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WYZNACZANIE CZASU MONTAŻU NA ETAPIE PROJEKTOWANIA WYROBU

Streszczenie: Czas montażu może być podstawą do porównywania różnych wariantów wyrobu oraz procesu produkcyjnego. W artykule czas montażu został wyznaczany na podstawie charakterystyki uwzględniającej cechy wyrobu oraz typowych narzędzi i wyposażenia z wykorzystaniem sztucznej sieci neuronowej (ANN). Analizowane cechy obejmują m.in. informacje określone podczas projektowania wyrobu takie jak: struktura wyrobu, charakterystyka części (np. ciężar, rozmiar) i rodzaj połączenia, a także informacje określone podczas planowania montażu, takie jak narzędzia (np. śrubokręt ręczny, śrubokręt elektryczny, szczypce), wyposażenie (np. prasa, podgrzewacz) oraz układ stanowiska pracy (np. odległości, sposób dostarczania). Do charakterystyki montażu zastosowano schemat obiekt-atrybut-wartość (OAV). Przedstawiono przykład zastosowania ANN do predykcji czasu montażu podzespołów mechanicznych takich jak montaż łożyska. Przedstawione podejście jest szczególnie istotne dla przedsiębiorstw oferujących produkty dostosowane do potrzeb klienta.

Słowa kluczowe: wytwarzanie, norma czasu, montaż, grafy, sztuczna sieć neuronowa

STANDARD ASSEMBLY TIME SETTING IN AN EARLY STAGE OF PRODUCT DEVELOPMENT

Summary: The standard assembly time is an important value in product development, applied to compare different product or manufacturing variants. In the article, the standard time is created using an artificial neural network (ANN) for standard manual and machine-manual operations, and taking into consideration product characteristics and typical tools, equipment and layouts. The analysed features include, among other things, information determined during product development, product structure, part characteristics (e.g. weight, size) and connection type, as well as the information determined during assembly planning, such as tools (e.g. hand screwdriver, power screwdriver, pliers), equipment (e.g. press, heater) and workstation layout (e.g. distances, feeding method). The object-attribute-value (OAV) framework was applied for the assembly characteristic. An example of the ANN application to predict standard assembly time was presented for a mechanical subassembly. The case study was dedicated to ANN-based standard time modelling for a bearing assembly. The presented approach is particularly important for enterprises that offer customized products.

Keywords: manufacturing, time standard, assembly, graphs, artificial neural network

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1. Introduction

The important trends in manufacturing are mass customization and product personalization, which come from the market pressure to introduce product innovations with a competitive pricing strategy (Pine, 1993; Mateus, Claeys, Lim`ere, Cottyn,·Aghezzaf, 2019). The mass customization paradigm is focused on providing customized products at near mass production cost (Pine, 1993; Hu, Ko, Weyand, ElMaraghy, Lien, Koren, Bley, Chryssolouris, Nasr, Shpitalni, 2011). A customized product is designed according to the product family architecture, where the customer can choose among given product modules. The modules in customized products have standard mechanical, electrical and informational interfaces to allow for their easy assembly and disassembly. The concept of personalized products enabled the involvement of customer design in the product architecture. A personalized product has an open architecture and consists of three types of modules: common modules that are shared across the product platform; customized modules that allow customers to choose, mix and match; and personalized modules that allow customers to create and design (Hu, Ko, Weyand, ElMaraghy, Lien, Koren, Bley, Chryssolouris, Nasr, Shpitalni, 2011). Due to the increasing number of product variants in both concepts, assembly is an important stage in the manufacturing process for products that consist of several components (Hu, Ko, Weyand, ElMaraghy, Lien, Koren, Bley, Chryssolouris, Nasr, Shpitalni, 2011; Lien, 2018; Zha, Lim, Fok, 1998).
The decision-making issues related to the assembly process in production planning were discussed by Ho and Ji (2007) and included setup management (assigning products to assembly lines, grouping placement machines, grouping parts into families, sequencing the production) and process optimization (allocating component types to placement machines, determining the sequence of component placements, assigning component types to feeders at each machine). In product and production planning, the standard assembly time is an indicator that helps assess a given solution. Most assembly operations are carried out manually. In manual assembly, the standard time of an operation is determined by manual effort, even if some sub-operations are performed by machines, like electric screwdrivers or similar devices (Lien, 2018). Many assembly systems combine some automatic operations with manual work, e.g. robots can serve as tools for lifting, moving, and positioning heavy objects while the operator deals with the more delicate tasks that require human dexterity and fingertip feeling (Lien, 2018). Assembly tasks can be precisely planned and the standard time, which is understood as the time required by an average skilled operator, working at a normal pace, to perform a specified task using a prescribed method (Zandin, 2001), is the measure of their optimality.
In the time measurement method, the standard time is the product of the following factors (Aft, 2000; Niebel, Freivalds, 2008) observed time (the time to complete the task is measured) and performance rating factor (the pace the person is working at. 70–95% is working slower than normal, 105–120% is working faster than normal, 100% is normal and paces lower than 70 and higher than 120% are out of scope for the analysis. This factor is estimated by an experienced worker who is trained to observe and determine the rating).
Predetermined Time and Motion Study (PMTS) methods are typically used to estimate the standard times of operations before their execution (Cohen, Singer, Golan, Goren-Bar, 2013).

Subjective estimates of times are focused on time setting with an experienced worker. Research by Chan and Hoffmann (2013; 2016) showed that people can estimate task times with reasonable accuracy (Cohen, Singer, Golan, Goren-Bar, 2013).
There is a gap in time standard setting methodology. Methods used so far depend on human experience, so it is necessary to support this field of data analysis using intelligent methods, such as artificial neural networks (ANN), which can be used regardless of the experienced worker.
Standard time is an important characteristic of a manufacturing system. It can be defined as a combination of humans, machinery, and equipment that are bound by a common material and information flow (Caggiano, 2014). Based on this definition, factors affecting time standards in assembly processes were determined.
The standard time depends on the product and manufacturing characteristics and comes from different sources. Methods useful in product and manufacturing data determination were discussed by Molloy et al. **(Molloy, Warman, Tilley**, 1998) who used Quality Function Deployment (QFD) to support the determination of data from customer requirements, used CAD for the product data characteristics, and applied Failure Mode and Effect Analysis (FMEA) to support the product and manufacturing quality. Eigner et al. (Eigner, Ernst, Roubanov, Deuse, Schallow, Erohin, 2013) created a model in which the process planning know-how is described using product assembly information classified into the following categories: information to be saved and automatically detected in CAD, information to be selected during product development and information to be added during assembly planning.
The proposed approach is focused on creating standard time for standard manual and machine-manual operations, taking into consideration product characteristics and typical tools, equipment and layout.
The analysed features include:

- Information determined during product development (e.g. from CAD software)
    - product structure and part characteristics (e.g. weight, size)
    - connection type
- Information determined during assembly planning
    - Tools (e.g. hand screwdriver, power screwdriver, pliers)
    - Equipment (e.g. press, heater)
    - Workstation layout (e.g. distances, feeding method)

Collecting data is focused on standard time setting with correlation to the factors affecting it. The factors can be analysed according to the object-attribute-value (OAV) framework, in which the object is understood as an entity being described, an attribute is a feature characterizing a given object, and value is the measure of a given attribute. The assembly process analysis can use factors affecting the standard time, which are presented in Fig. 1 (see Kutschenreiter-Praszkiewicz, 2020).

There is a gap in the standard assembly time setting methods useful in an early stage of product development. This paper aims to provide an approach for the standard assembly time setting, which extracts information from a CAD product model and standard assembly workstation characteristics. The standard product assembly sequences, fixtures and constraints are defined.

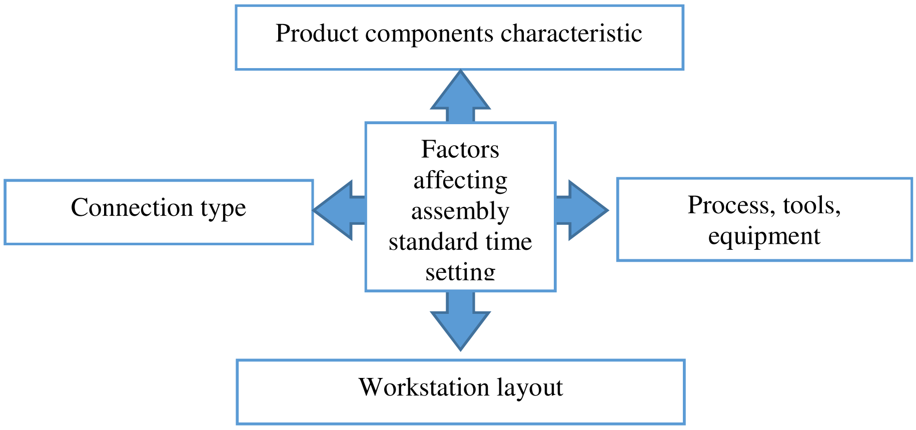

Figure 1. Factors affecting the standard time of an assembly process

2. Proposed approach

The proposed approach is focused on a standard assembly time setting method that is fast, precise, and adequate for a given group of products. The approach consists of four main blocks, as presented in Fig. 2. The first block is focused on extracting information from a CAD product model, such as dimensions, weight, shape, etc. The second block addresses decomposition of the assembly operation and defines tasks that allow successful assembly of the product. The third block addresses the assembly workstation characteristics, which include workstation layout and fixtures ordered according to the ergonomic requirements. The fourth block combines the information fixed in the previous blocks with the standard assembly time, which comes from, e.g., a time study or predetermined motion time system. This block is focused on the development of training, testing and verification sets and creates the ANN structure, which transforms the data from blocks 1 through 3 into the standard time.

2.1. Information extraction from a CAD product model

The product model is developed by managing the product structure and specifying the product geometric information (Demoly, Yan, Eynard, Rivest, Gomes, 2011). From the standard assembly time point of view, the product part dimensions, their weight and the part assembly sequence are crucial issues.

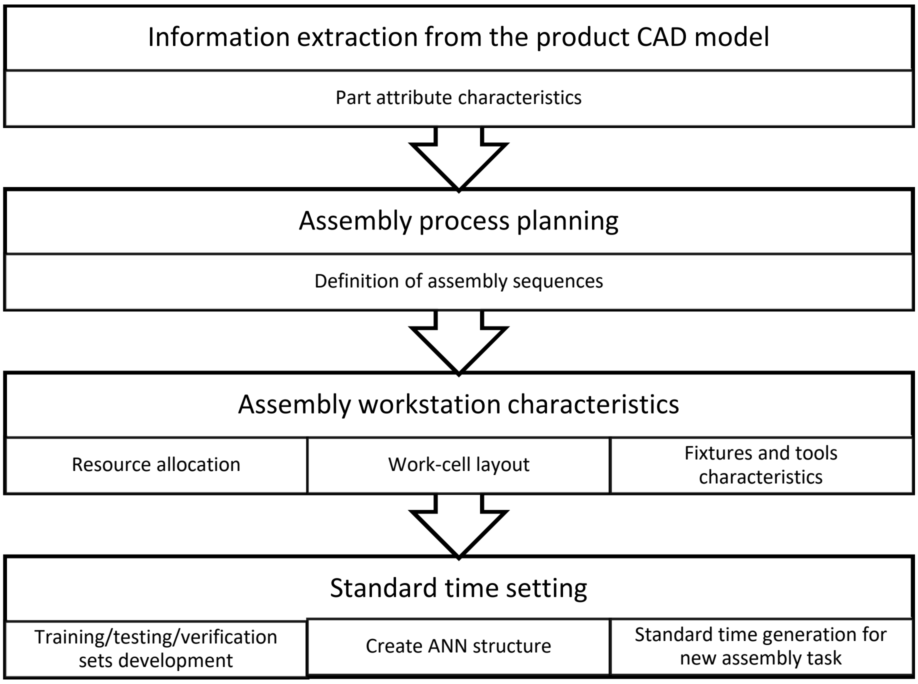

Figure 2. Standard assembly time setting in the early stage of product development for a mechanical product

Mane et al. (Mane, Jonnalagedda, Dabade, 2019) combined product features, such as weight, volume and length, from the CAD model with the part name and connection type between two elements.

The connecting elements are crucial data affecting the standard time of the assembly and disassembly process. A connecting element can be classified into the following categories (Eigner, Ernst, Roubanov, Deuse, Schallow, Erohin, 2013; Albers, Sauer, Steinhilper, 2008):

- Detachable (without destruction of the connecting elements): screw, pin, bolt, cone connection, press connection, profile,
- Detachable (with destruction of the connecting elements): rivets, clip connection,
- Non-detachable: soldering, sticking, welding.

The assembly sequence information extraction method from a CAD product model can be based on the graph described by Trigui et al. (Trigui, Ben Hadj, Aifaoui, 2015), Belhadj et al. (Belhadj, Trigui, Benamara, 2016), Hadj et al. (Hadj, Belhadj, Gouta, Trigui, Aifaoui, Hammadi, 2017), Mateus et al. (Mateus, Claeys, Lim`ere, Cottyn,·Aghezzaf, 2019) and Mane et al. (Mane, Jonnalagedda, Dabade, 2019) or from a simulation in virtual reality (VR), as described by Hongmin et al. (Hongmin, Dianliang, Xiumin, 2010), Xiong et al. (Xiong, Wang, Huang, Xu, 2016), Zaeh et al. (Zaeh, Wiesbeck, Stork, Schubo, 2009), and Gao et al. (Gao, Shao, Liu, 2016).

According to the graph method, a liaison graph was applied for determining assembly sequences and subassembly identification. According to Swain et al. (Swain, Sen, Gurumoorthy, 2014), the liaison graph is defined as a set of geometric entities on the parts being assembled and relationships between these geometric entities. The liaison graph is a graphical network where nodes represent parts and lines between nodes and edges represent certain user-defined relationships between parts, physical contact or connections between components (Whitney, 2004; Hu, Ko, Weyand, ElMaraghy, Lien, Koren, Bley, Chryssolouris, Nasr, Shpitalni, 2011). An example of the liaison graph built for a subassembly (Fig. 3, Fig. 4) is presented in Fig. 5.

Figure 3. Subassembly

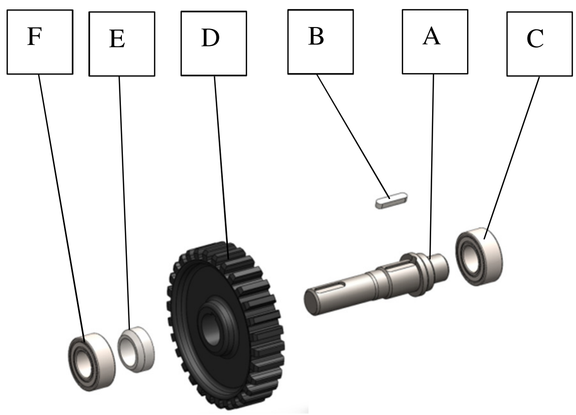

Figure 4. Subassembly components

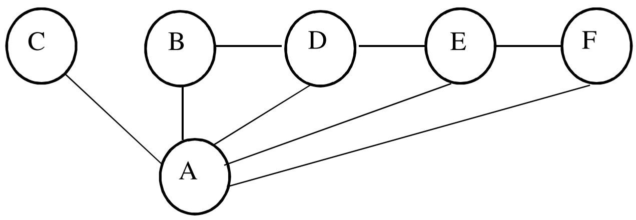

Figure 5. An example liaison graph

Liaisons have been used in manufacturing planning research as a means to capture the mating relationship between parts in an assembly. Various types of liaisons were analysed by Swain et al. (Swain, Sen, Gurumoorthy, 2014). The geometric entities associated with the liaison on each part could be either edges, faces or features of that part.

According to Swain et al. (Swain, Sen, Gurumoorthy, 2014), various types of liaisons include lap, butt, T, corner and edge joints, which can be assembled using welding or glutting, and lap joints with holes through both plates, which can be assembled with the use of riveting or bolt fastening. The schematic diagram of associativity between the product and production process models was presented by Swain et al. (Swain, Sen, Gurumoorthy, 2014).

Based on the liaison graph or liaison matrix, which was derived from a liaison graph or connections, it is possible to develop different product assembly variants. Methods used to find the best assembly sequence were discussed by Ghandi and Masehian (2015), Jiménez (2013) and Fanga et al. (Fanga, Onga, Neea, 2014).

An augmented version of the liaison graph, such as DFC (Datum Flow Chain), was developed by Mantripragada and Whitney (1998) who added information about the type of contact between parts (defined by their geometry), the type of connection associated with given contacts (glue, screw, pressure fit, etc.), and attributes of all the parameters in the assembly.

A single assembly sequence can be represented by an assembly tree, whose nodes represent partial assemblies occurring during the assembly process, the root node is the final assembly, and the leaves are the single parts (Jiménez, 2013).

Product features and types of mating conditions between different parts of the assembly were analysed using the liaison graph by Mane et al. (Mane, Jonnalagedda, Dabade, 2019).

2.2. Assembly process planning

Process planning maps the world of design ideas to production reality (Mantripragada, Whitney, 1998). The issue of assembly process planning was discussed by Kardos et al. (Kardos, Kova, Vancza, 2017), who defined assembly sub-problems, such as technology, fixturing, tooling, collision detection, part stability, quality, ergonomics, etc., and proposed the rule-based approach to finding a proper assembly technology.

In the proposed framework, the following constraints should be taken into consideration:

- Types of connections, including typical solutions, e.g. screwing, pressing, sticking.
- The assembly process can be analysed with movements such as:
  - Picking up a component.
  - Connecting two components.
  - Putting down a component.
- Fastening tools include, among others:
  - Hand fastening tools (manually operated assembly tools): hand wrenches, hammers, pliers, a woodruff key, an Allan key, screwdrivers,
  - Power fastening tools (electrically powered, air-driven): power drills, electric screwdrivers, electric nut runners.

Tools and fixtures can be included in the extended liaison graph (ELG) described by Kardos et al. (Kardos, Kova, Vancza, 2017), where tool-to-part and fixture-to-part contacts are represented as edges. An example is presented in Fig. 6.

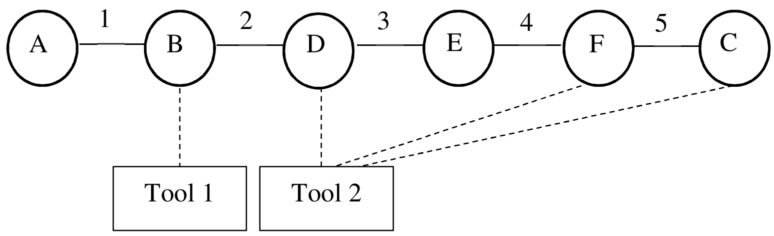

Figure 6. An example of an extended liaison graph (ELG)

Another approach was presented by Mane et al. (Mane, Jonnalagedda, Dabade, 2019) who use CAD data that was automatically extracted and converted into useful knowledge (matrices and configurations). They showed that the Hierarchical Directed Graph (HDG) can be effectively used for activities like assembly sequence planning and can be further enriched with some more information, like required tools, jigs, fixtures, handling equipment, assembly time and cost of each part.

The assembly process can be analysed using the following activity:

- Picking up a component, which depends, for example, on the variables presented in Fig. 7.
- Assembly – connection of two components.
- Putting down a component.

The time standard for the "picking-up" activity was calculated as the collective time of reaching, grasping and moving using the MTM (Method Time Measurement) method. The attributes that characterise the "picking-up" activity were related to the workpiece characteristics, as well as workstation characteristics. Data pre-processing was discussed by Kutschenreiter-Praszkiewicz (see Kutschenreiter-Praszkiewicz 2018).

2.3. Assembly workstation characteristics

The following assumption of workstation characteristics should be taken into consideration during assembly planning (Lien, 2018; Shinde, Jadhav; 2012):

- Product parts should be suitable for grasping and holding.
- Workstation layout should provide small distances for material handling.
- If necessary, assistance for heavy material handling should be available.
- Eye and body movements and stressed body postures should be reduced.
- Fixtures and tools should be easy to use.

The detailed characteristics of the assembly process of two parts (Fig. 7) are presented in Fig. 8 (see Kutschenreiter-Praszkiewicz, 2020).

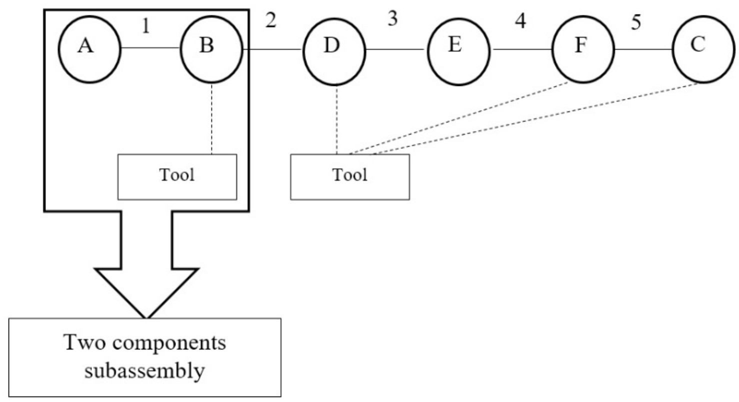

Figure 7. Subassembly in ELG

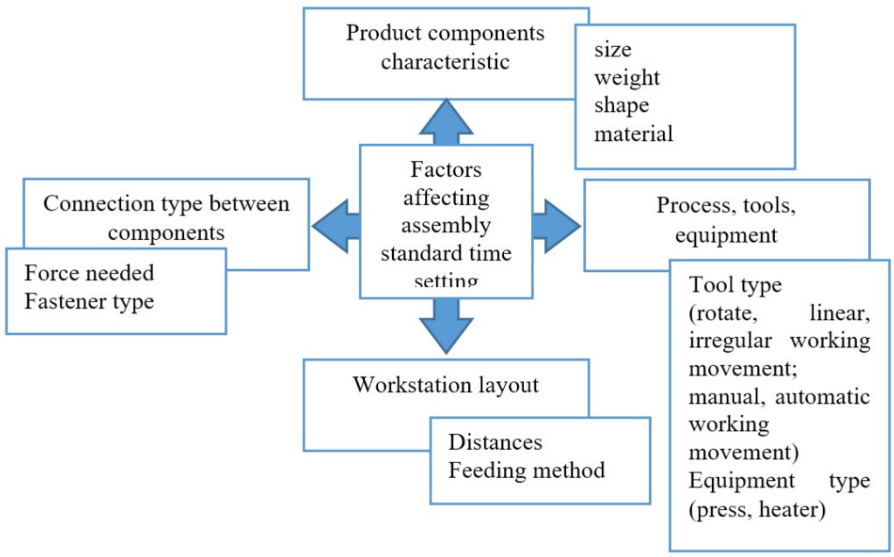

Figure 8. Factors (attributes) affecting standard assembly time of two components

The number of variables affecting the time standard is quite large, so it is necessary to use methods that can analyse such a complex process. ANN can be used in this field.

2.4. Standard time setting using ANN

ANN is a promising prediction tool (see Kuo Y, Lin K-P(2010)). ANN is composed of interconnected adaptive elements called neurons, which can respond to a given stimulus like the human brain. ANN is an interconnected group of artificial neurons that have the property of storing knowledge and making it available for use (Renuga Devi, Arulmozhivarman, Venkatesh, Agarwal, 2016). Studies on machine learning have mainly been concerned with automatic learning on examples, which allows developing the knowledge (Wang, 1999; Hayashi, Setino, Azcarraga, 2016; Jiang,

Jiang, Xu, Huang, 2017; Liu, Wang, Liu, Zeng, Liu, Alsaadi, 2017). The basic elements of ANN are synapses, which are responsible for signal transfer between neurons, an adder, which sums all the signals in a neuron, and activation functions, which are responsible for the neuron output. By using a learning algorithm and a given set of training examples, the weights representing a connection between neurons can be modified to minimize the difference between ANN predicted outputs and those that are in the training set. Different learning algorithms can be used.

The most widely studied supervised learning method is the feedforward neural network, in which a model is refined during the learning process (Wang,1999). Multi-layer perceptron (MLP) training, which is a class of feedforward neural network, is focused on minimizing the error between the training data set and the corresponding MLP network output by finding optimum values for the weights assigned to the neural connections (Roy, Koeppen, Ovaska, Furuhashi, Hoffmann, 2002).

Various researchers have applied many ANN models. Fernandez et al. (Fernandez-Delgado, Reboreda, Cernadas, Barro, 2010) used MLP and radial basis functions (RBF) to predict the performance times of production tasks. Chen et al. (Chen, Wang, Tsai, 2009; Chen, 2008; Chen, 2012) proposed a hybrid approach involving a self-organization map and fuzzy backpropagation network, where the cycle time prediction by the processing time and reliability ratio was predicted using a linear ANN (Kutschenreiter-Praszkiewicz, 2013).

This research is focused on predicting standard assembly time future values based on the values found using the predetermined motion time system. The predetermined motion time system is time-consuming, so it is necessary to apply a more efficient approach, such as ANN. The development of an ANN assembly process model can be based on the following steps:

- Development of training, testing, and verification data sets.
- Finding the best ANN structure to model the assembly process.

MLP is a well-known artificial neural network used for classification and regression, among other things, (Young, Tsai, 1994). A multi-variable regression MLP model of a given process is composed of a selected number of input and output neurons and neurons in hidden layers. The MLP approach presented in this article involves assembly standard time as the network output and work characteristics as the ANN input.

The number of ANN inputs can be established using sensitivity analysis, which indicates the error and regression ratio caused by removing a given ANN input.

The number of neurons in the hidden layer must be large enough to form a decision region that is as complex as required by the given issue (Roy, Koeppen, Ovaska, Furuhashi, Hoffmann, 2002). A wrong decision related to the ANN model (irrelevant inputs, too many hidden layers or neurons, an insufficient amount of training data, etc.) can cause ANN overfitting and deteriorate generalization capability (Wang, 1999).

2.4.1. Development of training, testing, and verification data sets

The standard time can be determined using methods such as a time study or predetermined motion time system (e.g. MTM, Work-Factor, MOST). A time study is focused on time measurement to complete the task and determine the performance rating factor. In MTM, the manual operations are broken down into standard movement elements like reach, grasp, move, position, realize, etc. Furthermore, the movement distance, weight of the handled object, precision of grasping and positioning, and the effect of simultaneous operation of two hands are considered. The time required to perform the different handling subtasks is described in tables (Lien, 2018; Zaeh, Wiesbeck, Stork, Schubo, 2009). Using MTM is time-consuming and a time study needs skilled workers to perform the assembly task, so there is a gap in the methods for standard time setting. In the presented approach, ANN was proposed for the standard assembly time setting.

Data acquisition is focused on obtaining the training, testing and verification data sets (Zhou, Duan, Huang, Cao, 2014; Roy, **Koeppen, Ovaska, Furuhashi, Hoffmann,** 2002). AI technologies can include knowledge bases, fuzzy logic and decision trees as well as neural networks (Yang, Wu, Zhu, Bao, Wei, 2013; Shiue, Guh, 2006; Priore, De La Fuente, Gomez, Puente, 2001). AI application for assembly planning needs feature modelling useful in automating the experience-based reasoning. Feature (attribute) analysis and conversion is an essential element for AI application. In the proposed approach, the assembly process is represented by the OAV scheme, in which an object is associated with a set of attributes and each attribute is described by appropriate values. The OAV scheme gives a concise data structure for organising the features of a selected process (Young, Tsai, 1994).

Development of a training set applies the OAV framework and assembly analysis. The OAV framework uses information to be saved in CAD, such as component type and characteristics, and information to be added in assembly planning, like workstation layout, tools, and equipment (Table 1). Attributes can be classified as constant or variable. Constant attributes can be used for product, tool, and layout descriptions, whereas variable attributes can be applied for a given assembly process description. Examples of constant attributes are shown in Table 2 and examples of variable attributes are presented in Table 3.

An ANN is established using a set of training samples, including attributes and their values. The training examples can be generated by simulations or by a real production system.

2.4.2. Finding the best ANN structure to model the assembly process

One of the most commonly used neural networks is MLP (Zhang, Gupta, 2000). In the MLP structure, neurons are grouped into layers. The first layer is called the input layer, the last layer is called the output layer, and the remaining layers are called hidden layers. The number of layers and neurons in the MLP structure determines its learning capability. ANN should be trained to represent any given issue behaviour. During the training process, the weighted connections between neurons are changed until, finally, a model of the given issue is created. The ANN structure depends on the modelled issue. Too many hidden neurons may lead to overlearning of the neural network. Experience can help determine the number of hidden neurons, or the optimal size of the network can be obtained through a trial and error process (Lee, An, Tsung, 2005).

Table 1. Two-part product assembly information

Product assembly information (two components assembly)			Information source
Object	**Attribute**	**Value**	
Components characteristics	Weight		Information to be saved in CAD
	Size		
	Shape		
	Material		
Connection type	Force needed		
	Fastener type		
Workstation layout	Distance		Information to be added in assembly planning
	Way of feeding		
Process, tools, equipment	Tool		
	Additional treatment		

Table 2. Examples of constant attributes

Product, tool, layout		Constant attributes
Attribute	**Value**	
Distance for picking up the first part	Small (less than 20 cm)	
	Medium (20–80 cm)	x
	Large (over 80 cm)	
Distance for picking up the second part	Small (less than 20 cm)	
	Medium (20–80 cm)	x
	Large (over 80 cm)	
Distance for putting down the subassembly	Small (less than 20 cm)	
	Medium (20–80 cm)	x
	Large (over 80 cm)	
Material	Flexible, fragile	
	Inflexible	x

Force needed	Low force	x
	High force	
Additional treatment	No	x
	Yes	

Table 3. Examples of variable attributes.

Product, tool, layout		**Variable attributes**
Attribute	**Value**	
Diameter	Min 50	x
	Max 210	x
Hitting	Yes	x
	No	x
No of bearings heating concurrently	Min 0	x
	Max 6	x
Tool	No	x
	Manual	x
	Automatic	

3. Implementation – empirical illustration

The case study was focused on predicting a bearing standard assembly time according to the proposed approach and a gully assembly time prediction. The analysed subassemblies were presented in ELG liaison graphs in Figs. 9 and 12.

In the bearing assembly example (Fig. 10), the training set included three inputs, bearing internal diameter (BID), the number of bearings heated concurrently (HC) and additional treatment (H). The ANN output is the standard assembly time calculated using a predetermined motion time system. The best ANN structure was found and a comparison of ANN structures is presented in Table 4. The ANN structure for the best training results with the lowest number of errors is presented in Fig. 10. The ANN response surface is presented in Fig. 11. The ANN output characteristics for the chosen network are presented in Table 5 and the training set analysis is presented in Table 6.

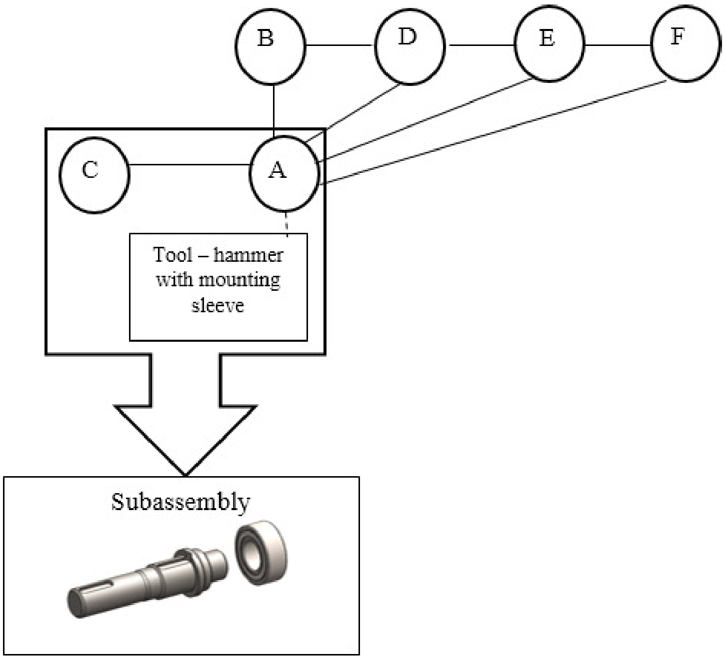

Figure 9. Subassembly analysed using ELG

Table 4. ANN comparison

No	ANN type	Number of inputs	Number of neurons in hidden layer 1	Number of neurons in hidden layer 2	Error in the training set	Error in the verification set	Error in the testing set	Performance in the training set
1	MLP	4	4	-	26.96598	42.66782	12.18509	0.07146
2	MLP	3	2	4	16.97517	35.34161	73.71668	0.1573405
3	MLP	2	3	3	114.735	28.04009	59.5909	0.2056696
4	MLP	4	8	5	56.22999	26.82816	19.18051	0.03061
5	MLP	4	4	-	193.9325	22.05249	80.06191	0.8643352
6	MLP	3	6	-	10.28764	21.96066	36.39989	0.09288
7	MLP	3	2	4	57.56206	21.49768	34.69016	0.2973801
8	MLP	3	3	-	104.6278	13.32886	51.16594	0.1858983
9	MLP	3	2	4	233.7202	11.32592	176.7063	0.9712075
10	MLP	3	6	-	22.36137	6.722654	13.65985	0.09359

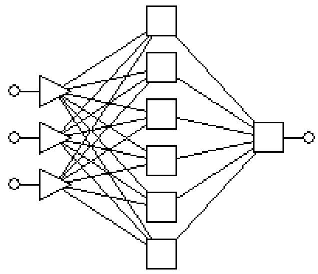

Figure 10. ANN structure

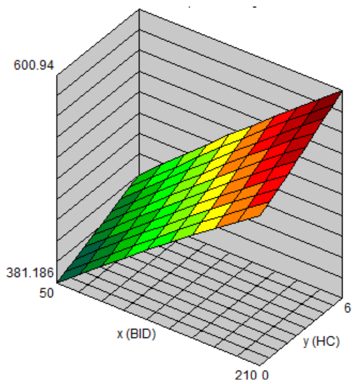

Figure 11. Response surface

Table 5. ANN output characteristics

Predicted ST	Training ST	Error ST	Error [%]
391.5754	385	6.57536	0.02192
588.8881	554	34.88813	0.11629
525.1548	505	20.15485	0.06718
552.3402	566	-13.65985	0.04553
727.2773	734	-6.722654	0.02241
703.2617	685	18.2617	0.06087

Table 6. ANN training set analysis

Indicator	Tr ST
Data Mean	532.25
Standard Data Deviation	124.138
Error Mean	19.97
Error Standard Deviation	11.6178
Abs Error Mean	19.97
Standard Deviation Ratio	0.09359
Correlation	0.9968815

In the presented approach, a sensitivity analysis was done and the most important attributes in the training set were found. The results of the sensitivity analysis are presented in Table 7. As a result of the sensitivity analysis, three important attributes were established: the first one is the “bearing internal parameter” with the training set error of 74.52644 and regression ratio of 3.332821; the second is the “heating”, with the training set error of 71.54082 and regression ratio of 3.199304, the third is the “number of bearings heated concurrently” with the training set error of 21.41731 and regression ratio of 0.9577815.

Table 7. ANN input characteristics - sensitivity analysis

	ANN Inputs		
	BID	**HC**	**H**
Rank for the training set	1	3	2
Error for the training set	74.52644	21.41731	71.54082
Regression ratio for the training set	3.332821	0.9577815	3.199304

Ten variants of the ANN configuration were compared and the network with the best performance was found. A comparison of the tested networks, Table 5, used error and performance (regression ratio) as the comparison criteria. Different MLP ANN structures were compared with different numbers of neurons in layers. The best network had 6 neurons in the hidden layer, three neurons in the input layer, and one in the output layer. The best network, Fig. 10, had a very good performance (regression ratio is 0.09359, correlation is 0.9968815). The root mean square (RMS) error was 19.97 for the training set. The data mean values number was 532.25 for the training set.
In the gully assembly example, Fig. 13, the training set was created with the use of MTM method.

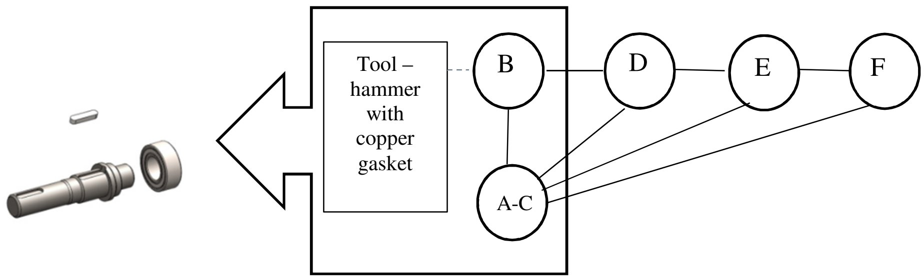

Figure 12. Subassembly analysed using ELG

The inputs of the neural network included attributes:
- Number of gullies.
- Weight of subassembly.

The output of NN is the time standard.

The best ANN structure was found and a comparison of chosen ANN structures is presented in Table 8. The ANN output characteristics for the chosen network is presented in Table 9 and the training set analysis is presented in Table 10.

Table 8. ANN comparison

No	ANN type	Number of inputs	Number of neurons in hidden layer 1	Number of neurons in hidden layer 2	Error in the training set	Error in the verification set	Error in the testing set	Performance in the training set
1	RBF	1	2	0	3	6.5	9.2	0.06
2	RBF	1	1	0	0.4	35.7	51.5	0.02
3	RBF	1	1	0	8.4	17.9	22.9	0.18
4	MLP	1	1	0	0.4	11.3	15.1	0.02
5	MLP	1	2	0	5.5	7.1	8	0.04
6	MLP	1	7	0	4.8	5.3	4.5	0.03
7	MLP	1	11	0	3.7	5.1	5.7	0.04
8	MLP	2	7	0	5.8	4.9	3.2	0.05
9	Linear	2	0	0	0.3	0.8	0.2	0.01
10	Linear	1	0	0	0.4	0.2	0.6	0.02

Table 9. ANN output characteristics

Predicted ST	Training ST	Error ST	Error [%]
38.3	39	-0.66	0.019
38.3	38	0.33	0.009
38.3	38	0.33	0.009
72	72	0	0
72	72	0	0
105.6	105	0.66	0.019
105.6	106	-0.33	0.009

Table 10. ANN training set analysis

Indicator	Tr ST
Data Mean	46.75
Standard Data Deviation	16.83
Error Mean	1.77
Error Standard Deviation	0.47
Abs Error Mean	0.33
Standard Deviation Ratio	0.02
Correlation	0.99

Ten variants of the ANN configuration were compared and the network with the best performance was found. A comparison of the tested networks, Table 10, used error and performance (regression ratio) as the comparison criteria. Different ANN structures were compared with different numbers of neurons in layers. The best network had a very good performance (regression ratio is 0.02, correlation is 0.99).

The root mean square (RMS) error was 1.77 for the training set. The data mean values number was 46.75 for the training set.

4. Results and discussion

The present study concerned developing an approach for predicting standard assembly time. The proposed standard time prediction can be useful for product variant assessment at an early stage of product development. In the proposed approach, the standard assembly time was predicted using an ANN.

This study aimed to develop an approach for setting standard assembly time that is easy to use and sufficiently precise. The main contribution of this research is the holistic identification of product and manufacturing assembly characteristics that are useful in predicting the standard assembly time. In this research, an ANN was applied as the prediction tool. Data that is easy to obtain in an enterprise was used for experiments. The industrial application of the proposed approach was presented in the case study. Product and process engineers are likely users of the proposed approach.

In the presented approach, an OAV framework was applied, where the object is interpreted as a group of assembly factors, attributes were analysed as a set of variables that influence the standard assembly time, and attributes can assume particular values that can be qualitative or quantitative. In the case study, different ANN variants were compared as tools for predicting the standard assembly time. The best ANN, with a very good performance, was found.

5. Conclusion

There is a gap in the standard assembly time setting methods useful during an early stage of product development. ANN can be successfully applied for standard time setting in the assembly process. The development of an ANN model for the assembly process can be based on the following steps: developing training, testing and verification sets and finding the best ANN structure, which is the assembly process model. The assembly process was analysed and features (attributes) that influence the standard time were selected. The attributes were divided into the following categories: workstation layout attributes, such as distances and feeding method; connection type between components, such as fastener type and force needed; product component characteristics, such as size, weight, shape and material; and tools and equipment, such as tool type and equipment type. The features that influence the standard time can be divided into two main categories, constant and variable attributes. Constant attributes have the same value for the whole assembly process and can be used for process characteristics. Variable attributes are different for various assembled products. An ANN training set can be created using attributes that have a value variable. Predetermined motion time systems are useful methods of setting the standard time for the development of ANN training set.

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