Management Systems in Production Engineering

2023, Volume 31, Issue 3, pp. 306-311

Date of submission of the article to the Editor: 03/2023
Date of acceptance of the article by the Editor: 07/2023

DOI 10.2478/mspe-2023-0034

ANALYSIS OF THE IMPACT OF EFFECTIVE TIME MANAGEMENT ON WORKSTATION EFFICIENCY USING A MULTI-CRITERIA OPTIMIZATION APPROACH

Marek Krynke
Czestochowa University of Technology

Abstract:
The aim of the article is to analyze the impact of effective time management on the performance of workstations in the context of the conflict between maximizing workstation utilization and minimizing the number of items waiting in the queue. The article utilized the FlexSim program to build a simulation model of the workstation and conducted optimization using the built-in optimizer. The research demonstrated that effective time management has a positive impact on workstation performance by reducing the number of items waiting in the queue, leading to increased throughput and reduced delays in production processes. An important aspect of the analysis was the application of a multi-criteria optimization approach, which allowed for achieving a balance between maximizing workstation utilization and minimizing the number of items waiting. Multi-criteria optimization considers diverse goals and decision criteria, leading to a more comprehensive approach to optimizing production processes. As a result, effective time management on workstations, based on analysis and multi-criteria optimization, can significantly improve the efficiency and performance of production processes. This analysis can be a valuable tool for organizations seeking to optimize their processes and achieve a competitive advantage in the market. The analysis conducted in the article confirms that effective time management has a beneficial impact on workstation performance. The use of a multi-criteria approach in optimization enables achieving a balance between various decision factors. The presented simulation model and research results can be useful for decision-makers in the manufacturing field who aim to make more informed decisions regarding planning and optimizing production processes to enhance efficiency, effectiveness, and customer satisfaction.

Key words: *process management, simulation, FlexSim, optimization*

INTRODUCTION

In today's dynamic business environment, effective time management is crucial for achieving high performance and efficiency in production processes [1, 2]. This is particularly important in the context of workstations, where the conflict between maximizing workstation utilization and minimizing the number of items waiting in the buffer area can present a challenge for organizations [3, 4, 5].

The aim of this article is to provide a detailed analysis of the impact of effective time management on the performance of workstations. The authors utilized the FlexSim program, which is a powerful tool for modeling and simulating processes, to build a precise simulation model of the workstation [6]. The built-in optimizer was then used to conduct optimization, taking into account multiple decision criteria [7].

The research results presented in the article indicate a positive impact of effective time management on workstation performance. Efficient utilization of work time contributes to reducing the number of items waiting in the buffer area, which in turn leads to increased throughput and reduced delays in production processes [8, 9].

An important aspect of the analysis is the application of a multi-criteria approach to optimization [10]. This allows for a balance between maximizing workstation utilization and minimizing the number of items waiting [11, 12]. Multi-criteria optimization enables the consideration of diverse goals and decision criteria, contributing to a more comprehensive approach to optimizing production processes [13, 14].

As a result, effective time management on workstations, based on analysis and multi-criteria optimization, can significantly improve the efficiency and performance of production processes [15]. This analysis can be a valuable tool for organizations aiming to optimize their processes and achieve a competitive advantage in the market [16, 17].

OPTIMIZATION THROUGH SIMULATION

Optimization is the fundamental process of seeking the best solution (i.e., optimal values of decision variables) [18]. The concept of "best" depends on the goals we want to achieve and the constraints or restrictions of the system [19]. To define goals and constraints, we use mathematical relationships expressed in terms of decision variables. The objective function is maximized (e.g., throughput) or minimized (e.g., total cost). It represents one or multiple performance indicators and determines whether one solution is better than another [20].

Constraints, on the other hand, are mathematical expressions that must be satisfied within the model (e.g., the number of operators (NumOps) must be between 1 and 5). Constraints are similar to the objective function but involve comparisons (e.g., 1 ≤ NumOps ≤ 5). Only solutions that satisfy all constraint comparisons are considered. Solutions that violate any constraint are deemed infeasible [21].

Optimization is a separate technique in operations research, distinct from simulation. It follows a completely different approach and methodology for problem-solving. Simulation is used to describe the operation and performance of a system, while optimization aims to find the best or improved solution based on a precisely defined system description and its behavior [6, 22]. There are many optimization methods, but many of them, such as linear programming, assume the problem is deterministic (i.e., all values in the problem definition are fixed constants, not variables) [23]. Simulations, on the other hand, involve one or multiple stochastic or random variables, meaning that the problem of simulation-based optimization is non-deterministic. This is why optimization of systems through simulation is particularly challenging and demanding [24]. Due to the stochastic nature of simulation, optimization results come with risks and uncertainties, meaning that there cannot be a strict guarantee of achieving optimal outcomes [25]. Simulation problems often involve multiple alternative solutions (i.e., they have a large solution space). The term "optimal" is used in the context of estimating the best-found solution during the search process. Simulation optimization typically involves an iterative approach (Figure 1).

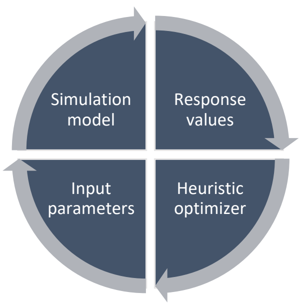

Fig. 1 Input to the optimizer

This means that the simulation model generates responses (results) based on a set of input values [26]. The optimizer, using heuristics, makes decisions regarding changing the input parameter values to improve the values of the output variables [27]. Heuristics are "shortcut" methods that are usually fast but do not guarantee finding the best solution. Nevertheless, good heuristics allow for finding better solutions that are likely close to the optimal solution [9, 28].

There are various approaches and concepts in simulation optimization [6, 18]. As indicated by April et al. [20], most commercial methods employ an evolutionary approach, which explores the solution space based on an evolving set of solutions. The set of solutions is used to create new trial solutions, meaning that the new solutions are typically combinations of solutions already present in the set. Popular evolutionary approaches include scatter search and genetic algorithms. The main advantage of these methods is the ability to explore larger solution spaces with fewer evaluations of the objective function (i.e., running the simulation model for multiple replications) [16].

Simulation models developed in FlexSim can be optimized using dedicated optimization software called OptQuest. OptQuest is a standalone commercial product developed by OptTek Solutions and is provided as a package with FlexSim [7, 29]. OptQuest is a widely used optimization engine seamlessly integrated with FlexSim through the Experimenter module. Laguna [7] provides a description of the OptQuest approach to simulation optimization. The objective function in OptQuest is constructed based on performance metrics defined in the Experimenter module. Objectives can be single, weighted, or patterned (Pareto-optimal). These types influence how the objective function is utilized in the search for an optimal solution.

The optimization process involves running the simulation model for one scenario - a specific set of variable values at a given time and number of replications - and then adjusting the variable values based on the objective function results and rerunning the scenario. Variable adjustment is performed by OptQuest's own algorithm. The optimization engine employs state-of-the-art evolutionary algorithms to efficiently search the design space.

The optimizer continues the search for an optimal solution until one of the following criteria is met: (1) all possible solutions have been considered, (2) a specified number of solutions have been considered, or (3) a specified search time (called the wall time) has elapsed. Upon completion of the optimization search, the optimizer reports the best-found solutions. Unless all possible solutions have been evaluated, which is rare, technically best solutions are not necessarily optimal [7].

RESEARCH PROBLEM

As part of the research analysis, the following multi-objective optimization problem of determining the processing time for products on a machine was considered.

In a manufacturing factory, there is a production line consisting of one machine tool that is responsible for processing various products (Fig. 2).

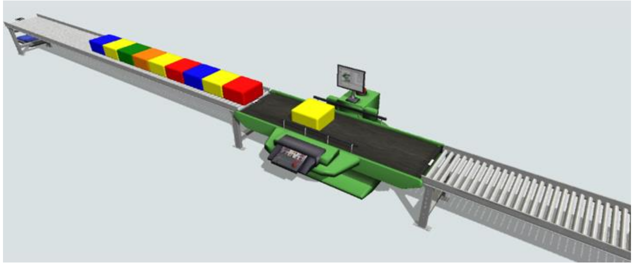

Fig. 2 Simulation model for the discussed problem built in the FlexSim environment

The incoming stream is described by an exponential distribution, with an average time of 45 minutes between consecutive arrivals. In this system, the machine tool can process products with different processing times. Due to the nature of the process, engineers have indicated that the processing time can range from 20 to 60 minutes. Thus, we have a situation where significant differences in service time exist.

A common approach in this situation is to use a generally flexible distribution with easily estimable parameters. One such distribution is the triangular distribution [6]. The parameters needed to define the triangular distribution are the minimum value, maximum value, and mode (most likely value). These parameters are usually easier to determine than the mean and standard deviation in the case of a normal distribution. Typically, these parameters can be estimated by discussing the modeled operation with domain experts who perform or supervise the operation. The mean value in the triangular distribution is calculated using the following formula (1):

$$\mu = \frac{min+max+mode}{3} \tag{1}$$

According to queueing theory, the average arrival rate must be smaller than the average service time. If this condition is not met, the system becomes overloaded, and the queue grows infinitely. Therefore, in this example, the average processing time cannot exceed 45 minutes. As a result, the mode will take values in the range of 20 to 55 minutes, and the average service time will range from 33.3 to 45 minutes. The density function plot is shown in Figure 3.

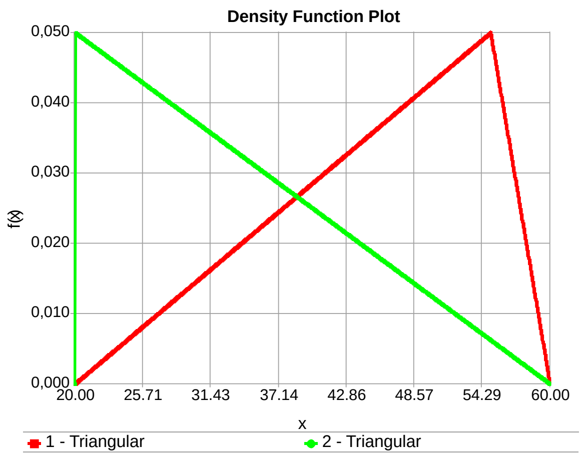

Fig. 3 Density function of the triangular distribution for the service time

The objective of the optimization is to find the optimal mode value in the triangular distribution that minimizes the waiting time of products for processing while maximizing the utilization of the machine tool. Clearly, these mentioned decision criteria are in conflict with each other. This simulation model will examine these two decision criteria for different service times.

The objective function is defined by two variables: the average queue content, which is minimized, and the machine utilization, which is maximized. These parameters need to be defined by adding them from the *Toolbox* library as *Performance Measure* variables (Fig. 4).

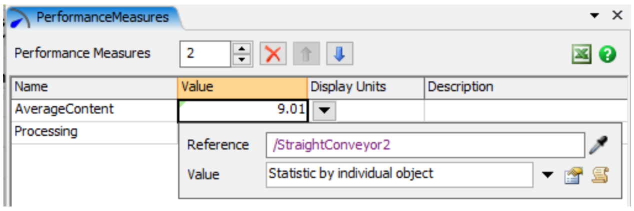

Fig. 4 Definition of the objective function - the output variable for average queue content and workstation utilization

In order for the optimizer to determine the optimal service time, it requires one input parameter – the mode value of the triangular distribution describing the service time, set in the global table and assigned to the processor. This is the variable that will be used in the optimization process and also where the optimizer will generate results from each iteration [30]. This parameter needs to be defined by adding it from the Toolbox library. Then, in the Value column, select Continuous as the variable type. The boundary conditions should be set according to the minimum and maximum values for the mode in the triangular distribution, 20 to 55 minutes (Fig. 5).

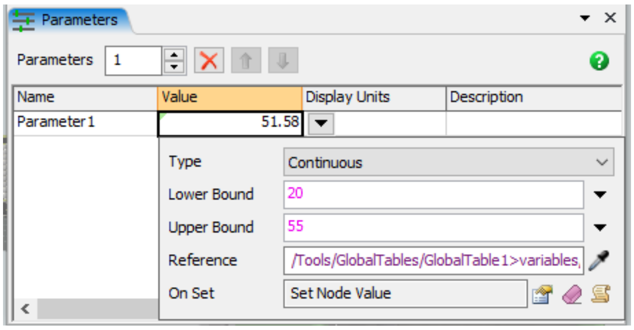

Fig. 5 Variable definition including the determination of the mode value of the triangular distribution describing the service time

In the optimizer settings (Fig. 6), 40 feasible solutions have been considered. For each of them, the model was replicated from 5 to 10 times.

The number of model runs for individual scenarios depends on how many replications are necessary to achieve an 80% confidence level obtained with a probability of 5%. In this task, the objective function has two criteria.

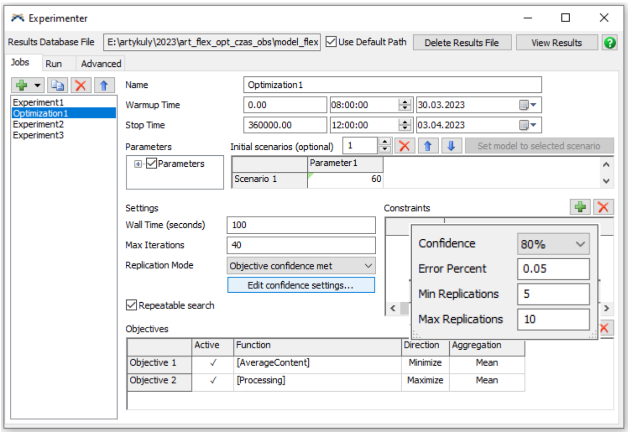

Fig. 6 FlexSim optimizer configuration

The first criterion aims at minimization since the company seeks to reduce the average queue content. The second criterion of the objective function aims at maximizing the utilization of the workstation. The optimizer will adjust the values of the defined parameters to achieve an optimal value where the queue content is minimized while the workstation utilization is high.

ANALYSIS OF THE RESULTS

As a result of the optimizer's work, multiple non-dominated solutions were obtained, forming a curve known as the Pareto optimal solutions front (Fig. 7). The front determines the best operating conditions for the studied system in terms of the degree of utilization and the average number of work-in-progress items in the queue.
The presented results can be highly useful for the decision-maker as they can choose the best settings based on a visible compromise between these two criteria.

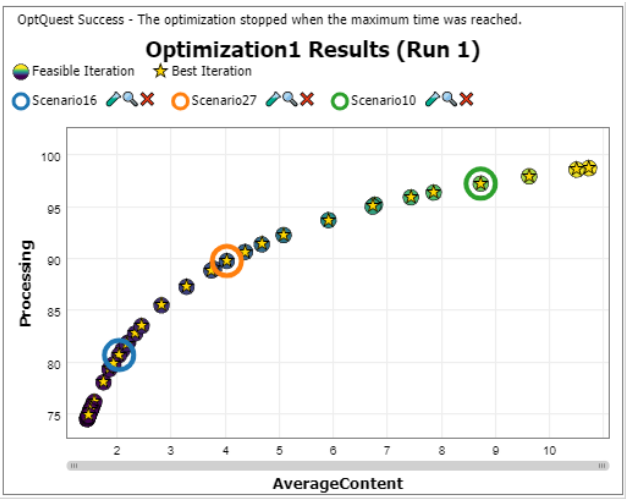

Fig. 7 Front of Pareto solutions for the service time optimization problem

Two exemplary solutions were selected for further analysis: Scenario 27 and Scenario 10. For Scenario 27, the service time mode was 41.13 minutes, while for Scenario 10, the mode was 54.84 minutes. Figure 8 presents a comparison of the results regarding the average queue content for both examined scenarios.

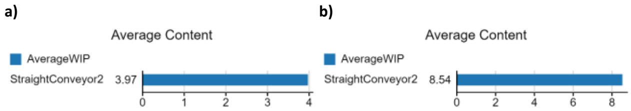

Fig. 8 Average number of items in the queue: a) Scenario 27, b) Scenario 10

Figure 9 shows a comparison of the workstation utilization level. Additionally, Figure 10 provides the average service time for these scenarios. When the workstation is utilized at 90% of its capacity, the number of items in the queue is approximately 4, and the average service time is 40.36 minutes. However, when the workstation is almost 97% loaded, the number of items in the queue increases to 8.54, and the average service time is nearly 45 minutes.

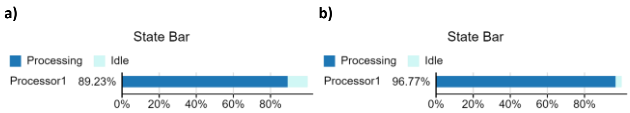

Fig. 9 Workstation utilization level: a) Scenario 27, b) Scenario 10

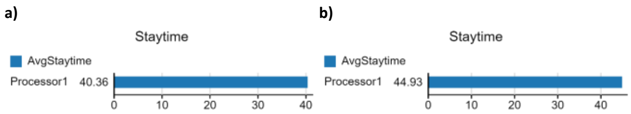

Fig. 10 Average service time: a) Scenario 27, b) Scenario 10

In summary, the analysis of results for Scenarios 27 and 10 indicates that Scenario 27 achieves better outcomes in terms of the average queue content, workstation utilization, and average service time compared to Scenario 10. This means that adopting Scenario 27 can bring benefits related to the optimization of the product processing process. By using this scenario, the company can reduce the number of objects waiting in the queue, shorten the service time, and make more efficient use of available workstations.
When the workstation is utilized at 90% of its capacity, the system maintains a low average queue content (around 4 objects) while providing an acceptable average service time (40.36 minutes). This means that the company can effectively handle the majority of products, minimizing customer waiting time.
However, when the workstation is almost 97% loaded, the number of objects in the queue increases to 8.54, and the average service time is nearly 45 minutes. In such a situation, the company may face challenges related to system performance and longer service time, which can lead to customer dissatisfaction and a decline in service quality.
Therefore, considering the analysis of the results, it is recommended to adopt Scenario 27 as the preferred solution. With proper utilization of workstations, the company will have the opportunity to minimize the number of objects waiting in the queue, shorten the service time, and ensure efficient resource utilization, contributing to improved service quality and increased customer satisfaction.

CONCLUSION

The presented article discusses research on the impact of efficient time management on workstation performance in the context of the trade-off between maximizing workstation utilization and minimizing the number of items waiting in the queue.

By employing a multi-criteria optimization approach, the researchers had the opportunity to minimize the waiting time of products for processing while simultaneously maximizing machine utilization. Using a flexible triangular distribution to describe the service time, simulations and optimizations were conducted, leading to the creation of a Pareto optimal solutions front.

The analysis of results for various scenarios confirmed that efficient time management yielded favorable outcomes. Specifically, Scenario 27 achieved better results in terms of the average queue content, workstation utilization level, and average service time. By balancing the workload of workstations and minimizing waiting time, decision-makers have the opportunity to make optimal choices in settings, considering the compromise between these two factors.

The presented example illustrates the potential of discrete event simulation models in enhancing production processes by identifying optimal time and resource management strategies. Decision-makers in the field of production can utilize these results to make more informed decisions regarding planning and process optimization, which can lead to significant benefits in terms of performance, efficiency, and customer satisfaction.

REFERENCES

[1] M. Krynke, "Management optimizing the costs and duration time of the process in the production system," *Production Engineering Archives*, vol. 27, no. 3, pp. 163-170, 2021, doi: 10.30657/pea.2021.27.21.

[2] M. Krynke, "Personnel Management on the Production Line Using the FlexSim Simulation Environment," *Manufacturing Technology*, vol. 21, no. 5, pp. 657-667, 2021, doi: 10.21062/mft.2021.073.

[3] S. Luscinski and V. Ivanov, "Management and Production Engineering Review," 2020.

[4] M. Ingaldi and D. Klimecka-Tatar, "Digitization of the service provision process - requirements and readiness of the small and medium-sized enterprise sector," *Procedia Computer Science*, vol. 200, pp. 237-246, 2022, doi: 10.1016/j.procs.2022.01.222.

[5] R. Ulewicz and K. Mielczarek, "Machine operation efficiency in the production of car equipment," in *13th International Scientific Conference 2022*, p. 50070.

[6] M. Beaverstock, A. Greenwood, and W. Nordgren, *Applied simulation: modeling and analysis using FlexSim,* 5th ed.: Published by FlexSim Software Products, Inc., Canyon Park Technology Center, Building A Suite 2300, Orem, UT 84097 USA., 2017.

[7] M. Laguna, *OptQuest*, 2011. [Online]. Available: https://www.opttek.com/sites/default/files/pdfs/optquest-optimization%20of%20complex%20systems.pdf

[8] M. Frantzén, A. H. Ng, and P. Moore, "A simulation-based scheduling system for real-time optimization and decision making support," *Robotics and Computer-Integrated Manufacturing*, vol. 27, no. 4, pp. 696-705, 2011, doi: 10.1016/j.rcim.2010.12.006.

[9] M. O. Mohammadi, T. Dede, and M. Grzywiński, "Solving a stochastic time-cost-quality trade-off problem by meta-heuristic optimization algorithms," *BoZPE*, vol. 11, 2022.11, pp. 41–48, 2022, doi: 10.17512/bozpe.2022.11.05.

[10] Z. Čičková, M. Reiff, and P. Holzerová, "Applied multi-criteria model of game theory on spatial allocation problem with the influence of the regulator," *PJMS*, vol. 26, no. 2, pp. 112-129, 2022, doi: 10.17512/pjms.2022.26.2.07.

[11] . N. Ivanova, W. Biały, A. I. Korshunov, J. Jura, K. Kaczmarczyk, and K. Turczyński, "Increasing Energy Efficiency in Well Drilling," *Energies*, vol. 15, no. 5, p. 1865, 2022, doi: 10.3390/en15051865.

[12] D. Siwiec, A. Pacana, and R. Ulewicz, "Concept of a model to predict the qualitative-cost level considering customers' expectations," *PJMS*, vol. 26, no. 2, pp. 330-340, 2022, doi: 10.17512/pjms.2022.26.2.20.

[13] O. Shatalova, E. Kasatkina, and V. Larionov, "Multi-criteria Optimization in Solving the Problem of Expanding Production Capacity of an Enterprise as a Method of Modeling Strategic Directions for the Development of Production Systems," *MATEC Web Conf.*, vol. 346, p. 3105, 2021, doi: 10.1051/matecconf/202134603105.

[14] N. L. P. Hariastuti and Lukmandono, "A Review on Sustainable Value Creation Factors in Sustainable Manufacturing Systems," *Production Engineering Archives*, vol. 28, no. 4, pp. 336-345, 2022, doi: 10.30657/pea.2022.28.42.

[15] M. Krynke and D. Klimecka-Tatar, "Production costs management in process supported by external entities – Process flow optimization," in *13th International Scientific Conference 2022*, p. 50068.

[16] S. M. Kalinović, D. I. Tanikić, J. M. Djoković, R. R. Nikolić, B. Hadzima, and R. Ulewicz, "Optimal Solution for an Energy Efficient Construction of a Ventilated Façade Obtained by a Genetic Algorithm," *Energies*, vol. 14, no. 11, p. 3293, 2021, doi: 10.3390/en14113293.

[17] V. V. Borisova, O. V. Demkina, A. V. Mikhailova, and R. Zieliński, "The enterprise management system: evaluating the use of information technology and information systems," *PJMS*, vol. 20, no. 1, pp. 103-118, 2019, doi: 10.17512/pjms.2019.20.1.09.

[18] J. April, F. Glover, J. P. Kelly, and M. Laguna, "Practical introduction to simulation optimization," in *Proceedings of the 2003 Winter Simulation Conference: Fairmont Hotel, New Orleans, LA, U.S.A., December 7-10, 2003*, New Orleans, LA, USA, 2004, 2003, pp. 71–78.

[19] C. Kardos, C. Laflamme, V. Gallina, and W. Sihn, "Dynamic scheduling in a job-shop production system with reinforcement learning," *Procedia CIRP*, vol. 97, pp. 104–109, 2021, doi: 10.1016/j.procir.2020.05.210.

[20] J. April, M. Better, F. Glover, J. Kelly, and M. Laguna, "Enhancing Business Process Management with Simulation Optimization," in *Proceedings of the 38th conference on Winter simulation*, Monterey, CA, USA, Dec. 2006 - Dec. 2006, pp. 642-649.

[21] F. P. Santos, Â. P. Teixeira and C. G. Soares., "Modeling, simulation and optimization of maintenance cost aspects on multi-unit systems by stochastic Petri nets with predicates," *SIMULATION*, vol. 95, no. 5, pp. 461-478, 2018, doi: 10.1177/0037549718782655.

[22] M. W. Sari, Herianto, I. B. Dharma, and A. E. Tontowi, "Integrated Production System on Social Manufacturing: A Simulation Study," *Management Systems in Production*

Engineering, vol. 30, no. 3, pp. 230-237, 2022, doi: 10.2478/mspe-2022-0029.
[23] M. Krynke, K. Mielczarek, and O. Kiriliuk, "Cost Optimization and Risk Minimization During Teamwork Organization," *Management Systems in Production Engineering*, vol. 29, no. 2, pp. 145-150, 2021, doi: 10.2478/mspe-2021-0019.
[24] V. A. Zherebko, O. A. Pisarenko, and V. P. Drabynko, "Simulation and genetic optimization of control systems by labview programming" *Problems in programming*, no. 2-3, pp. 288-295, 2018, doi: /10.15407/pp2018.02.288.
[25] J. Tabor, "Ranking of management factors for safe maintenance system based on Grey Systems Theory," *Production Engineering Archives*, vol. 27, no. 3, pp. 196-202, 2021, doi: 10.30657/pea.2021.27.26.
[26] M. Daroń, "Simulations in planning logistics processes as a tool of decision-making in manufacturing companies," *Production Engineering Archives*, vol. 28, no. 4, pp. 300-308, 2022, doi: 10.30657/pea.2022.28.38.
[27] M. Rostek, "Productivity and improvement of logistics processes in the company manufacturing vehicle semi-trailers – Case study," *Production Engineering Archives*, vol. 28, no. 4, pp. 309-318, 2022, doi: 10.30657/pea.2022.28.39.
[28] T. Pukkala and J. Kangas, "A heuristic optimization method for forest planning and decision making," *Scandinavian Journal of Forest Research*, vol. 8, 1-4, pp. 560–570, 1993, doi: 10.1080/02827589309382802.
[29] A. Jerbi, A. Ammar, M. Krid, and B. Salah, "Performance optimization of a flexible manufacturing system using simulation: the Taguchi method versus OptQuest," *Simulation*, 2019, doi: 10.1177/0037549718819804.
[30] FlexSim, *User manual*, 2017.

Marek Krynke
ORCID ID: 0000-0003-4417-1955
Czestochowa University of Technology
ul. Dabrowskiego 69, 42-201 Czestochowa, Poland
e-mail: marek.krynke@wz.pcz.pl