AI-based Decision-making Model for the Development of a Manufacturing Company in the context of Industry 4.0

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***Abstract*— Managers are looking for solutions that will be helpful when deciding on the purchase of new technologies, in order to adapt the enterprise to the Industry 4.0 concept. Nowadays, many approaches suitable for smart manufacturing systems involving maintenance workers are based on Artificial Neural Networks (ANN). This paper presents an approach to measuring the effectiveness of the use of an IT system supporting the realisation of business processes in the maintenance department and describes the empirical research results of maintenance workers (121) within Polish manufacturing companies with automotive branches. Finally, this paper seeks to integrate the first two main research results and ANN, into a novel, decision-making model regarding the implementation of activities and investments aimed at increasing the level of a company's automation. The architecture of ANN classifier was chosen in a series of experiments. The Levenberg-Marquardt method and genetic algorithms were used in training process. The performance of the classifier was measured using the sum of squared errors and the error function with the regularisation term in the form of the sum of squared norms of Jacobian matrices. The best performing classifier achieved 95.8% accuracy on the test dataset.**

Keywords—data-driven artificial intelligence techniques, decision making, manufacturing company, industry 4.0

I. INTRODUCTION

A manufacturing company can be competitive in the market, not only due to the high-quality of the products and services it offers but also by implementing new solutions and technologies, such as, robotics, artificial intelligence (AI), augmented reality (AR) and smart technologies, in the context of the Industry 4.0 concept [1], [2].

Implementing Industry 4.0 is a very complex and difficult process [3], due to the need to undertake investments that are very cost-intensive, among other things. The need for in-depth research, into Industry 4.0 has already been pointed out [4], [5]. It can be observed, that data analysis techniques, including data mining approaches and combining AI tools are researched in the context of improving production quality and increasing manufacturing performance and quality [6], [7]. Managers are also looking for solutions that will be helpful when deciding on the purchase of new technologies, in order to adapt the enterprise to the Industry 4.0. concept. Knowing that there is increased interest in the methods and algorithms, used in decision-making in the area maintenance [8], an innovative model for supporting decision-making, in the context of improving the efficiency of maintenance departments, is developed in the current paper.

Data driven intelligence is used as support mechanisms within manufacturing companies [9]. According to the literature, the most popular data-driven, decision-making approaches include Support Vector Machine (SVM), Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA); Random Forest, K-Nearest Neighbours and the Hidden Markov model have also been used [10], [11].

Nowadays, many approaches suitable for smart manufacturing systems involving maintenance workers are based on Artificial Neural Networks. An example of the successful application of the use of Artificial Neural Network (ANN) is presented by Wuest et al., 2016 [12]. By using data-driven artificial intelligence techniques, it is possible to develop an advanced analytics tool for smart manufacturing [13], [14], the same also applies in the context of decision-making approaches. The most commonly used neural networks architectures for classification tasks are Multi-layer Perceptrons (MLP), radial basis function networks (RBF) and probabilistic neural networks (PNN). In this paper, the Multi-layer Perceptron has been adopted to solve our classification tasks. Having a set of classified, or labelled, cases, we build a model that can be used to classify unlabelled cases which is a classical classification task. Building an appropriate model allows us to assess the degree of automation within a company based on the questionnaire formulated for this study.

This paper has three main research results. Firstly, it presents an approach to measuring the effectiveness of the use of an IT system supporting the realisation of business processes in the maintenance department. The second objective of this paper is to describe, in the context of Industry 4.0, the empirical research results of maintenance workers (121) within Polish manufacturing companies with automotive branches, in order to define the effectiveness of the use of an IT system within a company. Finally, this paper seeks to integrate the first two main research results and ANN, into a novel, decision-making model regarding the implementation of activities and investments aimed at increasing the level of a company's automation. So, the interpretative fuzzy rules to coding the degree of a company's automation are proposed. Then, the architecture of ANN classifier was chosen in a series of experiments. The Levenberg-Marquardt method and genetic algorithms were used in training process. The performance of the classifier was measured using the sum of squared errors and the error function with the regularisation term in the form of the sum of squared norms of Jacobian matrices. The best performing classifier achieved 95.8% accuracy on the test dataset.

II. DECISION MAKING APPROACHES FOR SMART MANUFACTURING IN THE CONTEXT INDUSTRY 4.0

One of the factors determining the degree that an enterprise is compatible with the Industry 4.0 concept, is the

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level of its automation and robotisation. Between 1993-2018, the number of industrial robots in the world increased from 557 thousand to 2.4 million. In 2018, the largest number of industrial robots in the world was used by China, Japan, South Korea, the USA and Germany. In total, these countries have over 70% of all industrial robots currently in use [15] Taking the average annual growth dynamics of the number of robots between 2010-2018, Poland, with a result of 19% is comparable to the Czech Republic (18.7%) and with Slovakia (19.5%), but it is significantly behind Hungary (25.2%) (IFR, 2019). Most industrial robots in Poland are used in the processing industry sector (81.5%), especially in the automotive industry (38.6%) [16]. In Poland, 22% of large enterprises use robotics, which is also below the EU average [17].

Our motivation to conduct research is the need to build methods and tools, the implementation of which, in Polish manufacturing companies will allow them to increase their adaptation to the Industry 4.0 concept. The development of industry is inextricably linked to automation. Global competition, the digital revolution and changing consumer attitudes are becoming the foundation of the economy of the future. The development of the Polish economy will depend on the results that will be achieved in creating the industry of tomorrow (Industry 4.0). There is a need for changes that largely depend on innovation and the ability to implement new solutions and technologies in the construction of Industry 4.0, as well, in fact, as changes in the Polish economy. All this means that global and Polish industrial leaders are using robots and solutions that are part of Industry 4.0, to an ever greater extent.

Examples of data-driven, artificial intelligence techniques, used as support mechanisms within manufacturing companies - in the context of Industry 4.0. - can be found in the literature. Patalas-Maliszewska and Halikowski [18] where the use of a Convolutional Neural Network with a Support Vector Machine (CNN-SVM), in order to generate workplace instructions, was proposed. The article by Contuzzi et al. [19] analysed an innovative model based on the multi-level control of production processes. The model focusses on the innovative process control systems involving artificial intelligence (AI). This methodology improves the decision-making process supported by the facilities of Industry 4.0. The model can be applied to different sectors in industries and represents a tool for the ISO 9001:2015 check and control system. In the article by Ramezani et al. [20] a practical solution was presented in the light of Industry 4.0. The aim of this study was to propose a Hybrid Expert Decision Support System (EDSS) model, which integrates the Neural Network (NN) and the Expert System (ES) in order to detect unnatural CCPs and to estimate the corresponding parameters and starting point of the CCP detected. For this purpose, Learning Vector Quantisation (LVQ) and Multi-Layer Perceptron (MLP) networks architecture have been designed to identify unnatural CCPs.

In this paper, we present an innovative approach to decision making for smart manufacturing in the context of Industry 4.0 that combines the empirical evidence from Polish manufacturing companies with the use of artificial neural networks (ANN) for generating a model in order to forecast the degree of automation in a manufacturing company. As has already been pointed out, the proposed model allows knowledge of the level of automation, within a Polish production company, in the context of Industry 4.0, to be acquired and transferred to other managers in the form of a decision support system.

III. AI-BASED, DECISION-MAKING MODEL FOR THE DEVELOPMENT OF A MANUFACTURING COMPANY IN THE CONTEXT OF INDUSTRY 4.0

The proposed research model for assessing the level of a company's automation is presented below (Fig. 1).

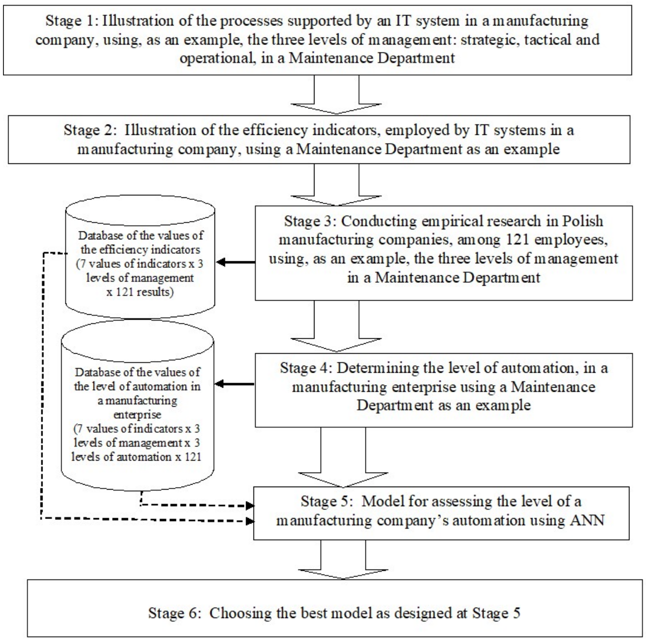

Fig. 1. AI-based, decision-making model for the development of a manufacturing company, in the context of Industry 4.0.

Primarily, business processes supported by an IT system are defined in a manufacturing company along the lines of the Maintenance Department (Stage 1, Fig. 1): P={P.1, …, P.46}, where: P.1 – introducing the recording of the reviewing of devices and machines, P.2 – introducing the recording of the testing and tuning devices and machines, P.3 - order management, P.4 - tracking device / machine status in real time (on-line), P.5 - requesting external service, P.6 - monitoring and tracking the production schedule and plan, P.7 - downtime planning, P.8 - identification of bottlenecks on each machine or device, P.9 - registering parts and perishables for equipment and machinery, P.10 - monitoring of the inspection, maintenance, prevention, repair and refurbishment of devices and machines, P.11 - review of technical documentation for devices and machines, P.12 - checking the availability of parts in stock, P.13 - reporting the demand for parts and perishables, P.14 - registering and selecting operations from the list of activities performed, P.15 - introducing the recording of the refurbishment of devices and machines, P.16 - recording the decommissioning of devices and machines, P.17 - reporting on the readiness for work of repaired devices and machines, (post review), P. 18 - simulation of retrofitting devices, machines and the production line, P.19 - generating reports for machines / devices and other events, P.20 - alerting device / machine downtime, P. 21 - alerting / information re- failures / wear of parts / blockages / failure to close guards / etc., P.22 - alerting / information on the readiness for work of devices / machines and of the production line, P.23 - conducting on-line video training, P.24 - planning training, P.25 -monitoring of training, P.26 – scheduling and planning human resources, P.27 - creating SUR job standards, P.28 - reporting / indicating improvements, such as modernisation, improvement of machines, devices), P.29 - reporting / indicating solutions that improve work, such as the flow of information, P.30 - notification via SMS or e-mail about an upcoming event, such as planned preventive maintenance and repairs, P.31 - generating/ manually activating a failure alarm, P.32 - generating/automatically activating an alarm vis-à-vis the occurrence of a failure, P.33 - notification by SMS or e-mail of a failure, P.34 - implementation of improvements, such as modernisation, improvement of machines, devices, P.35 - implementing solutions to improve work in such as information flow, P.36 - monitoring the testing of technical equipment / machines, P.37 - maintaining a repairs log, P.38 - console access to menus and desktops of a higher or lower level, as well as access to other users, P.39 – monitoring of the MTTR indicator (Mean Time To Repair), P.40 – monitoring of the MTTF indicator (Mean Time to Failures), P.41 – monitoring of the MTBF (Mean Time Between Failures), P.42 - analysis of the availability of devices and machines, P.43 - monitoring of the OEE indicator (Overall Effectiveness of Equipment), P.44 - SUR cost analysis, P.45 - recording of accidents at work, P.46 –archiving of data.

Each of the defined processes is carried out by workers in the Maintenance Department at three levels of management: strategic, tactical and operational and is either completely or partly supported by IT or is carried out without any IT system.

Next (Stage 2, Fig. 1.), the indicators of effectiveness that allow assessment of the use of an IT system are defined. It has been assumed that the rules are created according to (1), (2), (3), (4), (5), (6), (7), where:

E1, E2, E3, E4, E5, E6, E7 – in minutes
t_i – the time, in minutes, of an activity P.i carried out by the operators/leaders/managers during the week, either completely using an information system or partly using an information system or without using any information system
w_i – coefficient determining how activity P.i is performed,1- for activities completely using the information system, 2- for activities partly using the information system, 3- for activities without using any information system
n – number of activities carried out by operators/leaders/managers, $n \in \mathbb{N}$
d – number of operators/leaders/managers, $d \in \mathbb{N}$
m – number of machine devices, $m \in \mathbb{N}$

- E1: indicator of the effectiveness of preventive actions

$$E1 = \frac{d}{n\,m} \sum_{i \in \{1 \dots 6,\, 8 \dots 10,\, 14 \dots 18,\, 20 \dots 22,\, 28,\, 34\}} w_i\, t_i \qquad (1)$$

- E2: indicator of the effectiveness of preventive actions

$$E2 = \frac{d}{n\,m} \sum_{i \in \{4, 8, 10, 30, 32, 33, 36, 39, 40, 42, 43\}} w_i\, t_i \qquad (2)$$

- E3: indicator of the effectiveness of predictive actions

$$E3 = \frac{d}{n\,m} \sum_{i \in \{1 \dots 4,\, 6 \dots 14,\, 18,\, 19,\, 23,\, 26 \dots 30,\, 34 \dots 38,\, 42,\, 46\}} w_i\, t_i \qquad (3)$$

- E4: indicator of the effectiveness of reactive actions

$$E4 = \frac{d}{n\,m} \sum_{i \in \{1 \dots 5,\, 8,\, 9,\, 11 \dots 15,\, 17,\, 20 \dots 22,\, 28 \dots 33,\, 36,\, 38,\, 46\}} w_i\, t_i \qquad (4)$$

- E5: indicator of the effectiveness of alerting

$$E5 = \frac{d}{n\,m} \sum_{i \in \{20 \dots 22,\, 28 \dots 33\}} w_i\, t_i \qquad (5)$$

- E6: indicator of development

$$E6 = \frac{b}{n\,d} \sum_{i \in \{23 \dots 27,\, 29,\, 35\}} w_i\, t_i \qquad (6)$$

- E7: indicator of development

$$E7 = \frac{d}{n\,m} \sum_{i \in \{1 \dots 46\}} w_i\, t_i \qquad (7)$$

In Stage 3 (Fig. 1), on the basis of the business processes defined and the effectiveness indicators, a questionnaire was developed to assist with the main research into Polish automotive manufacturing companies, with special reference to the level of automation in the context of Industry 4.0. This study also assumes that those workers who were involved in the survey completed at least 80% of the processes defined (Fig. 1, Stage 1).

Empirical research was carried out on 121 maintenance service workers, in three Polish manufacturing enterprises which were representative of the automotive industry in the production of car parts. In the first company, 110 operators worked 456 machines; in the second company, 4 employees worked 20 machines while in the third enterprise, 13 employees worked 380 machines and devices. Based on the results of the survey of the 121 employees, a database on the values of the indicators of effectiveness was obtained: (7 values of indicators x 3 levels of management x 121 results).

Appendix 1 presents the database of indicators of the effectiveness obtained.

In Stage 4 (Fig. 1), based on the results of the empirical research, the automation level of a manufacturing enterprise, when using an IT system, as exemplified by a Maintenance Department was determined (Table I).

TABLE I. THE AUTOMATION LEVEL, WHEN USING AN IT SYSTEM, AS EXEMPLIFIED BY A MAINTENANCE DEPARTMENT – EVIDENCE FROM POLISH MANUFACTURING COMPANIES

Level of management	**The indicators of effectiveness**	**A manufacturing enterprise automation level**		
		1 – a low degree of automation	***2 – a medium degree of automation***	***3- a high degree of automation***
Operational (.1)	**E1.1**	*<1.1;58.6>*	*<3.6;14>*	<0;3.5>
	E2.1	*<4.1;13.2>*	*<2.6;4>*	<0;2.5>
	E3.1	*<11.6;44.60>*	*<3.6;11.5>*	*<0;3.5>*
	E4.1	<11.1;31.60>	*<2.6;11>*	<0;2. 5>
	E5.1	*<8.1;39.40>*	*<2.1;8>*	*<0;2>*
	E6.1	*<35.1;218.30>*	*<20.1;35>*	<0;20>
	E7.1	<10.1;37>	<2.7;10>	*<0;2.6>*
Tactical (.2)	**E1.2**	<2.1;5.5>	<0.6;2>	*<0;0.5>*
	E2.2	<2.1;4.7>	<0.6;2>	*<0;0.5>*
	E3.2	<2.1;6.3>	<0.6;2>	*<0;0.5>*
	E4.2	<2.1;5.3>	<0.6;2>	*<0;0. 5>*
	E5.2	<2.1;3>	<0.6;2>	*<0;0.5>*
	E6.2	<11.1;26.3>	<1.6;11>	*<0;1.5>*
	E7.2	<2.1;5.5>	<0.6;2>	*<0;0.5>*
Strategic (.3)	**E1.3**	<2.1;7>	<0.5;2>	<0;0.4>
	E2.3	<1.6;4.5>	<0.4;1.5>	*<0;0.3>*
	E3.3	<2.1;6.5>	<0.26;2>	*<0;0.25>*
	E4.3	<2.1;6.8>	<0.26;2>	*<0;0.25>*
	E5.3	<1.6;5.3>	<0.22;1.5>	*<0;0.21>*
	E6.3	<9.1;20>	<4.1;9>	*<0;4>*
	E7.3	<2.1;5.8>	<0.62;2>	*<0;0.61>*

ANN architecture was employed as Multi-layer Perceptron (MLP) (Stage 5, Fig. 1). Several experiments for a different number of neurons on the hidden layer, different training methods and different error functions were performed (section IV). Studies proved that the ANN model was able to achieve a test accuracy of ≈95.8% (section IV) using the dataset [Appendix 1, Table I].

IV. Model for assessing the level of a manufacturing company's automation using ANN

The AI-based decision-making model presented (Fig. 1) which uses a database built with the data from empirical research, carried out in the maintenance department of Polish manufacturing companies, allows the level of the automation of a production company, in the context of Industry 4.0, to be assessed. The values for the indicators of effectiveness, obtained at three management levels: strategic, tactical and operational, allowed the use of ANN to build the decision model. According to the block diagram shown in Fig. 1 – and having completed stages 1 – 4, a dataset was obtained which can be used to create the model.

A. *Dataset*

Stages 2 and 3, Fig. 1 introduced 121 cases into our dataset. Each case is described by 7 indicators of effectiveness derived from answers to questions on the completion times of selected business processes, as completed by maintenance department employees. Additionally, due to the fact that surveys were conducted on three levels of management (strategic, tactical and operational), each case includes information about the level of management. Based on the empirical research results achieved in Stage 4 (Appendix 1, Table I), we have determined the level of automation for our cases and have assigned them to one of three classes: a low, a medium and a high degree of automation. Finally, having collected the data and having pre-processed the phase in Stages 2-4 we determined the dataset of 121 cases, with each case having 8 attributes and belonging to 3 classes.

B. *Neural network classifier*

The basic idea of MLP networks was developed by Werbos, in 1974 and by Rumelhart et al., in 1986 [21], [22]. The Multi-layer Perceptron is a feed forward network consisting of neurons (nodes) arranged in successive, fully connected layers. MLP has input and output layers so-called, and one or more hidden layers. In order to fully characterise the network, its architecture, the activation functions of its neurons and its training method should be given. Due to typical MLP training methods based on gradient descent, continuous activation functions are used. Common choices are sigmoid functions such as the logistic function and the hyperbolic tangent. We have decided to use the logistic function for all neurons in our classifier.

To determine the architecture of the network, the number of input and output nodes, hidden layers and hidden nodes should be specified. The number of input nodes results from the number of attributes considered during classification, so our neural network classifier must have 8 input nodes. In the classification tasks, output nodes represent the class of the case analysed. A common approach for describing classes is using the 1-of-*c* coding scheme [23], where *c* is the number of classes and, simultaneously, the number of output nodes. Such a scheme, in combination with the logistic activation functions adopted, allows us to treat signals from the output nodes as the probabilities of a particular case, belonging to classes describing the degree of automation. In the approach presented here, classes based on the interpretative fuzzy rules have been coded as follows:

TABLE II. CODING SCHEME FOR THE DEGREE OF AUTOMATION

Degree of automation	Output nodes		
	node 1	*node 2*	*node 3*
low	1	0	0
medium	0	1	0
high	0	0	1

To determine the number of hidden nodes we used the 'growing method' so-called [23]. According to this approach, we started with one hidden layer and one hidden node and after checking the accuracy of the classifier which had been unsatisfactory, we increased the number of hidden nodes. The neural networks architecture used in this study -after increasing the hidden layer by one node- is shown in Fig. 2.

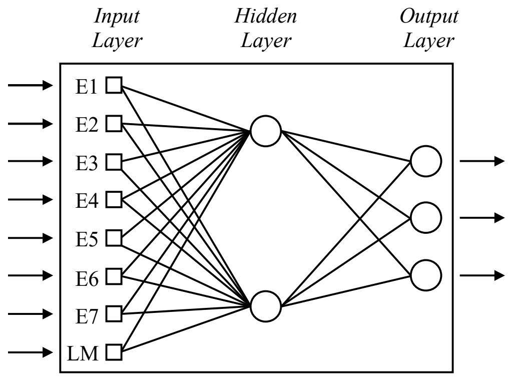

Fig. 2. MLP with two hidden nodes, where E1 – E7 are efficiency indicators and LM is the level of management.

C. *Network training*

The training algorithms of MLP are based on minimising the error functions describing the misfit between the modelled y^k and the desired t^k outputs of the network. The most common measure of misfit is a sum of squared errors (8):

$$e = \frac{1}{2n}\sum_k \|y^k - t^k\|^2, \tag{8}$$

where *n* is the number of output vectors compared.

It has been shown that for the 1-of-*c* coding scheme and networks, trained by minimising the sum of squared errors, the network outputs correspond to posterior probabilities [24], [25] and that they sum to one, so each output node represents the probability that the case analysed belongs to the corresponding class. During the training process the measure of misfit decreases and the accuracy of the model (the percentage of good classification) increases. However, the accuracy obtained at the end of the training process it is not the most important measure. The model should also be precise with regard to previously unseen data – this feature is called generalisation. To allow the generalisation capabilities of the model to be checked the original dataset is usually split into two or three parts. The training process is performed on the training dataset and the generalisation possibilities of the model are checked against the test dataset. In order to improve the generalisation capabilities of the neural networks, different techniques may be used, such as early stopping, training with noise or regularisation. In this study we have focussed on regularisation. According to Du and Swamy [26] generalisation by regularisation involves introducing an additional penalty term into the error function (9):

$$e_r = e + \lambda e_c, \tag{9}$$

where λ is a small positive coefficient describing the strength of penalty and e_c is a term which introduces a penalty for generalisation. Various forms of this term are used in the literature, they penalise the excessively large values of neural network weights or non-smooth network mapping [27]. It is known that the generalisation property of the neural network classifier depends on the smoothness of network mapping, therefore the penalty term can be taken in the form of the sum of squared norms of Jacobian matrices [27]:

$$e_c = \sum_k \|J^k\|^2, \tag{10}$$

where elements J_{ij}^k of matrix J^k are equal to $J_{ij}^k = \partial y_i^k / \partial x_j^k$ and x_j^k, y_i^k denote the *j*-th and *i*-th elements of input and output vectors, respectively.

Another important issue connected to the training of neural network is the choice of training method. The most commonly used for MLP networks are, based on gradient descent, back-propagation and Levenberq-Marquardt algorithms. In addition to algorithms based on a gradient, there are also those that do not need the calculation of derivatives such as the Nelder Mead Simplex method. The training methods mentioned above have significant drawbacks: these are local algorithms and depend on the initial choice of the network weights. In addition to local algorithms, there are also global algorithms, such as simulated annealing and genetic algorithms [28]. A comparison of convergence of different training methods can be found e.g. in [29].

In subsequent experiments, network training was performed in two different ways. In the first case we trained the network using the Levenberg-Marquardt method, however, we used the Monte Carlo approach and undertook the training process, repeatedly starting from various, randomly chosen initial weights.

In the second case we took advantage of the global approach and used the genetic algorithm to optimise neural network weights. Additionally, we tested both the sum of the squared error function (8) and the error function with the regularisation term in the form (10).

Our original dataset was randomly split into training and test datasets, in the ratio 80:20. To define and train the neural network, we used the MATLAB environment. At the beginning, we trained the neural classifier via the Neural Network Toolbox and the **`trainlm`** method and used the Levenberg-Marquardt algorithm. In order to carry out training, based on the genetic algorithm, we then implemented our own neural classifier and used the **`ga`** function from the Genetic Algorithm and Direct Search Toolbox.

D. Model creation

To determine the best architecture of the multilayer perceptron we first built the network with one hidden layer and one hidden node. The performance of MLP was measured using the sum of squared errors (8). The training process was performed both by the Levenberg-Marquardt method and genetic algorithm. We mostly used default MATLAB parameters except that the maximum number of epochs to train for **`trainlm`** method was changed to 1000. Additionally, due to the local nature of the Levenberg-Marquardt method, the training process in this case was repeated 100 times with initial weights initialized using a uniform random distribution from 0 to 1.

TABLE III. RESULTS OF THE FIRST EXPERIMENT

Subset of dataset	**Percent correct**			
	total	***low***	***medium***	***high***
Levenberg-Marquardt algorithm				
training	91.8	100	96.2	45.5
test	91.7	100	94.1	50.0
genetic algorithm				
training	91.8	100	96.2	45.5
test	91.7	100	94.1	50.0

Uniform random distribution over the interval [0, 1] was also used in genetic algorithm to create individuals for the initial population.

Accuracy of the model was measured as 'percent correct' i.e. proportion of cases classified correctly. Classification results for the best models obtained in this experiment are shown in Table III. This table presents the 'percent correct' measure for both training and test sets. The values in columns 'low', 'medium', 'high' and 'total' correspond to correctly classified cases for each of our degree of automation (low, medium, high) and for all classes together (total).

As it can be seen in Table III classification results for both MLP networks are the same but we found this accuracy of the model to be unsatisfactory and in the second experiment we built the MLP networks with two hidden nodes. Classification results for this experiment are shown in Table IV.

In this case accuracy of the model calculated using training set is slightly better for training process based on genetic algorithm (97.9% and 94.8%), however, accuracies obtained for the test set are the same (95.8%).

In the last experiment, the influence of the regularisation term (3) on the generalisation ability of the classifier was investigated. Accuracies of the both MLP networks for the test set were the same as in the second experiment, but in the case of the MLP network trained by Levenberg-Marquardt algorithm we obtained this result in 2 cases out of 100 in the second experiment and in 6 cases out of 100 in the third experiment.

Additionally, including the regularisation term allowed to improve generalisation capabilities of the classifier in 16% of cases (classification rate had not changed in 71% cases).

TABLE IV. RESULTS OF THE SECOND EXPERIMENT

Subset of dataset	**Percent correct**			
	total	***low***	***medium***	***high***
Levenberg-Marquardt algorithm				
training	94.8	100	96.2	72.7
test	95.8	100	94.1	100

genetic algorithm				
training	97.9	97.0	98.1	100
test	95.8	100	94.1	100

Classification results obtained in the second experiment, and the same obtained in the last experiment, show that the MLP classifier with two hidden nodes can be used to assess the degree of automation of the manufacturing company. The prediction accuracy of the obtained neural network model i.e. classification performance on the test set was equal to 95.8% and we found this accuracy to be satisfactory. This model had the worst prediction accuracy for the medium degree of automation (94.1%), for the low and the high degree classification accuracy on the test set was equal to 100%.

V. An Example of Use AI-based Decision-making Model

The model (Fig. 1) was verified according to the example of a Polish manufacturing company, for which the indicators of effectiveness were calculated (Table V).

Based on the received indicator it was found that maintenance services employees carry out separate activities as part of their daily activities at a given workplace partly using an IT system; on the other hand, the enterprise researched had a rather under-developed IT system. The recommendations were received for the managers of the manufacturing company in the form of:

- Process P.23: conducting on-line/video training requires the implementation of methods and techniques which, when utilised, increase the level of automation of the training. Augmented Reality (AR) technologies can be implemented here; these have also been widely implemented in companies on account of the work of assistant workers [30].
- Processes P.24: planning the training and P.25 – monitoring the training require the implementation of methods and techniques which, when utilised, increase the level of automation of the training. It is proposed to use a Convolutional Neural Network with a Support Vector Machine (CNN-SVM), in order to generate workplace instructions [18].
- Process P.26: human resource scheduling / planning, pProcess. P27 – creating a SUR job requires the implementation of methods and techniques, which, when utilised, increases the level of automation of the SUR job. This will be the subject of further work for the authors.
- Process P.29: reporting/alerting solutions that improve work, such as information flow, process P.35 - implementing solutions, such as information flow, in order to improve work, requires the implementation of methods and techniques which, when utilised, increases the level of its automation. It is proposed to implement the Business Intelligence module, integrated with the IT system currently in use in the company.

TABLE V. The Values of the Indicators of Effectiveness within a Polish Manufacturing Company

Indicator of effectiveness	E1	E2	E3	E4	E5	E6	E7
Values	7.34	4.13	7.39	6.41	3.54	12.35	5.26

The model for assessing the level of a manufacturing company's automation using ANN (section IV) is as follows:

$$Y = f\left(E1, E2, E3, E4, E5, E6, E7, LM\right) \qquad (11)$$

where:

LM = {1,2,3},1- the operational level, 2- the tactical level, 3- the strategic level

Y – the vector describing the automation level in the context of using a Maintenance Department's IT system: Y = [1,0,0] - a low degree of automation, Y = [0,1,0] – a medium degree of automation, Y = [0,0,1]- a high degree of automation

This model (11) was applied to determine the automation level in the context of using a Maintenance Department's IT system of discussed Polish Manufacturing Company. It was achieved a medium degree of automation.

Many examples of the usefulness of the different types of artificial neural networks for Manufacturing have been discussed in the paper [31]. From the point of view of maintenance 4.0 technologies, the development of new technologies has significantly affected the subject of maintenance operations (machines and equipment) [32]. With the proposed approach (Fig. 1), it is possible to specify business processes within a manufacturing enterprise, the implementation of which affects the level of automation in an enterprise. This can be done by conducting a survey in the company and subjecting the received data to the diagram of the presented model. The model can also be used as an additional tool to support design work, such as the development of information systems, in order that companies may adapt them to the Industry 4.0 concept.

VI. Conclusions

The use of data-driven artificial intelligence techniques offers great potential to smart manufacturing in the context of developing the new approaches of decision-makers. The innovative AI-based decision-making model for the development of manufacturing companies, using, as an example, a maintenance department, integrates the results of empiric research surveys in Polish manufacturing enterprises which are aimed at implementing the concept of Industry 4.0 and the use of artificial neural networks, in order to build a model to assess the degree of automation of the manufacturing company. By checking the quality of the model, using a test accuracy of $\approx$ 95.8%, this model is usable in other manufacturing companies.

Despite the promising results reported so far, there are still some limitations and significant challenges for further research. This model can be applied to manufacturing companies with automotive branches. In order to extend the proposed model to other industries, empirical research should be carried out in relevant enterprises. Also the teaching set on the basis of which the ANN was trained will be increased and in this way we will focus our research on increasing reference material and improve our ANN model. Moreover implementation of the model, in the form of an IT system is also planned to support decision making in the maintenance departments of manufacturing companies.

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VII. APPENDIX

LoM		E1	E2	E3	E4	E5	E6	E7
Operational	1	*41.28*	*9.56*	*32.81*	*24.24*	*17.41*	*74.12*	*28.63*
	2	*16.39*	*0.00*	*14.46*	*7.74*	*10.61*	*48.04*	*12.07*
	3	*19.79*	*2.42*	*11.12*	*12.27*	*1.88*	*0.00*	*10.23*
	4	*12.72*	*3.49*	*10.30*	*8.48*	*0.00*	*0.00*	*7.01*
	…	…	…	…	…	…	…	…
	121	*3.08*	*2.25*	*3.07*	*2.13*	*1.17*	*92.31*	*2.4*
Tactical	1	*0.34*	*1.52*	*1.77*	*1.43*	*1.43*	*0.88*	*1.34*
	2	*0.32*	*0.81*	*1.59*	*1.33*	*0.84*	*0.80*	*1.15*
	3	*0.32*	*1.14*	*1.61*	*1.19*	*0.97*	*0.89*	*1.15*
	4	*0.36*	*1.14*	*1.82*	*1.30*	*1.11*	*0.87*	*1.34*
	…	…	…	…	…	…	…	…
	8	*0.21*	*0.31*	*0.45*	*0.49*	*0.38*	*10.38*	*0.43*
Strategic	1	*0.51*	*0.28*	*0.87*	*0.32*	*0.20*	*4.97*	*0.56*
	2	*0.59*	*0.28*	*0.95*	*0.34*	*0.21*	*5.26*	*0.60*
	3	*6.83*	*4.11*	*6.40*	*6.71*	*5.25*	*19.82*	*5.78*
	4	*0.24*	*0.12*	*0.20*	*0.20*	*0.13*	*2.95*	*0.17*