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Research Article

Weight and target value-based algorithm for predicting Overall Equipment Effectiveness

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Abstract: For industrial companies, accurate short and medium-term production planning is crucial for resource allocation and maximum utilization of manufacturing capacities. If the efficiency of the production units is predicted reliably, the company can operate more economically due to predictability. Automotive companies usually monitor their efficiency and productivity using the Overall Equipment Effectiveness (OEE) as a standard Key Performance Indicator. This article presents a new approach in which the OEE value is predicted using different weights, target values and historical time data. The aim of this article is to determine the weight combination that allows for the most accurate prediction for three types of welding technologies. Firstly, a literature review demonstrates scientific relevance. Secondly, the proposed algorithm is described. In the third section, the prediction algorithm is presented through a case study. Several different weight combinations are applied and then compared using the Root Mean Square Error indicator. Last section concludes the paper. The presented algorithm can be easily and quickly applied in many cases of industrial environment.

Keywords: Overall Equipment Effectiveness; prediction; algorithm; production; welding

I. INTRODUCTION

Nowadays, the majority of manufacturing companies examine, analyse and make forecasts for future business opportunities. Within production domain, accurate short and medium-term production planning is crucial for resource allocation and maximum utilization of manufacturing capacities [1, 2]. If the efficiency of the production units is estimated reliably, the company can operate more economically due to predictability.

In industrial practice, there are many methods for measuring performance, but the most common tool is the Overall Equipment Effectiveness (OEE) indicator and additional metrics derived from it, including Overall Line Efficiency (OLE), Overall Environmental Equipment Effectiveness (OEEE), Overall Process Effectiveness (OPE) and Overall Factory Effectiveness (OFE) [3-5]. In each case, the purpose is to continuously monitor, follow-up, develop, and optimize the given production activities and processes [6-8]. In addition to constant, systematic measurement, the accuracy, simplicity and speed of the forecast play an important role.

There are many methods for predicting efficiency, but within artificial intelligence, data mining and machine learning have created additional opportunities [9-12]. Even though these methods sometimes require deep knowledge of programming and mathematics, they are still widely used, but only when solving a given type of problem [13, 14]. The Manufacturing Execution System (MES) provides the data that underpins the entire forecasting process, so this data can be considered reliable, continuous and consistent [15, 16]. In addition to technical conditions, the human factor also plays a significant role, as machine operators and setters also influence performance, availability, quality, and thus the OEE percentage [17, 18].

This article presents a new approach in which the OEE value is predicted using different weights, target values and historical time data. The aim of this article is to determine the weight combination that allows for the most accurate prediction for MAG (Metal Active Gas), Laser and Resistance welding technologies.

The paper is organized as follows. Section 2 focuses on the relevant scientific work regarding to OEE estimation. Following, section 3 presents the weight and target value-based algorithm for OEE prediction. Section 4 demonstrates through a case study how the algorithm works in industrial environment. Last section concludes the paper.

II. Literature review

There are numerous scientific researches on Overall Equipment Effectiveness prediction, most of which are based on mathematical, statistical methods and machine learning algorithms and tools.

Mjimer et al. predicted OEE with machine learning methods as Least Angle Square (LAR), Automatic Relevance Determination Regression (ARDR) and Bayesian Ridge Regression. LAR showed the most accurate result based on Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) and Mean Absolute Error (MAE) metrics [19]. At the domain of mining industry, the efficiency of core drill rigs was forecasted with Box Jenkins and Artificial Neural Networks (ANN). This combined method achieved better estimation than auto regressive moving average and non-linear auto regressive neural network approach [20]. Saylam et al. attempted to estimate the value of production line downtime and OEE percentages using Extreme Gradient Boost (XGB), Prophet, Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM). Based on MAE the LSTM model received the best ranking and was recommended [21]. In plastic industry, availability rate, performance rate, quality rate and OEE values were predicted with Decision Tree (DT), Feed Forward Neural Networks (FFNN) and Support Vector Machine (SVM). Using Root Mean Square Error (RMSE) indicator the FFNN model achieved the best score [22]. Based on research work of Anusha et al., Simple Moving Average (SMA) and Holt's double exponential smoothing method also can apply to predict OEE [23]. According to research work of Brunelli et al., Temporal Convolutional Network (TCN) and LSTM architectures were compared within the framework of Deep Learning (DL) in terms of predicting manufacturing efficiency values. Regarding to OEE, TCN achieved better results in terms of MSE [24]. Okpala et al. used Design Expert software for predicting OEE in mass production environment. The estimation was supported with descriptive statistical analysis, Pearson correlation, and one-sample t-test. An equation created takes into account availability (A), performance (B), and quality (C) with different weights [25]. Ignoring non-significant values, they presented the following formula:

$$OEE = 15.76 + 6.10A + 5.34B + 0.17C + 2.06AB - 1.67AC - 0.92BC \quad (1)$$

For a production line of six machines, Souza et al. estimated OEE values using the Grid Search algorithm of Python program. Among the MSE values obtained, the DT regression showed the lowest result (0.33%-1.1%) ahead of the K-Nearest Neighbor (2.02%-4.9%), ANN (1.02%-5.65%) and SVM (1.8%-6.0%) methods [26]. OEE percentages were estimated at a manual transmission assembly line using SVM with an accuracy of 97.1%, outperforming naive Bayes-based Machine Learning (NBML) (accuracy: 96.0%), DT (accuracy: 89.6%), and Logistic Regression (accuracy: 84.0%) [27, 28]. El Mazgualdi et al. predicted the OEE value and compared the following methods: Support Vector Regression (SVR), Cross Validation Support Vector Regression (CVSVR), Genetic Algorithm Support Vector Regression (GASVR), Random Forest (RF), Random Forest Cross Validation (RFCV), XGB, Extreme Gradient Boost Cross Validation (XGBCV) and DL. The comparison was based on MAE, MAPE and RMSE indicators. They concluded that DL and RF were the recommended methods in the automotive cable manufacturing environment [29, 30]. A summary of the mentioned algorithms for OEE prediction is shown in **Table 1**.

Table 1. *Summary of prediction algorithms*

	Prediction algorithms	References
1	Least Angle Square	[19]
2	Automatic Relevance Determination Regression	[19]
3	Bayesian Ridge Regression	[19]
4	Box Jenkins and Artificial Neural Networks	[20, 26]
5	Extreme Gradient Boost	[21, 29, 30]
6	Prophet	[21]
7	Multi-Layer Perceptron	[21]
8	Long Short-Term Memory	[21, 24]
9	Decision Tree	[22, 26]
10	Feed Forward Neural Networks	[22]
11	Support Vector Machine	[22, 26, 27, 28, 29, 30]
12	Simple Moving Average	[23]
13	Holt's double exponential smoothing	[23]
14	Temporal Convolutional Network	[24]
15	Deep Learning	[24, 29, 30]
16	Design Expert software	[25]
17	Grid Search	[26]
18	K-Nearest Neighbour	[26]
19	Naïve Bayes-based machine learning	[27, 28]
20	Logistic Regression	[27, 28]
21	Random Forest	[29, 30]

III. Algorithm for OEE prediction

In this chapter, Overall Equipment Effectiveness values for three types of welding technologies are predicted based on a new algorithm. The entire model is based on the fact that the expected values are influenced by a combination of recent data and the target value. The following main factors are behind the recent data:

- the current state and reliability level of the production equipment
- the stability of the established processes
- the knowledge, training, and practice of the operators, setters.
- the structure of orders.

The target number is primarily influenced by the following factors:

- specific, measurable, achievable, relevant, time-related (SMART)
- common effort within the company to achieve the goal (motivation, organization, etc.)
- preliminary cost calculation
- may vary by technology
- product life cycle.

The weight and target value-based prediction algorithm is shown in **Fig. 1**. A weekly summary is prepared from the OEE data measured at the shift level. Weights are assigned to the weekly data, from which a preliminary OEE forecast is made. The final OEE percentage forecast is made from the arithmetic mean of the value thus obtained and the previously determined target value. The independent variables in the algorithm are the predicted OEE values, while the dependent variables are the OEE data, weights, OEE targets.

It is advisable to run the algorithm over several cycles (weeks) so that the target value is not modified frequently according to the real situation.

IV. Case study

In this section, the weight and target value-based algorithm is demonstrated through an industrial example. The model uses real data from a European company without bias. The original data were extracted from the Manufacturing Execution System (MES). This system provides validated Overall Equipment Effectiveness values about welding areas. MES contains also predefined machine target numbers. The data came from the period between March 2021 and September 2024. During the case study, three welding technologies are examined: MAG (Metal Active Gas), Laser and Resistance welding. The OEE data used is shown in **Fig. 2**. For ease of understanding and calculation, the target values for all three technologies were 80% throughout the entire study period. During the research, a total of 80.551 OEE data were analysed. From the original dataset (83.557 lines), records where the OEE values were less than 20% (e.g.: trial runs, tests, machine modification, etc.) were excluded. Data where OEE values were greater than 100% (run time lower than planned standard time, e.g.: outperforming welding operators, etc.) were removed. The values are presented in **Table 2**.

Table 2. *Data source and filtered data*

	Count	Percentage
Total records	83 557	100.00 %
OEE < 20%	507	0.61 %
OEE > 100%	2499	2.99 %
Useable records	80 551	96.40 %
MAG welding	28 014	34.78 %
Laser welding	32 308	40.11 %
Resistance welding	20 229	25.11 %
Useable records	80 551	100.00 %

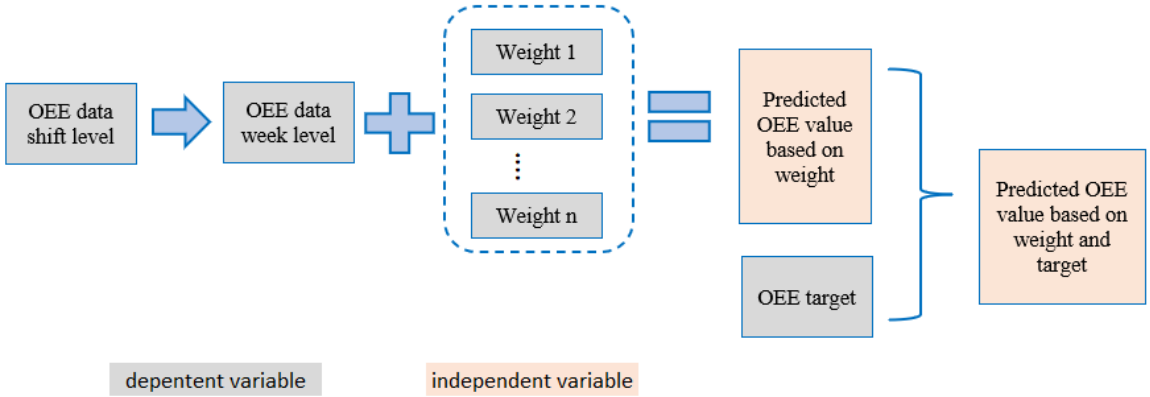

Figure 1. *Weight and target values-based prediction*

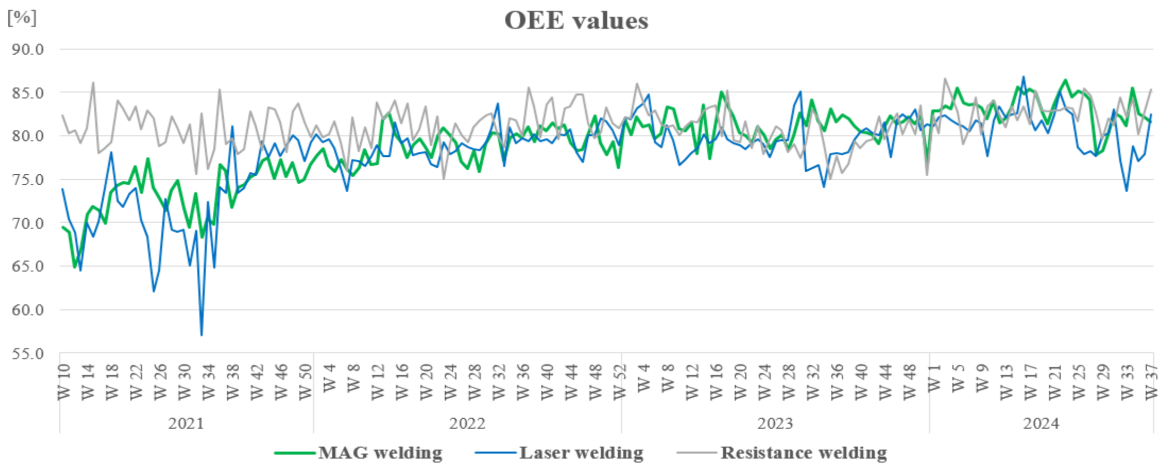

Figure 2. *Welding OEE values*

As a second step, the descriptive statistics are shown in **Table 3**. This table summarizes the most important statistical data for MAG, laser and resistance welding.

Table 3. *Descriptive statistics*

	Welding technology		
	MAG	Laser	Resistance
Mean	79.0567	78.0280	81.2575
Standard error	0.3067	0.3357	0.1723
Median	80.0598	79.1171	81.3928
Standard deviation	4.1258	4.5159	2.3177
Sample variance	17.0226	20.3937	5.3717
Kurtosis	0.5631	3.5999	-0.0131
Skewness	-0.8478	-1.6267	-0.3056
Range	21.4944	29.7211	11.6371
Minimum	64.8846	57.1023	74.9776
Maximum	86.3789	86.8235	86.6147
Count	181	181	181

Based on **Fig. 1**, three main case groups were defined when predicting OEE values. In each case, OEE data for the 10 weeks preceding the prediction date was taken into account. The cases are as follows:

- Case A: 2 weight groups, period before the forecast date from the first to the fifth week (T-1 → T-5, 60% weight ratio), and from the sixth to the tenth week (T-6 → T-10, 40% weight ratio)
- Case B: 3 weight groups, the first week before the forecast (T-1, 60% weight ratio), the period of the second and third week (T-2 → T-3, 10% weight ratio), and from the fourth to the tenth week (T-4 → T-10, 30% weight ratio)
- Case C: ten identical one-week groups (T-1, T-2, … T-10) with a 10% weight.

Two additional approaches were applied to each case:

- normal approach: simple calculation without optimization process
- solver application: support with optimization algorithm (Excel, Solver function), target value is the minimum of the RMSE value. The weight percentage is also optimized.

The results of each case were compared using the Root Mean Square Error (RMSE) indicator based on (2).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\bar{y}_i - y_i)^2}{\text{n}}} \tag{2}$$

where:

n – number of fitted points
$\bar{y}_i$ – actual value
y_i – predicted value

For the three welding technologies, the normal approach RMSE results for Case A are presented in **Table 4**, and the solver support results are shown in **Table 5**.

Table 4. *Case A – Normal approach*

	Welding technology		
Weight	MAG	Laser	Resistance
T-1→T-5	60%	60%	60%
T-6→T-10	40%	40%	40%
RMSE	0.0237	0.0317	0.0227

Table 5. *Case A – Solver support*

	Welding technology		
Weight	MAG	Laser	Resistance
T-1→T-5	63.8%	99.1%	100.0%
T-6→T-10	36.2%	0.9%	0.0%
RMSE	0.0237	0.0313	0.0226

For the three welding technologies, the normal approach RMSE results for Case B are presented in **Table 6**, and the solver support results are shown in **Table 7**.

Table 6. *Case B – Normal approach*

	Welding technology		
Weight	MAG	Laser	Resistance
T-1	60%	60%	60%
T-2; T-3	10%	10%	10%
T-4→T-10	30%	30%	30%
RMSE	0.0231	0.0305	0.0230

Table 7. *Case B – Solver support*

	Welding technology		
Weight	MAG	Laser	Resistance
T-1	63.7%	64.3%	22.9%
T-2; T-3	1.8%	27.1%	45.8%
T-4→T-10	34.5%	8.6%	31.3%
RMSE	0.0231	0.0304	0.0225

For the three welding technologies, the normal approach RMSE results for Case C are presented in **Table 8**, and the solver support results are shown in **Table 9**.

Table 8. *Case C – Normal approach*

	Welding technology		
Weight	MAG	Laser	Resistance
T-1	10%	10%	10%
T-2	10%	10%	10%
T-3	10%	10%	10%
T-4	10%	10%	10%
T-5	10%	10%	10%
T-6	10%	10%	10%
T-7	10%	10%	10%
T-8	10%	10%	10%
T-9	10%	10%	10%
T-10	10%	10%	10%
RMSE	0.0237	0.0317	0.0227

Table 9. *Case C – Solver approach*

	Welding technology		
Weight	MAG	Laser	Resistance
T-1	57.8%	51.3%	22.0%
T-2	10.0%	37.8%	26.3%
T-3	0%	0%	15.1%
T-4	0%	0%	4.7%
T-5	0%	0%	18.3%
T-6	0%	0%	0%
T-7	2.6%	10.9%	0%
T-8	16.5%	0%	0%
T-9	8.8%	0%	13.7%
T-10	4.4%	0%	0%
RMSE	0.0229	0.0300	0.0224

Based on the calculations, the best prediction result, according to the RMSE indicator, was shown by the solver-supported forecast with the weighting ratio optimized for the 10-week period. The summary results are shown in **Table 10**.

Table 10. *Summary of RMSE values*

	Welding technology		
Case	MAG	Laser	Resistance
A – Normal approach	0.0237	0.0317	0.0227
A – Solver support	0.0237	0.0313	0.0226
B – Normal approach	0.0231	0.0305	0.0230
B – Solver support	0.0231	0.0304	0.0225
C – Normal approach	0.0237	0.0317	0.0227
C – Solver support	0.0229	0.0300	0.0224

In the article so far, the weighted values for MAG, Laser and resistance welding have been analysed separately. In order to achieve a possible universal approach, the best values (Case C – Solver approach) have been arithmetically averaged in the following. Due to the similar results, this can be considered uniform. The optimized average weighting ratios for MAG, Laser and resistance welding are shown in **Fig. 3**.

It can be stated that it is more practical to take the value of the weights for the period immediately before the prediction higher in order to make the forecast more accurate. For the three welding technologies, the recommended weight for the T-1 period is 43.7% and for the T-2 period it is 24.7%.

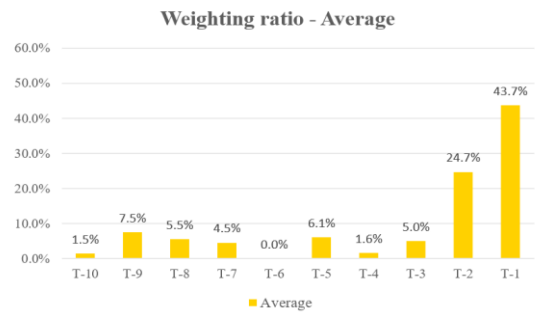

Figure 3. *Solver supported weighting ratio*

V. Conclusion

In this article discussed the prediction a key metric, Overall Equipment Effectiveness (OEE). The forecast was based on an algorithm that takes into account designated machines target values and weighted data from the period before the estimation. The weight and target value-based algorithm is demonstrated through an industrial example. In the manufacturing with MAG, Laser and resistance welding technologies, several different weight combinations are applied and compared using the Root Mean Square Error indicator. During the prediction, normal and solver supported approaches were used. The best forecasting results were shown by the solver-supported algorithm. The conclusion of the research is that in the case of welding technologies, when dividing the period preceding the forecast into 10 equal parts, it is advisable to consider the data of the first two weeks with greater weight. It could be a further research goal to examine other weighs and targets combination.

The author can make the real data included in the article available for further scientific research.

AUTHOR CONTRIBUTIONS

P. Dobra: Conceptualization, Experiments, Theoretical analysis, Writing, Review and editing.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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