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MANUFACTURING LEAD TIME PREDICTION FOR EXTRUSION TOOLS WITH THE USE OF NEURAL NETWORKS

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Abstract
Due to fast-paced technical development, companies are forced to modernise and update their equipment, as well as production planning methods. In the ordering process, the customer is interested not only in product specifications, but also in the manufacturing lead time by which the product will be completed. Therefore, companies strive towards setting an appealing but attainable manufacturing lead date.
Manufacturing lead time depends on many different factors; therefore, it is difficult to predict. Estimation of manufacturing lead time is usually based on previous experience. In the following research, manufacturing lead time for tools for aluminium extrusion was estimated with Artificial Intelligence, more precisely, with Neural Networks.
The research is based on the following input data; number of cavities, tool type, tool category, order type, number of orders in the last 3 days and tool diameter; while the only output data are the number of working days that are needed to manufacture the tool. An Artificial Neural Network (feed-forward neural network) was noted as a sufficiently accurate method and, therefore, appropriate for implementation in the company.

Keywords
Manufacturing lead time, Neural Network, Artificial Intelligence, extrusion.

Introduction

Nowadays, companies are being faced with the challenge of how to produce quality products in the shortest possible time with minimum costs. As a result of a dynamic environment, along with changing goals that are usually not even clearly defined, production processes are generally subjected to deviations from normal conditions. Dynamic behaviour is typical for both external and internal environments (orders, disturbances, unforeseeable conditions of machines, tools, processes, variability of raw materials). In these circumstances problems cannot be solved using merely deterministic methods.

The use of computer programs such as Computer Aided Design (CAD) and Computer Aided Manufacturing (CAM) is already widespread in engineering practice, and implementation of advanced methods has lately been in full swing. With Industry 4.0 on the rise, advanced Artificial Intelligence technologies are becoming more and more involved in the processes of the production preparation and planning [1–7]. Those methods have been proved as the most successful approaches for solving engineering problems in the future.

Computer simulations, by which products are checked for eventual defects that can, therefore, be eliminated in advance, are being applied widely by the Production Planning Department in order to avoid additional costs of errors found on the finished real product. Sales order conditions should be adhered to strictly. To show reliability and to gain customers' trust the delivery date should be respected. A kind of software which estimates products' manufacturing lead time with sufficient accuracy can contribute significantly to a company's success. If anticipated correctly, the manufacturing lead time is not only important to customers, but also to the organisation of production in the company itself.

This paper is organised as follows: Firstly, we present a literature review on ways of solving the problem of manufacturing lead time and Job Shop Scheduling on the usage of Artificial Intelligence in Mechanical Engineering. The following Section shows the problem of manufacturing lead time, and explains the reason for choosing this topic for research. How to estimate manufacturing lead time with neural networks is described in the next Section, where input and output data are also presented, along with the specifications of the neural networks. The Results and Discussion Section provides the results of the research, which are supported by graphs. The key findings of the research are pointed out in the Conclusion.

Literature review

A significant amount of research has been done on the application of Artificial Intelligence to the field of Production Planning. The following methods have been proven successful for Job Shop Scheduling:
- Hybrid Genetic Algorithm [8],
- Particle Swarm Optimisation [9, 10],
- Improved Genetic Algorithm [11],
- Neural Network [9, 12],
- The immune algorithm and simulated annealing method [13].

Neural networks can be used to achieve flexibility of the production system. Yildirim proposed a framework that utilizes parallel Neural Networks to make decisions on the availability of resources, due date assignments for incoming orders, and dispatching rules for scheduling [14].

A huge research has been done on the example of wafer fabrication, where fulfilling the due date is very important. A predictive model of due date related performance has been modelled based on decision tree. Due date fulfilling performance was classified to 5 categories (from "Extreme earliness" to "Extreme lateness") based on a decision tree trained by a great quantity of historical data. Furthermore, different combinations of order releasing rules and dispatching rules have been considered in the simulation tests. In the results of simulation and statistics, the average rate of classifying correctly was more than 90% [15].

A numeric prediction (a tree-indexing approach) has also been proven on the due date assignment problem in a dynamic job shop environment. The tree-indexing approach organises the cases in the memory by inducting a tree-shaped structure, in order to improve the efficiency and effectiveness of case retrieval [16].

However, our focus is the usage of neural networks to predict the manufacturing lead times. Zhang has integrated due date assignment and shop scheduling successfully into one optimisation model using a double-layered heuristic optimisation algorithm. In the upper-layer Genetic Algorithm, which performs coarse-granularity optimisation, Bayesian networks are used to learn the distribution of optimal due date values. As the second-layer algorithm, a parameter perturbation method is applied for a finer-granularity neighbourhood search. Computational experiments proved the efficacy and efficiency of the algorithm [17].

An integrated algorithm based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) was proven as suitable method for forecasting weekly lead time. The algorithm was applied to the database of weekly lead time of the Motogen Company in Iran for 70 weeks [18].

Hsu and Sha were engaged in estimation of due dates [19]. Among a wide variety of prediction methods proposed to improve due date quotation accuracy, Artificial Neural Networks are considered the most effective. Patil paid attention to the intrinsic shortcomings that undermine the accuracy of the Neural Network method. He developed an enhanced due date quotation model based on an Artificial Neural Network using Machine Learning and Metaheuristics learning concepts [20].

Comparison between the performance of six regression-based due-date assignment rules and due dates determined by a Neural Network was made by Philipoom. He found out that the Neural Network outperformed all six conventional rules according to mean-absolute-deviation criteria, and standard-deviation-of-lateness criteria [21].

Silva investigated the use of Artificial Neural Networks (ANN) for flow time prediction and, consequently, to estimate Due Dates (DD) in a hypothetical dynamic job-shop. Results showed that ANN based DD assignment models are more effective than other tested methods [22].

Problem description

Individual made to order production of tools is carried out in the extrusion tool-making companies. Production time is usually between 2 and 4 weeks. Companies' customers are those companies which extrude profiles. Profiles are earmarked for the customer, who could be the final element in the whole chain or just a link up to the end user (e.g. a profile could be ordered by a company which produces some component in the car industry; the end user is, therefore, the automotive company). Because of that long chain between end user and the tool making company it is important that delivery dates are assumed precisely as soon as the order is accepted. Otherwise, delivery dates are challenged across the entire chain (Fig. 1) and, consequently, the delays increase.

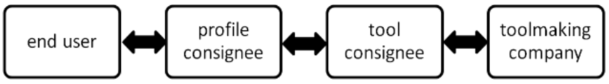


Fig. 1. Flow chart of the order.

In the small tool-making companies manufacturing lead times are usually estimated by a Production Manager, who generally relies on experience from the past. The problem arises when that person is not present, and therefore his/her work has to be done by someone else. A computer system, which assumes manufacturing lead time objectively depending on input data, would solve the problem.

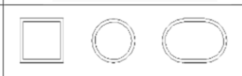
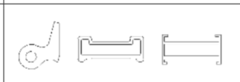
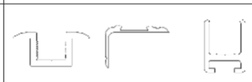
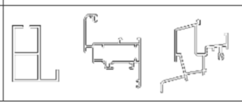
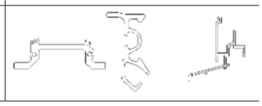
Manufacturing lead time prediction with the use of neural networks

Model database

The database for this research consists of data from 54 samples (orders). For each order the following data were collected:

- Number of cavities or outflows of the profile (multi cavity tools are more productive, because a large number of identical profiles can be extruded simultaneously). During production planning there is no significant difference in the time needed for one and for multi cavities tools, since during this phase of construction the same geometry is copied several times in the drawing, and the process is similar with CNC-programming. The main time difference between one and multi cavity tools is in their production – multi cavity tools need more time because every cavity has to be milled separately, and also cut separately with wire erosion and die sunk, etc.):
- Tool type (hollow dies for extruding profiles with one or more holes in the middle (closed profiles) and flat dies for open profiles) – shown in Table 1;
- Tool category (this piece of information indicates the complexity of the tool, where category A refers to simple and C to complex tool geometry. Categorisation is the property of the company Kaldera.) – shown in Table 1;
- Order type (there are four different order types: A completely *new* tool, an existing tool which has to be *modified* or *corrected*, a reorder of an *existing* tool without any changes);
- Number of orders in the last 3 days (this piece of information represents capacity load);
- Tool diameter (in principle, more material has to be removed by tools with larger diameter, so it takes more time);
- Manufacturing lead time (number of working days between order date and the date when the tool is finished).

Table 1
Types and categories of profiles.

Categories	Tool Type	
	Hollow die (closed profile)	Flat die (open profile)
A		
B		
C		

The input data form is shown in Table2. The complete database is in Annexes 1 and 2.

Table 2
Review of database configuration.

Number of cavities	1 2 4 6 8
Tool type	0 = hollow 1 = flat
Category	0 = A 0.5 = B 1 = C
Order type	0 = existing 1 = new 2 = modification 3 = correction
Number of orders in the last 3 days	
Tool diameter	[mm]
Manufacturing lead time	[working days]

The first six categories represent input in the Neural Network, while the last column (manufacturing lead time) is the output, or so-called target. Manufacturing lead times for the tools will therefore have to be predicted with neural network.

Normalisation of the database

Normalisation is a technique often applied as part of data preparation for Machine Learning. The goal of normalisation is to change the values of numeric columns in the dataset to a common scale, without distorting differences in the ranges of values. Training in such a manner is more effective [7], and convergence of the Neural Network during the training phase has a superior role. The data with the lowest value in each category receive a new value 0, and the ones with the highest value get 1. For the i-th value of the variable A a value a is assigned in the following way:

$$a_i = \frac{A_i - A_{\min}}{A_{\max} - A_{\min}}. \tag{1}$$

Schematic representation of inputs and output is in the Fig. 2.

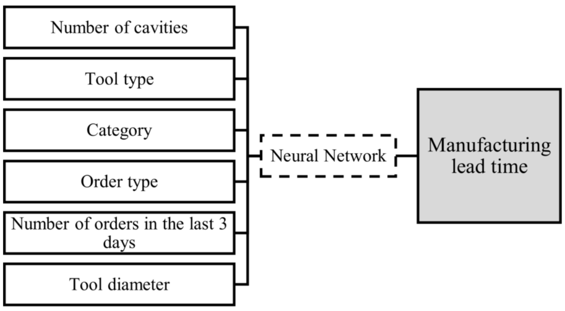


Fig. 2. Schematic representation of inputs and output.

Training

Six random samples (approximately 12% of the data) will be used for testing a Neural Network, and were therefore excluded from the whole database of 54 tools. Data of the other 48 tools represent a database for training a Neural Network. The topology of a Neural Network had to be defined before the training was performed. A feed-forward Neural Network was used in our case. This is a simple type of Artificial Neural Network, where the information moves only in one direction – forward. As seen in Fig. 3, information gets from the input, through hidden layers, to the output layer.

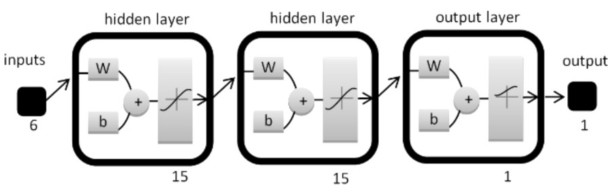


Fig. 3. Topology of the Neural Network.

Different topologies of the Neural Network were tested. Parameters were alternated during the research, and manufacturing lead times were predicted for each combination. The following parameters gave the most accurate prediction:

- Number of neuron layers: 2 hidden and 1 output layer;
- Activation functions: 'Tansig' for both hidden layers and 'logsig' for the output layer ('logsig' was chosen because output values were only positive);
- Number of neurons: 15 in each hidden layer and 1 in the output layer
- Number of iterations: 40 (a larger number of epochs did not lead to better results) – Fig. 4.

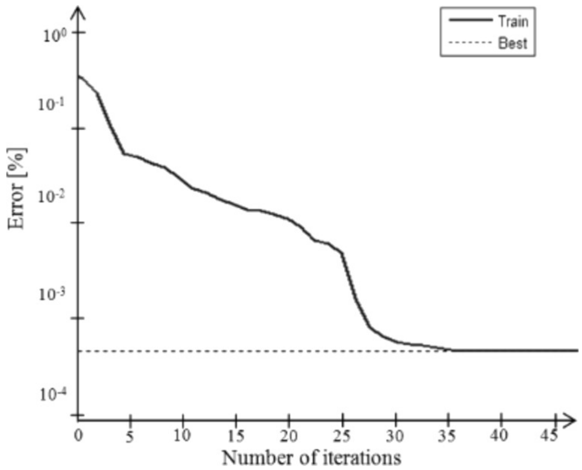


Fig. 4. Reducing the training error depending on the number of iterations.

Results and discussion

Training database

The chart in Fig. 4 shows that the solution converged to average percentage error between 10^{-3} and 10^{-4}. Relative errors of particular predictions from the training database are presented in Fig. 5, while estimated manufacturing lead time deviations from the actual manufacturing lead time are shown in Fig. 6.

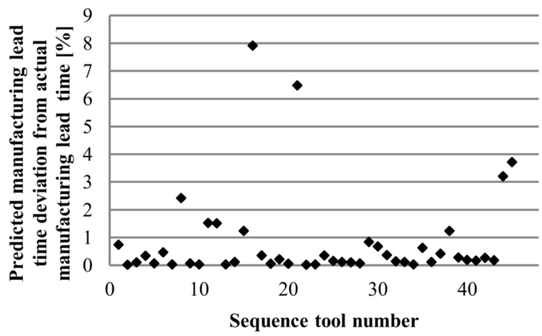


Fig. 5. Percentage error of predicted manufacturing lead time for the training database.

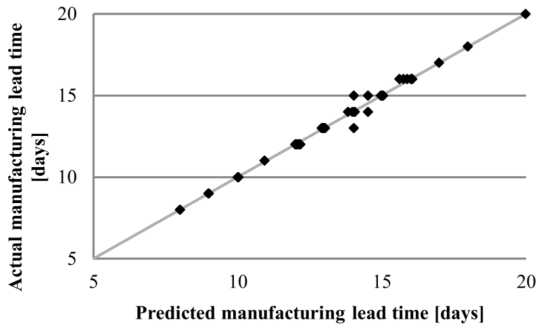


Fig. 6. Actual manufacturing lead time depending on the predicted one.

Maximum deviation was approximately 8%, although most samples had much smaller deviation (less than 1%), which means that the Neural Network had been trained successfully.

Test database

Results acquired for test samples carry more importance for evaluation of a Neural Network. Six samples, which were excluded randomly from the training database, were used for examination of a trained Neural Network. Estimated manufacturing lead times and deviations from actual values are gathered in Table 3. The average prediction error amount is 6.7%. An integer rounding of predicted manufacturing lead times shows that three samples were estimated accurately, for two of them there is a difference of 1 day, and one sample has a major error – about 20 %, which is 2 days (Fig. 7). Four estimations gave too short manufacturing lead times; two of them were too long (Fig. 8).

Table 3
Results for test database.

Actual manufacturing lead time [days]	Predicted manufacturing lead time [days]	Deviation [days]	Error (absolute value) [%]
17	16.97	−0.03	0.2
13	13.03	0.03	0.2
15	13.87	−1.13	7.5
12	9.59	−2.41	20.1
8	8.47	0.47	5.9
11	10.31	−0.69	6.3

Considering the small training database (only 48 samples), the accuracy of results is sufficient. Error of prediction could be reduced by enlarging the training database.

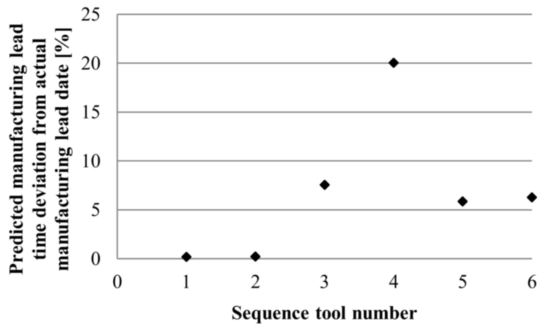


Fig. 7. Percentage error of predicted manufacturing lead time for the test database.

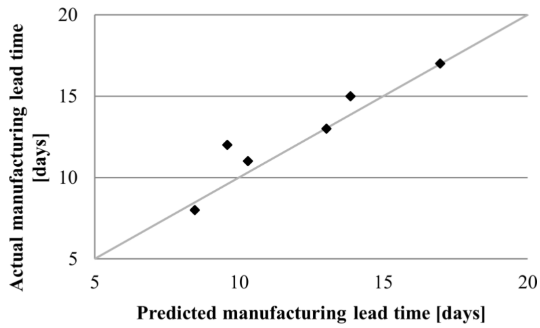


Fig. 8. Actual manufacturing lead time of test samples depending on the predicted one.

Conclusions

The problem of manufacturing lead times‘ estimation is addressed in the research. Data concerning orders and manufacturing lead times were collected in the toolmaking company Kaldera d.o.o. These data represent input into a Neural Network, the topology of which was determined with various parameters. Network training was based on data needed for 48 orders from the training database. The Neural Network was tested on both training and test databases. As expected, there was an excellent match for the training database, while an average deviation for test samples amounted to 6.7%. Since the testing database was rather small, the results are good enough to confirm the usability of Neural Networks for estimation of manufacturing lead times.

Annex 1 – Training database

Number of cavities	Tool type 0 = hollow 1 = flat	Category 0 = A 0.5 = B 1 = C	Order type 0 = existing 1 = new 2 = modification 3 = correction	Number of orders in the last 3 days	Tool diameter [mm]	Manufact. lead time [working days]
6	0	1	0	16	220	16
1	0	0.5	0	16	220	15
6	0	0	2	25	290	13
4	0	0	0	25	220	15
1	0	1	3	25	350	9
1	1	0.5	0	19	290	14
1	0	0.5	3	48	350	20
8	0	1	0	48	290	16
1	0	1	3	22	290	18
1	0	0.5	3	22	290	15
6	0	1	3	22	290	16
2	0	1	1	47	290	12
4	0	0	1	47	220	9
4	1	0	0	47	290	12
8	0	1	0	47	290	12
1	0	0.5	3	26	220	13
8	0	0.5	1	26	290	16
6	1	0	3	26	220	10
2	0	1	2	26	290	16
2	0	0.5	3	26	290	16
1	0	0.5	3	26	220	15
1	1	0.5	0	40	220	13
2	1	0	2	40	290	12
6	1	0	0	40	180	14
2	0	0.5	3	40	350	15
4	1	0	3	14	180	8
1	1	0	1	14	220	8
1	1	0.5	1	18	220	10
1	0	1	3	18	220	12
2	0	1	0	18	290	13
6	1	0	0	9	220	12
8	0	1	0	9	290	14
2	1	0.5	1	16	220	12
2	0	0.5	3	16	350	9
1	0	1	1	2	220	11
8	0	1	3	2	290	17
2	0	0.5	0	34	290	13
6	0	0.5	0	34	220	14
1	0	1	0	34	220	10
4	0	0.5	0	27	220	13
1	0	1	3	27	350	15
1	0	0.5	3	27	220	13
2	0	0	3	27	220	12
2	0	0.5	0	22	290	15
2	0	0.5	0	22	290	14
6	0	0.5	0	22	220	14
4	1	1	3	22	220	15
8	0	1	0	22	290	15

Annex 2 – Test database

Number of cavities	Tool type 0 = hollow 1 = flat	Category 0 = A 0.5 = B 1 = C	Order type 0 = existing 1 = new 2 = modification 3 = correction	Number of orders in the last 3 days	Tool diameter [mm]	Manufact. lead time [working days]
2	0	1	0	19	290	17
4	1	0.5	0	19	180	13
2	0	0.5	0	47	290	15
1	0	0.5	0	18	290	12
4	1	0	1	16	220	8
1	1	0.5	2	22	290	11

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