DUE DATE ASSIGNMENT USING NEURAL NETWORKS FOR STANDARD PRODUCTS IN SMALL BATCH AND MULTI ASSORTMENT MAKE-TO-ORDER COMPANY

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Abstract

The purpose of the article is to investigate artificial neural network ANN use in due-date assignment DDA for standard products in the real-life small batch and multi assortment make-to-order production company. The research was conducted with the historical data and resulted in the ANN aided DDA encoded into the company ERP system. The paper contains a comparison between different due-date assignment methods. The methods include company's own procedure, multi variable linear regression and multilayer feedforward neural network. The details of quantitative and qualitative input variables, an output variable, the neural network structure and its training are presented in the paper. DDA approach incorporating material deliveries uncertainty was applied to both the linear regression and the neural network methods. DDA using neural networks proved to outperform the other analysed methods.

Keywords: Due-date assignment, neural network, machine learning, production flow-time

1. INTRODUCTION

Many organisations exercise the make-to-order MTO production system to manufacture wide product-portfolio in a short period of time to be competitive in the global market. The MTO production systems often require proper due-date assignment rules to reduce inventory costs and ensure on-time deliveries. DDA takes place whenever customer orders are received. DDA is a process where due-date of an order is estimated. The estimation usually equals the order release date increased by predicted flowtime of the job or jobs related to the order.

There are many DDA approaches covered in the literature, among them conventional regression methods (total work TWK, number of operations NOP, TWK+NOP, jobs in queue JIQ, work in queue WIQ etc.) [3,4], scheduling based methods and artificial neural networks ANN methods. The literature shows that ANN methods are generally the most precise production flowtime prediction approach [3, 7-9]. The linear regression approach is often used as a benchmark to assess and compare various methods. The classical or multivariable linear regression MLR is a linear equation which models relationships between variables. In the paper, the company's own DDA procedure, MLR and ANN based DDA has been compared and evaluated. The evaluation has been conducted on real data, with real-life noise and exemptions, which is different to majority of the papers on the DDA topic, where researchers work on the data they generate through simulation models themselves e.g. in [3-4, 7]. Such data is usually greatly simplified in comparison to real-life data.

Artificial neural networks are computational structures. They are designed to imitate the accumulation of knowledge in the biological nervous system. In contrary to conventional computational methods, ANN can solve nonlinear and unstructured problems. In the last 20 years, the use of ANN has significantly increased in business. This has led to development of many different scientific applications, and intensive exploration of practical issues. ANN proved to be a valuable method for classification, decision support, financial analysis, credit scoring etc. The ANN success and popularity is proven by a growing number of publications in respected journals. There are numerous types of neural networks. The most popular is a multilayer feedforward network, in which neurons are organised into series of layers and information signal flows through the network in one direction - from the input layer to the output layer. The neurons (or nodes) can, but do not need to be connected to each neuron in the next layer. Neural networks are taught using different learning techniques, e.g. supervised or unsupervised training, with use of different learning algorithms. The most popular are backpropagation algorithms, where wages connecting nodes are modified according to the difference between the output generated by a network and its correct value - an error. The error is back-propagated to modify wages in each iteration of learning [12, 13]. The degree of the modification is partially controlled by the learning rate. There are numerous types of backpropagation algorithms, and one of the most effective is the improved resilient backpropagation iRpop. Another important element of ANN structure is an activation function. There is a variety of activation functions to choose from, and one of them is the activation function proposed by David Elliot. It is important to standardise learning data so that its range suits the chosen activation function. The learning data can be used more than once in the learning. The number of learning cycles the data is used is called epochs. During the learning, an overfitting should be avoided. The overfitting is a decrease of ANN efficiency due to too much learning. A neural network structure is problem specific, so neuron numbers, connections, number of layers, learning rate, activation functions etc. can all be set according to a researcher's wish - no simple guideline exists at the moment.

The purpose of the article is to present a comparison between different due-date assignment methods for standard products of a small batch and multi assortment MTO production company in Poland - ANGA Uszczelnienia Mechaniczne sp. z o. o. It is a medium company with a job-shop workshop, that allows machining of wide high-tech product portfolio. Standard products, standard mechanical seals, may significantly vary in size and design between each other. They include numerous product types, assembly dimensions and materials they are built of designated for particular working conditions. Usually, the standard products have most of their critical parts in stock. The lacking rest of the parts is manufactured according to an order. Many of the products are tested on specialised testing stands before being shipped. The company has its own DDA procedure for standard products. For the simplest group of standard products (77.5 % orders) simple DDA rules are applied. If all of the parts listed in a bill-of-materials for a product are in stock, the due-date is usually set for the same day. Depending on the code of these simplest products, some have their due-date set to 2 or 4 working days counting from an order release moment. The rest of the products (22.5 % orders) - all without full parts in stock, all which do not belong to the simplest standard products category - are send to a human production planner responsible for a manual DDA. The assigned due-dates play an important role in the internal scheduling method in the company.

2. DATA AND RESULTS EVALUATION METHOD

The data, including all of the defined input variables and the output variable, were imported from the company's database. The data - in terms of the input variables - comes from historical production orders at the exact moment of their due-date assignment. It means, that the input variables for each production order in the data are the same as at the time these orders had their due-date assigned. The total number of orders in the dataset was 32,990. It is worth to mention, that importing the data was the most time consuming and difficult part of the research.

To ensure possibly high objectivity, the data was divided into learning data (28,344 in total, 11,106 standard products) and certification data (4,646 in total, 1,791 standard products). The learning data was used to learn ANNs and compute MLRs. The certification data was used to assess the DDA methods. This concept comes from ANN literature [3,13], as well as the share of certification data - 14 %.

To properly assess effects of the methods and to compare them, a few criteria of DDA methods evaluation have been chosen: mean absolute error MAE, mean earliness ME, mean lateness ML and a share of orders on time, late and early. Among them, MAE was chosen as the most important criteria. The criteria were chosen on the basis of literature [2-3, 8], as well as the statistical comparison of the results approach using paired *t*-test [4, 16-17].

For the company's DDA procedure, there is an unavoidable bias resulting from the fact, that after assigning a due-date to an order all production department staff is doing their best to make sure the order is on-time. The on-time delivery ratio is an important part of the financial motivational system within the company. This fact naturally and artificially increases the results of the company's DDA procedure, when compared to other methods - to an unknown extent.

3. OUTPUT AND INPUT VARIABLES

The output has been defined as total production flowtime of standard products including waiting time for necessary materials/parts. The flowtime is calculated as a period of time starting from the moment the order is created to the moment production of the items related to the production order is completed and the items are moved to the pre-sale stock. The chosen output unit is working days. The output histogram is presented in **Figure 1**.

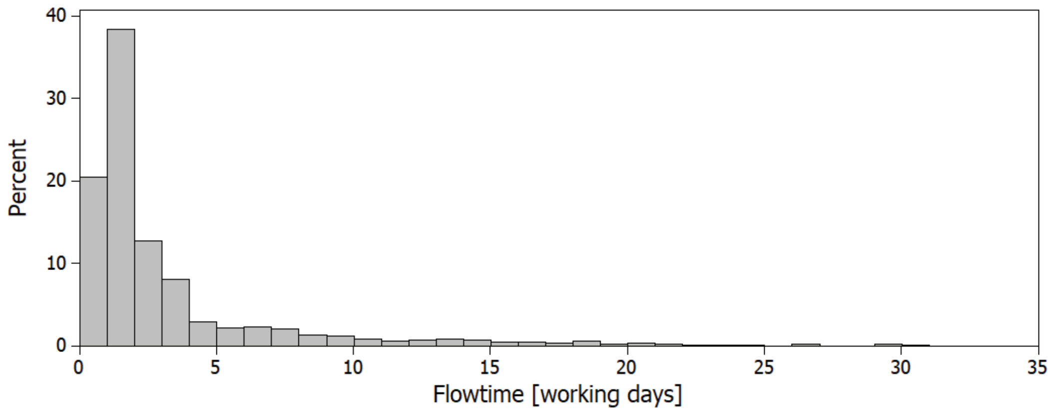

Figure 1 Histogram of flowtime for standard products production orders

When a human production planner decides on due-dates, they use various reports and calculations which help them to accurately estimate the flowtime and resulting due-date. The use of linear regression and neural network requires almost similar information the planner uses, but it does not need to have the same form. The brainstorm meetings were organised to list the inputs that might be important for DDA. Some of the chosen input variables are universal to other production systems, whereas others are company specific. In total, 47 inputs have been identified. They describe the product related to the production order, state of the production system and historical performance of suppliers:

- total work load present in the workshop [hours]. 10 separate inputs for general workstation types, e.g.: lathes, milling machines, grinders, lapping machines and manual processing;
- total work load of testing and final assembly processing time [hours],
- sum of resources available in a month counting from the moment the analysed production order's due-date was set [hours]. The resources are calculated using archival scheduling data for selected workstation groups: lathes, milling machines, grinders, manual processing - 4 inputs,
- sum of the maximum delivery time among all missing materials/parts regarding the production order and of the average production time for the item/items related to the production order [working days],
- total machining time related to the production order [hours] - irrespective of workstation types,
- sum of hours planned for product testing related to the analysed production order,
- total number of technological operations to be conducted outside the company - from all of the production orders active in the company,
- number of technological operations to be conducted outside the company for the analysed production order,

- number of turning or milling operations planned for the analysed production order - 2 separate inputs,
- delayed material orders ratio multiplied by the arithmetic mean of delays related to the material - the inputs are calculated solely for the analysed production order. The products of the multiplications are calculated for 4 main material groups e.g. steel, elastomers. Each combination - supplier specific material size and type - is calculated separately basing on the historical records in the ERP system;
- production order type - 6 inputs. The types include standard products, customised, prototypes etc. If a production order is of the type, then the input's value is 0.7, otherwise 0.01;
- product type - 9 separate inputs. The product types indicate different construction, resulting materials and production processes. If a product is of the type, then the input's value is 0.7, otherwise it is 0.01;
- shaft diameter - a key technical parameter in the company's industry area [mm],
- critical path processing time of the production order - excluding material/parts delivery time [hours],
- critical path processing time of the production order - material/parts delivery time included [hours],
- percentage of materials/parts not available in the company's stock for the production order,
- expected period of time until the least available material/part needed for the production order arrives [working days],
- order's flowtime expected by a customer - the company internal parameter [working days],
- holiday season (July, August or December) - value 1 if yes, 0 otherwise.

The input and output values used in ANN should be standardised in such a way that they suit the activation function. Many standardisation techniques have been tested, but for this paper only two are relevant. Standardisation G, where each of an input value was divided by the maximum value in the input category and then deducted by 0.5, and standardisation T3-40, which was used only for output standardisation for some of the tested networks:

$$output_{standardised} = \frac{output}{output+40} \quad (1)$$

T3-40 standardisation was proposed by Mr Rafał Laszczak (KLL), who was involved in the research. Except for the inputs with values already in between -1 and 1, all the other inputs have been standardised G. Depending on the tested neural network configuration, output values were modified either with standardisation G or T3-40. The latter seemed to improve the resolution of the output for the standard products.

4. MULTIVARIABLE LINEAR REGRESSION MODELS

The raw, not standardised inputs and the output were used to compute multivariable linear regression models with use of Statgraphics Centurion XVIII software. Two models, without a constant, were calculated:

- MLR-1 - computed using only standard products dataset (11,106 records),
- MLR-2 - computed using all available orders' dataset (28,344 records).

Inputs without statistical significance were removed from the models. Inputs regarding the suppliers' performance were statistically significant and were not removed.

5. ARTIFICIAL NEURAL NETWORKS

Once the data were obtained from the company's database, ANN different structures and learning configurations were tested. In contrary to MLR, no inputs were eliminated. Until the most effective structures, learning algorithm and activation functions were found, approx. 40,000 different ANNs were taught and assessed. All 3 of the presented in the article neural networks were taught with iRpop algorithm, using David Elliot's activation function. Some of the networks were taught with all the learning data available while others with only standard products data.

The selected, best performing, ANNs are presented in **Table 1**. E.g. the 47-12-1 structure means, that there are 47 inputs, 12 neurons in the hidden layer and 1 neuron in the output layer. Essential programming was carried out using open source FANN library , in collaboration with Mr Rafał Laszczak from KLL company. The computing took place on the ANGA company server.

Table 1 Tested neural networks structure, output standardisation and learning details

	Structure	Learning dataset size	Learning dataset range	Output standardisation	Learning rate	Epochs
ANN-1	47-12-1	11,106	Only standard orders	G	0.05	1000
ANN-2	47-368-1	28,344	All orders	T3-40	0.7	1500
ANN-3	47-192-2-1	28,344	All orders	T3-40	0.3	3000

6. RESULTS

The results of the flowtime estimation using the certification data (1,791 records) are shown in **Table 2**. Before the results were calculated for the ANN-1, ANN-2 and ANN-3, the standardised output values were restored to their previous form using formula (1) and rounded. **Table 3** presents the paired *t*-student test results for null hypothesis that MAEs are equal H_0: $\mu_d = 0$, and alternative hypothesis H_1: $\mu_d \neq 0$.

Table 2 The results of the flowtime estimation using the certification data: company's DDA procedure, multivariable linear regression and artificial neural network methods

	company's DDA procedure	MLR-1	MLR-2	ANN-1	ANN-2	ANN-3
MAE	1.359	1.609	2.176	0.83	0.843	0.873
S_{AE}	3.709	2.809	3.465	1.301	1.216	1.277
ML	4	2.966	3.88	1.773	1.755	1.805
ME	3.008	1.9	1.876	1.408	1.406	1.385
on time [%]	55.3 %	34.73 %	20.88 %	46.57 %	45.28 %	44.05 %
late [%]	1.56 %	34.9 %	34.51 %	21.38 %	21.16 %	23.45 %
early [%]	43.14 %	30.37 %	44.61 %	32.05 %	33.56 %	32.5 %

Company's DDA procedure results show the highest on-time rate and share of orders completed too early comparing to their due dates, and also the smallest share of orders completed too late regarding their due-dates. The result is a typical picture of a DDA approach utilised in practise, where often it is better to quote longer lead-times to a customer, in contrary to shorter ones with associated delay risk. The company's procedure includes a safety buffer, which cannot be said about other DDA methods present in **Table 2**.

Table 3 Paired t-student test results for null hypothesis that MAEs are equal H_0: $\mu_d = 0$, and H_1: $\mu_d \neq 0$

		company's DDA procedure	MLR-1	MLR-2	ANN-1	ANN-2	ANN-3
ANN-1	t-value	-5.97	-13.37	-18.60	-	-0.67	-2.17
	p-value	0.000	0.000	0.000	-	0.501	0.030
ANN-2	t-value	-5.82	-13.90	-18.81	0.67	-	-1.79
	p-value	0.000	0.000	0.000	0.501	-	0.074
ANN-3	t-value	-5.44	-13.66	-18.53	2.17	1.79	-
	p-value	0.000	0.000	0.000	0.030	0.074	-

Both linear regression models performed poorly, achieving the lowest on-time rate, the highest values of MAE, ML and ME criteria. Comparison between MLR-1 and MLR-2 reveals that using all available orders data to compute the MLR-2 model impaired its prediction abilities. It contrasts to the ANN methods, where difference in all criteria between ANN-1, ANN-2 and ANN-3 are miniscule **(Table 2)** or statistically insignificant (**Table 3**).

The **Table 2** shows clearly that all ANNs outperformed other methods in production flowtime estimation. The lead with on-time rate for company's DDA procedure is caused by great effort of production staff to keep production on-time. A handicap the other tested methods did not have. The ANNs results in **Table 2** and their structure indicate that more data probably needs more complex structure to find all existing in the data patterns. It also shows that differently structured and taught networks can estimate the flowtime with similar and accurate results.

Results in **Table 3** show the significant difference in the estimation precision between ANN methods and company's own DDA procedure, MLR-1 and MLR-2. The differences between presented ANNs prediction mean absolute errors are generally low and often not statistically significant - negligible from the practical perspective.

7. CONCLUSION

The purpose of the article is to investigate ANN use in DDA task for standard products in the real-life small batch and multi assortment MTO production company. The comparison between company's own DDA procedure, MLR and ANN based DDA methods was presented. The data used in the research comes from a real-life production company. Some of the presented inputs may be universally used in other enterprises, researches, while other inputs would have to be rearranged. A few of the inputs included material/parts deliveries uncertainty in the form of the material/part supplier historical performance (delay ratio, mean delay). Obtaining the proper data was the most difficult and time-consuming part of the study. The inputs do not exhaust all potentially important data - the inputs categories, quantity and quality. More research on the inputs for ANN based DDA is needed.

ANN based DDA methods outperformed the other compared in the study. Especially MLR DDA results are disappointing. ANN methods made significantly smaller prediction mistakes than company's own DDA procedure, where the real due-dates had an important handicap - everyone in the company tried to ensure the assigned due-dates, because it was related to the motivational system and also because of the top-down pressure to manufacture on-time. Regarding the ANN methods production flowtime estimation precision, it is difficult to imagine better results to the achieved in the research from the practical perspective - regarding the particular company and its industry.

The results prove ANN methods are effective in estimating the production flowtime, but do not include any safety buffer in their predictions, which the company visibly did in its own DDA procedure. Adding some standardised safety buffer to an ANN estimation could increase the ANNs feasibility in the area. Nevertheless, the ANN-1 was built-into existing ERP production module in the company to help a human production planner in their estimation and for future comparisons. As the company's own DDA procedure for standard products only partially included a human decision making, it cannot be determined whether ANN are more effective than people in DDA, but this kind of research is planned for future for other product groups in the company, where due-dates are set solely by experienced human production planners.

The results also showed that learning data, regarding very different product groups, have not impaired the ANNs performance in DDA. The ANNs structure indicate that more data may need more complex structure to encode all of the important patterns present in the data. This suggest ANNs for DDA problems may offer more general solutions - one artificial neural network for a wide variety of products. This idea should be investigated in the future research.

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