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Smart Maintenance with IoT and Artificial Intelligence: A Case Study on Slat Conveyors in the Automotive Industry

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Abstract

The concept of mechanization in industry has evolved over time, gaining new capabilities with the advancement of modern technologies. Maintenance activities associated with mechanization have also become a frequently studied topic, driven by these technological developments. To align with contemporary requirements and industrial technologies, equipment maintenance practices are being modernized, moving away from traditional methods. Artificial intelligence technologies are replacing conventional maintenance approaches, enabling more efficient, reliable, predictive, and cost-effective solutions. Among these advancements, predictive maintenance activities, which are rapidly growing both in theory and practice, stand out as a key area of focus. This study was conducted in an automotive factory housing numerous machines and equipment. Specifically, the slat conveyors in the assembly unit of the factory were examined. The aim was to detect and predict failures in the slat conveyors using historical current data collected through IoT sensors. Within this scope, the EWMA (Exponentially Weighted Moving Average) method, a statistical control technique, was employed to identify data points with potential failure risks. Subsequently, the Isolation Forest method was used to assign anomaly scores to these data points. Due to the absence of pre-labeled failure data, potential failure-indicating data points were labeled based on the analysis. By evaluating the scores of the labeled data, high-risk failure points and their estimated occurrence times were identified. As a result of this study, improvements were made to the existing maintenance plans, enabling the creation of more accurate maintenance schedules. Additionally, a reduction in equipment maintenance activities and enhanced predictability of potential failures were achieved.

Keywords
Maintenance Planning, Fault Diagnosis, Exponentially Weighted Moving Average (EWMA), Isolation Forest

1. Introduction

The concept of mechanization in industry, which dates to the Industrial Revolution, has enabled faster and more reliable production of goods. The systems and equipment used in mechanization represent one of the most significant investment expenses for businesses. Among the equipment used in industrial systems are conveyor systems.
Conveyors, utilized in most industrial facilities, are mechanical systems designed to transport materials from one location to another. They are particularly useful in scenarios requiring the movement of heavy or bulky materials. From a mechanical perspective, the movement of the transported object is facilitated by one or more chains to which slats, rollers, or belts are attached. This system is powered by either a motor or gravitational energy.

Conveyor systems vary depending on the products manufactured or the specific needs of industries. Therefore, it is inevitable to encounter a wide range of conveyor types across different industries. Among these diverse conveyors, chain conveyors, roller conveyors, slat conveyors, gravity conveyors, belt conveyors, and overhead conveyors are widely used in various industries such as mining, automotive, agriculture, computing, processing, food, electronics, aerospace, and more, each serving distinct purposes and applications.

The slat conveyors discussed in this study consist of one or more endless chains to which horizontal slats are attached to facilitate the movement of transported objects. In other words, slat conveyors are a type of conveyor system that operates by transporting products on pallets connected between chains (Figure 1). They are commonly used in vehicle assembly lines.

Figure 1. Conveyor at the facility where the work was carried out

Another critical issue that has come to the forefront of businesses with mechanization is the maintenance of equipment. This is because equipment tends to wear out or lose its original performance over time, depending on usage conditions, characteristics, and duration. Equipment that has worn out or underperforms can lead to delays in planned operations and significant costs for businesses. Additionally, in the absence of proper maintenance planning, substantial production losses may occur. Maintenance is defined as all activities carried out to prevent potential future failures in a system's machinery and equipment, ensuring that they operate efficiently and without breakdowns throughout their lifespan (Swanson, L., 2001). On the other hand, the maintenance activities represent between 15% and 60% of the total operating costs of production (Haarman et al., 2017). To avoid these adverse outcomes, the most important step for businesses is to select and implement the most appropriate methods using maintenance technologies.

In the literature, various maintenance strategies exist, such as periodic maintenance, preventive maintenance, condition-based maintenance, and predictive maintenance (Figure 2). With the advancement and widespread adoption of Industry 4.0 technologies, applications related to "Big Data" and the "Internet of Things" (IoT) have gained momentum in businesses. This has enabled the collection and detailed analysis of historical and real-time data from equipment. These technological advancements have significantly influenced maintenance activities, increasing the focus on predictive maintenance strategies among maintenance approaches.

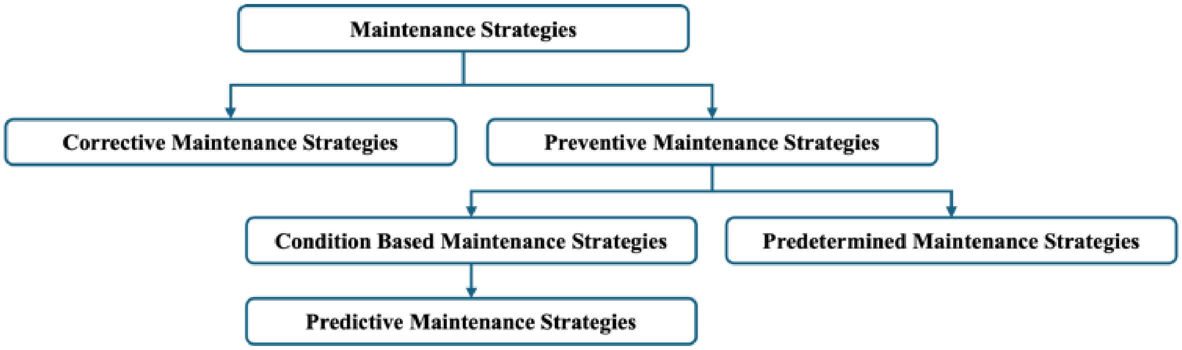

Figure 2. Overview of maintenance strategies (Source: Own drawing in Schenk, 2013)

As a popular and modern maintenance policy, predictive maintenance aims to perform necessary tasks to optimize the lifespan of machines and processes based on the condition of equipment parameters, without increasing the risk of failure (Garcia et al., 2006). The goal of predictive maintenance is to perform maintenance just in time before equipment failures occur. To achieve this, it is necessary to collect real-time data from equipment through sensors and analyze the historical trends of this data. In this way, maintenance activities can be updated in real time. This ensures that machines requiring maintenance are not unnecessarily stopped, avoiding production and cost losses.

1.1 Objectives
Within the scope of this study, the aim is to conduct predictive maintenance by developing a system and methodology that can provide early warnings for failures in slat conveyors, which are widely used in automotive factories.

The remainder of the study is organized as follows: The introduction section outlines the general framework of the study. The second section, the literature review, discusses the research on the methods used in the study. The third section, the methodology, explains the EWMA and Isolation Forest algorithms employed in the study. The fourth section, the application, describes a real-world application of the methods and prediction algorithms discussed in the third section. Finally, the fifth and concluding section evaluates the results of the study, highlights its original contributions, and provides suggestions for future research.

2. Literature Review
In businesses, especially in manufacturing plants, almost every type of machinery and equipment can experience expected or unexpected failures, regardless of usage conditions. Therefore, it is necessary to plan maintenance to address such failures and even predict them in advance to take preventive measures. This approach, known as predictive maintenance, has gained importance in multidisciplinary research groups by proposing the creation and integration of research lines related to data collection, infrastructure, storage, distribution, security, and intelligence (Zonta et al., 2020).

Today, predictive maintenance is addressed within the framework of three main methods: reliability-based, physics-based, and data-driven (Carvalho et al., 2019). Reliability-based predictive maintenance relies on using statistical methods and historical failure data to predict failures and maintenance needs (Hu et al., 2022). Physics-based predictive maintenance involves establishing mathematical models using physical laws to represent equipment mechanisms and performance degradation (C. Kong, 2014). Data-driven predictive maintenance, on the other hand, uses large-scale production data to create mathematical models for the evolution of equipment failures (Çınar et al., 2020). The literature includes numerous studies that address approaches incorporating one, two, or all three of these methods.

Chen et al. (2021), in this context, developed a data-driven predictive maintenance strategy using NASA aero data to make applicable maintenance decisions. Liu et al. (2021) proposed a prediction and data-driven maintenance method using deep adversarial learning to improve the accuracy of predicted errors. Su and Huang (2018) developed HDPass, a real-time predictive maintenance system based on Apache Spark, to detect potential hard disk drive (HDD) failures in data centers. Shamayleh et al. (2020) used IoT technology and machine learning tools to predict and classify failure conditions in medical equipment, achieving significant detection and maintenance cost savings of up to 25%. Geng and Wang (2022), in their study on a power grid in China, proposed a failure prediction-based maintenance scheduling method for large-scale power equipment, demonstrating the superiority of their planning method.

In addition to such studies, many statistical methods are used in planning maintenance activities. In studies where maintenance planning is treated as a process, statistical process control methods are commonly employed. Among these, statistical process control charts are prominent, developed to monitor variables within a process and detect out-of-control conditions (Noorossana and Vaghefi, 2006: 191). The choice of control chart depends on the characteristics and monitoring requirements of the process. One widely used chart type today is the Shewhart control chart (Russo et al., 2012: 36). These charts are useful for measuring process precision and identifying the causes of problems in industrial processes (Topalidou and Psarakis, 2009: 773). A Shewhart chart is a time-ordered graphical display of observations with a centerline and upper and lower control limits set at a specific distance from the centerline (Vries and Conlin, 2005: 320). While Shewhart control charts are effective for assessing overall process control and detecting special causes, they are often insufficient for equipment maintenance, which requires more specific management.

As an alternative to Shewhart control charts, Roberts (1959) developed EWMA (Exponentially Weighted Moving Average) control charts. EWMA control charts are a good alternative to Shewhart charts for detecting small shifts in processes. In some cases, EWMA can also be used to predict the next observation (Ege, 2000). EWMA control charts are frequently used in time series analysis and forecasting, in addition to process control. EWMA can be thought of as a weighted average of all past and current observations (Yılmaz, 2012). The decision within the EWMA control technique depends on the EWMA statistic, which assigns decreasing weights to older observations (Testik, 1999). Numerous studies in the literature have explored this approach. For example, Schmid and Schöne (1997) extended the classical EWMA control scheme for autocorrelated processes. Young and Winistorfer (2001), in their study at an MDF plant, found that Shewhart control charts were insufficient, and that positive autocorrelation produced false alarms in continuous systems. They compared Shewhart and EWMA control charts and concluded that EWMA charts provided more accurate alarms.

Given the issues of false alarms and misdirection in the literature, machine learning methods that detect anomalies using statistical techniques are also employed. One such method, the Isolation Forest, was developed by Liu et al. (2012). Zhong et al. (2019) applied the Isolation Forest method in their study to monitor the health of gas turbines, particularly for timely detection of abnormal behavior, ensuring operational safety, and preventing costly unplanned maintenance. They demonstrated that the method could achieve high accuracy in anomaly detection with unlabeled data and small datasets. Chen et al. (2020) applied the Isolation Forest method to wind turbine data to detect anomaly samples, identify critical features related to performance degradation, and improve product reliability. Nagavi et al. (2024) proposed the Isolation Forest method for solving anomaly detection and predictive maintenance problems in industrial machinery, achieving 88.07% accuracy in predicting the remaining useful life of a machine.

3. Methods

In this section, the EWMA, isolation forest algorithm methods and solution methodology used in the study are discussed.

3.1. EWMA (Exponential Weighted Moving Average)

Real-time data obtained through IoT sensors and ThingWorx IoT software will primarily be labeled as faulty data. While providing this, the EWMA (Exponentional Weighted Moving Average) method, which is one of the statistical quality control methods, was used since only the current data was examined in the data set.

The EWMA method is used to determine the statistical status of the process, such as Shewhart control charts. These charts are more effective in variable processes and can respond faster to changes in normal processes.
Features:

- It considers the changes in the process average by looking at the changes in the slope of the chart.
- It can be thought of as a weighted average of all past and current observations.
- Since the current data in the project shows a decrease or increase compared to previous values, it also considers the effect of previous data.
- It is calculated by giving the highest weight to the newest data. The moving average is calculated exponentially.

$$z_i = \lambda x_i + (1 - \lambda)_{z_{i-1}}$$

According to this expression, $0 < \lambda \leq 1$is a fixed value and the equation $z_0 = \mu_0$ can be used for the initial value of λ.

EWMA Parameters:
λ: exponential smoothing parameter

- If it is high, the effect of the sample is low.
- If $\lambda = 1$, the EWMA value will depend only on the last observation value. In other words, the previous data will have no effect.
- If we want to consider small deviations, small λ values are used.
- If we want to consider large deviations, large λ values are used.
- If large and small deviations are desired at the same rate, the value $\lambda = 0.05$ is used.
- Generally, values between $0.05 < \lambda \leq 0.25$ are used.
- The values 0.05, 0.10 and 0.20 are the most used values.

L is the parameter that determines the lower and upper limits and is determined depending on λ (Table 1).

Table 1. EWMA Parameter values (Source: (Montgomery, 2005:412)

λ	0.05	0.1	0.2	0.25	0.3	0.4
L	2.615	2.814	2.962	2.998	3.023	3.054

3.2. Isolation Forest

It applies an Isolation Forest model to an input dataset to predict anomalies or outliers.
The method has two outputs.

- One of them is the prediction, which includes the normalized anomaly score. The higher the score, the higher the probability of anomaly.
- The other output includes the average length of the estimated decision tree paths of each observation.
    - The shorter the paths, the higher the probability of an anomaly.

According to the method, anomaly scores take values between 0-1. Values less than 0.5 are normal values. Values close to 1 indicate data with potential failure.

3.3. Solution Methodology

Predictive maintenance to predict the failure status in slat conveyors is generally considered as the application of feature engineering after the application of the abnormal situation detection method and finally the application of risk scoring steps related to the data to be obtained. In more detail, a methodology based on machine learning covering six steps is proposed. The steps of the solution methodology are presented in Figure 3.

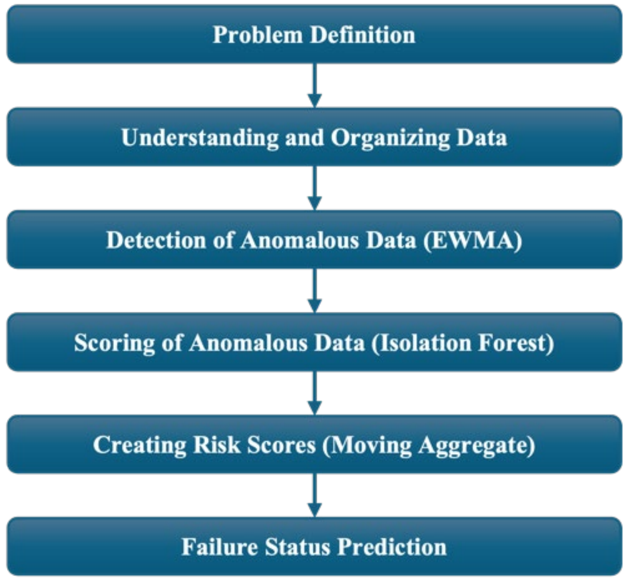

Figure 3. Proposed solution methodology

4. Solution Methodology

Step 1: Defining the Problem

The study was conducted to predict motor failures in slat conveyors located in the assembly unit of one of Turkey's leading automotive companies. It is aimed to develop an ML model over current values to detect assembly line slat conveyor motor failure in advance and to plan the necessary maintenance (Figure 4). The method and process features used to detect motor failures in the current situation are as follows.

- Current data can be monitored instantly via the Thingworx IoT software used in the company where the study was conducted.
- To smooth the oscillation-fluctuation in the current data, alarms are created according to certain threshold values by taking the moving average of the current value after non-production periods (for values where the speed is below zero) in line with a certain time period (for example, the last 30 data).
- An alarm is generated when the moving average of the current exceeds a certain value.
- This fault detection and prediction method remains reactive for the situation where the anomaly is really intended. In addition, since the current value changes according to speed, false alarms can also be generated.

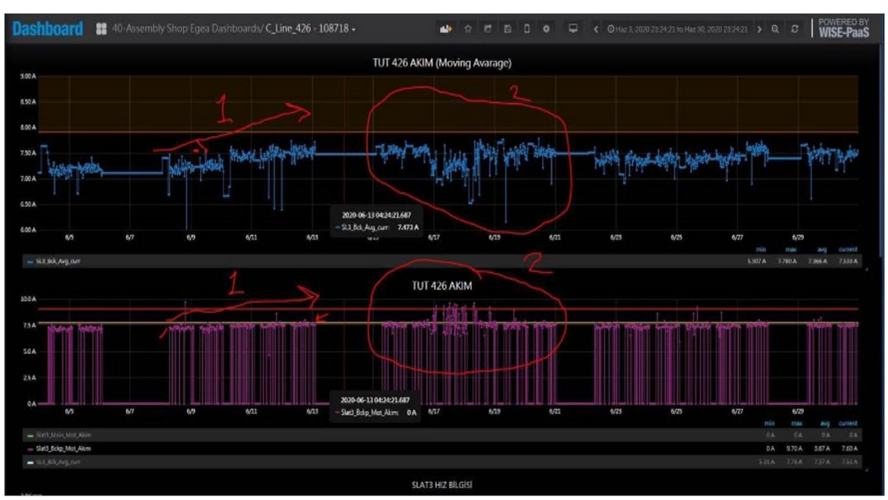

Figure 4. Status current data and method used

Step 2: Understanding and Organizing Data

The conveyors in question operate under constant load. The company's technical team has provided information that the vibration parameter is insignificant in equipment failure. Data has been collected in the Thingworx IoT environment since May 27, 2023, with a data frequency of 1 in 3 seconds. The graph of the data kept is shown in the figure below (Figure 5).

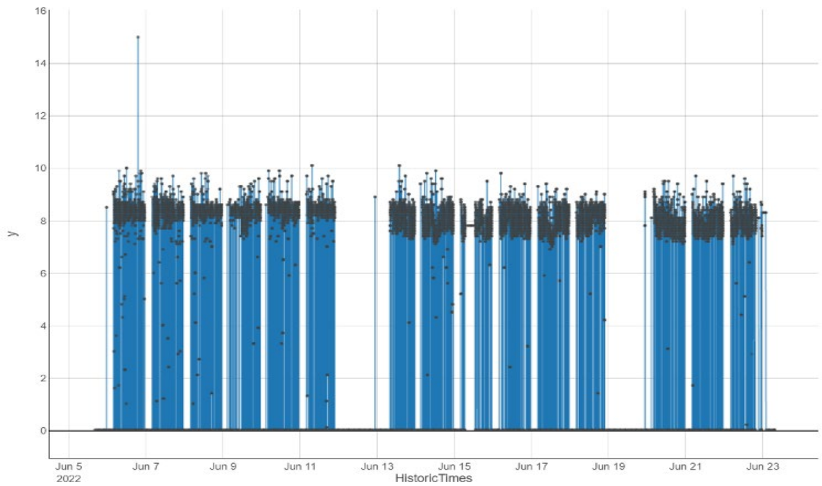

Figure 5. Data pattern

Within the scope of the study, the data was obtained by integrating Knime ML and Thingworx IoT software. The integration allows working with a maximum of 500,000 data. Based on this, the number of data used within the scope of the study is 500,000. The situations where the current value in the data set shown in Figure 5 is 0 indicate that there is no production, that is, the conveyor is not working. In the data editing phase, first, the “0” values were removed from the 500,000-row data set and the situations where the conveyor was only working (production was present) were evaluated. When the 0 values were removed from the data set, the resulting data set contained 280,378 data. Then, outliers were removed from the data set so that the extreme values do not mislead the models to be applied. Finally, the final data set was obtained (Figure 6).

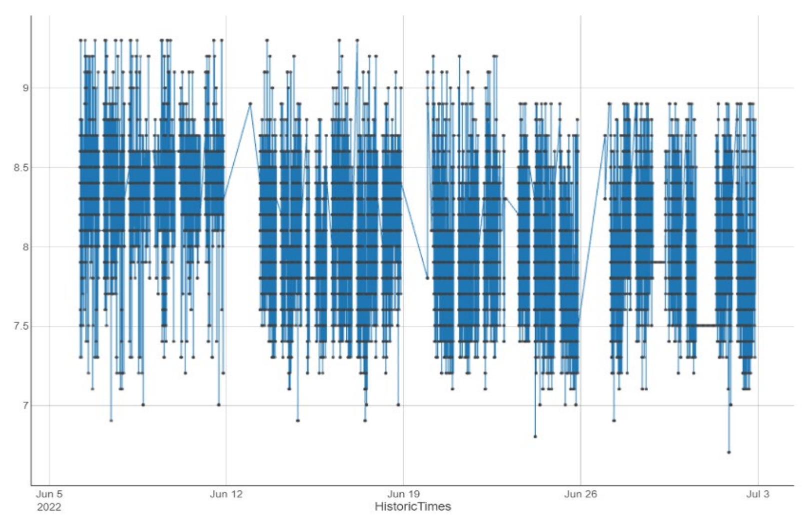

Figure 6. Final data set design to be used in the study

Step 3: Detection of Abnormal Data

To better understand and analyze the current situation, in addition to the detection of abnormal data in the current situation, lower and upper control limits were added after the moving average of the data was taken (Figure 7).

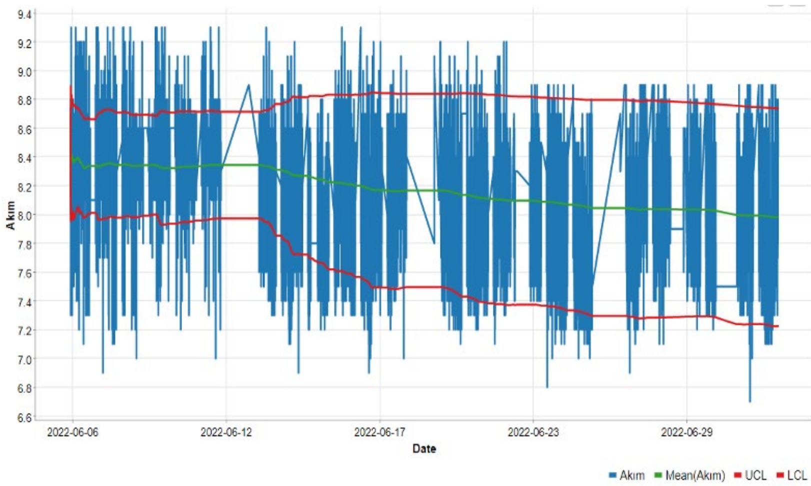

Figure 7. Moving average pattern of data

However, the data outside the limits are still not sufficient for the detection of all abnormal data. Because the moving average method does not consider small changes and only considers the past 30 data when taking moving averages. In the current data used in the study, there is autocorrelation in the data. In other words, the data are interdependent. Each data obtained instantly is affected by past data. Therefore, it was considered to further detail this method and the work was continued with the EWMA method, and the abnormal data were labeled (Figure 8). Here, the parameters for the EWMA method were taken as λ=0.2 and L=2.86. Roberts (1959), Crowder (1987) and Lucas Saccucci (1987) showed that in the detection of shifts at the mean level, large λ values provide optimal results in the detection of large-scale shifts and small λ values provide optimal results in the detection of small shifts at the process level (Oktay, 1994: 123).

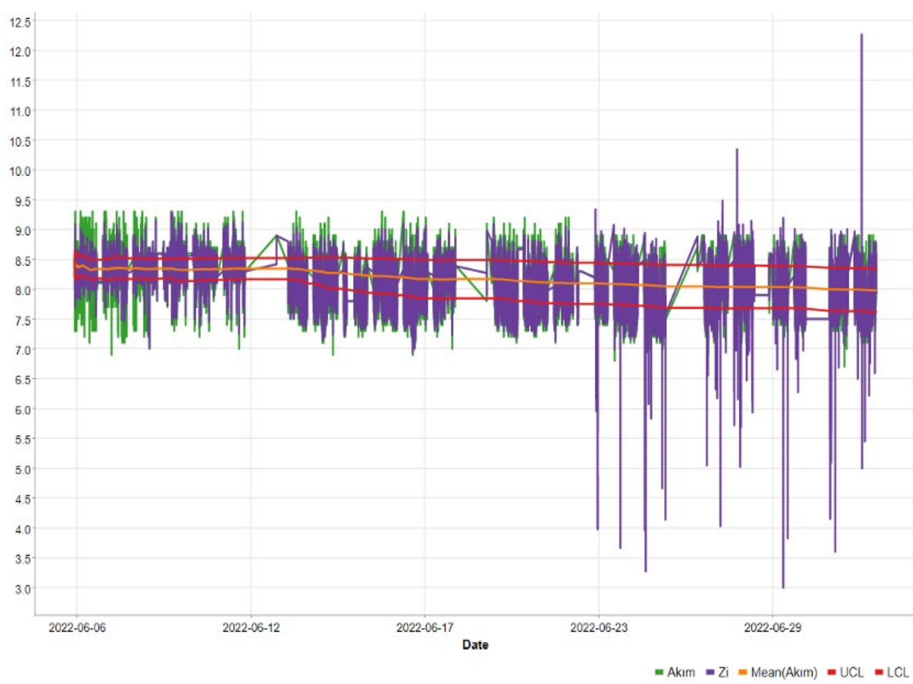

Figure 8. Detection of anomalous data with EWMA method

After the calculations were made, the data falling outside the lower and upper control limits of the EWMA method were labeled as abnormal data in the data set (Figure 9). The data falling between the EWMA lower and upper control limits were labeled as normal data in the data set (Figure 10).

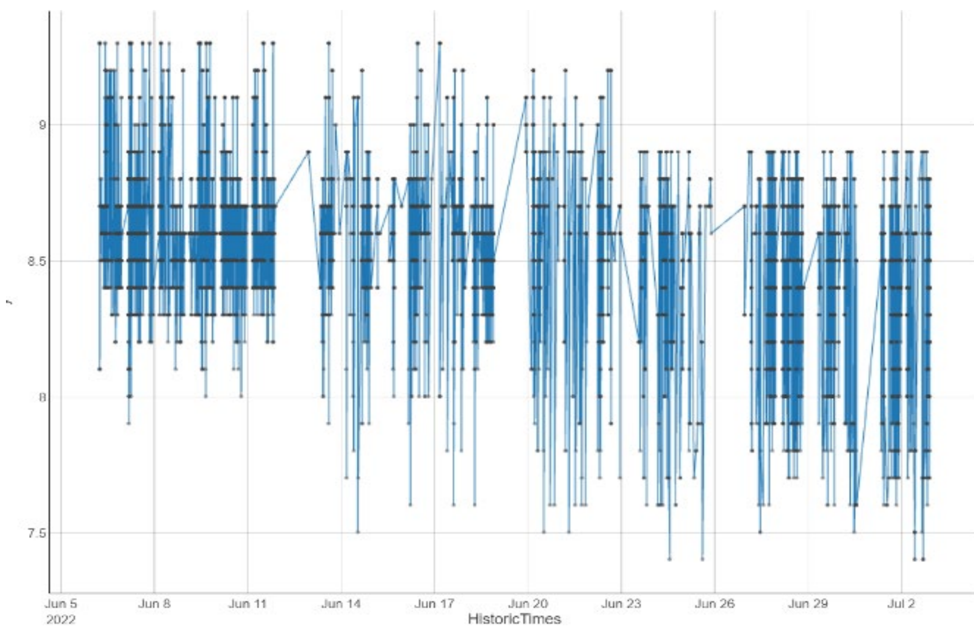

Figure 9. Anomalous data in the dataset

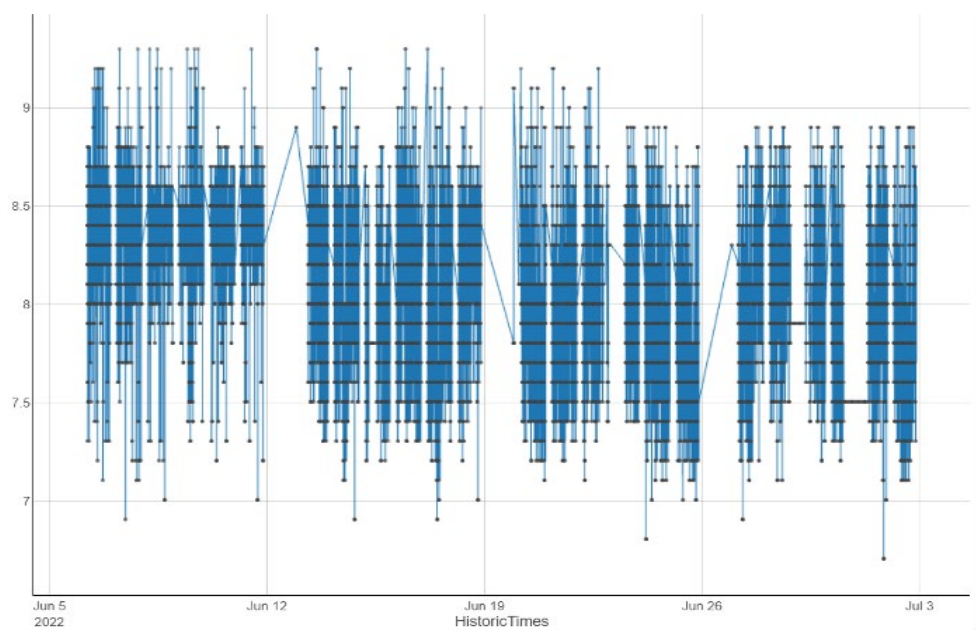

Figure 10. Normal data in the dataset

Afterwards, the mean and standard deviations of the data labeled as abnormal and normal were calculated and their normal distributions were examined (Figures 11-12).

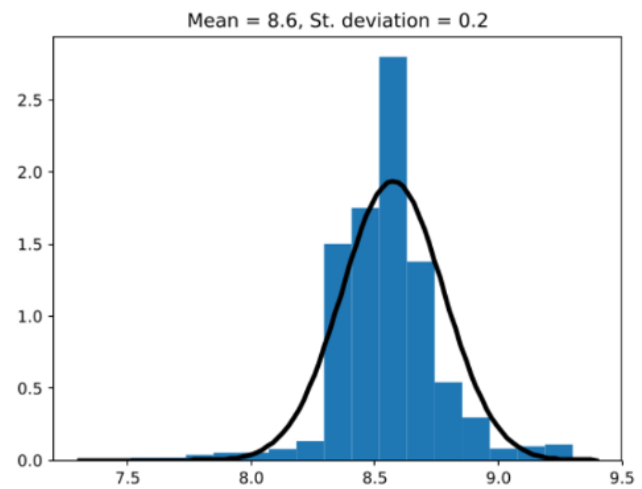

Figure 11. Distribution of anomalous data.

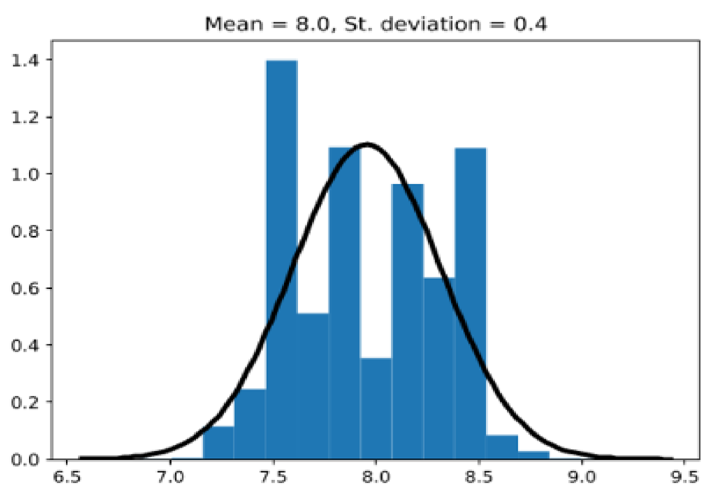

Figure 12. Normal distribution of data

In normal distribution graphs, it was observed that the statistical properties of the data labeled as normal and abnormal were similar. The criticism that the labeled abnormal data did not create a real fault condition and created a misconception was evaluated. As a solution to this criticism, it was considered to score the labeled abnormal data and obtain abnormal data that could create a real fault according to these scores.

Step 4: Scoring Abnormal Data

The data labeled as abnormal with the EWMA method was scored using the "isolation forest" method, one of the machine learning methods, to obtain abnormal data that has a high potential for failure. According to the isolation forest method, abnormal data scores are between 0 and 1 (Figure 13). Values less than 0.5 indicate normal data, while values closer to 1 indicate data with a high potential for failure.

Based on this information, the entire data set labeled as abnormal was scored using the isolation forest method.

Table "default" - Rows: 12718 | Spec - Columns: 5 | Properties | Flow Variables

Row ID	HistoricTimes	D Akım	S Anomaly	D Anomali Score
Row0	2022-06-06T05:24:18....	9.3	1	0.922
Row1	2022-06-06T05:24:21....	9.3	1	0.922
Row2	2022-06-06T05:24:24....	9.3	1	0.922
Row3	2022-06-06T05:24:27....	9.3	1	0.922
Row4	2022-06-06T05:24:30....	9.3	1	0.922
Row5	2022-06-06T05:24:33....	9.3	1	0.922
Row6	2022-06-06T05:24:36....	8.1	1	0.039
Row7	2022-06-06T05:24:39....	8.1	1	0.039
Row8	2022-06-06T05:24:42....	8.1	1	0.039
Row9	2022-06-06T05:24:45....	8.8	1	0.627
Row10	2022-06-06T05:24:48....	8.7	1	0.445
Row11	2022-06-06T05:24:51....	8.7	1	0.445
Row12	2022-06-06T05:24:54....	8.7	1	0.445
Row13	2022-06-06T05:24:57....	8.7	1	0.445
Row14	2022-06-06T05:25:00....	8.5	1	0.239
Row15	2022-06-06T05:25:03....	8.7	1	0.445
Row16	2022-06-06T05:25:06....	8.7	1	0.445
Row17	2022-06-06T05:25:09....	8.7	1	0.445
Row18	2022-06-06T05:25:12....	8.7	1	0.445
Row19	2022-06-06T05:25:15....	8.7	1	0.445
Row20	2022-06-06T05:25:36....	8.7	1	0.445
Row21	2022-06-06T05:25:39....	8.5	1	0.239
Row22	2022-06-06T05:25:42....	8.5	1	0.239
Row23	2022-06-06T05:25:45....	8.7	1	0.445
Row24	2022-06-06T05:25:48....	8.7	1	0.445
Row25	2022-06-06T05:25:51....	8.7	1	0.445
Row26	2022-06-06T05:25:54....	8.5	1	0.239
Row27	2022-06-06T05:25:57....	8.8	1	0.627
Row28	2022-06-06T05:26:00....	8.6	1	0.337
Row29	2022-06-06T05:26:03....	8.6	1	0.337
Row30	2022-06-06T05:26:06....	8.6	1	0.337
Row31	2022-06-06T05:26:09....	8.6	1	0.337
Row32	2022-06-06T05:26:12....	8.6	1	0.337
Row33	2022-06-06T05:26:15....	8.6	1	0.337

Figure 13. Scoring abnormal data with the isolation forest method

Step 5: Creating Risk Scores
The aim of this step is to observe abnormal data in certain periods and create a risk score. For this purpose, a risk score of the data was created using the moving average method with a determined number of historical data (Figure 14). To predict abnormal situations in the short term, the number of historical data was taken as 21. The parameter used when calculating moving averages is the anomaly scores calculated with the isolation forest method.

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Row ID	HistoricTimes	D Akım	S Anomaly	D Anomali Score	D Mean(A...
Row11686	2022-06-06T17:31:18....	8.7	1	0.445	0.522
Row11687	2022-06-06T17:31:21....	8.7	1	0.445	0.511
Row11688	2022-06-06T17:31:24....	9.1	1	0.815	0.518
Row11689	2022-06-06T17:31:27....	9.1	1	0.815	0.524
Row11690	2022-06-06T17:31:30....	9.1	1	0.815	0.531
Row11691	2022-06-06T17:31:33....	9.1	1	0.815	0.537
Row11692	2022-06-06T17:31:36....	9.1	1	0.815	0.544
Row11693	2022-06-06T17:31:39....	9.1	1	0.815	0.551
Row11694	2022-06-06T17:31:42....	9.1	1	0.815	0.568
Row11695	2022-06-06T17:31:45....	9.1	1	0.815	0.586
Row11696	2022-06-06T17:31:48....	9.1	1	0.815	0.603
Row11697	2022-06-06T17:31:51....	9.1	1	0.815	0.621
Row11698	2022-06-06T17:31:54....	9.1	1	0.815	0.639
Row11699	2022-06-06T17:31:57....	9.1	1	0.815	0.656
Row11700	2022-06-06T17:32:00....	9.1	1	0.815	0.674
Row11701	2022-06-06T17:32:03....	9.1	1	0.815	0.692
Row11702	2022-06-06T17:32:06....	9.1	1	0.815	0.709
Row11703	2022-06-06T17:32:09....	9.1	1	0.815	0.727
Row11704	2022-06-06T17:32:12....	8.7	1	0.445	0.727
Row11705	2022-06-06T17:32:15....	8.7	1	0.445	0.727
Row11706	2022-06-06T17:32:18....	8.7	1	0.445	0.727

Figure 14. Creating a risk score

Step 6: Fault Status Prediction
In the last step of the methodology, fault estimation was made by determining threshold values for the risk scores calculated in the fifth step. Here, the threshold value was determined as 0.6. Data were interpreted as warning status

for current data corresponding to values greater than this value, and current data corresponding to values smaller than this value were interpreted as non-abnormal current values (Figure 15).

Row ID	HistoricTimes	Akım	Anomaly	Anomali Score	Mean(A...	Anomaly Durumu
Row11686	2022-06-06T17:31:18....	8.7	1	0.445	0.522	Sıkıntı yok
Row11687	2022-06-06T17:31:21....	8.7	1	0.445	0.511	Sıkıntı yok
Row11688	2022-06-06T17:31:24....	9.1	1	0.815	0.518	Sıkıntı yok
Row11689	2022-06-06T17:31:27....	9.1	1	0.815	0.524	Sıkıntı yok
Row11690	2022-06-06T17:31:30....	9.1	1	0.815	0.531	Sıkıntı yok
Row11691	2022-06-06T17:31:33....	9.1	1	0.815	0.537	Sıkıntı yok
Row11692	2022-06-06T17:31:36....	9.1	1	0.815	0.544	Sıkıntı yok
Row11693	2022-06-06T17:31:39....	9.1	1	0.815	0.551	Sıkıntı yok
Row11694	2022-06-06T17:31:42....	9.1	1	0.815	0.568	Sıkıntı yok
Row11695	2022-06-06T17:31:45....	9.1	1	0.815	0.586	Sıkıntı yok
Row11696	2022-06-06T17:31:48....	9.1	1	0.815	0.603	Uyarı
Row11697	2022-06-06T17:31:51....	9.1	1	0.815	0.621	Uyarı
Row11698	2022-06-06T17:31:54....	9.1	1	0.815	0.639	Uyarı
Row11699	2022-06-06T17:31:57....	9.1	1	0.815	0.656	Uyarı
Row11700	2022-06-06T17:32:00....	9.1	1	0.815	0.674	Uyarı
Row11701	2022-06-06T17:32:03....	9.1	1	0.815	0.692	Uyarı
Row11702	2022-06-06T17:32:06....	9.1	1	0.815	0.709	Uyarı
Row11703	2022-06-06T17:32:09....	9.1	1	0.815	0.727	Uyarı
Row11704	2022-06-06T17:32:12....	8.7	1	0.445	0.727	Uyarı
Row11705	2022-06-06T17:32:15....	8.7	1	0.445	0.727	Uyarı
Row11706	2022-06-06T17:32:18....	8.7	1	0.445	0.727	Uyarı

Figure 15. Anomalous Situations

5. Results and Discussion

In the study, a study was conducted to estimate slat conveyor failures arising from the equipment maintenance needs of an automotive factory and within the scope of predictive maintenance. Thanks to the proposed method for maintenance prediction, the feasibility of estimation with a single data parameter was demonstrated. After obtaining the data, which is the first stage in the proposed method, the data editing stage was started. In the 3rd step, the faulty data in the data set was labeled with the EWMA method and these labeled data were scored with the isolation forest method in the fourth step. Data above a certain threshold value were determined as having high failure potential. Then, a risk determination method was applied to observe how long these scores continued and to understand how close we were to the failure. After the risks were determined, it was finally determined which current values were real abnormal data. As a result of the study, it was observed that the proposed method worked correctly and with the desired qualities.

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