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A MODEL FOR ASSESSING THE LEVEL OF AUTOMATION OF A MAINTENANCE DEPARTMENT USING ARTIFICIAL NEURAL NETWORK

Abstract

With regard to adapting enterprise to the Industry 4.0 concept, the first element should be the implementation and use of an information system within a manufacturing company. This article proposes a model, the use of which will allow the level of automation of a maintenance department to be forecast, depending on the effectivity of the use of the Manufacturing Executions System (MES) within a company. The model was built on the basis of the actual times of business processes completed which were supported by MES in the maintenance departments of two manufacturing enterprises using artificial neural network. As a result of research experiments, it was confirmed that the longer the time taken to complete business processes supported by MES, the higher is the degree of automation in a maintenance department.

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1. INTRODUCTION

Maintenance services are now an important element in the structure of a manufacturing company, since there is a need to adapt the operation of companies to the requirements of the Industry 4.0 concept. One of the elements of the "Industry 4.0" concept is the so-called "*smart factory*", which seeks to automate processes within an enterprise, particularly production processes which require special maintenance procedures which, in turn should be supported by an IT system. Within this context, developments, such as Industry 4.0 and information technology offer great potential (Seitz & Nyhuis, 2015).

The aim of the article is to build a model for assessing the degree of automation in a maintenance department, using artificial neural network (model AC-MD) based on an example using Manufacturing Executions Systems (MES). The implementation of MES in the maintenance department of a manufacturing company provides information that allows production operations to be optimised; at the same time, MES is used to support activities carried out in the maintenance department of production enterprises (Jacobson, Masson, Smith & Souza, 2005; Jacobson & Masson, 2006).

Good examples are to be found in the literature, on the use of artificial neural network in maintenance, for the monitoring of such as tool wear, diagnosing vibration in machining systems, in the thermal analysis of machines, in analysing other malfunctions affecting production, not to mention the geometrical analysis of the product as well as the diagnostics of the finished product (Gawlik & Kiełbus, 2012). The AC-MD model was built using artificial neural network on account of their usefulness both in reactive and preventive maintenance and, finally, in predictive maintenance.

Model AC-MD was formulated based on the real data, obtained from the maintenance departments of two, automotive industry companies. In the first manufacturing company analysed, workers at the strategic, tactical and operational levels in the maintenance department service 380 machines while in the second, the workers service 20 machines. For the purposes of the analysis, the time taken by the employees to perform the actions using MES, was adopted.

2. APPLICATION OF ARTIFICIAL NEURAL NETWORK IN MAINTENANCE

The automation of manufacturing processes, together with the minimisation of costs, (Wu, Tian & Chen, 2013) the shortening of production cycles and a reduction in the size of inventories, has improved the importance of repairs and maintenance as a service function of companies (Bojar & Żółtowski, 2011). This aspect of a company's operation is an important element in the development of a company in accordance with the Industry 4.0 concept. Ensuring continuity of the production process and the desired quality of manufactured products, requires the use of appropriate tools to supervise the condition of the machines and technical devices (Kosicka, Mazurkiewicz & Gola, 2016). The solution is the implementation of IT systems in maintenance departments, which support activities implemented at the operational, tactical and strategic levels. An example of an IT system that is used in a maintenance department is MES. MES systems enable the effective collection of data and information from business processes in real time; this data and information is collated in the production and maintenance departments and then subsequently transferred to other completed processes in the enterprise. Data and information on production can only be collected directly from machines and from employees working in production and maintenance departments.

The difficulty in applying the MES system is to assess whether the use of this system by employees is effective and whether it contributes to an increase in the degree of automation of a department. Does the application of MES allow the company to adapt to the requirements of Industry 4.0?

We are, therefore, looking for a model for assessing the degree of automation in a maintenance department, the use of which will allow an increase in efficiency in a company, when using the MES system.

Artificial neural network for the construction of the AC-MD model was selected. The operation of artificial neural network is based on the classification and generalisation of individual features or facts; their use is particularly justified in the case of the high complexity of a problem with little knowledge of the rules (Gawlik & Kiełbus, 2012). The use of neural network may refer, for example, to the problems of classifying or predicting time data for individual tasks. Examples of the use of artificial neural network for the parallel processing of data in real-time control systems (Wu, Tian & Chen, 2013; Li, Wang & Wang, 2017) indicate the validity of their use in the AC-MD model. In addition, examples of using artificial network for the purpose of identifying and forecasting the wear of machine elements or of the thermal distortion of grinders were found, as well as in the geometric identification of wear indicators, in such as the blades and the surface layer of an object. (Gawlik & Kiełbus, 2012; Wu, Tian & Chen 2013). With regard to the possibility of using artificial neural network in maintenance, additional examples of models were found, *viz.*, the analysis of the wear patterns of circular saw blades, forecasting the course of the abrasive wear of cutting tools' blades (Gawlik & Kiełbus, 2012), the grouping of machine construction elements (Lipski & Pizoń, 2014), infrared thermography for the detection of defects in elements (Huda & Taib, 2013) and the monitoring of the operation of ship machinery (Raptodimos & Lazakis, 2016).

3. MODEL AC-MD

Building an AC-MD model, using the artificial neural network, requires real input data to be obtained, regarding the realisation of selected business processes in the maintenance department of manufacturing enterprises. The following business processes were carried out in those departments whose execution times were defined over the course of one working week [in minutes] on three levels of management, namely, the strategic, tactical and operational levels. The activities designated were performed, either with the support of the MES system (*either partially or fully*), or without the support of the MES system, respectively at the three levels defined (Table 1):

Tab. 1. Activities carried out in the maintenance department of manufacturing companies

	Business processes	Time taken up by activities over a week: Manufacturing company 1			Time taken up by activities over a week: Manufacturing company 2		
		strategic level	tactical level	operational level	strategic level	tactical level	operational level
1.	Making entries in the records regarding the inspection of equipment/machines		100	100		25	25
2.	Making entries in the records regarding the testing/tuning of devices and machines		100	50		5	5
3.	Order management	100	30		100	50	
4.	Tracking the status of devices/machines in real time (on-line)	50	50	50	40	50	25
5.	Reporting the demand for external service	30	20		50	30	
6.	Monitoring/Tracking schedule/Production planning	10	20	25	10	20	
7.	Planning downtime	10	20		30	30	
8.	Identification of bottlenecks on each machine/device	30	60	100	40	50	60
9.	Registering parts/consumables for equipment/ machines		30	100		50	60
10.	Monitoring repairs to equipment/machines	50	20		55	50	40
11.	Review of technical documentation	30	50	50	35	50	30
12.	Checking the availability of parts in the warehouse	50	50	50	55	50	60

Tab. 1. Activities carried out in the maintenance department – continued

13.	Reporting the demand for parts/consumables	100	150	50	80	75	40
14.	Recording/making a selection from the list of actions performed	50	50	50	45	50	60
15.	Entering the write-up for devices/machines	25	50	50	25	50	30
16.	Recording the withdrawal of equipment/ machines from service	1	8		5	10	
17.	Reporting the availability for work of repaired devices/machines, *post* overhaul	100	60	50	60	50	70
18.	Simulation of re-tooling devices, machines/ production lines	60	8	120	120	150	150
19.	Generating reports for machines/devices	100	20		70	25	
20.	Signalling the downtime of equipment/machines	50	20	50	70	10	10
21.	Informing about failure/blockages	10	25	20	15	10	10
22.	Signalling/informing about the availability of equipment/machines/ production line	50	50	50	60	10	10
23.	Conducting on-line/video training	30	40		20	30	
24.	Training planning	3			5		
25.	Monitoring of training	8	5		10	10	
26.	Human resources planning	3	30		50	40	
27.	Creating procedures	15	20		20	30	
28.	Reporting/signalling improvements, such as modernisation, improvement of machines/devices	60	60	50	60	60	40
29.	Reporting/signalling solutions to improve work (e.g. information flow)	30	30	50	40	50	40
30.	Notification by SMS or e-mail about planned, preventive maintenance/repairs	10	10	6	15	10	20
31.	Generating the alarm manually on failure	10	10	12	8	15	20

Tab. 1. Activities carried out in the maintenance department – continued

32.	Generating the alarm automatically on failure	10	15	5	12	15	15
33.	Notification by SMS/e-mail of a failure	10	20	15	15	30	20
34.	Implementing improvement solutions (e.g. modernisation, improvement of machines, devices)	60	60	100	40	50	20
35.	Implementing solutions that improve work (e.g. information flow)	30	20		40	50	
36.	Monitoring the technical testing of equipment/machines	15	30	25	10	15	
37.	Running a repairs calendar	25	100		15	20	
38.	Access from the console to the desktop of another level	15	15		10	15	
39.	Monitoring MTTR indicator (Mean Time to Repair)	20			25	50	
40.	Monitoring MTTF indicator (Mean Time to Failure)	20			30	50	
41.	Monitoring MTBF indicator (Mean Time Between Failures)	20			30	50	
42.	Analysis of the availability of a device/ machine	20			20		
43.	Monitoring the OEE indicator (Overall Equipment Effectiveness)	15			60		
44.	Analysis of costs in a maintenance department	15			60		
45.	Recording accidents at work				30		
46.	Archiving data	100	100	25	180	120	10

To build the AC-MD model, an artificial, neural network with a linear, activation function was used. Weighting factors were determined, in the neuron training process, by supervised learning. To generate the neural network, **Matlab R2018a** was used with the built-in Neural Network Tool. The model of the neural network used in the study is shown in Fig. 1.

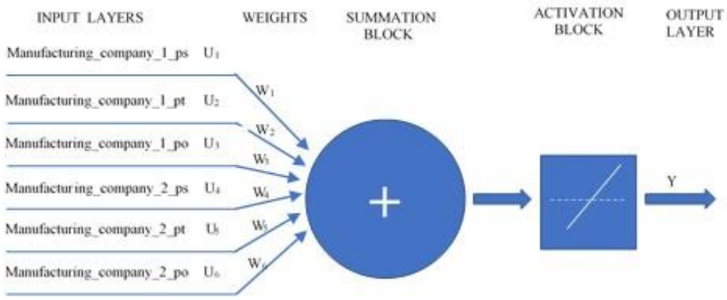

Fig. 1. Model of the neural network applied, based on a linear neuron (W1…W6 – weights; Y – level of automation of a maintenance department at the strategic, tactical and operational level in a company)

Based on the data analysed by the neural network with a linear activation function, the following AC-MD model was obtained.:

$$\begin{aligned} Y = 0,0294 \times P_1 + 0,1756 \times P_{17} + (-0,0201) \times P_{18} \\ + (-0,2453) \times P_{20} + 0,0020 \times P_{34} + 0,1104 \times P_{46} \end{aligned} \tag{1}$$

where: P_1 – business process: making entries in the records upon the inspection of equipment/machines,
P_{17} – business process: reporting the availability for work of repaired devices/machines, *post* overhaul,
P_{18} – business process: simulation of re–tooling devices, machines/ production lines,
P_{20} – business process: signalling equipment/machine downtime,
P_{34} – business process: implementing improvement solutions (e.g. modernisation, improvement of machines, devices),
P_{46} – business process: archiving data.

The AC-MD model includes business processes in a production enterprise, the implementation of which, influences the level of a maintenance department's automation index. It seems that these processes should be performed in an enterprise using the MES system and therefore their weekly time, performed with the support of the MES system should be increased. In order to verify the AC-MD model obtained, research experiments were carried out.

4. THE USE OF THE AC-MD MODEL

In order to find the answer to the question as to whether any increase in the use of the MES system in completing activities carried out in a maintenance department has any influence on the increase of the degree of automation of that maintenance department, the following working times were taken over the period of one working week [in minutes], Table 2.

Tab. 2. Time taken to complete activities carried out at manufacturing companies in a maintenance department – experimental data

	Business processes	Time taken up by activities over a week: Manufacturing company 1			Time taken up by activities over a week: Manufacturing company 2		
		strategic level	tactical level	operational level	strategic level	tactical level	operational level
E1	P_1 – Making entries in the records on the inspection of equipment/machines		100	100		25	25
E2			120	120		40	40
E3			140	140		60	60
E4			160	160		80	80
E1	P_{17} – Reporting the availability for work of repaired devices/machines, *post* overhaul	100	60	50	60	50	70
E2		120	80	70	80	70	90
E3		140	120	90	100	90	110
E4		160	140	120	120	110	130
E1	P_{18} – Simulation of re-tooling devices, machines/production lines	60	8	120	120	150	150
E2		80	20	140	140	170	170
E3		100	40	160	160	190	190
E4		120	40	180	180	210	210
E1	P_{20} – Signalling equipment/machine downtime.	50	20	50	70	10	10
E2		60	40	70	90	20	20
E3		80	40	90	110	40	40
E4		100	60	110	130	60	60
E1	P_{34} – Implementing improvements, such as, modernisation, improvement of machines, devices	60	60	100	40	50	20
E2		80	80	120	60	70	30
E3		100	100	140	80	90	50
E4		120	100	160	100	110	70
E1	P_{46} – Archiving data	100	100	25	180	120	10
E2		120	120	50	200	140	20
E3		140	140	70	210	160	30
E4		150	160	90	220	180	40

Based on the data (Table 2), the values forecast for the automation index of a maintenance department, were calculated (Figure 2).

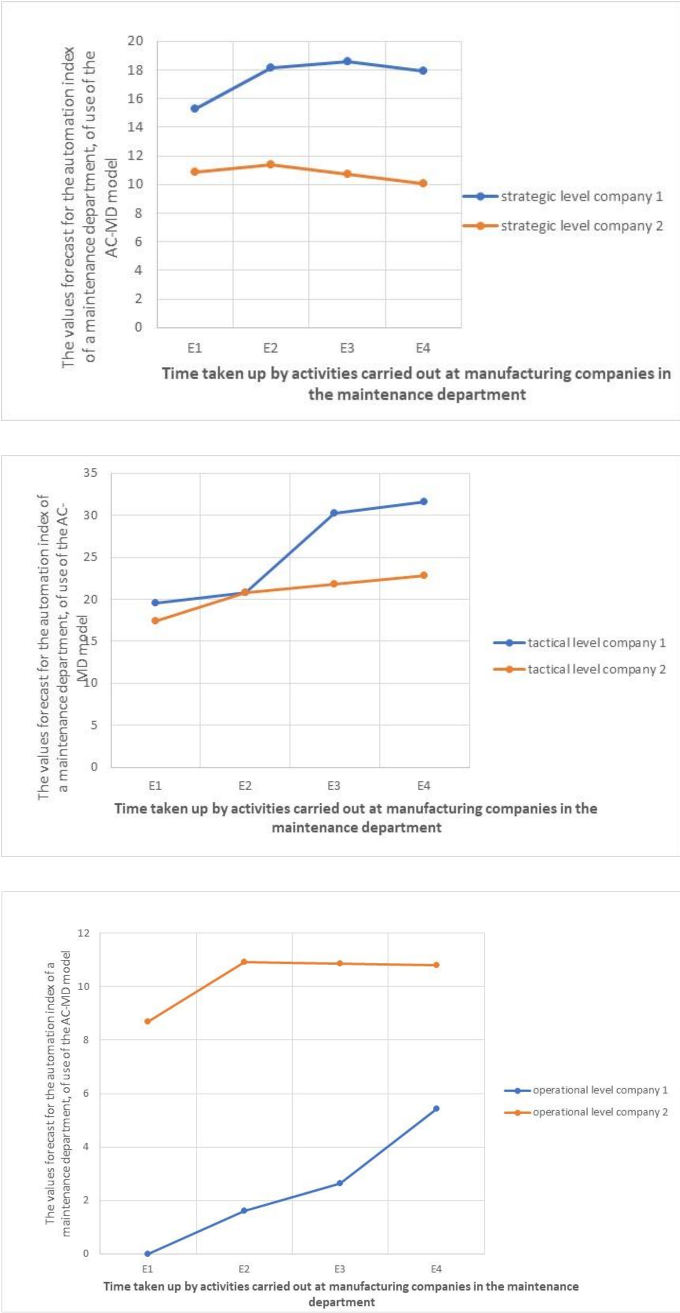

Fig. 2. The values forecast for the automation index of a maintenance department, at the strategic, tactical and operational level of use of the AC-MD model

Based on the data, it was found that the processes of making entries into records regarding the inspection of equipment and machines; the reporting of the availability for work of repaired devices and machines, *post* overhaul; the simulation of re-tooling devices, machines and production lines; the signalling of equipment and machine downtime; the implementation of improvements, such as modernisation and the improvement of machines, devices and archiving data, all have a significant impact on the level of the automation index in a maintenance department. In addition, the more these processes are supported by the MES system, the higher is the level of the automation of the whole department. Thus, increasing efficiency by implementing the use of MES, in a maintenance department, should be the first step in preparing an enterprise to implement the Industry 4.0 concept.

5. CONCLUSIONS

The article presents that the implementation and effective use of the **MES** system in a production company in a maintenance department can lead to an increase in the level of automation of the whole department. In further work, the authors will present IT tools and their application in the production enterprise which will allow the company to forecast the effects of investing in the implementation of the **Industry 4.0** concept.

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