The Predictability of Planned Downtimes, with Linear Regression and the Impact on Overall Equipment Effectiveness

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Abstract: *Nowadays, most industrial companies try to maximize the use of any available resources. Therefore, within the automotive industry, the primary goal is to increase the efficiency of assembly lines and production machines, and to approach and achieve theoretical capacity. There is a need for the efficiency of production units to be monitored and the values of key metrics to be predicted. In this article, based on real data, the impact of planned downtime on Overall Equipment Effectiveness (OEE) is presented across several manufacturing areas. The aim of this paper is to predict planned downtime and OEE, using linear regression by exponential smoothing with additive error, additive trend and a non-additive seasonality (ETS AAN) approach. First, a literature review demonstrates any scientific relevance. Second, a detailed data analysis is performed and descriptive statistics are presented. In the third section, the planned downtime and OEE values are predicted through a given area. The presented method can be easily and quickly adapted and applied to many areas of industrial practice.*

Keywords: OEE; planned downtime; prediction, linear regression; descriptive statistics

1 Introduction

In today's turbulent industrial environment, most industrial companies are trying to maximize the use of all available resources, especially machines, tools and human resources, in order to achieve higher profits. Therefore, within the automotive industry, the primary goal is to increase the efficiency of assembly lines and production machines and to approach and achieve theoretical capacity.

Efficiency can be measured in many ways, but Overall Equipment Effectiveness (OEE) is used most widely in electronics, automotive industry, mechanical engineering, food industry, pharmaceutical industry, textile industry and plastic industry [1-4].

Since 1992, OEE has been standardized in the manufacturing industry by Semiconductor Equipment and Materials International (SEMI) [5][6]. This standard is currently used by many automotive assembly plants, partially adapted to their own business environment. In industrial practice, the indicator is usually measured at the shift level, but monitoring is done on a daily, weekly and monthly basis. With systematic use, production processes can be improved, performance can be increased, and losses, including machine downtime and quality defects, can be reduced [7-9].

In addition to measurement, it is particularly important to predict efficiency, which can be done according to the following most used scientific methods:

- **Use statistical analysis**: Apply statistical methods to reveal patterns and correlations in the data. Tools as regression analysis can support predict future performance based on historical trends [10-12].
- **Predictive analytics**: Apply predictive maintenance models to identify potential downtime and maintenance needs, which can impact availability [13, 14].
- **Simulation models**: Use simulation techniques to model different scenarios and their impact on OEE and/or OEE components. This way helps to understand potential improvements [15, 16].
- **Machine learning**: Apply machine learning algorithms to predict OEE based on real-time data inputs, adapting to changes in equipment or assembly lines performance [17-19].
- **Combined approaches with Artificial Intelligence**: Combining the mentioned methods can result the best prediction OEE values [20-22].

No matter how OEE forecasting is approached, the goal is always to achieve the highest accuracy in the shortest time.

This article primarily focuses on the impact of planned downtime on the OEE values at the domain of production. The aim of this paper is to predict planned downtime and OEE using linear regression by exponential smoothing with additive error, additive trend and non-additive seasonality (ETS AAN) approach.

The paper is organized as follows. Section 2 focuses on the relevant scientific work regarding to predictability of planned downtimes with linear regression. Following, section 3 presents the data analysis and results. Section 4 discusses the planned downtime and OEE prediction. Finally, Section 5, concludes the paper.

2 Literature review

In this paper the planned downtimes and Overall Equipment Effectiveness (OEE) values estimation were made using simple linear regression. Linear regression line equation is written in the following form:

$$y = a + b\,x \tag{1}$$

Where:
- y: dependent variable that lies along Y-axis
- a: Y-intercept
- b: slope or regression line
- x: independent variable that lies along X-axis

This type of machine learning regression as a mathematical approach used to perform predictive analysis and find association between two variables [23, 24].

Widespread interpretation of OEE based on Nakajima's Total Productive Concept (TPM):

$$OEE = A \times P \times Q \; [\%] \tag{2}$$

Where:
- A: Availability
- P: Performance
- Q: Quality [25]

Planned downtime appears within availability alongside planned production time and unplanned downtime. The performance component refers to the ratio of actual amount of production and planned amount of production, while quality refers to the distribution of good and not good pieces [26].

In industrial practice, there are many linear regressions in the field of efficiency prediction including simple linear regression, multiple linear regression, logistic regression, polynomial regression, support vector regression [27]. Within machine learning methods, support vector machine (SVM) offers further opportunities for choosing linear settings, such as using kernel function. The kernel function modifies the training set by transforming nonlinear equations into linear equations in multiple dimensions [28].

Brunelle et al based on historical production performance data attempt to predict OEE percentages with deep learning methods in industrial packaging environment [29]. Jimenez-Cortadi et al used linear regression model based on real data for predict remaining useful life at CNC machining area. This approach can be applicable to other processes in production [30]. Souza et al analyzed and predicted OEE in manufacturing industries using machine learning methods. It was concluded that the Decision Tree Regression approach was the most effective of the methods tested. During the analysis Mean Squared Error (MSE) indicator was used [31]. Szaller et al attempt to predict lead time, a key performance indicator similar to

OEE, using linear regression in a dynamic production environment. Two types of settings were used for linear regression: static (training only first seven days) and adaptive (daily re-training). It was found that the operation of the models stabilized later than expected and that the decision tree approach could be applied more effectively [32]. In the field of automotive cable manufacturing, after data selection, pre-filtering and transformation, El Mazgualdi et al. predicted the OEE value applying machine learning algorithms using several input variables (e.g., number of changeovers, downtime, number of production orders, etc.). They concluded that in the case of linear regression models, the application of Support Vector Regression had better accuracy than Multiple Linear Regression, Polynomial Regression and Decision Tree Regression [33]. Saylam et al predicted planned and unplanned downtime with the support of machine learning methods. Long Short-Term Memory (LSTM) model achieved the best prediction results compared to Multi-Layer Perceptron (MLP), Xgboost and Prophet. The methods were compared using Mean Absolute Error (MAE) [34]. Lindegren et al modeled several manufacturing processes using discrete event simulation. The impact of planned and unplanned downtime on OEE was examined by considering the number and duration of occurrences. The analysis showed that if the number of defects is reduced by 5%, the OEE value increases by 0.34%, while in the case of a 10% reduction, it increases by 0.69% [35].

3 Data analysis and results

Production data from a Central European automotive supplier were used during the research and analysis. The original real data were extracted from the Manufacturing Execution System (MES). This system provides reliable OEE and downtime information. The data came from the period between March 2021 and September 2024 and are scaled with no factors.

During data analysis and prediction, commonly applied steps were used such as: exploring the data, cleaning the data, data visualization, building forecasting model, training the model, predicting with the model, evaluation the performance of the model. In this paper, the individual steps are not described separately, only the key elements necessary to understand the results.

During the research, a total of 152.130 OEE data and the corresponding planned downtime were examined.

From the original database (158.451 lines), records where the OEE values were less than 20% (e.g.: trial production, tests, etc.) were excluded. Data where OEE values were greater than 100% (run time lower than planned standard time, e.g.: excellent operators with high work speed, extra human resource, etc.) were removed. Records where the planned downtime was more than 1 hour during 8-hour shifts were also excluded. The values are presented in Table 1.

Table 1
Data processing

	Count	Percentage
Total records	158451	100.00%
OEE < 20%	956	0.60%
OEE > 100%	5044	3.19%
Planned downtime > 01:00:00	321	0.20%
Usable records	152130	96.01%

Downtimes can be divided into two parts for planning aspect:

- **Planned downtime**: during production planning systematically allocate time for no production. Main categories are the followings: shift change, cleaning, break, training, preventive maintenance.
- **Unplanned downtime**: that period when production line or machine are unexpectedly out of service due to an issue, failure, or malfunction. Includes, among others, equipment failures, power outages, system problems, human errors, supply chain issues.

Based on the analysis of the records, planned downtimes can be separated into four main groups according to their duration:

A: No planned downtime (continuous production is ensured, during legal breaks apply plus operators for uninterrupted operations)

B: Short planned downtime (e.g., short legal breaks)

C: Medium planned downtime

D: Long planned downtime

Analyzing the entire data set, the four groups (A – D) are shown in Figure 1. The horizontal axis shows the duration of downtime, the vertical axis shows the number of cases. In addition, the 100% OEE value (horizontal dashed line) and the OEE value as a function of the planned downtime (orange line) are also displayed. It can be seen that each minute spent on non-production results in a 0.208% OEE reduction based on (3) over an 8-hour shift.

$$\Delta 1\% = \frac{100\%}{480\ min} = 0.208\frac{\%}{min} \tag{3}$$

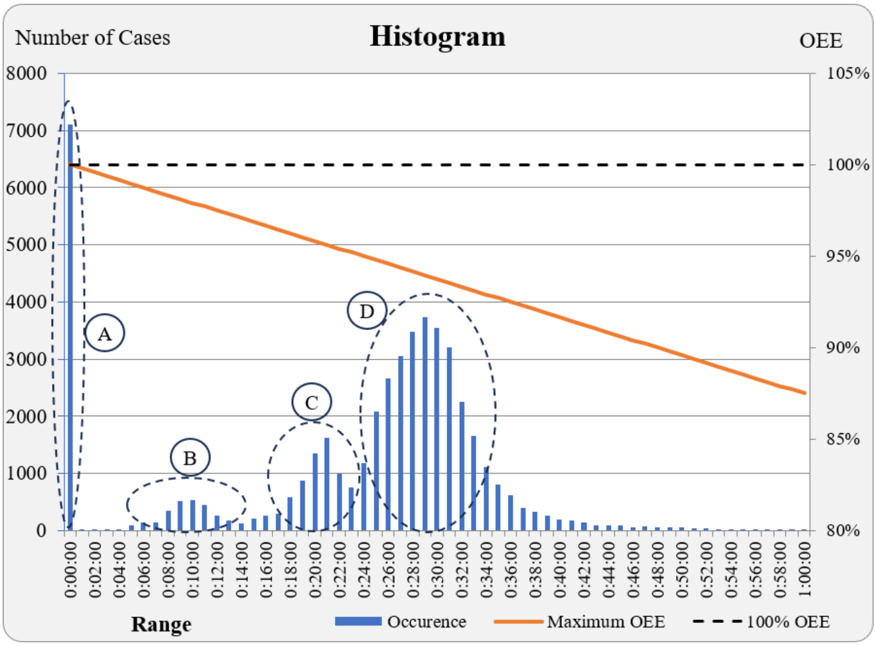

Figure 1
Planned downtime and OEE

Table 2 presents some of the main types of planned downtime depending on which group it can be classified into.

Table 2
General occurrence

	A	*B*	*C*	*D*
shift change		✓		
short legal break (10 min)		✓		
long legal break (20 min)			✓	
training		✓		
meeting		✓		
preventive maintenance		✓		
combined or mixed				✓

Based on the available dataset, the descriptive statistics for the planned downtimes for five selected technologies (assembly, laser welding, MAG welding, resistance welding and riveting) are shown in Table 3. The Total column shows the values for the entire dataset. Time values are displayed in [hh:mm:ss] format.

Table 3
Descriptive statistics of planned downtimes

	Types of production technology					
	Assembly	***Laser welding***	***MAG welding***	***Resistance welding***	***Riveting***	***Total***
Number of machines	36	21	19	17	19	122
Mean	00:22:43	00:22:51	00:23:33	00:20:39	00:22:52	00:22:39
Standard error	00:00:03	00:00:04	00:00:04	00:00:05	00:00:05	00:00:02
Median	00:26:31	00:25:29	00:27:55	00:24:51	00:27:22	00:26:29
Mode	00:00:00	00:00:00	00:00:00	00:00:00	00:00:00	00:00:00
Standard deviation	00:11:36	00:10:35	00:12:04	00:12:40	00:12:19	00:11:46
Range	00:59:59	00:59:58	00:59:52	00:59:37	00:59:52	00:59:59
Minimum	00:00:00	00:00:00	00:00:00	00:00:00	00:00:00	00:00:00
Maximum	00:59:59	00:59:58	00:59:52	00:59:37	00:59:52	00:59:59
Count	48 729	32 259	27 932	20 189	23 030	152 130

For the same technologies, the descriptive statistical characteristics for OEE are presented in percentage format in Table 4.

Table 4
Descriptive statistics of OEE

	Types of production technology					
	Assembly	***Laser welding***	***MAG welding***	***Resistance welding***	***Riveting***	***Total***
Number of machines	36	21	19	17	19	122
Mean	80.52%	78.59%	79.56%	81.77%	82.45%	80.39%
Standard error	0.05%	0.07%	0,07%	0.08%	0.08%	0.03%
Median	82.44%	80.90%	81.79%	83.72%	85.02%	82.62%
Mode	82.50%	93.75%	83.33%	83.33%	83.39%	83.33%
Standard deviation	11.17%	12.08%	11.81%	10.70%	11.48%	11.55%
Range	79.99%	79.83%	79.87%	79.71%	79.88%	79.99%
Minimum	20.00%	20.16%	20.11%	20.28%	20.12%	20.00%
Maximum	99.99%	99.99%	99.98%	99.99%	99.99%	99.99%
Count	48729	32259	27932	20189	23030	152130

Looking at the entire database, the downtimes are distributed as shown in Figure 2. First is the planned downtime (average: 22:39 min/machine/shift; 51.9%) followed by technical issues (6:43; 15.3%), process settings (6:22; 14.6%), changeovers (3:49; 8.7%), others (2:26; 5.6%), logistics issues (1:10; 2.7%) and quality problems (0:32; 1.2%).

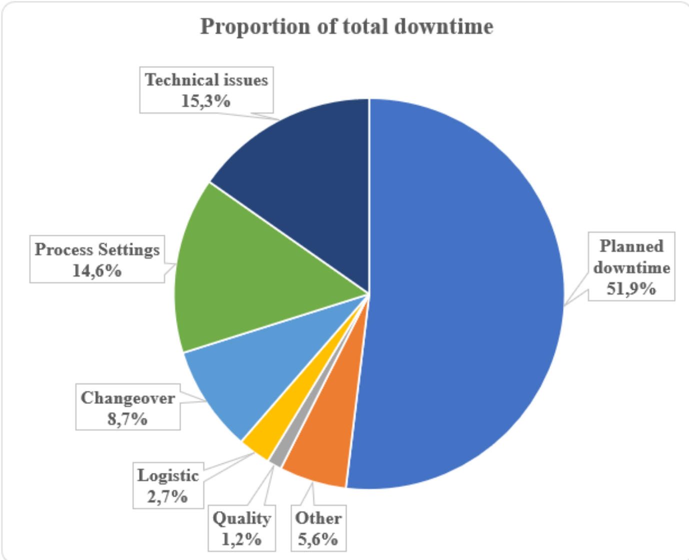

Figure 2
Proportion of total downtime

Based on Figure 3, the OEE value is directly influenced by the total downtime. The total downtime largely depends on the planned downtime; therefore, it is important to examine first.

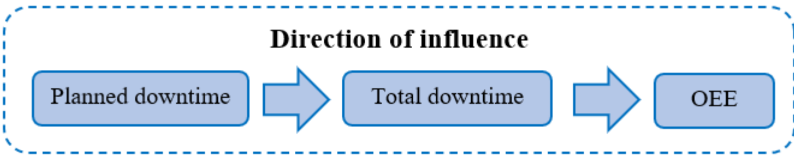

Figure 3
Influence direction

In most cases, the OEE value depends on other factors, this article only examines the effects of planned downtime.

4 Planned downtime and OEE prediction

This section is about predicting the value of planned downtime. If the value of planned downtime can be predicted, then the value of OEE can also be partially predicted. In the case when planned downtime dominates among the downtimes in a given production area, then the accuracy of the forecast will be higher. The forecasting research was conducted based on the framework shown in Figure 4.

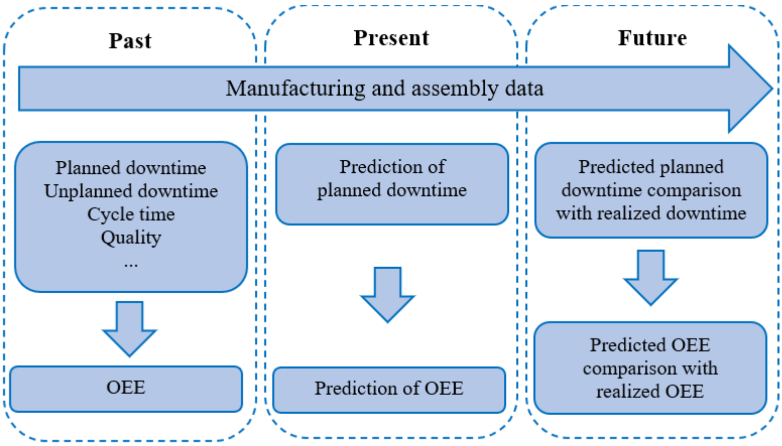

Figure 4
Prediction framework

During manufacturing and assembly processes, data (past, present, future) are continuously generated, which includes planned downtime values and OEE percentages. As shown in Figure 3, the predicted planned downtime influences the predicted OEE value. The predicted planned downtime and OEE values can be compared with the actual planned downtime and OEE values, based on which the prediction accuracy can be calculated and evaluated.

The planned downtimes and OEE values prediction were made using linear regression by exponential smoothing with additive error, additive trend and non-additive seasonality (ETS AAN) approach. There are no seasonal effects in the stochastic data, and a simple linear trend has been determined in the forecast. The ETS ANN was calculated in Excel to make it more widely available due to reproducibility. The results obtained for the prediction of planned downtime at assembly area are shown in Figure 5. The related predicted OEE values are presented in Figure 6.

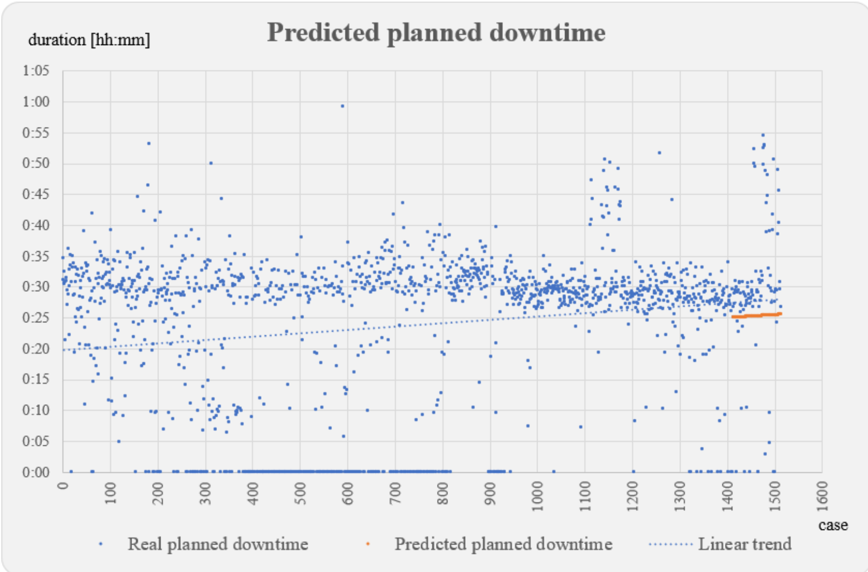

Figure 5
Predicted planned downtime

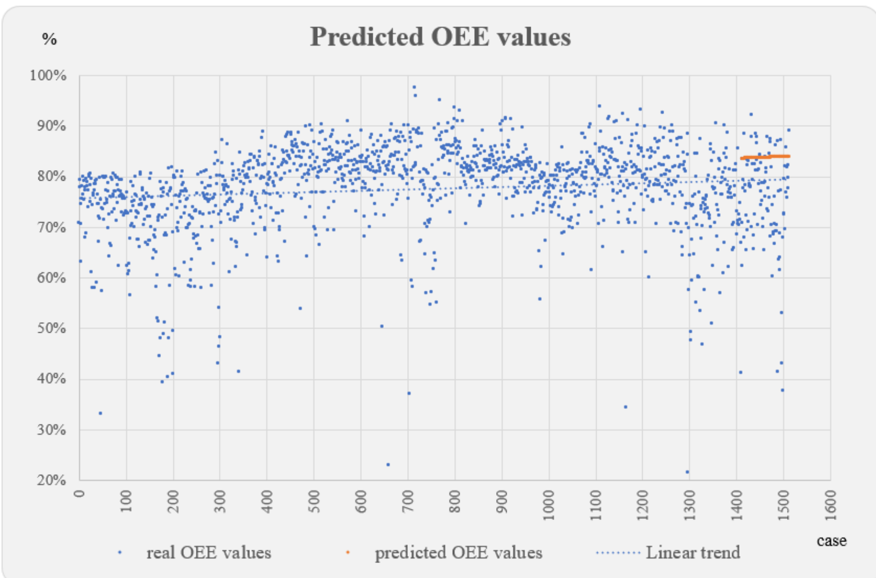

Figure 6
Predicted OEE values

In each case, 100 future values were predicted based on the available data (1413 input records). The comparison of predicted values and actual values can be done in several ways, including using Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), etc. indicators. For ease of understanding, the extent of the deviations is presented in a bar chart (Figure 7). Based on these, in 52 cases the planned downtime was predicted within 5 minutes, and in 13 cases planned downtime was predicted, despite this, no downtime actually occurred.

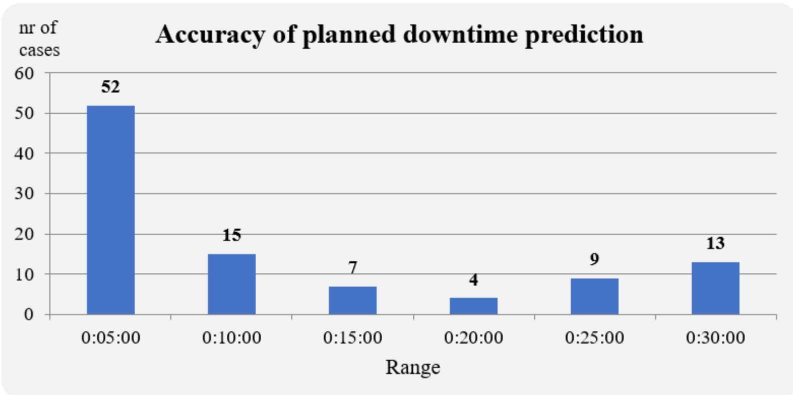

Figure 7
Accuracy of planned downtime prediction

Compared to the simple linear trend, the linear regression ETS AAN predicted a lower planned downtime, which resulted in a higher OEE value. By fine-tuning the settings, the accuracy can be increased, or a smaller sample of historical data can be considered. In addition, OEE values depend on other factors, so the use of more complex regressions is recommended for this production environment. In general, linear regression can be used to predict planned downtime and thus OEE values, but extreme values (e.g., zero actual downtime) reduce the accuracy of the predictions.

5 Conclusions

In this work, the impact of planned downtime on Overall Equipment Effectiveness (OEE) in industrial manufacturing and assembly, is analyzed. The various types of planned downtime were identified, and it was determined that each minute over an 8-hour period (1 production shift) reduces the OEE value by 0.208%. Based on real data, the planned downtime value and the OEE value were predicted using linear regression.

During the research, the predicted values and linear trend were achieved by exponential smoothing with additive error, additive trend and non-additive seasonality (ETS AAN) approach. Compared to the simple linear trend, the linear regression ETS AAN predicted a lower planned downtime, which resulted in a higher OEE value. Linear regression can be used to predict planned downtime and thus OEE values, but extreme values (e.g., zero actual downtime) reduce the accuracy of the predictions.

In further research, the impact of unplanned downtime (unexpected technical failure, material shortage, etc.) on OEE can also be examined. It could be a research goal to examine the impact and prediction on OEE using other regression methods and machine learning tools.

The author can make the real data, included in this work, available for further scientific research.

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