. Reducing the production process cycle time results not only in the ability to provide more customers with orders but also in increasing the level of resources usage (machines, operators etc.). In order to reach the aim of improving production effectiveness, the simulation modeling was used. It is a computer method that supports a decision-making process and allows to perform experiments on production without interfering with the real process. The paper also includes a risk analysis performed to evaluate the imperfections of simulation modeling, based on the rules of fuzzy logic.

Keywords
simulation, models, batch, resources, efficiency, computer applications, production.

Introduction

Production resources management is a task that needs to be performed in every manufacturing company. It is one of the factors that determine if the process is efficient or not. Thus, in order to be competitive and meet customer's requirements, companies need to perform continuous improvement in this area (Hamrol, 2018; Zwolińska, Grzybowska, Kubica, 2017; Sobaszek, Gola, Kozłowski, 2017). There are a lot of methods that support production resources management. One of them is simulation modeling, the method that allows to experiment on production without the need to interfere with the real process (Grzybowska, Kovács, 2017). This is a very important and desired advantage for industry. Because of it, the decisions about improvements can be performed without the necessity of taking breaks in a production process.

The aim of the research was to improve the production process effectiveness, which included the evaluation and improvement of machines and operators' utilization rate, lowering the cycle time and performing an analysis of the risk associated with the simulation modeling imperfections. In order to fulfill the aim, an optimal batch amount in the process flow was found and standardized, and the risk evaluation was performed using fuzzy sets. The article presents the results of the research realized in the company from the electronic industry, using the simulation modeling as a supporting method of a decision-making process in the resources management area. As the criteria of improvement results the resources (machines and operators) utilization rate was chosen.

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Literature review

Production process simulation modeling

Simulation models are a symbolic interpretation of the input-output relationship of real processes, which are represented by symbols and mathematical relations (Rosienkiewicz et al., 2018; Erickson et al. 2018; Łukaszewicz, 2019). The model allows to achieve the solution of the analyzed problem by performing simulations until the results are satisfying (Kikolski, 2017; Bohàcs, Kovàcs, Rinkàcs, 2016; Elomari, Svensson, Olsson, 2018). Nowadays, simulation modeling is widely used, for example in the industry 4.0 solutions like an automatization of discrete processes, application of IoT systems, flexible manufacturing systems, various types of software, etc. (Tan, Yang, Yoshida, 2018; Kłos, Patalas-Maliszewska, 2017; Kuric et al., 2017). The advantages of performing different scenarios of production problems solving caused the increase of the frequency of using the simulation models in the production process improvement. These can be used in various areas, i.e. in the production process efficiency improvement by increasing the machine working period by manipulating only the production batches data (Gwiazda, Sękala, Banaś, 2017), combining the simulating modeling and description languages in logistic tasks (Grabowik et al., 2019), determining the bottleneck of the process and its overall efficiency (Ratnayake, Stadnicka, Antosz, 2013) and many many more. The huge amount of publications about simulation modeling in the literature, especially in the case-study papers, allows to conclude that it is an effective method of improving production processes. This observation can also be confirmed by the increasing number of publications that are published with the "*simulation modeling in production process*" tag included. The data about this increase is shown in Fig. 1.

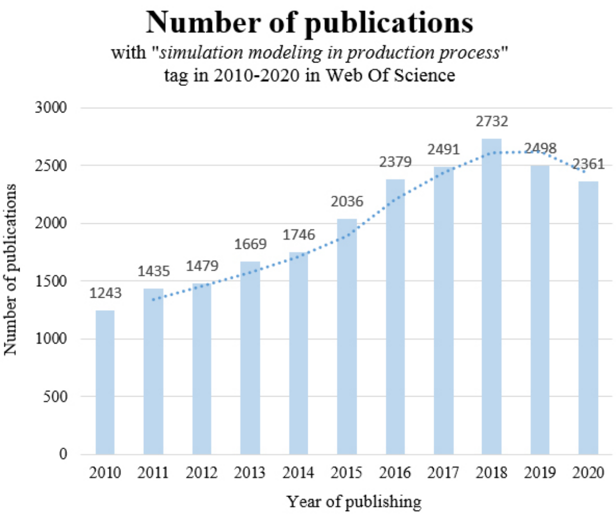

Fig. 1: Number of publications with "*simulation modeling in production process*" tag in 2010–2020 in Web of Science

The data about the number of publications were taken from the Web of Science articles database. The trend-line shows that there was a continuous increase of publications that concern the simulation modeling as the method to be used in the production process area in years 2010–2018, with the stabilization at the level of over 2.000 articles per year.

However, it is very difficult to find simulation modeling papers that take into account the risks associated with manufacturing processes. It is probably caused by the fact that a risk assessment is often a complex task due to the unpredictable nature of many situations related to performing a production process (e.g. machine failures, delivery delays, etc.). Thus, in this paper, simulation modeling was extended by the use of fuzzy sets in the risk assessment. Simulation models based on technological data often do not take into account the risk and, for the model to be useful, it must take into account the risk in a production system even though it is often a very complex task.

Risk assessment with the use of fuzzy sets

The application of fuzzy sets to different types of problems is particularly evident in decision-making processes, which are not only inherent in all processes, but are also nowadays "*highly impacted by the different levels of uncertainty present in real-world information*" (Mittal et al., 2020). These are being used in manufacturing processes (Aqlan, Lam, 2015; Pedroso et al., 2017) and is considered to be very practical tool (Caiado et al., 2021). Fuzzy sets are used in the cases related to the processes connected to the services and production realization, like the logistic services (Rudnik, Pisz, 2014), project prioritizing (Marek-Kołodziej, Lapunka, 2020), risk assessment (Vinodh et al., 2021; Ghadge et al., 2017, Markowski, Mannan, 2009) etc. Fuzzy sets allow to perform an analysis with imprecision data where no sharp boundaries (or problem definitions) are possible (Markowski, Mannan, 2009). In this case, the risk was assigned with linguistic values (*low, moderate* or *high*) and the whole process was performed with the use of Mamdani fuzzy interference system (FIS), which is based on *if-then* implication that allows to "*model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analysis*" (Yuanyuan, Limin, Zundong, 2009). Thus, fuzzy sets are successfully used in the situations where it is difficult to determine the data in the form of specific numbers but easier in the form of a linguistic value, which is common when identifying risk factors with their random character (Abdelgawad, Fayek, 2010; Chang, Sun, 2009; Chang, Cheng, 2009; Garcia et al., 2005; Gargama, Chaturyedi, 2011).

There are number of others examples of using simulation modeling tools in literature (however it is often the practical implementation) and the use of fuzzy sets is increasingly being applied to risk assessment in production. The significant difference in this case is the idea to use of fuzzy sets in assessing the risk of imperfections in the simulation model comparing to the real production process. It allowed to include, to some extent, random factors that are practically impossible to evaluate in the basic type of models. To perform the fuzzy risk assessment, the MatLab software with the Fuzzy ToolBox module was used.

The model development process

Simulation modeling can be a very helpful method in a decision-making process, however it needs to be done correctly. A model that is based on low-quality or too detailed data is a kind of waste for a company. This is described more precisely in the next part of the article. Thus, models need to be developed by experienced people who know the production process well enough to decide whether the data is useful or not. The models which do not reflect a real situation of the company are even a worse example of bad models. They can lead not only to the waste of time, but also to make incorrect decisions about improvements, what can result in making mistakes in the production process management and effect the real process. Moreover, in order to maintain the possibility of using the model in a real process, the data on random risk factors (i.e. machines breakdowns) should also be taken into account. In this paper, the production process improvement with the use of simulation modeling was divided into 3 stages. It is shown in Fig. 2.

The production process improvement diagram was elaborated as the extension of literature sources (Taylor et al., 2009) and the research experience. It is a kind of general division of the tasks done in improving a production process with simulation modeling. There are 3 stages that include steps which are usually done when modeling:

Stage 1: the first stage, which is research and modeling, is the base of the whole improvement implementation process. Step I is data research, and step II is a model development based on these data. The proper performing of the research and model development are conditions that need to be fulfilled in order to get a useful model. The data research and model development are also the steps that allow to prepare the base for the further steps. Step III, which is the model verification and validation, allows to find out if the model and data are correct or detailed enough to reflect the real production process.

Stage 2: The second stage, an improvement analysis, is based on the experiments that can be performed as simulations. They show whether the changes that are planned in a production process will lead to its improvement or not. If the data are collected and implemented correctly, the experiments should be performed until finding satisfying results.

Stage 3: When the results are satisfying and the company is ready to implement the improvement, it is recommended to perform pilot studies. It allows to verify the improvement method in only a part of the real process (i.e. one production line). It is a safe solution to compare the simulated state with the real process. In order to perform continuous improvement of the production process, the pilot implementation should be monitored and analyzed by the production process experts (i.e. process engineers). When the pilot studies results are satisfying, the company is able to expand the improvement implementation to whole production process. However, the improvement should be still monitored because of an individual character of each process in the production system.

Nevertheless, these stages are general and show a universal modeling process in production. In the in-

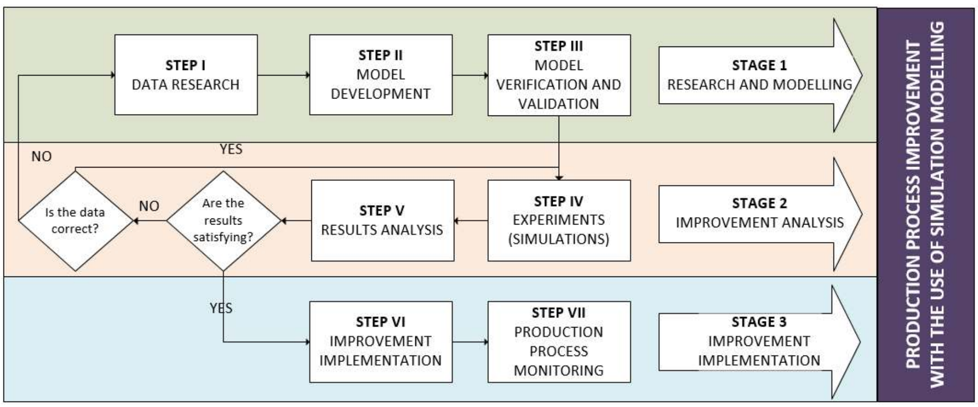

Fig. 2: Production process improvement with the use of simulation modeling

dustry reality they need to be upgraded and fitted to the need of a specific company. Moreover, the simulation modeling process is always related to the constraints and assumptions that are necessary to build the model. It can be caused by the software limitations but also by a random nature of some situations that occur in the production process. These are for example machine breakdowns or delivery delays which are often impossible to be predicted. Thus, to make the model usable, the risk of these situations should be considered too. It is a very complex task because the risk factors occurring in the production system have often a random character.

Case study

Simulation modeling was also chosen to be used in the case of the production process in this case. The discussed company produces components used in the electronic industry. Based on the research performed in the company in a 3-month period, the main problem that affects the efficiency of the process was a non-standardized batches amount. The lack of standardization led to extreme differences in the batches amount which caused the production stops and an overall chaos in the realization of the company aims. The simulation modeling was chosen as a solution method because of its verified efficiency in the production process improvement, especially when the problem involves a lot of different possibilities to be analyzed. In this case, the company struggles with problems like a low utilization rate of resources and a long lead time. They include a lot of unnecessary actions what makes the whole process longer. According to the research, the most problematic and chaotic part of the production process in the analyzed case was a material flow. A lot of operators were overloaded despite the fact that meanwhile other were waiting or idle. The similar situation was with machines. Some of them worked almost without breaks and some of them were used very occasionally. It affected the production in a significant way making differences between operators and machine utilization, which were not only seen as a result of calculations but even visible while analysing the process.

The model is a representation of the real object in a simplified form. The need of simplification is usually the result of restrictions that every modeling software has. There are a lot of programmes that allow to perform simulations of a production process, i.e. AnyLogic, ProModel, FlexSim etc. The ProModel software allows to implement the model of various production elements, among the others the number and competences of operators, production process flow, material supplies, layout, etc. Moreover, it also allows to implement the inner transport data and the whole logistic process, which was very important in this case. It also had the module with the simulation results, which are diagrams that show the data in the a simple way to be analyzed. Thus, the ProModel was used.

Input data

The first and very important task in the described research was to collect proper data from the company. The data need to be inclusive enough, to represent a production process in a realistic way. However, too detailed data has a negative influence too. It results in increasing the time of modeling as well as the costs and clarity of the model (Taylor et al., 2009; Kamińska, Parkitna, Górski, 2018). Thus, collecting data should be done by an experienced researcher who has the knowledge about simulation modeling and the software that is used. In this case, the data was collected for 3 months in the real process of production in the usual conditions (without any breaks). Then, the collected data were verified by comparing them to the measured time of the production process. The formula used to count a relative error (Re) is based on an absolute error (Ae), and includes the operation time in the simulation (Ots) and the operation time in measurements (Otm), which are the real data (1).

$$\mathrm{Re} = \frac{|\mathrm{Ots} - \mathrm{Otm}|}{\mathrm{Otm}} \cdot 100\%, \tag{1}$$

where:

Re – relative error [%],

Ots – operation time in simulation [min],

Otm – operation time in measurements [min].

The results of the verification allow to analyze whether the model is good enough to make experiments or not. The calculations performed in the analyzed case study are listed in Table 1.

An average error of the data simulated in ProModel and measured in the real process was about 20 minutes (an absolute error), which is about 0,03% (a relative error). That means that an error, in relation to the operation time in the real process, is almost nonsignificant. It allows to conclude that the simulation model is realistic enough to perform experiments and find an improvement method that should be proper to implement in this case.

Table 1
Production process – verification of simulation data with real process

Operation	Ots [min]	Otm [min]	Ae [min]	Re [%]
Plastic forming	168.65	170.50	1.85	1.09
Cleaning	782.56	781.00	1.56	0.20
Hybrid treatment	1558.37	1560.90	2.53	0.16
Heat treatment 1	2975.06	2972.20	2.86	0.10
Heat treatment 2	917.48	917.40	0.08	0.01
Assembly 1	2394.89	2398.00	3.11	0.13
Pre-selection	398.02	400.40	2.38	0.59
Assembly 2	647.63	650.10	2.47	0.38
Assembly 3	74.21	74.80	0.59	0.79
Plating 1	971.45	974.60	3.15	0.32
Metal elements selection	661.13	660.00	1.13	0.17
Glass elements selection 1	3083.00	3081.00	2.00	0.06
Connection	5882.66	5883.00	0.34	0.01
Connection quality control	991.69	992.00	0.31	0.03
Washing	6975.54	6976.00	0.46	0.01
Glass heat treatment	411.52	414.50	2.98	0.72
Glass elements selection 2	2752.44	2750.00	2.44	0.09
Glass elements parting	296.83	297.00	0.17	0.06
Glass plastic forming	5498.13	5500.00	1.87	0.03
Glass plastic forming quality control	67.46	68.75	1.29	1.87
Gas filling	8797.01	8800.00	2.99	0.03
Chemical treatment	728.59	728.75	0.16	0.02
Measurements A	877.00	880.00	3.00	0.34
Stand	1436.94	1440.00	3.06	0.21
Measurements B	553.19	550.00	3.19	0.58
Measurements C	17324.18	17325.00	0.82	0.00
Packing	134.92	134.75	0.17	0.13
Total/average	**67360.55**	**67380.65**	**20.10**	**0.03**

Improvement criteria

The next important task that needs to be done is choosing the criteria of improvement. It allows to determine if the improvement idea actually results in the production process effectiveness and facilitates a decision-making process. The described problems are very important issues because the proper resources management results in its utilization rate which greatly affects the whole production process effectiveness (Taylor et al., 2009). Thus, the resources (machines and operators) utilization rate was chosen as the first criteria of improvement performed with the use of simulation modeling. The second criteria that was chosen to compare the results was the production cycle time, which is an overall production effectiveness factor.

Experiments and model analysis

Based on the data on errors in the model, it was possible to analyze a current state of the company. A production process model allowed to conclude that the most important waste in the production process is waiting for components to be delivered. In order to be able to compare the results, the production capacity was calculated (2).

$$Cp = \frac{P}{T} \quad \left[\frac{\text{pcs}}{\text{month}}\right], \tag{2}$$

where:
Cp – production process capacity [pcs/month],
P – number of products manufactured in one month,
T – worktime in one month.
In order to perform experiments, the batch amount changes were implemented in the model.

Production cycle and lead time

The first analyzed factor of improvement was the production cycle time. An average batch size in the company equals 5500 pcs. The amounts from 1 to 500 batches were chosen, divided into 10 experiments and the cycle time was measured. The results are shown in Table 2.

The results show that increasing the amount of batches from 1 to 50 results in the decrease of the cycle time. However, further batch amount increasing did not influence the cycle time significantly. Thus, the cycle time and batch amount had a hyperbolic correlation, which is shown in Fig. 3.

As it can be seen in Fig. 3, the amount of batches higher than 50 does not affect the cycle time in a significant way. Wider results are shown in Fig. 4.

The cycle and lead time changes in the batch amount increasing confirm that the amount of 50 batches seems to be the limit where the production

Table 2
Influence of batch amount changes on cycle time

Experiment no.	Amount of batches	Products manufactured [pcs]	Production capacity [pcs/month]	Cycle time [min/pc]
1	1	5 500	1 644	12.27
2	2	11 000	2 845	7.09
3	5	27 500	5 423	3.72
4	10	55 000	7 893	2.55
5	20	110 000	10 499	1.92
6	50	275 000	13 043	1.55
7	100	550 000	14 207	1.42
8	200	1 100 000	14 842	1.36
9	300	1 650 000	15 057	1.34
10	500	2 750 000	15 261	1.32

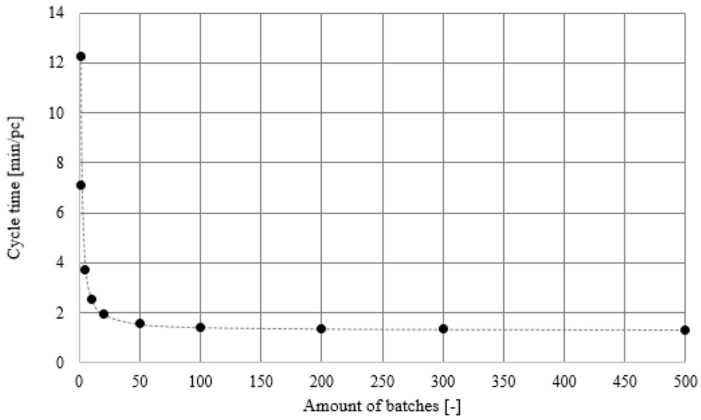

Fig. 3: Correlation between cycle time and amount of batches in the production process

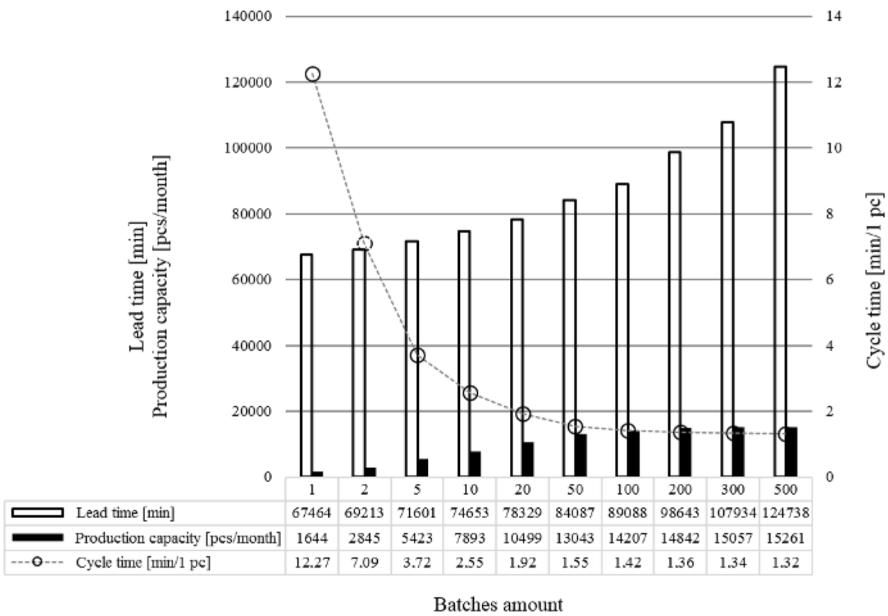

Fig. 4: Correlation between batch amount and production process parameters

process achieves the best parameters. It is the point where the cycle time and lead time are much lower than before and the production capacity reaches very high increase (about 11 400 pcs per month comparing to one batch). Further batches amount increasing also correlates in decreasing the cycle and lead times and increasing the production capacity, but the changes are much lower and slower than before the amount was 50 batches (Fig. 4).

Machines utilization

The second factor analyzed in improvement was the machines usage degree. The experiments were performed based on the same batch amount changes (Table 2), and the machines utilization [%] were measured. The data about every single machine were analyzed and the average usage of machines (in every batch amount) were calculated. The data are shown in Fig. 5.

With the batch amount increase, the machines utilization increases too – but it is significant only until gaining 50 batches. The load of machines is very different. The most used machine in the company is a washing station, and its utilization rate is almost 96% while producing 500 batches. It is the information about uneven machine utilization and the very overloaded washing machine, which is probably the bottleneck of the whole production process.

Operators utilization

The last factor analyzed in this case was operators' utilization rate. The most important time was the time that they spent in operation and the data are shown in Table 3.

The rate of operators' utilization was different among the operators' type because of various competences of the workers:

- Operator type 1 (Op. 1) – plastic forming and quality control,
- Operator type 2 (Op. 2) – metal parts manufacturing,
- Operator type 3 (Op. 3) – glass parts manufacturing,
- Operator type 4 (Op. 4) – electrical connector manufacturing.

The difference can be especially seen in the case of operator type 1 (Op. 1). This type of an operator has the lowest utilization rate which is caused by the fact that these operators work not only in the production process that is analyzed, but also with other products. That is why their utilization rate in this process is so low – in reality, it is much higher in the whole

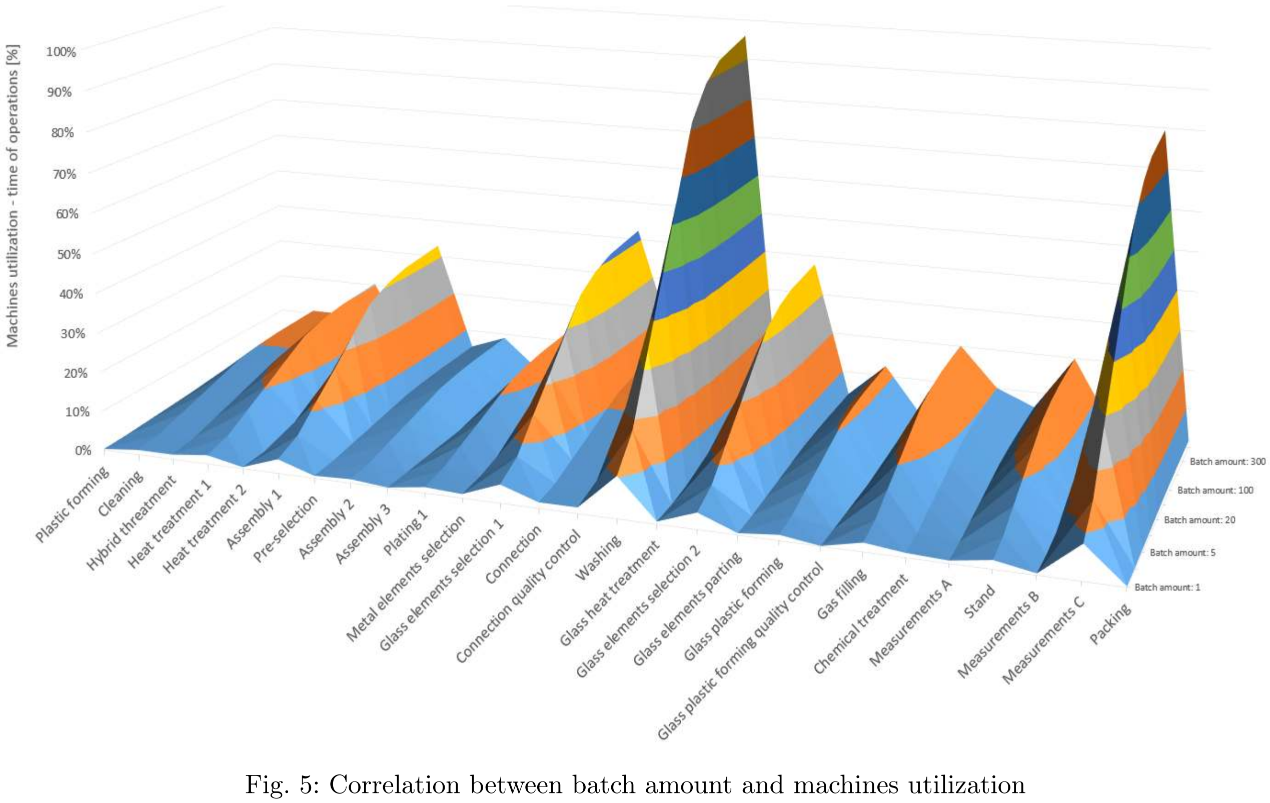

Fig. 5: Correlation between batch amount and machines utilization

Table 3
Operators utilization rate

Operator type		Op. 1	Op. 2	Op. 3	Op. 4
Number of operators		1	16	4	5
Experiment no.	Amount of batches	Utilization of operators [%]			
1	1	0.26	1.06	7.56	10.51
2	2	0.44	1.83	13.09	18.19
3	5	0.84	3.49	24.95	34.67
4	10	1.23	5.08	36.31	50.46
5	20	1.63	6.75	48.30	67.12
6	50	2.03	8.39	60.01	83.38
7	100	2.21	9.14	65.36	90.83
8	200	2.31	9.55	68.29	94.88
9	300	2.34	9.69	69.28	96.26
10	500	2.38	9.82	70.21	97.56

production because of other responsibilities. Thus, the operators type 1 do not need to be analyzed in this case. More important data are about other types of operators – op. 2, op. 3 and op. 4.

Before proceeding further with the analysis of the results of the research carried out, it is necessary to note that due to the limitations of the research methodology and the random nature of some factors affecting the degree of resource use, this study compared only three states in which operators may be found: waiting, transport and processing (operation). The study did not take into account external factors resulting from random causes, such as breakdowns, delays in the supply chain, etc. The duration of the planned breaks, such as lunch breaks, was also subtracted from the total time available for processing. Therefore, the degree of resource utilization in this paper should be understood as the share of the time spent on production in relation to the total time including transport and waiting for the delivery of items. This is the reason of the results of over 90% of utilization, which is most likely unachievable in the real process due to various issues i.e. breakdowns which were not considered in this case study.

The utilization rate of operators has a correlation with the batch amount – it also increases with the increase of the batch amount, analogically to the machines – until the amount of about 50 batches. After that, the increase slows. It is shown in the Fig. 6.

The correlation has – similar to the machines – a hyperbolic character and it does not increase the operators' utilization rate significantly after reaching the amount of 50 batches.

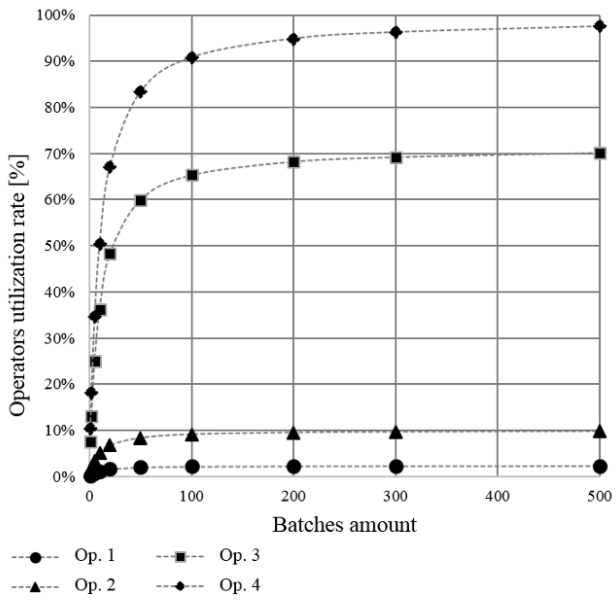

Fig. 6: Correlation between batch amount and operators utilization rate

The model risk assessment

According to the limitations described before, the risk assessment of the model imperfections in the utilization rate results was performed. It was done with the use of the data acquired from process engineers and logistic workers who evaluated the risk of three situations: the machines breakdown, operators' inaccessibility and delivery delays. These were done based on the risk valued as low, moderate or high (Table 4).

Table 4
Risk value evaluation – the criteria

Company risk evaluation	Risk value		
Linguistic value	low	moderate	high
Numerical value interval	< 5	1–5	> 5

The risk assessment of input was performed with the use of with the Gauss membership function (Fig. 7).

The rule base that was built in this case has 27 rules in total which covers all possible combinations of parameters risk. The example of the surface diagrams of the relationship between risk and parameters is shown in Fig. 8.

The results of the risk assessment, both before and after using FIS, are shown in Table 5.

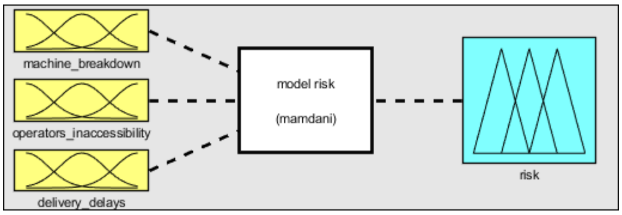

Fig. 7: Mamdani fuzzy interference system schema

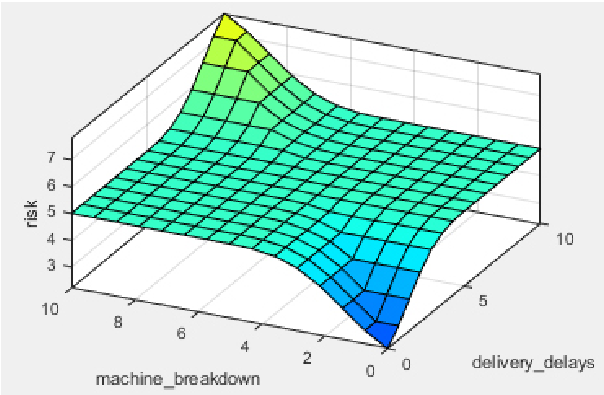

Fig. 8: The relationship between risk and parameters

Table 5
Risk value evaluation – the results

Parameter	Risk value			
	numerical	linguistic	total risk	
Machine breakdown	2	low	4.65	moderate
Operators' inaccessibility	4	moderate		
Delivery delays	3	low		

As it can be seen, even though a machine breakdown and delivery delays were evaluated as low-risk and the operators' inaccessibility as moderate, the total risk of getting the model imperfections is moderate and it is 4,65 out of 10 in total.

Conclusions

Simulation modeling allowed to analyze the most important problems in the company. Namely, they were the standardization of batches amount in a production process flow and improving the resources utilization rate. The aim of improving the production process capability was reached without the need to interfere with the real process (in the stage of decision-making about the way of improvement). Thanks to the simulation modeling, the company could decide which batches amount is the one that should be applied to the real process. The overall conclusion is that the batches amount of 50 seems to be the optimal one in the analyzed company. That is the best batches amount in the criteria of resources utilization – machines and operators. Batches amount under 50 was less effective in the case of resources utilization. However, further increasing of batches amount did not influence the utilization rate significantly. The second criteria of improvement was the production cycle time and the results on it confirm that the amount of batches seems to be the optimal one in the analyzed case. The data about the cycle time measurements and its reduction are shown in Table 6.

Table 6
Cycle time improvement

Data source	Cycle time [min]		Cycle time difference [min]
Current state measurements of cycle time	Longest	10.31	8.89
	Shortest	5.15	3.73
	Medium	7.73	6.31
Simulated cycle time [min]	1.42		n/a

The cycle time was measured many times. It was needed because of its random character with no standardization of batch amount. To the analysis, the shortest, longest and medium cycle times were taken. The shortest simulated cycle time, which was when using 50-batches amount type of production, is 1,42 minutes. It is much shorter than in any other case, even the shortest one, in the current state. The difference of the cycle time between the medium one of the current state measurements and the simulated one, which is the clue of implemented improvement, is shown in Fig. 9.

The reduction of the cycle time was based on the medium cycle time of measurements, which is the most realistic to show the current state in the analyzed company. The results show that it was possible to reduce the cycle time of production of one piece of the component from 5,15 minutes to 1,42 minutes. It means, that the cycle time can be shorter about 72% than in the current state only by determining and standardizing the optimal batch amount.

Simulation modeling, as a helping tool of a decision-making process, did allow to make numerous experi-

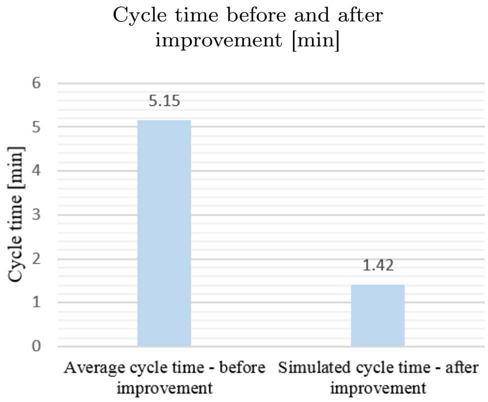

Fig. 9: Improvement results: the cycle time

ments without the need to interfere with the real process. That is the most important advantage of simulation modeling for companies because the need of making experiments in the real process could result in the need of stoppages and the production process flow breaks.

However, simulation modeling allows only to show an approximate situation of the real process and a lot of situations are too complicated to be simulated (i.e. machines breakdowns, etc.). Despite that, simulation modeling is a very useful method that helps the decision-making process of improvement in the production process. Especially when extended with a risk analysis, based on, for example, the principles of fuzzy logic, it seems to be a very useful tool to support key decisions in production processes.

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