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Challenges, Limitations, and Strengths for an Optimal Predictive Maintenance Application

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CHALLENGES, LIMITATIONS, AND STRENGTHS FOR OPTIMAL PREDICTIVE MAINTENANCE APPLICATION

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Dedication

This paper is dedicated to my beloved parents, mother, and father, who have always been my inspiration and motivation and continually provide their emotional, moral, and financial support in a long journey. Thank you for always supporting me in my dreams and being there whenever I felt like giving up. I love you, Mom and Dad.

To my sister, who was always there for me and provided me with her support and assistance. For sharing her knowledge and experiences to make me a better person.

To my girlfriend, who always believed in me and kept me motivated when I left Mexico to continue my education in the United States. Thank you for always being by my side and believing I can accomplish all my goals and dreams.

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Furthermore lastly, this paper is dedicated to all the professors, teammates, and colleagues that helped and assisted me in one way or another with their knowledge and education throughout my college education.

CHALLENGES, LIMITATIONS, AND STRENGTHS FOR OPTIMAL PREDICTIVE MAINTENANCE APPLICATION

by

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THESIS

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Abstract

Industry 4.0, the fourth industrial revolution, has emerged as the most recent digital transformation worldwide, expanding and reshaping the manufacturing industry by introducing novel technologies. In Industry 4.0, Smart Manufacturing (SM) and the Internet of Things (IoT) have collaborated to bring the best of both worlds and make the new manufacturing era more cost-effective, automated, and digitized. As a result, many businesses are putting sensors, intricate networks of integrated systems, big data analytics, cloud computing, and storage in place to use predictive maintenance (PdM) best. PdM uses IoT to convert physical activities into digital activities, also known as digitization. Predictive engineering has received the most academic attention of the six pillars of SM, demonstrating the need for complete integration of these technologies to improve data-driven decision-making.

In this research, we discuss the relevance of PdM and its challenges, limitations, and strengths for optimal PdM applications. In addition to our primary analysis, we created an application case to show how the principles of SM, IoT, and Industry 4.0 fit into the broad and robust PdM technology. Using assets such as temperature sensors, microprocessors, network antennas, and software, a remote monitoring system and the "*PAInOuTT*" model application flow were created to fully understand the framework and process behind applying a PdM model in a manufacturing machine from a local industry. Furthermore, this study provided a unique opportunity to comprehend the challenges and expertise encountered by small businesses attempting to integrate IoT and SM technologies into their operational systems with limited resources.

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Chapter 1 : Introduction

Industries must evolve and adapt to the rapid growth of new technologies to create the latest Industry 4.0 era. This unique idea relies on new technologies that have the potential to revolutionize manufacturing and the way products are made [1]. This term intends to lead to faster production times, lower costs, and make automated decisions to produce high-quality products and services.

In 2011, the German federal government introduced this concept as a project with academic institutions and private enterprises to maintain the country's manufacturing industry's competitiveness [1] [2]. Since the first industrial revolution in the late 18th century, the industry has attempted to adapt and overcome the production and cost challenges. As depicted in Figure #1.1, the second and third industrial revolutions demonstrate a significant advance from mass production to automated manufacturing. Once these hurdles are met, there is always space for development. The purpose of today's Industry 4.0 technologies is to facilitate the production of goods and meet the increasing global demand.

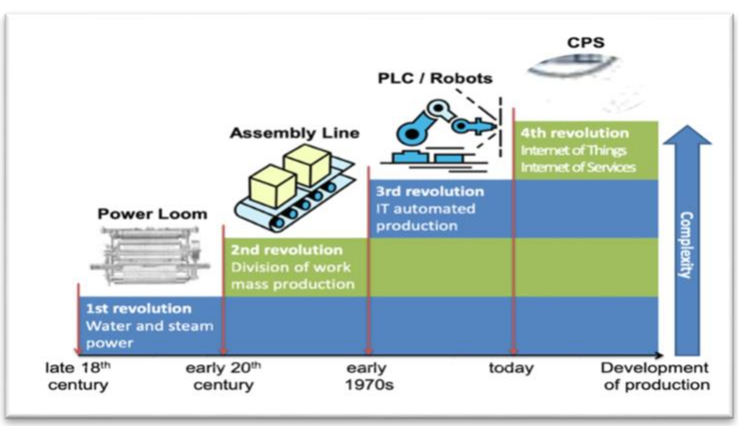

Figure 1.1 Four Industrial Revolutions [2]

In tandem with Industry 4.0, another concept intended to transform the current production era was introduced. The Smart Manufacturing (SM) concept was established as a research endeavor into the future of manufacturing by large firms from Japan, the United States, South Korea, and European countries [3]. SM asserts that it has the same objectives as Industry 4.0, such as meeting global customer expectations by expediting the production of goods using new technologies like IoT, cloud computing, big data, analytics, and sensor digitization.

The Predictive Maintenance (PdM) strategy is one of the critical concepts gaining traction in Industry 4.0 and SM. *PdM* is a maintenance technique to predict the equipment or asset failure time based on particular criteria or circumstances. This method relies on IoT, including monitoring equipment with sensors and other devices. *PdM* is a tool that has aided small and large businesses across the globe in increasing output by decreasing equipment failure and maintenance downtime. According to PwC, PdM can increase asset life by 20%, boost uptime by 9%, and reduce safety, health, environment, and quality risks by 14% [4].

In the early 21st century, PdM technology was adopted in the industry due to the introduction of new technologies that enable using PdM technology. Before introducing this method, the industry relied on alternative maintenance methods. First, *maintenance* is defined as "regular monitoring of the process, machine, material, or product conditions to ensure the greatest interval between repairs, thereby minimizing the number and cost of unplanned outages that reduce the manufacturing process's productivity, product quality, and overall effectiveness"[5].

Maintenance plays a significant part in modern manufacturing, as organizations' revenue may depend entirely on equipment output, meaning that any downtime represents a substantial financial loss for industrial enterprises. Presently, four distinct types of maintenance incidents may be distinguished, and Figure #1.2 explains how maintenance has evolved through time.

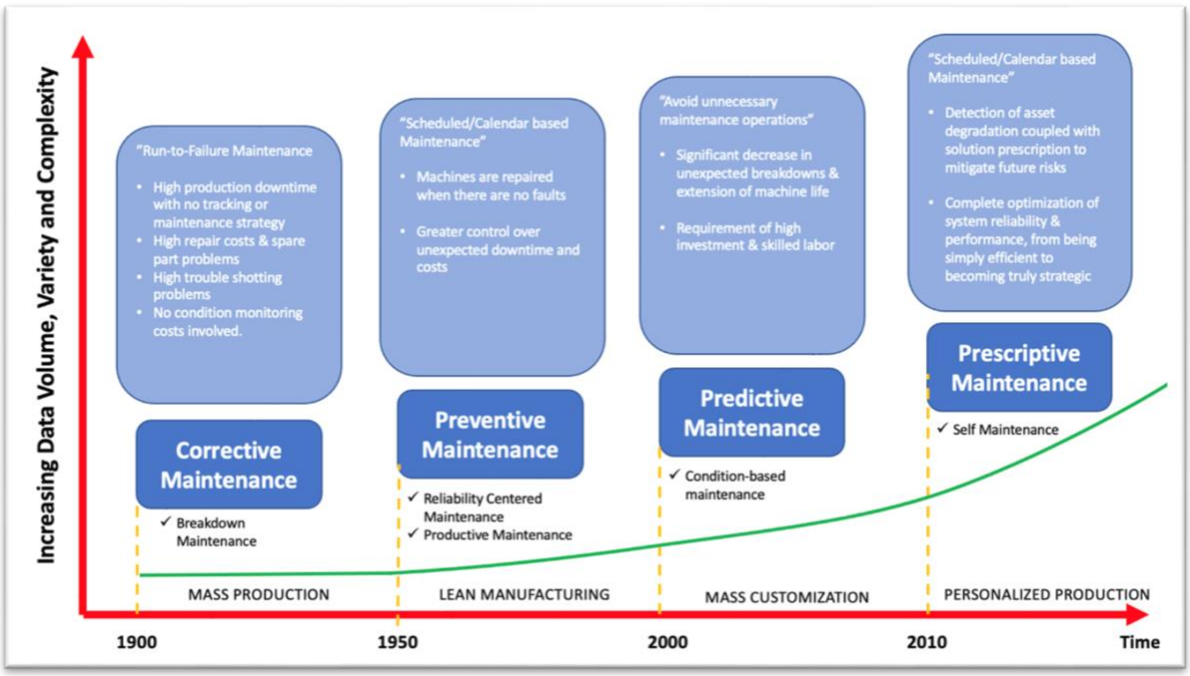

Figure 1.2 Evolution of Maintenance [6]

- Corrective or Reactive: this is the simplest straightforward technique. It is the process of replacing or repairing faulty equipment. For equipment failure, CM tasks determine the cause of the problem (a component or an item of equipment) and fix the loss so that the equipment may be reinstated and factory production can be restored [7]. Corrective maintenance is frequently linked to unscheduled downtime, costing three to four times as much as scheduled downtime.[6]
- Preventive: is one of the earliest and most effective maintenance procedures still in use today. It consists of the measures taken to keep an object in a particular condition by providing

systematic examination, appraisal, and prevention of impending failures. Simple preventive maintenance involves periodic actions based on assumed behavior, such as the mean time between failures [6].

- Predictive: It is a highly effective maintenance technique. It involves monitoring equipment for indications of aberrant functioning or variations.[7]
- Prescriptive: This maintenance can predict the future health status of a system. Also, it recommends autonomously timed judgments for specific maintenance activities (inspection, repair, and replacement) or action plans [8]. It goes beyond a simple failure prediction; this includes proactive and intelligent maintenance planning [6].

One of the most significant challenges with applying PdM techniques is that they need clarification with other terminology or methods. PdM is also known as Condition-based maintenance (CBM), Prognostics and health management (PHM), and Remaining Useful Life (RUL) (RUL). These ideas aim to accomplish the same objective but in different ways. These all-techniques are a component of the Predictive Maintenance model, but businesses need help comprehending or selecting the technique that best fits their needs or problems.

Businesses employing and correctly applying PdM strategies have observed considerable cost reductions, decreased maintenance costs, and downtime. According to most of the literature, a successful predictive maintenance program should generate a 10:1 to 12:1 return on investment [9]. In other words, the average return for each dollar invested in a PdM scheme should be between $10 and $12. As noted, utilizing PdM in business has numerous benefits and negatives. Emerson believes that only about twenty percent of predictive maintenance projects are successful [4].

This failure rate may be attributable to multiple factors. Some of these challenges are related to financial constraints; investing enormous sums of money without the desired return on investment or rapid outcomes may lead to the collapse of a project. Selecting the appropriate models, technology, and expertise is a further challenge in correctly applying PdM tactics. PdM procedures vary in complexity since each industry may have various needs and complicated assets; therefore, it is essential to understand which techniques (CBM, PHM, RUL) and technologies are required to meet project requirements. Not doing so may result in enormous financial waste and project failure.

The principles of a PdM model will be utilized in a case study to establish the foundation for how small or local businesses can be introduced to PdM techniques without having to make substantial financial investments, in addition to demonstrating the obstacles or limitations and benefits of this evolving technology. This case study also introduces the significance of illustrating how IoT, cloud computing, big data, analytics, and sensor digitization connect to PdM along with the proposed "*PAInOuTT*" PdM application flow model.

Since the beginning of the 21st century, businesses have attempted to adopt PdM projects; however, according to many surveys, only around 20% of PdM projects are successful [4]. Why are only 20% of projects successful? What is the most typical factor that causes organizations to fail while implementing PdM projects? What is preventing businesses from investing in PdM besides the low success rate? Is the concept lacking in benefits, expensive, or misinformed?

This study aims to define predictive maintenance vocabulary and the technologies involved in a PdM project. This study will provide a fundamental grasp of the workflow stages followed in Predictive maintenance by describing the steps in a PdM model and introducing a proposal of a generalized PdM application flow model, which is the process and framework for an optimal PdM application. It is crucial to comprehend the process so industries may relate it to the various prediction philosophies, such as CBM, PHM, and RUL. All three methods share a similar workflow, but a more in-depth examination of each will reveal that they may be applied to different situations and lead to distinct outcomes. The objective of using a CBM technique in a local manufacturing company is to establish the foundation for how enterprises should define their needs to translate them into the appropriate PdM project. This case study also demonstrates that a small business may be successful in PdM initiatives without significant investments by utilizing the right technologies, people, resources, and an overall application flow model.

Studying PdM methodologies from various authors is intended to aid the selection of models when planning a PdM project investment. While pretending to enter the realm of PdM, it is crucial to comprehend and be aware of the associated difficulties and constraints. Before investing in PdM methods, knowing the most well-known issues faced by past organizations and projects may help other companies make the correct option. Aside from that, displaying multiple case studies involving the successful application of various PdM techniques, such as in the automotive or aviation industries, should encourage initiatives to utilize the well-known technology and conduct valuable predictive maintenance projects. Advantages generated from this maintenance technique are also included to increase the value of the global output of this technology.

Solution framework development will only establish the fundamentals of the PdM project approach. A PdM project may be lengthy due to the extensive data collecting and maintenance report generation required to predict failures. The local company to which this case study was applied employs an obsolete machine without any sensors or alarms to indicate machine breakdown. All maintenance is preventative and corrective. This case study belongs to a private company, so particular material may be withheld per the company's request. Remember that the three methodologies presented in this paper are not the only ones, but they are the most common and widely utilized in PdM projects.

This paper contains five chapters. Chapter 2 describes the fundamental principles and technologies associated with PdM Models. In addition, it represents the PdM model and three most utilized methodologies, including the proposed "*PAInOuTT*" PdM Model that combines the best of all three methods, as well as the benefits and challenges/or limitations of PdM that other businesses have encountered. Chapter 3 presents a solution framework development using the "*PAInOuTT*" PdM methodology and a list of all the equipment used and the processes taken to initiate a PdM application project. Chapter 4 addressed the project findings and the advantages the local business received. Chapter 5 concludes with a conclusion following the application case within the local company and the outlook for implementing a proposed PdM model analysis in more industrial applications.

Chapter 2 : Methodology

2.1 Predictive Maintenance

Predictive Maintenance (PdM) is defined as a strategy used to estimate when maintenance should conduct on in-service equipment by using innovative scheduling preventative maintenance measures that eventually avert (or at least lessen the impacts of) unexpected equipment breakdowns [10]. PdM is gaining popularity in multidisciplinary research groups, which propose developing and integrating research lines relating to data gathering, infrastructure, storage, distribution, security, and intelligence. This section provides the essential information for comprehending PdM and guides the findings of this investigation.[11]

Industry 4.0 environments that collect data from various sensors offer new options for asset remaining life prediction systems. The idea that Predictive Maintenance (PdM) can produce scheduling actions based on equipment performance or circumstances over time becomes interesting and fundamental for the industry's future. A sufficient quantity of data from all aspects of the manufacturing process is one of the primary needs for efficient PdM achievement [40]. Consequently, it can reduce maintenance costs and downtime and boost productivity and quality.

2.1.1 PdM Workflow

Phase 1. What are the project needs?

Learning about the project's commercial aspects, challenges, and limitations is the first order of business. This phase requires in-depth familiarity with the project's critical systems, equipment, and functions. To implement this concept, one must specify the quantities to be monitored, choose the appropriate sensors, and maybe set them up. During this stage, it is also essential to identify the many failure modes that could occur.

Phase 2. Acquisition, Preprocessing, and Processing of Data

Sensors built into the apparatus can record and upload information to a server. In this step, it is crucial to determine which data will be scrutinized, evaluate the quality of that data, and assign meaning to it. Data cleaning and management encompasses a wide range of tasks, including but not limited to selecting and merging related datasets; deleting or imputing missing values; managing erroneous data by deleting it; looking for and handling outliers; using engineering software to construct new data and obtain new interpretation from existing data; formatting the unstructured data into the structured data; removing unnecessary rows or columns; and many others. Preparing the data to be analyzed is the most time-consuming part of a project, typically accounting for 70-90% of the entire endeavor.[10][12]

Phase 3. Creation of a Data Model

The data analysis process revolves around the data model. The model takes as input the results of the data preparation phase before it and produces the expected result. In this step, the business will decide on the algorithm based on whether they are trying to solve a classification, regression, or clustering problem. A model results from trying out different approaches and then fine-tuning their parameters.

Phase 4. Model Assessment and Implementation:

4.1—Assessment: The model's correctness (how well it functions and accurately represents the data) and applicability are the first to evaluate. (Original question needs to be answered). Similarly, we must ensure that the developed model is unbiased and can be applied to various contexts.

4.2—Implementing the model: This is the last step in gathering information for use in predictive maintenance. Each stage of the life cycle is discussed in detail below. All hard work will be for naught if even a single step is incomplete or sloppy. For instance, a representative model cannot be built if the knowledge is lost owing to insufficient data gathering. The accuracy and reliability of the model rely on clean data. The model will not deliver perfect outcomes in practice unless thoroughly tested. Each process step, from initial project understanding to final model deployment, calls for dedicated focus, time, and energy.

Phase 5. Solution Selection.

The process is used to help operators choose the best solution to a problem. Making decisions that benefit short- and long-term goals after careful consideration is much easier when following a step-by-step plan.

5.1—Identifying the output: Identifying the issue is essential to selecting the best action. Generating several possible intervention scenarios in this stage, each with estimated repair time and cost, is important.

5.2—Act: After a list of possible outcomes has been compiled, choosing one or combining them is vital to find the optimal combination of time and money savings. After verifying the availability of workers and replacement parts, the number of scheduled repair days is set.

5.3—Active monitoring: Given the cyclical nature of the predictive maintenance life cycle, this step is critical for gaining insights to fine-tune future interventions and evaluate the efficacy of those already implemented. [12]

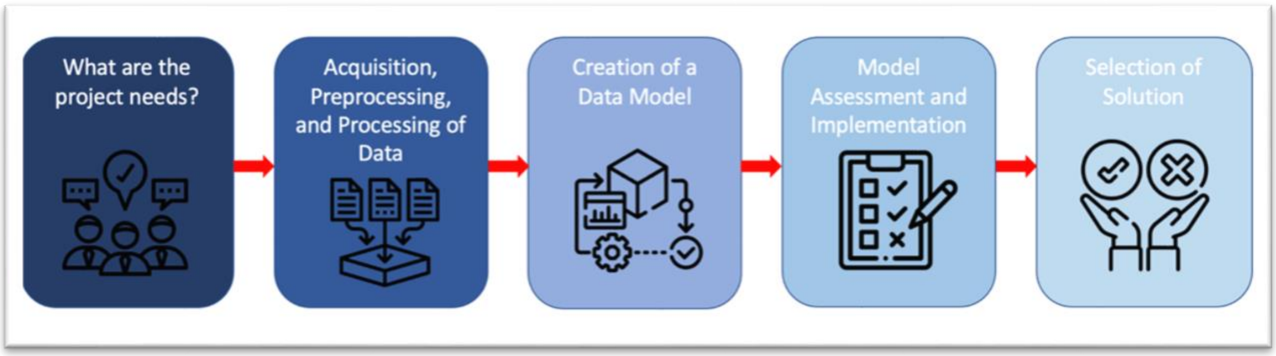

Figure 2.1 Predictive Maintenance Workflow

Certain technologies are required to complete these 5 phases of a PdM model (shown in Figure #2.1) to conform with them. These technologies may be engaged in one or all steps of the PdM workflow; therefore, the combinations, collaboration, and correct application will result in a reliable prediction of any problem a business may face. The Internet of Things (IoT), big data, analytics, cloud computing, and digitization play a significant role in developing or implementing a PdM model. If adequately implemented, combining these technologies can eliminate or reduce the amount of corrective and preventive maintenance produced by the global industry.

2.2 PdM Technologies

2.2.1 Internet of Things

The Internet of Things (IoT) and the Internet of Services are two concepts that are becoming increasingly prevalent in the manufacturing sector because of the fourth industrial revolution. [2]. The Internet of Things (IoT) is the term used to refer to the process of integrating computing and sensors into an online environment through a wireless connection.

The Internet of Things (IoT), creating a global information network comprised of many interconnected "Things," is a crucial enabling technology for intelligent manufacturing. Materials, sensors, actuators, controllers, robots, human operators, machines, equipment, products, and material handling equipment are only some of the "Things" that might be considered "manufactured" in this context [10]. The internet-based IoT architecture provides a once-in-a-generation opportunity to digitally integrate the entire industrial sector by connecting its "Things," services, and applications.

Large-scale IoT sensing produces and manifests large amounts of data, which can be kept locally or in data repositories dispersed across the cloud. To obtain the full benefits from big data in smart manufacturing, new approaches for managing large-scale Internet of Things (IoT) data, analyzing information, and controlling industrial processes are required [10]. For instance, the Internet of Things may use a large number of sensors to carry out ongoing monitoring of the state of a machine and then upload the resulting data to the cloud. The data obtained by the Internet of Things include sensor signals and measurements gathered from the equipment and online data collected through active monitoring of machines.

While working at the MIT Auto-ID Center, Kevin Ashton created the term "Internet of Things" in 1999[39]. IoT refers to the expansion of physical objects that are networked together. The Internet, in this context, is the worldwide system of interconnected computer networks that allow

"Things" to be linked together and managed from afar using the TCP/IP protocol. Ethernet, Wi-Fi, Bluetooth, ZigBee, Radio Frequency Identification (RFID), and barcodes (Table #2.1) are all examples of low-level wired and wireless technologies that could enable high-level communication based on the TCP/IP suite [10]. Physical or digital items with their identities and the ability to perceive their surroundings, collect data on those surroundings, and communicate that data with similar objects are collectively called "things."

Table 2.1 IoT data link protocols and their characteristics [10]

Protocol	Standard	Frequency	Range	Data Rates	Applications
Bluetooth	Bluetooth 4.2	2.4 GHz	50-150 m	1 Mbps	In-vehicle network wear-able sensing smart home.
ZigBee	IEE802.15.4	2. G GHz	10-100 m	250 kbps	Smart-home remote-control healthcare
Z-Wave **Wi-Fi**	ZAD12837 IEEE 802.11	900 MHz 2.4 GHz 5GHz	30m 50m	9.6/40/100 kbps 150 ~ 600 Mbps	Smart home healthcare laptops, mobile, tablets, and digital TVs
NFC	ISO/IEC 18000-3	13.56 MHz	10cm	100 ~ 420 kbps	Smartphones, contactless payment
Sigfox	Sigfox	900 MHz	30-50km (Rural) 3-10 km (Urban)	10 ~ 100 kbps	Smart city, industrial and environmental applications
Neul	Neul	900 MHz	10 km	10 ~ 100 kbps	Smart city, industrial and environmental applications
Cellular	GSM/GPRS/EDGE (2G), UMTS/HSPA (3G), LTE (4G)	900 MHz 1800 MHz 1900 MHz 2100 MHz	35 km (GSM) 200 km (HSPA)	35-170 kbps (GPRS) 120-384 kbps (EDGE) 384 kbps – 2Mbps (UMTS) 600 kbps - 10 Mbps (HSPA) 3-10 Mbps (LTE)	Cellular networks, mobile phones, and long-distance applications.

Bluetooth, Zigbee, Z-wave, Wi-Fi, and Near Field Communication are all examples of protocols used in short-range and local-area wireless networks [10]. Typically, they send information over distances between 10 centimeters and 100 meters. Bluetooth is widely used for in-car networking and wearable sensor uses. Since Bluetooth uses little power, ZigBee has become the de facto standard for WSN protocols. Due to its low data rate and low energy consumption, Z-wave is well-suited for domestic and medical IoT use. Unlike Near Field Communication (NFC), typically used in contactless payment via smartphones, Wi-Fi is a wireless computer network protocol used mainly in broad ways such as laptops and mobile laptops.

In terms of the industry, the main objective of IoT is to establish a connection between any asset companies may have and the network, which transforms this data into a digital space where it can be stored, shared, or displayed. This technology converts things (assets) into smart by making them able to be monitored from any place once connected to a specific network. This action eliminates the need to be physically on-site if data from the asset is needed or if asset monitoring needs to be done to avoid failures, downtime, or any other aspect that depends on the industry's needs.

2.2.2 Cloud Computing

Cloud computing is defined as the capability of storing data in a provider of internet server space, with the data being easily retrieved via remote access. While the devices do not need to be physically close to each other to communicate information and coordinate their actions, this feature makes it easier to integrate multiple devices.

Cloud deployment describes how a Cloud is configured to deliver a specific service. These deployment strategies will differ based on how a Cloud provides services to its users. Consequently, their deployment methods are user-specific. Three cloud deployment methods exist Public, Private, and Hybrid. Below are briefly discussed each type of these methods.

Public Cloud is the most common approach to deploying the Cloud, in which providers dynamically allocate resources to their users and charge them on a per-use basis for their utilization, which is called utility computing. It is a viable option for small businesses due to its low upfront cost, scalability, and flexibility, all of which are paid for on a pay-as-you-go basis. Then, Private Cloud involves allocating an entire data center to a single company. The fact that only one company controls these Clouds makes them safer. Consequently, Hybrid Cloud takes the best features of both the Public and Private Cloud approaches. For instance, in a Hybrid Cloud deployment, services with lower security requirements may be hosted on Public Clouds, while those with higher standards could be hosted on Private Clouds.[15]

Cloud computing services can be broken down into three broad groups: software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS). In what follows, this section provides an overview of some of the most popular Cloud Services on the market today. Figure #2.2 describes some of the most common services used for each cloud service.

- Infrastructure-as-a-Service (IaaS): This pay-as-you-go service offers storage and virtual servers. IaaS provides faster service by using cutting-edge computer infrastructure technology. IaaS lets companies quickly develop new software or environments without purchasing or configuring them. Resource virtualization and usage-based charging make IaaS appropriate for all sorts of companies.

- Platform-as-a-Service (PaaS): PaaS may offer application design, development, testing, deployment, hosting, and application services like team collaboration, web service integration and marshaling, database integration, security, scalability, storage, persistence, state management, application versioning, application instrumentation, and developer community facilitation. [15]
- Software-as-a-Service (SaaS): Some apps are hosted remotely. Internet access is not required, but data storage and communication capabilities are. Users can access the provider's application via thin client interfaces. Cloud companies provide software as a service.

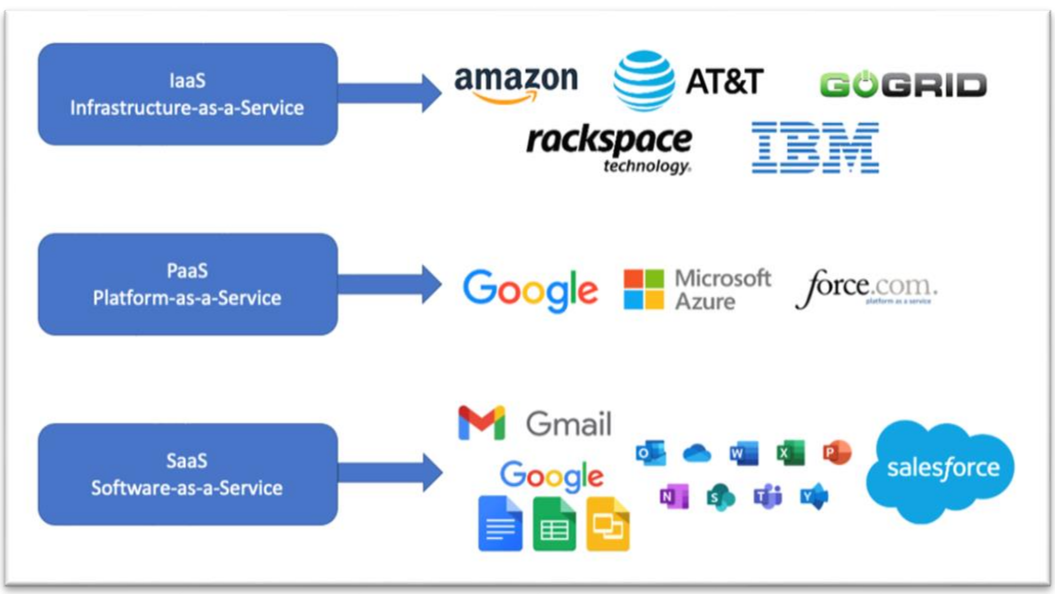

Figure 2.2 Examples of services for each type of cloud computing [15]

The Internet of Things and cloud computing make it possible to connect disparate pieces of hardware, resulting in the storage of massive amounts of data under the umbrella term "Big Data."

2.2.3 Big Data

Big data refers to large volumes of data that are too extensive, quick, and complex to be processed using standard methods [13]. Consequently, accessing and storing massive data for analytics has been difficult for data professionals. Moreover, big data includes numerous unstructured, semi-structured, and structured data types. However, specialists utilize it due to the complexity of sifting unstructured data. The storage size of extensive data varies from a few terabytes to several zettabytes.

Big Data is defined by different variables such as velocity, volume, veracity, variety, value, variability, scalability, and relational, as shown in Table#2.2.

Table 2.2 Big Data Variables [13]

Variable	Definition
Velocity	The rate at which data is generated in real-time situations.
Volume	Amount of data to handle, manage, and store.
Veracity	Capacity to confirm data accuracy with an accurate value.
Variety	• Structured data – Databases (Spreadsheet) • Unstructured data – Audio, Video, Images. • Semi-structured data -Email, Webpages
Value	Proportional to the time required for data refinement processing.
Variability	Raw data must be assimilated and merged into parts, and unstructured data can be eventually converted into structured data.
Scalability	Capacity to store massive amounts of data.
Relational	Data must be examined based on the elements of correlations that link them.

The following conclusions may be drawn from the above: First and foremost, data is a vital asset enabling intelligent production. The second strategic relevance of big data is not to control large amounts of data but to obtain value with unique meaning through specialized processing. The value of convergent data is significantly greater than that of a single data type.[14]

2.2.4 Analytics

Analytics is a discipline or approach that involves observing and analyzing complicated phenomena to extract anything useful. When this technique is used for data, helpful information and knowledge are removed. IoT's extensive data analysis can identify trends, hidden links, unexpected patterns, and new information.[16]

- *Descriptive Analytics*: This method evaluates data to answer the queries, "What occurred? What is going on?" The data is manually assessed and classified using standard business intelligence (BI).
- *Diagnostic Analytics:* This procedure analyzes the root source of the problem. This technique facilitates responding to the inquiry, "Why did something occur?" It is categorized using data mining, drill down, discovery, and correlations.
- *Discovery in Analytics*: It is visualizing or using guided complex analytics to find outliers and patterns. Data discovery relies on brain pattern detection and visualization.
- *Predictive Analytics:* Predictive analytics aims to develop patterns from existing data to predict future conclusions and trends. Predictive analytics forecasts "what is likely to occur in the future." It combines previous data and knowledge to anticipate future outcomes and provides the methods to evaluate the accuracy and dependability of these forecasts.
- *Prescriptive Analytics*: This statistical method uses mathematical model computations to provide recommendations and draw findings. It answers, "What should I do about what has happened or

is likely to happen?" Prescriptive analytics determines the best action based on timely data analysis and uncertainty. [16]

Using big data in conjunction with analytics can facilitate the self-organization of production lines and enhance the decision-making processes in every facet of an industrial enterprise.

2.2.5 Digitization

Digitization is the process of transferring analog information to digital or any information (picture, speech, text, sound) into a digital format, such as scanning paper into bytes or uploading an audio recording [13][17]. Often, it also encompasses the transition from manual to digital processes, such as replacing paper forms with online ones that are instantaneously uploaded to a database. The much-discussed and elusive "paperless workplace" represents the peak of digitization.

One of the many benefits of digitization is the ability to streamline processes and reduce human error. Envision a scenario where the doctor enters pharmacy orders into the electronic medical record. This information could then be forwarded to the pharmacist for preparation, the orderly transport to the floor, and the nurse for administration [17]. Alternatively, the factory manager can record the inventory of individual parts directly into a database, alerting purchasing of impending shortages and possibly leading to the creation of a purchase order. Additionally, it can make possible the collection of hitherto impracticable data, such as real-time performance data from sensor-equipped machinery.

Digitization converts analog formats humans can read to digital formats machines can only read, as depicted in Figure #2.3. With the assistance of information technology, it is becoming increasingly easier to keep up with the ever-increasing volume of information created in various formats and disseminated through multiple channels. Digitization enhances the availability of information resources. Digital projects enable users to do quick and exhaustive collection searches from any location. The digitizing process renders the invisible visible. Multiple users can access the same document concurrently without interference. It also eliminates the inconvenience of distance, as users are no longer required to travel to venues containing hard copies of materials. [13][17]

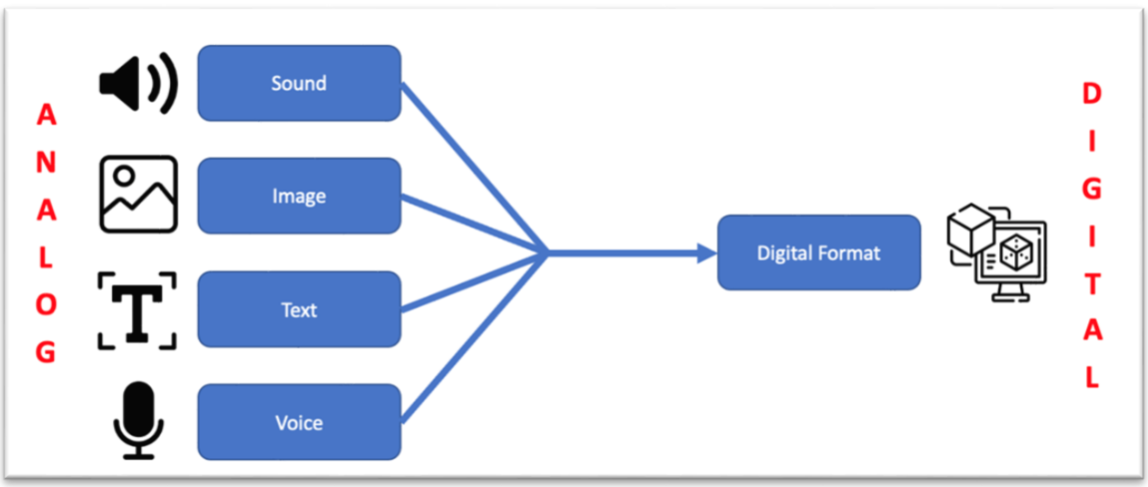

Figure 2.3 Digitization Concept [13]

Figure #2.4 shows the integration of IoT, digitization, cloud computing, big data, and analytics technologies. Nowadays, various technologies must work together and interact with one another. Since the introduction of Industry 4.0 and SM, these technologies have evolved, with more industries deciding to implement the concepts daily, resulting in many success stories that summarize better products, increased earnings, and better control of their assets. Creating a PdM model in which these concepts are thoroughly adapted to the PdM workflow described in the following section is one of the primary aims of integrating these technologies.

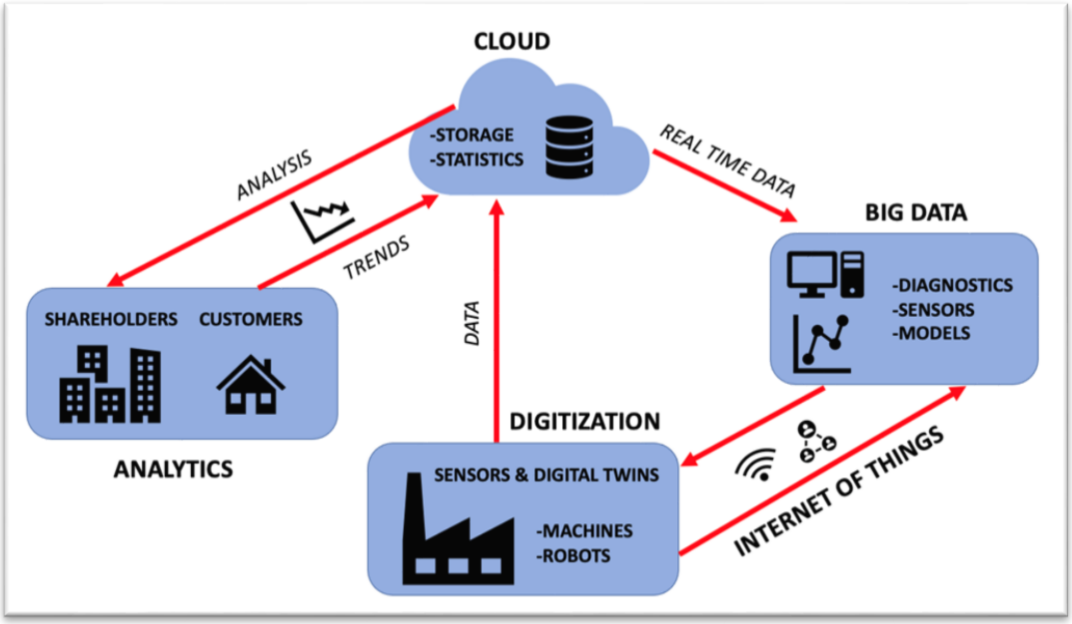

Figure 2.4 Integration of Smart Manufacturing & Industry 4.0 technologies. [18]

2.3 PdM Models

2.3.1 Condition-based Maintenance (CBM)

Managers use the philosophy of condition-based maintenance (CBM) to decide when and how to repair or replace machinery. Data collection, processing, and maintenance decision-making are the three essential components. It is a tool that monitors a system's health and recommends fixes based on the data it collects. [12]

CMB can be presented in 7 different modules and are represented as follows: data acquisition, data processing, status detection, diagnostic, prognostic, decision-making, and presentation. In Module 1, sensors convert the analog sensor or transducer readings into digital form for use by the CBM system. For the second module, the signal processing module receives the fixed signals and data from the sensor module or other signal processing modules. The sensor input is digitally filtered, frequency spectra are generated, and simulated sensor signals are produced as output from the signal processing module, among other CBM features. A sentient artificial intelligence (AI) could operate the signal processing module.

In the next module, the sensor module, signal processing module, and additional status monitors all provide information into the status monitor. Its primary function is to check actual results against predictions. In addition, the status monitor should be able to sound alarms based on user-specified thresholds. When a fault develops quickly, this feature can be invaluable. After this module, from various status monitors or other health assessment modules, this module gets data. The health assessment section's primary goal is to determine if the state of the monitored item has worsened. The health assessment module can suggest diagnostic records and potential failures. Patterns in past health, operations, and load/maintenance data provide the basis for diagnosis.

In the fifth module, the predictive component can integrate information from the uppermost layers. The prognosis module's primary goal is to predict an asset's health in the future by analyzing expected usage patterns. Future health status or remaining useful life should be displayed on the module. Module 6 passes the information collected by the prognosis and health assessment modules to the decision support module for processing. One of its primary functions is to suggest potential courses of action and solutions. The measures taken may involve maintenance but may also include continuing to operate the asset as necessary to finish the current task without an incident.

Finally, the last module involves implementing decisions on assets while continuously monitoring them. This may involve updating the models, changing the sensors, or refining the maintenance actions. Information from the diagnostic, prognostic, and decision-making tools and status-monitor-generated warnings are the most crucial components to convey. Getting a tighter hold at deeper layers is possible. It would be possible to incorporate the presentation module into a standard machine interface or Human-machine interface to visualize the asse data better. [12][40]

Table 2.3 Condition-based Monitoring Methodology [12][40]

	Module	Actions	Tools
CbM	❑ **Sensorization & Data Acquisition**	➢ *Select right sensor and obtain digitized data* ➢ *Data base creation* ➢ *Most relevant features to monitor*	✓ Sensors (Temperature, Humidity, Vibration) ✓ Data Loggers ✓ Cloud Services ✓ Remote Monitoring Systems
	❑ **Data Processing**	➢ *Obtain data to digitally filter data* ➢ *Validate and clean data*	✓ Microsoft Excel ✓ SQL ✓ Python ✓ MATLAB ✓ R
	❑ **Detection**	➢ *Monitor receive data from sensors, compared data with expected values and generate alerts based on operational limits* ➢ *Useful for rapid fault development* ➢ *Detecting changes in trends,*	✓ Fourier Analysis ✓ Time Frequency Analysis ✓ Statistical Analysis
	❑ **Diagnostic**	➢ *Collect data from health assessment modules, maintenance records, failure records, operational status and historic data* ➢ *Complement with expertise and theoretical background*	✓ Machine Learning Algorithms ✓ Physics-Based Models or Hybrid Models
	❑ **Prognostic**	➢ *Combine all data and analyze it to calculate the future health status* ➢ *Predict degradation based on assets properties (Materials, lifecycle and working experience)*	✓ Machine Learning (Python, TensorFlow, Keras) ✓ Algorithms ✓ Physics-based models, data-driven models, or hybrid models.
	❑ **Decision-Making**	➢ *Generate recommended solutions, actions or alternatives* ➢ *Plan and and coordinate maintenance actions using PdM information to address process required.*	✓ IBM Maximo ✓ SAP ✓ Microsoft Dynamics 365
	❑ **Continuous Monitoring & Improvement**	➢ *Implement decisions on assets while continues monitoring.* ➢ *Moving to a more optimized maintenance* ➢ *This may involve updating the models, changing the sensors, or refining the maintenance actions.*	✓ Human-machine interfaces(Dashboards, Alerts, and visualizations)

2.3.2 Prognostics and Health Management (PMH)

Prognostics is a form of predictive diagnostics that assesses a system's deteriorating health and accurately explains when a failure is likely to occur. The objective of prognostics is to detect deterioration and generate prediction information, such as estimates of a system's state of health (SoH) and remaining usable life (RUL).[5]

Acquiring data is the first and most crucial stage of PHM, and it entails gathering and storing information about the physical component or system under study for later diagnosis and prognosis. The data collected may consist of sensory information or information about events (ED). Events (such as failure, breakdown, and installation) involving the physical component are recorded in the ED, along with the maintenance actions (such as oil changes or repairs) performed. Sensory data (condition monitoring data) includes readings from devices attached to the asset. Sensory data can be collected for noise, vibration, heat, cold, electricity, temperature, and other parameters. Where ED encompasses activities carried out on a component or system by a maintenance technician, including but not limited to corrective maintenance, asset repairs, installation, breakdown, cleaning, and oiling. [19][20]

Following the data acquisition, the next phase is called data preprocessing, which consists of cleaning and analyzing the data. Removing mistakes and other noise sources from raw data improves the chances of working with reliable information in analyses. The second phase of data preprocessing is analysis, which entails the procedures of feature extraction, feature evaluation, and selection. A feature extraction method should cleanse sensory time series to draw out only the genuinely relevant features to monitor the system's health. The failure evolution of the system should be reflected in the extracted features. In the literature, the feature extraction methods are broken down into three distinct groups: those that use the time domain, those that use the frequency domain, and those that use both. Time-domain feature extraction methods (such as root-mean-square and kurtosis analysis) are employed to glean insights into the overall qualities of data.

Feature extraction methods, such as the Fourier transform and envelop analysis, can discover mistakes that could otherwise go unnoticed by time-domain methods because they reshape the information into the frequency domain. Fourier transforms, surround analysis, Hilbert-Huang transform, Wigner-Ville distribution, and similar techniques are examples of time-frequency domain-based methodologies [20]. The following steps after data extraction are evaluation and feature selection.

The transformation of raw data into actionable knowledge is essential for decision-making. Data reduction, preprocessing, and cleansing are standard practices in research and modeling. Data processing (including resolving conflicting or redundant data) can be conducted during preparation, whereas data cleansing is accomplished when the format is finalized. In most circumstances, data reduction requires processing, including collecting features or cases to translate the data into meaningful and reduced forms. [19]

After the preprocessing, processing, and cleaning of the data, detection modeling must account for the multiple causes that cause system components to age and lose their initial performance. "Health state detection" refers to finding anomalies or signs of impending failure in

CM data. In most cases, a problem can be detected by comparing the system's actual behavior in nominal conditions with predicted behavior.[20]

One of the essential phases is diagnostic and prognostic, meaning that when something goes wrong, it is up to condition monitoring's fault diagnostics procedure to figure out what went wrong, which parts are at fault, and how badly those parts are failing. Both total machine failure and poor operation present opportunities for diagnostic testing. When identifying a deteriorated condition instead of a complete failure, the results of a diagnostic might be used in either reactive or preventative maintenance.

Decision-making is the result of a procedure that leads to the selection of the most reasonable and appropriate course of maintenance action from a set of possibilities. Based on the diagnostics and prognostics findings, the maintenance team must evaluate the pros and cons of each step taken. The technician's ability to predict the outcomes of potential courses of action is crucial to making good choices. The results of decisions may have an operational or design focus. Optional operational activities may include fault tolerant control, hardware/software reconfigurations, and maintenance interventions (FTC). Changes in observability, redesign, and component location could be implemented due to the design process. [41]

Table 2.4 PHM Methodology

	Steps	Actions	Tools/Techniques
PHM	❑ **Data Acquisition**	➢ *Process of collect and storage data from physical assets (sensor data, events data, maintenance actions from events)*	✓ Sensors (Vibration, Temperature, voltage) ✓ Event Data (corrective maintenance, repairs, installations, breakdowns, cleaning
	❑ **Data Preprocessing**	➢ *Cleaning errors* ➢ *Feature extraction, evaluation and selection of processes*	✓ Time-domain based (Root mean square, Kurtosis) ✓ Frequency-based (Fourier Transform, Envelop Analysis) ✓ Time-frequency (Fourier Transform, Envelop Analysis, Hilbert-Huang Transform, Wigner-Ville Distribution)
	❑ **Detection**	➢ *Anomalies from condition monitoring* ➢ *Inconsistencies in behavior* ➢ *Health, faulty state or failed*	✓ Quantification of inconsistencies between accrual and expected behavior ✓ Time-to-failure Estimation ✓ Historical CM Data
	❑ **Diagnostics/Analysis**	➢ *Degradation level assessment (failure severity)* ➢ *Faulty detection* ➢ *Isolate failed components* ➢ *Failure mode identification*	✓ Diagnostics when complete failure or faulty state ✓ Quantification of the failure severity ✓ Post-mortem fault diagnostics
	❑ **Prognostics**	➢ *Predicting the RUL* ➢ *Support proactive decision-making* ➢ *Prevention of system from possible failures*	✓ Predicting Future States ✓ Software (IBM Maximo, SAP Predictive Maintenance, and GE Predix)
	❑ **Decision-Making**	➢ *Selection of logical and right maintenance actions* ➢ *Evaluate positive or negative feedback from each action taken* ➢ *Estimate outcomes (maintenance interpretations, hardware/software reconfiguration, fault tolerant control)*	✓ Maintenance Interventions ✓ Hardware/Software reconfigurations ✓ Fault Tolerant Control(FTC) ✓ Observation

2.3.3 Remaining Useful Life (RUL)

The RUL of a component indicates how much longer it will continue to serve its intended purpose before breaking down. The RUL of an element is the time remaining until it is no longer functional.[21] Using any one of numerous prognostic prediction methodologies can calculate the RUL of subsystems or components. Methods and procedures describe these approaches.

- *Model-based:* It may be used with methods from Statistics and Computational Intelligence (CI). These models can be used in maintenance decision-making based on configuration, usage, and run-to-failure data. Bearings and gear plates are two industrial components that have been the subject of analysis and documentation in the literature. Estimating RUL using a model-based approach is standard practice since it helps to influence maintenance decisions based on failure thresholds. The time-frequency features allow for more exact findings than time features; hence, a fixed wavelet packet' decomposition technique or Hidden Markov Models (HMMs) is proposed to forecast RUL. [21]

- *Analytical-based:* An analytical approach to RUL prediction exemplifies the physical failure method. The analytical-based model is about understanding the methodologies that contribute to the reliability estimates of the physics-based model due to Physics-of-Failure (PoF), the physical science of components, and developed experimental equations. According to the research of Coppe et al. [18], it is possible to forecast the RUL of an exhausted system by employing a straightforward crack growth model. Mathematical formulas estimate RUL for failure events, including cracks by fatigue, wear, and corrosion of components. Estimating damage in a specific failure mechanism using an analytical-based model calls for a synergy of experiment, observation, geometry, and condition monitoring data. [21]

- *Knowledge-based:* This approach incorporates both CI and practical knowledge. The knowledge-based approach is concerned with accumulating data from specialists and deducing meaning from a predetermined set of rules [21]. One way to think of it is as a service delivery performance system built on the foundation of service feedback for analysis. Estimates of reliability parameters are made utilizing knowledge of the asset and prior experience.

- Hybrid: A hybrid model is a data-gathering strategy. The RUL estimation accuracy of the hybrid model is enhanced by its usage of many methods. The RUL estimations in a hybrid model use parametric and non-parametric data. It makes independent RUL forecasts and, using probabilitytheoretic techniques, makes it easier to fuse two or more RUL forecasts into a single RUL. [21] [43]

Table 2.5 RUL Methodology

<table>
<tr><th></th><th>Model</th><th>Focus on</th><th>Methods</th><th>Data Required</th><th>Recommended Approaches</th></tr>
<tr><td rowspan="6">RUL</td><td>Analytical</td><td>✓ Fatigue
✓ Wear
✓ Corrosion
✓ Product Reliability
✓ Enhanced Performance</td><td><u>Physics-of-Failure</u></td><td>✓ Parametric data
✓ Condition Monitoring
✓ Observation
✓ Experiment</td><td>✓ Linear damage Rules
✓ Non-linear damage curves
✓ Two stage linearization
✓ Life Curve Modification Method
✓ Stress Load Interaction</td></tr>
<tr><td rowspan="2">Model</td><td rowspan="2">✓ Historical Run-to-failure
✓ Configuration
✓ Usage</td><td><u>Statistics</u></td><td>✓ Past Data
✓ Present Data
✓ Random variables</td><td>✓ Auto regressive moving average (ARMA)
✓ Exponential Smoothing
✓ Proportional Hazard Model</td></tr>
<tr><td rowspan="2"><u>Computational Intelligence</u></td><td rowspan="2">✓ Continues Monitoring
✓ Training Samples
✓ Data from sensors</td><td rowspan="2">✓ Fuzzy logic
✓ Neural Networks
✓ Artificial Neural Networks(ANN)
✓ Bayesian Prediction
✓ Support Vector Machines(SVM</td></tr>
<tr><td rowspan="2">Knowledge</td><td rowspan="2">✓ Feedback
✓ Subject mater experts
✓ Interpretation of rules</td></tr>
<tr><td><u>Experienced</u></td><td>✓ Historic Data
✓ Matter Experts
✓ Failure Events
✓ Developmental test events</td><td>✓ Datasets
✓ Observation
✓ Test Events
✓ Degradation Analysis</td></tr>
<tr><td>Hybrid</td><td>✓ Several techniques
✓ Improved accuracy
✓ Probability theories</td><td><u>Fusion</u></td><td>✓ Combination of one or more other techniques
✓ On-demand data from sensors</td><td>✓ Fuzzy method
✓ Principal Component Analysis (PCA)</td></tr>
</table>

As described previously, RUL methodology can be differentiated into four approaches, each employing distinct techniques. Based on the project's requirements, these techniques facilitate selecting the most suitable approach. Table#2.5 explains the data required and recommended practices for the physics of failure, statistics, computational intelligence, experience, and fusion techniques used as the primary input depending on the type of model selected when applying an RUL methodology.

Even though various methodologies exist for deploying a PdM model, the most crucial factor is the project's requirements or the industry's primary objective for which PdM may be required. No matter which method is used or chosen, all of these methodologies lead to the same result: prediction. The type of prediction will be specified alongside the primary objective of the undertaking. Before attempting to invest in a PdM project or selecting the best methodology for the industry, it is essential to understand the potential outcomes of deploying a PdM model. The benefits obtained from successfully deploying a PDM model and examples of PdM's success in various industries are presented in the following section.

2.4 Benefits of PdM

The practice of predictive maintenance takes advantage of the ability to deploy intelligent machines, which can alert maintenance teams before the machines break down. The benefits include a reduction in the amount of downtime experienced, an improvement in the effectiveness of the equipment, a decrease in the costs associated with maintenance, an increase in return on assets, risk mitigation, and, most crucially, profitable growth.[4]

The goal of PdM is to schedule maintenance interventions and forecast when problems will occur precisely. This goal is accomplished by installing sensors in industrial machinery to monitor their operations and relay the data they collect (which is often presented as a time series). PdM strategies try to foresee certain rare events that signify failures by analyzing this type of data to create models. In other words, sensors keep track of the activities carried out by a machine or at least a portion of those activities. The readings from these sensors reveal the machine's typical behavior when doing specific tasks. Anomalies are recorded whenever this pattern is broken; they may indicate that the equipment is deteriorating and may soon collapse. Consequently, the detection of irregularities is a crucial stage in the process of successfully putting PdM systems into operation.[4][9]

PricewaterhouseCoopers (PwC) reports that PdM can extend the life of an aging asset by 20%, reduce OPEX costs by 12%, increase uptime by 9%, and decrease hazards related to safety, health, environment, and quality by 14% [4]. Machines automatically generate log data about their regular (and abnormal) running. However, the business world has hesitated to adopt integrated data analytics methodologies to make sense of the enormous amounts of data collected.

The potential benefits of using predictive maintenance algorithms for maintenance management have decreased significantly, according to an analysis of 1,500 plants. The survey results determined that 89% of the plants currently use one or more of the traditional predictive maintenance technologies as an active component of their maintenance management activities and that 14.1% planned to initiate a program within the following three years.[9]. Five years ago, only 15% of assessed factories used this technology. This figure indicates that most plants have attempted to incorporate predictive maintenance into their maintenance management program due to its apparent value.

According to Mobley's survey, there are derived benefits aimed to measure the benefits that predictive maintenance systems have produced. Almost 91% (90.9%) of participants reported measurable cost reductions due to their predictive maintenance programs [9]. Reduced maintenance expenses and downtime have, on average, recouped 113% of the total cost of these projects. Based on these facts, the average program will deliver a 13 percent net improvement. Compared to the average maintenance budget of survey respondents ($12,053,000), the annual savings average is almost $1.6 million. According to most of the literature, a successful predictive maintenance program should yield a 10:1 to 12:1 return on investment. The plant should save between $10 and $12 for each dollar invested [9]. The poll results demonstrate conclusively that this event is not the case. According to the data, the average return on investment was only 1.13:1, marginally above breakeven. Few financial managers would allow predictive maintenance investments if this figure were accurate.

The survey's results could only tell part of the story. Looking closely at the responses, it can be noticed that only 26.2% of people said their programs recovered the money they put into them, 13% said they needed clarification, and 50.8% said they did not. Based on these numbers, it is reasonable to doubt the usefulness of predictive technology; however, the remaining 10% should be analyzed first. These 26.2% projects were more profitable than the other programs since they recovered their costs and found ways to save money. About half of these establishments had a return on investment of 5:1, meaning their profits were equal to or greater than their total costs. [9]

Although this return is far lower than the average recorded for successful predictive maintenance programs, it significantly impacts profitability. The numbers also reflect our assumption that only some plants employ predictive maintenance capabilities to their full potential. These technologies, when properly employed, can provide a return on investment substantially above 100:1, or $100 for every dollar invested. As often said, the technology is accessible but must be utilized effectively for optimal benefit. The poll results demonstrate that this issue is untrue for many businesses. [4][9]

2.4.1 Success Stories of PdM

Implementing predictive maintenance solutions has significant benefits in the industry. Table#2.6 briefly describes some use cases from our projects.

Table 2.6 Successful Case Studies using PdM [22][23][42][43]

Business	Approach	Prediction	Benefit
Offshore Oil Drilling	Real-time data of the oil temperature and revolutions per minute (RPM) of the drilling machine's gearbox	Identify triggers for gearbox failure.	Lowered maintenance expenses by 38% and enhanced safety.
Automotive Industry	Real-time measurements of the dust level, humidity, and temperature of molding machines	The rate of headlamp scrap will exceed the permitted threshold.	A greater understanding of the problems' causes and a 29% improvement in scrap rate.
Production of Domestic Appliances	Real-time measurements of punch vibration, seaming vibration, and seaming pressure during drum rotation.	Malfunctioning (resulting in scraps) or breakdown (resulting in downtime) of the dryer drum manufacturing process.	33% reduction in faults and 27% decrease in maintenance expenditures.
Aviation Industry	Real-time data of temperature, humidity, gyroscope, and acceleration of an extensive transportation jig for wing coverings of a commercial airplane.	The time-to-arrival at the repair provider and the quality of the jig.	Maximized the utilization of maintenance resources and reduced repair time by up to 22%.
Steel Industry	Real-time measurements from the vibration (acceleration and velocity), tachometer (RPM), and current (Amps) sensor	Failure of the cold rolling machine's rollers.	Maximized the running equipment's lifetime by up to 60% and reduced downtime.
Tennessee Snack Food Manufacturer	Infrared is used on electrical equipment, some rotating equipment, and heat exchangers. Quarterly IR analysis is performed in-house on all motor control center rooms and electrical panels.	Increased acid levels were detected in soil samples from a baked extruder gearbox, indicating oil degradation, which prevented a shutdown of Cheetos Puffs production.	Year-to-date equipment downtime is 0.75%, and unplanned downtime is 2.88% at PepsiCo's Fayetteville, TN, Frito-Lay plant.
Louisiana Alumina Refinery	Noranda Alumina tracks all motors and gearboxes at 1,500 rpm, higher with vibration readings, and most below 1,500 with ultrasound.	Put in the right amount of grease, know it was greased, and prove it with data on the date, time, and quantity.	60% decline in bearing changes in the second year, saving approximately $900,000 in bearing purchases and avoiding costly downtime.
Singapore Rail Operator	PDSS developed a data repository and analytics engine to consolidate and analyze all data for maintenance.	SMRT Trains implemented a Predictive Decision Support System (PDSS) based on AssetWise Linear Analytics from Bentley Systems.	Hundreds of manual planning hours have been eliminated, and about 20 maintenance train deployments per year are avoided.

2.5 Challenges & Limitations

Companies with a manufacturing focus are adopting the practices of Industry 4.0, which involve using the Internet of Things and the concept of Big Data. Implementing this method with their large amounts of data from production processes allows manufacturers to perform predictive maintenance and failure prediction. These fundamental classes provide a foundation for identifying the core application domains of knowledge discovery in manufacturing. In practice, however, there is considerable overlap between the methods employed in these core domains of knowledge-finding success application. [5]

According to Emerson, only about 20% of their predictive maintenance projects are successful [4]. Based on the recommendations in articles, papers, blogs, and other documents, the most common challenges and limitations are listed when implementing predictive maintenance projects. Some challenges include financial, data, maintenance, or industry limits.

2.5.1 Financial and Organizational Limits

Any new investment a for-profit company makes will be assessed against the costs they expect to incur. There are costs associated with implementing predictive maintenance strategies, such as sensor installation, data retrieval, model development and upkeep, and actual repair tasks. The price of this technology may vary depending on several criteria, including the equipment's type and complexity, the cost of consulting, installation, and information extraction, and whether the requisite expertise is available in-house. One approach to tell if predictive maintenance is worth it is to calculate the expected return on investment (ROI). Predictive maintenance results, payback time, and indicated costs must all be factored into ROI projections. Predictive maintenance's business case and practical implementation are both sensitive to the size and type of company that employs it [41][42].

2.5.2 Data Source & Quality

Building a production process management model with access to relevant data is possible. Nevertheless, only some businesses can access all relevant information when implementing production process management. After using the facts, it is crucial to pinpoint the gaps and progress toward filling them. The quality of the currently available information may also need to catch up to expectations. Suppose only a subset of the data could be of better quality. In that case, it may be possible to improve the situation during data preparation if there are enough data points to achieve statistical significance and defect detection can effectively isolate machine-critical hotspots.

Organizations using predictive maintenance approaches may encounter challenges if sufficient trust in the data is lacking, for example, if sensors, controllers, or other data sources provide erroneous or misleading readings. False alarms, incorrect estimations, and neglected maintenance are all possible outcomes of this problem. The fact that sensors often operate offline and do not offer online data is an additional challenge for sensor technology. In addition, sensors can be affected by things like noise, degradation of the instrument, malfunction, and outages. The data must be cleaned up before the predictive maintenance algorithm is applied so that it can make accurate predictions. [12][43]

Data collection and analysis at the field level of hierarchical control is difficult yet necessary for manufacturing. This data is the backbone for various control strategies, including decision support, failure analysis, and predictive maintenance. Data collected in the field is often aggregated as a decision-making tool.

Data mining applications in the manufacturing sector can be categorized into five categories.

- Correlating output quality and system parameters, like the settings of a machine, to identify the elements contributing to a deterioration in product quality through quality analysis.
- The process of learning from the causes and consequences of production resource failures, such as malfunctioning machinery.
- Maintenance effectiveness can be increased, among other ways, by careful analysis so that production assets are more readily available.
- Analysis of production schedules and plans to boost planning quality to maximize the use of production resources to their fullest potential.[5]

2.5.3 Maintenance Limits

Predicting how long a component will last allows for more accurate maintenance scheduling, but human interaction and a lack of self-maintenance still present challenges. Human operators are now required to monitor and maintain many machine components, making the level of human management and maintenance abilities crucial—industrial machinery functions by reflexively carrying out commands without questioning their design. Human job planning, on the other hand, relies on data and experience that a machine could also be able to access. The system's health, asset throughput, or product quality can benefit from the independent recommendation or execution of actions by an intelligent component. Other advances toward asset autonomy include asset awareness and autonomous maintenance. With the information currently obtained and stored in a predictive maintenance system, the assets can independently assess their current state, identify critical situations, and define maintenance actions. All the data needed to make predictive maintenance decisions and the degradation and prediction model would be scattered and available at the component level instead of a centralized system operating one or more assets. This method will allow the machines to organize routine upkeep tasks. Nevertheless, industrial machines still need to have this level of intelligence and upkeep. [12]

2.5.4 Deployment of Industrial Predictive Maintenance Models

After creating intelligent failure prediction models, integration, monitoring, and periodic update are three common challenges. Since the IT department is usually unrelated to the researchers and developers who produced the predictive maintenance models, model integration in the industry is challenging. The time and effort required to construct an appropriate IT infrastructure for data pipeline maintenance should be considered during the planning stages of a project. Updating the model is a part of the monitoring process. A feedback loop is added to the model to use new data as training inputs. The reliability of the predictions suffers because of the constant re-training of the models used to make them. Neither the integrity nor the relevance of the data is checked throughout the manufacturing process, allowing for the inclusion of outliers that affect future forecasts. It is crucial to maintain up-to-date models in machine learning to prevent the problem of conceptual drift. To update the prediction models, the company must change the code, the model, and the data all at once. This round of bettering predictive maintenance models is much more involved than routine changes to company software. [12][42]

2.6 "*PAInOuTT*" Model Methodology

After analyzing the three most prevalent methodologies for deploying the PdM model, a model proposal combining these three approaches was developed. This "*PAInOuTT*" model establishes the phases to follow and their actions, the expected inputs/outputs for each stage, the most common instruments used during each step, and the required team for each project phase.

This methodology guides initiating a PdM project and adheres to the stages recommended by various methods, including CbM, PHM, and RUL. The "*PAInOuTT*" model aims to comprehend the fundamental knowledge required for a PdM project by combining the steps, tools, and approaches. Even though not all PdM projects have identical objectives, they all aim to reduce unscheduled machine outages and save money on corrective and preventative asset maintenance [42][43].

Figure #2.5 depicts the "*PAInOuTT*" (Phases, Actions, Inputs, Outputs, Tools, and Teams) application flow diagram, which follows the steps/phases with the decisions required to proceed to the following process. The model is represented by eight distinct steps: asset selection, data collection, data preprocessing, data processing, diagnostic, PdM plan, act, and continuous improvement. In each of these eight stages, multiple actions and inputs are required to complete the specific activities. Following these steps with the suggested inputs will result in the expected outcomes for each phase, allowing users to continue deploying this methodology. Appendix A-1 contains the specifics and explanations of all the actions, inputs, outputs, tools, and teams utilized in each phase of this model.

To validate this proposed application flow model, it was incorporated into the solution framework presented in Chapter 3, in which a small local business decided to embark on its PdM technology voyage. The solution architecture adheres to the first four phases of the "*PAInOuTT*" model, which include asset selection, data acquisition, and data preprocessing/processing.

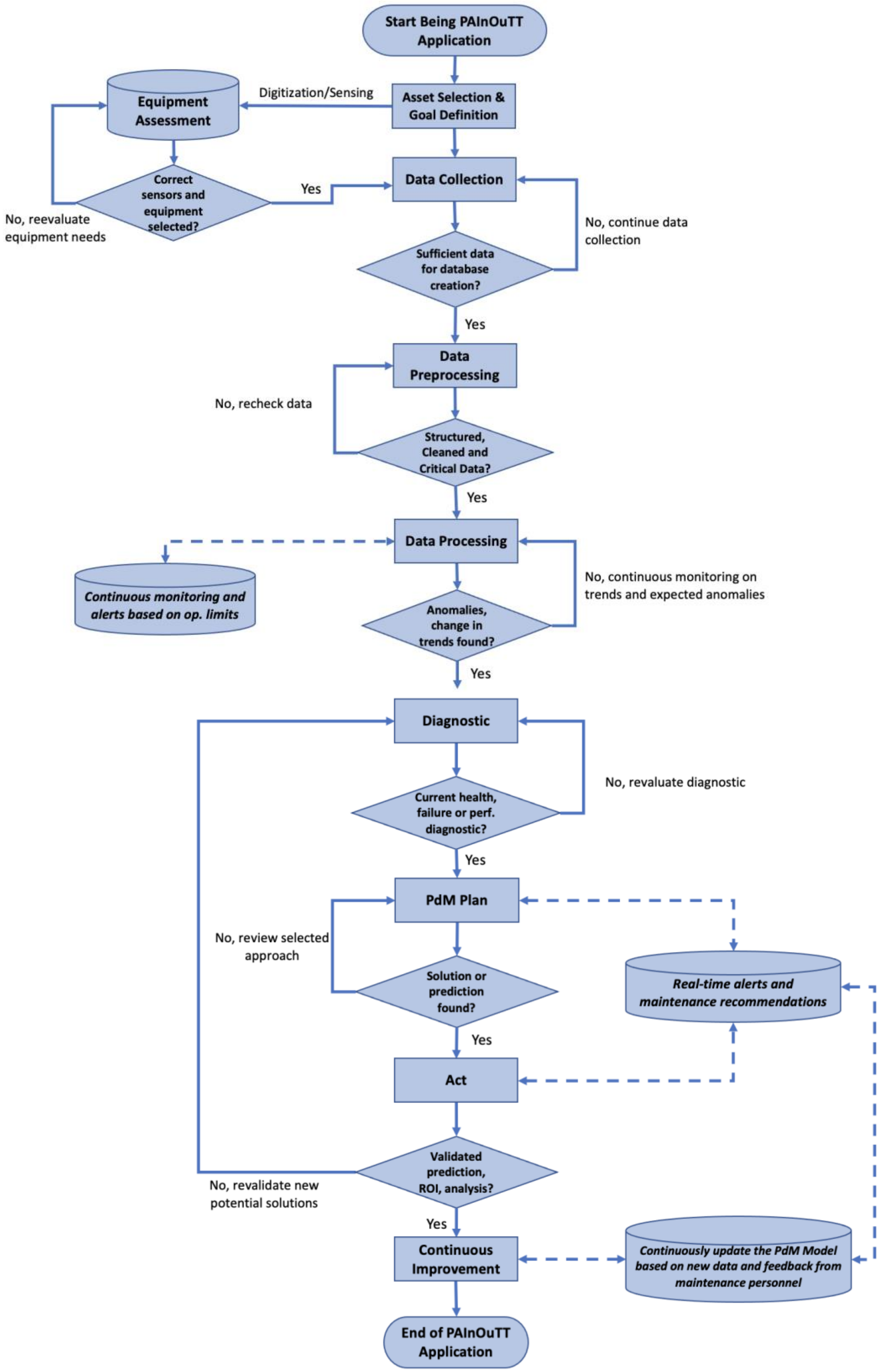

Figure 2.5 Proposed "PAInOuTT" Application Flow Diagram

Chapter 3 : Solution Framework Development

3.1 Problem Definition

Protect Extruder-Corrugator production and equipment from excessive temperatures using a temperature sensor module to collect and monitor actual temperature data to feed a database for potential predictive maintenance analysis.

Over the past few years, the company's maintenance crew has struggled to determine how to monitor machinery to prevent equipment from overheating. The maintenance staff addresses this issue by dispatching an individual to measure each machine's temperature with a temperature gun. This action is done to prevent the machine from overheating and burning out. In addition, excessive temperatures may damage or degrade the machine faster, necessitating predictive maintenance to avoid downtime and costly repairs.

The recommended answer is to digitize its machinery by putting temperature sensors at vital spots where high temperatures are more likely to occur or where temperature variations pose a more significant threat. By placing the sensors, they will be operational 24 hours a day, seven days a week, and they will send a report with all the temperatures at the specified period so that the company can monitor them. Secondly, the obtained data will be used to create and feed a database for the Extruder-Corrugator machine for potential predictive analysis. In addition, these sensors will be equipped with a red-light alert that will activate whenever any of the sensors reaches the maximum temperature allowed (approximately 90 degrees Fahrenheit), allowing a technician to identify and address the problem quickly. The temperature sensor module will also be connected wirelessly to the computer, monitoring and generating the data collection report.

This proposed solution consists of two phases:

Phase 1: Sensor Digitization of the Extruder Corrugator Machine, which includes the installation of temperature sensors in essential places and the development of a temperature sensor module. Secondly, Wireless Connectivity between the extruder-corrugator machine and the coordinator PC/computer must display real-time data for monitoring and generating anomalies reports and a dense database.

Phase 2: Focused on the Data processing of the data captured to obtain a diagnostic along with a PdM plan for the selected equipment. Finally, deploying the PdM model and continuously monitoring the equipment to improve accuracy will conclude the application case. Figure #3.1 illustrates the schematic of the proposed solution following the "*PAInOuTT*" methodology.

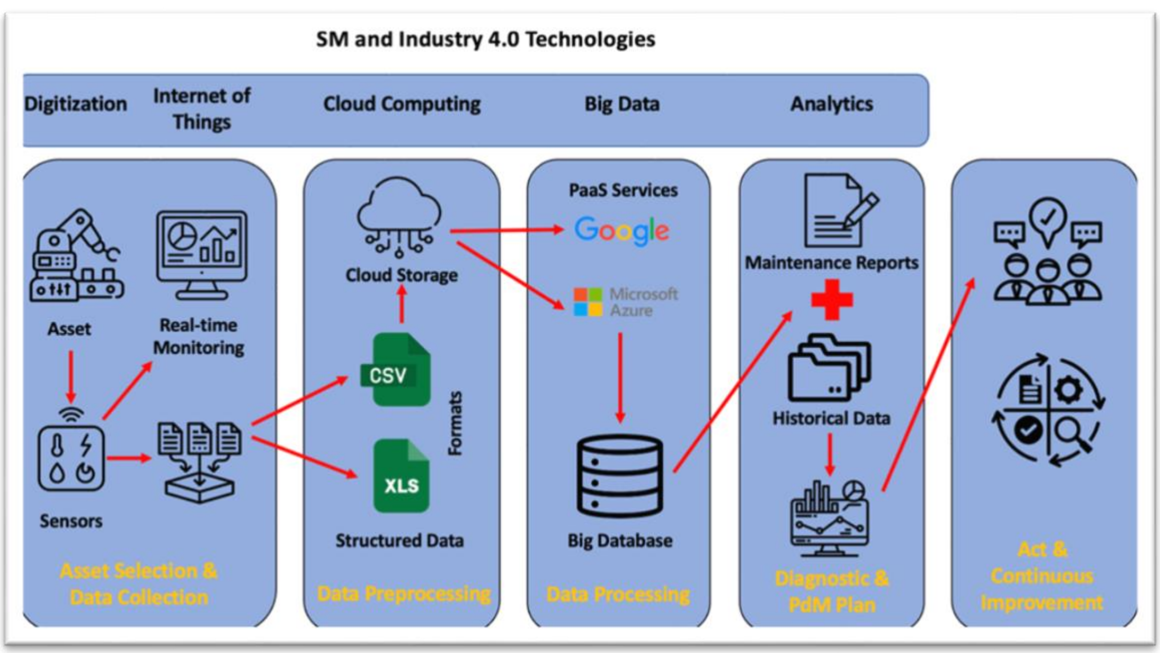

Figure 3.1 Proposed PdM Model for this Application

3.1.1 Equipment Specification

Areas to be monitored:

Area 1 - Extruder Motor, *Area 2* - Barrel Throat, *Area 3* – Cooling Unit for Electrical Cabinet *And Area 4* – Gear Box. The machine representation along all four areas is represented in Figure #3.2

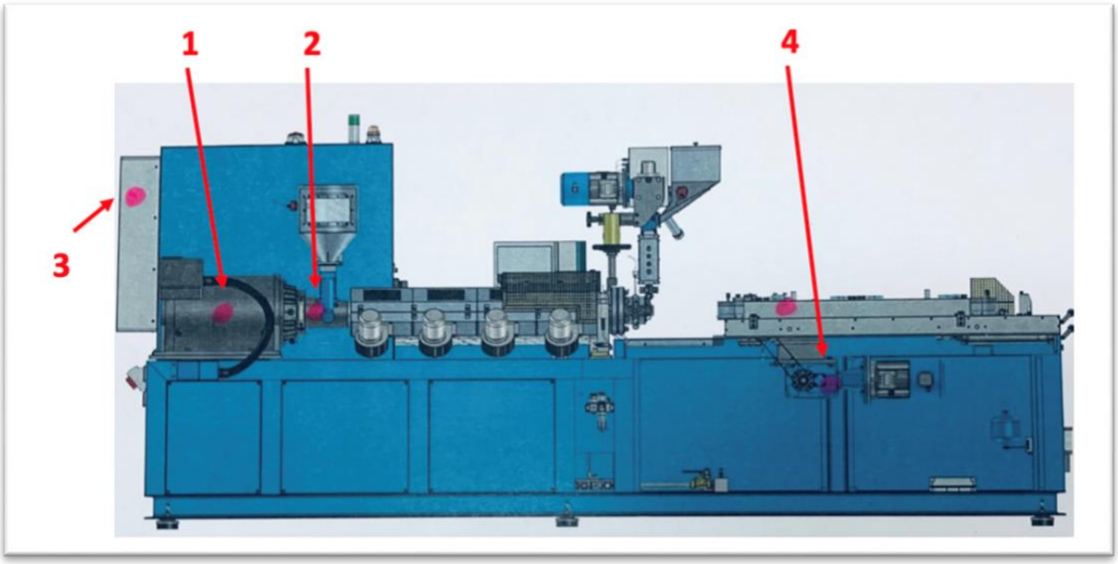

Figure 3.2 Extruder-Corrugator's Critical Areas.

3.2 Methodology & Equipment

3.2.1 Temperature Sensor

In this application case, it is crucial to understand that the machine used in this project needs to be more intelligent. In this context, the extruder-corrugator machine does not count with preinstalled sensors or any technology that enables machine monitoring. That is why part 1 was focused on making this machine a smart one by applying one of the concepts previously discussed in section #. Sensor digitization means obtaining desired data from a physical object and converting it into digital data. In this case, the purpose is to measure temperature using sensors and transfer these data into a digital platform. To do this, first, it is essential to define what types of temperature sensors are available in the market. After some research, it was found that the four most reliable and used temperature sensors such thermocouples, RTDs, thermistors, and local temperature ICs.

Thermocouples: A thermocouple consists of two dissimilar metals joined at one end, producing a small unique voltage at a given temperature. This voltage is measured and interpreted by a thermocouple thermometer [24]. The Seebeck effect, which happens when there is a temperature difference between junctions of dissimilar metals, is used by thermocouples to measure temperature. The difference in temperature between the part that is heated and the cooled area generates a voltage difference between the two junctions. This voltage difference can be used to calculate the temperature. [25]

There are numerous thermocouple types, each marked by a letter. The K type is the most employed. [25] Different types of thermocouples vary in material, accuracy, and temperature ranges, as shown in Table #3.1.

Table 3.1 Thermocouple Types

Type	Temperature Range (Celsius)	Sensitivity (Microvolts/Celsius)	Conductor Alloys
K	**-180 to +1300**	**41**	**Chromel (90% Ni, 10% Cr)** **Alumel (95% Ni, 2% Mn, 2% Al, and 1% Si)**
J	**-180 to +800**	**55**	**100%Fe** **Constantan (55% Cu, 45% Ni)**

N	**-270 to +1300**	**39**	**Nicrosil (84.1% Ni, 14.4% Cr, 1.4% Si,0.1% Mg)** **Nisil (95.6% Ni, 4.4% Si)**
R	**-50 to +1700**	**10**	**87% Pt, 13% Rh** **100% Pt**
S	**-50 to +1750**	**10**	**90% Pt, 10% Rh** **100% Pt**
B	**0 to +1820**	**10**	**70% Pt, 30% Rh** **94% Pt, 6% Rh**
T	**-250 to +400**	**43**	**100% Cu** **Constantan**
E	**-40 to +900**	**68**	**Chromel** **Constantan**

RTDs: Effectively, they are resistors with well-defined resistance versus temperature characteristics. Due to its chemical stability and very linear response to temperature fluctuations, platinum is the most popular and accurate wire material utilized in RTDs. Nickel, copper, and other metals may also produce RTDs. Platinum RTDs have a broad temperature range (up to 750°C or greater), superior accuracy and repeatability, and adequate linearity. Due to their accuracy, stability, and wide temperature range, RTDs are utilized in various precision applications, such as instruments and process control. [25]

Thermistors: Thermistors, like RTDs, alter their resistance in reaction to variations in temperature. Unlike RTDs, which are often composed of pure metal, thermistors typically comprise a polymer or ceramic substance. Exceptions exist, but thermistors are often less expensive and less accurate than RTDs. As its name implies, the resistance of an NTC thermistor lowers as the temperature rises. The typical thermistor temperature range is -90°C to +130°C, significantly lower than thermocouples and RTDs. [25]

Local Temperature Sensor ICs: A local temperature sensor is a popular name for an integrated circuit that uses the physical properties of bipolar transistors to measure its die temperature. Some local temperature sensors have analog outputs (voltage or current), but others have an internal ADC and generate a digital output in one of several formats. I2 C, SMBus, 1-Wire®, and SPI are the most common output formats; however, PWM and other structures are also available. [25]

After studying the many types of temperature sensors, a thermocouple was chosen to serve as the project's temperature sensor. A type K was selected since it is the most common, reliable, and inexpensively available in the market. The research was conducted to understand how it operates in practice and its numerous configurations. A thermocouple's merits are its temperature range, durability, quick response, and lack of self-healing. This application requires a quick response to prevent high temperatures in the machine's essential regions. The precision of thermocouples may be less precise. However, a 1- or 2-degree Celsius discrepancy will not be a problem because a conservative maximum temperature will be utilized before activating the alert.

Below are the specifications of the implemented thermocouple:

- Type: K
- Measuring Range: 32~1112°F (0~600°C)
- Probe Length: 6mmx20mm/0.23"x0.79"（D * L)
- Internal Insulation: Fiberglass; External Shielding: Metal Shield.
- Thread：1/4"
- Best used with a thermocouple amplifier such as the MAX31855, AD8495 or MAX31856

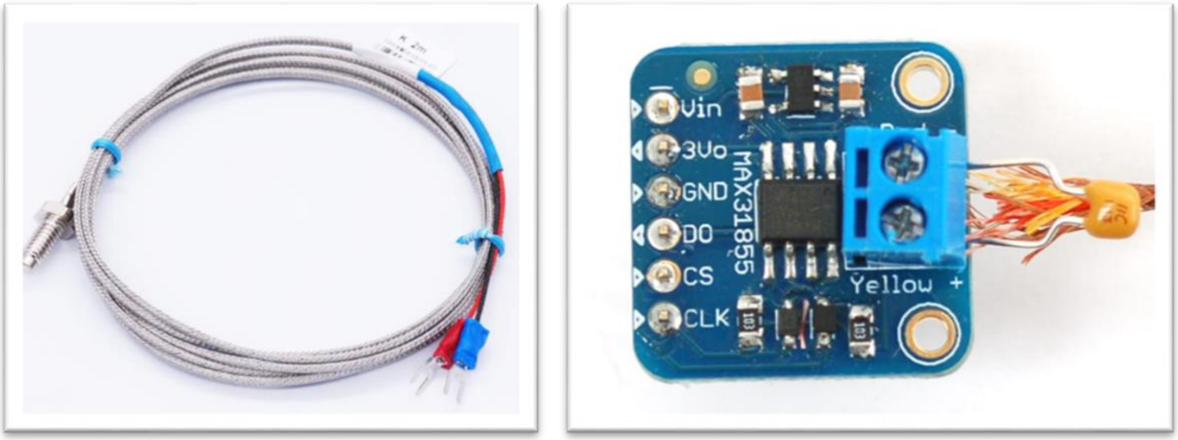

Figure 3.3 Thermocouple Type K & Thermocouple Amplifier MAX31855. [26]

3.2.2 Voltage Amplifier

Considering this fact, it was necessary to utilize an amplifier to acquire the readings from the thermocouple. Because thermocouples are sensitive, an amplifier is required to achieve stability and obtain correct readings [26]. As a result of this, it was decided to add the thermocouple amplifier MAX31855 breakout board after research was performed. It is essential to mention that this amplifier only works with type K thermocouples. This amplifier contains the negative and positive connectors for the thermocouple, and there are six pins (as shown in figure #3.3) that consist in:

- Vin – 3 to 5 V
- 3Vo – Only 3.3 V
- GND - Ground
- DO (Data out) – Carries each bit of data.
- CLK (Clock) - Indicates when to present another bit of data.
- CS (Chip select) tells the chip when to read the thermocouple and output more data.

3.2.3 Microcontroller

A microcontroller executes a user program stored in its program memory. This software receives data from external devices (inputs), manipulates the data, and then sends the data to external output devices. A *microcontroller* is a highly effective device that enables designers to develop complex I/O data processing algorithms. The most straightforward microcontroller architecture comprises a CPU, memory, and input/output. CPU and control unit make up the microprocessor (CU). [27] One of the most known microcontroller-based brands is Arduino. It is an open-source platform for electronic project construction. Arduino consists of a physical programmable circuit board (commonly called a microcontroller) and a piece of computer software, or IDE (Integrated Development Environment), used to create and upload computer code to the physical board. [28]

At the beginning of this project, an Arduino microcontroller could work to build a temperature reader, and it is easy to work with too many open-source tools and components, such as the MAX31855 amplifier. Then, the intention was to adapt the thermocouple and its amplifier to a microcontroller, in this case, Arduino Mega, for the prototyping. After that, it was needed to adjust the alarm light, and the Arduino could not withstand the 24V required by any industrial LED light, so a Rugged Mega replaced the Arduino Mega. Rugged is more robust, resilient, and efficient for industrial purposes, as shown in Table #3.2.

Table 3.2 Arduino Mega vs. Rugged Mega [29][30]

Features	Arduino Mega 2560	Rugged Mega
Microcontroller	ATmega2560	ATmega2560
USB Microcontroller	ATmega16U2	FT231X
Operating Voltage	5V	5V
Input Voltage	7-12V	3.5V-30V
Analog Input Pins	16	16
Protected Digital I/O	0	22
Protected Analog Input Pins	0	16
Vin Reverse Voltage Protection	None	Protected up to 30V
Vin Current Protection	None	500mA resettable fuse
Total Microcontroller Current Protection	None	Protection up to 150mA
Operating Temperature	N/A	-10 to +85 C
I/O Pin Current Protection	None	30mA resettable fuse
I/O Pin Voltage Protection	None	Withstands 24V

3.2.4 Shield 24V

Even though the Rugged Mega microcontroller can withstand 24V, it requires a shield to perform adequately (an illustrative image is shown in Figure #3.24). Adding the shield will establish a more secure connection between the microcontroller and the 24V from the LED alarm. As noted previously, the device will be directly linked to an external power supply to obtain the 24V required to activate the alarm; hence, this shield will convert this 24V into 5V to accommodate the microcontroller's ability to handle the higher voltage. This shield is linked to the microcontroller by placing it atop the microprocessor and attaching its pins to the corresponding connectors. In addition, the microcontroller and shield must be indirectly linked to the 24V power supply and ground using a breadboard. [31]

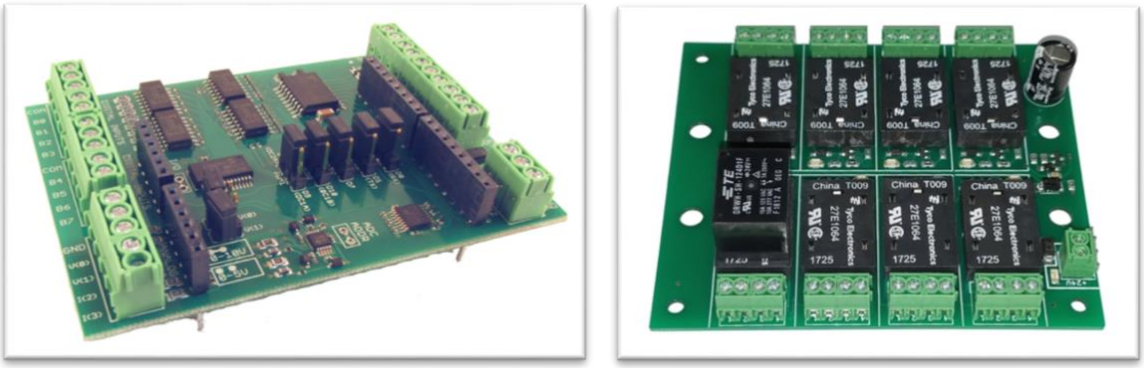

Figure 3.4 24V Shield [31] & Relay Board [32]

3.2.5 Relay Board

The relay board is another vital component of this temperature instrument, and it is represented in Figure#3.24 on the image on the right. It will be introduced to prevent any microcontroller malfunctions using the alarm light. Since the alarm will receive 24V and turn on/off as necessary, the relay will function as a switch for 24V. This relay board can provide power between 22VDC and 26VDC and resist input voltage between 3VDC and 26VDC. [32] One of the eight relay sockets is chosen to connect the relay board to the shield and microcontroller. Each relay socket has four connectors: CO (changeover), IN (input), NO (normally open), and NC (normally closed) (normally closed). This project utilizes solely CO and IN. IN is directly connected to the shield in P1, while CO is connected to the breadboard's 24V power supply. Lastly, the relay incorporates Ground and 24V to power the complete relay board. The 24V source is linked to the same breadboard as CO, and Ground is connected to the breadboard's general Ground.

3.2.6 LED Alarm Light

Lastly, after incorporating all preceding components, the LED Light was immediately attached to the relay board. The LED's power is linked to CO at the relay socket, and the second cable is connected to NO. Since the alarm is attached to a typically open relay so it can function as a button; if the temperature reaches the limit, the circuit will close, and the Red LED light alert will illuminate. The selected LED Alarm light with two different colors is illustrated in Figure #3.5.

- Power Voltage: 120VAC
- Current Rating: Max 18 mA RMS
- Color: Red & Green
- LED Lifespan: 20,000-50,000 Hours Typical

Figure 3.5 LED Alarm Light 2 Colors (Red/Green) [33]

3.2.7 Wireless Antenna

A wireless link was necessary for accurate machine temperature data gathering as part of the project. This section examines many types of antennas, whereas the previous section (Internet of Things) examined various data link protocols. Among these protocols were Bluetooth, ZigBee, Z-Wave, WiFi, and others; It was chosen to delve deeper into ZigBees, also known as XBees. ZigBee (XBees) is the current standard approach for WSN protocols compatible with microcontrollers and multi-hop mesh network topologies. Even though this project intends to design and evaluate on a single machine, the option can scale up to 32 machines.

Digi's website states, "The world-renowned XBee module is part of a family of cellular modems and RF modules that provide ultimate flexibility for IoT application developers, with three programmable form factors and a range of popular wireless protocols. The XBee family also includes IoT gateways and management tools to connect, monitor and manage the XBee network". [34]

Digi XBee offers different types of modules [34]:

- **2.4 GHz** – For low-power, point-to-point, and mesh networking applications.
- **Sub-1 GHz** – For long rang applications up to 60+ miles line-of-sight range and up to 250 kbps rate.
- **Cellular**-For global cellular applications are enabling low-power wide area networking (LPWAN).

Considering these modules are meant for usage in a manufacturing organization, the range may be essential. As a result, it was decided to utilize Sub-1 GHz modules, for which Digi offers a choice of solutions. In these alternatives, they provide a Digimesh kit that encourages and offers a hands-on method for learning to use XBees for device connectivity and sensor networking.

Digi XBee-PRO 900 HP Digimesh Kit: According to DIGI, this kit enables one to study and comprehend the basics of getting started with Digi XBee. One of the benefits of this XBee is the ability to allow embedded wireless connectivity with several modules at once (multi-hop mesh network topologies). As mentioned above, this project will be evaluated on a single machine. The manufacturing company possesses at least 30+ similar/equivalent machines. If the organization desires to monitor all machines, this can make a connection between all devices and transmit the data to a single receiver.

Some of the technical specifications are listed below [34]:

- Antenna Options: Wire, U. FL (Coaxial), and RPSMA (Reverse polarity)
- RF Data Rate: 10Kbps or 200 Kbps
- Indoor/Urban Range: 10Kbps up to 610 m, 200Kbps up to 305 m.
- Outdoor: 10 Kbps up to 14 km, 200Kbps up to 6.5 km

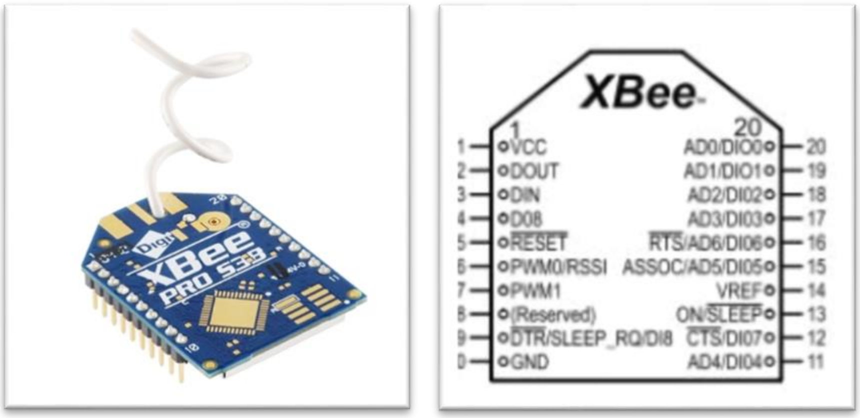

Figure 3.6 XBee Antenna [34]

XBee devices connect wirelessly by transmitting and receiving messages. The devices can only send wireless communications; they cannot manage incoming or outgoing data. Nonetheless, they can communicate with intelligent devices via the serial interface.

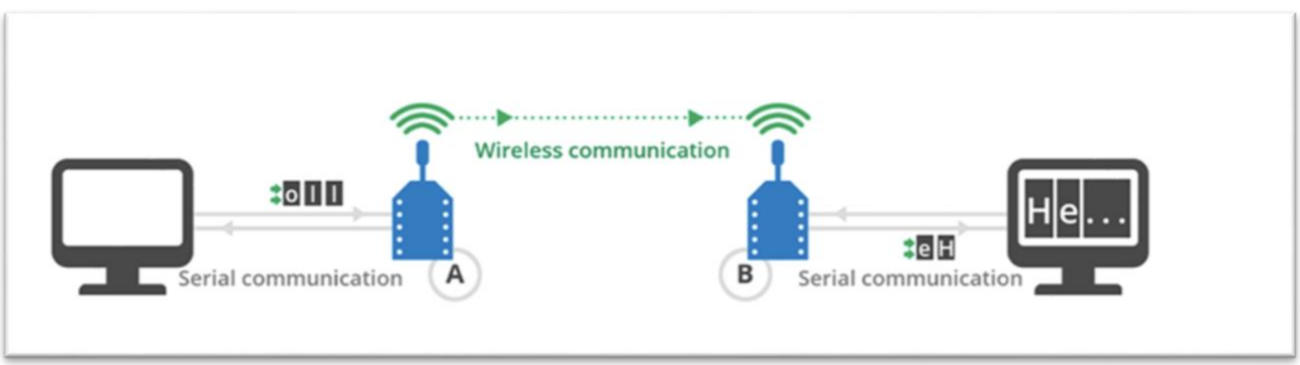

Figure 3.7 XBee's Working Principle [35]

The system consists of two types of devices: Coordinator and End devices, as shown in Figure #3.7. The coordinator is the system's focal point. It transmits the sensor readings to the user. The collector's function is broken into two components: the Web server and the XBee Interface to the WSN. Conversely, the end device is equipped with one or more sensor inputs. The device awaits the coordinator's data reading request (i.e., polling) before responding with the sensor's value. [36] The XBees offer two distinct modes of operation: application transparent and application programming interface. Below are the primary distinctions between these two modes.

Application Transparent ("transparent mode"): This mode is referred to as "transparent" since the radio transmits data precisely as it receives it. Xbee module wirelessly transmits all the serial data it receives to a remote location. When the other module gets the data, it is sent via the serial port in the exact format it received. *Application Programming Interface ("API mode"):* The operating mode of the Application Programming Interface (API) is an alternative to the transparent mode. In API mode, the exchange of information is determined by a protocol. Data is transmitted in packets (commonly called API frames). [35]

Due to the ease of operation, it was chosen to use the transparent mode for this project because XBee receives what it is sent in this mode. This model is compatible with any device with a serial interface, allowing it to function exceptionally well with the microcontroller utilized in the project's first phase. This mode works well when attempting to communicate between two XBee antennae.

After selecting the proper data link protocol (ZigBee/XBee), the appropriate model for this project, and transparent mode as the operating mode, it was just needed to link XBee and the microcontroller. The XBee has 20 pins, as shown in Figure #3.6; however, not all are necessary for this function. It was discovered through research that there is a module that simplifies communication between the XBee and the microcontroller. It is known as XBee Explorer regulated and is described below.

3.2.8 XBee Explorer Regulated

Power, RSSI, and DIN/DOUT activity LEDs are just some of the basics the XBee Explorer Regulated takes care of with its use. Connect any XBee module to a 5V (down to 3.3V) system thanks to this adapter's ability to convert 5V serial signals to 3.3V. The board was made to be directly compatible with the Arduino family of boards to facilitate wireless boot loading and USB setup. [37] This part reduces the number of XBee's pins from 20 to 4. All left is Ground, 5V electricity, noise, and uncertainty. The component is illustrated in Figure #3.8 for better representation.

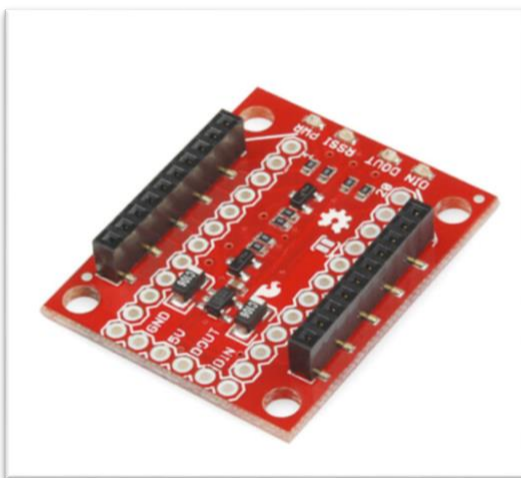

Figure 3.8 XBee Explorer Regulated [37]

An extra microcontroller is required to connect the antenna to add the XBee and Explorer antennas. Consequently, a second microcontroller is given, although an Arduino can be used in this section because it can manage the coding and power requirements of the XBee. For the connectivity between the XBee and the Explorer to be regulated, it is sufficient to position the XBee's Pins over the Explorer's connectors. The Explorer's four pins are then directly linked to the microcontroller. Ground to ground, 5V power to the 5V connector on the Arduino, and the digital wires Din and Dout are connected to the Microcontroller's Rx (Pin 0) and Tx (Pin 1) pins. Din is assigned to Tx, while Dout is assigned to Rx.

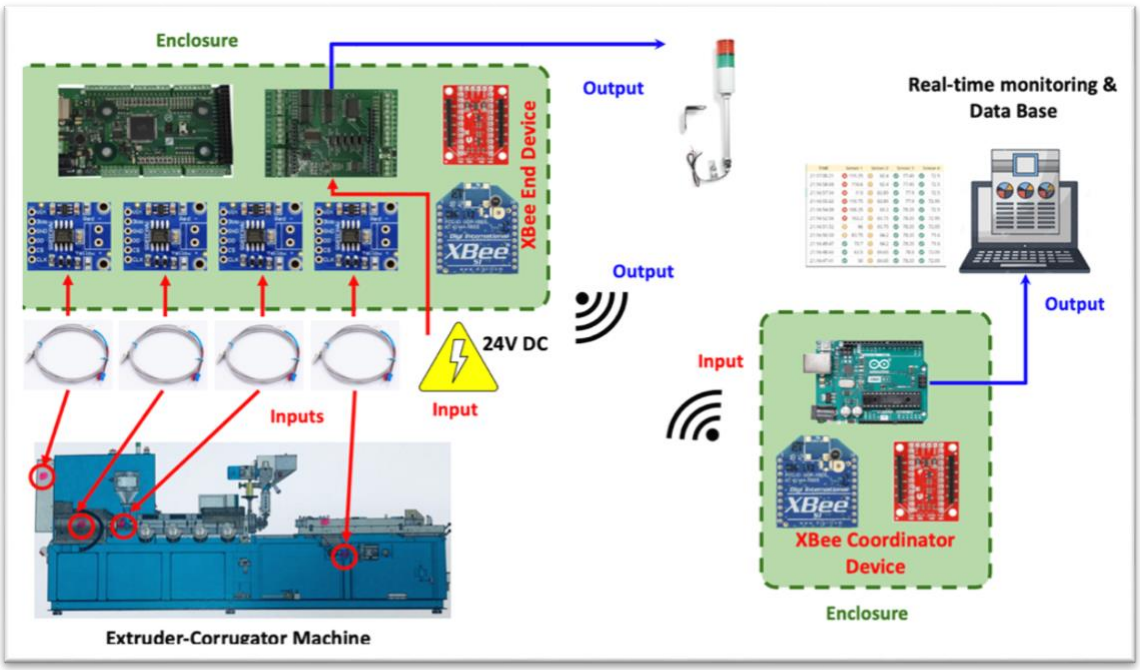

Figure 3.9 Component Schematic.

With all the components connected (as illustrated in Figure #3.9), the data produced from the thermocouples will be stored in a spreadsheet in Excel using the Data Streamer add-in. This recorded data will help better visualize the actual temperatures in the desired areas. The alarm light will turn on whenever any focused areas have reached the maximum temperature allowed. The electrical schematic can be found in Appendix B-1.

3.3 Software Specification

3.3.1 Arduino IDE 1.8.16

This open-source software is compatible with all Arduino boards, including the Rugged Mega. For the coding, Arduino Software was utilized. It is simple to write and upload code to a microcontroller. Components like the MAX31855 come with their library for coding, which must be included in the code.

Modifications were made to the microcontroller's code to incorporate the XBees modules. Now, two microcontrollers are being utilized, one to implement the temperature sensors and the other to create the XBee receiver module. The second microcontroller will connect to the PC immediately, populating an Excel spreadsheet with the readings. The code used in this project can be found in Appendix C-1.

3.3.2 XCTU Software

Creating connectivity between both antennas involves a list of steps to realize. First, XCTU software must connect both devices to the PC using the USB cable and antennas. Then, the software looks for the antennas and finds them in the software. Each antenna has its own MAC Address that makes it unique. To work in the transparent mode, XCTU must connect them by introducing the Mac address into the destination address, as depicted in Figure #3.10. The end device will have the Mac address of the coordinator device and vice versa.[35] This XBee setup will connect both devices (transparent mode only).

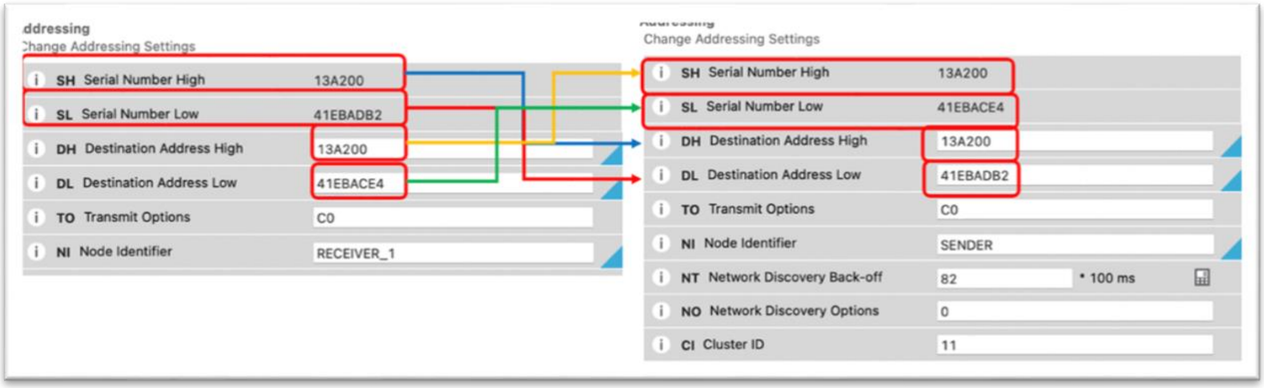

Figure 3.10 XBee set-up using XCTU Software

Using the XCTU program, a test was conducted to confirm the connection between both antennas. In the following graphic, the connection between the two antennas is depicted. Blue and red lettering is shown in the image on the left to distinguish between the receiver and transmitter. After checking the connectivity, it is time to ensure the microcontroller's programming is functional. Figure #3.11 shows the successful connection between the serial monitor from the microcontroller to send and receive data from the XBee.

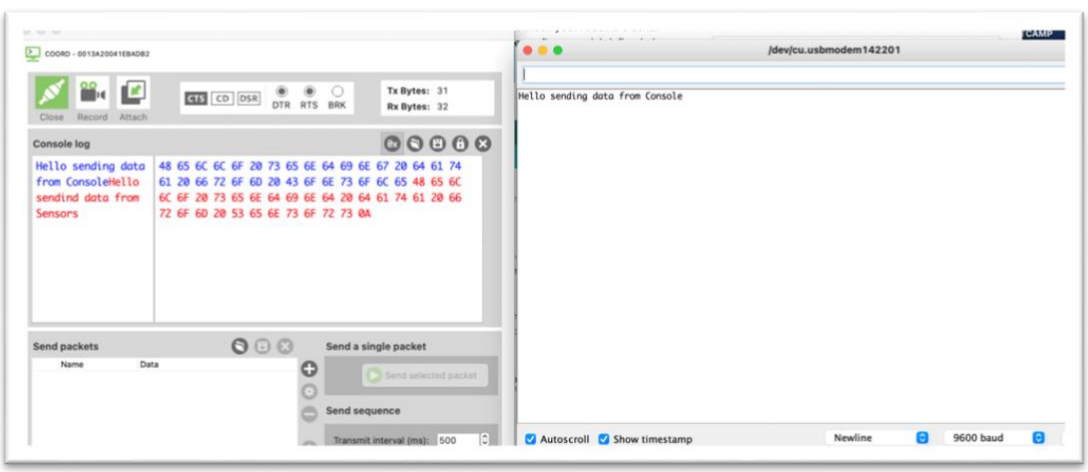

Figure 3.11 Successful Connection between XCTU and Serial Monitor

3.3.3 Data Streamer from Microsoft Excel

Microsoft Excel was used to display the temperature readings and be able to save the report to create a Database with all the data produced by the thermocouples. Data Streamer provides students a straightforward method for transferring data from the actual world into Excel's robust digital canvas. Data Streamer helps students to comprehend data science and the Internet of Things using a sensor, a microcontroller, and Microsoft Excel (IoT).[38] In other words. Data Streamer is a two-way data transfer for Excel that streams live data from a microcontroller into Excel and sends data from Excel back to the microcontroller. Figure #3.12 shows how the data streamer displays data from four different outputs and a graph showing the temperature vs. time behavior.

Figure 3.12 Data Streamer Dashboard.

Chapter 4 : Results

4.1 Digitization of Equipment

The initial prototype utilized the microcontroller, amplifier, and thermocouple. This was performed primarily to evaluate the thermocouple's coding and working principle for temperature accuracy. Both warm and cold water was used to examine the initial prototype. When compared to a thermocouple-equipped temperature gun, the obtained measurements were correct. With the initial prototype's success, it has chosen to go on to the next step, including all four thermocouples.

Secondly, the four thermocouples are merged for the second iteration. The enclosure was added to join assembly components to complete the component assembly. The code was modified to collect data from four unique sensors. With all four sensors functioning correctly and generating accurate temperature readings, we moved on to the final prototype, which included the other components.

In addition, the Shield, relay board, and warning light were added to the device during this phase. An extra power supply of 24V was used to activate the warning light for testing purposes. The power source supplies the Shield, which is connected to the relay board. The relay board prevents the microcontroller from overheating by deploying a warning light that illuminates when required. Since 24V is necessary to power the alarm, the relay helps to protect it. The microcontroller's I/O voltage range is limited to 5 and 3.3 V, and the Shield makes 24 V compatible with the microcontroller. Figure #4.1 illustrates the final device operating with the alarm light and four sensors.

Figure 4.1 Temperature Sensor Module

4.2 Asset Selection & Goal Definition

Posterior to completing the device's assembly and testing it using the Data streamer in Excel, the temperature device was tested at the manufacturer. The device was immediately attached to the machine to receive the 24V required to power the LED light alert—all four temperature sensors successfully transmitted accurate data, which is then displayed on the computer as depicted in Figure #4.2. Data Streamer allowed users to begin recording data and determine how frequently to receive data to prevent the creation of a massive file. Since the temperature may not change every second, it was decided to monitor the unit every minute to detect any anomalies or changes in behavior during high-temperature months during the year.

Figure 4.2 Temperature Sensor Module Tested On-Site

This module was subjected to the facility's final evaluation. The temperature module was mounted in the corrugator-extrusion machine, while the receiver was in the office adjacent to the computer. Approximately thirty to thirty-five meters separated the two antennas. All four sensors met the established temperature parameters at implementation, as indicated by the green light on the LED alert. In addition, thermocouples were insulated with a corrugated weave. This action is done because thermocouples are extremely sensitive, and their readings could be affected if they encounter one another or any other metal. The selected equipment for implementing the temperature monitoring system was machine labeled as #42, as shown in Figure #4.3.

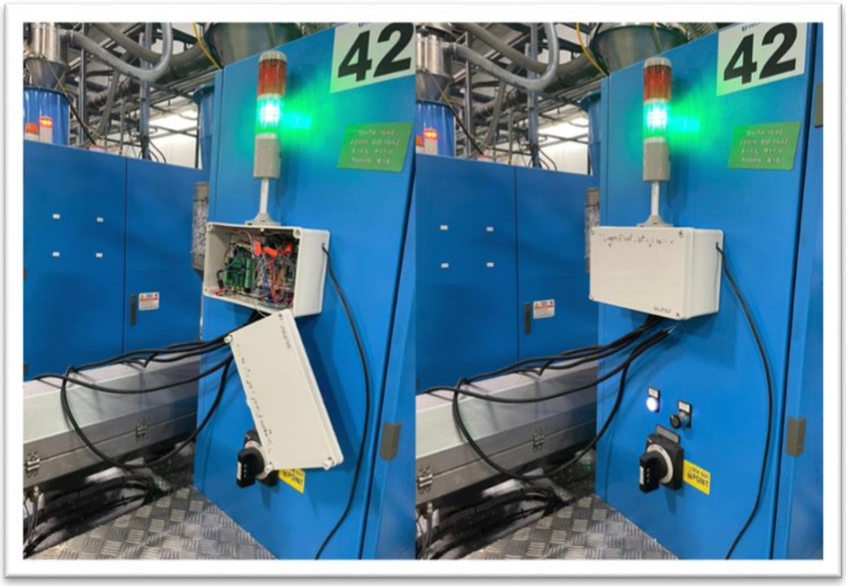

Figure 4.3 Temperature Sensor Module Installed on Equipment #42

4.3 Data Collection & Monitoring

Data collection is crucial to a PdM model and occupies most of the project's time. For this purpose, a Data streamer was used to enable the user to create a dashboard with a more appealing appearance to understand the received data better along with the data collection. As depicted in Figure #4.4, symbols were incorporated to aid comprehension of the true significance of each data collection. A green checkmark will be displayed whenever the temperature is below 80 degrees Fahrenheit. When temperatures are between 80 and 90 degrees Fahrenheit, a yellow sign with an exclamation mark is displayed. This warning symbol indicates that the temperature is near the maximum permissible level. Finally, the red logo with a cross indicates that the maximum temperature has been reached and that action must be taken to prevent machine damage. Unfortunately, only data from March 27th until April 30th has been collected until this point.

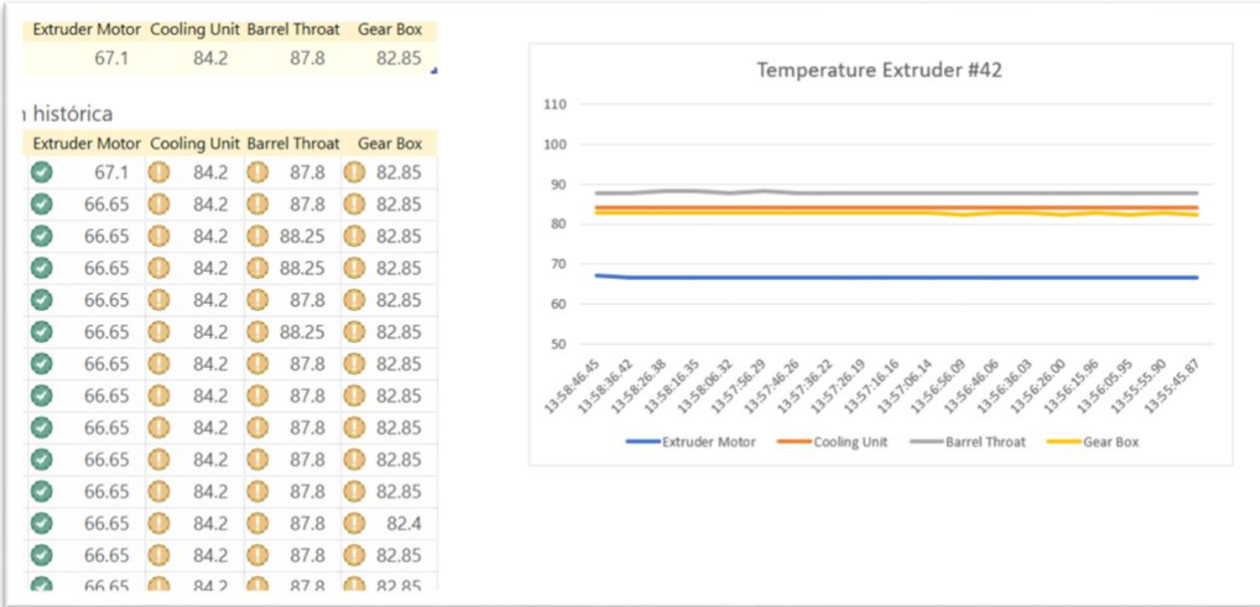

Figure 4.4 Behavior of the Temperature at the 4 Critical Areas.

4.4 Data Preprocessing & Processing

Following data collection, the data must be preprocessed with database creation. Figure #4.5 illustrates the temperature behavior at the extruder motor for the data collected. Data preprocessing enables the validation and cleansing of data so that only the essential data can be extracted. Also, Figure #4.5 is depicted several outliners that, if not cleansed, could affect the diagnostic and prediction of the failure by replicating or affecting the diagnostic. The additional tables for the other three areas measured can be found in Appendix D-1.

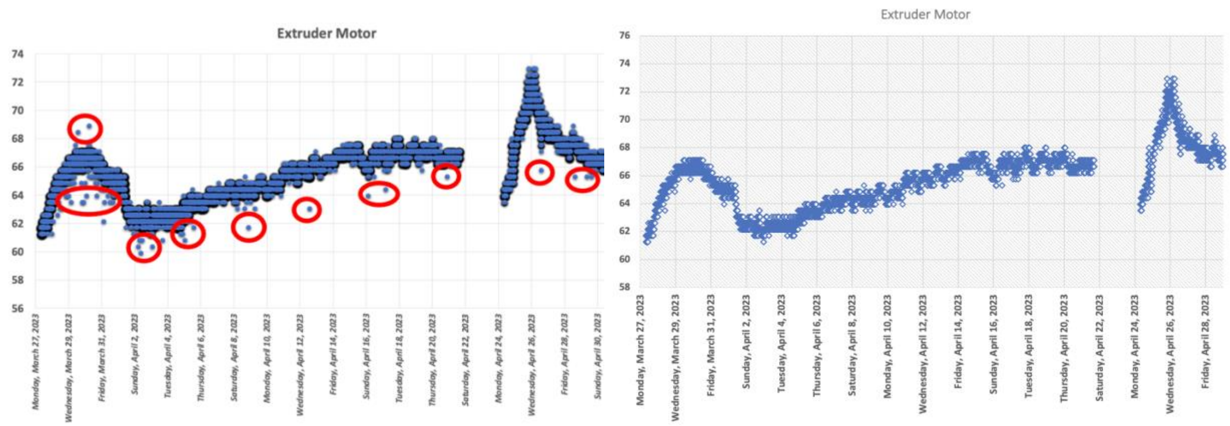

Figure 4.5 Raw Data vs. Cleaned Data at the Extruder Motor

In addition to being validated and cleansed, data must be organized in a structured format. This data structure consists of columns and rows, allowing for better visualization and comprehension of the data. Essentially, forms such as CVS and Excel workbooks function as structured data due to their rows and columns organization. The use of structured data enables the user to look up data in an organized manner, as depicted in Figure #4.6. It provides a user-friendly visualization for identifying anomalies and changes in trends.

Time	Extruder Motor	Cooling Unit	Barrel Throat	Gear Box
4/11/23 9:00 AM	65.75	82.4	84.65	82.85
4/11/23 9:01 AM	65.75	82.4	84.65	82.85
4/11/23 9:02 AM	65.75	81.95	84.65	82.4
4/11/23 9:03 AM	65.75	82.4	84.65	82.85
4/11/23 9:04 AM	65.75	82.4	85.1	82.85
4/11/23 9:05 AM	65.75	82.4	85.1	82.85
4/11/23 9:06 AM	65.75	82.4	84.65	82.85
4/11/23 9:07 AM	65.75	82.4	85.1	82.85
4/11/23 9:08 AM	65.75	82.4	84.65	82.85
4/11/23 9:09 AM	65.75	82.4	84.65	82.85
4/11/23 9:10 AM	65.75	82.4	84.65	82.4
4/11/23 9:11 AM	65.75	82.4	84.65	82.85
4/11/23 9:12 AM	65.3	82.4	84.65	82.85
4/11/23 9:13 AM	65.75	81.95	84.65	82.85
4/11/23 9:14 AM	65.75	82.4	84.65	82.4
4/11/23 9:15 AM	65.3	82.4	84.65	82.85
4/11/23 9:16 AM	65.75	82.4	84.65	82.85
4/11/23 9:17 AM	65.75	82.4	84.65	82.4
4/11/23 9:18 AM	65.75	82.4	84.65	82.4

Figure 4.6 Structured Data Collection

With the continuous deployment of a specific PdM model for this equipment, it is necessary to continue data collection until patterns or trends can be identified. The necessity of unexpected failures, changes in behavior, or anomalies is essential to perform a diagnostic. Data Processing works as a data filtration where all clean data extracted from the actual condition of the machine, plus all other important data such as historical data, failure reports, and maintenance logbooks, are combined to facilitate the analysis and diagnosis of the equipment. Due to the time limitations of this project and the necessity of continuous monitoring to understand the behavior of the equipment for at least an entire year, the project is presented until this point. This allows the company to understand the behavior of their equipment; in the meantime, data is extracted from their maintenance reports with all the registered failures related to any of the four critical areas.

This project intends to set up the bases for how small industries can start digging into PdM projects. Following the proposed methodology of the "*PAInOuTT*" application flow diagram, the first 4 phases of selecting the asset while digitalizing it, data collection, preprocessing, and processing are implemented before requiring expertise in data analytics/scientists to deal with the following phases of the project. Even before deploying a PdM solution, until this point, the industry had already started seeing benefits through the development of this project. The expected savings until this point are presented in the section below.

4.5 Expected Outcome

This initiative helped the manufacturing company achieve a 100 percent reduction in manual temperature monitoring for Extruder-Corrugator #42. By implementing this remote monitoring system, if the operator is no longer required for manual temperature surveillance of the apparatus, their annual savings can increase to $35,000. The implementation of the remote monitoring system will cost approximately $1000. Replicating this model on each of the 42 machines would cost $42,000 in addition to the anticipated errors and required monitoring system maintenance. This means that the operator's annual salary can readily cover the cost of implementing this system for long-term use.

In addition, according to this company's maintenance team, when the extruder motor or driver malfunctions due to high temperatures, the repair costs increase to $5,000 if repaired but to $8,000 if replaced. According to their internal logbooks, one of every 42 machines malfunctions every three months, resulting in downtime, costly corrective maintenance, and revenue loss. Due to the inability to provide specific revenue losses during an outage, only corrective maintenance costs are accounted for in this analysis. If only four of the forty-two devices fail and can be repaired, their annual loss increases to $20,000 in this case. Adding a new component increases the price to $32,000. They indicated a cost of approximately $70,000 for corrective maintenance (only extruder failure) plus the need for a monitoring operator under ideal circumstances where no other machines fail. These unplanned failures cost a lot of money, so implementing the PdM model would benefit this company's situation.

Chapter 5 : Conclusion and Future Work

According to numerous polls, businesses have tried implementing PdM projects since the turn of the millennium, but only around 20% are effective [4]. Ineffective PdM projects could go from the misconception of the PdM definition up to wide-ranging challenges or limitations that cause businesses to be unable to implement PdM projects successfully. Following an application case study in which the "*PAInOuTT*" model was implemented, this paper aims to show the main steps to avoid failure when deploying a PdM model. A PdM failure may have been avoided with better planning and execution.

The purpose of the "*PAInOuTT*" is to operate as a generic approach that may be tailored to meet the unique requirements of the industrial sector. By detailing the steps to take, the inputs/outputs needed at each stage, and the recommended tools and teams that should be involved, this guide makes it easier to launch a PdM project. This application flow solution was then used to analyze a manufacturing facility's assets. Validating that the equipment has been digitized is a crucial step in PdM. Since this model relies on information gleaned from the monitored industry's assets, having access to accurate data is essential.

The manufacturing company has benefited from the first four stages of the "*PAInOuTT*" model deployed in this extruder-corrugator asset, thanks to introducing a temperature monitoring system that eliminates the need for human intervention. Due to the asset's sensitivity to heat, the solution architecture provided significant value in the practical use of innovative manufacturing for small to medium industrial businesses. In general, the offered methodology and detailed solution framework are meant to help manufacturing organizations ease into the realm of PdM methods by outlining all the processes necessary for the most effective implementation of Predictive Maintenance initiatives.

Obtaining diagnostic, prognostic, and PdM models for the application scenario would be a natural next step along the proposed model approach already discussed in this research. The capacity to generalize the detailed flowchart to other projects and understand the reliability of this model in a new context or undertaking is also desired. Finally, successful PdM project deployment and acceptance of the internal model necessitate a constant evaluation of project outcomes to improve the model's correctness. The PdM model is also effectively implemented in the chosen system. The next step of this investigation will be to implement this methodology for all their Extruder-Corrugator machines to produce a higher value added to the manufacturing industry.

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Appendix

Appendix A: "PAInOuTT" Model Methodology

Phase	Actions	Inputs	Outputs	Tools	Team
1- Asset Selection & Goal Definition	➢ *Understand project needs.* ➢ *Equipment selection.* ➢ *Select appropriate sensors.* ➢ *Define operational limits based on lifetime of equipment.* ➢ *Verify equipment & understand equipment process.* ➢ *Define expected objectives/goals for equipment selected.*	✓ Existing sensor capabilities ✓ Asset/Equipment ✓ Equipment Id. ✓ Target definition	✓ Digitization (Sensing) ✓ Analog data transferred into digital world ✓ Sensor Validation ✓ Prevention Alarm	✓ Sensors (Humidity, Vibration, Temperature) ✓ Internet of Things (Antennas)	✓ Engineering ✓ Maintenance ✓ Operations ✓ Quality Control ✓ IT
2- Data Collection	➢ *Obtain data to digitally filter data.* ➢ *Collect data from various sources, such as sensors, machines, and other relevant sources.* ➢ *Storage Data (Cloud or Hard-drive)*	✓ Asset data ✓ Condition Monitoring ✓ Historic /Failure Data ✓ Actions taken ✓ Internal Maintenance reports	✓ Database Creation ✓ Visualization	✓ Cloud Platforms (Amazon Web Services, Google Cloud Platforms, Microsoft Azure) ✓ Data Loggers (SCADA Systems, SQL, NoSQL)	✓ IT ✓ Engineering ✓ Maintenance ✓ Data Science
3- Data Preprocessing	➢ *Validate and clean data.* ➢ *Preprocess data from various sources. This data should be cleaned, standardized, and structured to facilitate analysis.*	✓ Database ✓ Extracted Data	✓ Cleaned Data ✓ Structured Data ✓ Extracted Critical Data	✓ Python ✓ R ✓ Microsoft Excel	✓ Data Science ✓ Engineering
4- Data Processing	➢ *Monitor data from sensors, compared data with expected. values and generate alerts based on operational limits.* ➢ *Useful for rapid fault development.* ➢ *Detecting changes in trends.* ➢ *Filtering, aggregation, and transformation.*	✓ Cleaned Data ✓ Structured Data	✓ Anomaly Detection ✓ Changes in trends ✓ Analyze Data	✓ Algorithms ✓ Statistical Models ✓ Python Libraries(Pandas, NumPy, Scikit-Learn	✓ Data Science ✓ Engineering
5- Diagnostic	➢ *Collect data from health assessment modules, maintenance records, failure records, operational status and historic data.* ➢ *Complement with expertise and theoretical background.*	✓ Analyzed Data ✓ Anomalies Detection	✓ Expertise Feedback ✓ Historical background comparison ✓ Health Diagnostic	✓ Analytics Dashboards (Power BI, Splunk, Tableau)	✓ Data Science ✓ Maintenance ✓ Engineers
6- PdM Plan	➢ *Analyze all data to calculate the future health status.* ➢ *Predict degradation based on assets properties (Materials, lifecycle and working experience)*	✓ Health and Performance Assessment	✓ Model Prediction ✓ Solution Recommendation	✓ Machine Learning (Python, TensorFlow, Keras)	✓ Data Science ✓ Engineers
7- Act	➢ *Generate recommended solutions, actions or alternatives.* ➢ *Plan and and coordinate maintenance actions using PdM Plan to address process requirements.* ➢ *This application should provide real-time alerts and recommendations to maintenance personnel.*	✓ Solution Recommendation ✓ Failure Projection	✓ Implement Actions ✓ Schedule Maintenance Action ✓ Real time alerts	✓ IBM Maximo ✓ SAP ✓ Microsoft Dynamics 365	✓ Management Team ✓ Maintenance Team ✓ IT ✓ Production Team ✓ Quality Control
8- Continuous Improvement & Evaluation	➢ *Implement decisions on assets while continues monitoring.* ➢ *Evaluate the effectiveness of the predictive maintenance system by measuring key performance indicators.* ➢ *Continuously update the predictive model and the application based on new data and feedback from maintenance personnel.*	✓ Verify Recommendations ✓ Test Actions ✓ Scheduled Maintenance	✓ Feedback ✓ Validate Predictions ✓ Maintenance Costs ✓ Equipment Up-time ✓ System Reliability	✓ Performance Analysis ✓ Fault Diagnosis ✓ Root Cause Analysis ✓ HMI (Dashboards, Visualization)	✓ Maintenance Team ✓ Operations ✓ IT ✓ Quality Control

Table A-1 PAInOuTT Methodology Explained

Appendix B: Temperature Module Electric Schematic

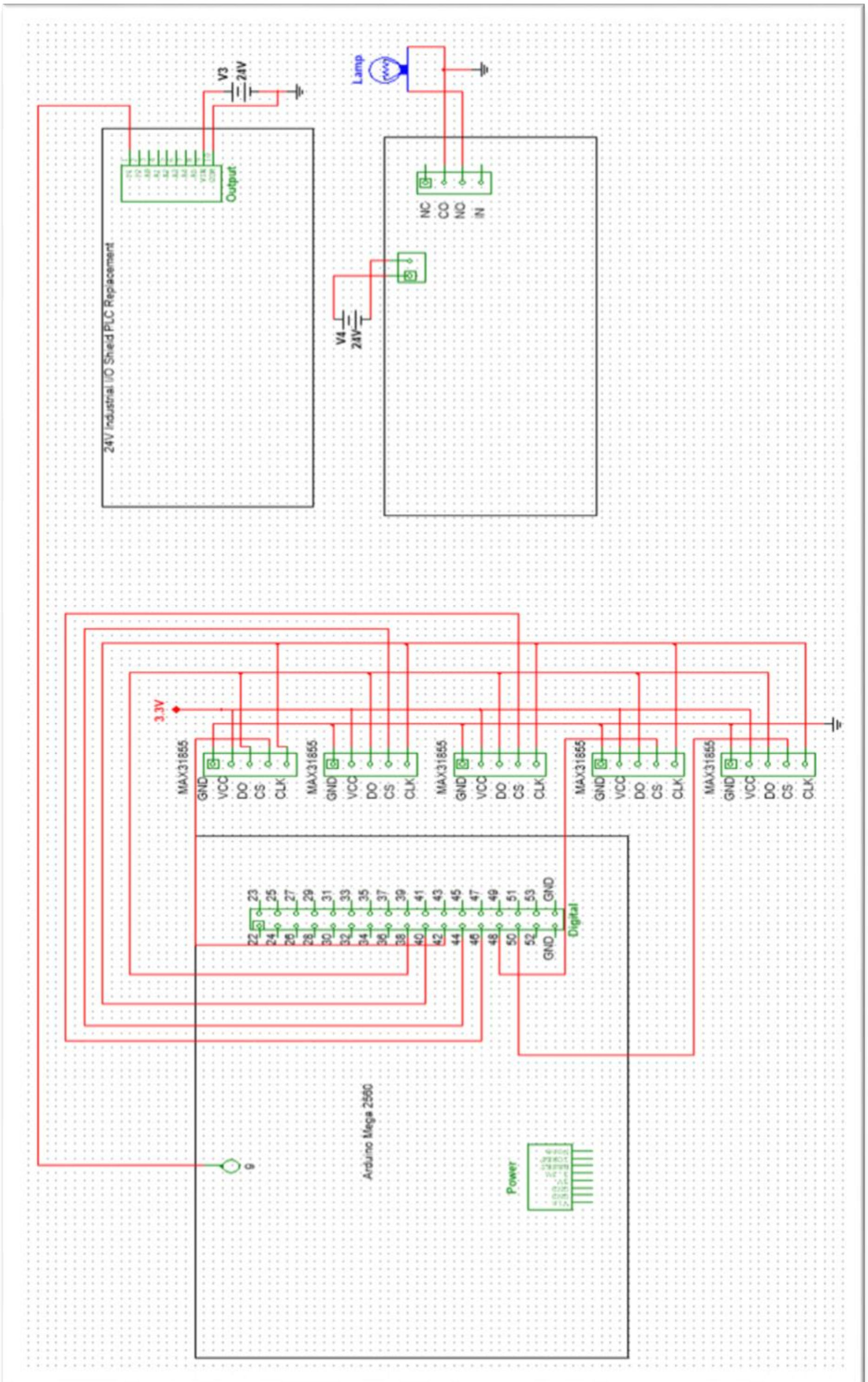

Figure B-1 Electrical Schematic

Appendix C: Coding

```
#include <SPI.h>
#include "Adafruit_MAX31855.h"
#include <SoftwareSerial.h>  //Added

// Default connection is using software SPI, but comment and uncomment one of
// the two examples below to switch between software SPI and hardware SPI:

// Example creating a thermocouple instance with software SPI on any three
// digital IO pins.
#define MAXDO   38
#define MAXCLK  40

//Sensors

#define MAXCS1 42
#define MAXCS2 44
#define MAXCS3 46
#define MAXCS4 48


SoftwareSerial XBee(30,31); // RX, TX // Added

// initialize the Thermocouple
Adafruit_MAX31855 thermocouple1(MAXCLK, MAXCS1, MAXDO);
Adafruit_MAX31855 thermocouple2(MAXCLK, MAXCS2, MAXDO);
Adafruit_MAX31855 thermocouple3(MAXCLK, MAXCS3, MAXDO);
Adafruit_MAX31855 thermocouple4(MAXCLK, MAXCS4, MAXDO);

// Example creating a thermocouple instance with hardware SPI
// on a given CS pin.
//#define MAXCS   10
//Adafruit_MAX31855 thermocouple(MAXCS);

void setup() {
  Serial.begin(9600);
  XBee.begin(9600); //Added


  while (!Serial) delay(1); // wait for Serial on Leonardo/Zero, etc
  pinMode(22,OUTPUT);

  Serial.println("MAX31855 test");
  // wait for MAX chip to stabilize
  delay(500);
  Serial.print("Initializing sensor...");
  if (!thermocouple1.begin()) {
    Serial.println("ERROR.");
    while (1) delay(10);
  }
  Serial.println("DONE.");
}

void loop() {
  // basic readout test, just print the current temp
   //Serial.print("Internal Temp = ");
   //Serial.println(thermocouple.readInternal());
  // if (Serial.available())
 // { // If data comes in from serial monitor, send it out to XBee
    //XBee.write(Serial.read());
  //}

   double c = thermocouple1.readFahrenheit();
   double c2 = thermocouple2.readFahrenheit();
   double c3 = thermocouple3.readFahrenheit();
   double c4 = thermocouple4.readFahrenheit();


   if (isnan(c)) {
     //Serial.println("Something wrong with thermocouple!");
   }
      else {
     //Serial.print("Sensor1 = ");
     Serial.print(c);
     Serial.print(",");
```

```
  //Serial.print("Sensor2 = ");
  Serial.print(c2);
  Serial.print(",");
  //Serial.print("Sensor3 = ");
  Serial.print(c3);
  Serial.print(",");
  //Serial.print("Sensor4 = ");
  Serial.print(c4);
  Serial.print(",");



  XBee.print(c);
  XBee.print(",");
  XBee.print(c2);
  XBee.print(",");
  XBee.print(c3);
  XBee.print(",");
  XBee.print(c4);
  XBee.print(",");


   delay(1000);
 }
 //Serial.print("F = ");
 //Serial.println(thermocouple.readFahrenheit());


   if((c >=90)||(c2 >=90)||(c3 >=90)||(c4 >=90)||(c5>=90)){
  digitalWrite(9,HIGH);
  delay(500);
  digitalWrite(9,LOW);
   }

 }
```

Figure C-1 End Device Coding

```
#include <SoftwareSerial.h>

SoftwareSerial XBee(0, 1); // RX, TX

void setup()
{
Serial.begin(9600);
XBee.begin(9600);
}

void loop(){

     if (XBee.available()>0) {
      Serial.write( XBee.read());
  }
}
```

Figure C-2 Coordinator Device Coding

Appendix D: Additional Graphs

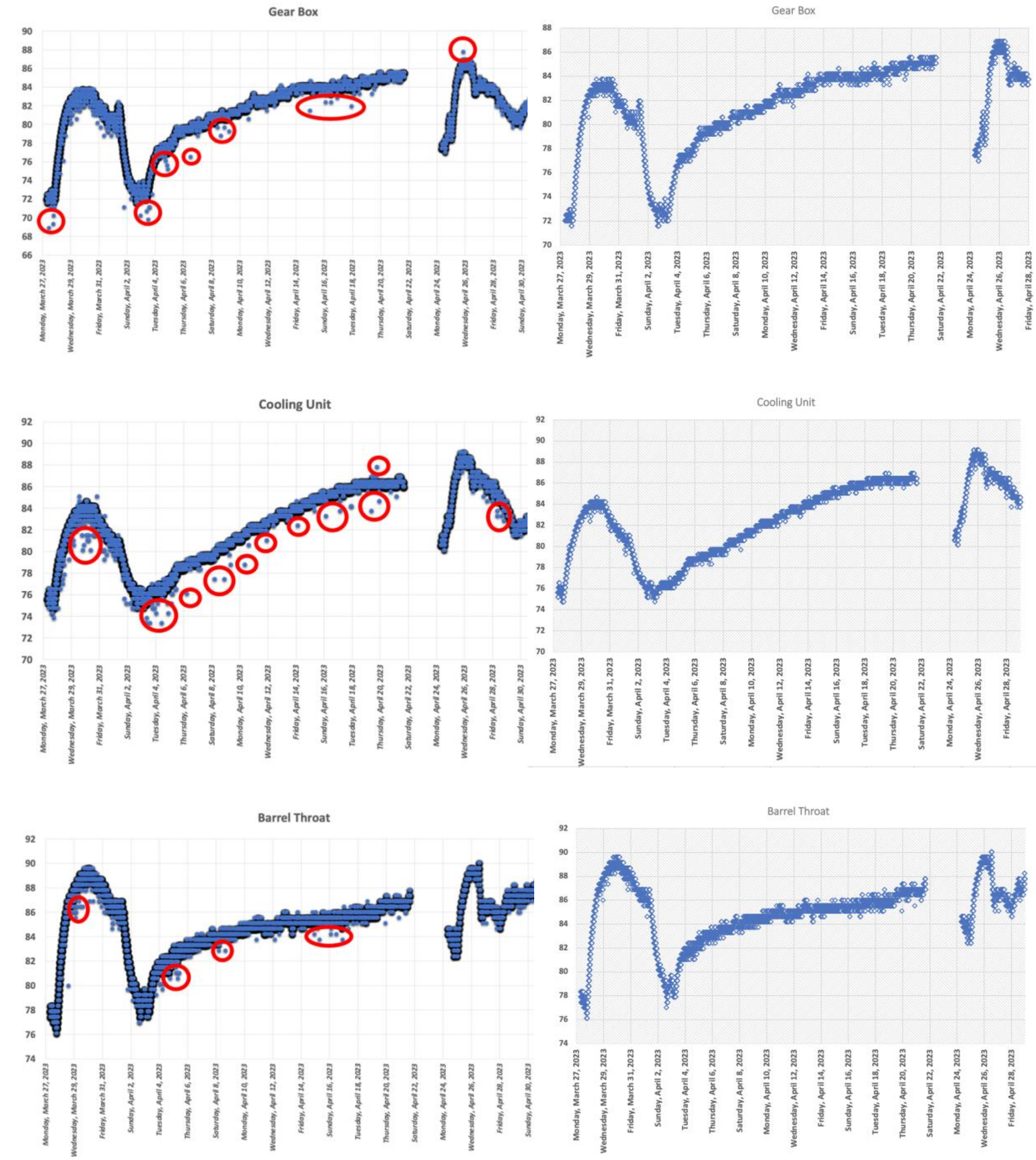

Figure D-1 Graphs showing data cleaning of Gear Box, Cooling Unit, and Barrel Throat areas.

Vita

Erick A. Rosales Cepeda was born in Cd. Juarez, Chih., Mexico, in 1996. He attended all of his elementary and high school years in Mexico and graduated from high school in 2014. The following August, he enrolled in a Fast Track English program at El Paso Community College, and in May 2015, he received the certificate of completion. In August 2015, he enrolled in the degree program of Associate of Science in Mechanical Engineering at El Paso Community College, and in December 2017, he received his associate with a 3.91 GPA. The following January, he entered The University of Texas at El Paso, and in December 2020, he obtained his Bachelor of Science in Mechanical Engineering with honors. In August of 2021, after the pandemic of COVID-19, he enrolled in the Master of Science in Manufacturing Engineering at the University of Texas at El Paso and received it in May 2023.

From 2021 to 2023, he was a research assistant for a manufacturing assistance center in Texas (TMAC). In 2022, he was employed as a manufacturing engineer in the assembly and test department of Cummins Inc. in Rocky Mount, North Carolina.

The research upon which this paper is based was begun in January 2022 under the guidance of Ph.D. Amit J. Lopes was completed in May 2023.

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