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Predicting the Impact of Product Type Changes on Overall Equipment Effectiveness Through Machine Learning

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Abstract

Nowadays, Industry 4.0 and the Smart Manufacturing environment are increasingly taking advantage of Artificial Intelligence. There are more and more sensors, cameras, vision systems and barcodes in the production area, as a result of which the volume of data recorded during manufacturing and assembly operations is growing extremely fast. The interpretation and processing of such production-type data by humans is no longer possible effectively. In the Big Data domain, machine learning is playing an increasingly important role within data mining. This paper focuses on the product change processes of semi-automatic assembly line batch production and examines the impact of product type changes on the Overall Equipment Effectiveness (OEE) and attempts to determine future values through supervised machine learning. Using decision tree technology, the effect on the OEE value can be predicted with an accuracy of up to 1%. The presented data and conclusions come from a real industrial environment, so the obtained results are proven in practice.

Keywords

OEE, machine learning, decision tree, assembly line, prediction

1 Introduction

In order to plan the assembly sequence of products properly and to use the available resources in the right way, it is necessary to know the efficiency of the production units. It is advisable to predict the change in efficiency, which can move in either a negative or positive direction in addition to the stagnant situation, because these have an impact on the financial profitability of the factory. Higher efficiency requires less manpower, less manpower generates lower costs (e.g., variable costs, etc.). Overall Equipment Effectiveness (OEE) is the most common efficiency Key Performance Indicator (KPI) in industrial practice today [1]. OEE, as a standard and best practice indicator, also includes downtime spent on product changes during manufacturing and assembly [2]. Despite Single Minute Exchange of Die (SMED), One Minute Exchange of Die (OMED) and One Touch Exchange of Die (OTED) used in day-to-day practice, the number and duration of changeover in batch-type assembly is still significant. These widely used methods analyze and optimize the process of product changes even during assembly operation in the case of tool changes. Therefore, it is important to predict future OEE values as accurately as possible.

The paper is organized as follows. Section 2 focuses on the relevant scientific work regarding to machine learning and OEE. Following, Section 3 revealed decision tree technology as applied machine learning with industrial prediction example. Section 4 concludes the paper.

2 Machine learning and OEE

Artificial Intelligence (AI) encompasses machine learning which can support the predictive analytics in exploiting hidden correlations and make estimation [3]. Machine learning methods are used in industrial manufacturing applications, process characterization, fault detection, quality improvement, predictive maintenance, decision support system and production scheduling [4–7]. When industrial data is processed, data preparation and cleaning are essential.

2.1 Applied machine learning methods

There are numerous machine learning methods among others regression, clustering and decision tree, regularization, rule system, dimensionality reduction, Bayesian, ensemble, neural networks and deep learning. Within the decision tree algorithms there are also several methods

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such as classification and regression tree, iterative dichotomiser, C4.5, C5.0, Chi-squared automatic interaction detection, conditional decision tree, etc. [8–12]. Machine learning algorithms can be divided into three categories: supervised learning, unsupervised learning and reinforcement learning [13]. All these types can be used for prediction in manufacturing and assembly domain [14].

Brunelli et al. proposed a deep learning-based approach for predicting future values of production performance. Temporal Convolutional Network (TCN) and Long Short Term Memory (LSTM) model were applied for forecasting [15].

Hassani et al. used different machine learning tools such as Support Vector Machine (SVM), Random Forest, XGBoost and deep learning to predict OEE percentages. They conducted that deep learning and random forest with cross validation were the best reliable methods [16]. Acosta et al. proposed a Derivative Integral Proportional PID machine learning algorithm with SVM for optimization of OEE [17].

Engelmann et al. compared ensemble classifier, SVM, naive Bayes, R and decision tree algorithms for changeover process. According to their work the fine tree algorithm reached 92.8% accuracy during the test period [18].

2.2 OEE and type change at the assembly lines

An important feature of assembly lines is that they are generally able to assemble multiple types of products from the same product family by making minor modifications to the line. Flexible and reconfigurable assembly systems operate at high level of customization [19, 20]. Various systems, among others Manufacturing Execution System (MES) and Enterprise Resource Planning (ERP), provide assistance in the automatic collection and storage of OEE values in the assembly lines of industrial companies [21–23].

All manufacturers are working to reduce product change durations with the help of numerous lean methods, including Singe Minute Exchange of Die (SMED), One Minute Exchange of Die (OMED) and One Touch Exchange of Die (OTED) [24–27]. However, even so, the duration of product type changes can range from a few seconds to several hours. Short-term changeovers require minor changes, while long-term changeovers (which usually occur only a few times a month) require major adjustment (e.g., pallet changes, workstations switching on, etc.). No matter how long the change of type lasts, it always results in a proportional decrease in the OEE values.

OEE as a part of Total Productive Maintenance (TPM) concept is calculated as follows:

$$\mathrm{OEE} = a\ p\ q, \tag{1}$$

where a is the availability [%], p is the performance [%], q is the quality [%] [28].

The effects of product type change examined in this article occur within the OEE in the availability and quality. The extent of the negative impact does not depend on the number of product changes, but on the length. Product changes are in most cases the result of planned activities, while to a lesser extent they are the result of some kind of disturbance (e.g., material shortage, material quality problem, urgent sales order, etc.). The planned changeover means:

- it starts at a specific time or at short intervals;
- it takes place in a given time;
- the assembly of a given product is completed and after adjustment, the assembly of another specified product begins;
- the product change process also includes inspections and documentation for both the product and the machines or stations;
- scrap may occur as a result of the setting operation.

There are plenty of articles in the scientific literature on how to increasing OEE using different methods, however, there are only a few analyses of the impact of product changes. Haddad et al. implemented SMED at an aluminum and profile company and reached 4.86% availability increasement while OEE is boosted by 3.26%. [29]. Anusha and Umasankar worked out a framework for major factors affecting the OEE and based on these data they developed a model for OEE prediction [30]. According to Backus et al. knowledge of cycle time is essential for estimating OEE, hence they used a data mining approach to predict cycle time and WIP [31].

3 Decision tree as the applied machine learning

Illustrated through a real industry example in Section 3, the decision tree is used as a classification method within supervised machine learning.

The analyzed automotive semi-automatic assembly line assembles twelve types of seat structure products in batches of 800–1200 pieces. The planned takt time (TT) is twenty seconds, so the expected number of products in one shift (eight hours) is 1350 pieces. Hence, there are 1 or 2 type changes per shifts. From an operational point of view, product changes can be divided into two types:

- minor type change – category "A" (adjustment operations can be performed quickly, no pallet change, raw material loading is fast and less), planned duration is 7 minutes;

- major type change – category "B" (adjustment operations takes longer, palettes are changed, material loading is slower and more), planned duration is 15 minutes.

Changes for different types can be described in a matrix (Fig. 1). This matrix is a key for assembly planning, because it is possible to determine the production sequence and the raw material and semi-finished product needed more accurately in time.

3.1 Decision tree for prediction

Based on the takt time (TT) data in main focus for each product that can be queried from the Manufacturing Execution System (MES) and SQL data base systems, a decision tree can be set up to distinguish between the normal manufacturing process and the type change. With this classification, the normal assembly process and the micro stops are not separated. In the case of type changes, based on the decision tree, the two different types of changes can be distinguished, and both successful and unsuccessful changes can be distinguished on the basis of the takt time. In addition, downtime is also classifiable. The complete decision tree is shown in Fig. 2.

With the support of the decision tree and the available past time data, the time of type changes can be easily classifiable and the exact changeover time can be determined.

3.2 Prediction based on decision tree

In this article, only the OEE value associated with product changes is examined. In order to predict negative changes in the OEE value, it is necessary to take into account the effect of a one-minute loss of assembly for any reason on the OEE value of a given shift (480 minutes):

	Product type											
Product type	1	2	3	4	5	6	7	8	9	10	11	12
1		A	A	A	A	B	B	B	B	B	B	B
2	A		A	A	A	B	B	B	B	B	B	B
3	A	A		A	A	B	B	B	B	B	B	B
4	A	A	A		A	B	B	B	B	B	B	B
5	A	A	A	A		B	B	B	B	B	B	B
6	B	B	B	B	B		A	A	A	A	A	A
7	B	B	B	B	B	A		A	A	A	A	A
8	B	B	B	B	B	A	A		A	A	A	A
9	B	B	B	B	B	A	A	A		A	A	A
10	B	B	B	B	B	A	A	A	A		A	A
11	B	B	B	B	B	A	A	A	A	A		A
12	B	B	B	B	B	A	A	A	A	A	A	

"A" category: Type change - short type change (7 min)
"B" category: Type change - long type change (15 min)

Fig. 1 Type change matrix for planning

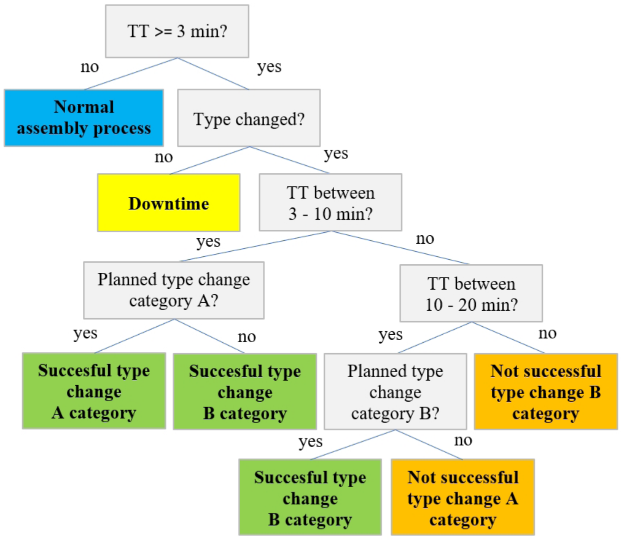

Fig. 2 Decision tree for type change

$$\Delta OEE = \frac{1}{480} = 0.2083\%. \quad (2)$$

Based on these, planning "A" type changeover per shift for the planned time (7 min) reduces the OEE value by 1.45% while a "B" type changeover (15 min) reduces the OEE value by 3.12%. In the following, based on the one-year data of the examined semi-automatic assembly line, the average type change time of the two categories was analyzed and classified according to the decision tree. With the forecasting support of Excel, the values obtained were used to predict the average type change duration for the next two months, taking into account the seasonal values. For prediction the exponential smoothing forecasting based on the AAA (additive error, additive trend and additive seasonality) of the Exponential Triple Smoothing (ETS) algorithm was used. Fig. 3. shows the predicted data and trend for minor type changes (category "A") and Fig. 4 shows the predicted data and trend for the major type changes (category "B"). In addition to the direction of the trend, the values obtained

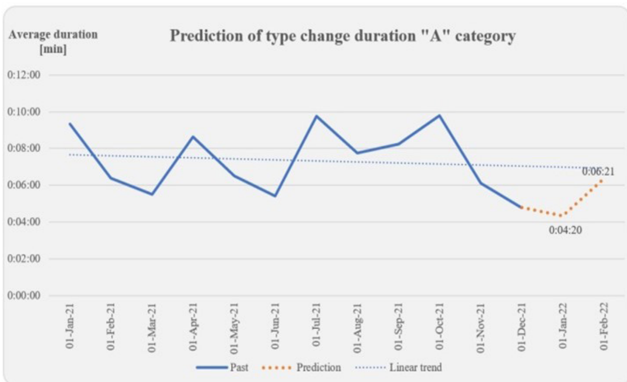

Fig. 3 Prediction of type change duration "A" category

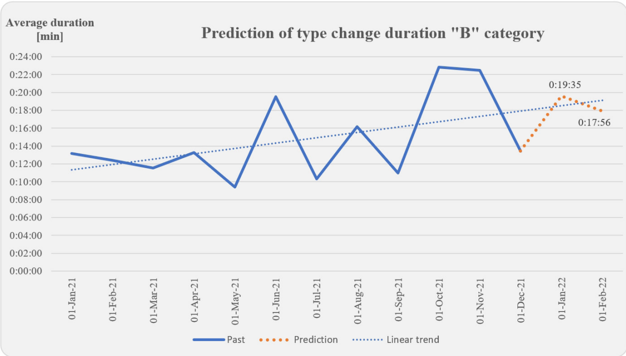

Fig. 4 Prediction of type change duration “B” category

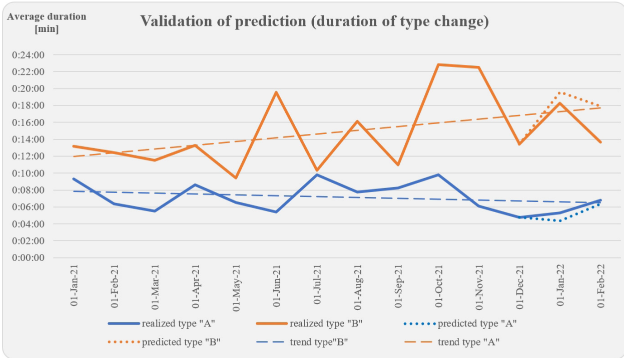

Fig. 5 Validation of predictions

were also important. The authors are aware of a number of data analysis and forecasting applications, software exists (e.g., R, Rapidminer, Matlab, Python, GMDH Shell, etc.), but the goal was to demonstrate the forecasting capabilities in a clear and understandable way, and the focus is on the method rather than the details of the algorithm used.

Based on the average values obtained, the percentage of OEE will decrease by type change according to Table 1.

After the prediction, in reality it was confirmed that the forecast was correct and the extent of the deviation was considered acceptable. The real values and trend of both minor and major type change together with the forecasted values are shown in Fig. 5.

Based on the validation results the following statements can be made:

- in both cases (minor and major type changes) the trends were based on the prediction;
- decrease in OEE value within one month with a deviation of 0.2%, within two months maximum with a deviation of 0.9% can be predicted;
- major type changes (category "B") are most difficult to predict in the longer term;
- classification of the two types of product changes based on the decision tree is correct (two categories and the planned and real time of the changeover).

Table 1 Type change effect on OEE

Type change catergory	Prediction			
	Average time of type change [min]		Effect on OEE [%]	
	Next month	Next second month	Next month	Next second month
A	04:20	06:21	−0.90	−1.32
B	19:35	17:56	−4.08	−3.74

The predicted and the validated data for the 2 months are shown in Table 2.

Based on the results, it can be concluded that the decision tree in the assembly area was constructed correctly and the forecast used was also successful. The forecast can be examined in more depth, taking into account not only the duration of the transitions but also the number of transitions. However, this will be proportionate to the data obtained previously.

4 Conclusion

Predicting future Overall Equipment Effectiveness (OEE) values of semi-automatic assembly lines is essential for resource planning and proper use. In this article, one of the methods of supervised machine learning, the decision tree, was used to classify the types of product changes and then a two-month forecast was made for them. The forecast was compared with subsequent real data and based on the results it can be concluded that it is possible to predict the impact of product type changes on OEE with an accuracy of less than 1%. Further research area could be the application of machine learning to predict OEE values for the occurrence of machine errors and material shortages.

Table 2 Comparison of prediction and validation

Type change catergory	Prediction		Validation	
	Average time of type change [min]		Effect on OEE [%]	
	Next month	Next second month	Next month	Next second month
A	04:20	06:21	−1.09	−1.41
B	19:35	17:56	−3.80	−2.84

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