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ORIGINAL PAPER

THE USE OF A HYBRID MODEL OF THE EXPERT SYSTEM FOR ASSESSING THE POTENTIALITY OF MANUFACTURING THE ASSUMED QUANTITY OF WIRE HARNESSES

Anna Burduk[1], Katarzyna Grzybowska[2], Andrii Safonyk[3]

1) Wroclaw University of Technology, Wroclaw, **Poland**, 2) Poznan University of Technology, Poznan, **Poland**, 3) National University of Water and Environmental Engineering, Rivne, **Ukraine**

ABSTRACT. **Background:** Control plays the main role in ensuring the stability of production processes, while digital models of processes and methods of artificial intelligence are used more and more commonly in it. Production of highly diversified items in small lots at low inventory levels is characterised by a much lower stability as compared with large-lot manufacturing. Additionally, innovations created for items or processes result in disturbances to current work. Although this turbulence is usually momentary, it may lead to a loss of function or manufacturing stability, which in turn translates into financial losses, as well as losing customers. This paper presents the potential of using simulation models and artificial neural network models to assess the stability of a reorganized production system.

Methods: The problem analysed in the paper is that of merging a simulation model with an ANN model by designing a hybrid model. A direct connection of both types of models is not possible due to their various structures, specificity, and different purposes, as well as the various types of input and output data. Therefore, the idea of merging these two types of models through an expert knowledge base and fuzzy inference was proposed. The results from the simulation model and the ANN model were used to gather the knowledge on the production system being analysed. It has been proposed that the output from the simulation model provided knowledge of the risk level, while the output from the ANN model provided knowledge of process stability.

Results: The paper presents the idea of projecting a hybrid model of the expert system in order to assess the stability of a reorganized production system. A model of a hybrid expert system was developed to assess the potential of executing the assumed production plans. The level of risk and the level of stability determined by the simulation model and the ANN model are entered into the system. The output from the expert model is the value of the variable determining the potential of achieving the goal. In the construction of the model, fuzzy inference was used, which uses linguistic variables and is characterized by a knowledge system in the form of fuzzy rules "if ... then ...". For both the independent variable and for the dependent variable, a set of membership functions representing accepted linguistic variables was proposed, and then decision rules were determined.

The idea of merging simulation models with ANN models was tested on a practical example in production system that manufactures products for dishwashers.

Conclusions: The potentiality to execute production plans depending on the level of risk and the level of stability of the production system is too complicated to be modelled mathematically, but based on the analysis of data from the simulation and ANN models, it is possible to obtain information concerning the relations between corresponding input and output values.

Key words: production system, risk assessment, artificial neural networks, fuzzy logic, stability, variability.

INTRODUCTION

A modern customer requires that an item should not only be of the proper quality and sold at a low price, but also diversified, i.e. available in various versions and variants. In order to meet these demands, manufacturers are forced to manufacture items in small batches and deliver quickly them to the market.

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Manufacturing planning is a complex engineering problem which requires a combination of theoretical methods, computer-based simulation approaches and artificial neural networks. Unfortunately, contemporary production and manufacturing systems are marked by dynamic changes. This is a result of the amount and type of item produced, and varying cycle times of executing inflictions [Zwolińska, Grzybowska, Kubica, 2017]. Variation is an integral part of every system, it is also inevitable in any process [Deming 1993, Cyplik, Hadaś, Fertsch 2009, Grzybowska, Gajdzik 2012, Johnston 2016, Sitek, Wikarek 2016, Kiedrowicz, Nowicki, Waszkowski, et al. 2016]. However, a problem with ensuring the stability of production appears here. Production in small batches with highly diversified items and low inventory levels is indicated by a much lower stability as compared with large-lots manufacturing. Although these disturbances are usually momentary, they may lead to a loss of function or production stability, which in turn translates into financial losses, as well as losing customers. For these reasons eliminating variety and factors leading to uncertainty, as well as assuring stability of the production systems is a key matter [Zwolińska, Grzybowska, Kubica 2017]. In order to ensure the smooth functioning of a production system, the stability of its processes must be ensured and, on the other hand, fast decisions, which would be encumbered with the lowest possible risk and uncertainty, should be made [Antosz, Stadnicka 2017]. The concept of stability is derived from systems theory and means the ability of a system to return to a stable state after the disturbances have ceased.

Ensuring the stability of the production process is a prerequisite for achieving the planned production level. Control plays the main role in ensuring the stability of production processes, while digital models of processes and methods of artificial intelligence are used more and more commonly in it [Gola, Klosowski 2019].

Considering the new manufacturing paradigm – Industry 4.0 – future factories are indicated by a more flexible structure to produce highly customized items in smaller quantities, at a lower cost, of an advanced quality within the required time window. Against such a sweeping trend, it is only possible when the factories layout and processing flow are correctly designed and modified quickly [Zhang 2019].

Computer modelling and computer simulation have been widely used in the analysis, assay and optimization of production systems by scientists for almost 60 years [Taylor et al. 2009]. Matching an appropriate type of model to the nature and character of the decision is a highly important aspect here (Burduk, Grzybowska, Kovacs, 2018). Artificial neural networks are another very significant group of models more and more commonly used when making decisions concerning the control or management of production processes. Can and Heavey even indicate the advantage of ANN over modelling and computer simulation due to its advanced efficiency and the ease of designing the model [2012]. Artificial neural networks learn to solve global problems in a reasonable amount of time [LeCun et al. 2015].

Most of the previous papers in this field only suggested various algorithms to optimize production planning, which could be very time-consuming in reality. Therefore, this paper will also pay attention to the integration of simulation-based methodology and artificial neural networks to make a trade-off between work performance and planning cost.

Therefore, this study aims to enrich the theoretical foundation of production planning by taking advantage of a simulation-based methodology and artificial neural networks.

The aims of the study are to present the results of a simulation test that has been conducted and to perform an empirical analysis. The publication has the following structure: Section 2 describes the characteristics of the company and the process of manufacturing products. Section 3 presents an assessment of the risk in the production system analysed. In next part, we present assessment of the stability of the production system. Section 5 focuses on the hybrid model, while the final section contains a summary and conclusions.

CHARACTERISTICS OF THE COMPANY AND THE PROCESS OF MANUFACTURING PRODUCTS

The idea of merging simulation models with artificial neural networks models was tested using a practical example. A model of the hybrid expert system was built for this purpose in the Matlab software with Fuzzy Logic Toolbox in order to assess the potential of executing the assumed production plans depending on the level of stability and the level of risk. A production system that manufactures products for Electrolux dishwashers was used as an example.

In the period when the research was conducted and the data were collected, the factory planned to increase its production by 30% over two years in order to handle its growing number of orders. At the same time, a decision was made to reduce the production costs by decreasing the inventory levels. These actions could lead to disturbances in the course of the production process (loss of stability). An agreement entered into with a key customer of the factory means that the order processing times must be very short. In order to expand its production plan, the factory intends to introduce a number of organizational changes involving an increase in the production capacity at stations that are bottlenecks. However, these changes will not be discussed in this paper.

The problem of the potential to execute production plans depending on the level of risk and the level of stability of the production system is too complicated to be modelled mathematically. Data analysis shows that through simulation and artificial neural networks models it is practicable to obtain information about the relations between corresponding input and output values. The major items of the proposed expert system will be a knowledge base and rules of inference. Burduk et al. [2018] proposed the fuzzy inference method, which is characterized by a knowledge system in the form of fuzzy rules "if ... then ...".

The factory analysed produced approximately 700 various types of product. All these items are characterized by high level of similarity in their structure and in the manufacturing process. Each wire harness consists of so-called modules, while a module consists of wires ended with terminals. Both the number of modules and the number of wires may differ depending on the type of wire harness. Some wires are connected with the use of insulating tape. The modules are connected in the enclosure [Burduk, 2013]. Figure 1a shows the structure of the wire harness, while Figure 1b presents a schematic diagram of a sample harness.

The selected types of products are manufactured on the same production floor. Transport between stations is carried out by production employees. Harnesses are transported on so-called hangers. Figure 2 presents the names of stations, their locations, the order of tasks, and the flow of materials.

The work centres at which wires are inserted into electrical connectors, operate in parallel with the assembly centres. After the increase in the production plan and the introduction of organizational changes, it is estimated that the highest load will be on assembly centres (even 75%). The load on remaining stations will be from 26% (packaging, taping) to 60% (cutting of electrical wires). The production system analysed here is controlled in accordance with the principles of the pull system. The process is stimulated by assembly centres. Production takes place at the customer's request in small lots of approx. 250–350 pieces.

The reliability structure of the production system is a combination of series and parallels. Figure 3 schematically presents the tasks performed during the production.

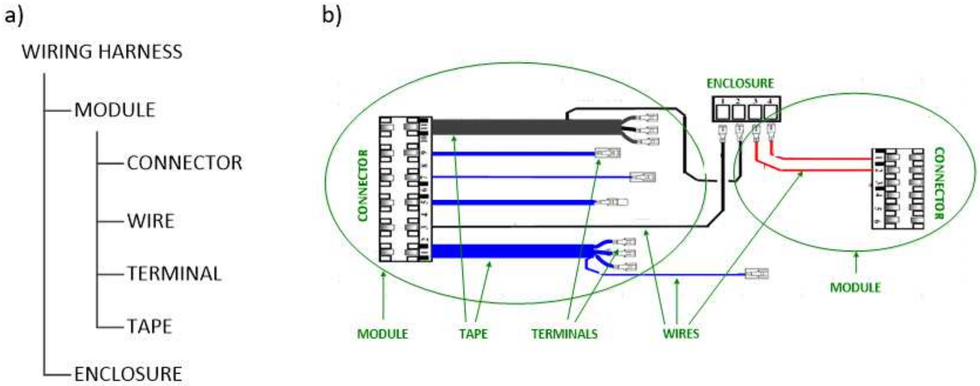

Fig. 1. a) Structure of a wire harness, b) schematic diagram of the selected wire harness

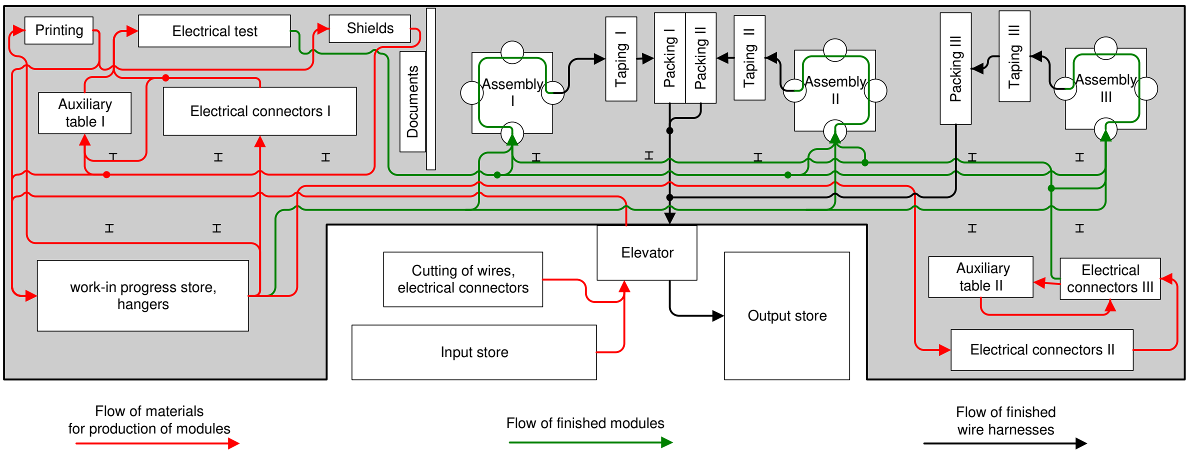

Fig. 2. Layout of the production floor and the flow of components in the process of production of wire harnesses

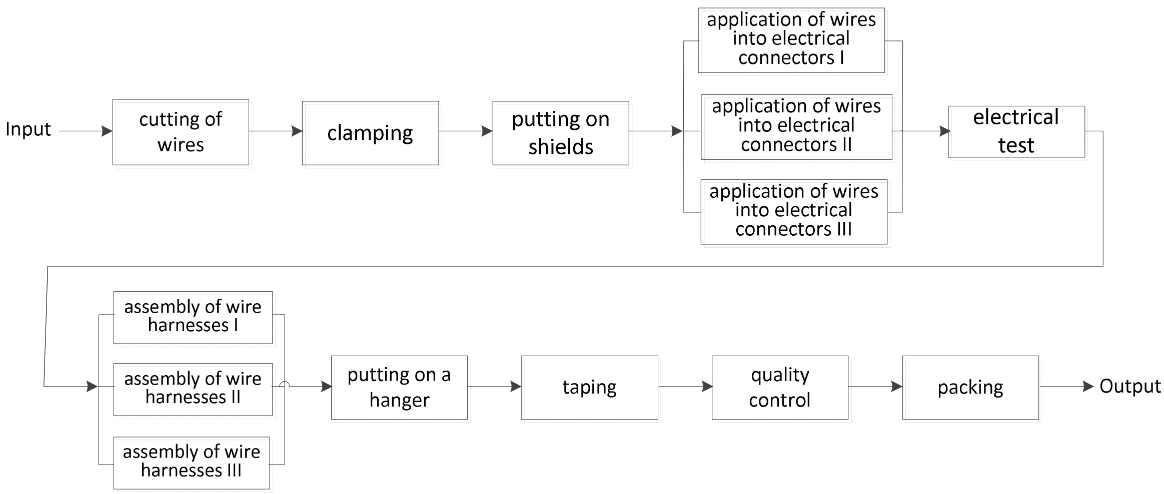

Fig. 3. Flowchart showing the stages of the production of wire harnesses

The assembly takes place on three stations operating in parallel (Assembly I, Assembly II and Assembly III). The time of assembly of products depends primarily on the number of the modules included in it. This is associated with the fact that more components need to be assembled and taped. The material flow in the assembly centre is presented in Figure 4.

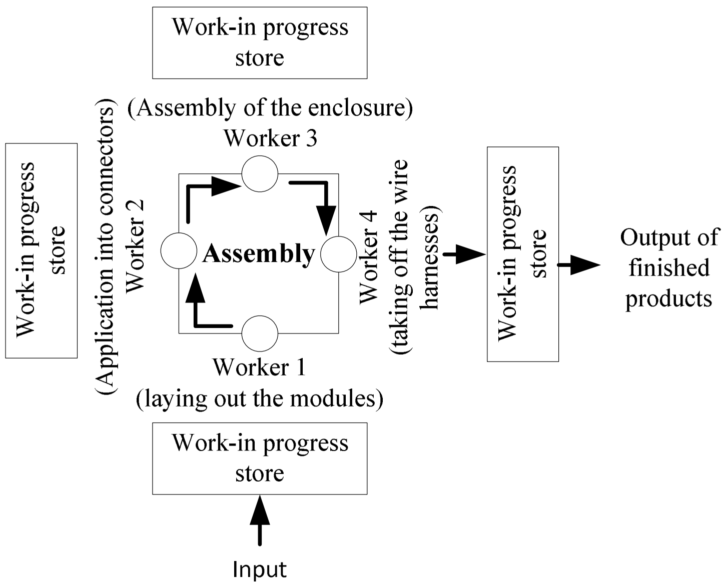

Fig. 4. Material flow in the assembly centre

The assembly stations are bottlenecks as they are the critical place in the process. Assembly tasks are performed on a rotary table by three employees. Employee 1 lays out the prepared modules on the assembly table in accordance with the drawing of the item to be assembled, which is shown on the table. Employee 2 inserts additional wires into connectors, Employee 3 assembles modules in enclosures, while Employee 4 picks up harnesses and places them on a transport hanger. If one of the modules or additional wires has not been installed correctly, the item is considered defective at the final quality control.All assembly tasks require precision and high skills among the employees. An incorrect arrangement of modules causes a significant extension of the time needed for the application of additional wires in the next task. Both the work of laying out the modules and taking off the products must be performed cautiously, because the wires may slip out of the connectors or enclosure. As the final assembly centres operate on the principle of a swivel, the skills of the works are important, as they need to work with the same pace.

In connection with the factory's plans to increase production capacity, a decision was made to assess the level of risk in the production system using the modelling and simulation methods, and then to examine the level of stability with the use of an artificial neural network. Analysis performed with the use of the models will allow the potentiality of achieving an advanced level of production to be assessed.

ASSESSMENT OF THE RISK IN THE PRODUCTION SYSTEM ANALYSED

For the needs of the risk analysis, a standard production plan was adopted, in which the planned increase in the production capacity was taken into account and the limits of the process stability were determined as ± 5% of the plan. Table 1 presents the production plan adopted for further analyses and the assumed limits of the process stability.

Table 1. The production plan and the adopted limits of the process stability depending on the number of modules in a wire harness

Number of modules in a wire harness [pcs]	Production plan [pcs/shift]	Limit of the stability of the production plan [pcs/shift]
2–4	370	352–388
5–6	350	333–367
7–9	330	314–346
9–12	250	238–262

Due to the fact that risk factors occur in the production system at random, a representative period (T) should be adopted for the analysis. It has been assumed that this period should be 3 months, because this is the time that allows the full characteristics of the risk factors to be gathered. The factory operates in a two-shift system, which for the assumed representative period gives a total of 120 production shifts. For this representative period, the production volume should be:

$$W = 1300 \frac{pcs.}{working\ shift} \cdot 120\ working\ shifts = 156000 \frac{pcs.}{12\ weeks}$$

The next step was to identify the risk factors occurring in the production system and to compile their characteristics. It involved observations, an analysis of the specification of previously completed production orders, and measurements of process times, as well as consultations and interviews with employees on various organizational levels. The data collected in this way are presented in Table 2.

Table 2. Identified risk factors and their characteristics

Name and designation of risk factor	Characteristics of the impact on the production system
Risk of absence of employees (r_1)	Caused by an absence which is at the level of 10% of working days a year per employee.
	Resulting from sick leaves, which translates annually into 7% of the working time per 1 employee.
Risk of rotation of employees (r_2)	Rotation concerns 33% of production employees a year. The negative impact of the rotation on the production system results from the fact that a new employee must undergo training and gain experience. In the case of assembly workers, the decrease in the performance is approx. 50% – the workers reach the assumed efficiency only after a period of 1 month of work.
	With respect to other work centres, the decrease in the efficiency is at the level of 30% and lasts about 1 week.
Risk of quality errors (r_3)	Apart from the defects that occurred in the assembly centres, repairing defective elements takes place at separated workstations and does not have a significant influence on the production process.
	In the case of assembly centres: - typical number of elements to be corrected at the level of 5 elements/shift/assembly station. in the case of occurrence of employee rotation, the number of elements to be corrected is 20 elements/shift/assembly station on average; a decrease in quality lasts for approx. 2 weeks.
Risk of downtimes on the production line (r_4)	Failures of the machines, for which the average downtime of the workstation in the period analysed ranged from 0.4 to 1.5 h a week.
	Unplanned changeovers resulting from the need to execute orders with a higher priority; The following data concerning the additional changeovers of workstations were obtained: semi-automatic machines for the applications of wires into electrical connectors – from 8 to 16 min depending on the number of wires in a module.

In order to determine the increases in production times resulting from the occurrence of risk factors, two simulation models were built in ProModel v.4.0 software. The first model did not include any risk factors and the purpose of its construction was to assess the potentiality of executing the production plan and to validate the model. The results of the simulation confirmed that the increased level of the production plan could be achieved the production system. The simulation for the assumed number of 156,000 items ended after 57,208 minutes, which was after 119.2 production shifts.

The objective of building Model 2 was to investigate how the risk factors presented in Table 2 affect the potentiality of execution of production plans. The results from Model 2 showed that the increase in the time caused by the occurrence of the risk factors was at the level of 39.6 (33%) working shifts for the production plan assumed. This means that at the current risk level it is not possible to execute the increased production plan. The results of the simulation showed also that the problem of the occurrence of risk factors concerned only assembly centres — for them the load in Model 2 even reached 89%. Therefore, in the later part of the study, the analysis was limited only to the assembly centres.

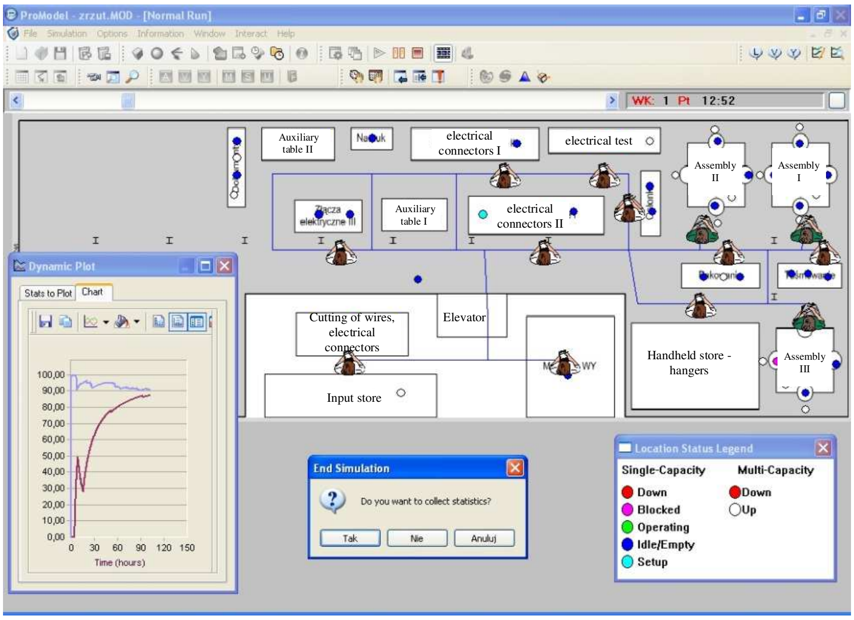

Fig. 5. Screenshot of Model 1

For each assembly centre, the losses (S) (the number of products not manufactured due to the occurrence of risk factors in the system) were calculated according to the formula [Burduk & Chlebus, 2009a, Burduk & Chlebus, 2009b]:

$$S_i = W_i \cdot \frac{\Delta t_i}{T}$$

where:

S_i – loss on the number of the manufactured products caused by the occurrence of risk factors in individual assembly centres (M1, M2 and M3),

W_i – the indicator (here productivity) analysed in the production system, theoretically possible for the production system to obtain,

$$W_i = \frac{156000\, pcs.}{3} = 52000\, pcs.,$$

$$\Delta t_i = 39.6\, working\ shifts,$$

$$T = 120\, production\ shifts$$

Thus, for individual assembly centres, the losses caused by the occurrence of risk factors will be as follows:

$$S_{M1} = S_{M2} = S_{M3} = 52000 \cdot \frac{39.6}{120} = 17160\, pieces$$

The risk of not achieving the production goal for each assembly centre will be [Burduk, 2010]:

$$R_{M1} = R_{M2} = R_{M3} = \frac{S_{Mi}}{W} = \frac{17160}{156000} = 0.11$$

Due to the fact that the assembly centres operate in parallel, while it has been established that the remaining work centres do not have any impact on the risk of this system, the total risk R_C will be [Burduk, 2010, Burduk & Chlebus, 2009a]:

$$R_C = R_{M1} + R_{M2} + R_{M3} = 0.11 + 0.11 + 0.11 = 0.33$$

The value of R_C for the entire production system is 0.33. This means that with a probability of 33% the production system will not achieve the assumed goal, i.e. the production of 1300 pcs of wire harnesses per production shift.

ASSESSMENT OF THE STABILITY OF THE PRODUCTION SYSTEM

The purpose of designing an artificial neural network model was to assess the stability of the wire harness assembly process. The assembly process can be deemed stable if the production volume is consistent with the production plan adopted. Otherwise, corrective actions should be taken that consist in changing the values of input parameters of the production resources used in the process.

In order to predict the quantity of the products manufactured at the given input parameters, a unidirectional neural network (multilayer perceptron) was built. The quantity of assembled products of good quality, i.e. those which passed the electrical test successfully, was to be the dependent variable. The independent variables were selected as follows:

X1 – the number of modules in the wire harness,
X2 – the skills level of Worker 1,
X3 – the skills level of Worker 2,
X4 – the skills level of Worker 3,
X5 – the skills level of Worker 4,
X6 – time of taping,
X7 – the number of defective elements detected at the electrical test station.

In order to evaluate the parameter of workers' skills levels, 4 values have been introduced:

1 – a worker who works less than 1 week,
2 – a worker who works less than 2 week,
3 – a worker who works less than 4 week,
4 – an experienced worker.

The data were collected from observations and measurements of an actual process, as well as from the analysis of the organizational specification and quality control reports. In total, 378 measurements were available for each variable. This set was divided into two parts, one of which served as a training set, while the second part was used for testing the network. The test was performed in the SAS Enterprise Miner 6.2 environment. The first step was to investigate the correlation between independent variables and the dependent variable. The results containing the correlation value are shown in Table 3.

Table 3. Values of the correlation between the analysed variables

Independent attribute (variable)	Correlation value
number of modules in the wire harness	0.16583
skills level of Worker 1	-0.16872
skills level of Worker 2	-0.22465
skills level of Worker 3	-0.14535
skills level of Worker 4	0.03276
time of taping	0.02104
number of defective elements detected at the electrical test station	-0.02957

The results indicate that there is no point in using the linear regression method to solve the problem being analysed here and it is reasonable to use the ANN model that builds non-linear regression models. Further tests were performed with a multilayer perceptron network, with modified values of the number of neurons in the hidden layer

Further investigations involved changing various numbers of independent variables. Their aim was to find such a combination of independent variables that the neural network would provide the best prediction of the number of products manufactured per shift. Selecting the variables depended on the results of previous tests, specifically on the absolute value of the correlation (Tab. 3). In the first test, all input attributes were used, in the second test, the 'taping time' attribute was discarded (the lowest absolute value of the correlation), and in the third test the 'number of defective components found at the electrical test station' attribute was additionally discarded (the next lowest absolute value of the correlation). The results are shown in Table 4, where the values obtained represent the network selection criterion – the mean square error; the results involve an analysis of the input data set, which was also used for the ANN training process [Burduk 2013].

Table 4. The results of the experiments for different variants of the neural ANN built

Neural network model	Mean squared error			
	Experiment No. 1	Experiment No. 2	Experiment No. 3	Experiment No. 4
MPN – NN=4	999.05	2443.71	1056.1	427.08
MPN – NN=8	2537.86	1369.98	1437.86	1019.25
MPN – NN=16	327.08	767.69	375.39	526.14
MPN – NN=32	1219.25	754.22	327.15	2088.12
MPN – NN=48	2375.39	872.49	999.05	368.14
GLM	1851.50	1450.28	1851.50	2569.8

where:
MPN a multilayer perceptron network,
NN number of neurons in the hidden layer,
GLM generalized linear model.

In the case of each test, the worst results (with the advanced mean squared error) were obtained for a neural network built according to the generalized linear model. The best results were obtained for a multilayer perceptron network with 32 neurons in the test no. 3, a schematic diagram of which is presented in Figure 6. This model was then used for further tests, i.e. for the assessment of the stability of the wire harness assembly process for various values of independent variables.

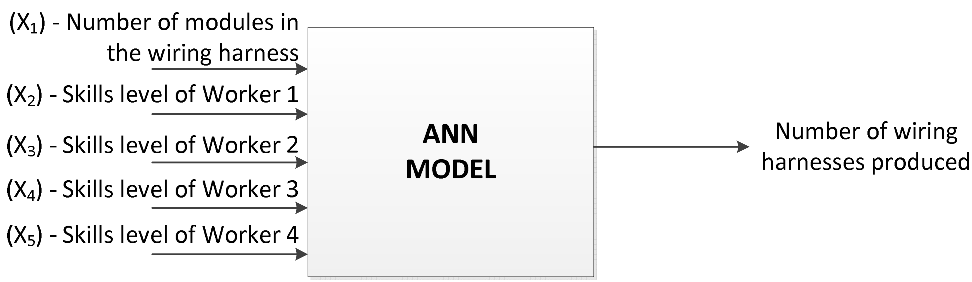

Fig. 6. Independent variables and the dependent variable used to build the ANN model

For the neural network designed in such a way, a series of tests using the test data was carried out in the SAS Enterprise Miner 6.2 environment. The test data contained various variants of changes in input attributes (independent variables). For such data, the neural network model predicts the values for manufactured products, which are interpreted in the context of the stability of the assembly process. The purpose, course and results of one of the tests are described below.

The purpose of the test was to examine how the skills levels of the employees at the assembly centre affect the stability of the process analysed. A wire harness with 7 modules was selected as an example. The production plan for products consisting of 7 modules was assumed at the level of 330 pcs/shift. For the needs of the study it was assumed that the production process is stable if the absolute value of the quantity of the components produced is within the range (314–346 pcs of products per production shift) [Burduk 2013]. Table 5 shows the production volume predicted by the artificial neural network model, which depends on the skills level of Employee 3, assuming that the level of skills of other employees is high.

Table 5. The predicted production volume for different skills levels of Worker 3 and a fixed number of modules to be assembled

Network inputs					Network outputs
Quantity of modules [pcs]	Skills level of Worker 1	Skills level of Worker 2	Skills level of Worker 3	Skills level of Worker 3	Predicted production volume
7	4	4	4	3	340
7	4	4	3	3	328
7	4	4	2	3	308
7	4	4	1	3	269

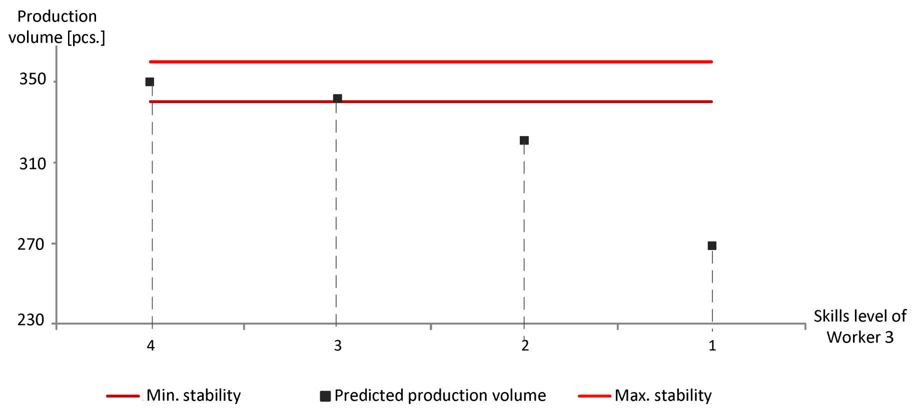

Fig. 7. The predicted production volume of wire harnesses for a fixed number of modules and different skills levels of Worker 3

The data included in Table 5 are also presented in the context of the process stability in Figure 7.

As can be seen from Table 5 and Figure 7, the process loses the steady state if Employee 3 works for a period shorter than two weeks. This result confirms the observations made when collecting the data and analysing the process. It also confirms the opinions of employees and process managers after a month of performing. Assembly works a new employee is able to work in accordance with the pace adopted for the assembly centre and the number of defective items returns to the assumed level.

Subsequently, other tests were conducted which confirmed that this neural network can be used to assess the stability of various variants of independent variables. The results obtained with the use of the neural network and the results obtained with the use of the simulation models for determining the level of risk in the system will be used to build a hybrid model of the expert system.

BUILDING A HYBRID MODEL

For the needs of the project, a fuzzy hybrid model was built and the following linguistic variables were determined:

– risk level = {low, average, high},
– stability level ={below the range, in the range,above the range},
– possibility of executing the plan (achieving the goal) ={low, high}.

For the variables specified above, their membership functions were defined. Figure 8 shows the membership function for the "risk level" linguistic variable.

The membership function proposed for the "risk level" linguistic variable is universal and can be adopted for all the production systems examined. Figure 9 shows the membership function for the "stability level" linguistic variable describing the production plan of products consisting of 9-12 modules.

Figure 10 shows the membership function for the linguistic variable "potentiality of executing the plan (achieving the goal)".

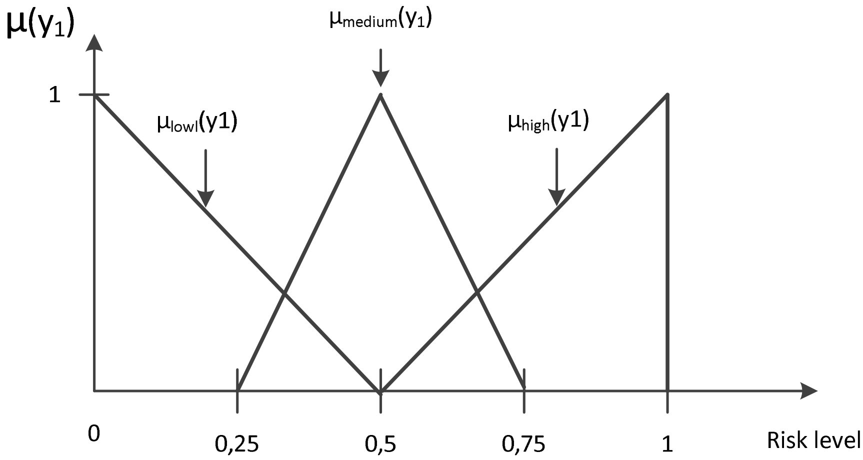

Fig. 8. Membership function for the "risk level" linguistic variable

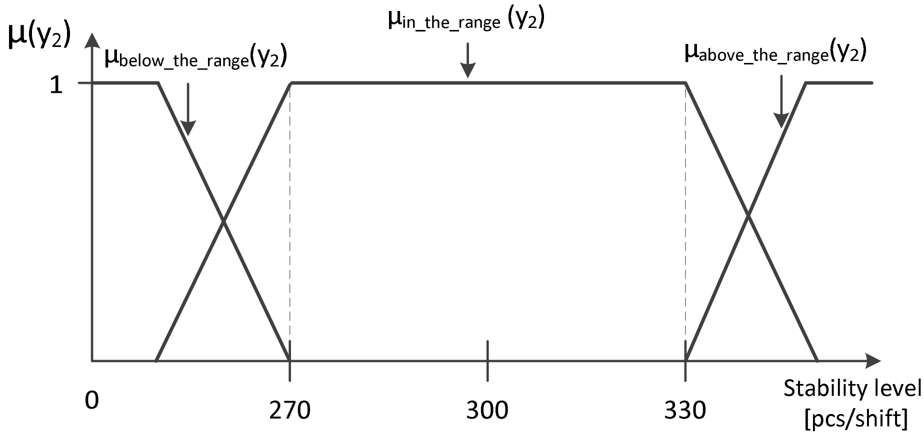

Fig. 9. The membership function for the "stability level" linguistic variable in the production process of wire harnesses consisting of 9-12 modules

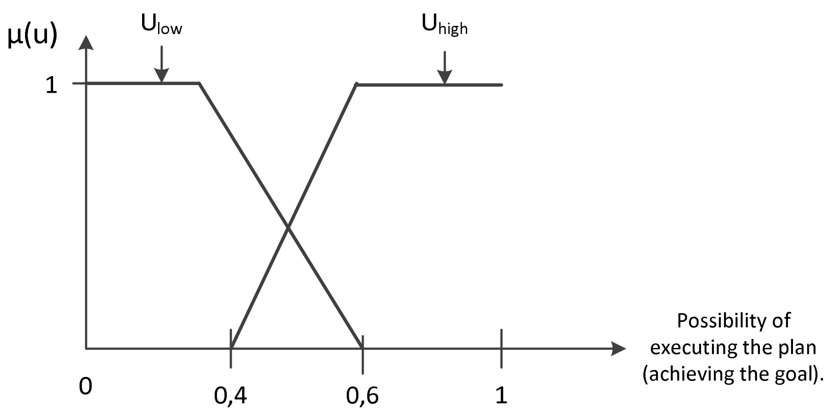

Fig. 8. The membership function for the linguistic variable "possibility of executing the plan (achieving the goal)"

As in the case of the "risk level" linguistic variable, the proposed membership function for the linguistic variable " potentiality of executing the plan (achieving the goal)" is universal and can be adopted for all the production systems tested.

Stage 1. Building a knowledge base

After that, a database was built of rules describing the relationships between individual values of variables, i.e. the rules describing the potentiality of executing the production plan depending on the level of risk in the production system and on the level of its stability.

If WR is low and PS is above range, then RC is high
If WR is low and PS is within the range, then RC is high
If WR is low and PS is below the range, then RC is low
If WR is medium and PS is above the range, then RC is high
If WR is medium and PS is within the range, then RC is low
If WR is medium and PS is below the range, then RC is low
If WR is high and PS is above the range, then RC is low
If WR is high and PS is within the range, then RC is low
If WR is high and PS is below the range, then RC is low

where:
WR – risk value,
PS – stability level,
RC – possibility of achieving the goal.

The database of decision rules can also be presented in the form of a decision table (Table 6).

Table 6. Decision table of the rule base

Y_1 / Y_2	below the range	within the range	above the range
low	low	high	high
medium	low	low	high
high	low	low	low

Stage 2. Operation of the expert system

The first step in the work of the fuzzy model of the expert system will be fuzzification. This step boils down to converting the sharp values of system inputs into fuzzy values. This is done on the basis of membership functions defined earlier (Figure 8, Figure 9, Figure 10). In the next step (b), the inference rule is selected from the knowledge base defined earlier. In the example of production system analysed, the use of Mamdani architecture is proposed. Each rule is fulfilled to some extent, because the inputs had certain degrees of membership in the corresponding fuzzy sets. If the premise of the rule consists of two premises concerning two inputs connected by the conjunction "and", the degree of membership in the entire rule is determined typically as the degree of membership in the entire relationship which is the combination of two fuzzy variables. The resulting fuzzy set is obtained as the sum of conclusions from individual rules. As the final result of the step of inference (b), the value of the output variable is obtained in the form of a fuzzy set. The last step of the stage 2 is sharpening (step c). It allows converting the output fuzzy set to the form of the sharp value. The literature suggests several methods of defuzzification. The most popular of these include the middle of maximum method, the centre of gravity method and the centre of sums method.

A decision was made that the best method for verifying the work of the model of the expert system for assessing the potentiality to achieve the production goals is to use specialized software. Matlab software with Fuzzy Logic Toolbox was selected and its general view is shown in Figure 11.

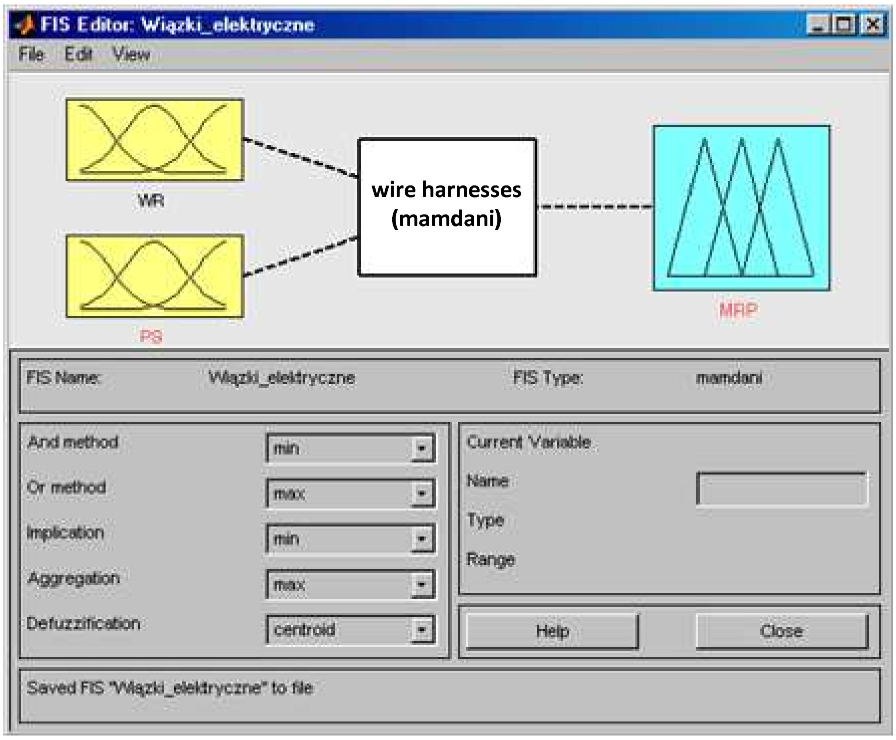

Fig. 11. The expert system designed – view of a screen from Matlab software with Fuzzy Logic Tool

This allowed the use of the fuzzy rule-based system in Mamdani architecture to determine the value of the probability of executing the plan (achieving the goal). For the following input data to this system: Y1=0.2 and Y2=280, the value U=0.95 was obtained. This means that for these values of the independent variables, the probability of executing the plan (achieving the goal), i.e. to produce 300 pcs of products per production shift, is high (95%).

CONCLUSIONS

The paper presents an idea of designing a hybrid model of the expert system in order to assess the stability of the production system, which was verified on a practical example. This model proves that a combination of the simulation modelling method and the ANN method would bring considerable benefits in the analysis of production systems and in ensuring their stability. Such a construction of the expert system model combines the advantages of the simulation models and artificial neural network models and allows assessing the potentiality of achieving the goals set for the production system in the conditions of a randomly occurring risk factor.

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REFERENCES

Antosz K., Stadnicka D., 2017. An Intelligent System Supporting a Maintenance Process of Specialised Medical Equipment, Burduk A., Mazurkiewicz D. (eds.), Intelligent Systems in Production Engineering and Maintenance – ISPEM 2017, Proceedings of the First International Conference on Intelligent Systems in Production Engineering and Maintenance ISPEM 2017, Advances in Intelligent Systems and

Computing, Springer International Publishing, 23-32. http://doi.org/10.1007/978-3-319-64465-3_3

Burduk A., 2015. Artificial Neural Networks as Tools for Controlling Production Systems and Ensuring Their Stability, Saeed K., Chaki R., Cortesi A., Wierzchon S. (eds.), Computer Information Systems and Industrial Management Applications – CISIM 2013, Proceedings of the 12th IFIP TC8 International Conference on Computer Information Systems and Industrial Management Applications CISIM 2013, Lecture Notes in Computer Science, Springer International Publishing, 8104 487-498., http://doi.org/10.1007/978-3-642-40925-7_45

Burduk A., Chlebus E. 2009a. Methods of Risk Evaluation in Manufacturing Systems. Archives of Civil and Mechanical Engineering, 9(3), 17–30. http://doi.org/10.1016/S1644-9665(12)60215-5

Burduk A., Chlebus E. 2009b. Evaluation of the Risk in Production Systems with a Parallel Reliability Structure, Eksploatacja i Niezawodność – Maintenance and Reliability, 2(42), 84–95. http://www.ein.org.pl/pl-2009-02

Can B., Heavey C., 2012. A comparison of genetic programming and artificial neural networks in metamodeling of discrete-event simulation models, Computers & Operations Research, 39, 424–436. http://doi.org/10.1016/j.cor.2011.05.004.

Cyplik P., Hadaś Ł., Fertsch M., 2009. Production Planning Model with Simultaneous Production of Spare Parts, International Journal of Production Research, 47, 8, 2091-2108, http://doi.org/10.1080/00207540802644837

Deming W.E., 1993. The new economics for industry, government, education, Cambridge MA: MIT Press.

Gola A., Klosowski G., 2019. Development of computer-controlled material handling model by means of fuzzy logic and genetic algorithms. Neurocomputing, 338, 381–392. http://doi.org/10.1016/j.neucom.2018.05.125

Grzybowska K., Gajdzik B., 2012. Optimisation of equipment setup processes in enterprises, Journal Metalurgija, 51(4), 563-566, http://doi.org/65.01:669.013.003:658.5:658.8=111.

Johnston Ch., 2016. Crafting a System of Profound Knowledge Management in Long-Term Care, Walden University. https://scholarworks.waldenu.edu/dissertations/3173/

Kiedrowicz K., Nowicki T., Waszkowski R. et al., 2016. Method for assessing software reliability of the document management system using the RFID technology, International Conference on Circuits, Systems, Communications and Computers, 76, N. Mastorakis, V. Mladenov, and A. Bulucea, Eds., http://doi.org/10.1051/matecconf/20167604009

LeCun Y., Bengio Y., Hinton G., 2015. Deep learning. Nature 521, 436–444. http://doi.org/10.1038/nature14539.

Pawlewski P., 2014. Multimodal Approach to Modeling of Manufacturing Processes, Variety Management in Manufacturing. Proceedings of the 47th CIRP Conference on Manufacturing Systems, Procedia CIRP 17, 716–720. http://creativecommons.org/licenses/by-nc-nd/3.0/.

Sitek P., Wikarek J., 2016. A Hybrid Programming Framework for Modeling and Solving Constraint Satisfaction and Optimization Problems, Scientific Programming, http://doi.org/10.1155/2016/5102616.

Taylor S., Eldabi T., Riley G., Paul R., Pidd M., 2009. Simulation modelling is 50! Do we need a reality check? Journal of the Operational Research Society, 60(1), 69-82. http://doi.org/10.1057/jors.2008.196.

Zhang Z., Wang X., Wang X., Cui F., Cheng H. 2019. A simulation-based approach for plant layout design and production planning. Journal of Ambient Intelligence and Humanized Computing 10, 1217–1230. http://doi.org/10.1007/s12652-018-0687-5.

Zwolińska B., Grzybowska K., Kubica Ł. 2017., Shaping production change variability in relation to the utilized technology, 24th International Conference on Production Research (ICPR 2017), 51-56. http://doi.org/10.12783/dtetr/icpr2017/17582

HYBRYDOWY MODEL EKSPERCKIEGO SYSTEMU OCENY STABILNOŚCI SYSTEMU PRODUKCYJNEGO

STRESZCZENIE. **Wstęp:** W artykule przedstawiono koncepcję sterowania systemem produkcyjnym, pozwalającą na zachowanie jego stabilności, a tym samym na realizację założonych planów produkcyjnych. W tym celu zaproponowano połączenia modeli symulacyjnych i modeli sztucznych sieci neuronowych (SSN) systemu produkcyjnego. Połączenie obydwu typów modeli było możliwe dzięki opracowaniu hybrydowego modelu systemu ekspertowego do oceny możliwości realizacji planu produkcji (celu) w zależności od wielkości ryzyka i poziomu stabilności analizowanego systemu produkcyjnego. Analizowany problem – możliwość realizacji planów produkcyjnych w zależności od wielkości ryzyka i poziomu stabilności systemu produkcyjnego – jest trudny do zamodelowania matematycznego. Jednak na podstawie analizy danych, pochodzących z modelu symulacyjnego i modelu ANN, można uzyskać informacje dotyczące zależności odpowiadających sobie wartości wejściowych i wyjściowych.
Metody: Na podstawie przedstawionego sposobu zarządzania procesu produkcyjnego z wykorzystaniem modeli komputerowych, przeanalizowano możliwości zastosowania modeli symulacyjnych i modeli ANN w ocenie stabilności i ryzyka systemów produkcyjnych. Dokonano analizy i porównania obydwu typów modeli ze względu na sposób budowy oraz rodzaj danych wejściowych i wyjściowych.
Wyniki: Na bezpośrednie połączenie modeli symulacyjnych i modeli SSN nie pozwala ich odmienna budowa, specyfika oraz inne rodzaje danych wejściowych i wyjściowych. Dlatego prezentowana w artykule koncepcja fuzji obydwu typów modeli odbywa się poprzez bazę wiedzy eksperckiej i wnioskowanie rozmyte.
Wnioski: Na potrzeby sterowania systemem produkcyjnym, zaproponowano budowę hybrydowego modelu systemu ekspertowego do oceny możliwości realizacji celu w zależności od wielkości ryzyka i poziomu stabilności systemu produkcyjnego.

Słowa kluczowe: system produkcji, ocena ryzyka, sztuczne sieci neuronowe, logika rozmyta, stabilność, zmienność

Anna Burduk ORCID ID: https://orcid.org/0000-0003-2181-4380
Wroclaw University of Technology
Mechanical Department
5 Lukasiewicza St., 50-371 Wroclaw, **Poland**
e-mail: anna.burduk@pwr.wroc.pl

Katarzyna Grzybowska
Poznan University of Technology
Faculty of Engineering Management
11 Strzelecka St., 60-965 Poznan, **Poland**
e-mail: katarzyna.grzybowska@put.poznan.pl

Andrii Safonyk ORCID ID: https://orcid.org/0000-0002-5020-9051
National University of Water and Environmental Engineering
Department of the Automation, Electrotechnical and Computer-Integrated Technologies
Soborna str., 11, Rivne, 33028, **Ukraine**
e-mail: safonik@ukr.net