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Synergies between Lean and Industry 4.0 for Enhanced Maintenance Management in Sustainable Operations: A Model Proposal

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Abstract: Companies actively seek innovative tools and methodologies to enhance operations and meet customer demands. Maintenance plays a crucial role in achieving such objectives. This study identifies existing models that combine Lean Philosophy and Industry 4.0 principles to enhance decision-making and activities related to maintenance management. A comprehensive literature review on key concepts of Lean Philosophy and Industry 4.0, as well as an in-depth analysis of existing models that integrate these principles, is performed. An innovative model based on the synergies between Lean Philosophy and Industry 4.0, named the Maintenance Management in Sustainable Operations (MMSO) model, is proposed. A pilot test of the application of the MMSO model on a conveyor belt led to an operational time increase from 82.3% to 87.7%, indicating a notable 6.6% improvement. The MMSO model significantly enhanced maintenance management, facilitating the collection, processing, and visualization of data via internet-connected devices. Through this integration, various benefits are achieved, including improved flexibility, efficiency, and effectiveness in addressing market needs. This study highlights the value of integrating Lean Philosophy and Industry 4.0 principles to improve maintenance management practices. The proposed MMSO model effectively leverages these principles, fostering agility, optimized resource utilization, heightened productivity and quality, and reduced energy consumption. The model not only serves as a tool for operational optimization and customer demand enhancement but also aligns with sustainability principles within the energy transition. Its successful application in the pilot test phase further reinforces its potential as a reliable approach for maintenance management and sustainable operations in both production and decision-making processes.

Keywords: maintenance; maintenance management; model; Lean Philosophy; TPM; Industry 4.0; sensors; sustainability; energy transition

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1. Introduction

In an increasingly competitive market, companies must focus on improving their production processes, answering more promptly and effectively to market needs, maintaining product quality, and reducing costs. Consequently, they must actively pursue novel and innovative management and organizational tools, making efforts in areas spanning production, maintenance, and beyond to optimize overall operations [1–4].

Maintenance is one area with the potential to significantly enhance the efficiency of industrial companies, and, over time, it has gained increasing importance within companies. Previously, maintenance activities were solely performed in response to equipment breakdowns, leading many to perceive it as a 'necessary evil' to be carried out only when necessary [5–9].

To be able to keep up with this dynamic and constantly growing environment of the increasingly globalized market, those responsible for the maintenance area have sought to insert new tools and methodologies that can support maintenance management, as well as in each of their technical interventions. Such efforts aim to attain the expected levels of excellence while ensuring manufactured products meet intended specifications with utmost quality, thereby broadening customer satisfaction and fostering the attraction of new clients [10–12].

To enhance competitiveness, numerous companies adopt work methodologies that guide and steer them toward continuous improvement. In this context, the Lean Philosophy (LP) is an already tested approach, yielding effective results by aiming to eliminate or minimize waste, thereby reducing production costs [13–15].

The Lean Philosophy (LP) encompasses several associated tools, one of which is the Gemba Walk (GW). This practice involves conducting regular visits to the factory floor, enabling the observation of processes and serving as one of the most effective approaches for identifying potential safety issues, sources of waste, equipment status, and fostering dialogue with employees. Consequently, it provides the means for improved control and oversight of all operations within the factory floor. However, this methodology has certain limitations arising from inadequate communication between operators and those responsible for conducting the GW. This communication gap can hinder the collection of relevant information and, hence, compromise data analysis [16–20].

The continuous evolution and integration of new technologies into production processes are revolutionizing industries, requiring companies to constantly seek for and adapt to differentiation in the increasingly competitive market. To secure enduring competitive advantages against their rivals, companies are embracing strategies such as Industry 4.0 (I4.0), which has obtained significant prominence. This transformative process combines and disseminates new technologies and innovations at a faster and more extensive pace than previous industrial revolutions, enabling the creation of novel virtual and physical manufacturing systems thereby fostering the development of smart factories. [21–24].

Smart factories, as part of I4.0, are increasingly complex in terms of technological equipment, maintenance, and control of manufacturing processes in general. The dynamic environment leads to an adaptation of maintenance processes and almost all organizational aspects [24–28].

As previously mentioned, the exclusive use of methodologies and tools inherent to the concepts of Maintenance, LP, and I4.0 are already widely used in an industrial context. Concerning the LP, Arsakulasooriya et al. [29], Gupta et al. [30], Ebeid et al. [31], Palmeira et al. [32], Pinto et al. [33], Costello et al. [34], Lopes et al. [35] and Hassan et al. [36], state that the successful application of this philosophy in the area of maintenance allows achieving better levels of management, as well as improving decision-making, maintenance interventions and their quality. Moreover, it allows for reducing equipment delivery times, reducing manufacturing and distribution costs, increasing productivity (obtaining larger benefits from manufacturing the same products), and improving product quality, as well as better waste control in manufacturing processes and maintenance interventions. On the other hand, with the emergence of I4.0, predictive maintenance (PdM) is becoming very relevant as an alternative to traditional assets maintenance management. This maintenance strategy makes it possible to have intelligent physical assets, allowing the acquisition and storing of the history of failures, repairs, and costs. This condition promotes the improvement of maintenance planning accuracy and effectiveness, offsetting the disadvantages of traditional maintenance management systems. Anh et al. [37], Rousopoulou et al. [38], Jasiulewicz–Kaczmarek et al. [39], Converso et al. [40], Ahmed et al. [25], Senthil et al. [41], and Mey et al. [42] state that the increase in I4.0 allows achieving significant improvements in the area of maintenance, such as early detection of failure, thereby executing interventions when strictly necessary while extending the useful life of equipment and increasing the availability of assets. Although the referred models are widely used to fill the gaps in the traditional maintenance management system, these are mostly developed to carry out real-time monitoring of the condition parameters related to PdM. However, sometimes, the data still need to be acquired and recorded in a traditional way (manually), reducing the efficiency of the maintenance management in the long term. Therefore, it is necessary to develop new systems that allow the acquisition of related information such as operating time and repair time, among other indicators, as well as enabling decision-making support and carrying out more sustainable maintenance interventions, which, to date, are not bridged with the systems developed in the literature. Thus, the objective of this study is the development of a new system called Maintenance Management in Sustainable Operations (MMSO) to support decision-making and all activities inherent to maintenance management through sustainable operations. The MMSO aims to generate valuable information that can contribute to substantially improving maintenance management, as well as to enable the optimization of production systems, and consequently lead to better and more efficient decision-making in an environment of sustainable operations in the industry in general. Hence, the novelty of this study relies on the results that can be used to help the maintenance management and the productive sector, as well as improve the environmental performance of the industries.

2. Review of Existing Models Combining I4.0 and LP Concepts

Through the bibliographic review conducted by Mendes et al. [43], it was possible to identify a wide variety of scientific works addressing the continuous improvement of maintenance management. The following research questions were used as a basis for the investigation: “Is there an interest among researchers and the academic community in these concepts, either individually or collectively?”; “Which companies have followed this trend?”; “What tools, methodologies, or technologies are commonly employed?”; “What types of work are being done concerning these concepts?”. The search was conducted within these databases using the keywords Maintenance 4.0, Intelligent Maintenance, Lean Maintenance, Lean Maintenance Techniques, Lean and Industry 4.0, Lean 4.0, Lean Smart Maintenance, and Lean 4.0 Maintenance [43].

For the selection of relevant works, the following criteria were established: publications in journals and conference proceedings available in the specified electronic databases between 2015 and 2021. It was also established that the works would have to be written in English, Portuguese, and Spanish, addressing the concepts under study. Conversely, bibliographic reviews, duplicate publications, studies unrelated to the topic, and works from platforms other than the specified ones were excluded [43].

The initial search yielded 552 articles from Google Scholar, 643 from B-On, and 501 from Science Direct, resulting in a total of 1696 articles identified. In the following step, the titles of each work were assessed to determine their relevance and significance. The evaluation was extended to include reading the titles, abstracts, and keywords. In the final step, after a refined search process, 68 articles were identified for a more detailed and comprehensive analysis. The remaining articles were excluded either due to not meeting the specified criteria or not aligning with the focus of the conducted research [43].

Thus, for the construction of the system, and after analyzing several published scientific articles, 26 models were chosen [43]. Table 1 summarizes the type of research, results, limitations, and performance of these models in the methodology section. This section analyzes the interaction of Maintenance (M), LP, and I4.0.

Table 1. Summary table of the 26 publications analyzed.

Authors	Industry	Interaction Concepts	LP Tools	I4.0 Technologies	Type of Study	Benefits	Limitations
Mayr et al. [44]	Electrical/electronics industry	LPI4.0	TPM	Cloud computing (CC); Condition monitoring; Sensors; Graphical use interface	Model and case study	It aims at perfection in all daily activities. Integration of employees. Equipment monitoring.	In addition to technical challenges, future research should focus on how to implement lean 4.0 as a holistic concept. One key area is employee onboarding to avoid replicating the failures of the introduction of computer-integrated manufacturing. Furthermore, trade-offs and goal conflicts provide a promising avenue for future research.
Phuong & Guidat [45]	Textile industry	LPI4.0	Value Stream Mapping (VSM)	Radio Frequency Identification (RFID)	Case study	Visualization of potential problems in real time, quantity produced, number of stops on the line, among others.	Studies should be carried out regarding social and environmental indicators and their interactions should be considered when further developing the proposed scheme. Big Data (BD) can be used for forecasting purposes to avoid potential waste in resource consumption and any harm to the worker.
Spenhoff et al. [46]	Transport and logistics industry	LPI4.0	Heijuka; Every Product Every Cycle 4.0 (EPEC 4.0)	Cyber-physical systems (CPS)	Model and case study	Operate the production system as flexible and efficiently as possible.	The presented proposal has not yet been tested by its implementation in practice. Even if the proposal has been validated in the company, it cannot be considered a general application solution, despite being a promising proposal. Utilizing CPS and moving to I4.0 will require massive investments in hardware, software and the associated information technology infrastructure wich needs to be aligned with operations and business strategy.

Table 1. *Cont.*

Authors	Industry	Interaction Concepts	LP Tools	I4.0 Technologies	Type of Study	Benefits	Limitations
Rifqi et al. [47]	Facilities Management and Maintenance Company	LPI4.0	Kaizen	Internet of Things (IoT); Computerized Maintenance Management System (CMMS)	Case study	Reduction rate of complaints. Improvement of operational, social and economic performance.	Organizational change and acceptance of this change can be a limitation. Another limitation has to do with the fact that employees require a considerable amount of training and are involved in continuous improvement environments.
Ramadan & Salah [48]	Electrical/electronics industry	LPI4.0	5S; Standard Work; Poka-Yoke; DynamicVSM	Information and Communication Technologies	Model and case study	Real-time data collection. Production control. Waste reduction.	In order to improve the proposed, an intelligent real-time waste system must be developed to detect the root causes of the seven types of waste in real time to anticipate failures in advance, to avoid them and reduce their negative impacts on the overall level of leanness.
Ma et al. [49]	Automotive	LPI4.0	Jidoka	CPS; Internet; IoT; CC; Function Block	Model and case study	Considerable improvement in production performance at a global level. More decentralized controllers. Cost reduction.	New SLAE-CPS tools based on C-PaaS must be developed to achieve agile implementation and remote data analysis. Other limitation is related to security. Thus, the general security mechanism for SLAE-CPS should be considered such as detection, communication, actuation control and feedback security. Further tests should be carried out to verify the stability of the system.
Frontoni et al. [50]	Shipping industry	LPI4.0	Lean principles	RFID	Case study	Reduced cost and Lead Time, with a higher level of asset security and a real-time data sharing policy.	The prediction task, Remaining Lifetime is often affected by uncertainty in the presence of non-linear and non-stationary conditions.

Table 1. *Cont.*

Authors	Industry	Interaction Concepts	LP Tools	I4.0 Technologies	Type of Study	Benefits	Limitations
Ferreira et al. [51]	Wood Industry	LPI4.0	iLean Define, Measure, Analyze, Improve, and Control (DMAIC); Single-Minute Exchange of Die (SMED); VSM	-	Model and case study	It helps to solve problems easily and accurately. Reduction of the time required to change the machine.	One of the limitations is that it requires specialized personnel to use and understand the appropriate to search for problems. As well as it re-quires that they are able to define modes of action for their resolution. Another constraint in-volves the companies' resistance to change, which could be a problem when applying this methodology. A better tracking of the gains obtained through the improvements achieved should be implemented.
Kostoláni et al. [52]	Automotive	MI4.0		Augmented reality (AR); IoT; BD; E-maintenance; CC; Condition monitor (CM)	Model and case study	Increased productivity, efficiency and quality of processes. Downtime due to an unexpected equipment malfunction has decreased significantly.	The system must be validated in other industrial areas to verify its application flexibility as well as possible gaps. In addition, it would be interesting to verify the integration of AR systems to existing multilevel control structures and the extension of the application's functionalities, such as visualization without reference, control of spare parts and documentation.
Paolanti et al. [53]	Cutting Machine	MI4.0		PdM; Sensors; Programmable logic controller	Model and case study	Prediction of machine status with high precision. Improved system performance.	In order to verify its applicability, it should be ap-plied to a more robust dataset, investigating diverse failure scenarios, exploring a different set of resources, particularly in the frequency domain.

Table 1. *Cont.*

Authors	Industry	Interaction Concepts	LP Tools	I4.0 Technologies	Type of Study	Benefits	Limitations
Ghouat et al. [54]	-	LPI4.0	Lean principles	Cyber Physical Production Systems; BD	Model	Real-time data analysis. Improvement in decision making and responsiveness of the system.	Failure to correctly identify the indicators can compromise the effectiveness of the Lean approach levers. Lean integration needs to be further studied and validated.
Deuse et al. [55]	-	LPI4.0	GaProSys 4.0	Joint structure of Lean and I4.0	Model	Good connection between Lean and I4.0. Assist companies in the evaluation and selection of approaches depending on the structure of the company	A selection guide should be developed to assist companies in evaluating and selecting suitable approaches, depending on the structures of the company. The implication for other lean methods should also be analyzed.
Itani et al. [56]	Window manufacturing company	LPI4.0	Decision-Making Tool (e.g., Just-in-Time (JIT), VSM, TPM, SMED)	Simulation	Model and case study	Increased productivity. Reduction of the number of employees in the processes, waiting time and time consumed by activities without added value. Allows you to determine the best resource allocation scenario to increase productivity.	The limitations of the study are the input data for the simulation model, which is restricted to three days of production, the sequencing of orders that can influence productivity and the operating time which has constant numbers. An algorithm should also be developed to an extent which allows performing line balancing dynamically utilizing the simulation model, changing different factors simultaneously and implementing the linear line balancing method.

Table 1. *Cont.*

Authors	Industry	Interaction Concepts	LP Tools	I4.0 Technologies	Type of Study	Benefits	Limitations
Koenig et al. [57]	Aeronautical industry	MI4.0		IoT; CC; Wireless data transmission; Sensors	Case study	Effective monitoring. Detection of failures in the initial phase. Improved maintenance performance.	The application of the system contributes to improving maintenance management and its interventions. however, the use of the sensors after exhausting the batteries, must be replaced to enable the system to function. Replacement that entails a high number of hours and cost. To be cost-effective, as well as ideal for continuous use, the perfect sensor would have an external power supply, measure vibration and temperature, and be configurable for minimal downtime. the study of a prototype of a more suitable sensor must be carried out, as well as the study of the software, due to its high cost.
Bumblauskas et al. [58]	Electrical circuit breakers	MI4.0		Smart maintenance decision support system; PdM; BD; Analytical hierarchy process	Model and case study	Improved asset lifecycle. Cost reduction. Establishment of maintenance plans and remote monitoring.	It would be interesting to add Industrial CPS, IoT, artificial intelligence to support decision-making by maintenance managers.
Lewandowski & Olszewska [59]	Automotive	MI4.0		Automated task scheduling system	Model and case study	Reduced maintenance time. Improved maintenance quality. Prioritizes and selects tasks.	The study does not critically present the problems related to cybersecurity and should be explored further.

Table 1. *Cont.*

Authors	Industry	Interaction Concepts	LP Tools	I4.0 Technologies	Type of Study	Benefits	Limitations
Ceruti et al. [60]	Aeronautical industry	MI4.0		Additive manufacturing; AR	Case study	Improved performance and maintenance flexibility. Ease of learning and maintenance. Reduction of errors in the processes.	One of the limitations stems from the fact that there is no regulation by the aeronautical authorities that should start to address the problems related to the introduction of this new technology to allow its wide diffusion in the aeronautical field. Another limitation has to do with the need to develop ergonomic hardware devices robust enough to support AR, and software tools capable of dealing with problems related to different lighting conditions, object occlusion, among other problems. Early stage that raises costs, making it unrealistic to apply the technology to a high number of spare parts, requiring consideration of spare parts availability, component criticality, manufacturing feasibility and regulations.
Kolberg et al. [61]	-	LPI4.0	Kanban	CPS; ICT	Model	Improvement of the production process. Highly customized products.	However, more lean methods should be developed, deepened and combined with existing lean solutions along with the integration of inferior CPS work stations of architectural interface.
Arrascue-Hernandez et al. [62]	Textile industry	MLP	5 S; VSM; Ishikawa; SMED; Hierarchical Analytical Process; TPM (Autonomous maintenance)		Model and case study	It allowed to improve the production line, reducing the delivery time of the orders and the delivery time. Increased sales.	Presents a model, however this does not present the implementation phases in a succinct and schematic way, having a short description of the phases, which may raise doubts in the use of the respective model in another business area.

Table 1. *Cont.*

Authors	Industry	Interaction Concepts	LP Tools	I4.0 Technologies	Type of Study	Benefits	Limitations
Meddaoui [63]	Automotive	MLP	TPM; Overall Equipment Effectiveness (OEE)		Model and case study	Performance improvement of your operational processes and OEE. Cost reduction.	The limitation of the proposed model is to link and restrict the study of the maintenance process to two main processes, preventive and corrective.
Epler et al. [64]	-	MLP	Technical Systems for Special Purposes; 5S; Visual system; Kanban; Technical systems maintenance; Layout		Model and case study	Reduction of maintenance cycle time. Improvement of intervention and maintenance management. Increased efficiency and effectiveness.	The application of the proposed model must be extended to other industrial types and sizes to verify its applicability and verify possible limitations.
Ramakrishnan & Nalusamy [65]	Industry in general	MLP	TPM; Kaizen; Standard Work		Case study	Reduced downtime and runtime. Improved maintenance performance.	The authors present a structure, however it should be more developed in order to be able to help/show the order in which they suggest the implementation of TPM or other pertinent indications for replication in other industrial areas.
Wenchi et al. [66]	Liquefied Natural Gas Industry	MLP	VSM; Kanban		Case study	Improvement of the efficiency of production processes. Identification of activities that do not add value and waste in the process. Reduction of lead time and total cycle time.	A root cause analysis of the low level of usage and success in manufacturing and non-manufacturing should be done; building information modeling (BIM). BIM is a demonstration of the entire construction lifecycle that allows redefining the scope of the work and has been widely used in engineering (Shou et al. 2014).

Table 1. *Cont.*

Authors	Industry	Interaction Concepts	LP Tools	I4.0 Technologies	Type of Study	Benefits	Limitations
Lacerda et al. [67]	Automotive	MLP	VSM; Kaizen; SMED		Case study	The cycle time in the assembly sub-process, the number of operators, the waste and the level of existence have been reduced and one of the main bottlenecks has been eliminated.	The study does not present a structure to be more easily replicated.
Pombal et al. [68]	Management of maintenance workshops	MLP	5S; Kanban; Visual management; Mizusumashi.		Case study	Reduction of waste, in the time needed to locate and replace consumable material. Better inventory control and workshop management.	Despite mentioning the methodologies to be applied, the study does not present a structure to be more easily replicated.
Konstantinidis et al. [69]	Automotive	MI4.0		Mobile AR maintenance assistance; AR; Computer Vision	Model and case study	Support in the development of maintenance technicians. Allows the visualization of detailed instructions.	Other test scenarios should be considered, including different operators with varying levels of expertise.

Subsequently, five models were chosen for a more detailed analysis as they effectively integrated the concepts of Maintenance, Lean Production (LP), and Industry 4.0 (I4.0). The selection of these five models was based on various criteria, including their potential for enhancing production and decision-making processes, monitoring equipment effectively, driving continuous improvement in processes, optimizing maintenance-related procedures, enabling smart maintenance practices, and demonstrating flexibility and ease of application.

Kinz et al. [70] developed an intelligent maintenance model for resource and risk optimization, which aims to improve asset management. The smart component of this model embodies the efficiency perspective known as Lean Smart Maintenance (LSM), which emphasizes intelligent maintenance management and continuous improvement. The Lean aspect of this methodology stems from the principles of Lean Philosophy, wherein the model seeks to minimize losses at the onset of maintenance management systems, all the while prioritizing the sustainable utilization of resources. The authors successfully implemented this model in the steel industry, specifically within a steel rolling mill. For the successful implementation of the model proposed by Kinz et al. [70] (Figure 1), a systematic evaluation and classification of assets must be carried out. This evaluation entails employing a tool that assesses and identifies the critical assets within a production system. This is an important phase as it ensures that limited resources are effectively directed toward managing critical assets. The assessment is carried out by a team consisting of maintenance elements and operators with experience in factory floor assets, using the Failure Modes and Effects Analysis (FMEA) methodology [70].

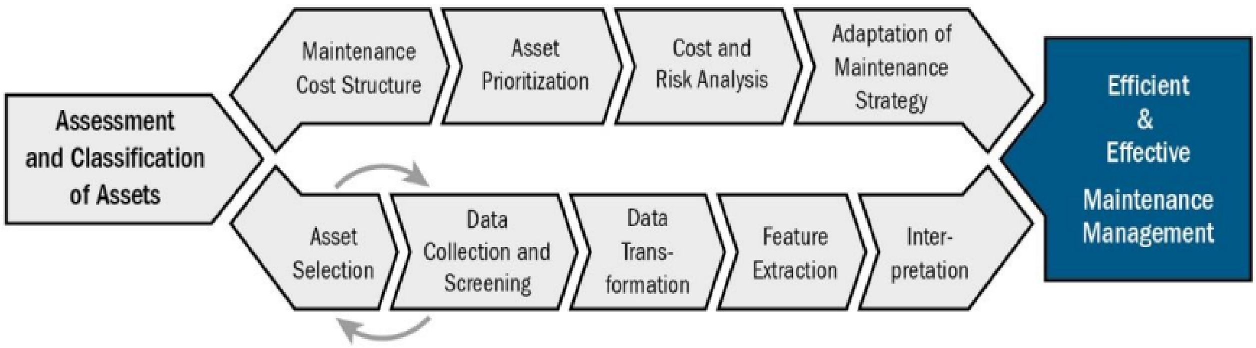

Figure 1. Model of the LSM process [70].

The entire process must be documented, as it will support the knowledge of maintenance management following the LSM. Following the asset evaluation and classification conducted using MATLAB, risks are grouped using the K-means algorithm. Once the evaluation, classification, and risk analysis are completed, the selection of assets for readjusting maintenance activities takes place. Subsequently, these chosen assets undergo monitoring and surveillance [70].

The model proposed by Kinz et al. [70] and its subsequent implementation in the case study revealed several opportunities for improvement. The risk assessment process significantly enhanced decision-making concerning the management of strategic assets. By adopting LP principles, the maintenance strategy was adapted, resulting in the reduction of several risks without necessitating substantial investments. Furthermore, the integration of I4.0 facilitated the development of a failure prognosis model [70].

Shahin et al. [71] developed a cloud-based Kanban Estimated Actual Total (EAT) decision support system to showcase the feasibility and benefits of integrating Industry 4.0 technologies (cloud computing) with lean tools (Kanban).

Kanban, while effective in resource management, does present certain limitations when applied to an enterprise-wide perspective. To address these limitations, Shahin et al. [71] devised a cloud-based platform that leverages the inherent capabilities of I4.0 technologies. This platform, when well-implemented, holds the potential to significantly enhance overall business management. Shahin et al. [71] developed and implemented this model within a generic service operations management company.

The structure proposed by Shahin et al. [71] comprises six interconnected elements that are accessible, expandable, and toggleable from any modern web browser. Each element is secured with authentication/password, determining its size and scale (Service Plan). The platform's database stores essential production information, while a cloud-based server hosts all web elements. The user interface encompasses various menus, granting access to authorized employees.

According to Shahin et al. [71], there is a 5-step process for implementing the system. Step 1 involves building the estimated total value of the work and the individual activities to be performed. Step 2 entails establishing a timeline for the tasks. Step 3 comprises simulating the decision support system. Step 4 consists of gathering the actual production quantities. Step 5 focuses on displaying the work and activity progress based on the Kanban EAT system, accessible through various internet-enabled devices [71].

Magadán et al. [72] proposed a monitoring system for electric motors based on I4.0. The developed system serves as the basis for a PdM and operational anomaly detection system. To ensure cost-effectiveness, the system was developed using low-cost hardware and software components, such as multi-sensor and gateway modules, open-source software, and a free version of the IoT.

The system works through sensors connected to the electrical motors, collecting the data subsequently transmitted to the gateway. The gateway serves the purpose of receiving and forwarding the sensor data to the cloud, which can be stored, processed, and visualized via ThingSpeak. Accessible through both mobile and fixed devices with internet connectivity, this cloud-based architecture facilitates data management [72].

Figure 2 shows the proposed system, consisting of sensors and other devices in the first layer, enabling the collection of the desired information, although all data processing is conducted within this layer.

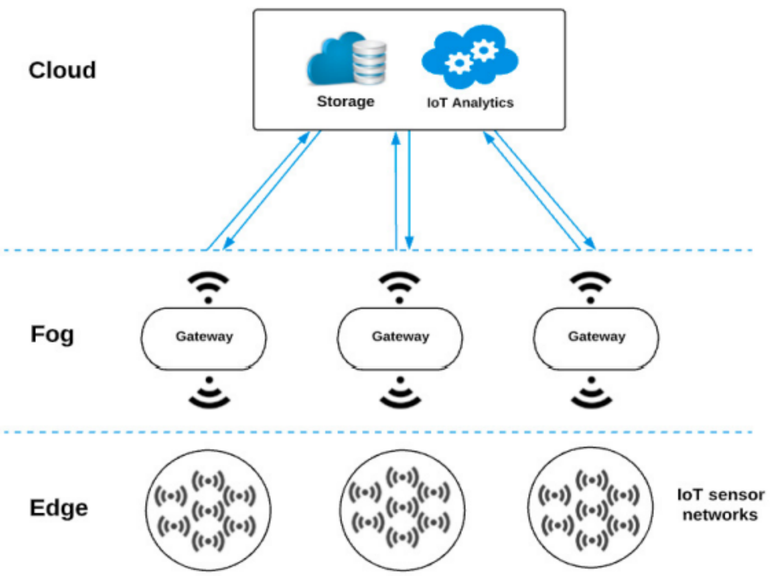

Figure 2. The architecture of the low-cost real-time monitoring system for electric motors [72].

This layer comprises a cost-effective multi-sensor module, SensorTag CC2650, equipped with an ARM Cortex-M3 processor and five integrated sensors, including motion sensors (MPU9250) and humidity sensors (HDC1000). It also includes an accelerometer, a magnetometer, and a gyroscope. The second layer consists of gateways responsible for gathering data from the various sensors and establishing connectivity with the third and final layer. The elements that make up the second layer are the gateways, composed of Raspberry Pi 3 Model B+ on-board computers. The last layer enables the storage of the collected data, which, in turn, are analyzed and visualized through a storage system and an IoT analysis service [72].

The model also incorporates the use of the Fast Fourier Transform (FFT) on the measured motor accelerations. The FFT was calculated on the multi-sensor module and the gateway. CMSIS DSP V1.10.0 software is used with the module, designed for devices based on Cortex-M processors. The multi-sensor modules and gateways communicate via Bluetooth, enabling the transmission of small streams of sensor-collected data. To establish a connection with the final layer, the gateways transfer the data via HTTP to the ThingSpeak REST API [72].

Ashjaei and Bengtsson [73] proposed a system to improve maintenance management. The first layer is composed of physical resources: factories, machines, tablets, operating rooms, and other devices for storing and processing data. The primary function of the latter is to establish connections and filter the data collected from the factory, machines, and equipment, sending it to the second layer. The last layer, the cloud layer, is composed of a data processing and storage unit. Communication between the two layers is possible through the local network. However, the system can support data coming from outside through the long-distance network also existing in the system. The operation of the system consists of collecting data through sensors that are coupled to the physical resources. Subsequently, the collected data are processed and transmitted to the monitoring room and mobile devices, enabling real-time monitoring of the status of the physical resources. Both the local and long-distance networks facilitate control and monitoring, and in the event of detecting parameters outside the established range, the system issues an alert.

Islas et al. [74] developed a system dedicated to the continuous monitoring of aluminum melting furnaces. Given the critical significance of temperature control in the casting process for product transformation, the system enables the monitoring of furnace operations within the temperature range of 600 °C and 620 °C.

The system uses XBee technology to establish a wireless sensor network. The network controller is responsible for transmitting the collected furnace operation data to a Local Area Network (LAN) via the internet [74].

The wireless sensor network is responsible for measuring the electric current in the furnace and transmitting the data to the coordinator. Serving as the network manager, the coordinator receives the data and identifies the origin of each data stream. Once the data are stored and processed, they become accessible for visualization through a web server. Through an IoT platform, maintenance services can access or receive an alert by email [38]. For the implementation of the prototype proposed by Islas et al. [38], some software and hardware are required, including X-CTU software, Xbee Pro S2B modules designed with the Zigbee protocol, XBee shield, Arduino Uno, Raspberry Pi, power supply, transformer, local area network, IoT, Dashboard, among others [74].

Identification of Advantages and Limitations of Selected Models

Although the five selected models address some of the concepts of interest to the present study and have some similarities, such as real-time monitoring of the condition of physical resources, they show some specific advantages and limitations.

Although the LSM model addresses the three concepts of Maintenance, LP, and I4.0, as intended, it is not specific at all stages of its implementation. For instance, the asset monitoring phase is not thoroughly described, leaving uncertainties regarding the hardware and software components used and the approach taken for monitoring selected assets. Another limitation lies in the fact that the proposed model has only been implemented in an industry characterized by high-cost assets and a production chain system with high failure costs, raising questions about its replicability in small or medium-sized companies. Moreover, risk assessment within the LSM model is a time-consuming process. Even with the creation of a criteria assessment tool, it was not possible to assess all the important objectives.

The system developed by Shahin et al. [71] effectively addresses two of the three concepts, LP and I4.0, not addressing the concept of Maintenance. The system's primary advantage lies in its ability to offer real-time visualization of the production process, including metrics such as the actual quantity produced, hours of work used, the number of items with poor quality, and the occurrence of line stops. The proposed system contributes to improving the production system and obtaining important indicators of it, allowing better decision-making. Although the system is described, it lacks a detailed description of the constituents needed to compose the system (hardware and software), as well as the implementation phase. A more detailed description of these aspects would be beneficial in understanding the system's technical and operational aspects, facilitating potential replication or adaptation in other contexts. To enhance the applicability and understanding of the proposed system, future studies should focus on providing a more thorough account of its components and implementation process. This would allow researchers and practitioners to gain valuable insights into the system's practical deployment and potential benefits in various manufacturing settings.

The system proposed by Magadán et al. [72] involves the concepts of Maintenance and I4.0, presenting itself as a straightforward and cost-effective solution for the industrial environment. Although economically appealing, it still needs to be further developed to be more complete. The areas for improvement include the creation of an automatic anomaly detection system, proper labeling of all received and stored data in the cloud, and the development of a predictive model to estimate the probability of electrical motor failure. By addressing these aspects, the system can effectively contribute to reducing maintenance costs and provide a more robust and reliable solution for industrial applications.

Ashjaei and Bengtsson [73] propose a system that integrates the concepts of Maintenance and I4.0. The primary focus of this system is to address challenges related to the speed of data transmission and data security. This system enables vibration monitoring, offering the capability to implement certain actions remotely, such as adjusting rotation speed to mitigate vibrations. This feature significantly contributes to vibration reduction and improves overall operational efficiency. Moreover, the system facilitates communications through both the local network and the long-distance network, extending its capabilities to interact with external elements. This integration with external devices brings added advantages, as it enables efficient communication between internal and external devices, fostering enhanced system functionality and broader applicability across various operational scenarios.

The system proposed by Islas et al. [74], which is designed to monitor furnaces' temperature, can improve maintenance performance. This system exhibits versatility, making it applicable in various domains and adaptable to monitor different parameters. However, it should be noted that the system does not address the concept of LP. Despite this limitation, its potential for expansion and diversification in monitoring various aspects renders it valuable for maintenance optimization and potential integration with other frameworks that may include LP principles.

Thus, the five systems address some of the three targeted concepts, with the model proposed by Kinz et al. [70] encompassing all three. However, it is worth noting that this model is more complex compared to the others. The system proposed by Shahin et al. [71] involves the LP and I4.0 concepts but does not include the Maintenance concept. On the other hand, the architectures presented by Magadán et al. [72], Ashjaei and Bengtsson [73], and Islas et al. [74] are based on Maintenance and I4.0 without incorporating LP in their respective models. Integrating the LP philosophy into these systems would bring forth numerous advantages, fostering enhanced performance and continuous improvement both in the production system and the maintenance department. By incorporating LP principles, these systems could optimize resource use, streamline processes, and promote efficiency and flexibility in both production and maintenance activities. This synergy of concepts would contribute to a more comprehensive and effective approach to industrial management, ultimately leading to improved overall operational performance and competitiveness.

The five proposed systems have some similar limitations. One limitation shared among these models is the maximum distance constraint between various devices, which can vary depending on factors such as sensor type, communication protocol, and gateway specifications. If the maximum connection distance is exceeded, data transmission becomes challenging, resulting in a reduced amount of collected data. Another limitation concerns the volume of data to be collected and analyzed. The complexity of data collection further compounds this issue. While one of the proposed systems considers enhancing system security, all analyzed systems still present certain gaps in this aspect. Addressing these limitations would be important in optimizing the performance and efficiency of the systems. Overcoming the distance constraint through improved communication protocols and gateway designs would facilitate data transmission. Moreover, devising strategies to handle and analyze large and complex datasets effectively is relevant for gaining meaningful insights and making informed decisions. Enhancing system security would also be indispensable for ensuring data integrity and protection against potential threats, promoting the overall reliability and trustworthiness of the systems. By addressing these common limitations, the proposed systems can be refined and made more robust, contributing to their successful implementation and yielding valuable results across various industrial settings.

3. Proposal for a Lean Maintenance Methodology in an Industry 4.0 Environment

Upon analyzing existing architectures, it becomes evident that there are several models and systems designed to enhance the management of maintenance services, with most of them being comparatively more complex in terms of implementation. Among the analyzed architectures, some stood out for their system simplicity and versatile applicability. However, none of these models integrated all three concepts simultaneously. The model presented in this work introduces a monitoring system that combines I4.0 and TPM with Lean methodologies. The development of this monitoring system drew inspiration from the approach presented by Magadán et al. [72]. By integrating these concepts, our model aims to create a comprehensive and streamlined system that facilitates efficient maintenance management and supports continuous improvement in the company's operations.

The MMSO was developed following a thorough analysis of various existing models in the literature, tailored to align with the primary objective of this study. During its design, it was determined that the system would be built upon the I4.0 concept. This decision was driven by the ease and flexibility that the I4.0 concept offers in continuous monitoring through sensors and other devices. This capability enables the system to collect, process, and store a large amount of data in real-time, facilitating the accurate collection of crucial parameters. Through careful analysis of these data, the system contributes to enhanced decision-making in the management domain, leading to improved resource management and utilization.

I4.0 brings with it significant advantages for companies, and the maintenance sector is no exception, benefiting from the newfound capabilities of remote controls and access, as well as the automation of processes and devices. The increase in technologies facilitated by I4.0 leads to enhanced data collection and analysis of important data such as downtime, cycle time, and repair time, among others. These advancements yield several benefits, such as minimizing unscheduled downtime, continually improving production efficiency, mitigating risks, enhancing safety, and promoting environmental sustainability.

To exploit the advantages offered by I4.0 and to enhance the existing systems analyzed alongside the one developed by Magadán et al. [72], LP was integrated. This strategic management methodology, combined with I4.0, enables the attainment of continuous improvement in both the production system and the maintenance department. Maintenance plays a crucial role in the production process of any industry, and the introduction of LP contributes significantly to the enhancement of this department, not only in terms of management but also in the quality of its interventions.

The MMSO was developed to be implemented in the production and maintenance areas. Its simple and expedient configuration allows for easy application. Moreover, the system is composed of cost-effective elements, turning it into a highly versatile and economical solution for monitoring machines and equipment. This adaptability promotes its replication and deployment across other industrial sectors of the companies. By adopting I4.0 and LP, the organization can achieve multiple benefits, including significant reductions in energy consumption and a smoother transition towards energy-efficient practices. These methodologies enable an organized, efficient, and optimized production process, allowing for better energy management, identification of energy wastage, and more sustainable operational practices. Moreover, continuous improvement driven by I4.0 and LP can lead to the implementation of energy-saving measures and the adoption of innovative technologies that support the organization's energy transition goals. In this way, the combined application of I4.0 and LP not only enhances production and maintenance but also contributes significantly to the organization's energy efficiency and sustainability initiatives.

Figure 3 shows the developed model, which comprises three distinct layers. The first layer is composed of physical resources that constitute the factory floor. In the second layer, communication components provide the connection between the various layers and other devices like switches, smartphones, and tablets, among others. The third layer, the cloud, is composed of an IoT platform service and a data storage and processing system. While the model encompasses real-time monitoring capabilities, there is scope for further enhancement through the implementation of Total Productive Maintenance (TPM). By integrating TPM into the existing framework, the system can achieve a more comprehensive approach to maintenance, fostering improved equipment reliability, efficiency, and overall production performance.

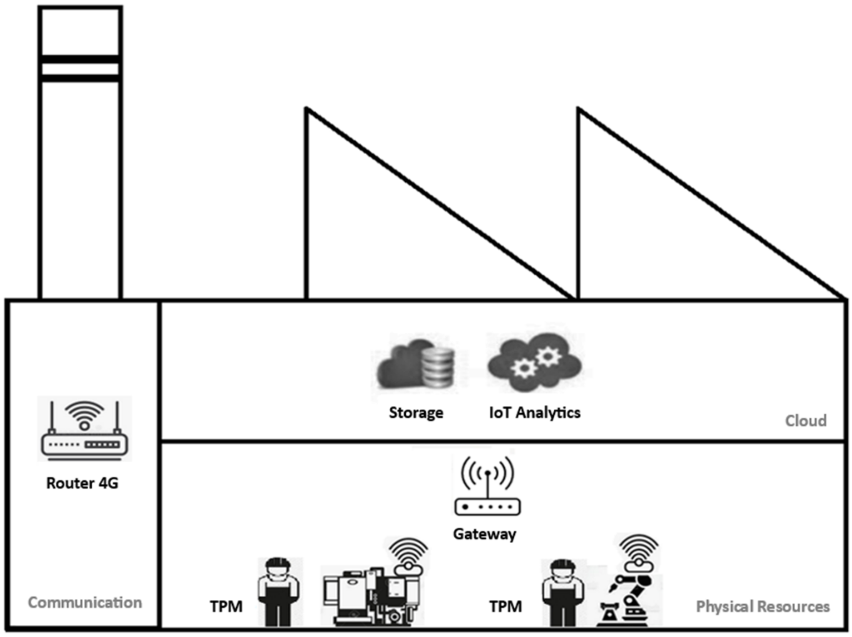

Figure 3. Model proposal that integrates the 3 concepts under study to improve maintenance management.

It must be highlighted that the MMSO was based on maintenance management and its corresponding indicators. Furthermore, this approach has the potential to yield valuable insights that can significantly enhance the management of production processes. The integration of maintenance-related data into the overall production management strategy can lead to more informed decision-making, increased operational efficiency, and optimized resource allocation.

3.1. Description of the Operation of the Proposed Methodology

To enable communication between the different components comprising the system, various solutions such as Wi-Fi, Global System for Mobile (GSM), or Bluetooth Low Energy (BLE) can be explored. For inter-component communication, the BLE technology was selected, as it offers wireless connectivity with reduced energy consumption in devices that do not require the transmission of extensive data. This makes it an ideal choice for applications with limited energy capacity, ensuring efficient and extended operation while conserving valuable resources [75].

The monitoring of machines and equipment, as well as the total number of parts produced with or without defects, is carried out using wireless sensors that collect and transmit data to the gateway (Figure 4). If a stop occurs, the operator can classify the type of stop using a tablet, smartphone, or device connected to the internet. The stoppage classification is carried out by accessing the ThingSpeak internet platform, where it is possible not only to enter the stoppage classification but also to provide comprehensive visibility into all associated machine indicators and other relevant data. The gateway bridges the gap between physical resources and the cloud through sensors that collect and send data (Figure 4a). This processes the data sent by the sensors, which, in turn, are transmitted to the cloud (Figure 4b).

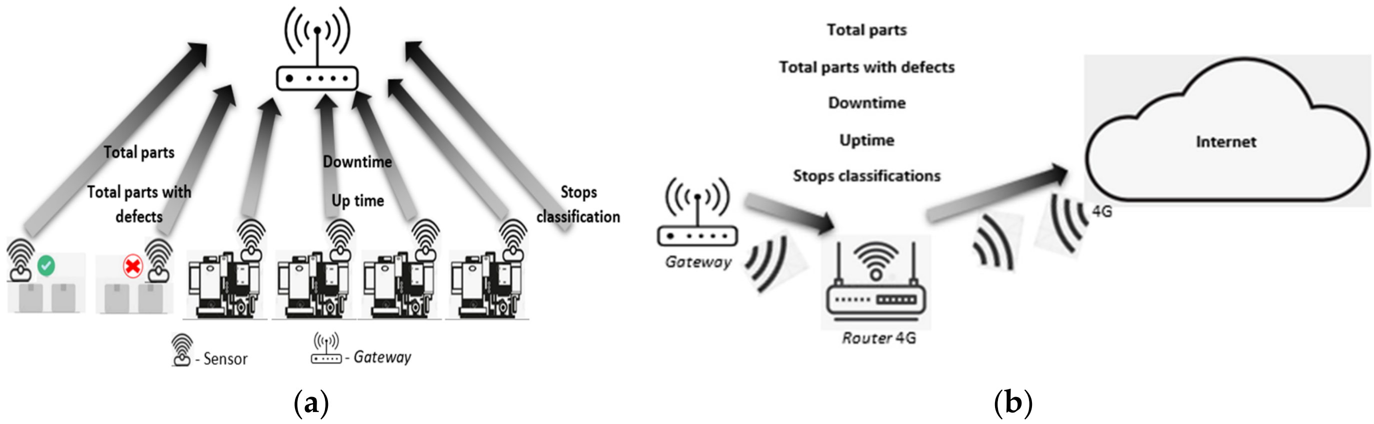

Figure 4. The interface between the three layers: (**a**) Monitoring of downtime, running time, and total parts with and without defects produced; (**b**) Gateway interface with the cloud layer.

In the last layer, the processor stores all the information and works as an interface for data visualization through a free version of ThingSpeak. This setup enables aggregation, analysis of data flow, and on-demand visualization through various devices such as computers, tablets, dashboards, touchscreens, and smartphones, among other devices. Figure 5 schematically and succinctly describes how the proposed model operates.

3.2. Description of the Proposed Hardware

Sensors are the components responsible for collecting and transmitting data to the gateway. The selected sensors for this system are the April USB Beacon 306 and the TCRT5000 infrared sensor module. The AprBrother's April USB Beacon 306 BLE sensor is USB powered, based on nRF52820, with an external antenna that has a range of up to 100 m, frequency 2.402 GHz to 2480 GHz, secure simple pairing and AES-128, ensuring effective machine monitoring and equipment. To account for items produced with or without defects, the TCRT5000 infrared sensor module can be utilized. This module serves as a counter, accurately determining the number of well-produced parts and/or defective items. The optical sensor module, LM393, has high accuracy in detecting obstacles and can identify an object up to 12 mm away. It has digital and analog output modules with working voltage from 3.3 V to 5 V. It has a comparator output with strong driving ability for more than 15 mA; adjustable precision potentiometer to adjust sensitivity; output form digital switch output (0 and 1); small board PCB size: 3.1 cm × 1.4 cm. However, for this accounting to be possible, the TCRT5000 sensor must be connected to the Arduino Nano 33 BLE microcontroller, thus allowing the design of devices at a short distance using the BLE protocol.

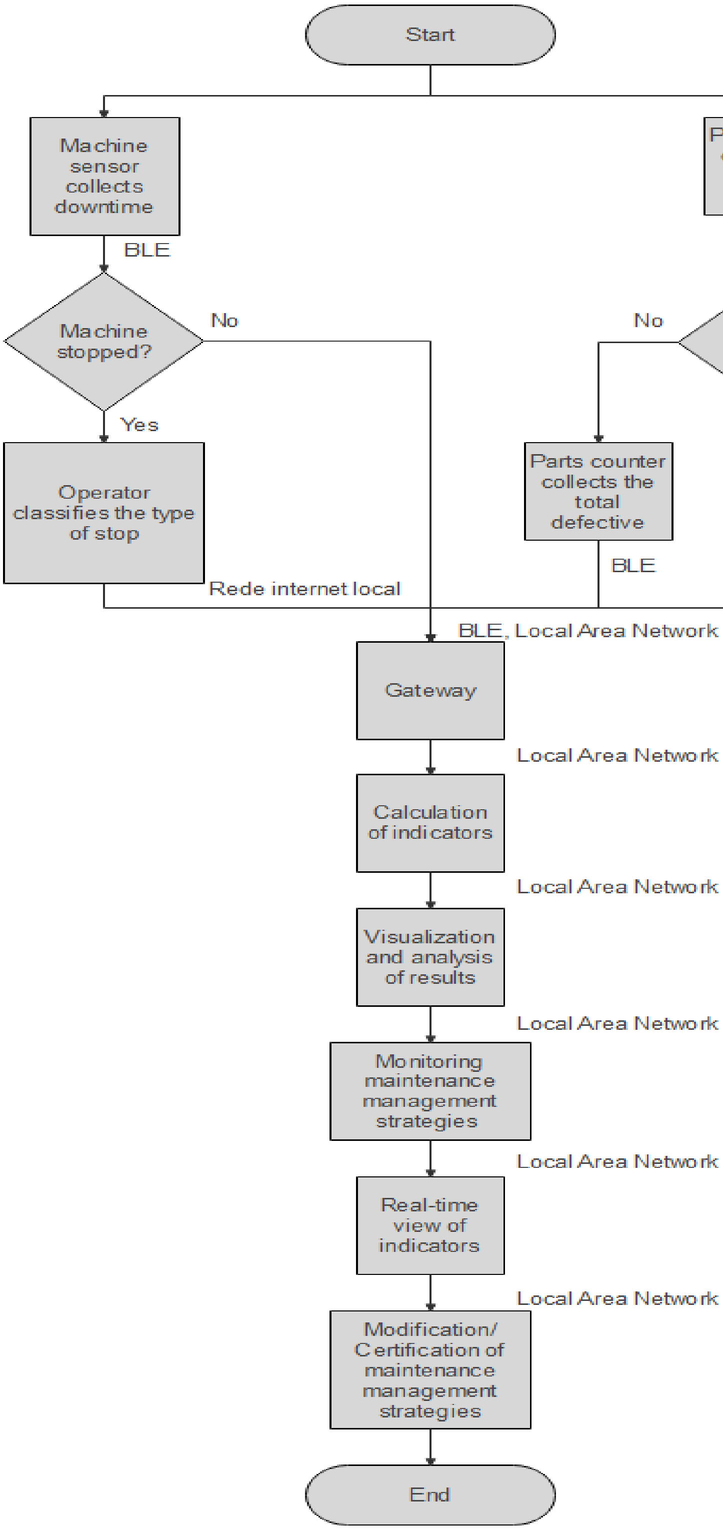

Figure 5. Flowchart describing how the system works.

The gateway has the function of receiving the signals transmitted by the sensors. For this purpose, the Raspberry Pi 3 Model B+ was chosen, as it possesses the capability to receive BLE signals. This device features 1 GB of RAM, 1 HDMI port, and 4 USB 2.0 ports, along with CSI and DSI ports that enable connectivity to cameras and touch screens. Additionally, the device supports Ethernet rates of up to 100 Mbps and may establish communication through both Wi-Fi and BLE protocols.

On the cloud layer, a free version of ThingSpeak is implemented, as previously mentioned. This platform enables data aggregation, as well as visualization and analysis of data flow through the information transmitted by the gateways (Figure 6).

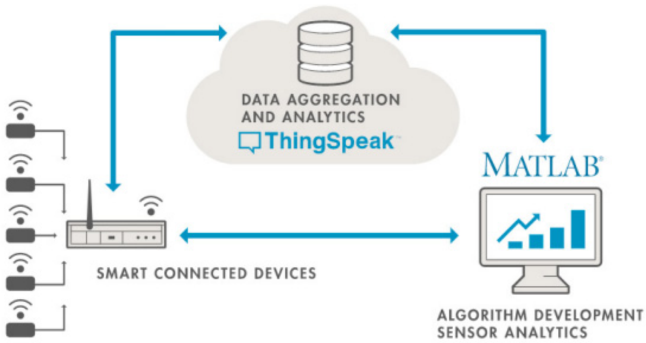

Figure 6. IoT analysis platform [72].

4. Discussion

The proposal of the presented model designated by MMSO presents a few similarities in its basic function with the monitoring systems proposed by Magadán et al. [72]: real-time monitoring of parameters, ease of application, and cost-effectiveness. However, the developed model was specifically designed to offer enhanced performance in various industrial areas and dimensions. This model stands apart from the ones previously presented and analyzed due to its innovative combination of the three targeted concepts and its primary focus on acquiring data related to maintenance and production management rather than solely monitoring condition parameters like temperature, vibration, and noise. The presented model can be easily adapted (with proper adaptation and programming) to remotely monitor the condition parameters of machines and equipment, as presented by Magadán et al. [72].

The integration of the model's components into machines occurs non-intrusively, facilitating its implementation in both older and newer machines while also fostering effective communication between them. The wireless communication between the devices renders the system modular and cost-effective.

The use of this model in companies brings several benefits both in terms of maintenance management and production, significantly enhancing overall performance. It enables an efficient and real-time exchange of information between these areas, empowering better and more informed decision-making processes.

The cost-effectiveness of the model is influenced by the communication range between its various devices. As the distance between them increases, communication quality diminishes. Nonetheless, this challenge can be addressed by altering the communication protocol and opting for different devices such as [76–78], though this choice would impact the implementation cost of the architecture.

As mentioned, the model lacks the implementation of Total Productive Maintenance. This methodology, when combined with the monitoring system, can yield numerous benefits for the company, involving and engaging various employees and technicians in day-to-day operations. It contributes to improving several key indicators, such as Overall Equipment Effectiveness, while ensuring machines are maintained in an ideal state to prevent unexpected breakdowns, losses in speed, and service quality. Furthermore, it reduces the occurrence of defects with the introduction of Autonomous Maintenance. By integrating Total Productive Maintenance, the model can enhance its potential impact across maintenance, production, and other operational areas, fostering continuous improvement within the company. The developed model offers significant benefits in terms of energy consumption reduction and energy transition. Considering as an example the food industry, the electrical energy consumption is very high due to continuous processes using conveyors for product movement and refrigeration to maintain the safety and quality of the perishable food products [79–83]. By enabling real-time monitoring of machines and equipment, the model helps identify inefficiencies and optimize energy usage. It allows companies to track energy-intensive processes, detect anomalies, and implement energy-saving measures promptly. Through the integration of IoT technologies and I4.0 principles, the model facilitates remote monitoring and control of machines, leading to more efficient energy utilization. By remotely accessing and analyzing data on energy consumption patterns, companies can identify areas of high energy usage and implement targeted energy-saving strategies, thereby reducing overall energy consumption. Achouch et al. [84] and Abidi et al. [85] developed a system that integrates I4.0 to support decision-making, as well as to enable strictly necessary maintenance actions to reduce the number of interventions and, consequently, maintenance costs, along with reduced material waste and contributing to the development of sustainable operations in the area of maintenance.

Susto et al. [86] developed a multiple-classifier machine learning methodology for PdM. This PdM approach allowed the implementation of dynamic decision rules for maintenance management. Furthermore, it was used to handle sensor data and high-dimensional data. The efficiency of this model was demonstrated through simulation in the standard semiconductor manufacturing industry.

Zenisek et al. [87] developed a model to identify wear as well as subsequent failure by examining real-time condition monitoring data reported by machines equipped with sensors. These developments demonstrated the possibility of reducing material and time costs, preventing failures, and improving performance.

Moreover, the model's focus on TPM further contributes to energy efficiency. TPM emphasizes preventive maintenance and optimal machine conditions, which reduces energy waste resulting from unexpected breakdowns or suboptimal operating states. Additionally, the real-time data provided by the model enables companies to make data-driven decisions to optimize energy-intensive processes and improve energy efficiency. This allows for continuous improvement in energy consumption practices, contributing to long-term energy transition goals. By promoting a culture of energy awareness and efficient resource management, the model can foster a more sustainable and environmentally friendly approach to manufacturing. It aligns with broader energy transition objectives by helping companies reduce their carbon footprint and mitigate environmental impacts. Thus, the model's ability to monitor, analyze, and optimize energy consumption in real-time, combined with its emphasis on preventive maintenance and energy-efficient practices, offers tangible benefits in terms of energy consumption reduction and supports the transition towards more sustainable energy practices.

In addition to the benefits mentioned above, there are other benefits to traditional maintenance management. Traditionally, after completing a maintenance intervention, each operator records the services that were carried out, thus establishing the history of failures and interventions, as well as storing the repair time. Each person responsible for the maintenance area must check every compliance of the procedure, time, and materials, among other aspects, and designate the performer of a certain intervention. In this sense, using the MMSO model, at each stop of a given asset, the operator, using a tablet, inserts information, such as: "Before stopping, there was a huge noise"; "The system lighting sometimes goes down when starting the equipment". Through this information, which can be accessed on the platform, those responsible for maintenance can issue more accurate work orders. On the other hand, one of the components for measuring the efficiency of maintenance management is availability. It is calculated by dividing the Mean Time Between Failures (MTBF) by the sum of the MTBF and Mean Time to Repair (MTTR). However, the availability of equipment depends on several factors that can often be associated with the material, conditions of use, and wear and tear, among other factors. In this sense, the MMSO model allows obtaining this information in real time through a fixed or mobile device that has internet access. Therefore, the information can be analyzed quickly and intuitively by reading a graph. Thus, the average operating time of the respective asset can be easily checked. The MTTR is also determined, helping to identify which type of asset and the predicted intervention time, helping maintenance managers to take action to reduce the repair time. Related to sustainable interventions by maintenance, the correct identification of spare parts promotes the correct management of stocks. On the other hand, through TPM, the culture of continuous improvement, autonomous maintenance, as well as the respective training of operators, including maintenance personnel, will enable a significant improvement in the reduction of machine and equipment stops. It will also advance employee management and the production of fewer parts with defects, contributing to the waste reduction of raw materials, natural resources used, and energy. The Lean Philosophy and its associated methodologies were not initially designed to improve issues related to the sustainability of companies. Their objectives were to enhance production processes, eliminate or reduce waste, and eliminate or reduce parts with defects or rework, among other objectives. Alves and Alves [88], Samadhiya et al. [89], Díaz-Reza et al. [90], and Bakri et al. [91] state that there are several environmental benefits linked to this philosophy.

It is only possible to quantify the importance of maintenance by monitoring the performance parameters of equipment and the maintenance process [92]. The importance of the parameters depends on the situation and the peculiarities of the system/company itself. It is important to point out that an indicator used by one company is not necessarily used by another. It all depends on the area of activity and type of business organization, among other aspects. Each indicator/parameter expresses the level of performance that was achieved, helping to directly and transparently compare management objectives and results obtained, simplifying a situation that would otherwise be relatively complex. Many parameters can be used to quantify maintenance performance. These can be equipment performance measures (for example, availability, reliability), cost performance measures (for example, cost of labor, material, maintenance), and process performance measures (for example, rate of planned and unplanned work, schedule compliance). Although reported above, three measures of equipment performance, such as cost and processes, equipment performance is one of the most relevant to support maintenance management. The performance of the equipment is related to the results of maintenance. These results can be obtained and crossed with various parameters such as availability, average time to failure, frequency of breakage, average time to repair, good operation time, and production rate, which allows maintenance managers to also perceive the frequency of scheduling and the respective time of each scheduling, intensity/criticality of the failure relating to the time required for intervention and the impact it had on the production system, turnover of the service order, compliance with the schedule and backlog of tasks. The MMSO was designed to support the activities of collecting data related to equipment performance, to support decision-making based on analyzing the data acquired in real-time, and to help maintenance managers in their tasks of planning and preparing maintenance activities. The structure of a maintenance performance parameter needs to be viewed from several angles; therefore, the Specific Measurable Attainable Realistic Timely (SMART) test can be used to verify the attributes of the indicators [93]. Maintenance indicators must be assessed for the objects being analyzed at a given time, and the analysis of the results can focus on the absolute values of this indicator or the trend it shows. Concerning the uncertainty in obtaining data using wireless sensors, these can have a high probability of noise, sensitivity, measurement range, resolution, and accuracy as characteristics associated with the sensors. However, the aspect more critical is the transmission/communication uncertainty class [92].

The MMSO test phase was conducted on a conveyor belt. The data analyzed before the implementation of the MMSO, referring to a 5-day work week, in which each working day corresponds to 7 h (less all scheduled stops), indicated that the belt conveyor operated about 82.3% of the expected execution time. With the implementation of the MMSO, the conveyor belt operated about 87.7% of the expected operating time during a work week, which represents an operating time increase of approximately 6.6%. The collection of data over time, as well as the refinement of actions by operators and the application of autonomous maintenance and preventive maintenance plans, will allow for more significant improvements in the medium to long term regarding the performance of the MMSO and its impact on the sustainability of maintenance activities and the production system.

Uhlmann et al. [94] presented a method to investigate and visualize offline information from various sources. Data collected from three sensors were used. The sensors showed typical machine tool operations and three fault conditions. The proposed method reduced failures by 15% to 20%, with the possibility of also reducing costs and, consequently, improving sustainable performance.

Zhou and Yin [95] presented a maintenance model to derive optimal maintenance plans for various turbine components under different climatic and operating load conditions based on continuous asset monitoring. The Lean Time of maintenance had a significant weight in the annual cost of maintenance. Through the model's application, it was possible to reduce maintenance costs by 32% to 39% compared to traditional maintenance management.

5. Conclusions

For companies to thrive in the increasingly globalized and competitive market, all the departments that constitute them must be aligned with the general objectives and maintenance policies, with none of them being an exception. Thus, maintenance is a determining and essential factor for any company.

In this way, the people responsible for maintenance have to search for and implement innovative tools and methods that can contribute to improving the production system. Therefore, effective maintenance management plays a crucial role in achieving optimal asset management and enhancing the performance of the production system, ultimately leading to customer satisfaction.

Regular visits to the factory floor or maintenance area have been used to collect important data, such as cycle time, downtime, and waste identification. However, this manual approach may suffer from communication gaps and inaccuracies, hindering the full potential of maintenance improvement. Although this methodology contributes significantly to improving the performance of the production and maintenance system, sometimes it is not properly applied, whether due to poor communication between those responsible for the GW and the operators or in the collection of times. To address this, a novel model combining the three concepts under study, denominated MMSO, was developed, enabling real-time monitoring of machines and equipment. This model allows for the collection of various critical data, such as repair time, operational uptime, and mean time between failures, empowering maintenance decision-making and efficient production management.

The model comprises sensors that gather data and transmit them to the gateway, which, in turn, forwards the data to the cloud for storage and processing through a free IoT application. This not only facilitates data processing but also enables real-time visualization and other valuable insights.

While the model is easy to apply, flexible, and cost-effective, it has some communication limitations if the recommended distance between the various constituents of the system is not respected. These limitations arise from the range of communication capabilities among the devices, potentially impacting data acquisition. Additionally, implementing Total Productive Maintenance, a crucial aspect of the model, requires dedication and training from top management and maintenance technicians to educate operators for better performance and autonomous maintenance tasks.

Moving forward, the implementation, testing, and validation of the proposed model will be pursued to evaluate its effectiveness and potential benefits. Despite the ongoing development and few limitations, the model holds promising potential for significantly improving maintenance and production management processes.

In conclusion, the integration of the three concepts—Industry 4.0, Lean Philosophy, and Total Productive Maintenance—presents a powerful opportunity for companies to optimize their production and maintenance processes, leading to significant benefits related to energy consumption reduction and energy transition. By combining real-time monitoring through Industry 4.0 technologies with the waste reduction and continuous improvement focus of Lean Philosophy and the systematic maintenance approach of TPM, companies can achieve higher efficiency, better asset management, and improved overall performance. Through the proposed model, companies can monitor critical indicators related to maintenance management and production systems in real-time, easing timely decision-making and enhancing communication between different departments. This enhanced communication and collaboration may also lead to a better understanding of energy consumption patterns, allowing for targeted improvements and reductions. Moreover, the versatility and low-cost nature of the model make it a valuable tool that can be easily adapted to various domains and industries, promoting its widespread adoption and applicability. Overall, the integration of Industry 4.0, Lean Philosophy, and Total Productive Maintenance not only fosters sustainable practices but also enhances overall organizational performance, customer satisfaction, and competitiveness. Companies that embrace this transformative approach can achieve a compatible balance between operational excellence and sustainable management through these synergies.

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References

1. Fortuna, G.; Gaspar, P.D. Implementation of industrial traceability systems: A case study of a luxury metal pieces manufacturing company. *Processes* **2022**, *10*, 2444. [CrossRef]
2. Proença, A.P.; Gaspar, P.D.; Lima, T.M. Lean optimization techniques for improvement of production flows and logistics management: The case study of a fruits distribution center. *Processes* **2022**, *10*, 1384. [CrossRef]
3. Cárcel-Carrasco, J.; Gómez-Gómez, C. Qualitative Analysis of the Perception of Company Managers in Knowledge Management in the Maintenance Activity in the Era of Industry 4.0. *Processes* **2021**, *9*, 121. [CrossRef]
4. Van Horenbeek, A.; Pintelon, L. Development of a maintenance performance measurement framework—Using the analytic network process (ANP) for maintenance performance indicator selection. *Omega* **2014**, *42*, 33–46. [CrossRef]
5. Hami, N.; Mohd Shafie, S.; Omar, S.; Ibrahim, Y.M.; Abdulameer, S.S.; Muhamad, M.R. A review of sustainable maintenance in the manufacturing companies. *Int. J. Sup. Chain. Manag.* **2020**, *9*, 935–944.
6. Poór, P.; Basl, J.; Zenisek, D. Historical overview of maintenance management strategies: Development from breakdown maintenance to predictive maintenance in accordance with four industrial revolutions. In Proceedings of the International Conference on Industrial Engineering and Operations Management, Pilsen, Czech Republic, 23–26 July 2019.
7. Chopra, A.; Sachdeva, A.; Bhardwaj, A. Prevalent general and preventive maintenance practices in Indian process industry. *Int. J. Product. Qual. Manag.* **2020**, *29*, 542–557. [CrossRef]
8. Heinonen, H.; Burova, A.; Siltanen, S.; Lähteenmäki, J.; Hakulinen, J.; Turunen, M. Evaluating the Benefits of Collaborative VR Review for Maintenance Documentation and Risk Assessment. *Appl. Sci.* **2022**, *12*, 7155. [CrossRef]
9. Bousdekis, A.; Magoutas, B.; Apostolou, D.; Mentzas, G. Review, analysis and synthesis of prognostic-based decision support methods for condition based maintenance. *J. Intell. Manuf.* **2018**, *29*, 1303–1316. [CrossRef]
10. Ivina, D.; Olsson, N.O. Lean Construction Principles and Railway Maintenance Planning. In Proceedings of the 28th Annual Conference of the International Group for Lean Construction (IGLC), Berkeley, CA, USA, 6–10 July 2020. [CrossRef]
11. Shou, W.; Wang, J.; Wu, P.; Wang, X. Lean management framework for improving maintenance operation: Development and application in the oil and gas industry. *Prod. Plan. Control.* **2021**, *32*, 585–602. [CrossRef]

12. Solaimani, S.; Veen, J.V.D.; Sobek, D.K., II; Gulyaz, E.; Venugopal, V. On the application of lean principles and practices to innovation management: A systematic review. *TQM J.* **2019**, *31*, 1064–1092. [CrossRef]
13. Maware, C.; Adetunji, O. Lean manufacturing implementation in Zimbabwean industries: Impact on operational performance. *Int. J. Eng. Bus. Manag.* **2019**, *11*. [CrossRef]
14. Rüttimann, B.G.; Stöckli, M.T. Going beyond triviality: The Toyota production system—Lean manufacturing beyond Muda and Kaizen. *J. Serv. Sci. Manag.* **2016**, *9*, 140–149. [CrossRef]
15. Jasti, N.V.K.; Kodali, R. Lean production: Literature review and trends. *Int. J. Prod. Res.* **2015**, *53*, 867–885. [CrossRef]
16. Ranjan, S.K.; Shinde, D.K. Implementing lean manufacturing technique in fabrication process planning–A case study. *Int. Res. J. Eng. Technol.* **2018**, *5*, 2600–2606.
17. Taggart, M.; Willis, C.; Hanahoe, J. Not Seeing the Wood for the Trees—A Gemba Walk through a Timber Framed Housing Development. In Proceedings of the 27th Annual Conference of the International. Group for Lean Construction (IGLC), Dublin, Ireland, 3–5 July 2019. [CrossRef]
18. Mičieta, B.; Howaniec, H.; Biňasová, V.; Kasajová, M.; Fusko, M. Increasing Work Efficiency in a Manufacturing Setting Using Gemba Walk. *Eur. Res. Stud. J.* **2021**, *24*, 601–620. [CrossRef]
19. Tyagi, S.; Choudhary, A.; Cai, X.; Yang, K. Value stream mapping to reduce the lead-time of a product development process. *Int. J. Prod. Econ.* **2015**, *160*, 202–212. [CrossRef]
20. Syafie, M.N. Re-layout moulding production line using gemba kaizen method and line balancing method. *Int. J. Res. Innov. Manag.* **2022**, *8*, 75–88.
21. Bousdekis, A.; Apostolou, D.; Mentzas, G. Predictive maintenance in the 4th industrial revolution: Benefits, business opportunities, and managerial implications. *IEEE Eng. Manag. Rev.* **2019**, *48*, 57–62. [CrossRef]
22. Culot, G.; Nassimbeni, G.; Orzes, G.; Sartor, M. Behind the definition of Industry 4.0: Analysis and open questions. *Int. J. Prod. Econ.* **2020**, *226*, 107617. [CrossRef]
23. Alves, J.; Lima, T.M.; Gaspar, P.D. Is Industry 5.0 a Human-Centred Approach? A Systematic Review. *Processes* **2023**, *11*, 193. [CrossRef]
24. Alcácer, V.; Cruz-Machado, V. Scanning the industry 4.0: A literature review on technologies for manufacturing systems. *Eng. Sci. Technol. Int. J.* **2019**, *22*, 899–919. [CrossRef]
25. Ahmed, U.; Carpitella, S.; Certa, A.; Izquierdo, J. A Feasible Framework for Maintenance Digitalization. *Processes* **2023**, *11*, 558. [CrossRef]
26. Shaheen, B.W.; Németh, I. Integration of Maintenance Management System Functions with Industry 4.0 Technologies and Features—A Review. *Processes* **2022**, *10*, 2173. [CrossRef]
27. Moyne, J.; Iskandar, J. Big Data Analytics for Smart Manufacturing: Case Studies in Semiconductor Manufacturing. *Processes* **2017**, *5*, 39. [CrossRef]
28. Reis, M.S.; Gins, G. Industrial Process Monitoring in the Big Data/Industry 4.0 Era: From Detection, to Diagnosis, to Prognosis. *Processes* **2017**, *5*, 35. [CrossRef]
29. Arsakulasooriya, K.K.; Sridarran, P.; Sivanuja, T. Applicability of lean maintenance in commercial high-rise buildings: A case study in Sri Lanka. *Facilities* **2023**. *ahead of print*. [CrossRef]
30. Gupta, S.; Gupta, P.; Parida, A. Modeling lean maintenance metric using incidence matrix approach. *Int. J. Syst. Assur. Eng. Manag.* **2017**, *8*, 799–816. [CrossRef]
31. Ebeid, A.A.; El-Khouly, I.A.; El-Sayed, A.E. Lean maintenance excellence in the container handling industry: A case study. In Proceedings of the 2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Bali, Indonesia, 4–7 December 2016. [CrossRef]
32. Palmeira, T.; Navas, H.; Morgado, T. Lean maintenance management activities in an oil terminal: Case study. In Proceedings of the 6th International Conference on Mechanics and Materials in Design, Ponta Delgada, Azores, 26–30 July 2015.
33. Pinto, G.F.L.; Silva, F.J.G.; Campilho, R.D.S.G.; Casais, R.B.; Fernandes, A.J.; Baptista, A. Continuous improvement in maintenance: A case study in the automotive industry involving Lean tools. *Procedia Manuf.* **2019**, *38*, 1582–1591. [CrossRef]
34. Costello, O.; Kent, M.D.; Kopacek, P. Cost-Orientation Maintenance Engineering: Case Study of an Irish Manufacturing Plant. *IFAC-PapersOnLine* **2019**, *52*, 409–414. [CrossRef]
35. Lopes, I.; Senra, P.; Vilarinho, S.; Sá, V.; Teixeira, C.; Lopes, J.; Alves, A.; Oliveira, J.A.; Figueiredo, M. Requirements specification of a computerized maintenance management system–a case study. *Procedia Cirp.* **2016**, *52*, 268–273. [CrossRef]
36. Hassan, M.N.; Barakat, A.F.; Sobh, A.S. Effect of applying lean maintenance in oil and gas fields. In Proceedings of the International Conference on Applied Mechanics and Mechanical Engineering. Military Technical College, Cairo, Egypt, 7–9 April 2020. [CrossRef]
37. Anh, D.T.; Dąbrowski, K.; Skrzypek, K. The predictive maintenance concept in the maintenance department of the "Industry 4.0" production enterprise. *Found. Manag.* **2018**, *10*, 283–292. [CrossRef]
38. Rousopoulou, V.; Nizamis, A.; Vafeiadis, T.; Ioannidis, D.; Tzovaras, D. Predictive maintenance for injection molding machines enabled by cognitive analytics for industry 4.0. *Front. Artif. Intell.* **2020**, *3*, 578152. [CrossRef] [PubMed]
39. Jasiulewicz-Kaczmarek, M.; Legutko, S.; Kluk, P. Maintenance 4.0 technologies–new opportunities for sustainability driven maintenance. *Manag. Prod. Eng. Rev.* **2020**, *11*, 133730. [CrossRef]

40. Converso, G.; Gallo, M.; Murino, T.; Vespoli, S. Predicting Failure Probability in Industry 4.0 Production Systems: A Workload-Based Prognostic Model for Maintenance Planning. *Appl. Sci.* **2023**, *13*, 1938. [CrossRef]
41. Senthil, C.; Sudhakara Pandian, R. Proactive Maintenance Model Using Reinforcement Learning Algorithm in Rubber Industry. *Processes* **2022**, *10*, 371. [CrossRef]
42. Mey, O.; Schneider, A.; Enge-Rosenblatt, O.; Mayer, D.; Schmidt, C.; Klein, S.; Herrmann, H.-G. Condition Monitoring of Drive Trains by Data Fusion of Acoustic Emission and Vibration Sensors. *Processes* **2021**, *9*, 1108. [CrossRef]
43. Mendes, D.S.; Navas, H.V.; Charrua-Santos, F.M. Relationship between Maintenance, Lean Philosophy, and Industry 4.0: Systematic Literature Review. In Proceedings of the 14th European Professors of Industrial Engineering and Management, Graz, Austria, 28 May 2021. [CrossRef]
44. Mayr, A.; Weigelt, M.; Kühl, A.; Grimm, S.; Erll, A.; Potzel, M.; Franke, J. Lean 4.0-A conceptual conjunction of lean management and Industry 4.0. *Procedia Cirp.* **2018**, *72*, 622–628. [CrossRef]
45. Phuong, N.A.; Guidat, T. Sustainable value stream mapping and technologies of Industry 4.0 in manufacturing process reconfiguration: A case study in an apparel company. In Proceedings of the 2018 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), Singapore, 31 July 2018–2 August 2018. [CrossRef]
46. Spenhoff, P.; Wortmann, J.C.; Semini, M. EPEC 4.0: An Industry 4.0-supported lean production control concept for the semi-process industry. *Prod. Plan. Control.* **2020**, *33*, 1337–1354. [CrossRef]
47. Rifqi, H.; Souda, S.B.; Zamma, A.; Kassami, S. Lean Facility Management 4.0: A Case Study. *Int. J. Emerg. Trends Eng. Res.* **2020**, *8*, 7363–7370. [CrossRef]
48. Ramadan, M.; Salah, B. Smart lean manufacturing in the context of Industry 4.0: A case study. *Int. J. Manuf. Technol. Ind. Eng.* **2019**, *13*, 174–181. [CrossRef]
49. Ma, J.; Wang, Q.; Zhao, Z. SLAE–CPS: Smart Lean Automation Engine Enabled by Cyber-Physical Systems Technologies. *Sensors* **2017**, *17*, 1500. [CrossRef]
50. Frontoni, E.; Rosetti, R.; Paolanti, M.; Alves, A.C. HATS project for lean and smart global logistic: A shipping company case study. *Manuf. Lett.* **2020**, *23*, 71–74. [CrossRef]
51. Ferreira, C.; Sá, J.C.; Ferreira, L.P.; Lopes, M.P.; Pereira, T.; Silva, F.J.G. iLeanDMAIC–A methodology for implementing the lean tools. *Procedia Manuf.* **2019**, *41*, 1095–1102. [CrossRef]
52. Kostoláni, M.; Murín, J.; Kozák, Š. Intelligent predictive maintenance control using augmented reality. In Proceedings of the 22nd International Conference on Process Control (PC19), Strbske Pleso, Slovakia, 11–14 June 2019. [CrossRef]
53. Paolanti, M.; Romeo, L.; Felicetti, A.; Mancini, A.; Frontoni, E.; Loncarski, J. Machine learning approach for predictive maintenance in industry 4.0. In Proceedings of the 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA), Oulu, Finland, 2–4 July 2018. [CrossRef]
54. Ghouat, M.; Haddout, A.; Benhadou, M. Impact of industry 4.0 concept on the levers of Lean Manufacturing approach in manufacturing industries. *Int. J. Automot. Mech. Eng.* **2021**, *18*, 8523–8530. [CrossRef]
55. Deuse, J.; Dombrowski, U.; Nöhring, F.; Mazarov, J.; Dix, Y. Systematic combination of Lean Management with digitalization to improve production systems on the example of Jidoka 4.0. *Int. J. Eng. Bus. Manag.* **2020**, *12*, 1847979020951351. [CrossRef]
56. Itani, A.; Alghamdy, M.; Nazir, H.; Sharma, S.; Ahmad, R. A decision-making tool to integrate lean 4.0 in windows manufacturing using simulation and optimization models. In Proceedings of the 32nd European Modeling & Simulation Symposium (EMSS 2020), Athens, Greece, 16–18 September 2020. [CrossRef]
57. Koenig, F.; Found, P.; Kumar, M. Improving maintenance quality in airport baggage handling operations. *Total. Qual. Manag. Bus. Excell.* **2019**, *30*, S35–S52. [CrossRef]
58. Bumblauskas, D.; Gemmill, D.; Igou, A.; Anzengruber, J. Smart Maintenance Decision Support Systems (SMDSS) based on corporate big data analytics. *Expert Syst. Appl.* **2017**, *90*, 303–317. [CrossRef]
59. Lewandowski, R.; Olszewska, J.I. Automated task scheduling for automotive industry. In Proceedings of the 24th International Conference on Intelligent Engineering Systems (INES), Reykjavík, Iceland, 8–10 July 2020. [CrossRef]
60. Ceruti, A.; Marzocca, P.; Liverani, A.; Bil, C. Maintenance in aeronautics in an Industry 4.0 context: The role of Augmented Reality and Additive Manufacturing. *J. Comput. Des. Eng.* **2019**, *6*, 516–526. [CrossRef]
61. Kolberg, D.; Knobloch, J.; Zühlke, D. Towards a lean automation interface for workstations. *Int. J. Prod. Res.* **2017**, *55*, 2845–2856. [CrossRef]
62. Arrascue-Hernandez, G.; Cabrera-Brusil, J.; Chavez-Soriano, P.; Raymundo-Ibañez, C.; Perez, M. LEAN maintenance model based on change management allowing the reduction of delays in the production line of textile SMEs in Peru. In Proceedings of the IOP Conference Series: Materials Science and Engineering, Banda Aceh, Indonesia, 18–20 September 2019. [CrossRef]
63. Meddaoui, A. A New Manufacturing Improvement Model Based on Overall Equipment Effectiveness and Lean Maintenance. In Proceedings of the Second International Conference on Smart Applications and Data Analysis for Smart Cities, Málaga, Spain, 27–28 February 2017. [CrossRef]
64. Epler, I.; Sokolovic, V.; Milenkov, M.; Bukvic, M. Application of lean tools for improved effectiveness in maintenance of technical systems for special purposes. *Eksploat. Niezawodn.* **2017**, *19*, 615–635. [CrossRef]
65. Ramakrishnan, V.; Nallusamy, S. Implementation of total productive maintenance lean tool to reduce lead time-A case study. *Int. J. Mech. Eng. Technol.* **2017**, *8*, 295–306.

66. Wenchi, S.; Wang, J.; Wang, X.; Chong, H.Y. An application of value stream mapping for turnaround maintenance in oil and gas industry: Case study and lessions learned. In Proceedings of the 31st Annual ARCOM Conference, Lincoln, NE, USA, 7–9 September 2015.
67. Lacerda, A.P.; Xambre, A.R.; Alvelos, H.M. Applying Value Stream Mapping to eliminate waste: A case study of an original equipment manufacturer for the automotive industry. *Int. J. Prod. Res.* **2016**, *54*, 1708–1720. [CrossRef]
68. Pombal, T.; Ferreira, L.P.; Sá, J.C.; Pereira, M.T.; Silva, F.J.G. Implementation of lean methodologies in the management of consumable materials in the maintenance workshops of an industrial company. *Procedia Manuf.* **2019**, *38*, 975–982. [CrossRef]
69. Konstantinidis, F.K.; Kansizoglou, I.; Santavas, N.; Mouroutsos, S.G.; Gasteratos, A. Marma: A mobile augmented reality maintenance assistant for fast-track repair procedures in the context of industry 4.0. *Machines* **2020**, *8*, 88. [CrossRef]
70. Kinz, A.; Bernerstaetter, R.; Biedermann, H. Lean smart maintenance–efficient and effective asset management for smart factories. In Proceedings of the 8th International Scientific Conference Management of Technology–Step to Sustainable Production, Porec, Croatia, 1–3 June 2016.
71. Shahin, M.; Chen, F.F.; Bouzary, H.; Krishnan, K. Integration of Lean practices and Industry 4.0 technologies: Smart manufacturing for next-generation enterprises. *Int. J. Adv. Manuf. Technol.* **2020**, *107*, 2927–2936. [CrossRef]
72. Magadán, L.; Suárez, F.J.; Granda, J.C.; García, D.F. Low-cost real-time monitoring of electric motors for the Industry 4.0. *Procedia Manuf.* **2020**, *42*, 393–398. [CrossRef]
73. Ashjaei, M.; Bengtsson, M. Enhancing smart maintenance management using fog computing technology. In Proceedings of the International Conference on Industrial Engineering and Engineering Management, Singapore, 10–13 December 2017. [CrossRef]
74. Islas, L.; Gutierrez, S.; Rodríguez, F. Wireless Sensor Network Prototype to Monitor the Condition of Holding Furnaces in the Aluminum Casting Plant. In Proceedings of the International Conference on Engineering Veracruz, Boca del Rio, Mexico, 14–17 October 2019. [CrossRef]
75. Tosi, J.; Taffoni, F.; Santacatterina, M.; Sannino, R.; Formica, D. Performance Evaluation of Bluetooth Low Energy: A Systematic Review. *Sensors* **2017**, *17*, 2898. [CrossRef]
76. Varandas, L.; Faria, J.; Gaspar, P.D.; Aguiar, M.L. Low-Cost IoT Remote Sensor Mesh for Large-Scale Orchard Monitorization. *J. Sens. Actuator Netw.* **2020**, *9*, 44. [CrossRef]
77. Gaspar, P.D.; Fernandez, C.M.; Soares, V.N.G.J.; Caldeira, J.M.L.P.; Silva, H. Development of technological capabilities through the Internet of Things (IoT): Survey of opportunities and barriers for IoT implementation in Portugal's agro-industry. *Appl. Sci.* **2021**, *11*, 3454. [CrossRef]
78. Gaspar, P.D.; Soares, V.N.G.J.; Caldeira, J.M.L.P.; Andrade, L.P.; Soares, C.D. Technological modernization and innovation of traditional agri food companies based on ICT solutions—The Portuguese case study. *J. Food Process. Preserv.* **2022**, *46*, e14271. [CrossRef]
79. Gaspar, P.D.; Silva, P.D.; Nunes, J.; Andrade, L.P. Characterization of the specific electrical energy consumption of agrifood industries in the central region of Portugal. *Appl. Mech. Mater.* **2014**, *590*, 878–882. [CrossRef]
80. Nunes, J.; Silva, P.D.; Andrade, L.P.; Gaspar, P.D. Characterization of the specific energy consumption of electricity in the Portuguese sausage industry. *WIT Trans. Ecol. Environ.* **2014**, *186*, 763–774. [CrossRef]
81. Silva, P.D.; Gaspar, P.D.; Nunes, J.; Andrade, L.P.A. Specific electrical energy consumption and CO_2 emissions assessment of agrifood industries in the central region of Portugal. *Appl. Mech. Mater.* **2014**, *675–677*, 1880–1886. [CrossRef]
82. Nunes, J.; Silva, P.D.; Andrade, L.P.; Domingues, L.; Gaspar, P.D. Energy assessment of the Portuguese meat industry. *Energy Effic.* **2016**, *9*, 1163–1178. [CrossRef]
83. Morais, D.; Gaspar, P.D.; Silva, P.D.; Andrade, L.P.; Nunes, J. Energy consumption and efficiency measures in the Portuguese food processing industry. *J. Food Process. Preserv.* **2022**, *46*, e14862. [CrossRef]
84. Achouch, M.; Dimitrova, M.; Ziane, K.; Sattarpanah Karganroudi, S.; Dhouib, R.; Ibrahim, H.; Adda, M. On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges. *Appl. Sci.* **2022**, *12*, 8081. [CrossRef]
85. Abidi, M.H.; Mohammed, M.K.; Alkhalefah, H. Predictive Maintenance Planning for Industry 4.0 Using Machine Learning for Sustainable Manufacturing. *Sustainability* **2022**, *14*, 3387. [CrossRef]
86. Susto, G.A.; Schirru, A.; Pampuri, S.; McLoone, S.; Beghi, A. Machine learning for predictive maintenance: A multiple classifier approach. *IEEE Trans. Industr. Inform.* **2014**, *11*, 812–820. [CrossRef]
87. Zenisek, J.; Holzinger, F.; Affenzeller, M. Machine learning based concept drift detection for predictive maintenance. *Comput. Ind. Eng.* **2019**, *137*, 106031. [CrossRef]
88. Alves, J.R.X.; Alves, J.M. Production management model integrating the principles of lean manufacturing and sustainability supported by the cultural transformation of a company. *Int. J. Prod. Res.* **2015**, *53*, 5320–5333. [CrossRef]
89. Samadhiya, A.; Agrawal, R.; Garza-Reyes, J.A. Integrating industry 4.0 and total productive maintenance for global sustainability. *TQM J.* **2022**. *ahead of print*. [CrossRef]
90. Díaz-Reza, J.R.; García-Alcaraz, J.L.; Figueroa, L.J.M.; Vidal, R.P.I.; Muro, J.C.S.D. Relationship between lean manufacturing tools and their sustainable economic benefits. *Int. J. Adv. Manuf. Technol.* **2022**, *123*, 1269–1284. [CrossRef]
91. Bakri, A.; Alkbir, M.F.M.; Awang, N.; Januddi, F.; Ismail, M.A.; Ahmad, A.N.A.; Zakaria, I.H. Addressing the issues of maintenance management in SMEs: Towards sustainable and lean maintenance approach. *Emerg. Sci. J.* **2021**, *5*, 367–379. [CrossRef]
92. Kamble, S.S.; Gunasekaran, A.; Ghadge, A.; Raut, R. A performance measurement system for industry 4.0 enabled smart manufacturing system in SMMEs-A review and empirical investigation. *Int. J. Prod. Econ.* **2020**, *229*, 107853. [CrossRef]

93. Daniewski, K.; Kosicka, E.; Mazurkiewicz, D. Analysis of the correctness of determination of the effectiveness of maintenance service actions. *Manag. Prod. Eng. Rev.* **2018**, *9*, 20–25. [CrossRef]
94. Uhlmann, E.; Pontes, R.P.; Geisert, C.; Hohwieler, E. Cluster identification of sensor data for predictive maintenance in a Selective Laser Melting machine tool. *Procedia Manuf.* **2018**, *24*, 60–65. [CrossRef]
95. Zhou, P.; Yin, P.T. An opportunistic condition-based maintenance strategy for offshore wind farm based on predictive analytics. *Renew. Sust. Energ. Rev.* **2019**, *109*, 1–9. [CrossRef]