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Original Research

PROBLEMS OF FORECASTING THE LENGTH OF THE ASSEMBLY CYCLE OF COMPLEX PRODUCTS REALIZED IN THE MTO (MAKE-TO-ORDER) MODEL

PROBLEMATYKA PROGNOZOWANIA DŁUGOŚCI CYKLU MONTAŻU WYROBÓW ZŁOŻONYCH REALIZOWANYCH W MODELU MTO (MAKE-TO-ORDER)

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Abstract

This article presents the problem of forecasting the length of machine assembly cycles in make-to-order production (Make-to-Order). The model of Make-to-Order production and the technological process of manufacturing the finished product are presented. The possibility of developing a novel method, using artificial intelligence solutions, to estimate machine assembly times based on historical company data on manufacturing times for structurally similar components, is described. It is assumed that the result of the developed method will be an intelligent system supporting efficient and accurate estimation of machine assembly time, ready for implementation in production conditions. Such data as part availability, human resource availability and novelty factor will be used as input data for learning the neural network, while the output variable during learning the neural network will be the actual machine assembly time.

Keywords: assembly cycle, machine assembly, forecasting, Make-to-Order, artificial neural networks, input signals, output signals, MatLab

Streszczenie

W niniejszym artykule przedstawiono problem prognozowania długości cyklu montażu maszyn w produkcji na zamówienie (Make-to-Order). Przedstawiony został model produkcji na zamówienie oraz proces technologiczny wytwarzania wyrobu gotowego. Opisana została możliwość opracowania nowatorskiej metody, wykorzystującej rozwiązania z zakresu sztucznej inteligencji, umożliwiającej szacowanie czasu montażu maszyn w oparciu o dane historyczne przedsiębiorstw, dotyczące czasów wytwarzania podobnych konstrukcyjnie elementów. Zakłada się, iż rezultatem opracowanej metody będzie inteligentny system wspomagający skuteczne i dokładne szacowanie czasu montażu maszyn, gotowy do implementacji w warunkach produkcyjnych. Jako dane wejściowe do uczenia sieci neuronowej wykorzystane zostaną takie dane jak: dostępność części, dostępność zasobów ludzkich oraz czynnik nowości, zaś zmienną wyjściową podczas uczenia sieci neuronowej będzie rzeczywisty czas montażu maszyny.

Słowa kluczowe: cykl montażu, montaż maszyn, prognozowanie, produkcja na zamówienie (Make-to-Order), sztuczne sieci neuronowe, sygnały wejściowe, sygnały wyjściowe, MatLab

1. Introduction

One of the key stages in the manufacturing process of customized products is the assembly cycle. An accurate analysis of the assembly time of a particular product that a customer wants to order affects the actual completion of the order within the agreed time, and consequently the shipment of the finished product within the time specified in the contract. Nevertheless, determining this time in a traditional way is in many cases impossible, which prompts the search for methods using the latest scientific and technological advances.

For complex problems that require multi-criteria analysis of large amounts of data, analytical and optimization methods give way to heuristic methods. Although they can be considered more accurate, the time-consuming nature of obtaining results can disqualify them in many situations such as the preliminary design of complex systems or acting in the face of an unexpected crisis. Combining heuristic methods with artificial intelligence in the areas of technological processes and machine assembly can increase the productivity and competitiveness of manufacturing companies [1].

The researchers discussed various aspects of the assembly system. Schedin et al. [2] discusses assembly system design, while Gorski et al. [3] deals with mass customization. The assembly-oriented method of process and assembly equipment included product and process analysis, identification of change drivers and responsibilities, assembly system modeling, technical design of modules, composition and design of the overall assembly system. According to Müller et al. [4], operational tasks in assembly can be divided into manipulation (including: feeding, transporting, blocking), joining (including: pressing, welding, bolting, etc.), commissioning (including: adjusting, setting parameters, function testing), auxiliary processes (including: storing, changing quantities, checking, etc.), and special operations (including: cleaning, reworking, packaging, etc.).

Mital et al. [5] present different assembly methods: manual assembly, automatic assembly (stationary), hard automation, and robotic assembly (soft automation). The estimation of manual assembly time was discussed by Chan et al. [6], who obtained assembly times using the MODAPTS predefined time system. Liu et al. [7] propose an assembly process modeling mechanism based on product hierarchy, and an assembly-by-dismantling approach is used to build an assembly process model.

Unfortunately, the number of publications in the field of assembly time prediction and estimation is very limited. Some attempt to estimate assembly time from data of a complex product was presented by Eigner, Roubanov and Sindermann [8]. An interesting proposal to support assembly time prediction using Markov model and hybrid developments was proposed by Gellert et al. [9]. More recently, an attempt to use artificial neural networks for assembly operation time prediction was presented by Rueckert, Birgy and Tracht [10]. Unfortunately, none of these solutions is not a comprehensive method for predicting the assembly time of complex products realized in nested production.

The research problem that has arisen is that it is not possible to predict machine assembly times at the quotation stage, i.e. at a stage where detailed assembly technology has not yet been developed. The aim of this study is to present the concept of an intelligent system for the prediction of cycle time for the assembly of complex products using artificial neural networks. In particular, the main input and output factors for the prediction of the assembly process duration will be identified and analysed.

The process of forecasting the assembly of complex products implemented in the MTO model is an area of constant improvement and search for new solutions. Modern science focuses on technological and organizational issues of the manufacturing process, leaving somewhat the area of industrial assembly technology in the background. This area of industry is characterized by a high dependence on the human factor, as it focuses its attention on human labor in conditions that are not digitally controlled and do not require advanced machinery and tools [11].

2. Make-to-Order Production

The purpose of custom manufacturing is to fulfill a production order within a specified period of time. The process based on the MTO model begins when an order is received from a customer for a specific product. Only after the order is received is the raw materials needed to fulfill the order ordered (or their reservation if they are in stock) ordered [12]. Production planning, purchase of materials or scheduling of production tasks in the short term take place on the basis of orders received. Since production is "triggered by orders," these systems are also known as pull systems [13]. Long-term planning is done on the basis of projections of sales plans. Custom manufacturing strategy characterized by long delivery times, low storage costs and a large variety of finished goods. For material demand planning, most often ERP-class information systems are used which can additionally serve as a source of data for analysis and decision-making related to production control [14], [15].

This production strategy is found in unit production and small batch production. A typical finished product is non-standard in nature and unique. The product can be individually designed to the customer's needs, configurable from available variants, or assembled from finished blanks only after the order is received. The production order is triggered at the start of the design process or at the start of assembly according to customer specifications. The main advantage of MTO is the ability to fulfill an order with the exact product specifications required by the customer.

The industries where MTO's manufacturing strategy is most commonly found are machinery, construction, IT or exclusive product manufacturing [16].

In the literature you can find a division of MTO strategies into several subcategories and varieties [17-21]:

- assembly to order (ATO) - involves using off-the-shelf (previously manufactured or purchased) semi-finished products and assembling them into the final finished product ordered by the customer. The assemble-to-order (ATO) strategy is appropriate for those situations where fast response is highly valued.
- configure to order (CTO) - is a special case of the ATO strategy. Individual semi-finished products are divided into subsets, and the customer selects items from these subsets. For example, a computer is configured by selecting a processor from several options, a monitor from several options, etc. The difference between a CTO system and an ATO system is important at the level of inducing demand,
- finish to order (FTO) - involves producing a not-quite-finished product (semi-finished), e.g., pre-extrusion of aluminum profiles - and then finishing (e.g., heat treatment, painting) the finished product according to the customer's order,
- engineering-to-order (ETO) design - involves designing and manufacturing the finished product according to customer specifications. When ordering a finished product, the customer also orders the process of designing that product to meet his individual needs.

For a comprehensive overview of custom manufacturing strategy knowledge and related issues, see the items [22-23].

3. Assembly of complex products

One of the main steps in the manufacturing process is assembly, which is a key stage in the production of customized products, where products are assembled according to customer needs. Time standards are among the of the most important indicators of the efficiency of the manufacturing process. Knowing the exact assembly time of a machine greatly increases the probability of completing all stages of production within the set time, and consequently, shipping the finished product on the date agreed with the customer. Nevertheless, the determination of this time by traditional methods is, in many cases, impossible, which urges the search for techniques using the latest scientific and technical achievements and technology.

The production process for the MTO model, from approved order to shipment of the finished product is labor-intensive and complicated (fig. 1). The process from receiving specifications to shipping the finished product is time-consuming. The received specifications are sent to the design departments, where the machine is designed and the material list is prepared. The bill of materials goes to the production preparation department, where it is imported into the system and then the process of ordering parts in the procurement department begins. The entire assembly process takes approximately two months. After this time, the process of testing and starting the machine as well as quality control begins. After positive receipt of the machine, a shipping specification is prepared and the process of packing the machine and shipping it to the customer begins.

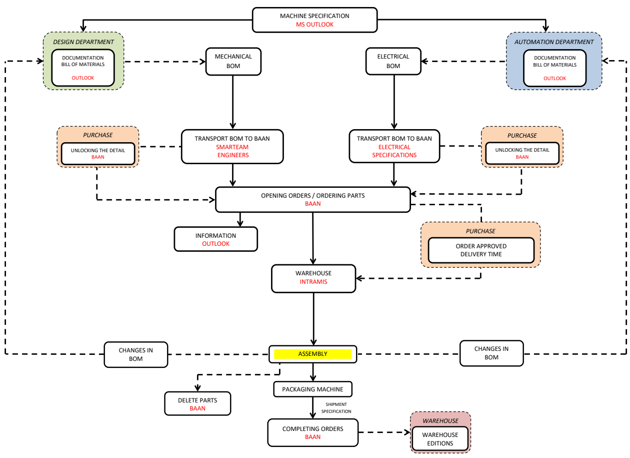

Fig. 1. Diagram of the production process in the MTO model

The assembly process of machine is shown in figure 2. The production process of the company from which the data is taken is carried out in production nests. The assembly of the machine begins with the frame, on which mechanical components, pneumatics, and the electrical board and cabinet are assembled one by one using an overhead crane and a forklift. At the final stage, covers are installed.

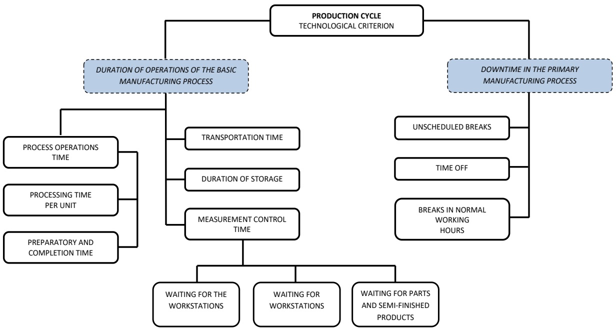

Fig. 2. Assembly manufacturing process

Table 1 shows the list of assembly components along with the with assembly times using one type of machine as an example. The process of building a machine can be divided into stages: construction of the frame, assembly of the components and assembly of the components into the previously prepared frame.

Table 1. List of assembly components with their assembly times

No.	Component name	Assembly and adjustment time (h)
1	Preparation time for machine components and subassemblies	24
2	Cleaning and threading of frame parts after painting	8
3	Installation of electrical trays	8
4	Assembling the machine frame	6
5	Arming the doors of electrical cabinets	4
6	Full tray conveyor	20
7	Empty tray conveyor	20
8	Unit for transporting and stacking full trays	8
9	Transport of trays and products	8
10	Alignment unit	4
11	Linear unit with full and empty tray	10
12	Cleaning unit	8
13	Tipping module for empty feeders	3
14	Installation and disassembly of the pneumatic system	14
15	Adjusting the machine after startup	12
16	Initial and final assembly of covers	26
17	Corrections due to independent errors	16

Preparation time for machine components and subassemblies before and during assembly includes:

- transporting the machine components + normals from the warehouse and receiving them,
- distribution of the machine elements on racks to facilitate their identification (subdivision into subassemblies),
- transport of components to and from the paint shop.

4. Factors affecting the assembly time estimation process

According to data from the assembly department of one of the unit/small batch manufacturing companies in the machinery industry, the key elements affecting the assembly cycle are human resources, part availability, bench availability, tool availability and the novelty factor (fig. 3). A complete database containing the above information was compiled from various databases and reports (ERP system, Power BI).

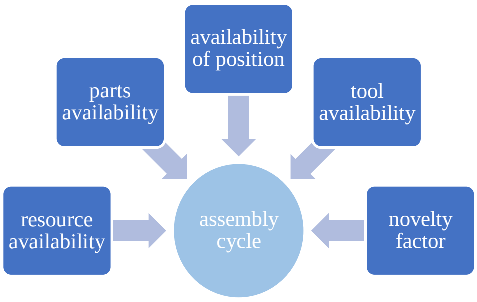

Fig. 3. Graphical interpretation of factors affecting machine assembly time

4.1. Availability of components of complex products

The biggest influence on the time of the entire assembly is the availability of parts to start the planned process at a specific moment. This fact is of great importance, since the lack of components (parts) increases the time of the entire process, and also introduces unnecessary chaos in production.

With part availability of less than 100%, it is difficult to plan the work so that the entire finished goods process is efficient. If this factor is not met, the start of assembly will be delayed, or if we start assembly there will be downtime during assembly due to waiting for parts, and we must take this into account as well. The delays are usually a few days, but this affects the entire production flow. One can then try to make up for those few days by shifting to a different stage of production or starting production with oversized working hours, but this also brings additional costs to the company. That's why 100% availability of parts to start machine assembly is such an important element.

Part availability data (input) determines the product assembly time (output). The parts availability factor can be estimated by comparing the dates of planned to actual delivery of parts: the planned start of assembly and the date, confirmed by suppliers, of actual delivery of parts to the warehouse.

4.2. Resource availability

The availability of human resources in production load planning often assumes a factor of seasonality of work, holiday periods and random events or sick leave. Employees are also selected for a particular production order because of their qualifications. The appropriate selection of an employee increases labor productivity and thus reduces product assembly time. Unfortunately, unplanned employee absenteeism (resulting, among other things, from sick leave or so-called "on-demand" leaves) is a difficult to predict factor that has a significant impact on the process. Consequently, there is always a difference between the normative and actual effective working time of an employee, which is difficult to predict at the stage of estimating the production cycle [24].

The resource availability factor can be determined from the planned and actual budget used by employees for the machine for a specific task and operation according to the recommended assembly technology (tab. 2).

Table 2. Hourly budget of employees

Task	Description	Budgeted	Total	Consumption
623	Mechanical Assembly	350	314,91	
624	Electrical Assembly	260	200,1	
625	Tooling	8	0	
628	Packing & Loading	16	0	
669	Other Activities	8	31,48	

Depending on the composition of the brigade and the sophistication of the workers, the assembly time may be shorter or get longer (in the case of new workers, for example, the time may increase).

4.3. Availability of an assembly station with appropriate instrumentation

Some assembly stations are equipped with tools/equipment that are designed only for a specific type of product and can only be assembled at these stations. This is also an impediment to predicting the assembly time of products, as the waiting time for a given workstation to be freed up for a particular type of product may be prolonged - which consequently causes postponement of the assembly process of subsequent products.

Disorganization of production as a result of lack of free space on the shop floor is a difficult planning situation, since it is impossible to start assembling a product using any substitute solutions. It is also a hindrance in forecasting the time of product assembly, as the waiting time for the release of a given workstation for a particular type of product can be prolonged, which causes a delay in the completion of the process of assembling subsequent products. An important element in the entire assembly process is the release of the assembly station at the right time, so that the assembly of the next product can begin at the right moment and there are no delays in further stages of the process.

Each production hall has its own limited space, and in small batch production, where specific assembly stations are designated, dedicated to specific products, it is very important to complete the assembly of a machine in a timely manner, so that the assembly of the next machine can begin at the planned time.

4.4. Availability of tools and assembly tooling

A factor that determines the efficiency of the execution of the assembly process is the availability of tools and assembly tooling dedicated to the execution of specific technological operations. In many cases, the number of tools and tooling used to manufacture specific products is less than the number of assembly stations and/or the number of products of a given type being assembled simultaneously. Consequently, situations may occur in which the lack of specific tools or tooling may prevent the timely execution (and thus delay) of the assembly process.

4.5. Novelty factor

By the factor of novelty we can define changes in the construction of the machine, which lengthen, but also shorten in some cases, the assembly time. Changing the components of a machine at the construction stage can significantly hinder its subsequent assembly due to the new assembly technology, or shorten the assembly time when, for example, the components for assembly come from the supplier already in an assembled subassembly.

The novelty factor was divided into two items:

1. New items - are calculated from the comparison of details (items) new from the material list to the quantity of all items from the material list. New items in the system are marked with a special code, which makes it easy to verify the number of new details entering the system for a given machine.
2. Changed items - are calculated by the number of items that have been changed from the initial revision (A) to the final and final revision (B) of the material list to the number of all items in the material list.

These changes are recorded in the system and downloaded as an A/B revision comparison report (tab. 3).

Table 3. Comparison of A/B revisions from the bill of materials

Engineering Item 1	: RM0930000-M-0081	Engineering Item 2	: RM0930000-M-0081
Revision	: A	Revision	: B
Status	: Approved by Production	Status	: Approved by Production

Component	Pos.	Type	Quantity	Unit	Component	Pos.	Type	Quantity	Unit
28-198132	16	E-Item	1,0000	pcs	28-199676	19	E-Item	1,0000	pcs

In table 4, we can see what items were added and/or removed from the first revision of the bill of materials from the final version.

Table 4. Value of A/B revision - items changed

REVISION	ITEMS DELETED „-”	ADDED ITEMS „+”
A/B	**2**	**6**
B/C	**0**	**1**
C/D	**0**	**2**
FINAL A/D	**2**	**9**

As can be seen from table 4, the sum of details changed: deleted and added is 11 items. Two items were removed from the initial list - revision A, and nine details were added to the material list - revision B. This amount is compared to the amount of all items in the material list, and then we get the percentage of novelty factor - items changed.

5. Input data for modeling the assembly time estimation process

Based on simulation studies, input signals that have a direct impact on the estimation of assembly time were selected for testing the network (fig. 4).

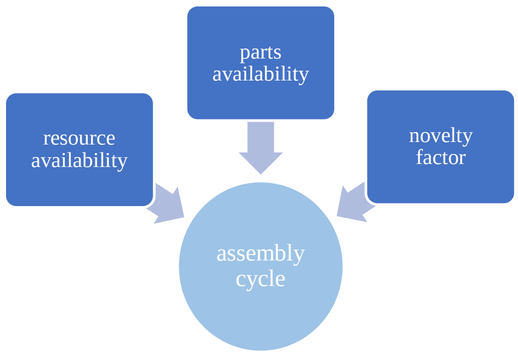

Fig. 4. Graphical interpretation of factors directly influencing machine assembly time

Figure 5 shows sample results from one type of machine, showing the variation of part availability, resource availability and novelty factor. The machine assembly time will depend on these results. The larger the deviations, the more difficult it is to verify the estimated machine assembly time. Therefore, using neural networks, we can create a model that will give us information at the output about the estimated assembly cycle of a given machine type [25].

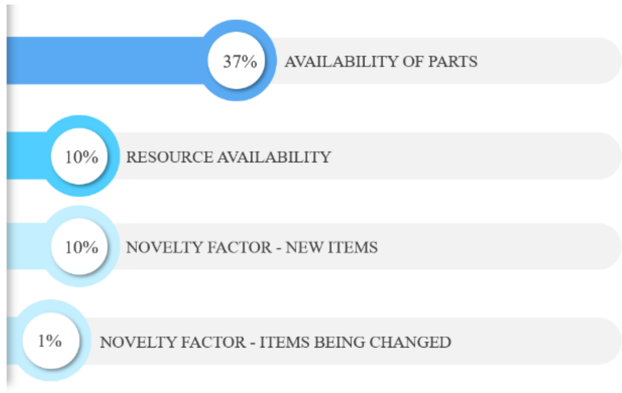

Fig. 5. Deviations of the factors of the example machine

6. Output elements of the modelled process

The purpose of neural network modeling is to predict the course of a nonlinear technological process using trained neural networks. Its analysis can contribute to the creation of an enterprise decision support system [26]. With the help of neural networks, we want to be able to estimate the assembly time of a machine so that the deadlines confirmed to the customer are met and the response to a new request goes to the customer in the fastest possible time.

The Neural Network library (fig. 6) in the MatLab computing environment can be used to model the process. At the stage of learning the neural network, it is necessary to indicate the chosen learning algorithm (Levenberg-Marquardt algorithm, Bayesian regularization or scalable coupled gradients algorithm), the number of hidden layers in the modeled network and the number of neurons in each hidden layer. In addition, the analyzed data set should be divided into learning, test and validation. Most often, they are determined in proportions of 70%:15%:15%. The selection of the best model is made on the basis of an analysis of the quality measures of the obtained networks - the mean square error (MSE) and the correlation coefficient (R). MSE is calculated according to formula (1):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i' - y_i^*)^2 \qquad (1)$$

where:
n - the number of cases analyzed, $y'i$ - the actual value of the assembly time for the i-th case, $y*i$ - the predictive value of the assembly time for the i-th case obtained as a result of the network.

The correlation coefficient (R) is calculated according to formula (2):

$$R(y',y^*) = \frac{cov(y',y^*)}{\sigma_{y'}\sigma_{y^*}} \quad R\epsilon < 0{,}1 > \qquad (2)$$

where:
cov(y′,y∗) - covariance between the variables y′ and y∗, *σy′* - standard deviation of the actual assembly time values, *σy** - standard deviation of the predictive assembly time values.

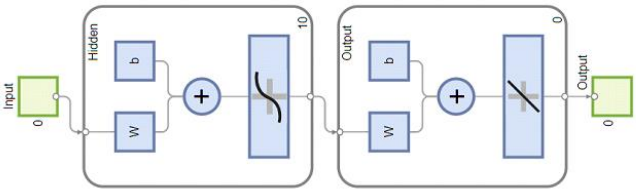

Fig. 6. The network model in the Neural Network library in MATLAB

Once a good quality network is obtained, the next step is to generate the model into the Simulink computing environment (fig. 7), so that the machine assembly time can be predicted. After inputting the following data into the model: availability of parts, human resources, availability of the assembly station and availability of tools after running the model, the output will receive the estimated machine assembly time.

The result of the model in the form of the estimated machine assembly time will then be able to go to the customer in response to their inquiry in a short period of time.

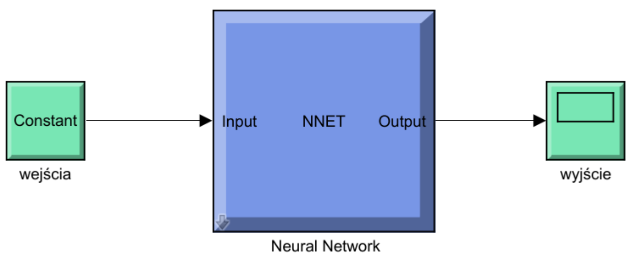

Fig. 7. Model in the Simulink computing environment

7. Summary and conclusions

An artificial neural network can be successfully used to determine and estimation of time in the assembly process. The development of a model using SSN can be based on the following steps: developing training sets and test sets and finding the best SSN structure. Preliminary results conducted on simulation data made it possible to determine what input factors should be considered for the model. The assembly process was analyzed and the features (attributes) that affect the time norm were selected.

By inputting into the model, the inputs of part availability, human resource availability and novelty factor after running the model, a predicted/estimated machine assembly time will be generated at the output of the model. The developed method will be able to be used in enterprises as an intelligent system to support efficient and accurate estimation of the assembly time of machines not yet ordered (tendered).

This will allow to increase the accuracy of enterprises' work, claims in meeting given production completion dates, and will increase competitiveness in the market. The system will be ready for implementation in production conditions for small batch and unit production. Knowing the exact assembly time of the machine significantly increases the probability of completing all stages of production within the set time, and consequently, shipping the finished product within the time agreed with the customer.

The next stages of work will be based on building and testing the model in the MatLab environment. Neural networks will be tested in various variants. The best model will be selected based on the analysis of quality measures of the obtained networks: mean square error and correlation coefficient. After selecting the highest quality neural network from all analyzed networks, a model will be generated in the Simulink computing environment that can be used to predict machine assembly times.

References

1. Akinc, U., Meredith, J. R. (2015). *Make-to-forecast: Personalization with rapid delivery*, Int. J. Oper. Prod. Manag., vol. 35, no. 5.
2. Brzeziński M. (2013). *Organization of production in an enterprise*, Difin.
3. Brzozowska J., Gola A., Kulisz M. (2022). *General concept of using artificial neural networks in the process of estimating the assembly time of complex products.* Management engineering: digitization of production. 4, Research News 2022.
4. Chan A.H.S., Hoffmann E.R., Chung C.M.W. (2017). *Subjective Estimates of Times for Assembly Work*, International Journal of Industrial Ergonomics, 61.
5. Ciechańska, O. (2018). *Manufacturing model for availability as a new approach to production planning*. Warsaw University of Technology.
6. Ciechańska O., Szwed C. (2020). *Characteristics and study of Make-to-Stock and Make-to-Availability production strategy using simulation modeling*. Management and Production Engineering Review, vol. 11, no. 4.
7. Danilczuk, W., Gola, A. (2020). *Computer-assisted material demand planning using ERP systems and business intelligence technology*, Applied Computer Science, vol. 16, no. 3.

8. Danilczuk, W. (2019). *Analysis of production data on the basis of transactions in the ERP system using business intelligence technology*, Bus Tech. Eksploat. Syst. Transp., vol. R. 20, no. 7-8.
9. Danilczuk W. (2023). *Method of suboptimal scheduling of discrete production realized in the MTO-MTS hybrid model*. Doctoral dissertation.
10. Eigner, M., Roubanov, D., Sindermann, S., Ernst, J. (2014). *Assembly Time Estimation Based on Product Assembly Information*. In D. Marianović, M. Štorga, N. Pavković, N. Bojčetić (eds.), DS 77: Proceedings of the DESIGN 2014 13th International Design Conference.
11. Fernandes, N. O., Silva, C., Carmo-Silva, S. (2015). *Order release in the hybrid MTO-FTO production*. Int. J. Prod. Econ., vol. 170.
12. Gellert, A., Precup, S.A., Matei, A., Pirvu, B.C., Zamfirescu, C.B. (2022). *Real-Time Assembly Support System with Hidden Markov Model and Hybrid Extensions*. Mathematics, 10(15).
13. Jacobs R. F., Berry W., Whybark D.C., T. V. (2011). *Manufacturing planning and control for supply chain management*. Mc Graw Hill. New York.
14. Karaśkiewicz F. (2018). *Methodology of using artificial intelligence tools and group technology in managing the design of non-automated assembly systems*. Doctoral dissertation.
15. Kulisz M., Zagórski I., Semeniuk A. (2016). *Artificial neural network modelling of cutting force components during AZ91HP alloy milling*, Applied Computer Science, vol. 12, no. 4.
16. Liu X., Ni Z., Liu J., Cheng Y. (2016). *Assembly Process Modeling Mechanism Based on the Product Hierarchy*, Int. J. Adv. Manuf. Technol., 82.
16. Meredith, J., Akinc U. (2006). *Characterizing and structuring a new make-to-forecast production strategy*. Elsevier B.V.
17. Mital A., Desai A., Subramanian A., Mital A. (2014). *Product Development*, Elsevier.
18. Mountain F., Zawadzki P., Hamrol A. (2016). *Knowledge Based Engineering as a Condition of Effective Mass Production of Configurable Products by Design Automation*, Journal of Machine Engineering, 16/4.
19. Müller R., Esser M., Eilers J. (2013). *Assembly Oriented Design Method for Reconfigurable Processes and Equipment*, In Schuh G., Neugebauer R., Uhlmann E. (eds) Future Trends in Production Engineering, Springer, Berlin, Heidelberg.
20. Roszkowska E. (2021). *Multi-criteria decisions and negotiations. Selected theoretical aspects and experimental studies*. University of Bialystok Publishing House.
21. Rueckert, P., Birgy, K., Tracht, K. (2023). *Image Based Classification of Methods-Time Measumerment Operations in Assembly Using Recurrent Neuronal Networks*. Advances in System Integrated Intelligence, 546.
22. Schedin J., Svensson-Harari N., Jackson M., Deleryd M. (2016). *Management of Newness in an Assembly System*, Journal of Machine Engineering, 16/1.
23. Schroeder, R. G., Goldstein, S. M. (2021). *Supply chain operations management: decisions and cases*. New York: McGraw-Hill Education.
24. Stevenson M., Hendry L. C., Kingsman B. G. (2005). *A review of production planning and control: The applicability of key concepts to the make-to-order industry*, Int. J. Prod. Res., vol. 43, no. 5.
25. Zennaro I., Finco S., Battini D., Persona A. (2019). *Big size highly customized product manufacturing systems: a literature review and future research agenda*, vol. 57, no. 15--16.