Standard Assembly Time Setting in an Early Stage of Product Development

Izabela Kutschenreiter-Praszkiewicz

University of Bielsko-Biala / Willowa 2, 43-300 Bielsko-Biała, Poland

Standard assembly time is an important piece of data in product development that is used to compare different product variants or manufacturing variants. In the presented approach, standard time is created with the use of a decision tree regarding standard manual and machine-manual operations, taking into consideration product characteristics and typical tools, equipment and layout. The analysed features include, among others: information determined during product development, such as product structure, parts characteristics (e.g. weight, size), connection type, as well as the information determined during assembly planning: tools (e.g. hand screw driver, power screw driver, pliers), equipment (e.g. press, heater), workstation layout (e.g. distance, way of feeding). The object-attribute-value (OAV) framework was applied for the assembly characteristic. An example of the decision tree application to predict standard assembly time was presented for a mechanical subassembly. The case study was dedicated to standard time prediction for a bearing assembly. The presented approach is particularly important for the enterprises which offer customized products.

1. Introduction

Standard time is the time required by an average skilled operator, working at a normal pace, to perform a specified task using a prescribed method [1]. Standard time is widely used in industrial engineering for workforce planning, line balancing, production system simulation, cost accounting etc. Standard time can be determined with the use of many techniques, including: time study, predetermined motion time system, standard data system or work sampling. Time standards are the basic data in ERP (Enterprise Resource Planning) systems. There is a gap in time standard setting method which can be effectively used for new product planning in ERP systems. The article presents decision tree application and rules induction focused on time standard setting for new product assembly in a production process. Time standard is especially important in assembly planning for manual and machine-manual operations. Authors [2][3] have focused their research on establishing an assembly information model to integrate product information from CAD model with assembly manufacturing information. The main difficulties are related to assembly complexity and plenty of data.

2. Time standard setting – the proposed approach

The proposed approach of time standard prediction for assembly tasks of a new product is based on the following steps:

- Decomposing the assembly process into subassemblies
- Calculating time standards for typical subassemblies,
- Assigning time standards to classes,
- Developing a training set with attributes and values characterising subassemblies,
- Building a decision tree,
- Formulating decision rules for assembly time standard prediction.

2.1. Decomposition of the assembly process into subassemblies

In the first step of the proposed approach focused on assembly process decomposition, it is possible to use the graph theory. According to literature review, two widely used methods for assembly problem decomposition are the graphs of precedences for assembly and disassembly, and the graph of connections between components [4] (liason graph), which is parcilularly useful.

2.2. Calculation of time standards for typical subassemblies

The next step in the proposed approach is time standard calculation. The following methods can be used to determine time standards [5]:

- Estimation
- Historical records
- Work measurement technique (time study, predetermined motion time systems, standard data system, work sampling)

The most useful methods of time standards calculation for typical subassemblies are time study or predetermined motion time system.

2.3. Assignment of time standards to classes

A catalogue of typical assembly operation can be used in the proposed approach. Standard time for classes can be created basing on the equation (1).[6]

$$w_j = \frac{e\sqrt{12T_m(t_n)_j}}{196} \qquad (1)$$

Where:
w_j- the width of the *j* class
e- accuracy at the confidence level of 95%
T_m- settlement period
$(t_n)_j$-time standard for *j* class
Each typical assembly task should be assigned to the appropriate class.

2.4. Development of a training set

In the proposed approach, the assembly process is represented by the object-attribute-value 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 [7]. The main attributes affecting assembly standard time are presented in Figure 1. [2]
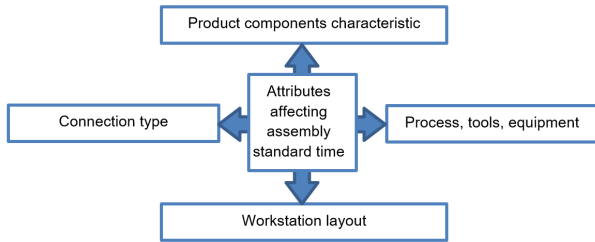

Figure 1. Attributes influencing assembly standard time

Based on the OAV framework, a training set can be created (Tab. 1).

Table 1. A training set

Attributes charactering assembly process (values)				Decisions (classes)
$A_1(v_1,..,v_n)$	$A_2(v_1,...,v_m)$	...	$A_k(v_1,..,v_z)$	$C_1,..,C_j$

The values in a training set can be divided into intervals according to the following method:

The number of intervals i_p in a training set for a given attribute can be calculated according to the formula (2) [6].

$$i_p = \frac{\log t_{max} - \log t_{min}}{\log q} \qquad (2)$$

Where:
t_{max} – max of time standard
t_{min} – min of time standard
q – quotient calculated according to formula (3) [6]

$$q = \frac{1+e_t}{1-e_t} \qquad (3)$$

Where:
e_t – precision

Based on formulas (4) and (5), the intervals are fixed.

$$t_i = t_{min} \cdot q_s^i \qquad \text{dla} \quad i=1,2,...,i_p \qquad (4)$$

$$X_i = \frac{t_i - b}{a} \qquad \text{dla} \quad i=1,2,...,i_p \qquad (5)$$

Where:
q_s- quotient for a total number of intervals
a,b – coefficients in relation between x (variable – attribute being analysed) and t (time fixed according to the regression analysis).

2.5. Building a decision tree

Classical decision trees belong to popular classification models [8]. A decision tree is a graph which can be used as a model of a categorical variable (attributes). A decision tree aims at predicting a categorical (numerical or linguistic) output variable from a set of numerical or linguistic input variables [9]. Decision trees are useful in solving classification and prediction problems [10], [11]. The structure of a decision tree involves a root node, internal nodes, leaf nodes and edges which joint nodes, also called branches (fig. 1) [12].

The well-known calculations of the decision trees is ID3 [13][14] [8] which use the information gain which based on the probability theory (Shannon entropy).

ID3 algorithm steps includes:
- Calculating the entropy of every attribute using the data set according to (equation (6)),
- Splitting the set into subsets using the attribute (formula (7)) for which entropy is minimal (or, equivalently, information gain is maximal),
- Making a decision tree node containing that attribute,
- Recursing on subsets using the remaining attributes.

Entropy *I* is a measure of the amount of uncertainty in a data set (i.e. entropy characterizes a data set).

$$I = \sum_{i=1}^{n} (-p_i \log_2 p_i) \qquad (6)$$

Where:
p – proportion of the number of elements in a class to the number of elements in a set (probability that element from *i* class occurs)

$$I(C/A_k) = \sum_{j=1}^{M_k} p(a_k, j) \bullet \left[-\sum_{i=1}^{N} (p(c_i/a_{k,j}) \bullet \log_2 p(c_i/a_{k,j})) \right] \qquad (7)$$

Where:
M_k number of values taken by attribute A_k
N number of classes
k number of attributes
$p(a_k, j)$ probability that a_k takes value j
$p(c_i/a_{k,j})$ probability that class c_i occurs, when a_k=j
Information gain is calculated according to formula (8).

$$\Delta I(A_k) = I - I(C/A_k) \qquad (8)$$

Decision tree induction is closely related to rule induction; each path from the root of a decision tree to one of its leaves can be transformed into a rule [15], which is

one of the most popular approaches to knowledge representation.

2.6. Formulating decision rules

Rule-based systems are built around rules, which consist of an *if* part and a *then* part [16].
Rules, sometimes called IF-THEN rules, can take various forms e.g.:

- − IF condition THEN action
- − IF premise THEN conclusion

3. An example of time standard setting with the use of the proposed approach

An example relates to a bearing assembly in toothed gear subassembly. An example of the liaison graph built for a subassembly (Fig. 2) is presented in Figure 3.
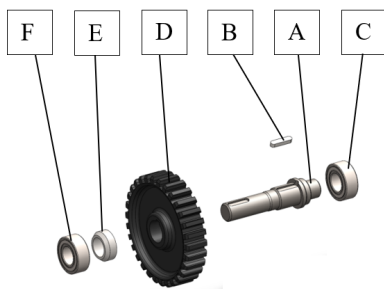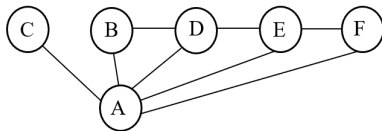

Figure 2. Subassembly

Figure 3. A Liaison graph

The connection A-C in the liaison graph was analysed. Bearing internal diameter BID, bearings heating concurrently HC and hitting H were the attributes taken into consideration. Standard time ST was calculated according to the predetermined motion time system and was divided into classes (tab. 2).

Table 2. ST classes definition

Class	Lower bound of the class [h]	Upper bound of the class [h]	Average value of the class[h]
A	0,00	0,15	0,07
B	0,15	0,32	0,23
C	0,32	0,49	0,41
D	0,49	0,67	0,58

The analysed attributes and theirs values were presented in table 3.

Table 3. The analysed data set

BID	HC	H	ST[h]	ST[s]	Class
60	0	No	0,106944	385	A
80	6	Yes	0,153889	554	B
50	2	Yes	0,140278	505	A
50	6	Yes	0,157222	566	B
200	6	Yes	0,203889	734	B
210	2	Yes	0,190278	685	B

Values of attributes BID and HC were divided into proper categories.

The BID analysis – intervals calculation (Fig. 4)

Ip= 1,591421
qs= 1,380758
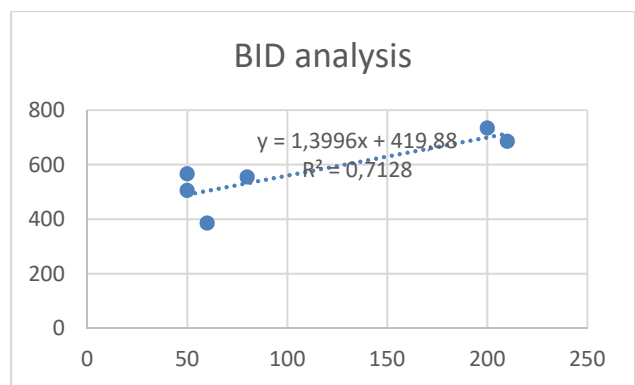t1= 532   x1= 79,81705
t2= 734   x2= 224,4356

Figure 4. The BID analysis

The HC analysis – intervals calculation (Fig. 5)

Ip= 1,591421
qs= 1,380758
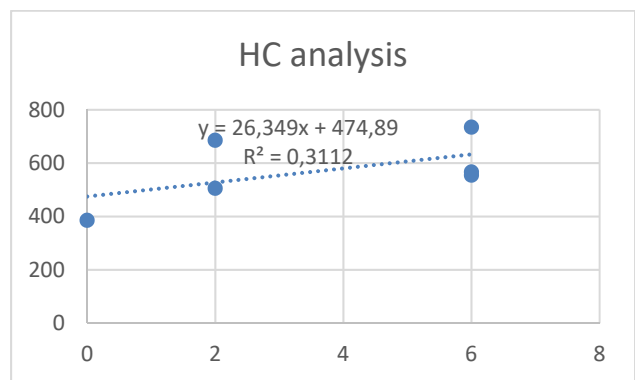t1= 532   x1= 2,167139
t2= 734   x2= 9,848951

Figure 5. The HC analysis

And finally the training set is presented in table 4.

Table 4. The training set

BID	HC	H	ST
<80	≤2	No	A
≥80	>2	Yes	B

<80	≤2	Yes	A
<80	>2	Yes	B
≥80	>2	Yes	B
≥80	≤2	Yes	B

Entropy calculation according to ID3 algorithm:

$$I = 0{,}918296$$
$$I(BID) = 0{,}540852$$
$$I(HC) = 0{,}540852$$
$$I(H) = -0{,}33333$$

The decision tree with the use of ID3 algorithm is presented in figure 6.
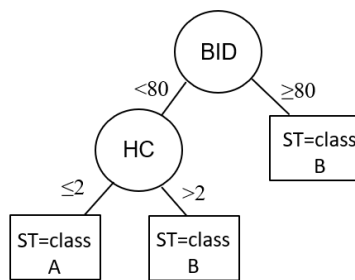

Figure 6. Decision tree

The rules inducted based on the decision tree are:
IF *BID<80 and HC≤2* THEN *ST=class A*
IF *(BID <80 and HC>2) or BID ≥80* THEN *ST=class B*

4. Conclusions

The presented approach is focused on time standard setting for assembly. The proposed rule based approach is useful in expert systems which can be joined with ERP systems. The proposed approach included the following steps: decomposing the assembly process into subassemblies, calculating time standards for typical subassemblies, assigning time standards to classes, developing a training set with attributes and values characterising subassemblies, building a decision tree, formulating decision rules for assembly time standard prediction which can be applied for assembly as well as for disassembly tasks. In the presented approach, it is especially important to identify the attributes which can be used in the modelled assembly process, and to divide the values into intervals. Too wide intervals can have a negative influence on the preciseness of the results. Too narrow intervals can cause difficulty in developing a decision tree which is easy to use. A decision tree can be updated when new cases in the training set are added.

Literature

[1] Zandin K.: Maynard's Industrial Engineering Handbook, Mc Graw-Hill, 2001
[2] Kutschenreiter I.: Neural network application for time standards setting in assembly and disassembly. Journal of Machine Engineering, 20 (3):106-116, 2020
[3] Chen Z., Bao J., Zheng X., Liu T.: Assembly Information Model Based on Knowledge graph. J.Shanghai Jiao Tong Univ. (Sci.), 25(5): 578-588, 2020
[4] Seabra Lopes L., Camarinha-Matos L.M.: Planning, Training and Supervision of Learning in Flexible Assembly Systems, in L. Camarinha-Matos et al. (eds.), Balanced Automation Systems, © Springer Science+Business Media Dordrecht, 1995
[5] Groover M.: Work Systems, Pearson, 2016
[6] Wołk R., Strzelecki T.: Badanie metod i normowanie pracy. Wydawnictwo Politechniki Warszawskiej, Warszawa, 1993
[7] Young, H. T., Tsai, D. H. An integrated expert operation planning system with a feature-based design model. International Journal of Advanced Manufacturing Technology, 9:305–310, 1994
[8] Wang X., Nauck D.D., Spott M., Kruse R.: Intelligent data analysis with fuzzy decision trees. Soft Computing, 11:439–457, 2007
[9] Voisine N., Boullé M., Hue C.: A: Bayes Evaluation Criterion for Decision Trees. Published in: F. Guillet et al. (Eds.): Advances in Knowledge Discovery and Management, SCI 292: 21–38. Springer-Verlag Berlin Heidelberg, 2010
[10] Micheal N.: Artificial intelligence: a guide to intelligence systems. Addison Wesley, Great Britain, 2002
[11] Zhou BH, Xi LF, Cao YS.: A beam-search-based algorithm for the tool switching problem on a flexible machine. The International Journal of Advanced Manufacturing Technology, 25(9–10):876–882, 2005
[12] Kuo Y., Lin K.-P.: Using neural network and decision tree for machine reliability prediction. The International Journal of Advanced Manufacturing Technology, 50:1243–1251, 2010
[13] Chandra I, Sivakumar N, Gokulnath CB., Parthasarathy P.: IoT based fall detection and ambient assisted system for the elderly. Cluster Computing volume 22:2517–2525, 2019
[14] Varadharajan R., Priyan M., Parthasarathy Panchatcharam K., Vivekanandan S.,· Gunasekaran M.: A new approach for prediction of lung carcinoma using back propagation neural network with decision tree classifiers. Journal of Ambient Intelligence and Humanized Computing. Springer-Verlag GmbH Germany, 2018
[15] Rokach L., Maimon O.: Decision Trees. Data Mining and Knowledge Discovery Handbook. Springer US, 2005
[16] Chryssolouris G.: The Design of Manufacturing Systems. In: Manufacturing Systems: Theory and Practice. Mechanical Engineering Series. Springer, New York , 2006