Process and Production Planning as a Part of Logistic Activities

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Abstract

Classification consideration of the product shape and process sequencing are important conditions for designing a general model for the estimation of production times. In fact, it means development of a technological knowledge base. As a result of our analysis, we have created eight regression equations with the obtained index of determination, with the most important independent variables different for 2D and 3D model. The observed level of subjectivity, constraints and errors were the reasons to use neural networks as the second approach to estimate production time. The survival and growth of businesses in today's market is based on constant innovation and new product development. Business innovation as other approach must take place at all levels, from products, and processes to the organization itself, in order to bring about improvements in competitiveness and business efficiency. We can respond to such demands and manage the appropriate tools to simulate the activities and processes within the factory in the virtual world. The simulation (as introduction to the logistic activities) of the entire flow of materials, including all significant activities of production, storage and transportation are key requirements for quality production planning and necessary manufacturing processes. Discrete simulations, i.e. the applications used for running this type of simulation provide the possibility of creating different scenarios concerning cases of different production parameters, the burden of production capacities, as well as their delays and failures. The simulation model was improved by genetic algorithm for the purpose of minimizing costs and delivery times of products.

1. Introduction

As the *first phase* in process planning it was necessary to establish a technological knowledge base, define features of the 2D drawing (independent variables), possible dependent variables, size and criteria for sample homogenization (principles of group technology) for carrying out analysis of variance and regression analysis, as a possible approach to production time/cost estimation. The *second phase* in the research was to investigate the possibility for easy automatic, direct finding and applying 3D features of an axial symmetric product to the regression model. The defined requirements resulted in the development of the procedure for retreiving parameters from the 3D model with a low level of subjectivity, a very fast and reliable process via CAD report to the regression model. The *third phase* in the research was to investigate the possibility for the application of neural networks in production time estimation and to compare the results between the regression models and neural network models. As it can be seen from references there are different approaches for data retreival from AD (STEP) [1], integration of CAPP, CAD/CAM and business activities [2], development of database system of mechanical components [3,4], and integrated product engineering [5] for costs estimation and rapid cost estimation [6], application of neural networks in estimation of production time [7], connection from CAPP, CAD, CAM; DFx to DFA through product development [8] etc. The most important characteristic of our approach presented in this paper is estimation of production times using group technology, regression analysis and neural networks [7], [9-11]. Our intention is included in the third phase – to make comparison of two approaches for production times estimation, i.e. regression analysis and neural networks. As a tool for optimization of production planning that is connected with process planning, discrete simulation was used. At the end of this work genetic algorithm was used as a tool for optimization of production times and production costs.

2. Drawing Features and Technological Database for Production Time Estimation

Very frequently (especially in the case of SMEs) it is necessary to respond quickly to some important requests for offers, generated for individual or batch production, like for instance in the case of:

1) a great number of requested offers for manufacturing of products at once,

2) small batches that are very rarely repeated,

3) frequent changes of priorities during production,

4) short deadlines for delivery,

5) market demands for bringing prices of individual or batch production close to the prices of mass production, etc.

It must be noted that technological knowledge and speed of process planning are often more important than the technological level of equipment, skills and knowledge of people who implement the technology. So, very often in practice we can be faced with the following:

a) A great amount of time spent on planning of the technological process for a product without any specific contract being made concerning the order for manufacturing of the product,

b) Signing of a contract without estimated precise production times/costs necessary for product manufacturing and realization in accordance with contracted production.

Technological processes are basically based upon product drawings with adequately defined dimensions, tolerances (dimensional and geometrical), surface roughness, batch size, shape and kind of material, heat treatment, requested delivery, disposable equipment, tools, etc. At the same time, process plans are primarily result of the planner's experience, intuition and decision support.

The fundamental idea in the approach [10,11] to production time estimation is investigation of the existence of some kind of relationship between the shape and data from the drawing and the process type, process sequencing, primary process, way of tightening, selection of tools, machine tools, production times, etc. As one of the *first steps in our project research*, we defined possible shapes of raw material and 30 potential basic technological processes.

3. Development of Stepwise Linear Multiple Regression

A desirable level of generalization in regression analysis will be an important indicator for the quality of regression equation. One of the most important problems was the process of homogenization of the sample of products. Adequate method for this action was one of the methods of group technology. For the sample of real products (420 parts) and considered features, we created, as a result of our research and step multiple linear regression (in previous research and papers), 8 regression equations for different groups of parts with different number and kind of independent variables. So, we can see for different values of parts' features (independent variables), the values for the estimation of production times (dependent variables). Logical operators during query process in database Access were very helpful in the process of homogenization of the sample of products. As the result of previous research, sample homogenization, classifier selection and stepwise multiple linear regression, we obtained: 7 independent selected variables, basic sample of 320 parts, constraints for data parts, 8 regression equations, percentage of explained effects, relative error (7-30%), etc. (Table 1). The lowest relative error 8.01% (Table 3, for grinded discs, AC102 No. 5) and the highest index of determination $r^2 = 0.9851$ for the grinded discs group are the consequence of the simultaneous action of logical operators (round bars, discs and fine machining, i.e. diameter tolerance better than IT7). Thus, with the simultaneous action of several operators, a lower scattering of production time values has been achieved, i.e. better homogeneity of the created group. Since there was too great subjective influence of workers in the process of filling up the values of independent variables, we continued with investigation in the 3D area. The question was how to get automatically the 3D features from CAD application (CATIA, PRO/E) in the application for developed regression equations and avoid thus this subjectivity factor. The *second phase* in the research was the investigation of the possibility for easy automatic, direct retrieval of 3D features of the considered axial symmetric product into the regression model. The defined requirement resulted in the development of the process for the transfer of parameters from 3D models with a low level of subjectivity. It is a very fast and reliable process via CAD report to the regression model [12].

Table 1. Explanation of the meaning of used symbols

Symbol	Physical unit	Meaning of the symbol
f_{ea}	-	Features of 3D model
K	-	Coefficient of time
K_s	-	All dimension lines
r^2	-	Index of determination
t	(min)	Machining time
x_1	(IT)	Tolerance of outside diameter
x_2	(mm)	Outside diameter of material
x_4	(mm)	Width of material
x_6	(mm)	Length of material
x_8	Class h	Roughness of open areas
x_9	HRc	Hardness of product
x_{10}	(mm)	Outside diameter of product
x_{11}	(mm)	Inside diameter of product
x_{15}	-	Number of product perspectives
$_{16}$	-	Number of descriptions of product
x_{18}	-	Number of location marks (geometry)
x_{19}	-	Number of dimension line tolerances
x_{20}	-	Number of special dimension lines
x_{21}	-	Number of usual dimension lines
x_{22}	(1/class)	Roughness request Ra
x_{23}	(1/mm)	Location request (geometry)
x_{24}	(1/mm)	Dimension request
x_{25}	(1/IT)	Diameter request

x_{26}	(mm^2)	Area of sketch
x_{29}	(N/mm^2)	Ultimate tensile strength of material
x_{30}	(m^2)	Requested area of sketch
x_{31}	-	Mass strength of material
x_{32}	(mm)	Thickness wall of products
x_{33}	-	Ratio of diameter and length
x_{39}	-	Number of all dimension lines
x_{40}	-	Product complexity
x_{42}	(Class h)	Difference in roughness
x_{43}	(dm^2)	Difference in superficial areas of material
x_{44}	(cm^3)	Volume of material
x_{45}	(kg)	Mass of material
x_{46}	(mm)	Difference in outside diameters
x_{47}	(mm)	Difference in outside diameter of products
x_{49}	(mm)	Difference in thicknesses
x_{50}	(mm)	Difference in lengths
Y	(min)	Production time

4. NEURAL NETWORK MODEL

Artificial neural networks (*ANN*) are inspired by the biologic neural system and its ability to learn through examples. Instead of following a group of well defined rules specified by the user, neural networks learn through intrinsic rules obtained from presented samples.

No	Shape of product representative of product group	Regression equations	Index of determ. r^2	Relative error [%]	Comment on regression equation
1	Whole sample **A0000**	$t = -11.69 + 16.95x_{45} + 1.22x_{40} + 0.54x_{47} + 127.47x_{22} - 3.24x_{18} + 0.15x_{32} + 0.03x_6$	0.736552	30.74	Model is developed with procedure in advance. Three independent variables are omitted: x_8, x_{19} and x_{33}.
2	Round bars **A00B1**	$t = 55.47 + 22.43x_{45} + 1.162x_{40} + 0.43x_{11} + 1.61x_{50} - 5.41x_8 - 3.26x_{18} + 1.78x_{42}$	0.74285	30.95	Model is developed with procedure in advance.Two independent variables are omitted: x_1 and x_{26}.
3	Shafts **AB101**	$t = 6.13 + 0.83_{x2} + 1.27_{x39} - 3.30_{x8} + 5.51x_{46} - 6.86x_{18} + 0.09_{x6} + 124.33x_{22}$	0.807626	25.90	Model covers more narrow field of rotational parts. It gives better results than No.2.
4	Discs **AB1C1**	$t = -5.17 + 0.73x_{47} + 0.93_{x40} + 5.25_{x20} + 0.52x_{24} + 139.11x_{30} + 0.23x_{32} - 0.51x_{33}$	0.809405	24.24	Simillar results as in No.3.
5	Discs-with fine machining **AC102**	$t = -60.78 + 0.59x_{47} + 047_{x9} + 0.74_{x1} + 0.25x_{10} + 0.84x_{39} + 291.07x_{25} + 5.9x_{15}$	0.985057	8.01	Model covers more narrow field of rotational parts. It gives better results than all the previous models.
6	Rotational parts **AB103**	$t = -37.11 + 0.94x_{40} + 0.03x_{29} + 319.22x_{26} + 0.13x_{23} + 114.67x_{43} - 80.98x_{45} - 0.46x_6$	0.893321	27.06	Model is better than No. 2 as a result of higher degree of homogenization of data. Solution is better with omitted variables x_2 and included variables x_6, x_{23}, x_{43} and x_{45}.
7	Flat bars **A0004**	$t = -10.96 + 0.58x_{40} + 34.50x_{45} + 218.42x_{22} - 5.48x_{50} + 185.03x_{26} + 0.39x_9 - 0.50x_{49}$	0.900332	15.92	Constraints are greater for all variables so results are better. Narrow field of homogenization.

8	Sheet metals **A0005**	t = 0.47 +1.27x_{40} +137.45x_{45} – 13.23x_{43} – 0.70x_{43} + 0.28x4 + 0.05x_6 +3.91x_{16}	0.900823	24.04	Model is characterized with the presence of complex variables x_{40}, x_{43}, x_{45}

Table 2. Presentation of created regression equations

The most commonly used *ANN* architecture is the multilayer *backpropagation neural network*. Backpropagation was created by generalizing the *Widrow-Hoff* learning rule to multiple-layer networks and nonlinear differentiable transfer functions [14]. Input vectors and the corresponding target vectors are used to train the network until it can approximate a function, associate input vectors with specific output vectors. Standard backpropagation is a gradient descent algorithm, as is the *Widrow-Hoff* learning rule, in which the network weights are moved along the negative of the gradient of the performance function. There are numerous variations of the basic algorithm that are based on other standard optimization techniques, such as conjugate gradient and Newton methods. The one used in this paper is the *feedforward backpropagation* training algorithm designed to minimize the *mean square error* (*MSE*) between the actual (estimation) output (*a, A*) and the desired (target) output (*d*, *T*). Figure 2. shows the principle of the *feedforward backpropagation* training algorithm,

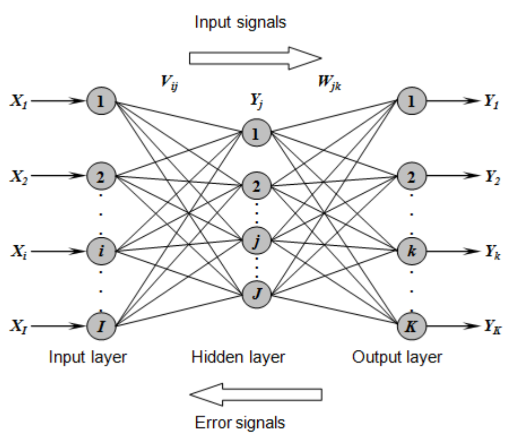


Figure 1. Principle of the feedforward backpropagation training algorithm

where: V_{ij} - weight between the input layer and the hidden layer, W_{jk} - weight between the hidden layer and the output layer, X_i - input signals (value of chemical composition), i - number of neurons of the input layer, I - number of inputs of neuron j in the hidden layer, Y_j - output of the hidden neurons, j - number of neurons of the hidden layer, J - number of inputs of neuron k in the output layer, Y_k - output signals (mass of eluted ions per gram of samples), k - number of neurons of the output layer. For the estimation of performance of the learning algorithm in solving the specified task, performance index was defined. Performance index enabled comparison of the applied neural network algorithm with other learning algorithms. The most frequent performance index is the normalized root mean square error – *NRMSE* .

$$NRMSE = \frac{\sqrt{\frac{\sum_{n=1}^{N}(d_n - a_n)^2}{N}}}{\sigma_{d_n}} \qquad \sigma_{d_n} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(d_n - \bar{d}\right)^2} \qquad \bar{d} = \frac{1}{N}\sum_{n=1}^{N} d_n \tag{1}$$

Where: *N* is the total number of patterns, d_n is the desired (target, *T*) outputs, a_n is the actual (estimation, *A*) outputs, σ_{dn} is the standard deviation.

5. EXPERIMENTAL RESULTS

As a better method for solving the problem of production time estimation, we proposed a three-layer backprogation neural network the simplified structure of which is shown in Figure 3. Presented input parameters (LM, NG, sl, SOK, mM, DUP, lZH) refer to the model A0000. Output parameter (TO) is the estimate of time in minutes. Parameters n_2=20 and n_3=15 represent the number of neurons in the second and third layer of the network. Between the layers the following transfer functions are applied: *tansig-tansig-purelin*. Data important for neural network training are: Performance goal: 0.0001, Learning rate-0.01, Ratio to increase learning rate-0.5, Maximum performance increase: 1.04, Maximum performance gradient: 1e-10, Momentum constant: 0.9, Number of layers: 3, Number of neurons: 20-15-1, Transfer functions: tansig-tansig-purelin, Number of epoch to train: 15000. For neural network training the available experimental data are divided in three sets: training set (70%), validating set (15%), and testing set (15%). The same model of experimental data division is applied to all models. The following parameters are selected as *key performance indexes* of the neural network model (*NNM*) in relation to the regression model (*RM*): R (correlation coefficient), R^2 (determination coefficient), RMSE (root mean square error) and NRMSE (normalized root mean square error). Below in Figure 4. through Figure 11., for each experimental model the graphical presentation of parameter R values and tabulated values of parameters R, R^2, RMSE and NRMSE are given.

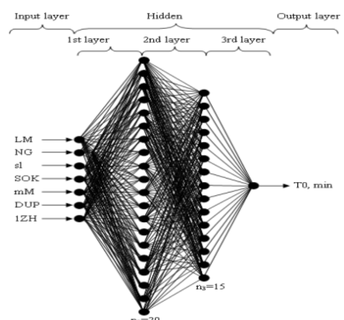
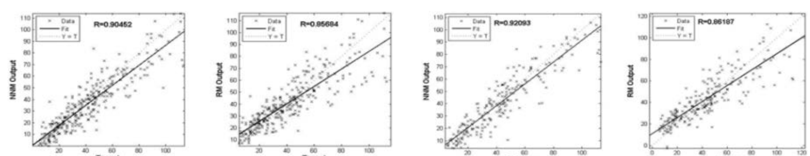


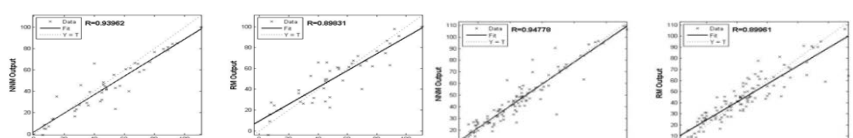
Figure 2. Simplified model of the used neural network of A0000 model



	R	R^2	RMSE	NRMSE
NNM	0.9045	0.8182	11.7595	**0.4798**
RM	0.8568	0.7342	12.6179	0.5148

	R	R^2	RMSE	NRMSE
NNM	0.9209	0.8481	10.2306	**0.3993**
RM	0.8619	0.7428	12.9643	0.5060

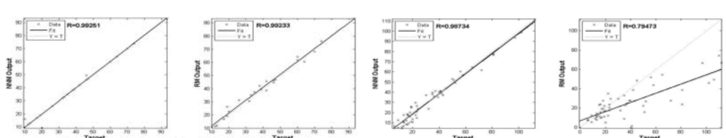
Figure. 3. Models: A0000 and A00B1



	R	R^2	RMSE	NRMSE
NNM	0.9396	0.8829	10.2404	**0.3813**
RM	0.8983	0.8070	11.6739	0.4347

	R	R^2	RMSE	NRMSE
NNM	0.9478	0.8983	7.4324	**0.3212**
RM	0.8996	0.8093	10.0620	0.4348

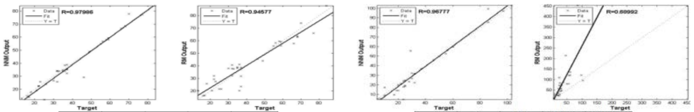
Figure 4. Models: AB101 and AB1C1



	R	R^2	RMSE	NRMSE
NNM	0.9925	0.9851	2.6437	**0.1213**
RM	0.9923	0.9847	2.8156	0.1291

	R	R^2	RMSE	NRMSE
NNM	0.9873	0.9748	4.6999	**0.1664**
RM	0.7947	0.6316	21.6993	0.7684

Figure 5. Models: Models: AB102 and AB103



	R	R^2	RMSE	NRMSE
NNM	0.9799	0.9601	4.1589	**0.2226**
RM	0.9458	0.8945	5.9891	0.3206

	R	R^2	RMSE	NRMSE
NNM	0.9678	0.9366	7.0218	**0.2789**
RM	0.6899	0.4760	97.8193	3.8854

Figure 6. Models: A0004 and A0005

6 Discrete Simulation as Logistic Activities – Possibility for Optimization

As an effective solution for connecting human resources, business processes and systems, product information and services is new business approach called PLM (Product Lifecycle Management). This approach enables collaborative creation, management, expansion and use of product information throughout the enterprise from initial concept to product disposal.

One of the tools of PLM systems are simulations and creation of digital production which is faster and cheaper way to plan production process. With the simulation of production and generation of all processes, digital production offers the possibility for optimization of the existing system. It is very difficult to mathematically describe complex processes, and for their execution a large amount of funds is required, because of that the solutions such as operations research methods are used less. In such an environment simulation technology is becoming an increasingly important tool for the analysis of real processes. The text below presents a particular case for which a simulation is developed as part of this project.

For creating a simulation it is necessary to dispose with information about the technological processes of each product, processing times and set-up times. After completion of capacitive sizing and programming of all the necessary methods of material flow, the initial model was created and among others the results of the availability of production resources were obtained while working in two shifts (Figures 7 and 8).

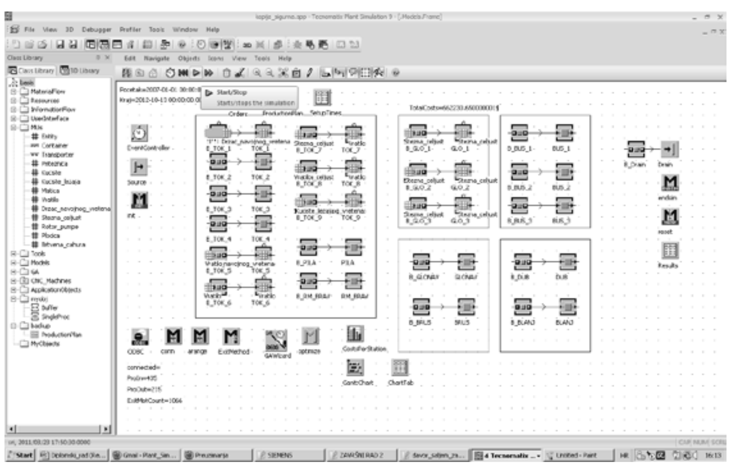


Figure 7 Initial created model in Plant Simulation

Figure 8 shows improvement in disposition of machine load comparing to the model without capacitive sizing, but some machines still remain much less used. Since the profit per product is in direct correlation with the cost of making products, the selection of the best variant is of great importance.

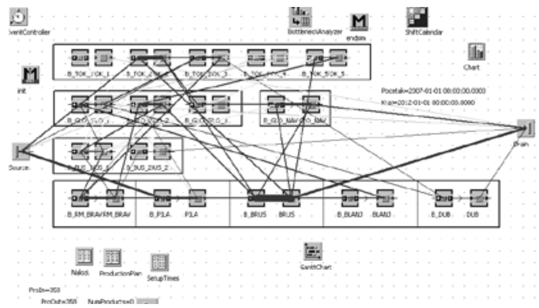


Figure 8 Sanky diagram of material flow for initial model

For creation of genetic algorithm in the simulation model the Genetic Algorithm tool was used. Some parameters are defined through the genetic algorithm method, and some are defined in the genetic algorithm Wizard. To use a genetic algorithm, it is necessary to define the objective function and constraints. For this model the objective function is more complex. Specifically, the aim is to produce all the products with the minimum cost, but also with the requirement to comply with the delivery date. Therefore, the algorithm is defined by a total of eleven objective functions. One of them is a requirement for the lowest cost of all products together, and the other ten are related to the request for minimum production time of each product series. Since there are several objective functions, it is necessary to determine their weight or priority factors. They are determined subjectively, where for each function a value from 0 to 1 can be assigned.

Due to the specific input of constraints we created a new variable *Series* which measures the number of products in the series. The constraint in the algorithm represents the number of machines that are available for a particular product to execute a particular operation. So each product has a number of constraints in accordance with the following expressions (2):

$$\begin{aligned} &(P1 \times K1_1 \times MK1_1 \times KP1) + (P1 \times K2_1 \times MK2_1 \times KP1) + ... + (P1 \times Km_1 \times MKm_1 \times KP2) \\ &\text{for product } P1 \\ &(P2 \times K1_2 \times MK1_2 \times KP2) + (P2 \times K2_2 \times MK2_2 \times KP2) + ... + (P2 \times Km_2 \times MKm_2 \times KP2) \\ &\text{for product } P2 \\ &(Pn \times K1_n \times MK1_n \times KPn) + (Pn \times K2_n \times MK2_n \times KP2) + ... + (Pn \times Km_n \times MKm_n \times KPn) \\ &\text{for product } Pn \end{aligned} \qquad (2)$$

where:

P_n = *type of product (numerical value 1)*
Km_n = *m-th type of operation for n-th type of product (numerical value 1)*
MKm_n = *number of possible machines for making m-th type of operation for n-th type of product*
KP_n = *quantity of product,*
With this a form of particular constraint can be defined, as in (2):

$$MKm_{n\text{-}min} > P_n \times Km_n \times MKm_n < MKm_{n\text{-}max} \qquad (3)$$

Besides the constraints and objective function, it is also necessary to define the size and number of generations and the number of observations per individual. Generation represents a number of solutions that the algorithm combines, and observation represents a number of simulations for each new generated individual [5]. Thus the total number of simulations are calculated by (4):

$$\text{Size of generation} \times (2 \times \text{Number of generations} - 1) \times \text{Observations per individual.} \qquad (4)$$

In this model the following parameters are set:
Size of generation = 25
Number of generations = 12
Observations per individual = 2

Hereby the genetic algorithm is defined, and the results are shown in the following section. With the same working conditions (working hour cost, machine availability, processing time per part) the developed genetic algorithm demonstrated very good results and is in correlation with the unoptimized model. Total processing time for all products in one year production has been reduced by 28 days and the reduction of production cost was in total $ 18000 (Figure 3). Total savings in money are even greater

Figure 3: Result comparison of two developed simulation models

since the optimized model finishes with production almost one month earlier, and in real continuous systems new processes could start earlier, bringing new profit per product. Because of this, the total costs of the optimized system should be diminished for the money value that the system is able to produce in the time of 28 days. With this, the costs of production for the optimized model are reduced and profit per product is increased. Genetic algorithm generates in total 570 individuals through 12 generations, and with 2 observations per individual runs 1140 simulations in total (computing time is 20 minutes). The best individual is generated in the last (12th) generation and the first observation. Also, the best fitness function of all simulations is 128755698.521.

7. Conclusion

On the basis of the presented results we can conclude that the assumption on the use of a neural network for the production time estimation in relation to a classical regression model is justified. For all experimental models (A0000, A00B1, AB1C1, AC102, AB103, A0004, A0005) the applied backpropagation neural network gives better values of key performance indexes (R, R^2, RMSE, NRMSE). The biggest difference between the key performance indexes for *NNM* and *RM* estimation models is in the case of model A0005 (input set of 35 data), and lowest in the case of model AC102 (input set of 25 data). The next differences in key performance indexes of individual models ranged from the highest to the lowest values are as follows: AB103, A0004, AB1C1, A00B1 and AC102. The lowest difference between the *NNM* and *RM* estimation model in AC102 (finely machined discs) follows from the nature of the model independent variables and their values that are from a relatively narrow range. The reverse is true for the biggest difference in A0005 (sheets), due to the relatively wide range of independent variables. The key performance indexes in *NNM* estimation models are significantly better than those in all proposed *RM* models, especially in the case of A0005. The reason for this is the proper selection of transfer functions (*tansig* - *tansig* - *purelin*) within the backpropagation neural network layers which provide approximation of linearities and nonlinearities within independent variables, as opposed to the regression model whose approximation is only linear. This project shows the idea of using simulations as a tool for production planning that allows user to optimize the results of existing systems. Although the simulation model has been made for a possible scenario of production, all input values are obtained from real observed processes and so the model is usable in real production systems for tactical and strategic planning. Simulation displayed differnet behaviour of the system in relation to variable production data (such as variations of machines, different cost production per machine, different availability of machines, variable delivery times and working shifts). Comparing to the unoptimized model, the production costs were reduced for 3% of the annual turnover and the production time (genetic algorithm) for all products in one year was 28 days less. The project achieved all conditions for further evaluation in real environment.

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