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Artificial Neural Network Model Based Setup Period Estimation for Polymer Cutting

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***Abstract*—**The paper presents the results and industrial applications in the production setup period estimation based on industrial data inherited from the field of polymer cutting. The literature of polymer cutting is very limited considering the number of publications. The first polymer cutting machine is known since the second half of the 20th century; however, the production of polymer parts with this kind of technology is still a challenging research topic. The products of the applying industrial partner must met high technical requirements, as they are used in medical, measurement instrumentation and painting industry branches. Typically, 20% of these parts are new work, which means every five years almost the entire product portfolio is replaced in their low series manufacturing environment. Consequently, it requires a flexible production system, where the estimation of the frequent setup periods' lengths is one of the key success factors. In the investigation, several (input) parameters have been studied and grouped to create an adequate training information set for an artificial neural network as a base for the estimation of the individual setup periods. In the first group, product information is collected such as the product name and number of items. The second group contains material data like material type and colour. In the third group, surface quality and tolerance information are collected including the finest surface and tightest (or narrowest) tolerance. The fourth group contains the setup data like machine type and work shift. One source of these parameters is the Manufacturing Execution System (MES) but some data were also collected from Computer Aided Design (CAD) drawings. The number of the applied tools is one of the key factors on which the industrial partners' estimations were based previously. The artificial neural network model was trained on several thousands of real industrial data. The mean estimation accuracy of the setup periods' lengths was improved by 30%, and in the same time the deviation of the prognosis was also improved by 50%. Furthermore, an investigation on the mentioned parameter groups considering the manufacturing order was also researched. The paper also highlights the manufacturing introduction experiences and further improvements of the proposed methods, both on the shop floor and on the quotation preparation fields. Every week more than 100 real industrial setup events are given and the related data are collected.

***Keywords*—**Artificial neural network, low series manufacturing, polymer cutting, setup period estimation.

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I. Introduction

USUALLY when we to talk about polymer part manufacturing, it is often associated with injection moulding or with other warm forming technologies. However, nowadays, we can find friction stir welding also in the frame of polymer manufacturing [1], [2]. The selection of cutting procedures is justified when the production volume is not large (in an optimal case 100-1000 pieces). In this situation, the tool (injection mould die) cost projected to one piece would be too high [3].

The setup is part of the cutting operation and manifested in the first step of the machine setting. The setup is computed from the time when the previous part production is finished and tools needed for the new product, material(s), devices or equipment are already prepared. We consider the setup as closed and successful if the machine produces an appropriate piece. The main goal is to minimise the time spent for the manufacturing of one product, so as to reduce the production cost. Some people consider that the setup period is part of the changeover, wherein the setup has been completed [4].

Das et al. [5] provide a comprehensive literature review of different methods for the setup period estimation. In their work, they present setup period estimation based on workpiece clamping for 3-axis machining. However, it should be noted that the literature is mainly considered for setup periods from a scheduling point of view [5]. Most of the works examined here are small volume (100-200 units), but it is not uncommon to have five-six series-pieces, either.

Annually we have to calculate with 10,000 setup operations (this is 20% of the total machine running time), and therefore a little time gain per setup represents an overall gain in production time.

II. Structure of the Setup Process: The First Calculations

Pre-measurements have been made with 15 sets of measurement analysis, part-time measuring and averaging. After un-tooling of the previous work, the preparation for the new machining has to be done. Average time of the preparation: 4 [min]. Replacement of collet, adjusting clamping force: 2 [min].

A. Programming, Cross-Checking, The First Piece and the First Good Piece

Equations (1) and (2) are the base of the linear approximations:

$$t_{pr} = N \cdot 1[\min] \tag{1}$$

where **N** is the number of tools used in the process and $\mathbf{t_{pr}}$ is the time required to re-write the program.

$$t_{bem} = N \cdot 2[\min] + B \cdot 2[\min] \qquad (2)$$

where **N** is the number of tools used in the process and **B** is the time required for cross-checking the counter spindle. When counter spindle is in use then **B**=1, else **B**=0. Due to the tight tolerance fields (it is not uncommon to have 0.02 mm) it is very rare when the first piece is appropriate. It further complicates the matter, if the piece can only be measured completely with a complex measuring method (for example with optical measurement system). Adjustments and repairs consume most of the time and the estimation of these parameters is difficult and may depend on several factors.

On the other hand, if a mistake does not occur, then a good approximation to calculate the time needed to manufacture the first good piece is:

$$t_e = (4+1) \cdot t_D + t_{HV} + t_{COR} = 5 \cdot t_D + 15[\min] \qquad (3)$$

where $\mathbf{t_e}$ is the time required to manufacture the first good piece, $\mathbf{t_d}$ is the time required to manufacture one piece and $\mathbf{t_{HV}}$ is the time required to set the coolant system.

The role of coolants and lubricants by the turning of polymers is the transportation of chips and the prevention of chip winding on the tool/workpiece. By applying adequate tool posts, $\mathbf{t_{HV}}$ can be greatly reduced and neglected. $\mathbf{t_{COR}}$ is the time required to perform the correction.

III. Correction Factors for Linear Model Building

Previous setup data (multiple years of data) have been analysed and correction factor are used to create a formula for setup period estimation. Three hypotheses are created, and on the basis of the results, a model is developed to calculate the correction factors:

1) The setup time depends on the product material.
2) The setup time depends on the requested surface quality.
3) The setup time depends on the width of the tolerance range.

IV. Building and Evaluation of the First Linear Model

After arranging the previously established fixed and tool amount (or manufacturing time) dependent parts, we receive (4) for setup period estimation:

$$t_{setup} = N \cdot 5 + K \cdot 5 + t_D \cdot 5 + B \cdot 4 + C + t_{COR} \qquad (4)$$

where **N** is the number of the tools, **K** is the number of tool holder exchanges, **B** stays for the presence of the counter spindle, $\mathbf{t_{COR}}$ is the correction factor and $\mathbf{T_D}$ is the time required to manufacture one piece. Furthermore, **C,** a constant time, is added which is the sum of all constant time values.

V. General Data Evaluation

By analysing more than 5,600 setups, real conclusions can be made from the time difference of real and planned times. However, as wrong conclusions can be drawn from the average of the percentage differences, the weighted average shall therefore be calculated, where the weighting will be the number of tools. The current model has an average plus difference (22%) from real time, which means 28 minutes' of extra time on one general setup, calculated with eight tools. This represents almost one and a half hours a day, which significantly reduces the scheduling accuracy.

The difference between the two setup times with the same number of tools can be huge; the differences have big deviations (approx. 86%). From this follows that it is difficult to create a formula that is able to give a reliable estimation for the time needed for a setup. In the next data analyses, we examine those works, where the setup period exceeded more than 100%. It is interesting that not only the new works can occur in this band, but he re-ordered products are also appearing with exceeded setup periods.

A. Setup Time - Material Relationship

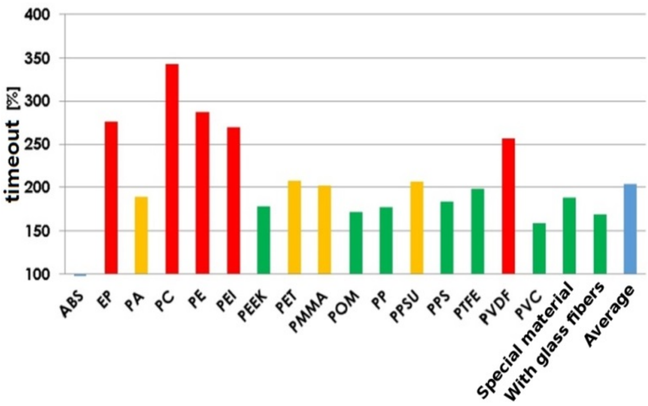

Fig. 1 Raw material distribution at problematic products

In Fig. 1, we can observe that the hypothesis related to material dependency was correct, and that there is a connection between the material and the setup time, and this must be taken into account.

B. Setup Time - Tolerance Zone Relationship

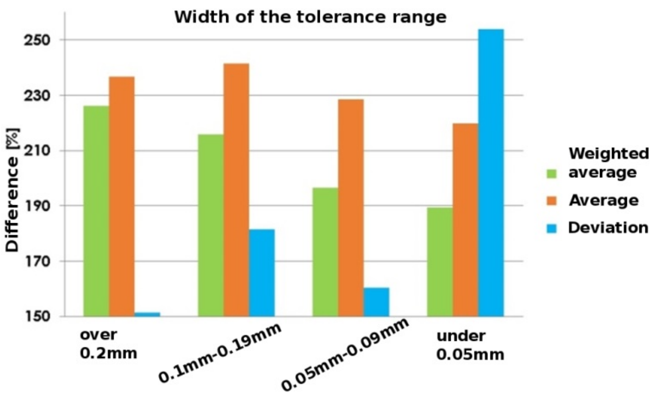

Fig. 2 Tolerance zone - time difference correlation

Fig. 2 shows that the weighted average paradoxically decreases with the ever decreasing tolerance zone width, but taking into account the corrected empirical standard deviation it appears that the oscillation around the mean is increasing. It can be said that based on the available data, no clear relationship can be found within the width of the tolerance zone, and the setup period.

C. Relationship of Surface Quality and Setup Time

Fig. 3 shows that a finer surface quality needs more setup time, and this must be compensated in the model.

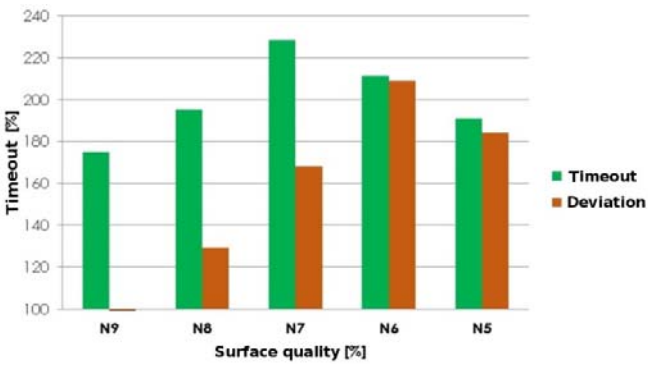

Fig. 3 Relationship of surface quality and setup time

VI. Comparison of the Old Model with Archive Data

The relationship of previous model and real setup times is shown in Fig. 4. The "theoretical" curve shows the currently used linear relationship, the "practical" curve represents the real time values. It can be seen that for up to 10 tools, the slope of the curve almost coincides with the theoretical formula, but even up to 15 tools it gives a good approximation. There is a constant difference between the two approximations.

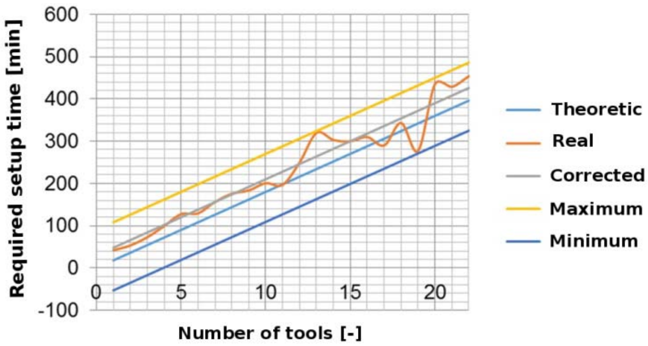

Fig. 4 Relationship of previous model and real setup times

It is important to note that none of the above mentioned approximations would give an adequate setup time, because the maximum limit - for most parts - would be over- and the minimum limit would underestimate the required times. Therefore, an adjusted average function is used, which estimates the setup time with reasonable accuracy, in the case the number of tools is fewer than 10.

$$T = N \cdot 18 \qquad [\min] \tag{5}$$

where **N** is the number of tools used in the process. However, above 10 tools, the relationship between setup time and number of tools is nonlinear, and therefore the estimation should be based on other considerations. Here, the application of the previously mentioned correction factors could be one solution.

VII. Compensation Parts

By compensation, additionally to the above mentioned tool holder exchanges, the material (**M**), width of the tolerance zone (**S**) and the surface quality (**F**) have to be taken into consideration.

Based on practical experience, materials are classified into three groups, the material machinability is characterised with **M** index-number.

The surface quality, as well as the tolerance zone can be divided into four classes, **S** and **F** depends on this value.
The values of the three parameters are listed in Table I.

TABLE I
Determination of Correction Factors

Material		Surface quality		Tolerance zone	
Machinability	M	Surface	F	Width	S
Good	1	N9 or	1	wider than	1
Average	2	N8	2	0.2 – 0.1 mm	2
Not good	3	N7	3	0.1 – 0.05 mm	3
X	X	N6 or finer	4	narrow than 0.05	4

VIII. Second Linear Model

Equation (6) should be followed in the case where the number of tools is more than 10:

$$T = [1 + 0{,}1 \cdot (M-1) + 0{,}1 \cdot (S-1) + 0{,}1 \cdot (F-1)] + K \cdot 5 [\min] \tag{6}$$

where **T** is the setup time, **N** is the number of tools **S**, **M**, **F** are the correction factors and **K** is the number of necessary tool holder exchanges.

IX. Evaluation of the Second Linear Model

The validation of the second linear model was examined with substitutions in recorded setups. The results are shown in Table II. It can be seen that the 2. Linear model gives better results, but only in some cases. To understand the relationships between the different parameters in this process, an Artificial Neural Network Model has been developed.

X. Artificial Neural Network Model for Setup Period Estimation

Artificial Neural Networks are efficient computational models, which are able to solve complex estimation and classification problems due to their high generalization capabilities and robustness. As the naming suggests, this model was inspired by the neural network working inside the brain. The network consists of individual computational units called neurons, which are connected by weighted links. This concept was born more than 70 years ago as a result of the work of W. S. McCulloch's and W. Pitts [6].

TABLE II
INVESTIGATION OF THE SUITABILITY OF THE MODEL

N	Theoretic [min]	Real [min]	S	F	M	2. Linear model [min]	Differ. using 1. model [min]	Differ. Using 2. model [min]
11	198	248	4	2	0	257.4	50	-9.4
12	216	299	1	3	3	302.4	83	-3.4
13	234	397	4	3	1	351	163	46
34	612	1189	4	3	1	918	577	271
15	270	487	3	2	3	405	217	82
21	378	631	3	3	3	604.8	253	26.2
20	360	1085	3	3	3	576	725	509
18	324	607	4	2	1	453.6	283	153.4
16	288	372	4	1	1	374.4	84	-2.4
26	468	659	4	3	1	702	191	-43

There are several ANN models, which differ mainly in their structures and training algorithms. They were created to serve the different needs of different application fields. One of the most popular and widespread models is the Multi-Layer Perceptron (MLP) [7].

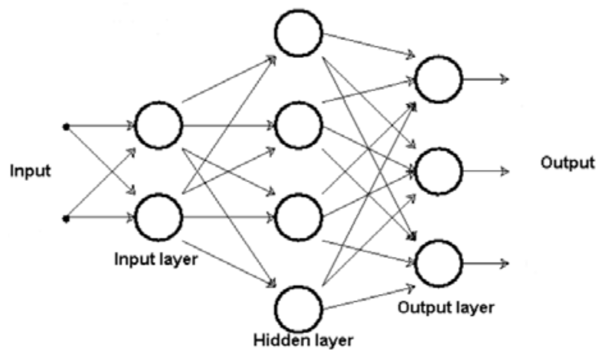

Fig. 5 The Multi-Layer Perceptron model

Fig. 5 shows the structure of the MLP model, where the neurons are organized in fully connected layers, e.g. each neuron of a layer is connected to each neuron of the next layer. The evaluation of the model consists of feeding values to the input neurons and propagating them through the network until the output neurons are reached. The values appearing in the output layer are the final outputs of the model. During the supervised training of the MLP, the weights of the connections are modified in order to decrease the difference between the output values of the model and the target values of the training dataset, which consists of input and output samples. The error backpropagation algorithm calculates the derivative of the error of the model (the difference between the model output and target values) subject to each weight and modifies each of them in the direction of the descent based on the derivative. The iterative application of this training method converges to the minimum of the model error, thus making the model an estimator of the output values in the function of the input values.

This research is an in-depth study of the polymer cutting process, which was defined in 24 main- and 10 subcategories. The main categories were grouped into:

- Product data (like name and quantity);
- Surface quality and tolerance (like finest surface quality and narrowest tolerance);
- Material (like type and colour);
- Setup data (like machine and shift).

All these parameters have been used to build the Artificial Neural Network Model.

XI. RESULTS OF THE ANN MODEL

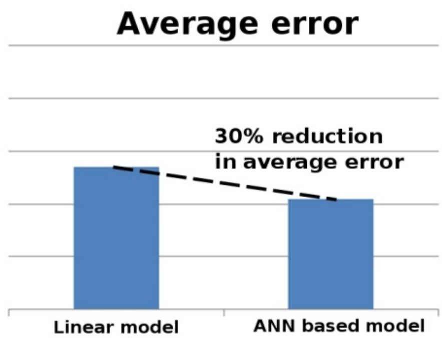

Fig. 6 Average error in linear- and in ANN based model

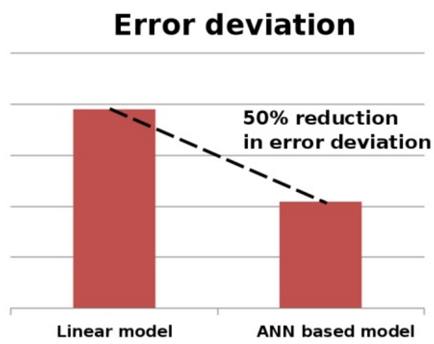

Fig. 7 Error deviation in linear- and in ANN based model

To summarise the results obtained from the ANN model building, the comparison figures are presented. Fig. 6 shows that by using the ANN approach, the average error of the estimations was reduced by 30%. However, the most promising results were obtained in error deviation, where the ANN-based model reached a 50% reduction (see Fig. 7) compared to the linear one. To enhance this new model, the antecedent production setup data sets have been used too. Unfortunately, only a 1% reduction in model error could be achieved with this investigation.

Distribution of the setup periods, the models' data points and their relationship with the real setup times is presented in Figs. 8-10. Further investigations have been made with the so-called tool sheets for fault detection, but these new factors need more examination, especially when we have to take into account the effect of new workers, too.

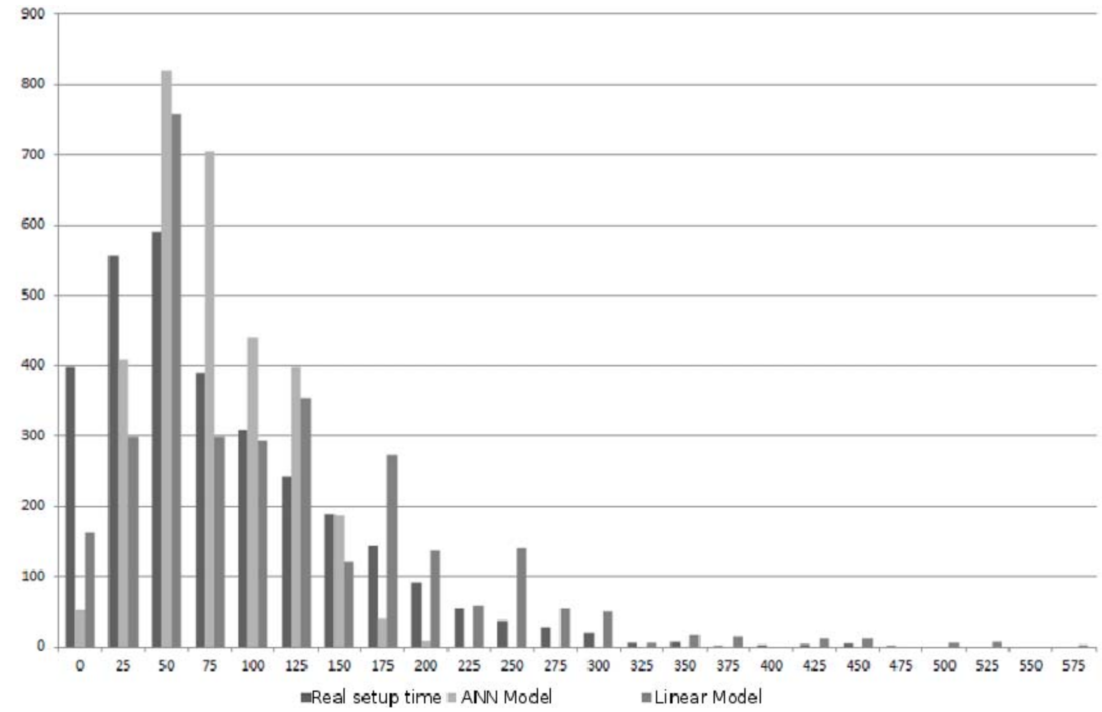

Fig. 8 Distribution of the setup periods in linear- and in ANN-based model

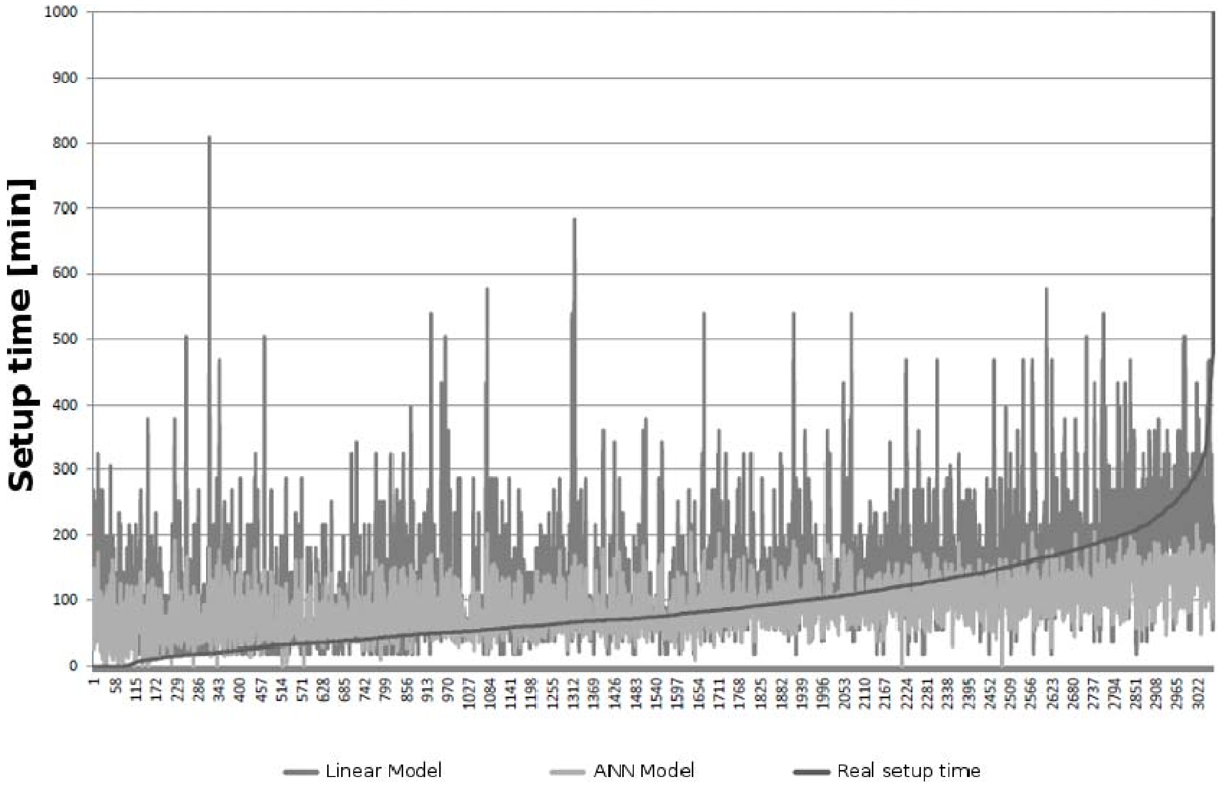

Fig. 9 Linear- and ANN-based model results with data points

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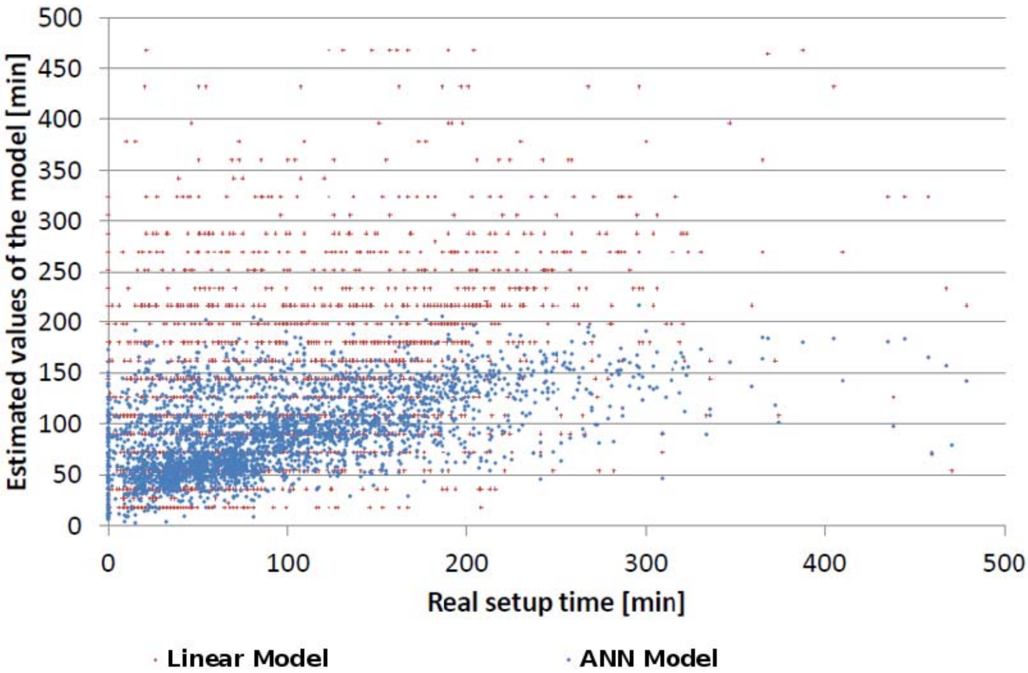

Fig. 10 Linear- and ANN-based model compared to real setup times

XII. Conclusion

The presented industrial use case showed that in flexible production systems the Setup Period Estimation has a high priority. Investigations of linear model building based on previously recorded detailed setup data were compared to a nonlinear solution.

With the extended datasets, long time data acquisition and with a trained learning algorithm, an Artificial Neural Network Model is capable to deal with nonlinear multidimensional data and achieve significant progress.

The documented solution has been validated on real industrial datasets. It has been proven that it is important to apply a learning algorithm also on a higher level in the production, not only on the machine and sensor level (like production planning).

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