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Enhanced Real-Time Maintenance Management Model—A Step toward Industry 4.0 through Lean: Conveyor Belt Operation Case Study

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Abstract: Conveyor belts (CBs) are widely used for the continuous transport of bulk materials. CBs must be extremely reliable due to the cost associated with their failure in continuous production systems. Thus, it is highly relevant in terms of maintenance and planning to find solutions to reduce the existing stoppages from these assets. In this sense, it is essential to monitor and collect real-time data from this piece of equipment. This work presents a case study, where a model that combines the Lean Philosophy, Total Productive Maintenance (TPM), and the enabling technologies of Industry 4.0 is applied to a CB. The proposed model monitors the CB and provides data on its operation, which, using the calculation of indicators, allows a more accurate and thorough view and evaluation, contributing to improving and supporting decision making by those responsible for maintenance. The data collected by the sensor help those responsible for maintenance and production, in the readjustment of more accurate and optimized planning, programming, and execution, supporting decision making in these areas. During the field test of a two-hour monitoring period (10 a.m. to 12 p.m.), the model identified six stoppages, resulting in approximately 88.6% of operational time for the conveyor. The field test showed that this model can result in more accurate maintenance decision making than conventional approaches. This research also contributes to the advancement of electronics and industrial automation sectors by empowering companies to transform maintenance methodologies. The potential of this approach and its implications for enhanced productivity and overall performance are therefore highlighted.

Keywords: maintenance; maintenance management; Industry 4.0; TPM; lean philosophy; IoT; sensors; real-time monitoring; conveyor belt; model

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1. Introduction

1.1. Contextualization and Formulation of the Problem

Conveyor belts (CBs) are widely applied in all types of industrial and service areas. The CB is a device for the transport of bulk materials using a reinforced rubber strip, moving over drums and rollers to provide a continuous flow with high speed and low cost, maintaining safe operation, and being versatile for a wide variety of applications [1,2]. Despite its versatility, the components that make up the CB require maintenance for a longer useful life, through the combination of technical and administrative actions to maintain or restore the asset to a state in which it can perform its function [3,4]. Although CBs are adaptable, they are also expensive. While other equipment such as crushers or screens can be relocated and adapted to new process conditions and/or production systems, CBs, when designed for a particular application and industry, are difficult to relocate, making them a critical piece of equipment in terms of investment [4,5].

Even if the design of the conveyor is correctly developed and of high quality, it may not achieve the expected performance and service life if some basic operating and maintenance conditions are not met, such as keeping the drums in the right state and coated; keeping the guides aligned and well adjusted; having well-supported rollers; and having well-regulated cleaning systems, i.e., scrapers and belt cleaners and turners that guarantee the removal of the remaining conveyed material on the belt. Misuse and preservation of the belt are also maintenance-related problems associated with this piece of equipment, as changing the belts forces the equipment to stop, in some cases for days [6,7]. To reduce the consequences of the production decrease during stoppage times, a large number of maintenance technicians are required, which, among other factors, contributes to the increase in maintenance costs [6,7]. Given the various operations necessary to maintain CBs, many of these operations are unable to achieve availability, cost, and production targets precisely because some of the basic tasks fail or the maintenance plan is not adequate given its operating regime [8,9]. Thus, the manuscript aims to show the implementation of a model to support decision making based on the evaluation of real-time data on CB failures. This approach contributes to an increase in the values of production indices, as it contributes to the identification of critical problems and the definition of maintenance strategies for their consequent mitigation.

1.2. Background

The CB is one of the pieces of equipment frequently used in the most varied industries and it is an essential part of their operations. According to Fedorko [10], Hou et al. [7], and Mendes et al. [11], the CB is one of the most important intra-company transport systems in a wide range of industries to handle bulk materials or other types of materials continuously, rapidly, at low cost, safely, and versatilely within a wide range of applications. Therefore, the maintenance area must maximize the useful life of assets and tools and provide successful recovery of parts and machines that are used during manufacturing, especially key production parts such as CBs to deliver the final product as expected, depending on its origin or production objective [12]. Numerous procedures and precautions need to be taken about this piece of equipment, including inspection of the alignment and wear of the belts. The maintenance department is fundamental to achieving these objectives [8,9].

Maintenance management activities inherent to CBs and industrial equipment in general are based on data previously collected by the various technicians who work in the maintenance area [13]. Those data include downtime, maintenance time, waiting time for spare parts, replacement time, inspection time, and reports. All of these data are collected and archived in the maintenance history record/database of the respective asset [14,15].

The problems associated with these types of activities related to maintenance management, as well as in these types of equipment, are often linked to some basic and simple tasks, which, given the high volume of data and tasks to be carried out in the management of these assets, can cause planning and other activities related to maintenance management to remain in the background and to be poorly prioritized or even unidentified [16]. Normally, these patterns cannot be discovered with traditional data exploration, because the relationships are very complex or, due to the amount of data, human resources cannot deal with such problems fast enough [17,18]. Thus, Shou et al. [19], Duran et al. [20], Moharana et al. [21], Mazurkiewicz et al. [22], and Burawat [23] reinforce the need for continuous research to promote the reliable operation of individual process automation, predictive maintenance (PdM), and efficient operation related to I4.0, together with the application of other methodologies and philosophies, such as the Lean Philosophy (LP). This approach facilitates the tasks and decisions inherent to maintenance management, as well as its continuation over time to increase the availability of these assets. Gupta et al. [24]

and Kiangala and Wang [25] have sought to identify how PdM can assist in those tasks, such as reducing maintenance interventions to improve the availability and operating rate of CBs, cost reduction, reduction in spare parts, among other factors that make these assets highly expensive within industrial companies. With the advances of Industry 4.0, PdM procedures can be developed to execute real-time monitoring of condition parameters, such as temperature, vibrations, and noise. Tortorella et al. [26], Rousopoulou et al. [27], Jasiulewicz-Kaczmarek et al. [28], and Liu et al. [29] state that the introduction of PdM is central to supporting maintenance activities, concerning decision support, thus allowing for reducing the number of failures, the downtime due to malfunction, and, consequently, the cost of maintenance. Analyzing the performance evolution of the physical asset during a given period helps to increase its performance and durability. Additionally, it will allow the maintenance responsible for developing maintenance plans based on the information collected by sensors and intelligent PdM routine procedures in line with I4.0.

Mazurkiewicz [22] has investigated how to improve maintenance management and its activities, and/or how decision making can be supported in this critical and fundamental area in the industry through other tools, methodologies, and models that are often not used in the maintenance area. A CB model was implemented, with the proposal being a better way of analyzing sequences compared to the traditional statistical analyses used, especially when the volume of data maintenance is large. In the same type of development, Moharana et al. [21] reported that normally, in many companies, maintenance managers suggest maintenance activities based on practical rules or based on their experience and physical monitoring of the equipment at regular intervals. It is pointed out that this enables a better approach to the selection of spare parts based on their similarity or correlation during maintenance activities.

Norddin et al. [12], Nurprihatin et al. [30], Virk et al. [31], and Sahrupi and Juriantoro [32] discuss the Total Productive Maintenance (TPM) methodology and state that it is an approach that seeks to maximize productivity, using the involvement and participation of all company employees, improving the management of maintenance and its assets, and increasing the useful life of assets, safety, the quality of manufactured products, as well as their availability.

So, based on the studies mentioned above, it is important to develop new models, as well as to carry out case studies to highlight and provide improvement to CBs maintenance management, and of the assets in the industry in general.

1.3. Goals, Objectives, and Manuscript Organization

To ensure the optimal work performance of physical assets, particularly of CBs, in the present study, the model developed by Mendes et al. [9] is implemented. This case study is motivated by the harsh environment in which this piece of equipment often operates, requiring additional maintenance oversight, which can be eased by the implementation of sophisticated Industry 4.0 (I4.0) technologies. The model involves a decision support system based on maintenance performance metrics that will contribute to efficient and effective decision making at a strategic level. The expected benefits shown in the case study through the application of the model developed by Mendes et al. [9] are as follows: (1) show that the integration of the concepts of the LP and I4.0, when applied correctly, can create synergies, which can support and improve decision making based on data collected remotely; (2) improve CB availability; (3) improve data acquisition that is traditionally recorded manually by the maintenance technician after an intervention while applying the model as it is carried out remotely; and (4) improve decision making in the maintenance area, adopting the visualization of maintenance performance metrics.

This work is organized as follows. Section 1 presents the background of the research content, the work carried out to date around the CB, as well as the goals and objectives of the present study, such as the methodology. Section 2 presents the Materials and Methods with a summary of the issues and a description of the methods. In Section 3, the results of implementing the model [9] in the CB are presented. In Section 4—the discussion of the results—the results are compared with the works developed by other authors, as well as the description of some limitations inherent to the model. Finally, Section 5 includes the conclusions.

2. Materials and Methods

The CB is a vital element of the conveyor system in various industrial applications, including ports and bulk terminals, chemical plants, power plants, and mines. This type of equipment is commonly susceptible to surface wear on the belt; misalignment of the belt; a lack of coating on the drums; poorly adjusted and/or misaligned guides; poorly supported rollers; poorly positioned scrapers, cleaners, and turners (cleaning system); and a lack of or poor lubrication, with these and other factors contributing to reducing CB availability. One of the ways to eliminate or reduce this type of failure is through efficient and effective maintenance management. However, one of the associated problems is related to the high number of activities carried out in this area, which does not always allow the correct collection of all data associated with CBs, or industrial equipment in general. Those data are related to downtime, maintenance time, waiting time for spare parts, replacement time, inspection time, and reports. All these data are collected and stored in the register/database of the maintenance history of the respective asset. This storage is of extreme importance to support decision making in this area. Given the importance of these data in designing maintenance plans and optimal inspection routines according to the use of CBs, it is important to carry out studies on this subject. This work applies the model designed by Mendes et al. [9] to a CB. The model and materials used are described below [9]. The first layer is made up of an architecture composed of sensors, April USB Beacon 306, to ensure the monitoring of machines and equipment and the TCRT5000 infrared sensor module to count parts with and without defects (if applicable). The active infrared sensor is composed of an infrared light emitter and a receiver that reacts to light, responsible for detecting objects that pass along the CB. Data collected must be transmitted to the gateway. To make communication between sensors compatible, more specifically the TCRT5000 infrared sensor, the Arduino Nano 33 BLE is used. The communication protocol used (second layer), Wi-Fi and BLE, allows interaction between different devices and communication protocols used in them. The Raspberry Pi 3 Model B+ establishes the gateway, allowing communication via Wi-Fi and BLE [9]. The third layer, the cloud, uses the ThingSpeak platform for visualization and analysis of real-time data streams in the cloud [9].

This architecture allows the collection of metrics and the calculation of various indicators such as operating time, downtime, repair time, availability, Overall Equipment Effectiveness (OEE), and operating rate, among other parameters. This methodology aims to improve the overall efficiency of equipment by achieving zero faults, zero defects, and zero accidents and eliminating other forms of waste and loss; improving the productivity of workstations; promoting the involvement of all departments (production, maintenance, management) and existing employees, from top management down to the workers; and promoting autonomous maintenance, in which operators feel that they "own" their machines.

This case study aims to verify the decision support opportunities related to the model developed by Mendes et al. [9] in the area of maintenance. The decision support is implemented in one of the pieces of equipment developed by the company MIME. The CB shown in Figure 1 is chosen to implement the model at an early stage. This CB is designed for the food industry. The food industry sector has a high energy intensity due to continuous operation using CBs for product movement as well as for cold storage requirements to maintain the safety and quality of products. Thus, proper maintenance is required to avoid equipment malfunction that may result in production delays. Moreover, CBs have electrical motors that can lead to a power phase unbalance and consequently high energy consumption [33–37]. In this sense, the inclusion of real-time monitoring of machines and equipment or traceability systems benefits the production flow [38–40].

Figure 1. Conveyor belt.

Figure 2 shows the adaptation of the proposal by Mendes et al. [9] to the present case study. With the inclusion of sensors in the CB, data regarding its operation can be acquired. The sensor collects and sends data to the gateway through the BLE communication protocol. The cloud, through the wireless local area network, receives the data sent through the gateway, which makes the bridge between the physical resources and the cloud. The cloud will allow the processing and storage of the data collected by the sensors, and the information is available through ThingSpeak. ThingSpeak (an IoT analytics platform) allows the aggregation, visualization, and analysis of real-time data streams in the cloud. Therefore, through ThingSpeak, and using the local wireless internet network, the operator, maintenance technician, or maintenance planning office can access and visualize indicators such as Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), availability, and notes submitted by operators, as well as send alerts.

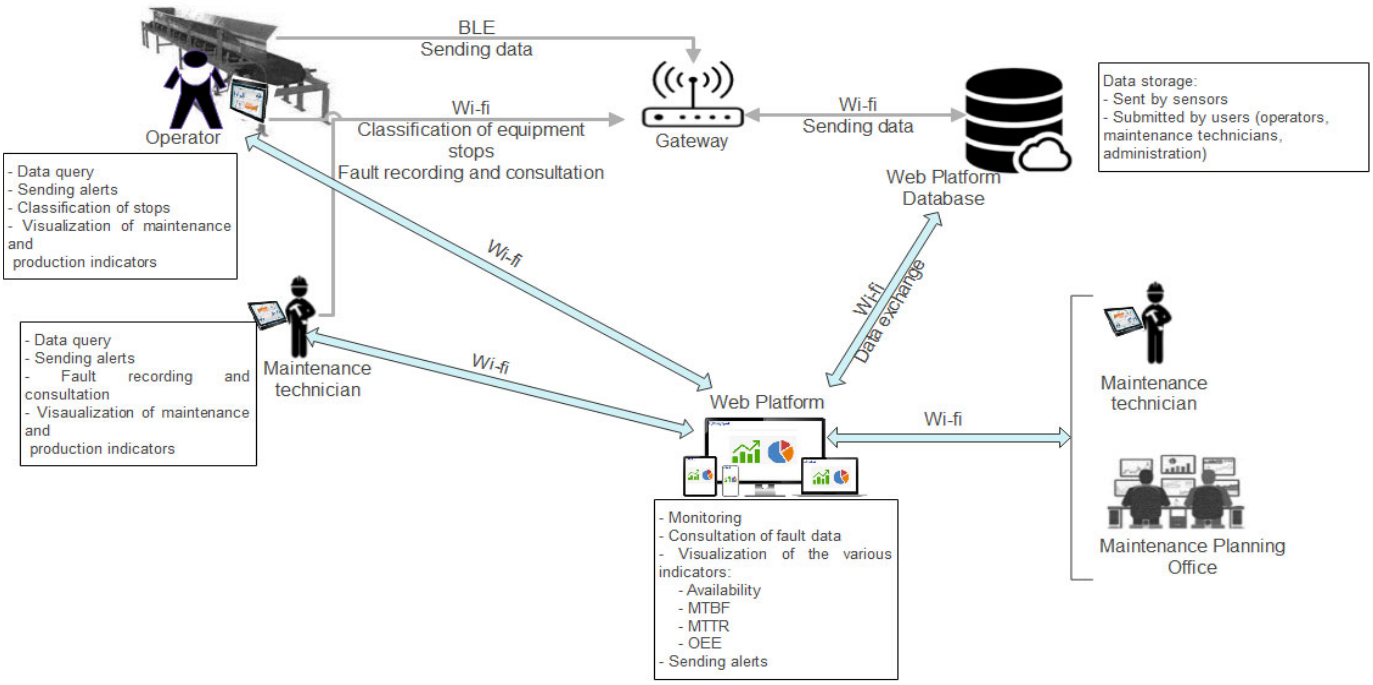

Figure 2. Model adapted to the case study.

To proceed with implementation, real-time monitoring of the CB required the installation of sensors to collect process variables. Thus, as described before, to monitor the CB, several devices had to be assembled: April USB Beacon 306 sensor, Raspberry Pi 3 Model B+, OUKITEL Rugged Tablet, the TCRT5000 infrared sensor module (if applicable), and Arduino Nano microcontroller 33 BLE (if applicable).

Initially, the operation of the CB was analyzed. In addition to analyzing its operation, it was necessary to understand and identify the respective meter or relay on the electrical panel. Analyzing the electrical scheme and the operation of the CB, it was possible to identify the electrical meter. To enable the connection of the chosen sensor, an AC-to-DC converter was used, commonly used in various types of chargers for mobile devices powered by USB. Figure 3 shows the connection diagram.

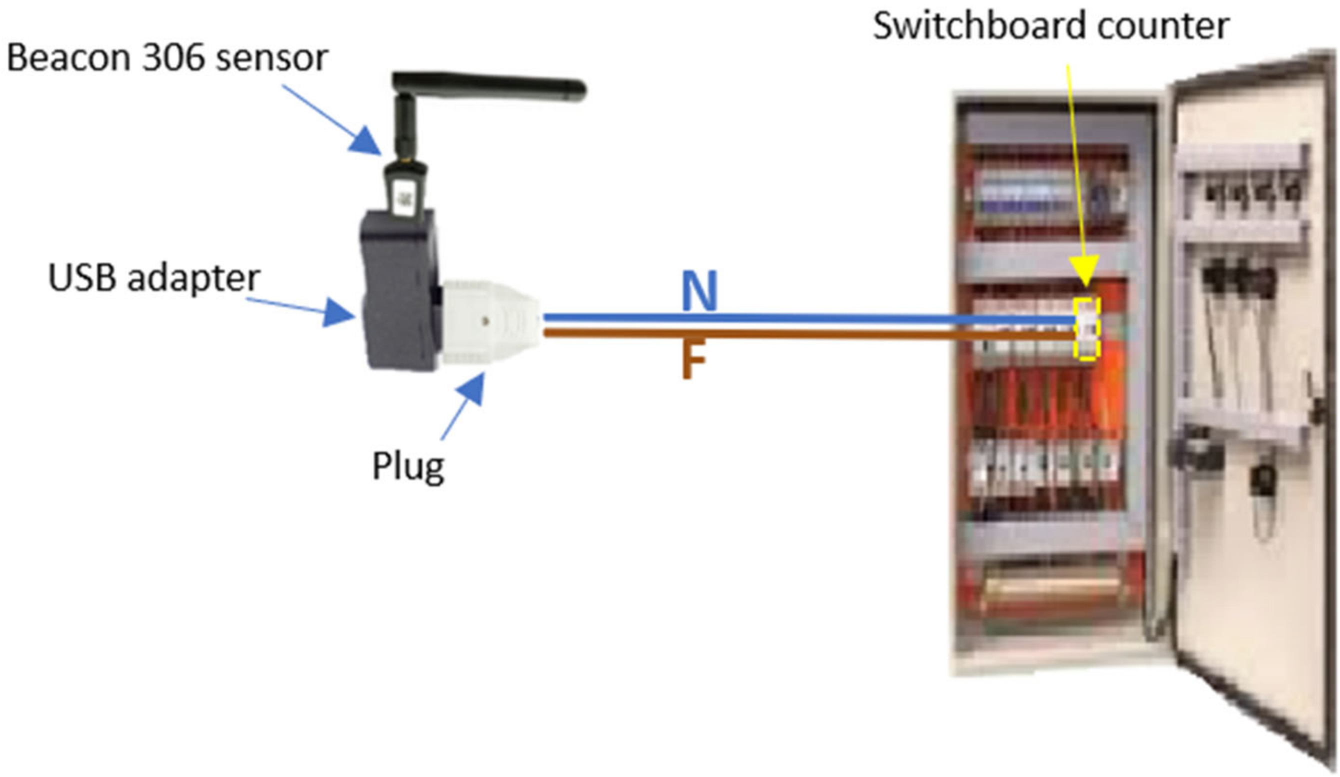

Figure 3. An electrical connection diagram was carried out in the electrical panel.

The data collected by the sensors are transmitted to the cloud, where the gateway facilitates this communication through the BLE communication protocol. The gateway serves as an intermediary, enabling seamless connectivity between the sensors and the cloud layer.

To enable the operator to classify the different stops, a dedicated tablet/smartphone/computer is provided for each machine and piece of equipment, simplifying the classification process. This fault classification is achieved using the platform offered by ThingSpeak. One suitable tablet for incorporation into the system is the OUKITEL Rugged Tablet, or any other tablet capable of accessing the internet network. Ultimately, at the cloud layer, a free version of ThingSpeak, an IoT analytical platform service, is implemented. This integration allows for real-time visualization and analysis of the data collected by the sensors in the cloud.

Figure 4 schematically and briefly shows how the system works. Once the monitoring system is installed, the April USB Beacon 306 sensor acquires the data and transmits it to the gateway through the BLE communication protocol. If there is a stop, the operator can use a tablet to classify it. On the other hand, the sensor module TCRT5000 accounts for the parts with and without defects (if applicable). Two sensors must be installed, one for counting the parts without defects and another for reading the defective parts. All collected information is transmitted to the gateway, where it is processed and analyzed. Using a device with internet access, it will be able to visualize the indicators in real time, which will allow the maintenance area to adjust its strategies [9].

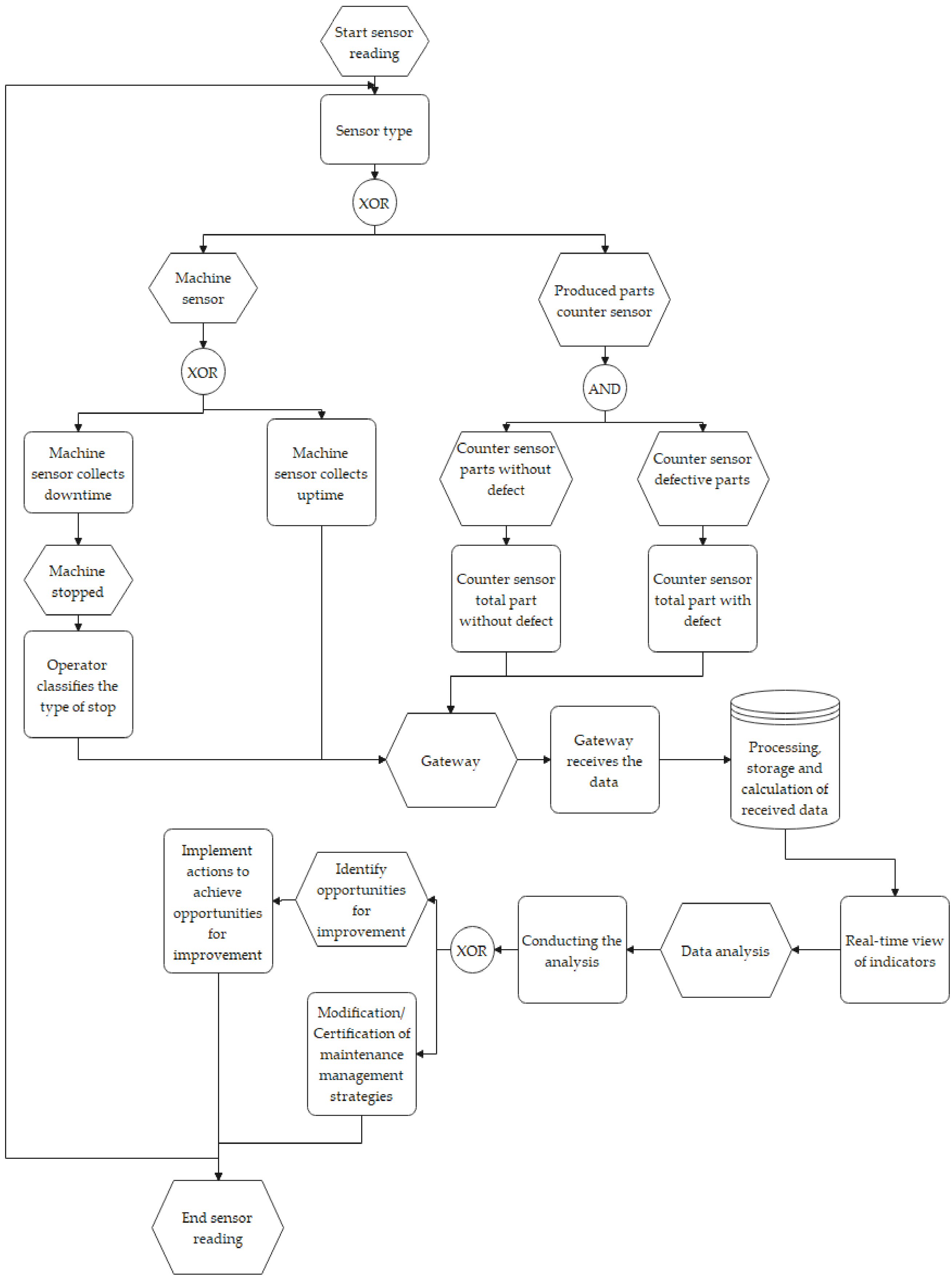

Figure 4. Flowchart describing how the system works.

3. Results

The model presented by Mendes et al. [9] was implemented in this study to a CB. This model differs from the scientific papers published on this topic so far [25–27,41,42] since those models were developed to enable the monitoring of condition parameters.

To contain costs and allow the system to be low-cost, its performance can be influenced by the maximum distance between the various devices that make up the system, as not all devices have the same communication range. This limitation can be overcome by changing the chosen devices and the communication protocol, which may influence the final cost. The frequency at which the gateway searches for the sensor data significantly influences its potential for experiencing blockages. When the search intervals are relatively short, it can lead to the gateway becoming overwhelmed and blocked. The processing of a large amount of data in wireless sensor networks is a critical challenge and a demanding processing task, where the collection of those same data becomes critical, and may lead to blockages. So, in this way and to solve this problem, it is advisable to adjust the search frequency for the various devices, extending the periods between searches. For instance, instead of the gateway searching for information every 10–30 s, it is recommended to designate longer intervals in the order of minutes. By implementing this approach, the chance of the gateway becoming blocked is reduced, ensuring a smoother and more efficient data collection process. It is worth noting that the accounting and weighing of the feed occur throughout the production chain. However, a final verification of the produced feed is performed by counting the number of bags. Any feed that falls outside the quality standards is manually weighed daily. This particular practice can be easily addressed by increasing the number of load sensors compatible with the existing communication protocols within the proposed monitoring architecture.

Table 1 shows the results obtained from different stops that occurred between 10 a.m. and 12 p.m. on a specific day. Within those two hours, six stops were recorded, amounting to 15 min and 43 s of downtime, with the CB operating at approximately 88.6% of the observed time. These stops were caused by issues related to binding and misalignment.

Table 1. Conveyor belt stop log (during 2 h).

Breakdown Time	Repair Time	Stop Classification
12:48:27	0 h:5 min:40 s	Conveyor belt jam
12:11:08	0 h:2 min:04 s	Conveyor belt misalignment
11:42:33	0 h:4 min:21 s	Conveyor belt jam
11:02:11	0 h:1 min:06 s	Conveyor belt misalignment
10:40:02	0 h:0 min:49 s	Conveyor belt jam
10:10:40	0 h:1 min:30 s	Conveyor belt jam

Regarding the misalignment, the technician carries out the inspection and must identify if the misalignment is due to the decentralized fall of the material, incorrect belt length, or if the belt is not tensioned properly. In this particular case, the problem was the decentralized fall of the raw material. Thus, to correct this problem, the correction and alignment of the dispenser were carried out so that the raw material would fall more to the possible center of the belt. Another cause that also leads to misalignment, as well as jamming of the CB, is the excessive accumulation of material. According to Table 1, the CB was ingrown four times. The technician inspects the CB and checks for the accumulation of material. They should adjust (if applicable) the scrapers and cleaners of the CB so that the cleaning system can be properly positioned. Then, the belt should be cleaned by removing the accumulated material with a brush or compressed air.

To verify the applicability and feasibility of the model, data were collected on the operation of the CB for one week before implementing the model. That period included working days with a 7 h shift (considering various breaks). Figure 5 shows that the CB had nine occurrences. The most problematic were related to the scraper and the skidding belt. Figure 6 shows that the CB, in 35 possible hours of operation, operated for 20.8 h, and was stopped for 14.2 h. The MTBF was 2.3 h and the MTTR was 1.6 h, thus leading to an availability of 59.4%.

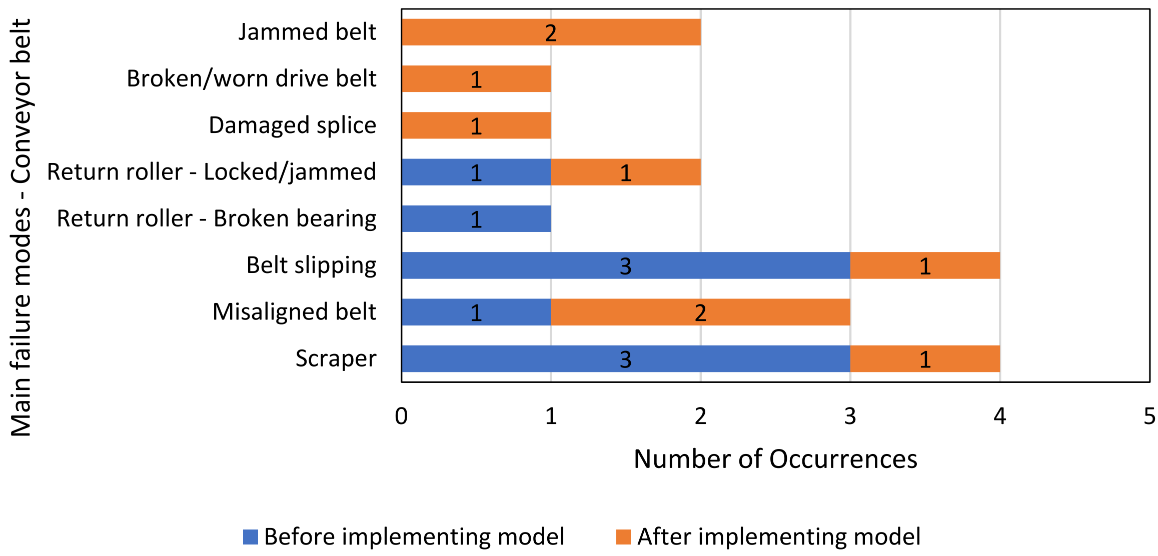

Figure 5. Number of occurrences during the observation week.

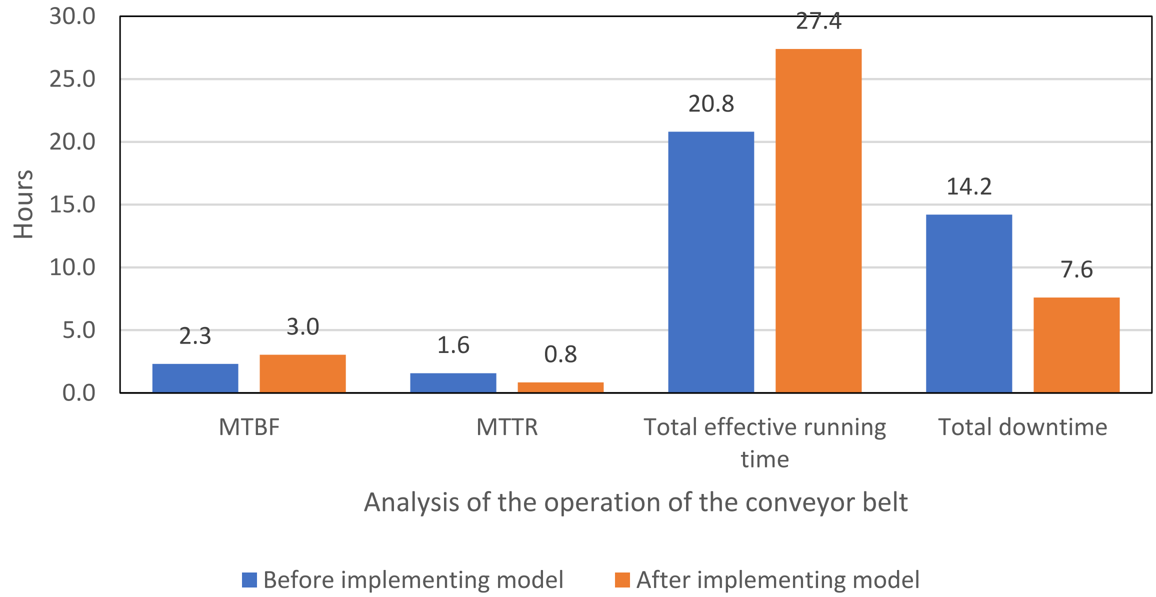

Figure 6. Overall summary of the conveyor belt operation.

After the implementation of the model and the respective test period, the operation of the CB was also monitored for one week. Figure 5 also shows that the CB had the same occurrences, nine in total, and the most frequent failure mode was the ingrown belt. The total operating time of the CB was 27.4 h, in which from 35 h, it was stopped for 7.6 h. The MTBF was 3.0 h and the MTTR was 0.8 h. The availability was 78.3% as shown in Figure 6, which compares results from both tests.

Thus, it is possible to verify that there was an increase in the availability of the CB by about 31.7%. The MTBF increased by 31.7% and the MTTR decreased by 46.5%. This reduction was partly linked to the rapid identification of the occurrence, facilitated by the model operation, which substantially reduced the response time in the face of the various occurrences that occurred. As for the occurrence of failures, it was possible to verify a reduction of 66.7% related to the failure modes: scraper and slip belt.

To implement TPM in the short term, and if it is implemented correctly, a new attitude and culture will be transmitted to employees in general, more specifically those who operate on the CB, and a gain in their autonomy can be achieved. By introducing autonomous maintenance, the 5S methodology will provide cleaner, tidier, and more organized areas around the CB. Together with the correct instruction and training of the operators and the proper planning of the autonomous maintenance plan, they will have a better awareness and understanding of its importance in the workplace, promoting responsibility and skills to perform small maintenance, cleaning, tightening, inspections, and even the identification of anomalies and their resolution, which can contribute to reducing failures such as ingrown belts, misaligned belts, scrapers, and damaged splices.

Figure 7 shows the data collected through the monitoring system. After the data collection, it is processed and stored through the website ThingSpeak, represented in a graph. Figure 7 shows the schematic representation of the MTBF, where zero represents the moment when the CB is stopped, and one represents the time of good operation. Thus, Figure 7 allows for verification that the CB stopped twice on 26 July, between 15 h and 20 h, and that on 27 July, stopped once.

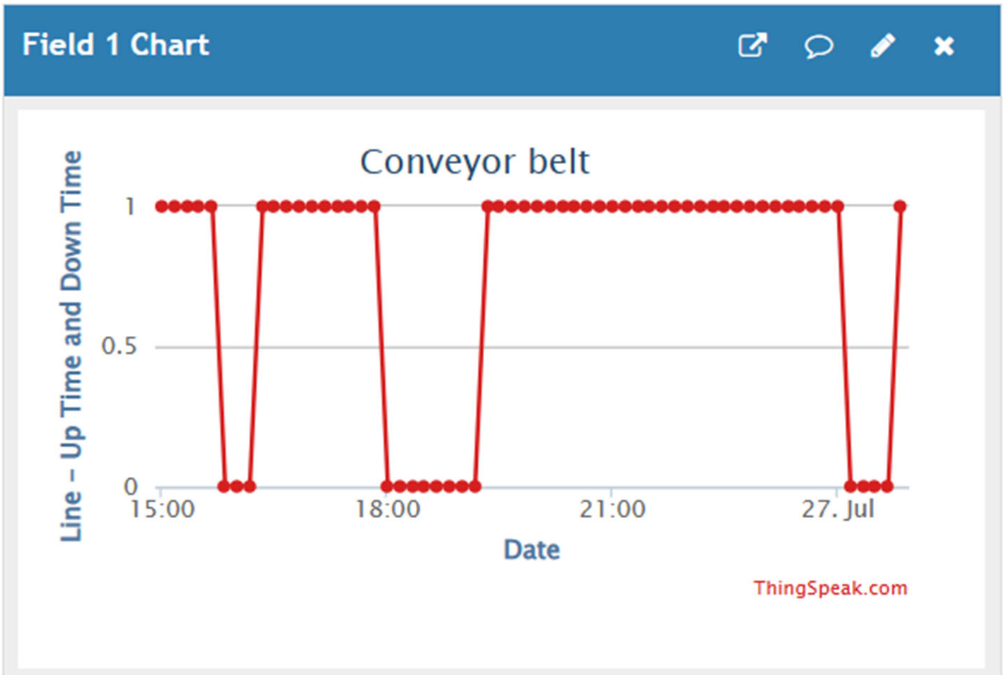

Figure 7. Schematic representation of the MTBF through the monitoring system.

4. Discussion

The evaluation of maintenance performance is measured through maintenance indicators that must translate as faithfully as possible the reality of maintenance activities within the company. However, data collection is not always performed easily, as it also requires a large investment in terms of the time spent due to the high amount of data that this process requires.

Given the inefficiencies of the traditional method of data acquisition and data recording concerning maintenance management activities, it is important to collect these data automatically and without the need for further processing. Real-time monitoring can help address such inefficiencies related to traditional methods. Through this work, it was possible to verify some of the important points to support the maintenance area, as well as to contribute to understanding and improving some aspects related to this vital area for any industry. This work highlights that the model developed by [9] is promising. If it is applied correctly, it contributes to ensuring the best conditions for using the CB and industrial equipment in general. (1) This allows, through real knowledge of the operating conditions, the adaptation of the maintenance and inspection plans to increase the useful life of the CB, as in industrial equipment in general. (2) This allows the reduction in the effective time since data acquisition and analysis compared to traditional data collection methods. (3) This allows a better adaptation of maintenance interventions (improve the times and intervals of maintenance interventions). (4) This contributes to achieve a reduction in corrective interventions, reducing failures and optimizing results. (5) This enables a reduction in maintenance costs. (6) On the other hand, this enables an increase in the availability of the CB. (7) It also allows for an improvement in the quality of maintenance. (8) Finally, it should be noted that data consultation is flexible, via any device with internet access, and the interaction, when properly implemented and programmed, is simple and intuitive. So, there is no need to constantly have highly qualified technicians to collect, process, calculate, and analyze data to identify the most appropriate strategies for the CB. (9) In this context, it is possible to reduce service staff and specialists during opening hours or enable them to focus on other tasks with greater added value. Such improvements are in line with the objectives of the maintenance area, contributing to improved management at a reduced cost to enable an increase in the profits of the companies, as well as to contribute so that they can increase their competitiveness and longevity in the current markets. It was noted that the implementation of this model improved the performance of the CB, which is no longer on hold when a fault occurs, increasing its availability. This increase stems not only from the possibility of faster communication by the operators by sending an e-mail to the maintenance department but also from the training courses that the company is providing to its employees in the area where this piece of equipment operates, to introduce TPM in the short term.

Although the field test was positive and promising, this study has some limitations. (1) The model [9] was only implemented on the CB, which limits the verification of its applicability and operability. It should therefore be tested in a more complex environment, where the model can be integrated with a significant range of equipment and possible limitations verified. (2) Although the model is low-cost and attractive, it will help micro- and small companies gain access to new technologies and methodologies that will enable them to improve maintenance and production, as well as provide a more efficient and effective response in the global market. However, its performance may be influenced by the maximum distance between the various devices that make up the system. Not all devices have the same communication range. This limitation can be overcome by changing the devices chosen and the communication protocol, which could influence the final cost. (3) The insertion of new technologies and platforms such as ThingSpeak within companies can lead to the occurrence of problems related to the management of large volumes of data and data protection, by possible computer attacks. And by increasing the common use of ThingSpeak and offering both paid and free versions, as the flow of information increases, its use can be compromised. Another drawback is associated with cybersecurity concerns [43,44]. Therefore, in the short term, the possibility of increasing the security system in the model [9] should be studied. This improvement can be achieved, for example, through blockchain for identifying devices, applications, and users, and through access control [45]. (4) The use of these new technologies in industrial installations with high electromagnetic noise may condition the use of BLE since it can cause temporary disturbances and data loss, system failures, and even loss of life. Electromagnetic interference (EMI) mitigation strategies can be used to prevent high-frequency coupling to sensitive signals, such as increasing the distance between the traces or adding an EMI Shield [46,47].

It should be noted that the introduction of the model is under development, having completed the installation of the various devices that make up the monitoring architecture, and the TPM will soon be introduced in the transport and bulk handling area of the respective company. The introduction of TPM, associated with the advantages of real-time monitoring of the implemented system, will allow the improvement in performance and agility of the maintenance function, improvement in production performance, and development of the motivation and professionalism of operators, as well as other surroundings of the bulk transport and handling area of the factory.

5. Conclusions

In the current global economy, efficient maintenance practices are assets for a company's competitiveness. Effective decision-making processes within maintenance management depend heavily on accurate and timely information that decision-makers rely on. Typically, data for maintenance decision making are collected through various methods, such as direct observation, regular visits, recording cycle times, downtime, repair time, and waiting time before or after a maintenance intervention. However, the traditional methods for obtaining this information are sometimes inefficient and the management of this information is time-consuming or is not correctly transcribed and properly processed and analyzed.

This paper therefore presents a case study in which the model developed by Mendes et al. [9] is implemented to verify its applicability and the advantages related to the introduction of I4.0-enabling technologies in the maintenance area. This model aims to overcome the inefficiencies and problems associated with managing all the information related to maintenance tasks, specifically in a CB. The model combines concepts from I4.0, LP, and TPM. This enables real-time monitoring of important indicators for the maintenance area and the personnel responsible for operations. The model [9] incorporates sensors to collect data such as stop time and cycle time, which are transmitted to a gateway. From there, the collected data are sent to the cloud and stored, processed, and analyzed using a free IoT application, ThingSpeak. This approach not only ensures data storage but also facilitates real-time visualization and the classification of stops by operators through an interface, such as a tablet, a smartphone, or a computer. The monitoring system within the model has been designed to be cost-effective, simple, quick to install, and compatible with various business contexts. Its non-intrusive integration allows for flexibility and adaptability. Moreover, the system enables continuous data collection in real-time, with easy accessibility through any fixed or mobile device with internet connectivity.

The results demonstrate that the model [9] adds significant value to companies by supporting maintenance decision making. By analyzing historical maintenance data alongside real-time monitoring, it can accurately predict future actions—the primary objective of the presented control system. Specific maintenance management parameters play a key role in this process. Once the model is correctly and fully implemented, and after observing its maturity, expansion to other areas of the shop floor is possible. This will lead to a cycle of continuous improvement, benefiting both the maintenance department and production processes.

For future work, it is recommended to conclude the model implementation and extend it to other areas within the factory. Evaluating the versatility and applicability of the model in different industrial settings will help identify potential gaps and opportunities for improvement.

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