Makine Öğrenmesi Kullanılarak Endüstriyel Pres Makinesine Uygulanan Kestirimci Bakım Çalışmaları

Predictive Maintenance Studies Applied to an Industrial Press Machine Using Machine Learning

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Özetçe—**Bu Endüstri 4.0 uygulamalarının temel amacı üretim zinciri boyunca maksimum çalışma süresini sağlamak, üretim maliyetlerini düşürmek ve verimliliği artırmaktır. Endüstri 4.0 teknolojilerinden olan Büyük Veri, Nesnelerin İnterneti (IoT) ve Makine Öğrenmesi (ML) sayesinde Kestirimci Bakım çalışmaları hız kazanmıştır. Endüstride Kestirimci Bakım uygulamak, bakım ve onarım süresi uzun süren arıza sayısını azaltmakta, üretim kayıplarını ve maliyetlerini minimum seviyeye indirmektedir. Makine öğrenmesinin kullanımıyla, ekipmanlarda bilinmeyen sebeplerle yaşanan arızalar ve ekipmanın bakım ihtiyacı tahmin edilebilmektedir. Makine öğrenmesi algoritmasını eğitmek için büyük miktarda veriye ve bunun yanı sıra probleme uygun yeterli analitik yöntem seçimine ihtiyaç vardır. Önemli olan, veri işleme ile veriyi gürültüden temizleyerek değerli sinyali elde edebilmektir. Makine öğrenmesi ile tahmin modelleri oluşturmak için doğru bilgi toplamak ve farklı sistemlerden gelen birçok veriyi kullanabilmek gerekmektedir. Kestirimci bakımla ilgili büyük miktardaki verinin varlığı ve gerçek zamanlı bu verileri izleme ihtiyacı, veri toplarken yaşanan gecikmeler, ağ ve sunucu problemleri bu süreçte yaşanan büyük zorluklardır. Bir diğer önemli hususta yapay zekanın kullanımı ile ilgilidir. Örneğin eğitim verilerini elde etme, değişken çevre şartları ile başa çıkma, belirli bir senaryoya daha iyi uyan ML algoritmasının seçilmesi, operasyonel koşullara ve üretim ortamına duyarlı bilginin gerekliliği yapılacak analizler için büyük önem taşımaktadır. Bu çalışmada otomotiv endüstrisinde kullanılan transfer pres makinesi için bakım ihtiyacı zamanı tahmininde bulunan ve anormal durumlar yaklaştığında ilgili kişilere uyarı mesajı verebilen kestirimci bakım çalışmaları incelenmiştir. Öncelikle makineye geçmişte meydana gelen arızaların tespitine yönelik çeşitli sensörler yerleştirilmiş ve bu sensörlerden hangi verilerin toplanacağı belirlenmiştir. Sonra toplanan verilerle anomali tespiti yapabilmek ve geçmişteki arızaları modellemek için kullanılan makine öğrenmesi algoritmaları oluşturularak otomotiv parçaları üreten bir fabrikada uygulama yapılmıştır.**

Anahtar Kelimeler—Kestirimci Bakım, Makine Öğrenmesi, Anomali Tespiti, Endüstri 4.0, Otomotiv Endüstrisi.

Abstract—**The main purpose of Industry 4.0 applications is to provide maximum uptime throughout the production chain, to reduce production costs and to increase productivity. Thanks to Big Data, Internet of Things (IoT) and Machine Learning (ML), which are among the Industry 4.0 technologies, Predictive Maintenance (PdM) studies have gained speed. Implementing Predictive Maintenance in the industry reduces the number of breakdowns with long maintenance and repair times, and minimizes production losses and costs. With the use of machine learning, equipment malfunctions and equipment maintenance needs can be predicted for unknown reasons. A large amount of data is needed to train the machine learning algorithm, as well as adequate analytical method selection suitable for the problem. The important thing is to get the valuable signal by cleaning the data from noise with data processing. In order to create prediction models with machine learning, it is necessary to collect accurate information and to use many data from different systems. The existence of large amounts of data related to predictive maintenance and the need to monitor this data in real time, delays in data collection, network and server problems are major difficulties in this process. Another important issue concerns the use of artificial intelligence. For example, obtaining training data, dealing with variable environmental conditions, choosing the ML algorithm better suited to a specific scenario, necessity of information sensitive to operational conditions and production environment are of great importance for analysis. In this study, predictive maintenance studies for the transfer press machine used in the automotive industry, which can predict the maintenance need time and give warning messages to the relevant people when abnormal situations approach, are examined. First of all, various sensors have been placed in the machine for the detection of past malfunctions and it has been determined which data will be collected from these sensors. Then, machine**

learning algorithms used to detect anomalies with the collected data and model past failures were created and an application was made in a factory that produces automotive parts.

Keywords— Predictive Maintenance, Machine Learning, Anomaly Detection, Industry 4.0, Automotive Industry.

I. INTRODUCTION

The Internet of Things (IoT) is the communication network where physical objects are linked with each other or with larger systems. This communication network enables devices and computers to collect and share data. Collected data are stored in local databases or cloud platforms. Thanks to IoT, devices can be remotely detected and monitored. With the merging of industry and IoT, the concept of Industrial Internet of Things (IIoT) has also emerged. IIoT enables machine data monitoring and control of the machine using various signals. In this way, it helps to improve the production process and plan the maintenance activities of the machines [1]. Companies pay attention to monitoring their systems in real time in order to increase their efficiency and to make correct managerial decisions [2].

Another important issue in the industry is the cost and time-efficient maintenance and repair of machines. It is necessary to plan the maintenance activities very well, taking into account the spare parts, personnel and production downtimes needed [3]. This requires providing reliable and accurate information about the machine in real time. This situation is of critical importance especially in factories that produce just in time (JIT) without stock. Machine failures bring production to a halt and cause shipping problems.

The maintenance and repair of the applied machine is done with the knowledge of the experienced people in the traditional method and these people can understand whether a machine needs maintenance or not from various factors (noise, vibration, heat, humidity, etc.). Various standards-based checks have been added to assess when equipment life will end and whether it is operating within specified limits. In recent years, data-based methods using machine learning, which we know as predictive maintenance, have also been added to the system [4]. Predictive maintenance methods can make highly accurate predictions about failures [5]. Looking at all these maintenance processes in general, the most accurate estimates can be made by blending them all.

A transfer press machine has many different parts with different failure mechanisms. Malfunctions are generally caused by engine malfunctions, mechanical transmission and gear malfunctions, unbalanced loads, wear problems, metal fatigue, temperature changes or electrical problems. This situation requires measuring and analyzing many different parameters. The classic maintenance activities of the press machine are the detection of defective parts after a malfunction and the replacement of parts from the high-cost spare parts stock kept in the warehouse [6]. This process is very time consuming, inefficient and causes high costs.

In this article, the predictive maintenance work on the industrial transfer press machine that makes automotive sheet metal parts forming process is discussed. Data collected from PLC (Programmable Logic Control) and sensors are analyzed with machine learning (ML) algorithms to detect anomalies. A system has been set up to automatically warn about the failure of the machine before it fails.

The article is organized as follows: In Chapter 2 material and method section; Fault analysis, selection of appropriate sensors, data analysis system architecture and machine learning algorithms are mentioned. Part 3 in the findings and discussion part; The malfunctions and outliers detected by machine learning algorithms are mentioned. Part 4 in the conclusion part; General results of the study were mentioned.

II. MATERİALS AND METHODS

In practice, first of all, the failure history of the machine should be examined and appropriate sensor selections should be made to solve the failures. Since there are many different types of sensors used in the industry, the choices should be made carefully. Wrong choices made at this stage will negatively affect the whole project. In order to perform fault analysis, the sensors must be positioned at the most optimum point and fixed. Next, a system architecture should be created for the analysis of the collected data and the data should be analyzed. Finally, fault predictions should be made with the appropriate machine learning algorithm to be selected.

A. *Breakdown Analysis and Selection of the Sensors*

The transfer press machine in which the study was conducted consists of 7 main regions, which are generally named as crown, uprights, destack feeder (DF), slide, moving bolster (MB), bed and conveyor.

In order to predict the malfunctions with machine learning algorithms, first of all, the malfunctions experienced in the past were examined and the methods to detect these malfunctions were investigated. Fault density analysis was performed for past failures recorded in 2010 and 2017. In particular, measures have been taken for regions with high fault density in the study. In addition to the breakdown density analysis, studies have been carried out on what kind of measures will be taken for major failures occurring in similar machines. The collected data are designed to affect the solution of 2325 faults at a 95% level, as indicated in Table 1. The places where the sensors will be placed were decided by examining the types of faults. Laser sensors to control wear, temperature sensors that can prevent overheating and metal fatigue, sensors that can measure vibration and temperature together for the control

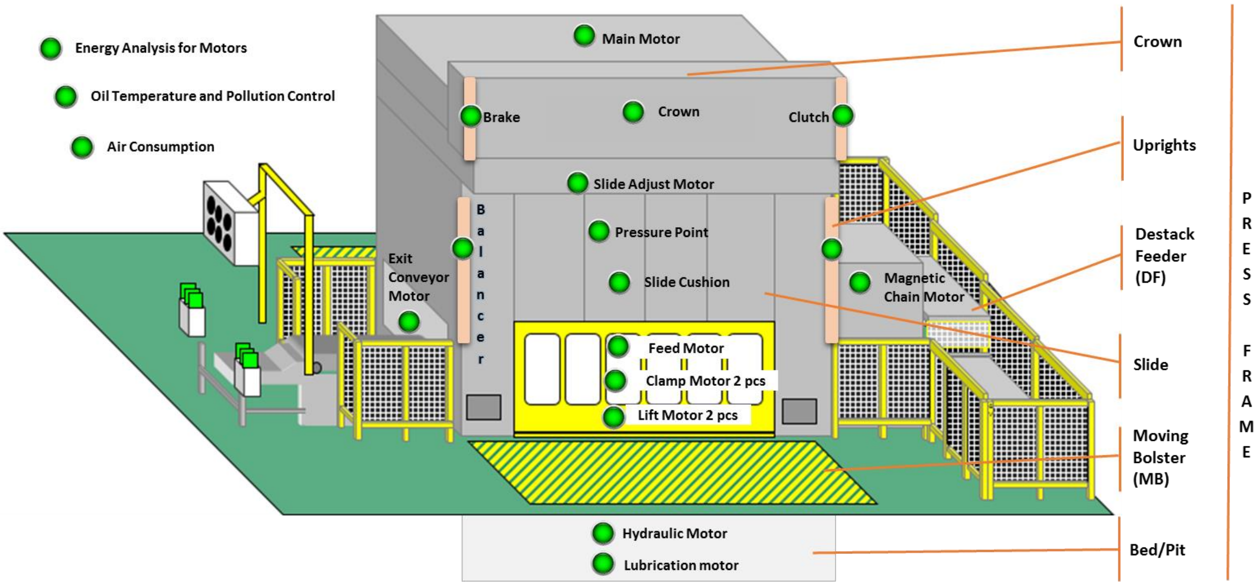

Figure 1. Transfer press machine structure

of engines and powertrains, and devices that measure oil contamination and filter oil are installed in the system.

Breakdown Area	Number of Breakdowns	Predictive Maintenance Equipments
Destack Feeder (DF)	726	Analog Infrared Temperature Sensors Temperature-Vibration Sensors Laser Distance Sensors Air Consumption Flow Sensor Lubrication System Monitoring (Temperature-Pollution-Humidity) Oil Filtering System Energy Analyzers (11 pcs) Tonnage Monitor System Strain Gauges (4 pcs)
Pit-Bed Area	353	
3-TR (Clamp-Lift-Feed)	336	
Main Bolster (MB)	268	
Other	214	
Conveyor	190	
Slide	79	
Electrical Problem	72	
Safety	37	
Crown	29	
Exit Area	20	
Cooling Unit	1	
Total	2325	

Table I. Breakdowns and Countermeasure Equipments

Controllers (PLC) used for the general functions of the machine predominantly generate alarms with the process sequence and lower and upper limits. In this structure, data analysis is not possible since the signals are generally digital. Thanks to the new sensors added, the basic structure on the press and line support equipment has been made traceable.

B. Data Analysis and System Architecture Design

Figure 2 shows the general structure of the created data analysis system. All data collected from the sensors and control unit are recorded in the InfluxDB time-series database. Since local databases have limited capacity for analyzing and storing data, data is also stored in the cloud simultaneously [7]. A data visualization platform is used to ensure the traceability of the collected data by individuals. Open source Python software is used to analyze data with ML algorithms.

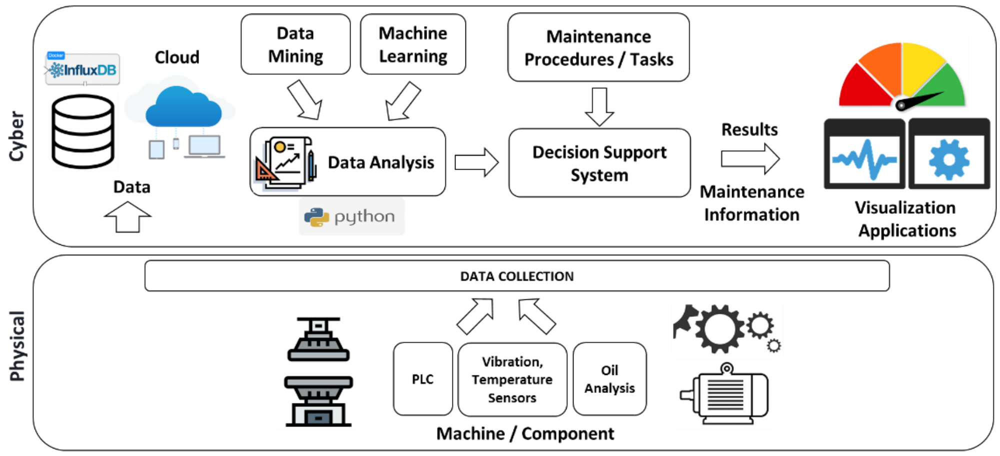

Figure 2. System architecture for PdM

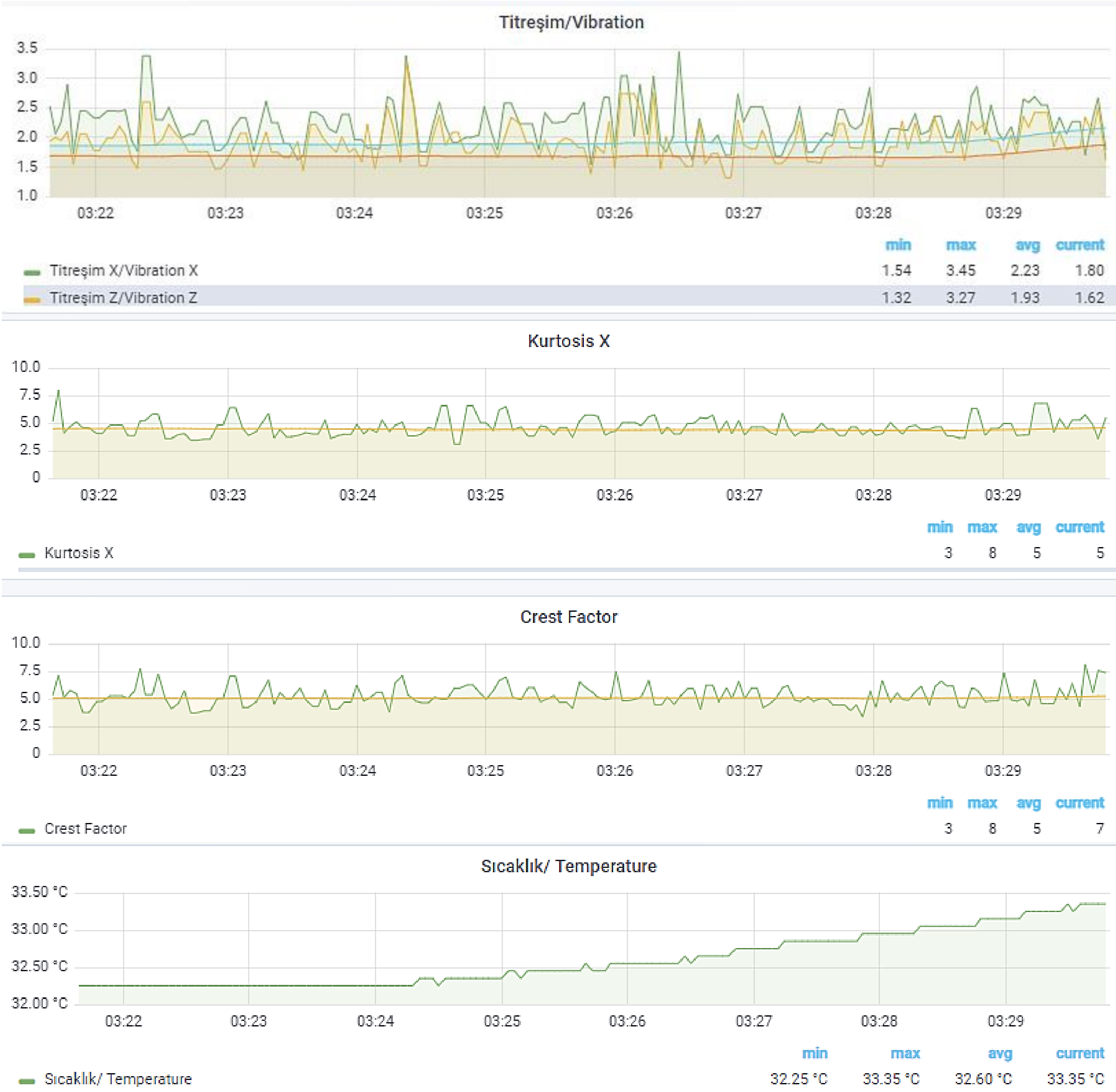

Figure 3. Real time data monitoring

C. Data Collection and Visualization

The temperature and vibration data collected from the sensors placed in the transfer press machine are shown in Figure 3 as an example. Data is collected and visualized instantly on the machine. Vibration is a powerful tool for diagnosing rotating machine elements [8]. Low frequency RMS (Root Mean Square) vibration (mm/sec) data is intended for the detection of problems such as alignment, load imbalance, axis shift [9]. High frequency kurtosis, crest factor and acceleration (G) data generate variables for detecting bearing failures [10]. Kurtosis is one of the indicators with clues as to whether the data is normally distributed. It has the advantage of being independent of the changes in the rotation speeds and loads of the machine. The kurtosis value of normal distribution is 3. Crest factor is defined as the ratio between the peak value and the effective value. If this value exceeds 6, it is a possible failure sign. Figure 3 shows the data collected on the machine in real time every 4 seconds. The minimum, maximum, average and real value of each data can be monitored.

D. Machine Learning Algorithm Selection

In order to predict malfunctions, studies have been carried out on machine learning algorithms that can show

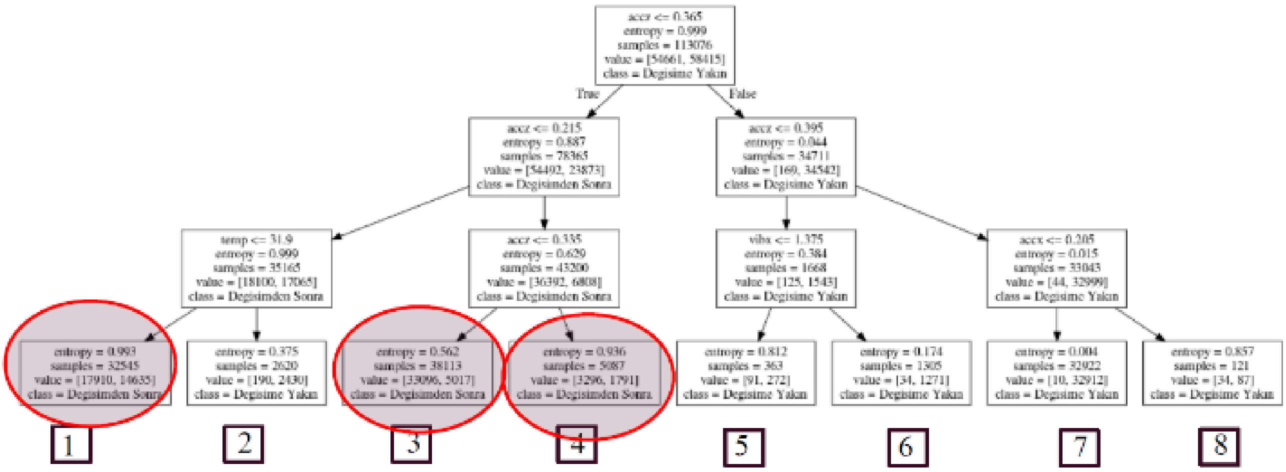

Figure 4. Decision tree algorithm structure-1

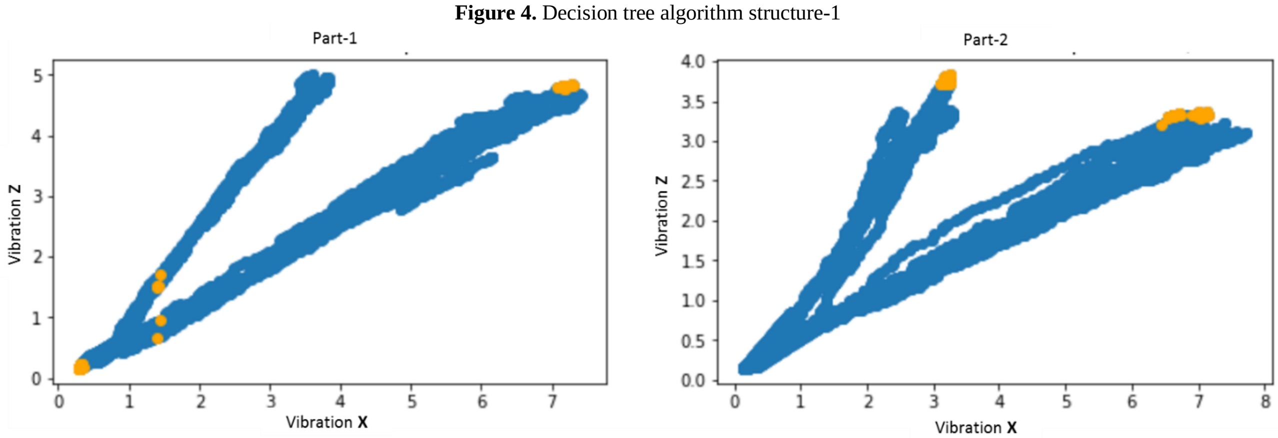

Figure 6. Isolation forest algorithm structure-1

the best performance. Studies have been conducted with the Decision Tree algorithm, one of the supervised ML algorithms, and the Isolation Forest (IF) algorithm, one of the unattended ML algorithms [11]. In decision tree learning, by creating a tree structure, class labels at the level of the leaves of the tree and the handles on the features with the branches leading to these leaves and emerging from the beginning are expressed. Figure 4 shows the decision tree leaves of an engine that has been modeled for failure. Isolation forest algorithm is one of the widely used techniques for anomaly detection [12]. Instead of creating a model of normal samples, it reveals abnormal points in the data set. In Figure 6 and 7, isolation forest modeling is shown with anomaly points in orange. Analyzes were made with two different methods.

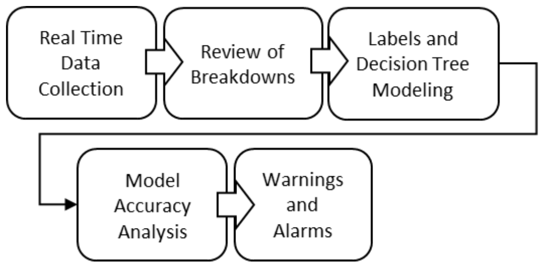

Figure 5. Decision tree algorithm structure-2

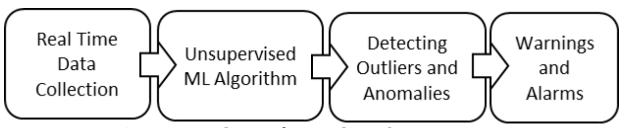

Figure 7. Isolation forest algorithm structure-2

III. RESULT AND DISCUSSION

Trend analysis and inter-parameter correlation studies were conducted in the data, and a decision tree structure was created for each different criterion with the Gini algorithm, which is a classification algorithm based on regression trees. A model has been developed that enables the malfunctions that may occur by using these methods to be detected in advance. When the received parameters tend to go beyond the lower and upper control limits, abnormal situation and information mails are automatically shared to the relevant people. For example, labeling and modeling have been made in the ML algorithm for the malfunction in January-February 2020, shown in Figure 8. The data indicating the failure give more than 20% warning. Thanks to the labeled fault data, the system gave the same warning again before the failure occurred in August. Necessary maintenance activities have been carried out on the machine.

With the isolation forest algorithm created to instantly detect outliers in the system, anomaly detection can be made as a percentage. A system has been established to give a warning when the machine's outlier values exceed 10%. Figure 9 shows the anomaly graph of the press main engine for the last 3 months, whose anomaly values were determined with the isolation forest algorithm. Since the production can be made with more than one mold of different tonnages in the press machine, it has been observed that the main engine is forced and exhibited abnormal situations in some production moments. The outliers in the main engine data were investigated.

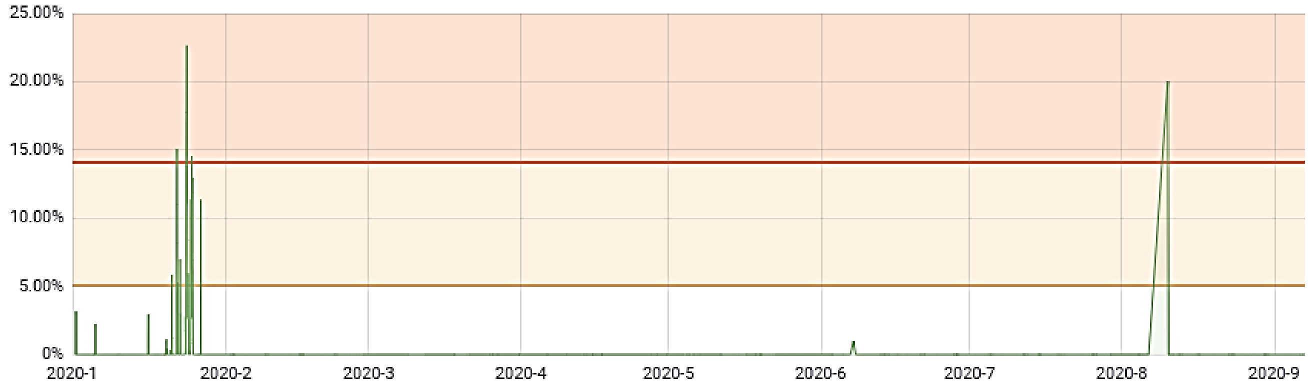

Figure 8. Decision Tree Algoritm Analysis

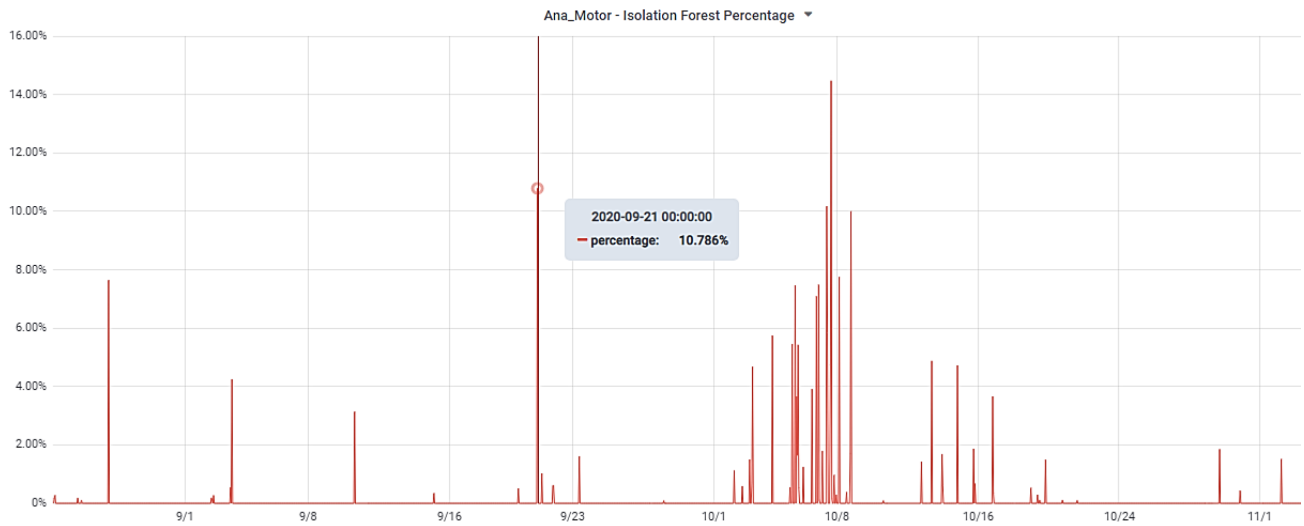

Figure 9. Isolation Forest Algoritm Analysis

IV. CONCLUSION

In this study, a predictive maintenance system was established that can predict possible failures before relying on a human evaluation with long-term studies and before failure occurs. The benefits of performing predictive maintenance work using machine learning have been demonstrated. It was understood how important it is to analyze temperature and vibration measurements in fault detection. Maintenance plans are carried out in the light of real data, updated and when necessary, maintenance and parts replacement are made. It is aimed to reduce maintenance costs by enabling the system to operate dynamically.

In order for the predictive maintenance system to detect malfunctions in advance, data collection and fault tagging processes are performed continuously. Since machine learning algorithms make the learning process based on the parameters at the time of failure, if there is no failure, the real results will not be achieved. As malfunctions occur in other areas on the press, the system will be taught and in the future, when the machine starts to show the same trend data, the malfunctions can be detected before the malfunction occurs.

Machine learning algorithms are generally not transparent, so relying on them takes time. The human factor is very important in data analysis. Companies should include personnel and data scientists who know the machine that can analyze the collected data very well. The more accurate the failures are taught to artificial intelligence, the more accurate the detections will be. A lot of laborious data preparation work is required to make the collected data quality suitable for modeling. If the accuracy and quality of the data are not appropriate, the studies and algorithms to be done will not reflect the truth.

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