Journal of Machine Engineering, 2018, Vol. 18, No. 2, 31-40
ISSN 1895-7595 (Print) *ISSN 2391-8071 (Online)*

Received: *09 November 2017* / Accepted: *15 February 2018* / Published online: *25 June 2018*

time standard, human activity,
SMED, artificial neural network

Izabela KUTSCHENREITER-PRASZKIEWICZ[1*]

MACHINE LEARNING IN SMED

The paper discusses Single Minute Exchange of Die (SMED) and machine learning methods, such as neural networks and a decision tree. SMED is one of lean production methods for reducing waste in the manufacturing process, which helps to reorganize a conversion of the manufacturing process from current to the next product. SMED needs set-up activity analyses, which include activity classification, working time measurement and work improvement. The analyses presented in the article are focused on selecting the time measurement method useful from the SMED perspective. Time measurement methods and their comparison are presented in the paper. Machine learning methods are used to suggest the method of time measurement which should be applied in a particular case of workstation reorganization. A training set is developed and an example of classification is presented. Time and motion study is one of important methods of estimating machine changeover time. In the field of time study, researchers present the obtained results by using (linear) multi-linear regression models (MLR), and (non-linear) multi-layer perceptrons (MLP). The presented approach is particularly important for the enterprises which offer make-to-order products. Development of the SMED method can influence manufacturing cost reduction of customized products. In variety oriented manufacturing, SMED supports flexibility and adaptability of the manufacturing system.

1. INTRODUCTION

The manufacturing process is constantly changing. Products are offered in many variants prepared according to customer requirements. Researchers, e.g. Gorski et.al. [1] discuss configurable products manufacturing process and notice that “a measure of flexibility of a manufacturing system is its capability of performing various tasks, as well as time at which it can be prepared for a new task (the shorter the better)”. Product configuration according to customer needs requires production process flexibility which allows it to use intelligent techniques supporting data analysis in enterprises in different fields of application. Application of intelligent techniques has been considered by many authors, e.g. by Uhlmann et. al. [2], who discuss intelligent production systems. Jedrzejewski et al. [3] discuss intelligent function in diagnosing machine tools.

Production process flexibility can be supported by SMED, which reduces changeover time. SMED can be supported by intelligent methods, such as NN and the graph theory, in setting changeover time standard.

[1] University of Bielsko-Biala, Bielsko-Biala, Poland
[*] E-mail: ipraszkiewicz@ath.bielsko.pl.
DOI: 10.5604/01.3001.0012.0923

2. REDUCING CHANGEOVER TIME - THE SMED APPROACH

Changeover time is defined as the period between the last good product from previous production order leaving the machine and the first good product coming out from the following production order [4-6]. Goubergen et al. [7] indicated three main reasons why changeover time reduction initiatives can be appropriate for any company:

– to increase flexibility by conducting more changeovers and reducing lot size;
– to increase bottleneck capacities in order to maximize line availability for production, and
– to minimize the cost, since production costs are related to equipment effectiveness [6].

SMED needs set-up activity analyses, which include:

– activity classification,
– time standard setting, and
– work improvement.

Shingo claimed that SMED is a scientific approach to set-up time reduction that can be applied in any factory to any machine. Shingo [8] bases his method on categorizing all set-up activities into internal and external ones, with internal activities being the ones that can be performed only when the machine is shut down, and external being those that can be conducted during normal machine operation, when it is still running. These internal and external set-up activities involve different operations, such as preparation, after-process adjustment, checking materials, mounting and removing tools, settings and calibrations, measurements, trial runs, adjustments, etc. SMED is composed of the following stages [8]:

– description of set-up conditions, where internal and external activities are not distinguished;
– separating internal and external set-up;
– converting internal activities into external ones;
– streamlining all aspects of the set-up operation [6].

SMED's main benefits include:

– increasing manufacturing capacity,
– improving equipment flexibility [5].

3. SETTING TIME STANDARD IN SMED

One of the important stages in the SMED method is setting changeover time standard. According to the Pareto analysis, it is possible to find main set-up activities which are responsible for long changeover time standard. Changeover activities mainly involve manual assembly and disassembly processing, so development of time standard setting methods focused on human motions is the aim of this article.

Standard time obtained as a result of applying a work measurement technique is defined as a sum of basic time and allowance time. Standard time is calculated for a manufacturing task which is performed using given method and equipment, under given conditions, by a worker with sufficient skills to do the job properly, by a worker who is physically fit for the job after adjusting to it, who is an average person who can perform the job, working at the pace of an approved pace standard [9]. According to [10], work measurement techniques include:

– time studies (recording and evaluation of actual times),
– calculation techniques using technological formulae as an aid,
– synthetic times,
– comparative estimation,
– subjective estimation.

The synthetic times technique uses time standards for defined work contents. Predetermined motion time systems, such as the family of MTM techniques and Work Factor, use time standards for separate human motions. The basic MTM-1 system offers a very detailed description of the working method, but it takes a long time to perform an analysis of a work cycle [9]. Several variants of MTM can be used, among which MTM-UAS is useful for manual processes that average around 1-3 minutes [11]. Chosen MTM systems are presented in Fig. 1 [12].

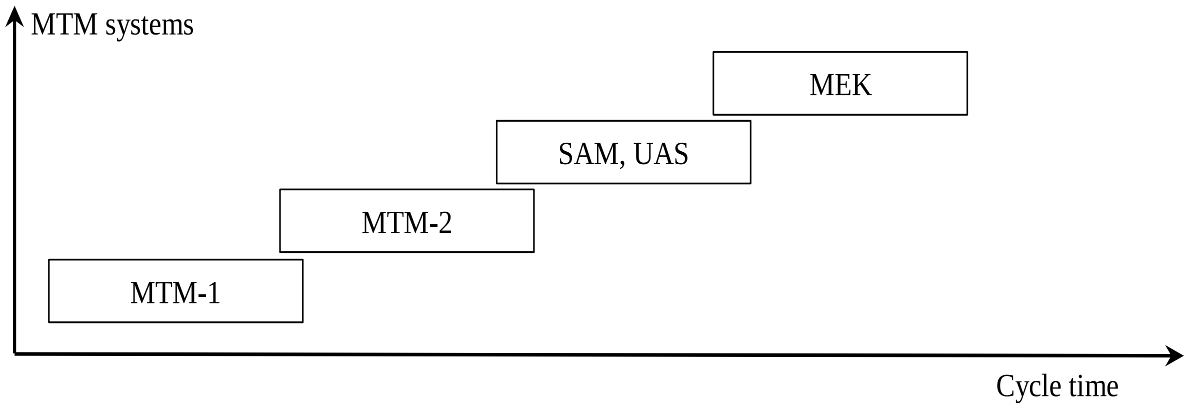

Fig. 1. Chosen MTM systems

MTM is a tool used to describe manufacturing operations to standardize the work method and optimise it [13]. Several computer software applications have been developed, such as MOST (Maynard Operation Sequence Technique), or TICON, which are useful in MTM (M-1, MTM-2, UAS, MEK, MOS) [12, 14].

A work process can be divided into sub-processes, which need evaluating the motions necessary to complete a work task. An example of hand motion analysis was presented on Fig. 2, which was developed basing on Bramley et al. [15], who present production planning state of art. In the presented example, hand motion was divided into activities which lead to completing a work task.

One of the methods useful in manual process analysis is MTM, in which work planning requires a definition of a sub-processes' sequence. A work task can be analysed as a hand, body and eye motion sequence. According to MTM, basic human hand motions include: reaching, grasping, moving, positioning, releasing. A motion needs to be planned, taking into consideration the ways in which an object may be handled.

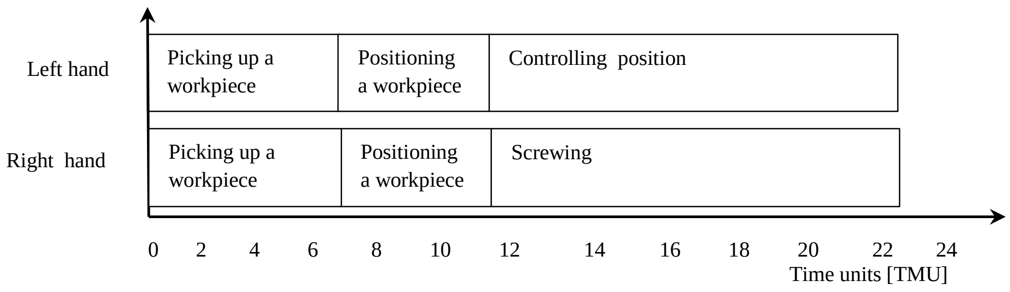

Fig. 2. An example of a sub-processes flow chart

The time required for a motion depends on a number of variables, such as, for example, distance or weight. In the proposed approach, basic motions are grouped into sets. The activity of "picking up an object" was analysed, and in the proposed approach, basic motions, such as reaching, grasping and moving were joined together, and next, common characteristic features (attributes) were found. In case of changeover activity time standard setting, MTM is too complicated and time consuming, so it is necessary to develop an approach which is fast and easy to use.

4. ANN APPLICATION FOR SETTING TIME STANDARD OF HUMAN MOTIONS

4.1. DATA ACQUISITION AND PRE-PROCESSING

Data acquisition is focused on obtaining training, testing and validation data sets [16, 17]. A model of data acquisition was presented in Fig. 3. The model features the relations between basic motions and standard operations, which were analysed by Yang et al. [18].

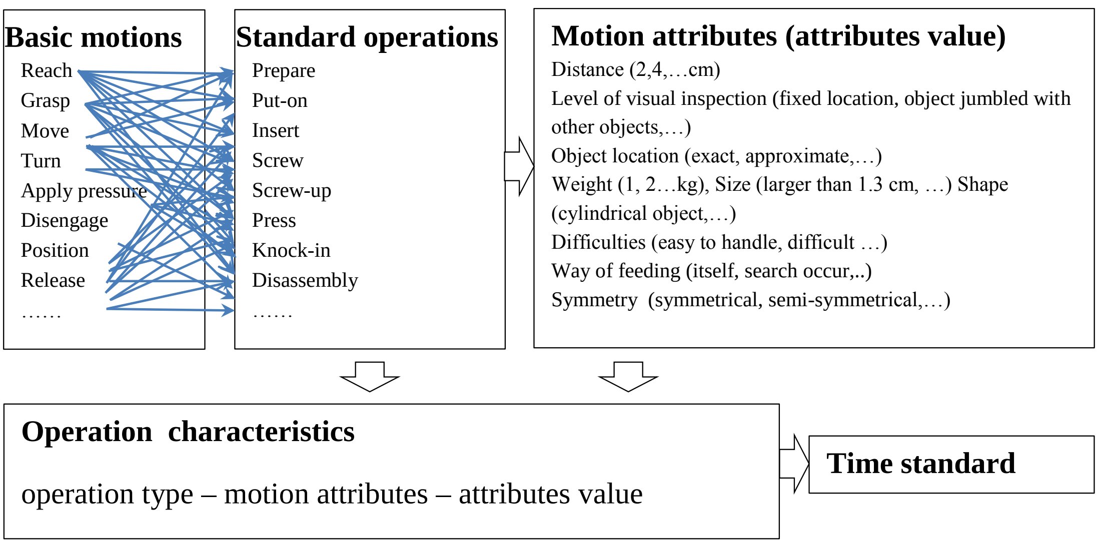

Fig. 3. A time standard data acquisition model

In the presented approach, time standard for the "picking-up" activity was calculated as a collective time of reaching, grasping and moving. The attributes which characterise the "picking-up" activity are related to the workpiece characteristics, as well as workstation characteristics. Data pre-processing is presented in Fig. 4.

MTM 1

Distance	Reach (TMU)				Grasp	TMU	Distance	Move (TMU)			Weight (kg)	W	SC
	R-A	R-B	R-C R-D	R-E				M-A	M-B	M-C			
2	2	2	2	2	G1A	2	2	2	2	2	1	1	0
4	3.4	3.4	5.1	3.2	G1B	3.5	4	3.1	4	4.5	2	1.04	1.6
6	4.5	4.5	6.5	4.4	G1C1	7.3	6	4.1	5	5.8	…		
8	5.5	5.5	7.5	5.5	….		8	5.1	5.9	6.9			
…							……						

Weight (<1 kg, 2, 4, …)	Size (>12; 6-12; <6 mm)	Distance – reach (cm)	Distance – move (cm)	Feeding (mixed p, separately s)	Pick-up time standard (TMU)
1	>12	2	2	p	11.3
1	>12	4	4	p	16.9
1	>12	6	6	p	19.6
…					

Fig. 4. A model of manual assembly time standard pre-processing

4.2. ANN CHANGEOVER TIME STANDARD MODELLING

AI technologies can include, e.g.: knowledge base, fuzzy logic, decision trees, as well as neural networks [19-21]. AI application for changeover planning needs feature modelling useful in automation of experience based reasoning. Feature (attributes) analysis and conversion is an essential element for AI application. In the proposed approach, the changeover 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. Figure 5 presents the relations between the analysed data structure elements. The OAV scheme gives a concise data structure for organising the features of a chosen process [22].

Various researchers have applied ANN as a tool for time prediction. Multi-layer perceptron (MLP) and radial basis functions (RBF) were used for predicting execution times of production tasks by Fernandez et al. [23]. A hybrid approach involving a self-organization map and fuzzy back propagation network were proposed for cycle time prediction by Chen et al. [24-26]. Processing time and reliability ratio were predicted with the use of linear ANN [27].

ANN is an interconnected group of artificial neurons which have a property of storing knowledge and making it available for use [28]. Studies on machine learning have mainly been concerned with automatic learning from examples, which allow to develop the knowledge [29-32]. The most widely studied supervised learning method is feedforward neural network, in which a model is refined during the learning process [29]. 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 [17].

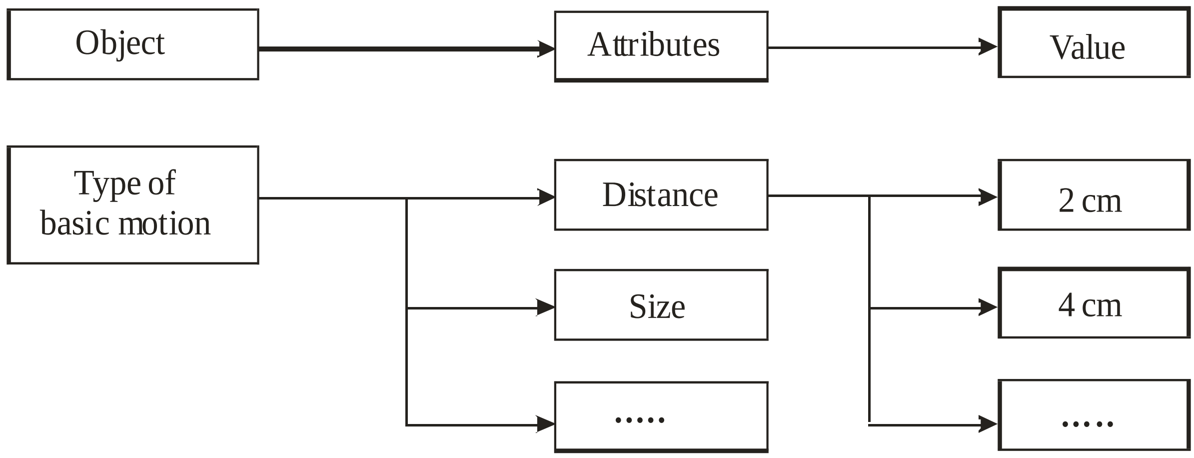

Fig. 5. Object attributes value scheme

ANN is established with the use of a set of training samples, including attributes and their values. The training examples can be generated by simulations or by a real production system. In the presented approach, the ANN training set contains time standards of human motions achieved with the use of MTM-1. MLP is one of well-known artificial neural networks used, among others, for classification and regression [22]. MLP consists of one or more hidden layers of neurons. A multi-variable regression MLP model of a given process is built with a chosen number of input and output neurons and neurons in hidden layers. The MLP approach presented in the article involves learning time standard as a network output and work characteristic as an ANN input. The attributes considered as the ANN input in the work process characteristics are: workpiece weight, workpiece size, workpiece reach distance, workpiece move distance, workpiece way of feeding.

An ANN model needs decisions related to:

– Number of input neurons;
– Number of output neurons;
– Type of input values;
– Type of output values;
– Number of hidden layers;
– Number of neurons in the hidden layers;
– Type of neurons;
– Training method;
– Number of examples in the training, testing and validation sets;
– Nature of examples in the training, testing and validation sets.

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

A 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 problem [33]. A wrong decision related to an ANN model (irrelevant inputs, too many hidden layers or neurons, insufficient amount of training data, etc.) can cause ANN overfitting and deteriorates generalisation capability [29].

In the proposed approach, a chosen human activity was modelled with the use of ANN. The case study was dedicated to modelling time standard for the “picking-up” activity with ANN.

4.3. CASE STUDY

Changeover task planning requires human motions analyses, so in the presented approach work time is calculated with elementary human motions and their standard times, according to the model presented in Fig. 4. A set of examples (274 cases) presented in Table 1 was divided into training, testing and verification sets.

Table 1. A set of examples

ANN Inputs					ANN Output
No.	Weight	Size	Distance - reach	Distance - move	Time standard
1	1	>12	2	2	11.3
2	10	>12	80	80	81.3
3	20	>12	2	2	27.1
…	…	…	…	…	…
274	20	>12	80	80	96.6

In the presented approach the Statistica software was used. Sensitivity analysis was conducted and the most important attributes were found. The results of the sensitivity analysis for training and verification sets were presented in Table 2. As a result of the sensitivity analysis, three important attributes were established: the first one is “move distance” with training set error of 9.196858 and regression ratio of 7.299076; the second is “reach distance”, with training set error of 7.956422 and regression ratio of 6.314606, the third is “weight”, with training set error of 7.069133 and regression ratio of 5.610409.

Ten variants of ANN configuration were tested and the network with the best performance was found. The best network has 7 neurons in the hidden layer, three neurons in the input layer, and one in the output layer. The best network, which was presented in figure 6, had very good performance (regression ratio of 0.082939, correlation of 0.996590). The root mean square (RMS) error is 1.26 for the training set, 1.431 for the verification set, and 2.058 for the testing set. Data mean values amount to 44.76745 for the training set, 44.31372 for the verification set, and 43.92147 for the testing set.

A comparison of the tested networks, which was presented in Table 3, used error and performance (regression ratio) in the training, verification and testing sets as comparison criteria. RBF, Linear and MLP ANN were compared with different number of neurons in *the input and hidden layers.*

Table 2. Sensitivity analysis

	ANN Inputs		
	Weight	Distance - reach	Distance - move
Rank for the training set	3	2	1
Error for the training set	7.069133	7.956422	9.196858
Regression ratio for the training set	5.610409	6.314606	7.299076
Rank for the verification set	3	2	1
Error for the verification set	7.214829	7.884785	9.064326
Regression ratio for the verification set	5.043492	5.511822	6.336374

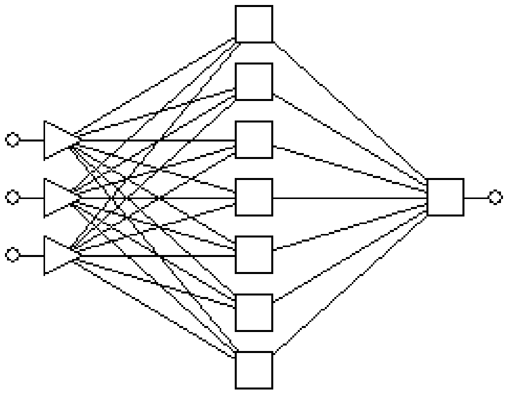

Fig. 6. Network with the best performance

Table 3. ANN comparison

No.	ANN type	Number of inputs	Number of neurons in hidden layer	Error in training set	Error in verification set	Error in testing set	Performance in training set	Performance in verification set	Perfor-mance in testing set
1	RBF	3	1	13.92865	14.60167	11.77032	0.8482831	0.8497279	0.9029566
2	Linear	1	-	9.565818	10.5149	9.117561	0.5825776	0.6104776	0.6925398
3	RBF	3	2	7.751826	7.75088	6.380776	0.4721019	0.4505856	0.4900851
4	Linear	2	-	6.91898	7.139971	6.395506	0.4213798	0.4150859	0.4907349
5	Linear	4	-	2.61497	2.681343	2.676967	0.159237	0.1560481	0.2052485
6	Linear	3	-	2.10324	1.97248	2.36675	0.1280915	0.1145515	0.1819099
7	MLP	3	4	1.503804	1.593164	2.072505	0.09153	0.09269	0.1597236
8	MLP	3	5	1.31492	1.487755	2.035874	0.08008	0.08627	0.1560586
9	MLP	3	6	1.286773	1.481432	2.073004	0.07804	0.0862	0.1596127
10	MLP	3	7	1.260003	1.430523	2.057526	0.07674	0.08294	0.1568522

The neural network presented in Fig. 6 generates time standard for the picking-up activity. Changeover process description should also take into consideration another activity. An example of a graph which supports decisions related to manual task description is presented in Fig. 7. The presented decision tree indicates the type of feeding and size of machine parts.

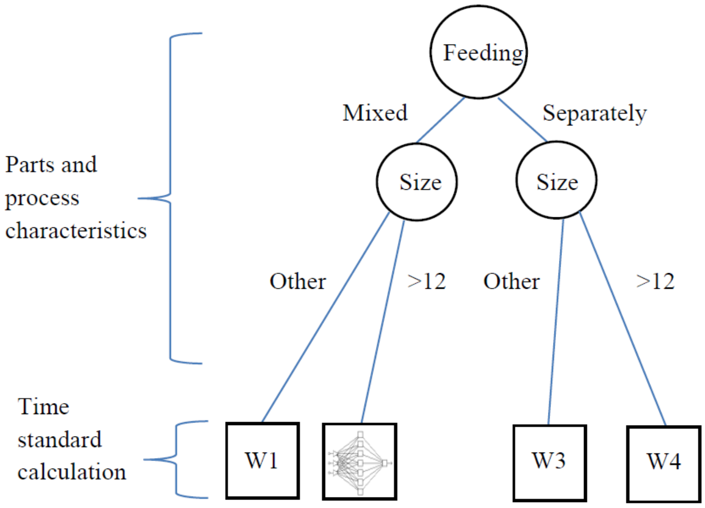

Fig. 7. An example of a decision tree – time standard calculation for activity of “picking up a workpiece”

5. CONCLUSIONS

The present study concerned developing a method of predicting human activity time standard. The proposed time standard predictor can be useful for changeover task planning. The proposed approach uses ANN as a tool of time standard prediction, and MTM, which is one of time standard setting methods useful in human activity task planning.

The aim of this study was to develop a method for setting manual task time standard, which is easy to use and sufficiently precise. Application of ANN for this purpose helps in connecting elementary motions into activities and reduces the number of needed attributes.

In the presented approach, an OAV scheme was applied, where an object is interpreted as a human activity type, attributes are analysed as a set of variables which influence the changeover process time standard, and attributes can assume particular values which can be qualitative or quantitative.

Different ANN variants were compared as tools for time standard prediction. The best one with very good performance was found for the “picking-up” activity.

Future research could be focused on defining another human manual activity and setting its time standard.

LITERATURE

[1] GORSKI 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.

[2] UHLMANN E., HOHWIELER E., GEISERT C., 2017, *Intelligent production systems in the era of industrie 4.0 – changing mindsets and business models*, Journal of Machine Engineering, 17/2.

[3] JEDRZEJEWSKI J., KWASNY W., 2015, *Development of Machine Tool Operational Properties*, Journal of Machine Engineering, 15/1.

[4] GEST G., CULLEY S.J., MCINTOSH R.I., MILEHAM A.R., OWEN G.W., 1995, *Review of fast tool change systems*, Computer Integrated Manufacturing Systems, 8, 205-210.

[5] COIMBRA E.A., 2009, *Total Flow Management: Achieving Excellence with Kaizen and Lean Supply Chains*, Kaizen Institute.

[6] FERRADÁS P.G., SALONITIS K., 2013, *Improving changeover time: a tailored SMED approach for welding cells*, Forty Sixth CIRP Conference on Manufacturing Systems 2013, Procedia CIRP, 7, 598-603, Published by Elsevier.

[7] GOUBERGEN D.V., LANDEGHEM H.V., 2002, *Rules for integrating fast changeover capabilities into new equipment design*, Robotics and Computer Integrated Manufacturing, 18, 205-214.

[8] SHINGO S., 1985, *A revolution in manufacturing: The SMED system*, Productivity Press, Stanford, CT.

[9] SAKAMOTO S., 2010, *Beyond World-Class Productivity*, Springer London.

[10] ARN E.A., 1975, *Group Technology*, Springer-Verlag, Berlin Heidelberg.

[11] GIRONIMO G., MARTINO C., LANZOTTI A., MARZANO A., RUSSO G., 2012, *Improving MTM-UAS to predetermine automotive maintenance time*, International Journal on Interactive Design and Manufacturing, 6, 265-273.

[12] CARAGNANO G., FISCHER H., 2010, *First time right. MTM-prawidłowo od samego początku*, Polskie Stowarzyszenie MTM.

[13] KUO C.F., WANG M.J., 2009, *Motion generation from MTM semantics*, Computers in Industry, 60, 339-348.

[14] LARINGA J., FORSMANB M., KADEFORSA R., ORTENGRENA R., 2002, *MTM-based ergonomic workload analysis*, International Journal of Industrial Ergonomics, 30, 135-148.

[15] BRAMLEY A., KNIGHT W., et al., 2011, *Dictionary of Production Engineering/Wörterbuch der Fertigungstechnik.*

[16] ZHOU J., DUAN B., HUANG J., CAO H., 2014, *Data-driven modelling and optimization for cavity filters using linear programming support vector regression*, Neural Computing and Application, 24, 1771-1783.

[17] ROY R., KOEPPEN M., OVASKA S., FURUHASHI T., HOFFMANN F., 2002, *Soft Computing and Industry*, Springer-Verlag London.

[18] YANG Q., WU D.L., ZHU H.M., BAO J.S., WEI Z.H., 2013, *Assembly operation process planning by mapping a virtual assembly simulation to real operation*, Computers in Industry, 64, 869-879.

[19] ZHA X.F., LIM S.Y.E., FOK S.C., 1998, *Integrated intelligent design and assembly planning: a survey*, The International Journal of Advanced Manufacturing Technology, 14, 664-685.

[20] SHIUE Y.-R., GUH R.-S., 2006, *The optimization of attribute selection in decision tree-based production control systems*, International Journal of Advanced Manufacturing Technology, 28, 737-746.

[21] PRIORE P., DE LA FUENTE D., GOMEZ A., PUENTE J., 2001, *A review of machine learning in dynamic scheduling of flexible manufacturing systems*, Artif. Intell. Eng. Des. Anal. Manuf., 15/3, 251-263.

[22] YOUNG H.T., TSAI D.H., 1994, *An integrated expert operation planning system with a feature- based design model*, The International Journal of Advanced Manufacturing Technology, 9, 305-310.

[23] FERNANDEZ-DELGADO M., REBOREDA M., CERNADAS E., BARRO S., 2010, *A comparison of several neural networks to predict the execution*, Neural Computing and Applications, 19/5, 741-754.

[24] CHEN T., WANG Y.-C., TSAI H.-R., 2009, *Lot cycle time prediction in a ramping-up semiconductor manufacturing factory with a SOM–FBPN-ensemble approach with multiple buckets and partial normalization*, International Journal of Advanced Manufacturing Technology, 42, 1206-1216.

[25] CHEN T., 2008, *A SOM-FBPN-ensemble approach with error feedback to adjust classification for wafer-lot completion time prediction*, International Journal of Advanced Manufacturing Technology, 37, 782–792.

[26] CHEN T., 2012, *A job-classifying and data-mining approach for estimating job cycle time in a wafer fabrication factor*, Journal of Advanced Manufacturing Technology, 62, 317-328.

[27] KUTSCHENREITER-PRASZKIEWICZ I., 2013, *Application of neural network in QFD matrix*, Journal of Intelligent Manufacturing, 24, 397-404.

[28] RENUGA DEVI S., ARULMOZHIVARMAN P., VENKATESH C., AGARWAL P., 2016, *Performance Comparison of Artificial Neural Network Models for Daily Rainfall Prediction*, International Journal of Automation and Computing, 13/5, 417-42.

[29] WANG X.Z., 1999, *Data mining and knowledge discovery for process monitoring and control*, Springer-Verlag London Limited.

[30] HAYASHI Y., SETINO R., AZCARRAGA A., 2016, *Neural network training and rule extraction with augmented discretized input*, Neurocomputing, 207, 610-622.

[31] JIANG C., JIANG M., XU Q., HUANG X., 2017, *Expectile regression neural network model with applications*. Neurocomputing, 247, 73-86.

[32] LIU W., WANG Z., LIU X., ZENG N., LIU Y., ALSAADI F., 2017, *A survey of deep neural network architectures and their applications*, Neurocomputing, 234, 11-26.

[33] COOK D., SHANNON R., 1991, *A sensitivity analysis of a back-propagation neural network for manufacturing process parameters*, Journal of Intelligent Manufacturing, 2, 155-163.