Research Article

Predictive Analytics for Production Line Downtime: A Comprehensive Study Using Advanced Machine Learning Models

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(First received September 14, 2023 and in final form December 25, 2023)

Reference: Saylam, A., Atlı, H. Predictive Analytics for Production Line Downtime: A Comprehensive Study Using Advanced Machine Learning Models. The European Journal of Research and Development, 3(4), 88-94.

Abstract

This study delves into predictive analysis, employing advanced machine learning models to predict downtime in production lines. The research follows a detailed methodology, starting by exploring production lines and their conditions. The focal point is Overall Equipment Effectiveness (OEE), which includes availability, performance, and quality, with a special focus on downtime impacts. Through an OEE tracking system, downtime is categorized into planned and unplanned, offering insights into critical components affecting production line availability. The datasets cover three years, including runtime, unplanned downtime due to equipment failures, and idle times, emphasizing instances prone to frequent equipment failures.

Examining relationships through a heatmap reveals essential correlations crucial for accurate predictions. We outline the feature selection process and fundamental data preprocessing steps to maintain dataset integrity. Introducing machine learning models such as Xgboost, Prophet, Multi-Layer Perceptron (MLP), and Long Short-Term Memory (LSTM), each model is carefully configured with past window parameters and forecast horizons. To prevent overfitting, the study employs K-fold cross-validation and early stopping mechanisms, ensuring robust model performance.

Two datasets, comprising runtime, equipment-induced downtime, and idle time, are utilized for analysis. Data preprocessing involves a heatmap for characteristic-target correlation and basic steps like mean-based *null value imputation. Results, presented in terms of Mean Absolute Error (MAE), underscore the superior performance of LSTM. The discussion interprets these findings, confirming the potential of LSTM for downtime prediction, supported by visualizations comparing actual and predicted downtimes. Future directions include comprehensive model comparisons, expanding metrics, and increasing datasets, building on the solid foundations established by this study.*

Keywords: *Machine Learning, Lean Manufacturing, OEE, Predictive Maintenance, Downtime Prediction*

1. Introduction

In today's fast-paced industry, streamlining production processes is crucial for efficiency and minimizing disruptions. Our research explores predictive analytics, using advanced machine learning models to predict downtime in production lines. We first explain our methodology, starting with an exploration of the production lines and their status. The OEE metric incorporates Availability, Performance, and Quality, with a keen emphasis on the impact of downtime. The OEE tracker system used to categorize downtimes into planned and unplanned, providing details on the critical components influencing production line availability. The datasets used cover the runtime, unplanned downtime due to equipment failures, and idle time of production lines over a three-year period. With a focus on lines with the most frequent equipment failures, the datasets form the backbone of our predictive modeling.

Exploring the relationships between runtime, downtime, and idle time through a heatmap, we reveal valuable correlations essential for accurate forecasting. Additionally, we outline the feature selection process and basic data preprocessing steps, ensuring the integrity and quality of our dataset. We then introduce the machine learning models employed for downtime forecasting. From Xgboost and Prophet to Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM), each model is precisely configured, utilizing past window, and forecast horizon parameters. Incorporating K-fold cross-validation and early stopping mechanisms, we secure the model against overfitting, ensuring robust model performance.

In the last section, we evaluate the performance of each model in predicting downtime through Mean Absolute Error (MAE). Finally, we explore the promising outcomes of the LSTM model, opening the way for in-depth discussions and future directions in predictive analytics for downtimes.

2. Materials and Methods

In this section, we explain the machine learning models and the data that we used to forecast the downtime of the production lines.

2.1. Production lines and their status

In this work, we utilize the Overall Equipment Effectiveness (OEE) [1] tracker system which is used to collect the production data from the shop floor and provide some useful information such as performance, the quality, and the status of the production lines [2]. As known in the literature, OEE is a metric that identifies the percentage of planned production time, and it is the multiplication of availability, performance, and quality of the production lines. Availability, which is the ratio of run time to the total production time, is one of the main components in OEE calculation. So, downtime on the production line plays an important role. The OEE tracker system provides two distinct downtimes which are planned and unplanned downtimes. In this work, we consider the status of the lines (run, down or idle) and the status' durations. Unplanned downtimes can occur due to equipment failures, labor constraints, etc. and they directly decrease the availability of the production lines. As a result, we can gather the status of a line and its duration thanks to the OEE tracker system.

2.2. Dataset

Throughout this work, we have utilized two distinct datasets each of which consist of the runtime, unplanned downtime caused by equipment failure and idle time of a single line as a time series whose timestamp is a day. Note that, we select the lines that have the most frequently failed equipment. Both datasets include almost 1000 samples which correspond to records of three years.

2.3. Data preprocessing and feature selection

In our dataset, we have three features (runtime, downtime, and idle time) so that we utilize a heatmap to observe the relation between features and the target variable which is downtime in this case. As shown in Fig.1, there is a negative correlation between idle time and downtime and there is positive correlation between downtime and runtime. After feature selection, we apply a basic process on the collected data such as filling the null values by the mean of the corresponding feature.

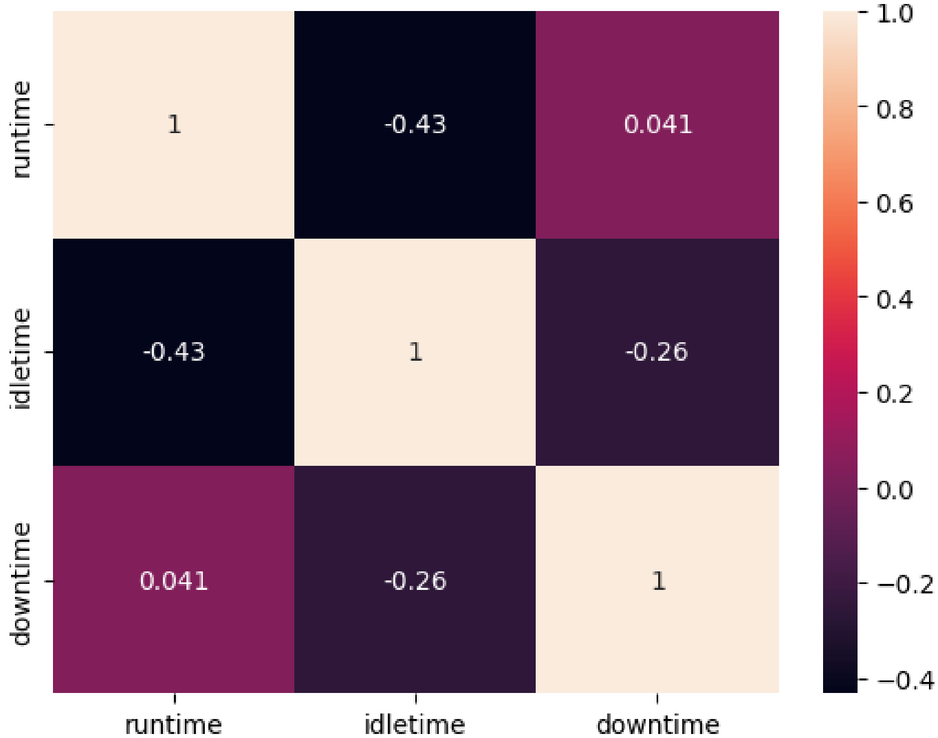

Figure 1: Heatmap of the Features

2.4. ML and DL models

In this work, we have used 4 distinct machine learning models which are Xgboost [2], Prophet [3], Multi-Layer Perceptron (MLP) [4] and Long Short-Term Memory (LSTM) [5] to forecast the downtime of the lines. We have set the past window to 5 days and the forecast horizon as 1 day for each model. We apply K-fold cross validation and early stopping in the training stage of the models to prevent the overfitting. In the K-fold, we split the data into the 10 folds. In Table 1, we show the architecture of each model.

Table 1: Models' Parameters

Model	Parameters
Prophet	Default parameters [3]
Xgboost	Number of estimators: 20
MLP	Number of layers: 5 Neurons in layers in vector notation: [7,16,8,4,1] Activation function: Relu Optimizer: Adam Epoch: 100
LSTM	Number of layers: 1 LSTM layer, 4 fully connected layers Neurons in layers in vector notation: [50,32,16,4,1] Activation function: Relu Optimizer: Adam Epoch: 100

3. Results

In this section, we will present and compare the performance of the models with respect to Mean Absolute Error (MAE) which represents the difference between the actual downtimes of the lines and the predicted downtimes of the line. In Table 2, we show the MAE score of each model. As shown in Table 2, LSTM model outperforms the other models with respect to the MAE score.

Table 2: Performance of the Models

Model	Mean Absolute Error (Hour)
Prophet	2.11
Xgboost	2.15
MLP	1.55
LSTM	1.17

Fig. 2 shows the actual downtimes and the predicted downtimes by the LSTM model. In this figure, the y-axis represents the downtimes with respect to hours and the x-axis represents the number of samples. We see that predicted results are so close to the actual ones in Fig. 2. So, we claim that the LSTM model is so promising for the downtime prediction in production lines.

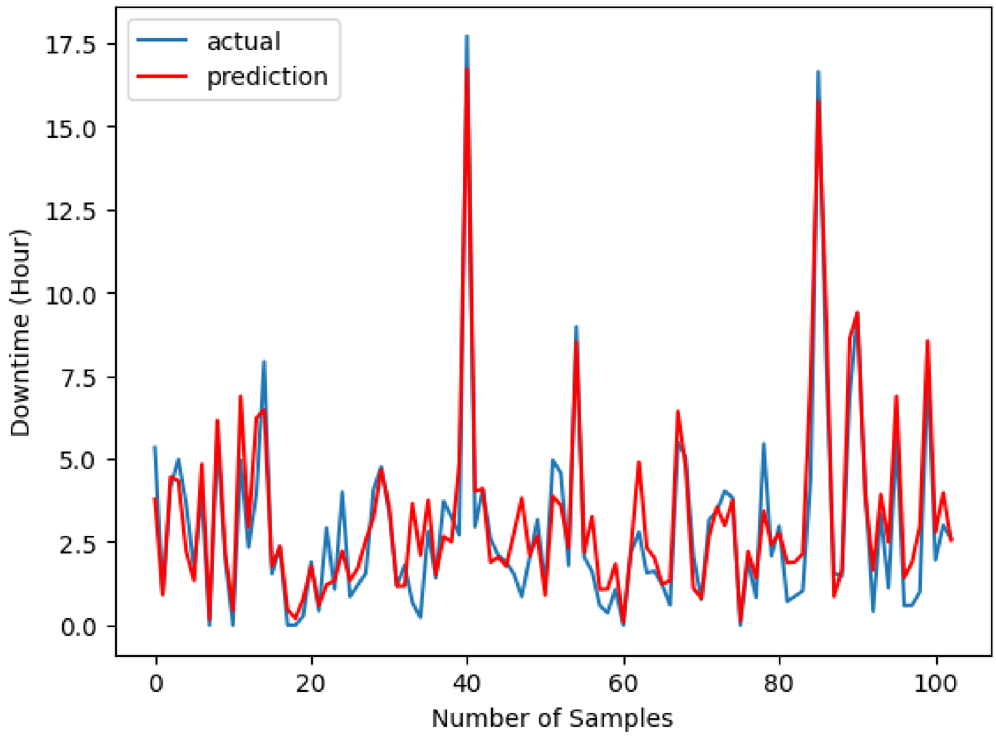

Figure 2: Actual downtimes vs predicted downtimes by LSTM model

The results show that the LSTM model significantly outperforms the other models that we used in this work and provides promising results for downtime predictions. In our future work, we will compare the LSTM model against the other Machine Learning models. In addition, we will extend our dataset which is currently two and each of which has 1000 samples. We will use the different performance metrics such as Mean Square Error (MSE) to compare the performance of the models.

4. Discussion and Conclusion

The presented methodology, based on the Overall Equipment Effectiveness (OEE) metrics and a robust dataset spanning three years, successfully explores the relationships between runtime, downtime, and idle time. The evaluation of model performance, measured through Mean Absolute Error (MAE), highlights the exceptional capabilities of the LSTM model. With a remarkably low MAE score of 1.17, the LSTM model outperforms its counterparts, providing more reliable downtime predictions in production lines. Our study lays the foundation for future endeavors, promising in-depth comparisons with other machine learning models and an expansion of the dataset.

5. Acknowledge

We express our gratitude to our colleagues at Supply Chain Wizard, who contributed to the completion of this research on predictive analytics for production line downtime. Their support and collaboration have been instrumental in advancing our understanding of efficient manufacturing processes and the application of machine learning in industrial settings.

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