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Predictive Modeling to Increase the Reliability of Production Planning in Single-item Production

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Abstract— **The lack of repetition effect in the single-item production in metal industry limits an exact determination of the necessary process parameters (e.g. welding time) for production planning and cost estimation and furthermore restricts the application of production planning systems. This challenge is especially noticeable in manual welding work stations. This work discusses a methodology to improve the prediction accuracy of orbital welding time in single-item production systems. In this approach the process times are estimated on basis of historical operating data and product design parameters through predictive analytics methodology. In this paper the predictive model is developed based on characteristic indicators through correlation analyses and different regression models. Standardized production processes and structure of data acquisition are also a strong requirement to apply this approach in single-item production systems. The structure of data acquisition is developed on basis of process model and design structure. This approach is applied in a practical case study, which is introduced in this paper. This methodology supports single-item producers to improve their production planning, and cost estimation quality in metal industry.**

Index Terms— **single-item and small series production, welding process, predictive modelling, reliability of production planning,**

I. Introduction

The reliability of production planning plays a critical role for the effectiveness and efficiency of modern production systems. The accuracy of the determination of production planning parameters like process and setup time is also a strong requirement for the reliability of production planning and cost estimation in single-item production. Differences between planning parameters and the real production parameters reduce the accuracy and reliability of production planning. Schuh, Potente, Thomas and Hauptvogel have shown that on average the deviation of the planning parameters may occur on 25% in only three days after system validation [1]. The lack of high repetition effect in the single-item production in metal industry limits an exact determination of the necessary process parameters. In single-item production, the different parts in a work station often have different dimensions. Therefor the estimation of process time is a big challenge in production planning. This problem is especially noticeable in welding processes. The actual state of art includes only few methods for the prediction of welding process time, which are based on welding technologies. For example, Masmoudi, Hachicha and Bouaziz suggest a method to estimate the welding cost and time based on feature concept [2]. Heimbokel has also suggested a similar approach based on technological aspects of welding to determine the welding process time [3]. The challenge for the application of these technological approaches is a very high level of complexity and a low level of flexibilities. For their implementation it is also necessary to determine many technological parameters, which is normally a big practical challenge in a real production process. Furthermore, the logistical and ergonomic aspect can't be considered in this approaches. Because of the high impact of not technological influence aspects like ergonomic and organizational parameters in the manual work stations, this challenge is also bigger in manual welding processes and the determination of process time based only on the usage of welding technological parameters like welding performance is very inaccurate. In this work we introduce the predictive modeling method as a possible solution. Through our approach, an output parameter, in our case process time, is estimated based on mathematical relation and correlation with different entry parameters. These entry parameters are design and construction parameters in single-item production, which are determined in the product design phase. The historical operating data is used as basis to develop the predictive model. In this methodology we apply the characteristic indicators to optimize the modeling and the regression models are used as a predictive tool. We also demonstrate the impact of process knowledge to simplify and optimize the modeling. The major advantage of this methodology is its accuracy and high flexibility. Furthermore, all process parameters whether technical, logistical, organizational or ergonomic are noted automatically in this solution.

II. State of the art

Predicative analytics is an advanced analytics method, which predicts unknown future events through techniques like data mining, statistics modeling, machine learning, and artificial intelligence [4]. Kuns and Johnson defined predictive modelling as "the process of developing a mathematical tool or model that generates an accurate

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prediction" [5]. There are several works that use this method to attain different goals but only a few of them apply this methodology in the field of production. For example Van der Aalst and Schonenberg have presented a new method for predicting the 'future of running instance' in production. Through their method they predict incidents like the end of production. However, their approach can be used easily for other aims in prediction [6].

In the current state of the art some works can be found, which introduce different approaches to predict the process time. For example, Müller has suggested the following three methods to estimate the process time: experiential knowledge (standard or estimated time), historical data and mathematical functions [7]. On this base, he has developed a hybrid method to estimate the process time in production. He has used the experience and knowledge method for new technologies, historical data for established processes and mathematical functions for interdisciplinary production processes. Faisst, Schneeweiß and Guenther have presented an approach based on a mathematical forecasting system to predict the process time [8]. This prediction system constitutes a learning effect through a larger data base, which improves the accuracy of the results continuously. Luehe has also introduced a similar approach to estimate process times by applying mathematical methods [9]. He has used a modular system to standardize assemblies and parts and has applied stochastic functions based on the acquired process data to determine the process time and cost. The calculated values are deposited behind the respective modules (as features) and this acquired knowledge is applied in the next project planning. The model of Seung-Jun, Jungyub and Sudarsan can also be viewed as a very interesting and relevant approach for determining the production parameters in complex production systems [10]. Even though, their model was developed to predict the energy consumption in production systems, but their approach can be used to predict the planning relevant production parameters. To develop the forecast model for energy consumption in manufacturing, they have applied the analytics methodology based on big data. In their model, the correlations of the input parameters like material, machine tools etc. with a determined unit of energy (output parameters) are analyzed and the predictive modelling has been developed based on a neural network. The model is developed based on a large proportion of existing data (10,000 records). Jodlbauer, Palmetshofer and Reitner have also used the predictive modeling to predict the process time. They have classified the process time as a constant characteristic for each material and machine based on historical data. These characteristics are used to predict the new process times. It is a big advantage of this method, that except historical data, no extra information is required [11].

III. Methodology

A. Requirement

The standardization of the production process and the work station is the main requirement to improve the reliability of production planning in single-part production. Through this process standardization it is ensured that the same process flow and technology is used to assemble the same or similar assemblies and components. There by:

1) The workers, processes, work tools, welding technology, logistic flow and work flow in a work station must be consistent and standardized.
2) In case of different types of welding processes, welding processes must be classified.
3) The new components and assemblies must be in the same product family.
4) The assemblies with similar forms should be manufactured in the same work station.

B. Machine learning as predictive tool?

Considering the state of the art, predictive analytics and machine learning software and algorithms can be used principally to developed the predictive model and estimate the output parameter based on more entry parameters directly. This modeling approach can be applied very effective in case of big data records like the work of Seung-Jun, Jungyub and Sudarsan [10] in series production. But because of limited production orders in single-item production systems compared to series production, collecting so many data records can take years and normally the old data records do not correspond with actual situations in production. Therefore, modeling methods, which are based on big data records, are generally not suitable for single-item production systems. This finding is based on results of a research project at Vienna University of Technology.

C. Approach

After process standardization the operation data like process time can be also gathered and stored in a harmonized form and structure and can be used to develop the predictive modeling. Collecting data in the required quality is a main demand to applicate this method. Principally this methodology focuses on the simplification of predictive modeling and the application of simple regression models as predictive tools to develop a practical solution for single-item production systems. The methodology can be described in the following steps:

1) *Collecting data:* After the process standardization, the data records should be classified. In single-item production, the assemblies can also have different materials or need to be assembled with different standard process flows or manufacturing technologies in the same work station, which influence the process time. Because of this, it is required to classify the saved data records in different categories based on relevant influence factors like manufacturing technology (for example: welding technology) or material. The correlation analysis is applied to support the decision about the data classes. In this case, a correlation analyses between entry and output parameter should be carried out once based on all data records and once based on data records in each class. If the results are similar with a big "coefficient of determination", the classification is not necessary. If the results are similar with a small "coefficient of determination", the entry

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parameter is irrelevant and if the results are different, the classification is necessary.

2) *Selection of entry parameters:* Principally two different approaches can be introduced to develop the modeling to predict the process time based on construction parameters. The first one is modeling without any kind of process knowledge and the second one is modeling with process knowledge. Correlation and regression analysis are used as tools to select the entry parameters with a strong relation to the output parameter (process time). In this case, entry parameters with a R^2 (coefficient of determination) value of more than 0,5 should be selected and applied for predictive modelling. An effective modeling with the first approach normally needs a bigger number of data records compared to the second approach, which uses process knowledge. In the second approach, it is tried to limit the entry parameters through process knowledge and simple correlation analyses and regression models are also used as predictive tools.

3) *Definition of characteristic indicators:* To simplify the analysis and modeling, the output parameter (process time) is integrated with one or more independent entry parameters and they are transformed to a characteristic indicator like work performance per minute or hour. Also it should be tried to reduce the number of entry parameters through the integration of parameters and their conversion to new entry parameters, eventually by using of process knowledge. This approach presents an effective solution to reduce the influence parameters and simplify the predictive modeling. The predictive model in this approach, estimates the indicator and not process time directly. The indicator must be transformed to process time based on (an) integrated entry parameter(s).

4) *Predictive modeling:* In this methodology it is tried to use simple regression models as predictive tools. Dependent on the number of entry parameters, this models can have one or more dimensions (single or multi regression models). A predictive formula is the result of predictive modeling.

5) *Model reliability:* In this methodology, only 75% of historical data records are used for modelling and 25% of them are used for validation and reliability. The data records, which are used for reliability, were not used for modeling. The average deviation between measured and predicted process times describes the reliability of the model.

IV. Case study

This case has considered the orbital welding of tank's bodies (cylinders and caps) in a welding work station with a not automated but standardized procedure. The cylinder parts of tank shells and tank caps are welded here with TIG process (tungsten inert gas welding) (fig. 10). Aforementioned, a major demand of this method is operating data, which were gathered in this study for about 4 months and includes 81 historical data records. Each data record contains process time, diameter, length, sheet thickness and number of tank shells in each tank (measurement data), that are different in various projects. The personal capacity at the work station is always constant. Collected data are classified to be ready for analyzing and modelling to estimate the process time and all data records are also from the same material. In this model, the process time is calculated through a specific indicator. This indicator describes the welding rate, which defines the welding performance in an hour (welding speed). Regression models are used here as predictive models and an average deviation of 5% is adopted as a goal for the reliable model.

A. Selection of entry parameters

In the first step the relation between the construction parameters as entry parameters and the process time as output parameter is analyzed through correlation and regression analysis (fig. 1-4). In this case, the parameters are considered isolated and each parameter, which had a coefficient of determination (R^2) over 0,5 with process time has been selected for modeling without process knowledge.

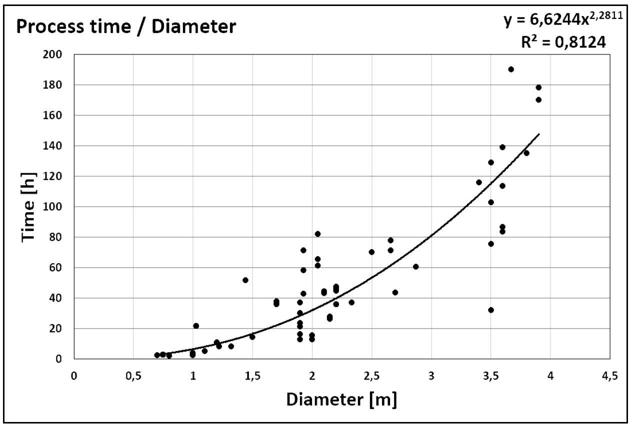

Fig. 1. Correlation of process time with diameter of cylinder

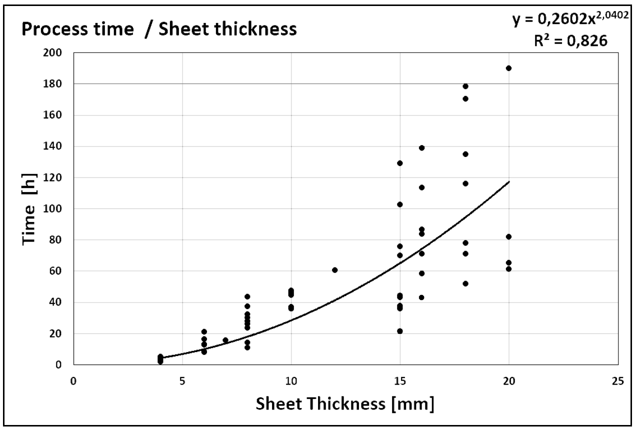

Fig. 2. Correlation of process time with sheet thickness

The following table compares the "coefficients of determination" of the different analyses with each other:

TABLE I. results of selection analysis

	Diameter	sheet thickness	length of tank	Number cyl. parts
R^2 with process time	0,812	0,826	0,355	0,378
Selected (yes/no)	yes	yes	no	no

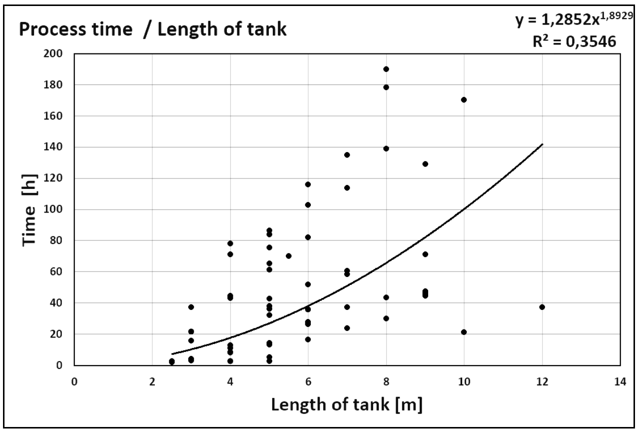

Fig. 3. Correlation of process time with length of tank

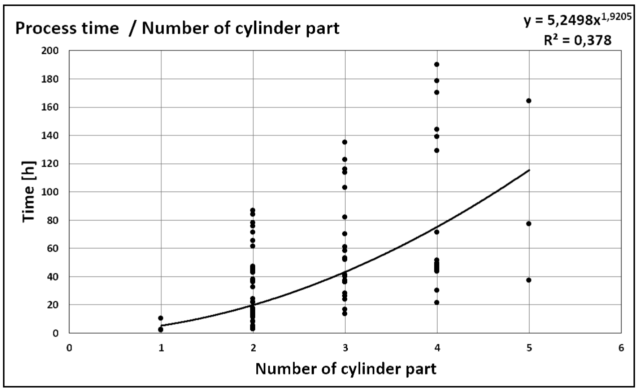

Fig. 4. Correlation of Man-hour with number of cylinder part

The results of the selection analysis have shown, that the diameter and sheet thickness as entry parameters, have strong correlation with process time and therefore they should be selected for predictive modeling.

B. Modeling without process knowledge

In this approach, which is also applied in modern predictive analytics software, the entry parameters are considered isolated and the process dependent relations are not considered. Based on selection analysis in this case, there are two construction parameters as entry parameters to develop the predictive modeling. Predictive modeling with two or more entry parameters needs the application of multi regression models and because of the non-linear relation of entry and output parameters in this case, the modeling would be extensive and complex. To simplify the modeling, it has been tried to integrate one additional entry parameter in the output parameter. In this case the tank diameter and process time are transformed to a specific and characteristic output parameter, which defines as welding performance the working rate in an hour based on diameter. Now, only sheet thickness has to be used as entry parameter, if it demonstrates a strong correlation with welding performance. The correlation analysis demonstrates a strong correlation between welding performance and sheet thickness with R^2=0,912 and therefore the sheet thickness can be applied now as entry parameter to predict the welding performance (fig.5). The simple regression model between welding performance and sheet thickness is also used as predictive model. After predicting the welding performance, it is converted to process time based on tank diameter.

The reliability of the predictive model is tested with 20 independent data records, which weren't applied for modeling. Through the reliability test, the process times of 20 manufacturing orders based on their tank diameter and sheet thickness have been predicted and the results have been compared with real measured values (fig.6). The reliability test demonstrates an average deviation of 23,7%, which is a poor result for this modeling. This result also has a very big deviation with the adopted goal of 5%.

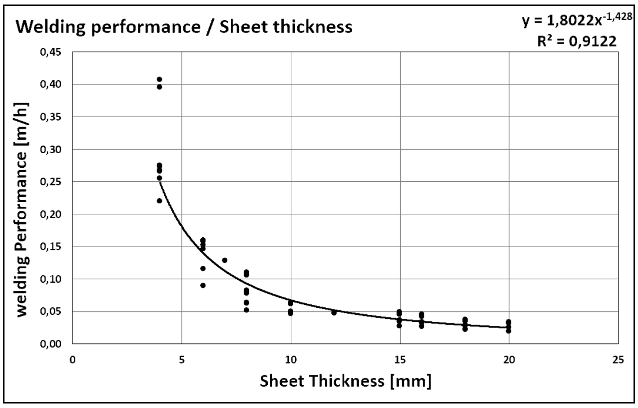

Fig. 5. Correlation of welding performance with sheet thickness based on tank diameter

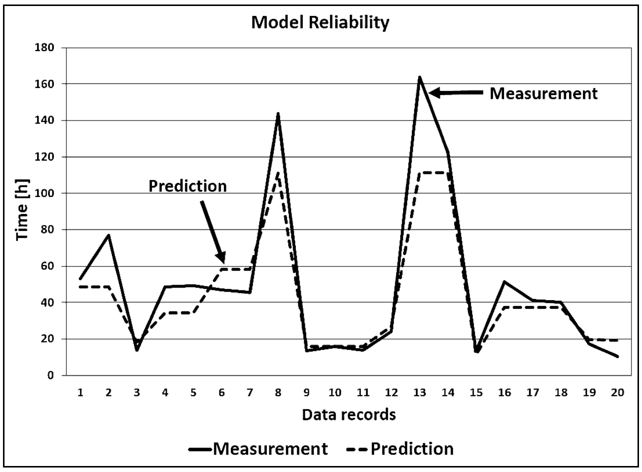

Fig. 6. Reliability test of predictive model based on tank diameter

C. Modeling with process knowledge

The process observation in the production salon has shown, that eventually there is a strong relation between the sum of welding length and the sum of process time in the welding station. The challenge is that the sum of welding length is not automatically in the parts list as construction parameter. On the basis of this process knowledge and to find the correlation with process time as output parameter, the sum of welding length was calculated. The result of the analysis has shown a strong correlation between this new entry parameter and process time (R^2: 0,801) and better data concentration on regression line compared to tank diameter (fig.7).

Here is the calculation formal of welding length:

Welding length = (Diameter X π) X (Number of cylinder parts + 1)

This new entry parameter is principally nothing else than an integration of two construction parameters (diameter and number of cylinder parts). The strong correlation of welding length with process time has also demonstrated, that not using of cylinder parts number in the predictive model by modeling without process knowledge, eventually is not the best decision. Now welding length and sheet thickness are two entry parameters for predictive modeling.

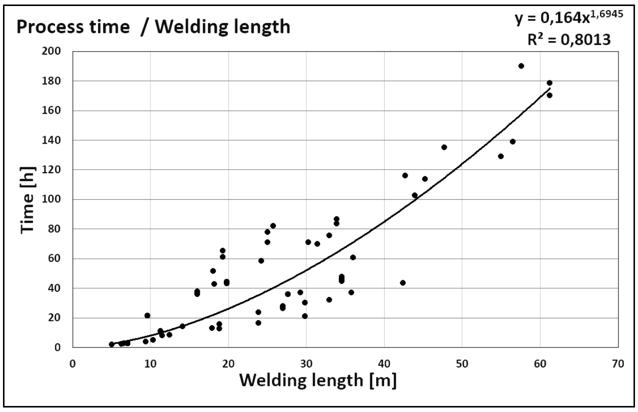

Fig. 7. Correlation of process time with welding length

In this case the welding length and process time are transformed to the characteristic output parameter, welding performance. Now, only sheet thickness has to be used as entry parameter. The correlation analysis demonstrates a very strong correlation between the new welding performance and sheet thickness with R^2=0,997 and therefore the sheet thickness can be applied now as entry parameter to predict the welding performance (fig.8). The simple regression model between welding performance and sheet thickness is also used as predictive model. After predicting, the welding performance is converted to process time based on calculated welding length.

The reliability test of the predictive model was carried out with the same system like modeling without process knowledge and has demonstrated an average deviation of 3,9%, which compared to the amount of data records is a very good result and better than the adopted 5% average deviation (fig. 9).

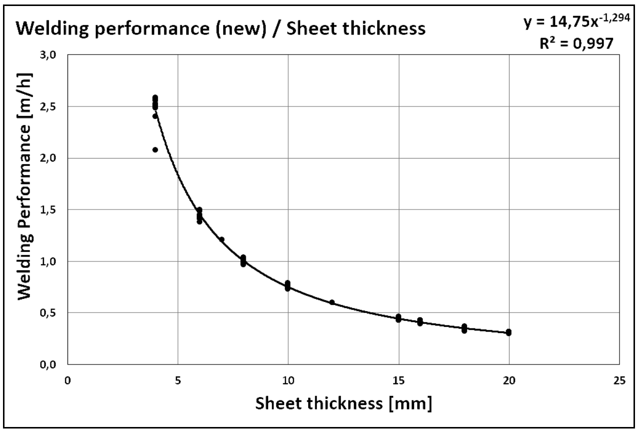

Fig. 8. Correlation of welding performance with sheet thickness based on welding length

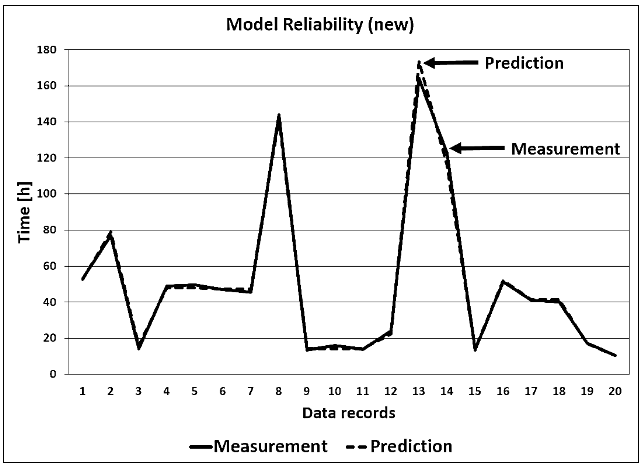

Fig. 9. Reliability test of predictive model based on welding length

D. Adaption of parts list

The result of modeling with process knowledge has demonstrated, that this methodology based on characteristic indicator is a very effective tool to predict the process time of manual welding process on basis of construction parameters. In this approach the process time is estimated based on tank diameter, number of cylinder parts and sheet thickness indirectly. The first step to apply this method is the calculation of welding length based on tank diameter and number of cylinder parts with introduced formula. In practice the manual calculation of this indicator for all manufacturing orders is very extensive. Because of this, in our case we integrated this indicator in parts list through a macro function in PDM (Product Data Management system).

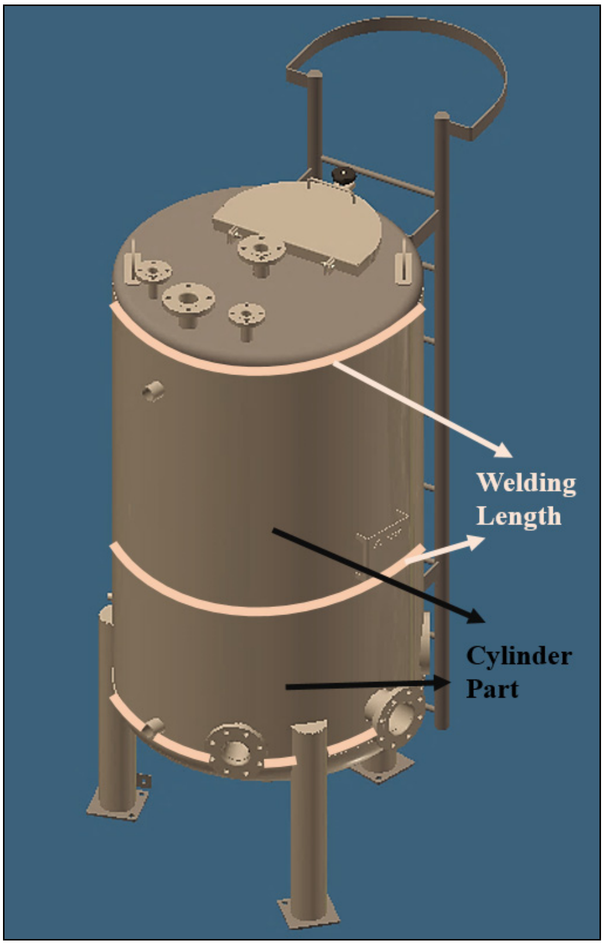

Fig. 10. Welding length and cylinder part in a tank

This function has been implemented in "Vault-Autodesk" PDM system. In our case, the constructors determine the welding lines through a function of PDM during construction. After the creation of parts list, the PDM system calculates the sum of welding length in each parts list position automatically and enters in a column at parts list. The predictive formula is also implemented in the PDM system and in the next step the system calculates the process time based on welding length and sheet thickness automatically and also enters it in the determined column at parts list. With this approach, the process time for welding stations is calculated and entered in parts list automatically.

V. Conclusion

The results of the case study have shown, that predictive modelling can be applied as effective solution to predict the welding process time in single-item production. The application of a characteristic indicator is also a good way to simplify the modeling. Through this methodology, the predictive modeling can be carried out based on simple regression models and the process knowledge supports the simplification of modeling and the reduction of entry parameters enormously. Because of the limitation of the number of data records in single-item production compared to series production, the introduced methodology based on process knowledge and characteristic indicators is much more effective and practical than other methodology based on big data and machine learning algorithms. The result of this work has also shown, that in some cases the development of a reliable predictive model without process knowledge is not possible. For example, in our case, the development of a reliable model without consideration of welding length was not possible. It should be also noted, that the introduced result is the outcome of process standardization in a high level. The first collected data records from the production have not shown any kind of correlation with each other and after process observation we found it out, that the workers sometimes have different process flows for the same situation in the work station. The introduced data records in this work have been collected after strong work and process flow standardization in production.

It is recommended, to carry out the analysis in constant time units (for example annually) based on more data records to actualize the predictive formula and minimize the average deviation. It is also expected, that a larger number of data records influences the accuracy of modeling positively.

Acknowledgment

The introduced methodology to predict the welding process time in single-item production system is the result of a research project in a real company. A direct prediction based on more entry parameters (without characteristic indicator) and the application of multi regression models as predictive tool, comparing of introduced methodology with this approach and especially, analysis of different predictive models and tools from IT aspect can be interesting concept for the next researchers.

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