UNIVERSITY OF RWANDA
COLLEGE OF SCIENCE AND TECHNOLOGY
AFRICAN CENTRE OF EXCELLENCE IN INTERNET OF THING
KIGALI - RWANDA

# IOT BASED REAL-TIME PREDICTIVE MAINTENANCE SYSTEM FOR MEDICAL EQUIPMENT USING AN INTEGRATED ADVANCED ANALYTICS (IAA) MODEL

PhD. Thesis submitted in the fulfilment of requirements of award of the Degree of
Doctor Of Philosophy in Internet of Things
Embedded Computing Systems

IRENE NIYONAMBAZA MIHIGO

July 2023

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By

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(218015276)

Supervisor: Dr. Marco Zennaro
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July 2023

# DECLARATION

I hereby declare that the dissertation entitled *"IoT Based Real-Time Predictive Maintenance System for Medical Equipment using an Integrated Advance Analytics (IAA) model. Case Study: Hospitals in Rwanda"* to be submitted for the Degree of Doctor of Philosophy is my original work and the dissertation has not formed the basis for the award of any degree, diploma, associateship, or fellowship of similar other titles. It has not been submitted to any other University or Institution for the award of any degree or diploma.

Irene Niyonambaza Mihigo

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Irene NIYONAMBAZA MIHIGO, a Ph.D. student of UR-ACEIoT student ID 218015276, successfully defended the thesis entitled "IOT BASED REAL-TIME PREDICTIVE MAINTENANCE FOR MEDICAL EQUIPMENT USING AN INTEGRATED ADVANCED ANALYTICS (IAA) MODEL", which she prepared after fulfilling the requirements specified in the associated legislations, before the thesis examination members whose signatures are below.

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# FOREWORD

This Thesis and all related research works would not have been possible without the guidance and assistance of several individuals who contributed and extended their valuable assistance throughout the entire research process:

I would like to express my sincere gratitude to University of Rwanda, College of Science and Technology (CST) through the African Center of Excellence in Internet of Things (ACEIoT) for funding and letting me be part of this incredible program.

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# Acronyms

AI: Artificial Intelligent

API: Application Programming Interface

CBM: Condition Based Maintenance

DNN: Deep Neural Network

EI: Edge Impulse

GPRS: General Packet Radio Service

GSM: Global System for Mobile

IAA: Integrated Advanced Analytics

IoT: Internet of Things

IoS: Internet of services

KFH: King Faisal Hospital

LSTM: Long Short-Term Memory

ML: Machine learning

MAE: Mean Absolute Error

NN: Neural network

NTC: Negative Temperature Coefficient

PDP: Physical-to-Digital-to-Physical

PdM: Predictive Maintenance

PM: Preventive maintenance

RNN: Recurrent neural networks

ReLu: Rectified Linear Unit

RUL: Remaining Useful Life

RMSE: Root Mean Square Error

SARIMA: Seasonal Autoregressive Integrated Moving Average

SMS: Short Messaging System

SMCs: mall and Medium sized Companies

TF: TensorFlow

TinyML: Tiny-Machine-Learning

# Summary

Today medical technologies are improving, chronic diseases are also increasing day to day. The healthcare sector, like other industries, is having a high demand to cope with those influencing factors to satisfy the expectations of customers. Again, the success of all industries relates to attaining satisfaction with clients with a high level of services and productivity. Among the success main factors, the maintenance of equipment plays a significant impact to the overall production and effective service delivery.

To date, the Rwandan hospitals that always have a long queue of patients waiting for service, perform a repair after failure as common maintenance practice that may involve unplanned resources, cost, time, and completely or partially interrupt the remaining hospital activities. Hence, hospitals need to be well equipped with equipment in good conditions ensured through the maintenance performed using different methods and technologies. Yet, regardless of effort put into ordinary maintenances, unplanned downtime due to discontinued monitoring of health status, deterioration or misuse of equipment may also happen and may take long to be corrected.

Aiming to reduce unplanned crucial equipment downtime associated time and cost, this research brings up an IoT based real-time predictive maintenance (IoT based PdM) system using an Integrated Advanced Analytic (IAA) model to save maintenance time, improve maintenance accuracy and reduce the related cost in referral hospitals of Rwanda by performing planned necessary preventive maintenance and working out from unplanned downtime. The proposed IoT based PdM comprises of three main parts.

The first part proposes the Predictive Maintenance (PdM) structure powered by Internet of Things (IoT) to be adopted by hospitals to predict early failure before it happens for mechanical equipment used in hospitals. Because prediction relies on data, the structure design consists of a simplest developed IoT device prototype with the purpose of collecting real-time data for predictive model construction, equipment health status classification and later to host adopted predictive model. The real-time sequential data in the form of time series have been collected from selected equipment's components in King Faisal Hospital Rwanda and then used to build a proposed predictive time series model to be employed in proposed structure. Since, the data from different components are independent from each other at some instant and that each part may push down the whole equipment independently, the Long Short-Term Memory (LSTM) Neural Network model was used to learn univariate data from different components and performed with an accuracy of 90% and 96% to different two selected components.

Considering that LSTM did not perform well on independent multi-variates time series data from different components of the equipment, and that on side of maintenance activities priority for complex equipment: maintainers are manually deciding on crucial actions to be performed prior to others. We claim that the integration of knowledge based expert system might combine different independent condition parameters to come up with abridged univariate data to be fed to the sequential model for an effective predictive maintenance analytics through accurate maintenance priorities. As results, the second part of this research proposed the maintenance activities prioritization using Fuzzy expert system for small and medium sized hospitals. It considers the expertise of maintainers in faults detection and classification through the various monitoring of the physical condition parameters from equipment's components. Parameters' condition severity in respect of the total equipment downtime are considered to predict maintenance activities’ priority. Reflecting to the need of precise and quick prediction as well as real-time monitoring on the Edge, the on device TinyModels to provide the real-time sights on fault roots and remaining useful life of the equipment was proposed in third part of this research work. Considering the labeled data as maintenance priorities by fuzzy logic based on the maintainer’s expertise, this part used the labeled data set to compute the actual remaining useful life and then presents the ability of the two real-time tiny predictive analytics models: tiny long short-term memory (TinyLSTM) and sequential dense neural network (DNN) from Edge Impulse models. Both models (TinyModels) are used to predict the remaining useful life of the equipment by considering the status of its different components. The equipment degradation insights were assessed through the real-time data gathered from operating equipment. The predictive analytic models were developed and performed well, with an evaluation loss of 0.01 and 0.11, respectively, for the LSTM and DNN model from Edge Impulse. Both models were converted into TinyModels for on-device deployment. Unseen data were used to simulate the deployment of both TinyModels. Conferring to the evaluation and deployment results, both TinyLSTM and TinyModel from Edge Impulse are powerful in real-time predictive maintenance, but the model from Edge Impulse is much easier in terms of development, conversion to Tiny-version, and deployment.

To conclude this work, adding to the effectiveness of this IoT based Real-Time PdM with an Integrated Advanced Analytic (IAA) model into hospitals, it may be adopted by any industry interested in real-time monitoring based on performance and conditional data from their equipment. And, since the data affect the performance of the model, maintenance decision making and assumption of Remaining Useful Life (RUL), the TinyModel shall be updated and customized for project implementation.

**Keywords**: Predictive Maintenance (PdM); Internet of Things (IoT); Equipment; Real-time data monitoring; Condition parameters; LSTM; Maintenance actions; Edge; Edge Impulse, Remaining useful life; TinyModel.

# Chapter 1:

## Background of the study

This chapter presents the background of the study where the problem area is defined together with the aims and objectives. Further, it discusses the contributions of the research and the structure of the thesis and the organization of the rest of the chapters.

## 1.1 Introduction

In the highly competitive corporate world of today, each sized industry needs to pay attention to even a single advantage to attain its functioning consistency and sustainability. Among other key success factors, industrial equipment play an important role to steady production so that to extend the profitability.

Industrial equipment do not performs faultlessly permanently. Breakdowns are common, thus, unintended losses in productivity and delays in service delivery may happen. Many of these defects show up as equipment-linked issues, such as breakdowns or maintenance-related corrective measures. Hence maintenance is frequently held responsible for all issues that affect production plants, deliverable facilities, and services as well as the overall business.

As per definition maintenance could be described as functions including servicing, corrective actions, or replacement of some equipment parts or components with purpose to improve the equipment availability and ensure the equipment reliability [1]. Whereas reliability on its turn may be defined as a function for assessing and sustaining the life cycle and treats management of the asset (equipment is this case) with purpose to extend the long-lasting productivity with minimum operating cost.

For equipment reliability, maintenance could not rely solely on quick responses to catastrophic failures that require extensive time to find out the root cause of the faults and to fix them. To reduce losses and to consistently maximize production, the admirable maintenance procedures and techniques must be regularly followed. This shall also increase the equipment’s usable life and improve its life cycle demanding cost.

Due to the rise in demand in recent years, industries and companies have been facing significant cost pressure when it comes to effectively maintaining their operational devices and equipment [2]–[6]. With the advancement in maintenance technology, [7] revealed  the ability of modern predictive maintenance such as decrease in maintenance planning time by 20 to 50 percent, boosting equipment availability and uptime by 10 to 20 percent, and lowering total maintenance expenses by 5 to 10 percent, thus the overall growth of the organization.

To date, only big production industries have advanced to such modern predictive maintenance that enables maintainers (maintenance technicians in this context) to manage their maintenance process more effectively and have accuracy on each maintenance part in the right place at the right time. It involves real-time monitoring and the prediction of premature defects of the machinery and equipment. Though, Small and Medium sized Companies (SMCs) which are economic booster in both developing and developed counties [8], are still applying old, time-consuming, and ineffective maintenance methods [9] where a wide selection of several spares are typically kept into stock waiting to respond with prompt collapse of equipment.

Taking the case of Rwanda as developing country, among SMCs, hospitals as healthcare service provider companies are experiencing the gradual increase of customers (patients) looking for treatment. Once more, it is challenging to approach healthcare as a single domain due to the complexity of its ecology and the interdisciplinary confluence that is necessary for its objective to treat clients and recover their life. Thus, the healthcare experience could not be esteemed without medical equipment.

Since the patients treatment is especially ensured after getting results from different diagnostics obtained with help of medical equipment [10], they are of big importance to ensure the precision on patient treatments in order to save their life [11], and to satisfy their expectations. Thus, medical equipment have to be effectively utilized in good health conditions [12] and well maintained with purpose to sustain associated services as well as reduce maintenance cost [13], [14].

Consequently, inspired by:

- The importance of healthcare service delivery which are sometimes abstained by the unavailability of medical equipment,
- The unattainability of universal modern predictive maintenance platform to be adopted by any sized company,
- Maintenance techniques in place which are less efficient to maximize the uptime of available equipment, and
- Good practices from literatures and that predictions are based on data from which their most analytics are done offline and on the cloud:

This research came up with the IoT based Real-Time Predictive Maintenance (IoT based PdM) architecture with analytics capabilities on the edge.

IoT stands for the Internet of Things which is a collection of varied physical objects, software, and systems that are interconnected online via the internet to interact, and exchange data. Among the hardware, sensors and other devices gather information on the condition of the equipment to identify any problems that may need to be fixed before unintended outages and downtime. Therefore, IoT based predictive maintenance is defined as maintenance techniques that utilize the Internet of Things to continuously acquire and analyze data regarding assets, machinery, or equipment.

The proposed architecture could be adopted by hospitals and other SMCs that maximize the usage of their equipment to:

- Maximize the full availability of the existing equipment,
- Continuously monitor their health status,
- Maximize their life cycles through performing only necessary maintenance activities in convenient time, and
- Reduce hiring external professional maintenance organs.

Maximizing the file cycle and availability of the equipment will overthrow the unnecessary maintenance that includes premature replacement and regular professional inspections, then steadily reduce the maintenance cost, increase the equipment uptime, contribute to continuous improved healthcare service delivery as well as improve the overall turnover of the hospitals [15].

In this perspective, the faults root-causes will be automatically detected, the maintenance activities will be specifically determined and executed without additional time for physical fault detection. Therefore, a well-built predictive maintenance system can totally improve the overall benefits to the company [16] by removing unintended downtime and unnecessary replacement of healthy parts, improve control and asset monitoring, as well as minimize the maintenance cost.

To evaluate the feasibility of the IoT based PdM, following to the maintenance 4.0 concept [17][18], along this research, we proposed a structured Predictive maintenance powered by IoT for hospital’s equipment. Considering the current maintenance practices (preventive and corrective techniques) in Rwanda hospitals, which are archaic, nervous, time consumer, unreliable and costly compared to new predictive technique; the research works concentrated on the case of Rwanda hospitals.

Different referral hospitals were visited to get general information on used maintenance practices in place, types of equipment, selection of equipment and interest of maintainers to support this research. Only teaching Hospitals (University teaching hospital of Kigali (CHUK) and King Faisal Hospital Kigali (KFH)) accept research works out of experimental medicine research. KFH provided an unlimited authorization to conduct the research till its end whereby CHUK allowed the research for only one year. Thus, the real-time data collection was performed at KFH. Due to the fact that biomedical equipment are maintained by outsourced maintenance companies, the hospital advised to work on compulsory hospital mechanical equipment which are self-maintained by hospital maintenance team.

Considering the effect of real-time data in prediction, the IoT device was developed and used to collect real-time data from operating equipment which was later used to build an analytics tool for detecting the operating failures before they happen. Different mechanical equipment presents the common condition parameters [19], [20] such as temperature, vibration, noise, oil level, power consumption, pressure, dust, etc.. Depending on the investigated equipment (Autoclave) in this works, the real-time data for temperature, vibration and power consumption were gathered.

Integrated analytics tools such as machine learning and intelligent systems are the key components of Intelligent maintenance to provide automatic and continuously real-time sights of the asset's health, suggestions, and predictions. With analytics tools, the remaining useful time of the entire equipment and its parts could be assumed. With this maintenance technique, the necessary maintenance activities shall be done only when an anticipated operational defect is detected but before failure happens.

Since the equipment degrades gradually over time, the sequential models were the candidates for this application. Among sequential models, Long Short-Term Memory (LSTM) was proved in literature [21]–[24] to perform well on long term dependency from time series data. Thus, after assessing Seasonal Autoregressive Integrated Moving Average (SARIMA) and LSTM on our data, LSTM was adopted with performance of 90% and 96% respectively for two selected components. The two models were built separately since the data from different components may be totally independent of each other and defects from one component may affect the overall system and push it down. Thus, it could not be efficient to summarize the combined model for the entire equipment. The details are in Chapter 3.

Considering that different components may individually affect the overall performance of the equipment regardless to other parts, and that LSTM could not perform well for multi - variate data without dependency: with goal to reduce a large number of models from different components with associated power consumption, in Chapter 5:, we developed the expert system that may help in prioritization of maintenance activities through considering health conditions from different parts of the equipment. The output priorities could be then fed to LSTM, or another predictive analytics model as summated equipment health status and maintenance need level. Fuzzy logic was analyzed and proposed as an expert system that may automatically anticipate expertise of maintainers in decision making on maintenance planning. Different conditional parameters from working equipment were considered in building our expert system. The maintenance priority and status from each component as results from Fuzzy were presented to maintainers and were appreciated.

To predict the remaining useful life (RUL) of the equipment based on their parts health status and to provide real-time responses at edge, Chapter 7: expanded the developed LSTM model with the maintenance priorities obtained by Fuzzy logic and assessed its applicability on edge. This chapter also compares LSTM to novel specialized DNN model for edge applications (Model from Edge Impulse) with target to provide the best options on edge model to maintainers. The same chapter details the conversion of these two models into TinyModel that could be employed on IoT device at the edge.

Tiny machine learning (TinyML) [25] is generally understood to be a rapidly expanding field of machine learning technologies and applications, which includes hardware, algorithms, and software capable of performing on-device sensor data analytics at extremely low power, typically in the mW range and below. It is a new trend for edge application in Artificial Intelligence (AI) which is a technology from which computers may carry out things that would typically require human intelligence.

The result of this chapter showed the competence of both models with minimum Mean Squared Error (MSE) of 0.01 and 0.11 respectively for LSTM and Deep Neural Network (DNN) Model from Edge impulse as well as coefficient of determination of 77% for LSTM and accuracy of 99.87 for DNN Model from Edge Impulse. Even though both models perform well, but through comparing the complexity and expertise posed into building up and deploying TinyModel, the DNN TinyModel from Edge Impulse platform is recommended to be adopted for real-time predictive maintenance applications at edge.

However, the proposed solutions are timely relevant to the case of hospitals in Rwanda they could be extended to other industries that regularly use their equipment.

## 1.2 Overview on the predictive maintenance perceptions

Along with the industrial revolution, a lot has changed in terms of manufacturing and maintenance techniques, but the last decades have marked the most significant changes. These modifications had an impact on the upkeep of industrial facilities. Industrial machinery was changed from big size, mechanical operations and somewhat slow-moving with simple instrumentation and control systems to the modern equipment on the current market. During that period of past years, downtimes were not a major concern in maintenance history because production demands were not as high as they are today.

Nowadays, the market has become considerably more competitive, technologies evolved so fast, and the perceptions from customers to improved quality of products and services have risen. These sparked the pressure on all sized companies to improve their strategies and techniques for consistent business. To mitigate these challenges, companies must focus on production's requirement for better maintenance systems that will improve maintenance plans and executions, as well as reduce downtimes of their equipment and associate higher repair costs.

However, maintenance has always had the same description throughout its history [1]. And, to satisfy the business goals, it is up to management, control, and execution to make sure that assets perform well in healthy state and are available according to design standards. The fact that company objectives change over time to cope with changing environment is the main influence to push maintenance into advanced practice.

Since the end of last century, plants and systems have gotten considerably more complicated. While maintenance expenses have escalated, all sized companies have had the demands of the competitive business and the prejudice of their equipment downtimes. Besides the demands for better reliability, a greater understanding of failure mechanisms, enhanced management strategies, and new technology enabled equipment and their components' health to be understood on a wider scale were questioned. It has become crucial to understand maintenance related risks to the overall business. The environment and safety are considered the most important.

Therefore, to mature the maintenance from actual to fully proactive and to attain reliable maintenance there have new concepts introduced by some maintenance companies and bigger industries such as condition-based monitoring using sensors, Internet of things, machine learning algorithms, expert systems, and different levels of maintenance applications. Yet, there are no common standards to adopt while upgrading the maintenance practice in place.

### 1.2.1 Maintenance Evolution

Over time, as technology improved, the manufacturing industry was developing from one stage to another to implant a certain level of intelligence into their equipment. Refers to fourth industrial revolution (Industry 4.0) [26]–[30], the Internet of Things (IoT) took manufacturing to the next level [31], [32], [33]–[42]]. Industry 4.0 reflects the new technological age that consists of several converged technologies to offer digital solutions.

#### 1.2.1.1 Evolution in maintenance intelligence levels

To deal with market demand, the companies that utilize industrial equipment in their daily operations need to improve their practice from the actual to new technology of maintaining their equipment according to the industrial level of their equipment. The maintenance techniques [43] also revolve from one lower level of intelligence to the improved one according to the technology growth. The Figure 1.1 shows different equipment faults detections techniques  and maturity [44]–[48] that have evolved up today.

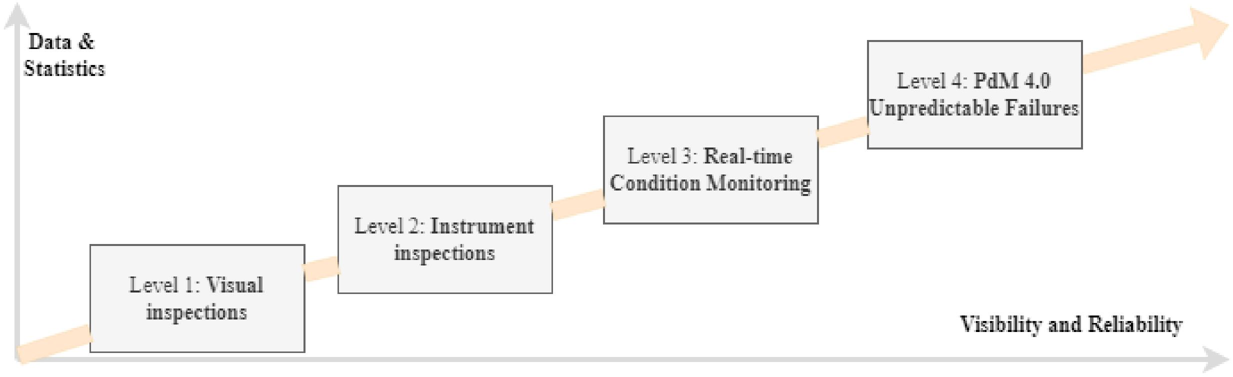

Figure 1.1. Fault detection maturity path

- In industrial level one of maintenance intelligence evolution which is still commonly applicable, maintenance technicians do a regular visual inspection (they also use different human body sensing organs) on the equipment by checking some physical performance signals like current flow, vibration, noise, temperature, pressure, lubrication, etc. According to their knowledge, familiarity, and discernment, they predict the needed services or repairs and then order a piece of equipment that shall be used in future when the shutdown will happen.

  To keep equipment in continuous working, unnecessary and repetitive inspections are inevitable, also the spare parts must be kept in store for unknown period. As result, adding to the anxiety labor of the maintenance technicians, the additional costs especially for premature replacement without tangible facts of degradation are obvious.

- Industrial level two involves planned and periodical inspection by experts to carryout specific and objective evidence on an equipment condition. This technique involves a lot of cost to compensate the experts' visits, but finally its results do not guaranty the long availability of the inspected equipment as the inspection is planned periodically regardless the performance conditions status of the equipment either if its operating status is in trouble or not.

- Industrial level three involves a sophisticated techniques based on real-time condition monitoring, by employing sensors to collect data of the targeted asset either on periodical basis or in continuous manner and conduct warnings based on pre-settled critical levels.

These three first industrial technical levels of predictive maintenance, of which the first two are currently the most applicable, have revealed a gap in making predictions from the periodical and less amount of data. Thus, to assure maintenance prediction performance, through gathering continuous more and more data from the equipment that may figure out all their different healthy states, maintenance technicians need be informed on cheap solutions that lead to improved reliability, lower downtime, rarer coincidences, and failures.

- Industrial level four is a new trend of maintenance at its infant stage and necessitates more industrial and researchers' contributions to attain its mature level. It is based on continuous real-time monitoring of an equipment with ability to predict future failures and providing suggestions on preventive actions by applying advanced analytic methods on the continuously enormous amount of performance data from operating equipment. Differing to the previous three levels, data analytics is the key component of this maintenance 4.0 through the internet's explosive growth. The analytics methods involve Artificial Intelligence (AI) components such as intelligent systems and /or machine learning algorithms and models.

Taking consideration to the equipment faults detections throughout all industrial levels, the maintenance techniques evolutions are also to date classified into generations from corrective to predictive approaches. All these approaches define maintenance to a collection of procedures and methods designed to guarantee the continuing and effective development and operation enhancement of the industrial assets such as equipment or machinery commonly utilized in any sized industry.

For the entire business to operate successfully and last for long time, a good maintenance program must be implemented with care to extend the equipment uptime, thus, to improve total business reliability. By lowering downtimes and enhancing equipment efficiency, maintenance plays a crucial factor in increasing production. The principal advantage of proper and effective maintenance may vary and not limited to:

- Extending the lifespan of the equipment, machinery, and other assets.
- Enhancing asset performance.
- Preventing unplanned downtimes thus to boost production.
- Cutting the costs from unpredicted breakdown and rushed correction measures.
- Reducing the operational cost.

Hence, it seems to be nearly impossible for any sized company to run smoothly and to meet production targets at a reasonable cost without needing to conduct strategic maintenance techniques.

#### 1.2.1.2 Maintenance techniques' generations

The only difference among maintenance generation refers to the innovation in maintenance actions, when they are implemented, cost involvement and probable risks. However, even though all generations are still applicable depending on the organization knowledge, choice and capability, most companies especially SMCs nearly exclusively rely on preventive and corrective maintenances. Referring to the practices in places as well as in literatures [1], [2], [31], [46], [49]–[52] Tables Table 1.1 to Table 1.4 summarize the description of each maintenance techniques.

Table 1.1. Corrective Maintenance

| **Corrective or Reactive or Breakdown Maintenance** | |
|---|---|
| **Definition** | Corrective or Reactive maintenance generally defines the approach of restoring equipment merely after reaching its failure point or after falling into breakdown state. It is also defined as run to fail maintenance. |
| **Time of action** | Repair take place only when the equipment goes down from function. |
| **Inspection tools** | Visual |
| **Decision making tools** | Expert or maintainers judgement |
| **Actions** | The only consideration for restoring jobs is how quickly the equipment or system can be put back into operation. Because most maintenance operations are reactive to failures or disruptions in production, maintenance is deemed successful if the machine can operate at a minimally acceptable level. Thus, it focuses on fixing the failure's evident symptoms rather than its underlying causes. |
| **Pros and Cons** | This maintenance management strategy can reduce expenses in the near term, but over time, it may result in more expensive repairs and lengthier downtime. Thus, it is both expensive and ineffectual. It is costly typically because the equipment has already failed and needs to be extensively repaired. It also adds burden because it needs more workers or professionals to complete the restoration. It is ineffective as it reduces equipment efficiency and overall lifetime. The primary drawback of this approach is poor planning and incomplete repairs which also mostly involve replacement that makes maintenance costs to be so high. There is also a time restriction imposed on production due to prompt unintended downtimes and may create financial burden to the company. This approach promotes a little use of people and effective maintenance resources. |

Table 1.2. Preventive Maintenance

| **Preventive maintenance (PM)** | |
|---|---|
| **Definition** | Preventive maintenance refers to planned maintenance. It requires regular maintenance activities to monitor the normal operation of the equipment to prevent unexpected interruptions. |
| **Time of action** | Regular check of the equipment. Maintenance actions are planned and conducted after fault(s) detection. |
| **Inspection tools** | Visual and measurement instruments |
| **Decision making tools** | Maintainers judgement based on the detected maloperation. |
| **Actions** | Preventive maintenance entails routine tasks intended to handle regular anticipated maintenance constraints during the lifespan of a part or piece of equipment. Preventive maintenance aims to do away with or avert the need for unplanned breakdown and corrective maintenance. This indicates that failure is avoided by such upkeep. Preventive maintenance's guiding principle is routine equipment inspection to assess its performance condition and take appropriate measures, but mostly regular inspections are done especially for crucial equipment of the company. The planned corrective tasks are also scheduled to address issues that have been found. |
| **Pros and Cons** | Preventive maintenance is an effective technique for avoiding issues that may be avoided. It reduces the unscheduled downtimes thus expands the equipment life, thus increasing the efficiency as well as associated labor and cost. But because the maintenance activities are done regularly, either needed or not, it can also lead to inefficiencies, such as spending money on maintenance that is not necessary at a certain moment. In addition, the regular maintenance initiatives are not genuine to totally prevent unintended breakdowns. Since it is based on theoretical functional failures instead of real performance conditions, it is not easy to justify the absence of unintended breakdown. Thus, to minimize such tragedies, the equipment' parts may be replaced while they are still in their usable life and spart parts must be kept in place for unknown period. This approach is less expensive than corrective approach due to lessening of unscheduled downtimes, but it is stressful to maintainers due to regular inspections and repairing activities. |

The typical Preventive, Conditional Based and Predictive Maintenance procedure are respectively depicted in Figure 1.2 to Figure 1.2.

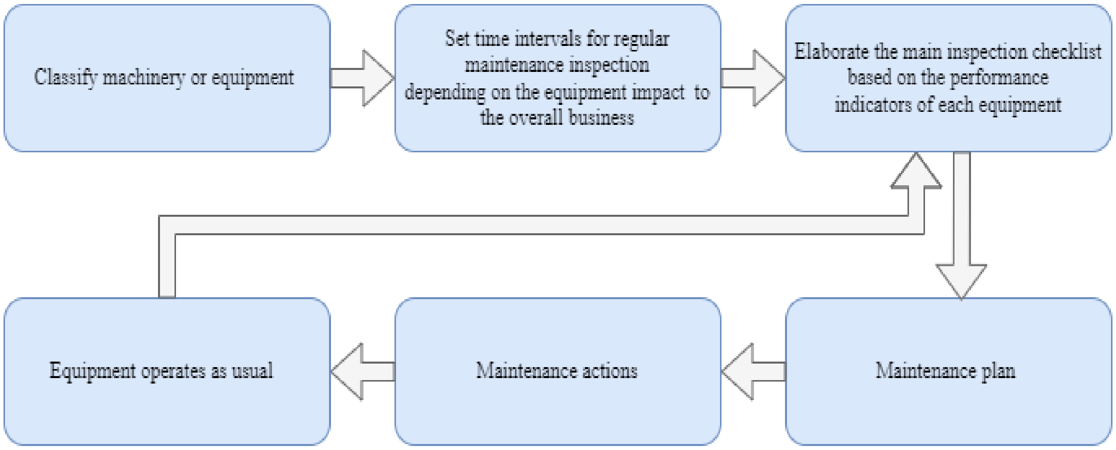

Figure 1.2. Preventive Maintenance roadmap.

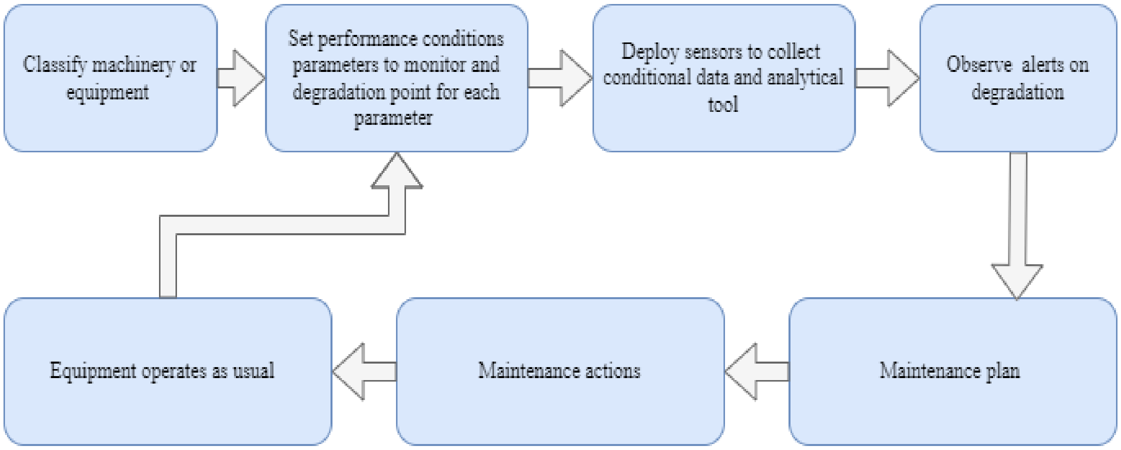

Figure 1.3. Condition Based Maintenance roadmap.

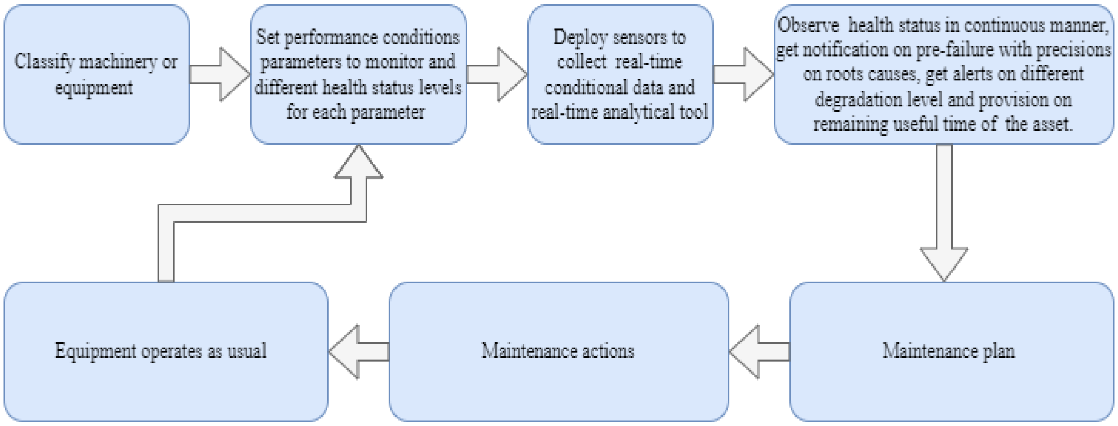

Figure 1.4. Predictive Maintenance roadmap.

Table 1.3. Condition Based Maintenance

| **Condition Based Maintenance (CBM)** | |
|---|---|
| **Definition** | Conditional Based Maintenance (CBM) is defined as regular proactive maintenance technique Maintenance that implies the monitoring of actual performance data from the equipment either captured through manual measurements or using sensors |
| **Time of action** | Inspections are and maintenance actions are planned and executed only when faults detected |
| **Inspection tools** | Industrial Sensors, visual and instruments |
| **Decision making tools** | Inspectors' analysis based on obtained data and data analytics tools may be used separately or combined to offer insights into the operation of the equipment and enable early warnings of future maintenance. |
| **Actions** | Condition-based maintenance entails regular inspections and a well-thought-out plan that guards against system faults. The real equipment condition is observed, and any additional maintenance needs are decided. Based on visual examination, predetermined tests, performance data, and other available data, the equipment condition is periodically examined. Maintenance is based on a variety of declining performance signs, such as impending failures, functionality, etc. Maintenance is planned when a failure or a hint of declining performance is detected. |
| **Pros and Cons** | CBM aims to reduce maintenance costs without compromising effectiveness. In terms of implementation, this approach is acknowledged as the most difficult type of maintenance. The technology needs to be understood and felt at ease by maintainers. |

Table 1.4. Predictive Maintenance

| Predictive Maintenance (PdM) | |
|---|---|
| **Definition** | Predictive maintenance is defined as continuous proactive maintenance technique powered by Internet of Things (IoT) and machine learning technologies that enable continuous real-time monitoring. It also defined as vital novelty under industry 4.0 [31], [53] with ability of intelligent maintenance to assure industrial competence and viability for the successful service delivery. It is also known as Maintenance 4.0. |
| **Time of action** | When faults detected |
| **Inspection tools** | Industrial Sensors |
| **Decision making tools** | Adding to CBM, PdM incorporates Artificial intelligent (AI) component such as machine learning (ML) and/or intelligent system, and Internet of things (IoT) capabilities. |
| **Actions** | Predictive maintenance primarily uses sensors and data science technologies to provide a sharp emphasis on reducing unexpected downtime and avoiding replacement of healthy parts while enhancing productivity. It is the next step in the progression beyond conditional based maintenance. The most up-to-date decision-making data is provided by predictive maintenance, which combines onsite and remote monitoring, round-the-clock modern technologies, and continuous data analytics to keep equipment functioning while boosting capacity and delivering orders on time. The maintenance plan and execution are based on the detected faults and predicted remaining time for the component to shutdown. |
| **Pros and Cons** | In maintenance ecology, predictive maintenance is currently the most efficient and reliable. Putting the components of technology and data-driven maintenance together provides tangible facts based on the continuous and real-time data analytics to all organizational levels for maintenance actions planning and decisions making.<br>Engineering professionals are required for the design of maintenance structures, developing data analytics tools, and other tasks. Merged with risen automation and rationalized operations, competent staff are a must as technology becomes more pervasive and essential to keep a competitive edge. Skilled labor and specialized training programs are therefore more crucial than ever. |

Summarily, traditional methods used by most maintenance experts to detect failure modes and reduce downtime in business facilities include both qualitative and statistical procedures. However, the development of new connected technologies can make it possible for machines to do these duties in their place, extending the usable lives of machine parts while still preventing machine failure.

Recent industrial research [7] showed that poor maintenance practices can lower an overall productivity capability by between 5 and 20% and that the unplanned downtime costs industrial firms an estimated of  $50 billion annually. This pushed many maintenance organizations and firms with equipment to decide on choosing the best technique to assure the extended useful life and reduces breakdowns of their machinery and equipment. Although, PdM is to date the ideal and most effective maintenance technique available even though it requires specific studies prior to being implemented.

### 1.2.2 Pertinence of Predictive Maintenance

The ongoing transformation of the industrial sector across the globe, as per defined [54] is referred to as "Industry 4.0.". Predictive maintenance (PdM) which is known as Maintenance 4.0 in the context of Industry 4.0[16], can be now achievable through smart and linked technologies that integrate both physical and digital elements. Smart technologies may also lead PdM to the name of Smart Maintenance. Physical-to-Digital-to-Physical (PDP) systems, the Internet of things (IoT), and the Internet of services (IoS) are all part of the revolution 4.0 concept.

The dual conversion process of Physical-to-Digital-to-Physical (PDP) requires different interconnected technologies that make PdM possible such as data gathering platform using sensors (both inbuilt and external), network protocol, data processing and analytics tools, data, and result visualization as well as digital to physical interaction tools.  The Internet of Things (IoT) and the Internet of Service (IoS) have also sparked shifts in consumer habits in line with Industry 4.0 through the creation and incorporation of PDP systems.

This revolution helped by a combination of information and electronics technologies will be marked by the digitized and automated processes. Industry 4.0 makes it possible for the manufacturing sector to grow into digital with sensors practically incorporated/connected into/onto every piece of production machinery, equipment, and product to collect enormous amount of performance data, which is then sent to the smart data analytics tool for analysis, evaluation, and decision suggestions. The ability to analyze related data within an omnipresent system with the merging of digital data and physical entities has the potential to renovate industries to evolve much more quickly and with more influences than previous industrial developments.

Thus, the Predictive maintenance revolution will pledge continuous and real-time control over machineries or equipment and will build a trust on the business's goods and services to both business owner and customers. The information acquired from linked intelligent machines and apparatus can anticipate when and where problems can happen, then, potentially increasing the efficiency of the parts and reducing needless downtime. This may explain the most effectiveness of PdM with regards to longstanding maintenance approaches. In this light, PdM is frequently regarded as a crucial skill in digital or smart maintenance.

A predictive maintenance task in industry 4.0 is based on the observation of a quantifiable system diagnostic parameters that indicate the system's state [31], [55]. Early indications of equipment anomalies such as faults and degradation state could be found based on the system's physical health status. Since the malfunction of production structure may result from machinery or equipment irregularities that are critically damaging for the machine functioning and to ensure that production lines run smoothly. Diagnostic activities shall be activated to identify the underlying cause of abnormalities as soon as potential equipment anomalies are identified or anticipated. Hence, predictive maintenance aims to take action before defects or breakdowns occur.

PdM uses cutting-edge sensing and data analytics technologies to comprehend and keep track of the tangible facts for maintenance processes. To increase the business reliability and proficiency, predictive maintenance implicates the Internet of Things (IoT) that comprises real-time reasoning through machine learning, data mining and expert systems as statistical components of Artificial Intelligence (AI) technologies, to identify and forecast probable deficiencies into real-time data sensed from the equipment in operation, and to automate suggestions on maintenance actions [46][56].

Enhancing the dependability, availability, and productivity of business is the goal of predictive maintenance. Predictive analytics [57] in the maintenance sector frequently use large volumes of heterogeneous data. Enormous data is gathered throughout operations by inbuilt or outer-connected sensors on machinery [6]. Statistical AI technologies are used to process the gathered large data and extract useful facts from diverse data sources. With the help of these technologies, decision-makers will be able to understand the data, derive insight from it and decide accordingly accurately and quickly.

The effectiveness and precision of decision-making are being greatly improved by statistical AI technologies' high computing capabilities. Any company can become self-aware and sustain themselves as a result. This enables the equipment to automatically maintain themselves while in use and to capture dynamic characteristics of operating environments.

Even though PdM is not a novel concept, its complexities have been accepted by large firms [53] especially in developed countries [58], and they are already working hard to introduce the necessary enabling technologies. Small and Medium Companies (SMCs) are still in use of traditional linear data and data transfer techniques. Yet they are the backbone of the economy in many countries as they contribute the largest portion of the gross domestic product and are significant employers. Thus, they must overcome the challenge of lacking the financial and trained human resources necessary to thoroughly examine the benefits and drawbacks of implementing maintenance 4.0 [59].

SMCs can profoundly change how they handle assets and reach goals by incorporating real-time data and intelligence access in existing systems. Valuing the available facilities including digital technologies, the SMCs shall consider the development, implementation, and use of the numerous connected technologies of PdM, while deciding on new values to avail their business.

The predictive maintenance is expected to play a vital role for the digital transformation of conventional SMCs into smart businesses toward the industry 4.0 as the provider of the efficiency and dependability of equipment and systems, particularly in the factory of the future namely “the smart factory”. Without methodical transformation of maintenance into smart maintenance to all sized companies, Industry 4.0's success will be in jeopardy.

Since the predictive maintenance mainly relies on the continuous condition monitoring of an equipment healthy performance indicators and forecasting of probable upcoming faults, it is possible to build its ecosystem even by SMCs centering on capabilities of available technologies and resources.

## 1.3 Motivating Case study

Considering the current maintenance practices, especially for SMCs, regular preventive and corrective maintenance dominates the predictive maintenance whereby unplanned downtown occurs and interrupt the remaining works of the organization. There is therefore a need to improve maintenance from classic to new and intelligent techniques. Special attention of this research goes to the improvement of maintenance in hospitals as one among SMCs. Since some healthcare services involve the usage of industrial equipment, and that their prompt downtimes may results to the aggravation of diseases or sometimes to the death, the hospitals must keep their equipment uptime and maximize their availability through advanced and effective maintenance.

To practice the feasibility of this research, we considered the hospitals in Rwanda as case study. Rwanda as small country with many populations have few hospitals mostly public with few privates especially in towns and not sufficiently equipped. Table 1.5 [60], [61] shows the number of all healthcare facilities across the country and their organizational pyramid diagram.

Table 1.5. Numbers of Health Facility Type in Rwanda

| **Health Facility Type** | **2016** | **2017** | **2018** | **2019** | **2020** | **June 2021** |
|---|---|---|---|---|---|---|
| National Referral Hospital | 8 | 8 | 8 | 8 | 8 | 8 |
| Provincial Hospital | 4 | 4 | 4 | 4 | 4 | 8 |
| District Hospital | 36 | 36 | 36 | 36 | 37 | 39 |
| Health Centre | 499 | 503 | 509 | 509 | 510 | 510 |
| Health Post | 471 | 505 | 885 | 885 | 1094 | 1179 |
| Private Dispensary | 125 | 130 | 123 | 123 | 122 | 122 |
| Private Clinics and Polyclinic | 123 | 128 | 149 | 149 | 158 | 180 |
| Private Hospital | 5 | 5 | 8 | 8 | 8 | 8 |

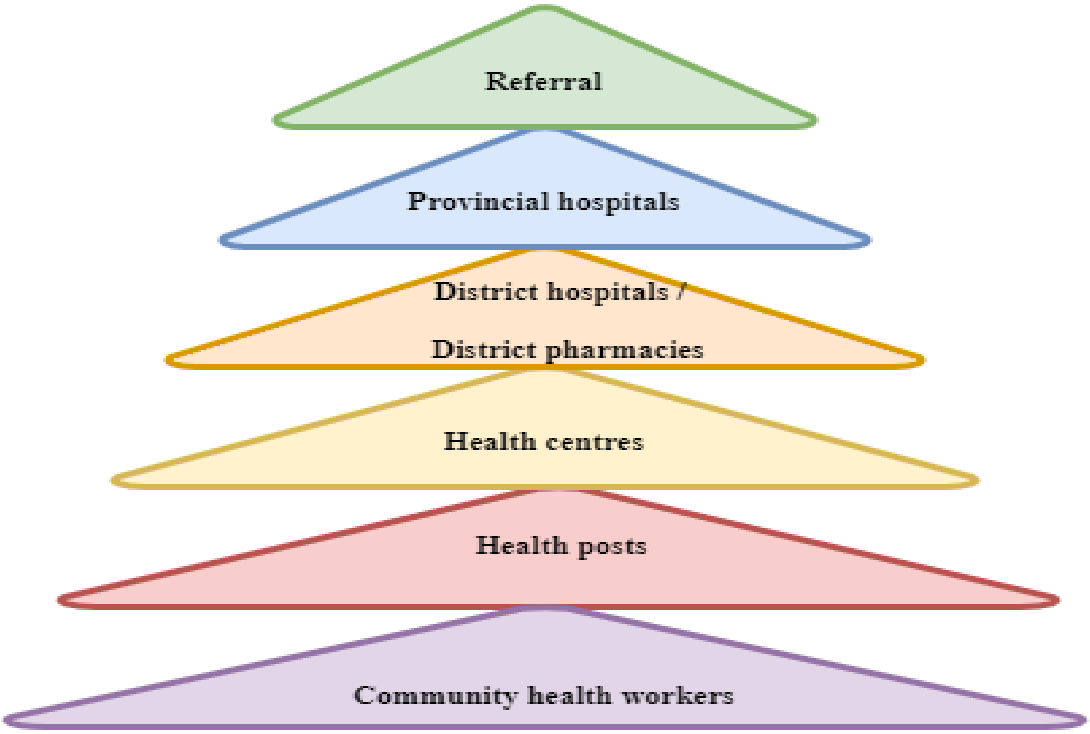

Figure 1.5. Rwanda Healthcare organizational pyramid diagram

Referring to the Rwanda healthcare system, most Rwandan citizen get healthcare in public institutions, which is structured in levels as shown in Figure 1.5 depending on facilities and capability of offered services [62]. Due to the complexity of disease, a patient can be transferred from the first contacted low level to the next level up to the referral hospital with higher capability of equipment, services, and advanced diagnostic.

Referral hospitals are well equipped in terms of both personnel and medical equipment compared to other levels of hospitals. Thus, they are always experiencing a long queue of patients from different areas of the country waiting for  diagnosis and treatment. To satisfy a huge number of patients coming from far, the hospitals at all levels need to keep their medical equipment in healthy condition and to avoid any cause that may put down any equipment.

Conserving the equipment healthy requires the repairing or maintenance management system [63]. At present, maintenance in Rwanda hospitals is often preventive, time-based rather than actual equipment conditions and predictive methods. Maintenance on each asset is performed at more frequent and regular intervals to minimize the likelihood of costly failures but till regardless how excellent preventive maintenance (PM) system is, the equipment could be out of services due to discrete controlled health status, overuse, and knowledge of maintainers on the performance of the assets.

Recognizing the high investment in maintenance [15], [64]–[66] that can harm the normal operation, service efficiency and business turnover, a new systematic approach rather than actual passive corrective or preventive maintenance might be adopted for the fully effective and proactive maintenance, control and equitable utilization of medical resources.

Adding to existing maintenance techniques, IoT based predictive maintenance architecture grounded on continuous monitoring of equipment, combined with diverse proven real-time analytics could be suitable [17]–[30]  to avoid unpredicted down time, and to reduce maintenance cost over routine preventive maintenance, or periodical conditions based monitoring (CBM) inspections by showing when the justified necessary maintenance could be done.

Even though, this novel technique may involve an additional capital for supportive infrastructure such as specific hardware, analytics and intelligent model (software), communication protocols and sometime a datacenter, but such capital may be less and powerful to cut future maintenance cost compared to accurately measured amount spent on old maintenance techniques [44].

In this appraisal, literature shows that the use of enormous performance data from various sensors and automated feeding them to integrated intelligent analytics bring on board new prospects for determination of remaining useful life estimate of an equipment [79], that offers appropriate early alerts to maintainers on convenient time to fix faults prior the total equipment failure.

## 1.4 Problem statement

All hospitals into different levels are mostly fully or partially supported by the government. Most of time, they are being equipped and maintained following to the complex governmental institutional procurement structure, thus a clear strategic maintenance of medical equipment decision marking is complex and challenging to hospitals' maintenance managers as it is involving high-cost demand [50], [80] and decisions from upper levels. A convincing fact to accelerate maintenance when it is needed before an equipment goes down is then highly needed.

Through assessing the current maintenance practices applied in hospitals, regular inspections of critical equipment are conducted but proven by literature to be inefficient to avoid unplanned downtowns. Yet, medical equipment play an important role into patient needs' satisfaction including getting services supported by such equipment, which are commonly few and sometime fall in unplanned out of service while there are pending appointments, and that might affect the diseases complication or puts patients on risks [11], [81] due to delayed treatment, hence, there is a lack of continuous monitoring of such equipment.

The maintainers do not observe the performance data from operating equipment, they do not have any perception of the health state of their system. This shortage creates some ambiguities in taking decisions on needed maintenance upgrading, plan of activities, and the convincing facts to the sustainable and effective maintenance.

Therefore, the current state of delivered medical care services versus the maintenance practices in place create a sequence of maintenance critical pillars and concurrent questions:

- Considering the patients' treatment demand versus the medical equipment availability: how the existing maintenance system can be improved to have a continuous insight into medical equipment, to reduce unnecessary maintenance actions and provide tangible facts to the needed services?
- To speed up the maintenance activities and maximize the equipment uptime: which tool can help to make a priority in identifying the needed maintenance activities, providing facts to the meticulous source of faults and execution of the maintenance plan?
- To enforce real-time monitoring and equipment health control: how the existing failure diagnosis practices can be improved into intelligent and automated real-time methods to eradicate the unintended breakdown of the equipment and associated cost?

Replying to the observed maintenance queries, this research works present the IoT based real-time predictive maintenance architecture that will combine various actual sensors readings together with IoT solutions to perform powerful analytics on captured data using the Integrated Advanced Analytics (IAA) model.

IAA will help to continuously predict failures ahead of time, process degradation and compute the probable Remaining Useful Life (RUL) of the equipment. Thus, the accurate prediction of upcoming maintenance activities shall be planned accordingly and will reduce the unnecessary preventive maintenances, unplanned downtime of the equipment as well as ensure their equitable usage in consistent and accurate healthy status.

## 1.5 Research Aim

Equipment manufacturing industries are developing as technologies rises. Different techniques for equipment maintenance to assure their wellbeing were described by different researchers [4], [17]–[26], [17], [82]–[86]. Maintenance techniques are advancing, implemented rapidly and provide a considerable improvement on foregoing maintenance techniques.

With consideration of the improvement carried by IoT in maintenance, and the current gaps and questions in predictive maintenance applicability, this research work aims to build up an IoT predictive maintenance platform which in turn will lead to greater accuracy in predicting equipment or component failure for medical equipment in Rwanda. The specific objective of the study includes:

i. Investigating the existing maintenance techniques applied to Medical Equipment maintenance management and developing the IoT based Maintenance Platform for effective and efficient predictive maintenance of medical equipment.

ii. Considering the complexity of equipment and that each of its part can separately cause the overall failure: Highlight the equipment physical performance indicators for effective maintenance monitoring and develop a maintenance prioritization tool to continuously provide health status of equipment’s components.

iii. Basing on the maintenance priorities, develop and evaluate an IoT based Real-Time PdM Integrated Advanced (IAA) Analytics Models that could be employed into the developed structure on the edge.

## 1.6 Research Significance and main contributions

The impact of medical technology development on patients' outcomes, hospital operations and financial resources is always changing. Healthcare organizations nowadays face a significant challenge in managing this transformation and its repercussions. A solid fit between demands and abilities, as well as between employees and technology must be ensured through successful technology management. To be effective, the hospital's continuing technology planning and management program must include an innovative technology assessment process that considers the needs of patients, the users, and the supporting staff.

The idea that the hospital setting cannot be made equipment-free is implicit in the definition of asset management. The fact that medical equipment are needed to diagnostic, correct, prevent, and keep observing the patients, they are invasively indicating that there is a jeopardy. As a result, an asset management standard that specifies sustainable assets in the current functioning context must be created.

Unfortunately, there is no existing, quantifiable standard that offers a universal procedure for monitoring of medical equipment, such as continuous operation status visibility, remaining time until failure, replacement, repairs, or maintenance cost.

To date, the historical mindset in medical equipment management is a corrective practice and regular preventive maintenance for some critical equipment which does not reply to the clear and justifiable asset management. It is also noticed that many of medical equipment are not functioning, not properly or fully used, and not well maintained.

Subsequently, some diagnostics and treatments such as infection prevention, diagnosis, treatment, and rehabilitation would not be proficiently feasible without medical equipment. Thus, there must be adequate medical equipment health management in place that can make use of continuous monitoring, progressive predictive maintenance techniques to allow the early-failures analysis [6] and that shall reduce the possibility of unintended incidences.

Triggered by technological shifts which is one of the healthcare's biggest economic challenges, particularly linked to a growing frequency of chronic and complicated diseases, [87] releveled the implications of medical equipment to the growth of healthcare conveyance and overall return. Therefore, hospitals to maximize needed comprehensive care, might be standing to improve the visibility into medical equipment performance by setting up a structured procedure for always keeping them in good operating condition, minimizing regular preventive maintenance cost (for hospitals in Rwanda, regular maintenance cost varies from 5 to 20 % of the overall budget plan) as well as expanding their useful lifetime.

As contribution to the full availability of medical equipment, along this work: an effective maintenance platform namely **IoT based Real-Time Predictive Maintenance system with Integrated Advanced Analytics Model** is developed to integrate the power of IoT advanced intelligence, to generate insights and to detect patterns and anomalies that may escape the human detection capability. It shows what was previously unpredictable and helps to fix the errors before surprised failures and downtime happen.

To Achieve the overall research contribution, the workflow was strategically developed in main three phases for three complement solutions shown in Figure 1.6. The three solutions have been published in journals and they represent the main subjects for the three main chapters of this thesis.

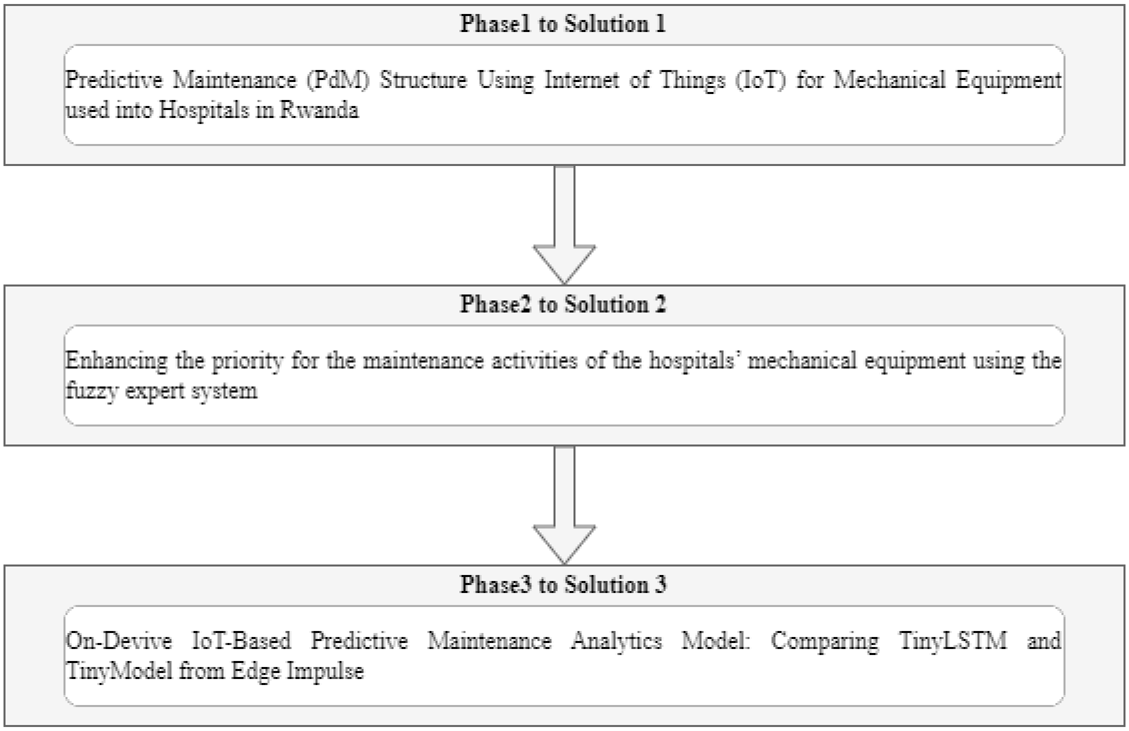

Figure 1.6. Research Solutions phases

Phase 1 supported the first objective by investigating the overall lifecycle of the medical equipment, their impact in healthcare services delivery, the maintenance practices in place, and then develop the improved architecture to provide advanced and intelligent predictive maintenance solutions.

Following to the existing maintenance practices, the historical maintenance records, and the complexity of equipment structure: the crucial equipment into hospitals were assessed with purpose to highlight the frequent failures, study their main roots' causes and to evaluate the equipment downtimes rate of occurrence, their grounds, as well as repairing procedures with demanding time. This helped to compile the equipment performance indicators and develop the expert system to prioritize maintenance based on the detected faults. These are supportive of the second objective.

Adding to the intelligent tool for maintenance prioritization, the development and testing of the effective machine learning model to be integrated into the IoT device on the edge were done in compliance with the third objectives.

## 1.7 Research Methodology

The research presented in this work uses the integration of novel technology and modeling techniques to propose practical solutions that can help to improve the maintenance of medical equipment and reduce the unnecessary regular associated cost. Exclusively, the focus of this research is the boosting of the existing maintenance techniques by integrating on edge machine learning techniques and IoT abilities in real-time monitoring and prediction. The proposed solutions are timely relevant to the case of hospitals in Rwanda.

Since historical data are the main source of information for new solutions, adding to self-collected real-time data, different maintainers as beneficiaries of this work from different hospitals were involved in the data collection. Hence both quantitative and qualitative research methods approaches are brought together along this work to complement each other with purpose to attain the defined objectives.

Qualitative method helped in finding out the indefinite in maintenance, whereby the findings transformed into knowledge to conduct experiments and test the expectations through quantitative method. Through the IoT technology abilities, the real-time data from the operating equipment was collected onto steam sterilizer machine at King Faisal Hospital (KFH) and utilized in experiments to train and test the predictive models.

Figure 1.7 illustrates research flow main steps following along of this work.

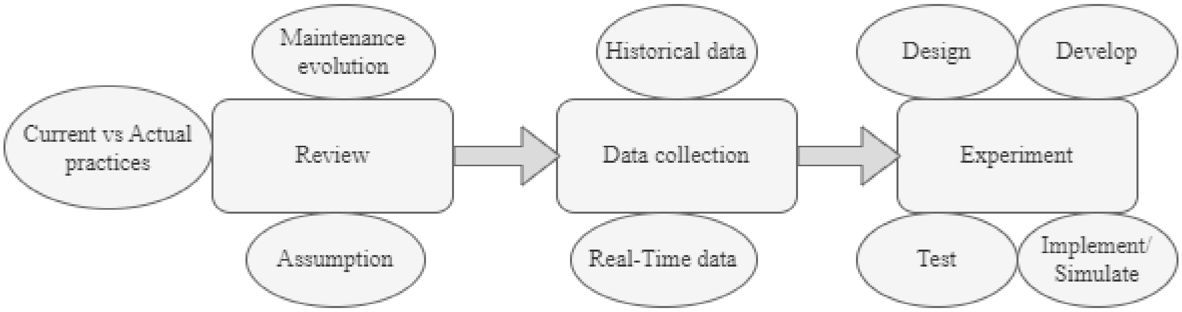

Figure 1.7. Research flow steps

We categorize the various research steps into three stages, namely: the review phase, the data collection phase, and the experiment phase. The steps applied to objectively acquire knowledge about the importance and influence of the maintenance to the sustainable businesses, from strategic perceptions to understand the current maintenance practices and to finally introduce the realistic intelligent technology for small and medium sized firms that regularly need maintain their industrial equipment in healthy state.

With strong knowledge from the literature, the historical data were gathered through interviews, observations, and discussions on the presented performance limitations, how to improve them, and identifying the needed data for further intelligent methods. With these qualitative methods, various visits to maintainers from different referral hospitals were made.

Using the quantitative method, an extensive analysis of the real-time prediction was also performed with the purpose of producing a solution to the real-time data collection and the powerful analytics tool to be adopted.

Since this research has different complement components and the used method to achieve the solutions in each part may differ from one to another, the detailed methods applied along this research are detailed into each component presented in the Chapter 3, Chapter 5, and Chapter 7 of this Thesis.

## 1.8 Thesis outline

This thesis is structured as a final research report based on published papers. It is made up by eight chapters from which the publications are detailed into Chapter 3, Chapter 5 and Chapter 7 are the main contributions of the entire research.

Chapter 3 describes the proposed predictive maintenance structure for hospitals. It details the necessary requirements to build the predictive maintenance framework including the simplest data collector that could be used by any sized hospital as well as other organizations. The same chapter studies the real-time data collected from an operating equipment and provides the results from the sequential deep machine learning model.

Noticing that the different parts of the equipment may independently cause the total breakdown of the whole equipment, and that the sequential model may not perform well on independent multi-variates data, Chapter 5 considers the maintainers expertise and data from different components of the same equipment to describe the expert system tool for maintenance prioritization which will be served to sequential model as a summed health status of equipment' parts.

Considering the maintenance priorities, the remaining useful life of the entire equipment have been computed in Chapter 7 and then fed to two sequential models to provide their comparison in term of their building up to their Tiny-Machine-Learning (TinyML) models that could be integrated into predictive maintenance structure to analyze data and provide real-time prediction results on the edge. The Simplest model to be implemented as predictive maintenance TinyModel on the edge is proposed.

Chapter 8 concludes the thesis by summing up the results from three contributions chapters and provides directives for further works to expend this research work.

The summarized outline of this thesis is graphically illustrated in Figure 1.8.

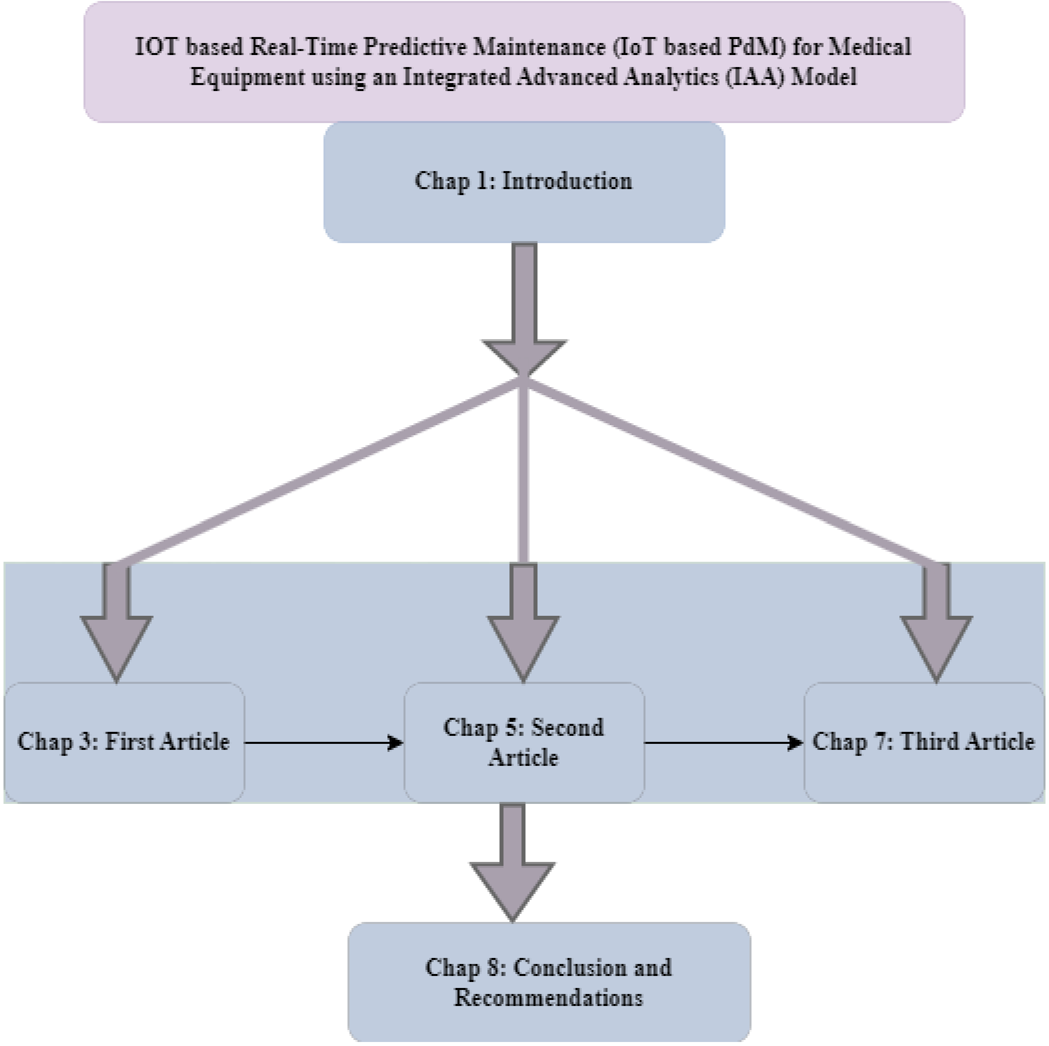

Figure 1.8. Thesis Organigram

# Chapter 2:

## Prologue to first article

### 2.1 Article details

Irene N.M., Zennaro M., Uwitonze A., “Predictive Maintenance (PdM) Structure Using Internet of Things (IoT) for Mechanical Equipment Used into Hospitals in Rwanda” in Future Internet, 2020, 12(12), 224; https://doi.org/10.3390/fi12120224

### 2.2 Personal contribution

Aiming to reduce unplanned medical equipment downtime and increase their reliability, after assessing the current maintenance practice in place, the Predictive Maintenance (PdM) structure while using Internet of Things (IoT) was proposed to predict early failures before they happen for mechanical equipment that is used in Rwandan hospitals. I did most of the article composition under the guidance of Zenarro M., and Uwitonze A.

### 2.3 Context

The success of all industries relates to attaining satisfaction for clients with a high level of services and productivity. The main factor for success depends on the extent of maintaining their equipment. To date, the Rwandan hospitals that always have a long queue of patients waiting for service, perform a repair after failure as common maintenance practice that may involve unplanned resources, cost, time, and completely or partially interrupt the remaining hospital activities. To overcome this shortage, the integration of IoT and analytics model into regular maintenance might improve the equipment availability and provide real-time monitoring of their status. Thus, the convenient Predictive Maintenance (PdM) structure is proposed.

### 2.4 Contributions

Since prediction relies on data, the structure design consists of a simplest developed real-time data collector prototype with the purpose of collecting real-time data for predictive model construction and equipment health status classification. The real-time data in the form of time series have been collected from selected equipment components in King Faisal Hospital and then later used to build a proposed predictive time series model to be employed in proposed structure. The Long Short-Term Memory (LSTM) Neural Network model is used to learn data and perform with an accuracy of 90% and 96% to different two selected components.

## 2.5 Recent developments

**S**ince the publication of this article, it was considered by some researchers to support their works, particularly:

Eyup Cinar in his work entitled “A Predictive Maintenance System Design and Implementation for Intelligent Manufacturing” [88],

Zehra Jahangeer Knan [89] in his work entitled “Predictive maintenance & Internet of Things”

YH Liu [90] in his thesis entitled “Data Quality and Data Processing on an IoT-based Ecosystem for Smart Maintenance in the Manufacturing Industry”,

Abood, Azhar M. [91] in the work entitled: “Predictive Maintenance of Electromechanical Systems Using Deep Learning Algorithms: Review”,

Yuehua Liu [92] in the work entitled: “An Evaluative Study on IoT ecosystem for Smart Predictive Maintenance (IoT-SPM) in Manufacturing: Multi-view Requirements and Data Quality”,

Bita Ghasemkhani [93] in the work entitled: “Balanced K-Star: An Explainable Machine Learning Method for Internet-of-Things-Enabled Predictive Maintenance in Manufacturing”,

Shadi Attarha [94] in the work entitled: “Automated Fault Detection Framework for Reliable Provision of IoT Applications in Agriculture”,

Saniya Raheen Patel [95] in the work entitled: “Harnessing IoT and Artificial Intelligence for Sustainable Healthcare”, and

Mrigank Kumar [96] in the thesis entitled: “Deep transfer learning for fault diagnosis of roller bearings under scarce data conditions”.

# Chapter 3:

## Predictive Maintenance (PdM) Structure Using Internet of Things (IoT) for Mechanical Equipment Used into Hospitals in Rwanda

### 3.1 Introduction

The success of industries relies on the level of production and level of services to satisfy their clients. The main factor in improved productivity is the effective maintenance of their equipment. Among medium and small industries, the medical industry, with its mandate to save human being life, is today experiencing an increase in chronic diseases that infers a high demand of healthcare to be efficient and is authoritative in keeping a high level of their equipment reliability through severe maintenance programs.

Looking to the few numbers of referral hospitals in Rwanda that have not yet adopted a new technology of virtual patient's health monitoring [97], hospitals do always have a long queue of people looking for diagnostics and treatment. In order to satisfy the patients through effective healthcare services delivery, medical equipment plays a big impact not only to patients, but also to the core business success [10]. Accordingly, there is a growing need for maintenance supervision programs with the purpose of minimizing unscheduled downtimes.

Unlike the equipment used in the diagnosis of diseases and treatment of patients commonly called biomedical equipment [98], [99] which are mainly maintained by expatriate companies, there are obligatory mechanical equipment that provide secondary supports and much necessary capabilities to these biomedical equipment. Like biomedical equipment, this category requires large capital investment to hospital and, for their maintenance, whether new or aged among them involve cost, time, and effort to maintain.

To date, repair after failure is common practice on this equipment due to the fact that they fail without any notification to the maintenance team; hence, fault detection and unplanned maintenance works can completely or partially interrupt the remaining hospital activities. Moreover, their unplanned downtime may even lead to considerably worse incidents [11], including patient death.

Coping with the technology, with the aim to increase equipment lifetime, availability, reliability, and reduce downtime, unnecessary preventive inspections, maintenance time, and untimely pressure on the maintenance team as well as associated costs, the maintenance team requires real-time conditional based evidence for effective maintenance [14], [100], [101].

Motivated by the aforementioned matters, noticing a gap in the adoption of existing predictive maintenance architecture for these types of equipment due to different mechanical behaviors from one to another and the nonexistence of historical or real-time performance data, this work:

- Proposes the Predictive Maintenance (PdM) Structure using Internet of things (IoT) for mechanical equipment used into Rwandan hospitals; and,
- Describes the whole process, from IoT device prototype development, real data gathering, up to the fault detection sights from equipment's components before they fail.

The data that were used to build a predictive model were gathered in King Faisal Hospital to two critical components of large hospital autoclave sterilizer with a built-in electric steam generator that uses steam as a sterilization agent. Long Short Time Memory (LSTM) Neural Networks was adopted to be suitable model for predicting the physical performance of two selected components with a fitting confidence of 90% and 96%, respectively, by mapping the model fitting parameters.

The remaining part of this chapter is structured, as follows: Section 3.2 introduces an overview of the predictive maintenance evolution, followed by Section 3.3, which summarizes the role of Internet of Things in predictive maintenance and highlights some previous works. Section 3.4 describes the used methodology and selected materials in order to develop a prototype that resulted in the proposed overall PdM structure powered by IoT in Section 3.5. The experiment results presented in Section 3.6. Finally, Section 3.7 concludes the chapter.

## 3.2 Predictive Maintenance Overview

Throughout the past decades, according to the technology improvement, the manufacturing industry was also developing from one generation to another [74], [78], [102]–[104]. Figure 3.1 shows the evolution in maintenance techniques and objectives for implanting a certain level of intelligence into equipment and systems. By considering the past literature and reflection of industrial live out [72], [77], [82], [104], [105], maintenance has been considered as the main factor in running a sustainable industrial business by optimizing the entire lifecycle of the entities from beginning to end of their lives. As result, maintenance has drastically transformed in compliance with the technology requirements and market demands.

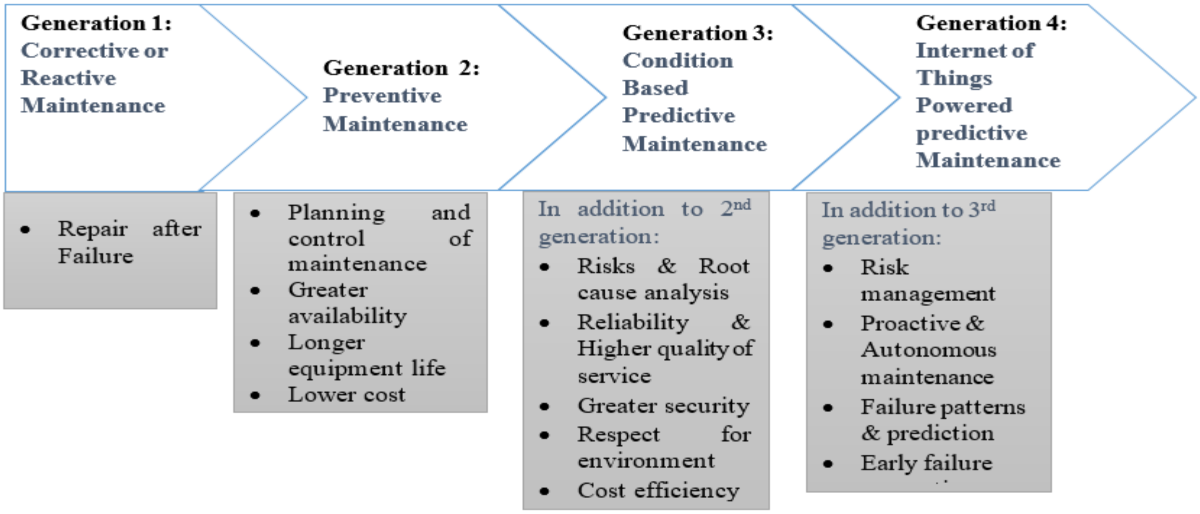

Figure 3.1. Industrial revolution maintenance techniques and objectives.

In the fourth industrial revolution, the IoT took manufacturing to the next level, commonly known as industry 4.0, which is able to compensate the older approaches, by enabling maximizing the useful life of equipment [28], [75], [78], [83], [86] through real-time health monitoring. This can be achieved through empowering the automated and digitized monitoring process by using integrated electronics, information technology, and standards protocols capabilities to smart systems [26], [27], [38], [54], [106]. The term "smart" infers the capability of an object to collaborate with another object flexibly, effectively, and safely in order to share information that is allied to the adjacent surroundings.

The maintenance 4.0 is at infant stage and still needs more development. Yet, to meet the customer demand and cope with new technology, the organizations that utilize industrial equipment also need to adopt new technology to step up and maintain their wellbeing. Even though the maintenance techniques revolve from one level to another according to the evolution in technology, each level techniques contain different activities to keep equipment in its best operating status by maximizing their reliability and assuring their availability.

For more innovative and competitive workflow, organizations need to continuously access useful data and be able to transmute them into information to adjust their works for better performance. Similarly, today's maintenance technology needs evidence to perform any action on operational equipment. The data from such equipment are crucial and the powerful evidence regarding their health status relate to their health trend observing, diagnosis, forecast, and planning for their reliability; hence, deciding on which component to repair or replace and when.

Taking into consideration the cost that is associated with premature replacement and of sudden failure, the plan on spare parts ordering, quantity, and time could be done conveniently. By gathering increased real-time performance data, the maintenance team shall be informed on cheap solutions that lead to improved reliability, lower downtime, rarer coincidences, and failures.

## 3.3 Internet of Things in Predictive Maintenance

Converging the internet and sensing network technology, after the introduction of Radio Frequency Identification and the Wireless Sensor Networks, the IoT concept has been growing and attracting both in industries and academia since 2000, with the goal of connecting distant remote objects (anything or anyone) at any time in any place by involving different hardware devices, software, and communication capability in order to make any object intelligent, so that they can communicate virtually, regardless of physical location [34], [36], [42], [107].

The IoT ability to connect physical objects and allow them to share information through the internet may facilitate collecting a great amount of real-time data that are the powerful strength for the success of any business, its future prediction and effective planning [40], [108]. In the maintenance world, embedded hardware that is made up by sensors and other smart devices powered by IoT is today reshaping the industrial and manufacturing maintenance processes [33], [37].

The internal equipment outfit is generally unobservable; thus, regular planned preventive maintenances do not provide enough or clear information involving the equipment status to maintainers, when it is operating without any physical symptom to depreciation, it is not practically easy to identify whether there is any root to cause future defect. Consequently, the routine schedule is retained, and sudden downtime may occur at an unexpected time, perhaps even during a heavy works' period.

The equipment gradually degrades overtime before reaching a complete collapse [109]. Furthermore, the insufficient maintenance accuracy of asset's conditions results in a thorough deterioration that reflect in service deficiency, clients' appointments postponement, and dismay while waiting for the procurement of new spare parts or equipment replacement that always goes together with an increase in cost demand.

Thus, with the power of IoT, the real-time predictive maintenance approach may be powerful in this game to integrate the direct monitoring of equipment through collecting continuous real-time data from its health physical parameters.

Late literature reviewed the IoT relevant concepts, technologies, architectures, services, applications, and business models [36], [37], [40], [110]. Among the applications, IoT offers predictive maintenance solutions in different scenarios from different industries; among them are healthcare industry [10], [73], [111], [112], energy [113]–[119], and industrial automation and machinery [14], [24], [31], [42], [59], [99]–[143], to which also this work belongs.

The PdM Structure using IoT involves sensors for capturing the continuous real data of highlighted key stress factors that lead to deficiencies, such as vibration, temperature, noise level, pressure, power consumption, etc., and other coupled devices to make an asset visibility to the user by getting continuous sights on their health changes.

The predictive maintenance using IoT cannot be efficient without advanced data analytics tools and machine learning techniques [30], [144], [145], that use historical performance data to discover the remarkable insights linked to the equipment performance, detect anomalies in variances, discover patterns or warning signals which could be a sign of impending failure, and from them:

- Estimate when the asset is probable to fail,
- Classify the equipment's part to cause the failure; and,
- Provides suggestions on the most effective interval of time to perform preventive actions.

Despite a thorough investigation of the denoted benefits, the predictive maintenance adoption by hospitals in Rwanda among other small- and medium-sized companies is still not mature due to differing reasons, either because of the historical data unavailability, trustless of the technology, or luck of usefulness information on the technology. Mainly, they need evidence [54], [102], [145]–[148] to prove that the early fault detection enables them to:

- Take early and necessary corrective measures,
- Intervene in effective manner, minimize unplanned outage, avoid unnecessary and improper works, and minimize premature replacement; and thus,
- Save time and resources, reduce valuable figures of maintenance costs, increase reliability and productivity to businesses' turnover, and extends the lifetime of aging assets.

## 3.4 PdM Structure Development Methodology

The health monitoring of equipment's components helps in detecting premature faults. Starting a PdM structure that is powered by IoT requires integrating a new and separate independent structure built with the ability to collect data, process them, and make data perceptions sharing across existing systems [149].

The preliminary works before stating the construction of system for predicting the forthcoming faults, includes the different steps:

- Highlighting the equipment in query and conducting its operational assessment.
- Collecting its data from maintenance history to discover and describe what type of faults mostly make it traumatized, their impact to the system, and how they were identified; and,
- Based on acquired information, highlight the critical components and their physical parameters to be monitored as well as the needed materials.

The PdM requires the embedded system that is powered by the IoT capabilities to keep spotting the continuous streamed sensors data, various linked hardware (microcontroller, sensors, communication module) to process data, as well as to provide feedback in continuous manner [145]–[150]. Figure 3.2 shows the process steps in constructing a supervised predictive maintenance structure up to early impending failures detection and providing insights regarding equipment life status.

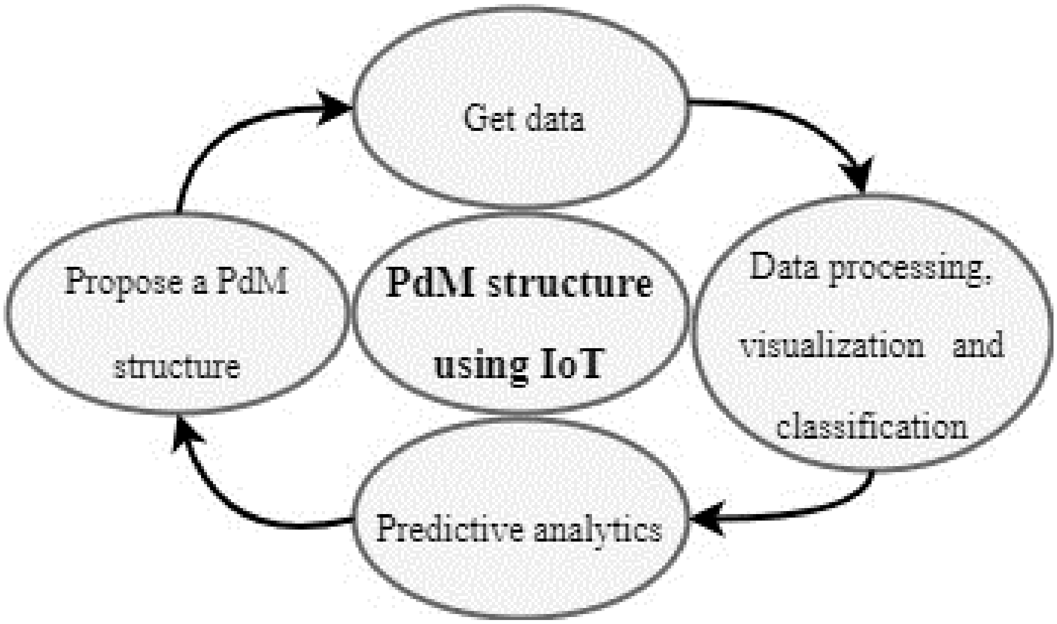

Figure 3.2. Methodological steps to construct a Predictive Maintenance (PdM) Structure using Internet of Things (IoT).

### 3.4.1 Get Data

The selection of suitable technology and linked protocols to obtain real and continuous data relies on the environment of targeted equipment that helps to define which type of data are to be captured, the amount of data, data format, data transmission protocol, transmission rate, as well as the needed materials for constructing a complete architecture suitable for queried solution. All equipment do not suit the same monitoring system, due to their normal characteristics and operation. Thus, the selection of targeted equipment could be done prior to designing the data collection tool.

### 3.4.1.1 Equipment and Critical Parts Selection

The hospital industry, like other industries, uses industrial and different equipment and these are different to serve the whole community. The selection of the equipment relates to its importance in the industry.

For this study, the hospital's maintainers helped in choosing the critical equipment to investigate, basing on their maintenance records, they suggested one of the most critical hospital mechanical machineries which is Autoclave. Autoclave sterilizer is mandatory in any hospital with the aim of avoiding the possibility of pathogen transmission from the medical object to patient or to hospital staff and environmental contamination. This machine uses saturated steam to produce high temperature and pressure as sterilization agent. Sterilization serves to destroy pathogenic microorganism that could lead to infection [151]–[153].

Some authors [122], [123], [154], [155] focused on sterilization chamber regulation and steam quality, but did not consider the main mechanical parts to generate the required agent for successful sterilization. This machine is structurally complex; consequently, its maintenance is stressful, and it requires reserving their spare parts in stock to avoid any kind of its' components failure that may lead to breakdown its operation.

Among its critical parts, there is a steam generator that is made up of water tank and heaters in order to generate saturated steam, which is the main agent of sterilization. Once one of the heaters slows down, the sterilization is affected. There are also pumps which are devices that move fluids by mechanical force. Pumps are also extensively used for small to large scale appliances in both domestic, enterprise, organization, and manufacturing industry appliances [124], [131], [132].

Pumps worse behaviors may cause the most amount of failure not only of itself, but of the whole critical system. For the autoclave, pumps occupy considerable importance in its normal working process, as any kind of defect could cause a total downtime of the whole system, which may result in expensive complications.

Autoclave presents two centrifuge pumps, namely water and vacuum pumps with the same mechanical and physical parameters. Water pumps serve to supply water to the steam generator, whereas vacuum pumps are used to evacuate air bulbs and moisture on the load in sterilization chamber to continually keep the effective vacuum condition for successful sterilization.

Pumping system contains different components, such as a pump itself, which feeds kinetic energy to fluid, a motor that supplies the mechanical force to pump for its working, piping, valves, measuring equipment, and beneficiary equipment. Any stress from one of these components results in pump behavior change, which is then transferred to the coupled motor.

Referring to literature, different researches put emphasis on the fault diagnosis of the pumps by analyzing changes in its associated motor quantities [68], [121], [128], [133]–[135], [137]–[139], [156], but did not consider the pumps as an individual unit that borrows stresses from its own inefficient operation or surrounded components.

The first pumps defects symptoms, such as bearing failure, misalignment, bed failure, and associated motor failure, lead to a rise in their operating temperature [126], [132], which, in turn, gradually shortens its life cycle and efficiency. In normal conditions, pumps keep their environment temperature and, for any change in temperature increase, the inner temperature is directly propagated to its metallic housing and then to a coupled motor.

The data gathering and processing experiment of this study focuses on steam generator and pumps temperature as main physical behavior for detecting failure. The collected data were used in constructing a predictive model that can learn the real-time data taken with a small interval of time and classifying the components' health status.

#### 3.4.1.2 Requirement for Data Collector Device Development

Data collection is a pillar step in predictive maintenance. The objective of this stage is to develop the IoT based real-time series data collection structure that allows the interaction between smartened physical object and virtual organization applications. Data collection can be subdivided into two main parts, namely maintenance historical data collection provided by maintenance team and sensors' raw data collection gathered while using the developed data collector.

From maintenance history data, you learn the equipment functionality and its maintenance history. This phase of knowing equipment gives an idea of which important components should be monitored and which monitoring is needed for specific possible faults.

In our experiment, we developed a data collector prototype in Section 3.5.1. The temperature was highlighted as a major stress symptom to be monitored on the identified components. The Negative Temperature Coefficient (NTC) thermistor [157]–[159], which is a thermal resistor that changes radically its resistance with temperature over exceedingly accuracy, was used to measure temperature.

### 3.4.2 Data Processing, Visualization and Classification

With the purpose of showing the component's health status, the collected data should be preprocessed, visualized, and classified into categories, depending on their changes versus a component health performance phase. This phase requires the equipment performance bulletin that is provided by manufacturer to know the normal working parameters of each component, past historical maintenance data, conducting a deep supervision of operating equipment to detect what happened when the collected data became different, as well as exploratory data processing and analysis. For final reporting, the health status categories must be defined before the deployment of the model to the application.

### 3.4.3 Predictive Analytics

The aim of this phase, as per the process shown in Figure 3.3 is to identify the appropriate predictive machine learning model for queried application by processing the raw historical data from sensors that have been kept for a certain period up to the chosen fitting model.

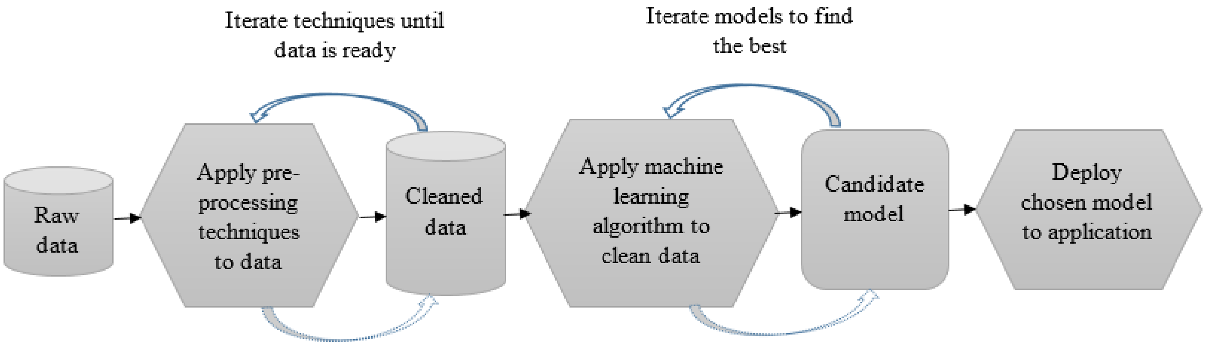

Figure 3.3. Predictive analytics and modeling process.

Data processing involves the understanding of data, cleaning data from outliers and other artifacts. This might lead to the easier extraction and selection of valuable information related to the parameter being monitored. The feature extraction focuses on the interesting signals from the preprocessed data that can be useful indicators for fault detection and failure point assumption.

Different machine learning models can be trained to classify data and provide prediction before the monitored component is likely to force repair or replacement. From the literature, traditional time-series techniques, such as Hidden Markov model [160], [161] and Kalman filtering [162], perform the prediction by detecting variations in data distribution based on predefined sequences, interval of time or distance, as well as thresholds. The main shortcoming of those algorithms is the ability to learn long term dependence for detecting the relation between features in different time series.

Our real-time monitoring requires a model with the capability to keep the long-time dependence performance data without predefined time steps ahead of time. Thus, the Seasonal Autoregressive Integrated Moving Average (SARIMA) and LSTM models are candidates, where LSTM performed well on our experimental data with a low root mean square error (RMSE) when compared to SARIMA.

The Long Short Term Memory (LSTM) predictive model that was introduced and modified in [163], [164] is proposed to this application with the aim of keeping the memories of long past time point to predict the tendency of future behaviors of the equipment.

It is an improved cell of recurrent neural networks (RNN) [164], which was developed to mitigate the gradient vanishing presented by the vanilla RNN. RNN, in its structure, presents a short memory to keep a current iteration output. It then feeds this output as an input to the following iteration. This makes RNN suitable to process the time series data by keeping a memory of the last iterations and recognizing the dependencies between iterations.

Bearing to the ordinary short-term memory of the RNN, LSTM adds long-term storage capability and gates that allow the algorithm to reflect on the long-term dependencies from the data of the past iterations and increase the learning process. This makes LSTM more suitable to handle sequential problems, especially with time series data. The information to be kept or forgotten from the LSTM memory is determined by its gates. The LSTM cell structure is shown in Figure 3.4, which presents four collaborating gates, namelyinput (I), forget (F), memory cell (M), and output (O) gates, which replace the hidden neurons of the ordinary RNN.

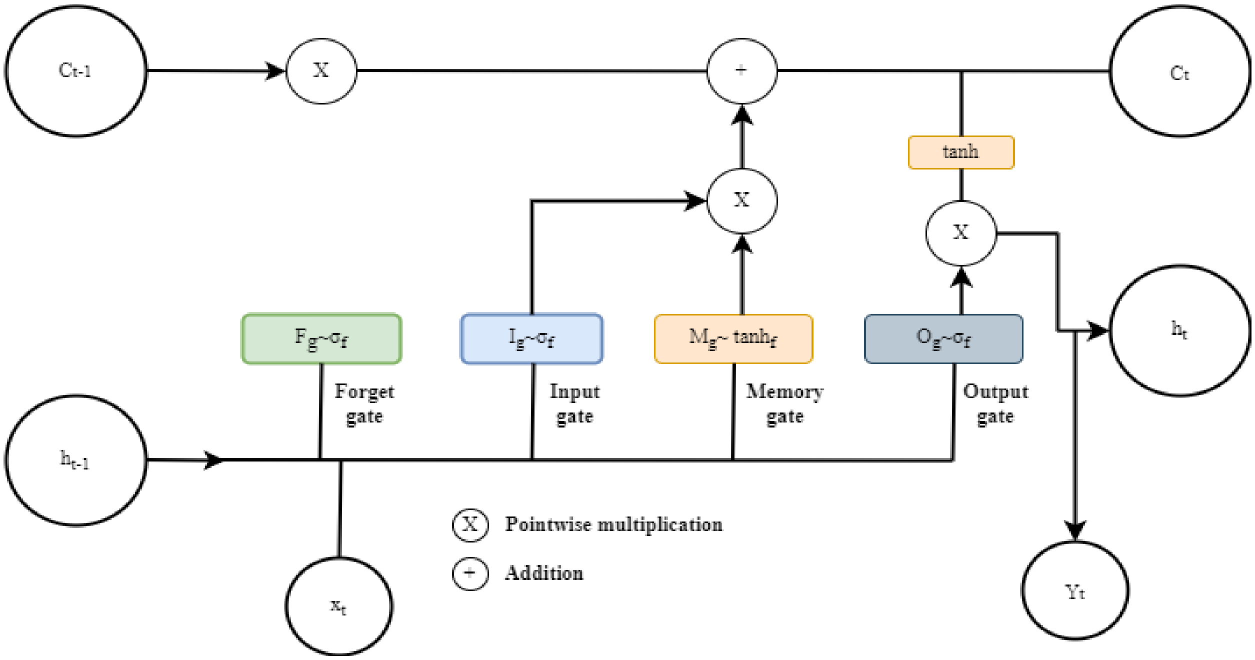

Figure 3.4. Predictive analytics and modeling process.

The LSTM unit performs the mathematical Equation

(1) to compute Equations (2) to (8), for four different gates with same size. The four gates also represent the four layers through the sigmoid (σ) and tangent activation (tanh) functions that compute each gate's task in order to update the cell state memory ($C_t$) and to control the output $Y_t$ at a specific time step t by taking the previous hidden state $h_{t-1}$ and current input $x_t$, stacking them, and then multiplying them with weight matrix, W, all being triggered by activation functions. The cell forgets the previous time step data, and then exposes part of cell as the hidden state at the next time step.

$$\mathrm{H_t}\begin{pmatrix} \mathrm{i} \\ \mathrm{f} \\ \mathrm{o} \\ \mathrm{u} \end{pmatrix} = \begin{pmatrix} \delta \\ \delta \\ \delta \\ \tanh \end{pmatrix} \mathrm{W}\begin{pmatrix} \mathrm{h_{t-1}} \\ \mathrm{x_t} \end{pmatrix} \tag{1}$$

Based on the previously hidden state information $h_{t-1}$ and current iteration $X_t$ at time t, using the sigmoid function, the forget gate compute Equation (2), to decide on which information in the memory state to keep or to throw away.

$$F_t = \sigma\left(W_f x_t + W_h h_{t-1} + b_f\right) \tag{2}$$

The sigmoid layer output varies between 0 and 1 and if the output is closer to or equal to zero, all information is thrown out. After the forget layer decides, the input gate decides on the new candidate data for the next layer. It performs Equation (3) using the sigmoid function to quantify the new information from the new iteration to update the memory state ($M_t$).

$$I_t = \sigma(W_i x_t + W_h h_{t-1} + b_i) \tag{3}$$

On the other side, the tanh layer residing in the memory gate generates a vector of new memory value ($M_t$) over Equation (4). The two gates' outputs are then combined and pointwise multiplied in Equation (5) to create an update to the cell memory state ($C_t$).

$$M_t = \phi(W_m x_t + W_m h_{t-1} + b_m \tag{4}$$

$$C_t = f_t * C_{t-1} + i_t * M_t \tag{5}$$

The output gate applies the tanh function to the cell memory, then computes Equation (6) to decide on the information to be output. Equation (7) is then computed todetermine the hidden information for the next iteration.

$$O_t = \sigma(W_o x_t + W_0 h_{t-1} + b_0) \tag{6}$$

$$H_t = O_t * \phi(C_{t-1}) \tag{7}$$

After all computation into the cell, it produces the predicted information (Yt) by performing Equation (8):

$$\mathrm{Y}_t = W_o h_t + b_o \tag{8}$$

**Notation**: F: forget, I: input, M: memory cell, O: output gate, t: time at current iteration,t-1: time at previous iteration, σ denotes an entry-wise application of the sigmoid logistic activation function, ϕ denotes an elementwise application of hyperbolic tangent (tanh) activation function, $\mathrm{x_t}$ represents an input vector to model, $\mathrm{h_{t-1}}$ is the activation delivered in the previous sequence step which also known as hidden state , $\mathrm{C_t}$ denotes the value of LSTM memory cell; all at the $\mathrm{t^{th}}$ time step and $\mathrm{h_t}$ is the probability distribution result function at a given step which is also the next hidden state. $\mathrm{W_i}$,$\mathrm{W_h}$, $\mathrm{W_o}$, $\mathrm{W_f}$ are input and hidden connection weight matrices to gates and b the bias vectors employed to create connection between input layer, output layer and memory block. $\mathrm{Y_t}$ is then the predicted label at each time step.

## 3.5 Proposed Predictive Maintenance (PdM) Structure Using Internet of Things (IoT)

The PdM structure depends on the queried environment as well as a predictive analytics tool to discover remarkable insights. Because the data type leads the remaining parts of the prediction: before proposing the PdM structure using IoT, we have developed an IoT device prototype to help in obtaining real-time data with purpose to learn a predictive model which will be used in our proposed structure and hosted by the same device.

### 3.5.1 Generating Data for Predictive Model Construction

Noticing the unavailability of the equipment performance data, we developed a data collector that was used to collect the real-time data to be used in the development of predictive analytics model. The collected data helped to observe data variations versus components health performance with the purpose of classifying the operating component health status. Figure 3.5 illustrates the main parts schematic of the IoT device that was used to gather and transmit data.

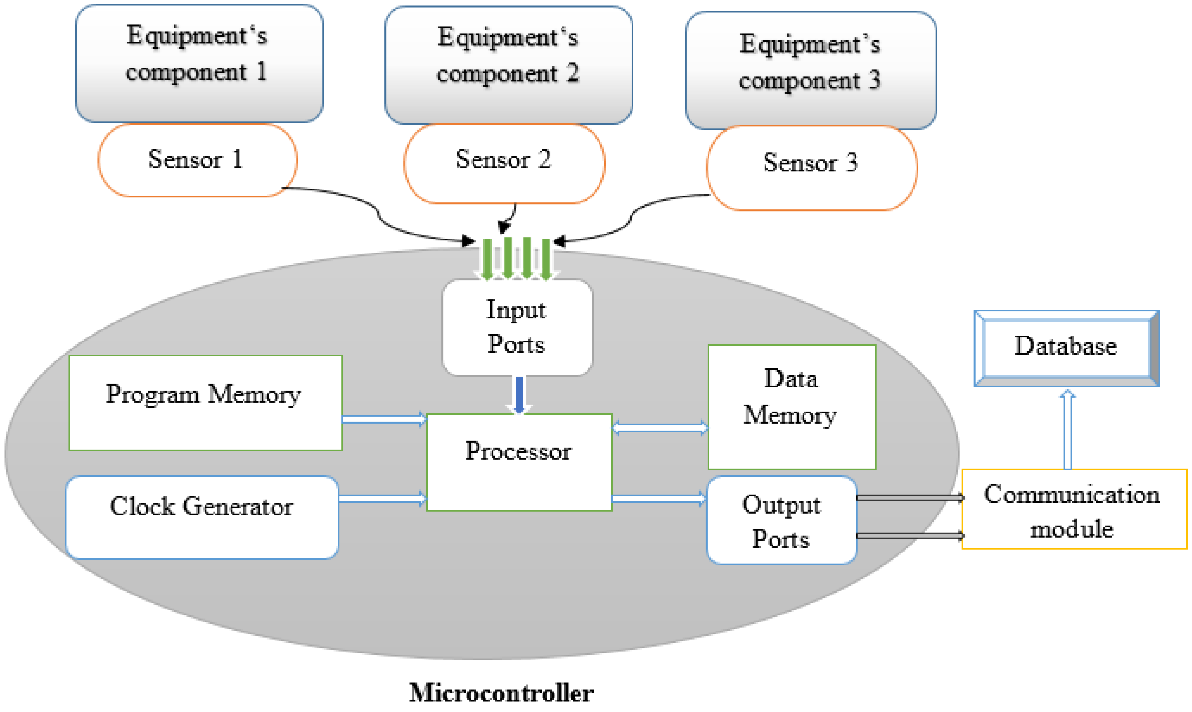

Figure 3.5. Data collector prototype main parts.

For our experiment, temperature was highlighted as the main defect symptom of the selected equipment's components. The developed embedded device was made up of temperature sensors for collecting real-time temperature, a microcontroller for processing data, and a communication module for transmitting data to the database.

### 3.5.1.1 Sensors

The real-time data might be collected while using specific sensors. In our experiment, due to the range of temperature for targeted components, we selected NTC thermistors with the capability to operate over -40 °C to +300 °C. Figure 3.6 illustrates the IoT device details, whereas Figure 3.7 shows the developed device connected to the equipment.

Equipment is not used all the time and its operating time keeps changing, depending on the available workload. Closer readings from sensor may provide clear performance sights even during short operating period. We made sensors to provide time series data every 30seconds.

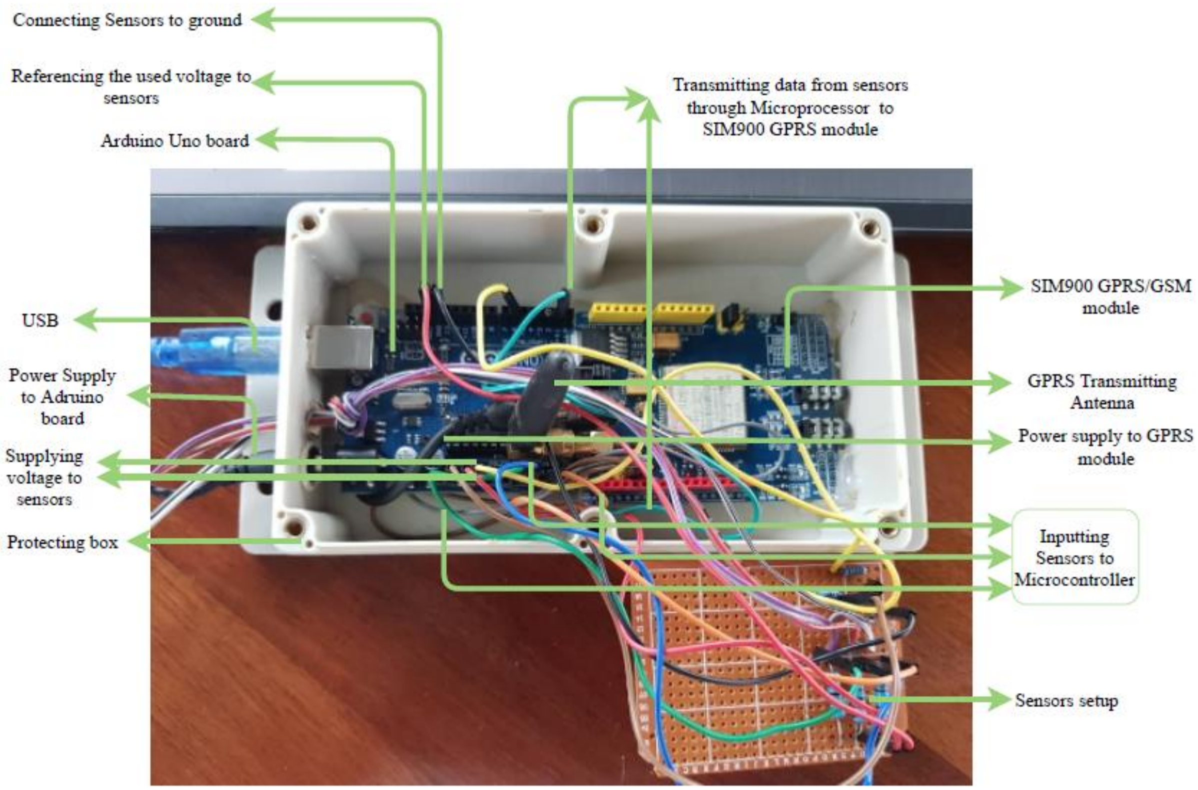

Figure 3.6. Embedded IoT device in box.

Figure 3.7. Developed IoT Device connected on autoclave's components.

### 3.5.1.1 Microcontroller

The microcontroller could be chosen, depending on the data processing activities. The Arduino Uno board [165] was used at our first stage of data collection due to the fact that required data were to train and test the model to be used as a predictive tool. It was chosen through considering the hardware simplicity and narrowing its associated cost. It is based on the microcontroller known as ATmega 328. It has a set of analog/digital input/output pins and communication interfaces that help the user to connect different sensors and communication module. For further data processing and analysis, the advanced Microcontroller must be used. Figure 3.8 shows the flowchart of the program that was running on Arduino Uno microcontroller board.

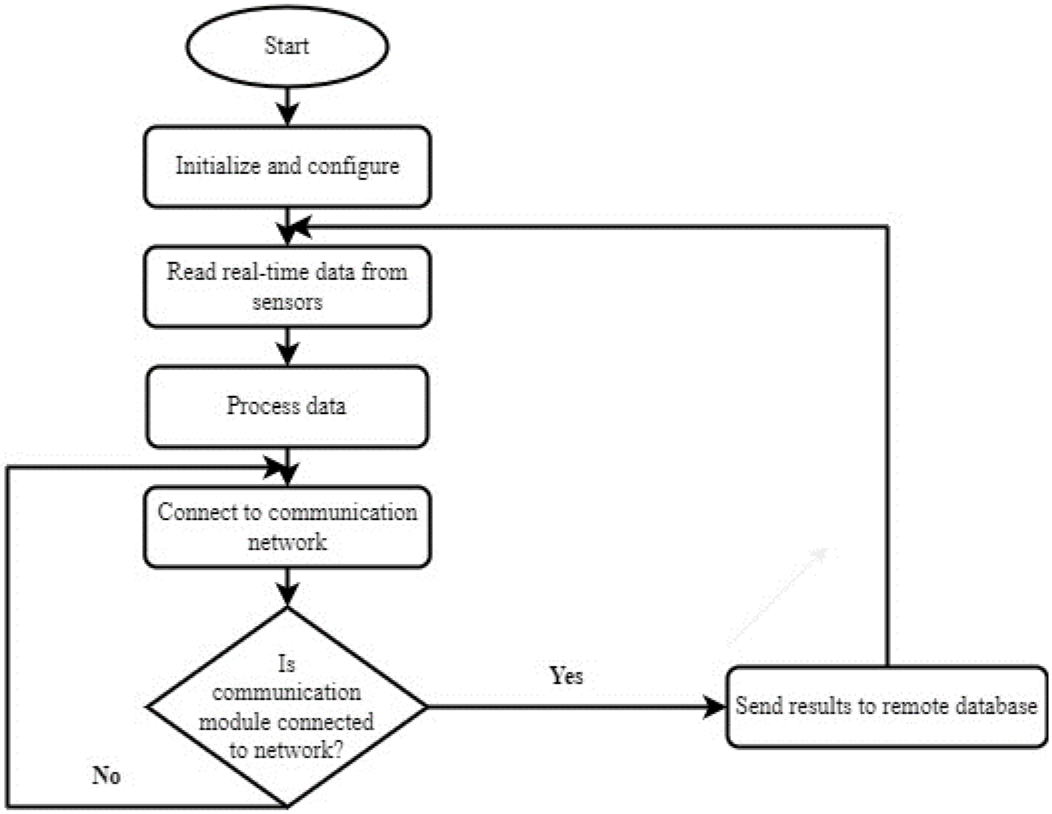

Figure 3.8. Flow diagram into Arduino Uno.

### 3.5.1.2 Communication Module

The Microcontroller output is fed to a communication module. This requires the data transmission setup that may increase the implementation cost. Based on the available infrastructure, SIM 900 GSM/GPRS (Global System for Mobile/General Packet Radio Service) was used to act as a gateway and enable data transfer to the database through internet via the GSM network.

### 3.5.1.3 Database

The real-time series data could be saved on the device if it has enough memory or on a remote database. For our experiment, to avoid regular visit to check if the data are being saved and keep monitoring virtually if the equipment is operating or not, the remote database was used to keep collected data. After compiling enough data, they have been used for predictive model construction.

## 3.5.2 Proposed PdM Structure Using IoT

Borrowing from the late studies and proposed architecture [34], [41], [42], [147], the new proposed PdM structure using IoT is presented by different interconnected components, as shown by the block diagram in Figure 3.9.

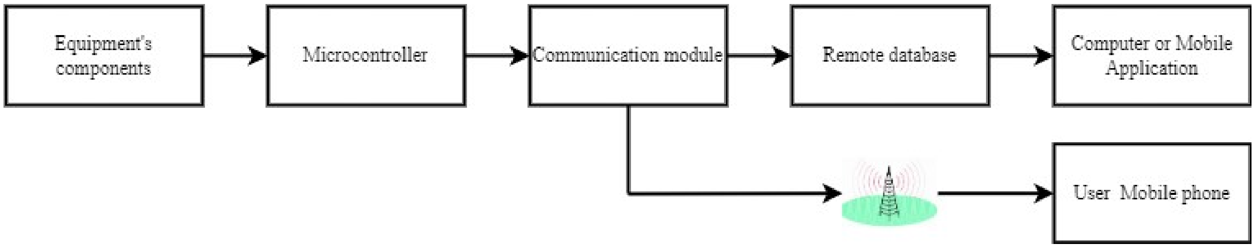

Figure 3.9. Proposed PdM Structure bloc diagram.

Based on the system components' role, the first two components must be settled together, as they serve for data gathering and processing. The communication module transmits data to a remote database from where the user can remotely obtain information through a computer or mobile application. At the same time, a Short Messaging System (SMS) may be sent to the user in case of critical condition. The detailed proposed PdM structure illustrated in Figure 3.10 is presented into three main interdependent parts, which are:

- Data acquisition, processing, and analytics.
- Results transmission.
- Application.

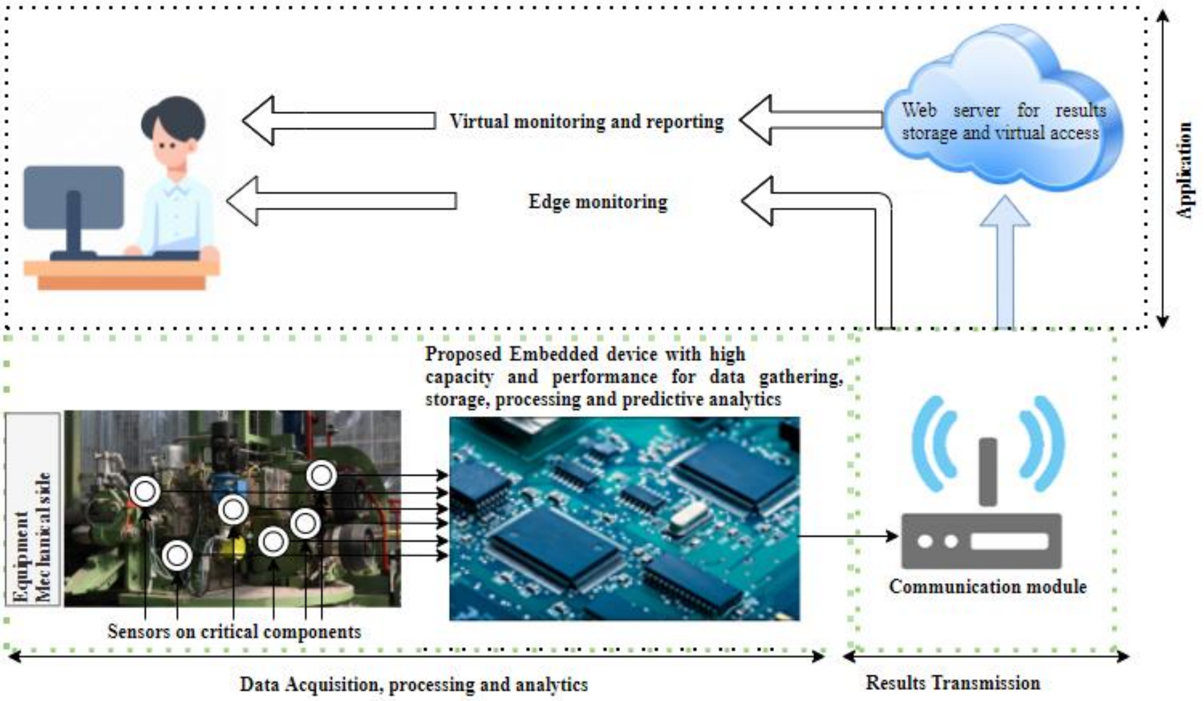

Figure 3.10. Proposed PdM structure using IoT.

### 3.5.2.1 Data Acquisition, Processing and Analytics

It is made up of sensors that are installed on the equipment components, different electronic devices, and a microcontroller that can convert and manipulate data based on the aims of its custom application. With the purpose of data processing and predictive analytics at edge, microcontroller might have greater capacity and performance than Arduino Uno board which was used to collect data for our predictive model construction. Based on the functionality of the equipment and its components basic information, this part involves initializing, configuring, gathering, processing, and analyzing the data.

Sensors should be selected, depending on the physical behaviors to be monitored. With the purpose of performing the edge data processing and analytics, the microcontroller might have enough storage capacity to store and process data. Figure 3.11 shows the program executed by microcontroller of proposed structure.

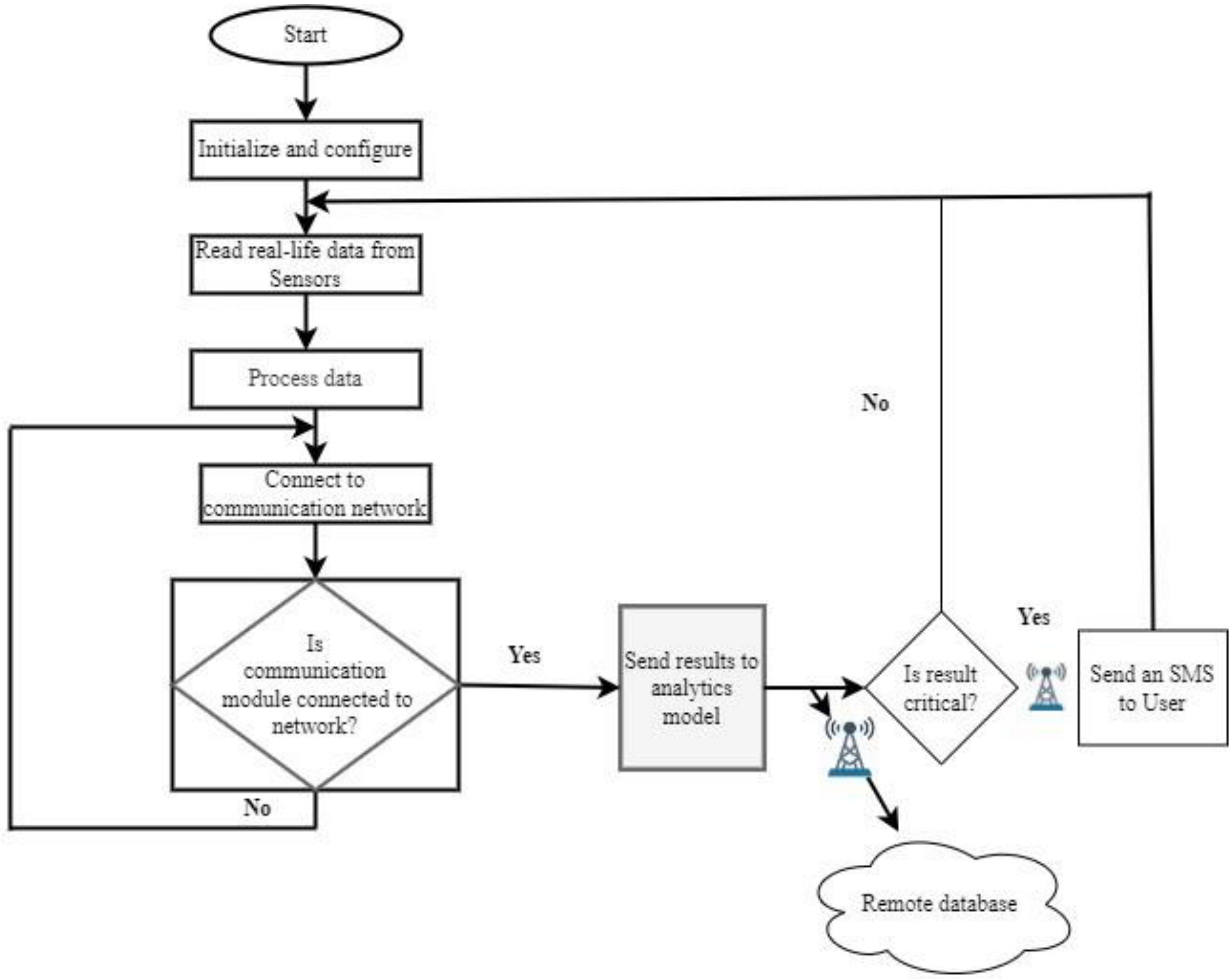

Figure 3.11. Flow diagram in Microcontroller of the proposed structure.

The Flow diagram of program running into microcontroller of proposed PdM structure to collect, process and transmit data is performed through seven phases:

1. Ports for sensors and communication module are initialized and configured.
2. Read the voltage corresponding to received data from sensors.
3. Save received data locally.
4. Saved data are fed to a predictive model for analysis and prediction.
5. Try to connect to GSM network.
6. If microcontroller is connected to GSM network, then the data are sent to analytics model, otherwise, the microcontroller keeps trying to connect to GSM network.
7. Send result to remote database and if the result shows an equipment's component critical condition, then an SMS alert is sent to the user.

Based on real-time data, time dependence has great influence on predictive data analytics due to the fact that the present time points are likely to be related to the previous time point or a time point in the long past. Such independence can be helpful in detecting a feature for the present abnormal occurrence, which may be mapped to the previous one.

The prediction of the health status of mechanical equipment relies on the unstable long time dependence performance data. In order to propose the fitting predictive model, the Seasonal Autoregressive Integrated Moving Average (SARIMA) and LSTM models were used to learn and predict from our real-time collected data, where LSTM performed well with a low root mean square error (RMSE) of 22.89 and 2.9 when compared to SARIMA, with 29.97 and 3.68 RMSE, respectively, for different component's univariate data. Since the data from different equipment are not dependent, each dataset was considered separately.

On top of the predictive model results, the microcontroller could be programmed, depending on results displayed, such as client access limit, reports generation, alerting message, like a short notification message or email sending, customized dashboard outlook, etc., all for the purpose of monitoring.

#### 3.5.2.2 Results Transmission

The analyzed data results will be transmitted to a remote database and a user in the case of alerting results through a communication module that uses internet connection for real-time monitoring. In order to avoid the additional cost for new network setup, the existing infrastructure, such as GSM, shall be used.

#### 3.5.2.3 The Application

The findings' report shall be transmitted to the maintenance team members for monitoring and to a remote database for storage and virtual access. Users may access the database from anywhere through a computer or mobile application. Through monitoring, the generated reports from the streamed data will be processed and analyzed, the early detected faults shall be triggered, and the user may optimize and act on maintenance plan. The reports shall be in a graphic format for ease of interpretation.

When considering the nature of the maintenance works, maintainers keep moving from one place to another, due to different equipment in different locations, and may be out of network coverage. For them to obtain warning information in a timely manner, the proposed system may send a short notification message to their phones for their actions in the case of critical condition.

## 3.6 Predictive Model Experimental Results

### 3.6.1 Data Preprocessing

The real-time temperature performance data were collected from three components of the autoclave equipment while using a developed device which is described in Sections 3.5.1 and saved on a database for a period of three months. A total of 130,140 timesteps data were collected from each component. The collected data were extracted from database, processed using python, and then used to train and test a predictive model that may fit into the proposed structure.

The data distribution from mid-November 2019 up to mid-February 2020 is presented in Figure 3.12. The distribution of collected data shows that the average temperature in November is less when compared to other months. From the partial analysis of the data, we noticed that the collected data from inoperative equipment might mislead the prediction and decided to capture and use data only when the equipment operates.

Among three components, two are similar pumps whose data are shown by Figure 3.12b,c, which present different changes in physical behaviors. Both data are used in order to train the same model and predict with the aim of checking the model performance for different data from similar components. For both data, the performance is the same (96%).

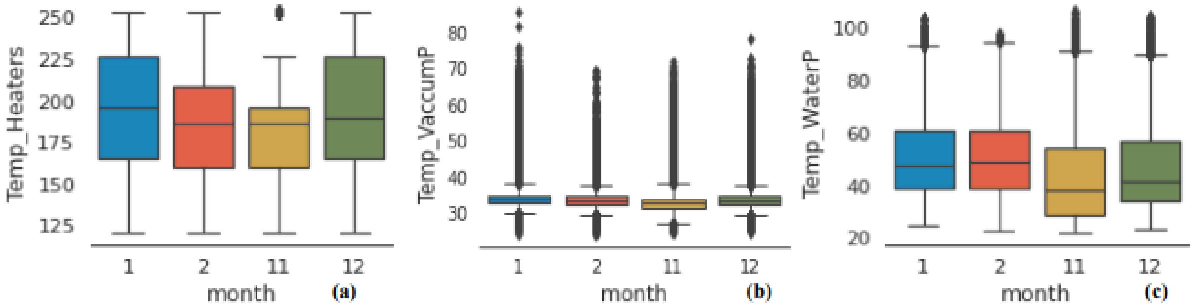

Figure 3.12. Distribution of collected data. (a) represents the data from steam generator, (b & c) represent the data from two different pumps.

Data preprocessing consists of special values consideration, which involves the dropping of some data that were taken during out serviced equipment to avoid unnecessary long data dispersion. The real timestamps are also converted into datetime format in order to create a suitable time series dataset with Python. We define a function to create a balanced dataset in order to build a relationship between timestep X, with time dependence t.

Because LSTM acquires a series of past observations to build a function for new input series, our data are sampled into small subsequences in order to comfort the LSTM learning. Each subsequence is made up of a sample of timesteps from which LSTM learns to predict the next time steps. To fix the length of sample, we iterate the process of model training and prediction using different lengths to obtain their optimal number with minimum error. Our minimum model error obtained a sample size of 70 steps.

In order to comply with the time steps LSTM array structure, we transformed our data to be in a three-dimensional array in the form of [sample, time steps, features]. Prior to starting to learn our model, we randomly split our data into the train dataset, which is indexed to 80%, whereas the remaining 20% were reserved for test dataset.

### 3.6.2 Modelling Results

A particular predictive model has to be developed for different components due to the fact that physical behaviors and thresholds differ from one component to another. Two models with slightly different parameters have been constructed while using Keras library [166] in Python through the sequential model Application Programming Interface (API).

Given a sequence of train data x at each time step t; $x_t$ = (x1, X2,…, $x_n$), where t = 1,2,… n and x is a time step from train data whose arrangement is shown in Figure 3.13.

| | | | | |
|---|---|---|---|---|
| 0 | 2019-11-13 15:08:43 | 84.95 | 34.39 | 41.19 |
| 1 | 2019-11-13 15:09:13 | 90.34 | 33.98 | 41.55 |
| 2 | 2019-11-13 15:09:44 | 80.85 | 34.32 | 43.44 |
| 3 | 2019-11-13 15:10:16 | 82.15 | 34.18 | 41.19 |
| 4 | 2019-11-13 15:10:47 | 84.46 | 34.18 | 39.71 |
| 5 | 2019-11-13 15:11:18 | 82.15 | 33.98 | 40.48 |
| 6 | 2019-11-13 15:11:49 | 83.98 | 34.79 | 40.66 |
| 7 | 2019-11-13 15:12:20 | 83.51 | 33.98 | 40.83 |

| | | | | |
|---|---|---|---|---|
| **130132** | 2020-02-07 09:23:38 | 195.81 | 32.14 | 51.25 |
| **130133** | 2020-02-07 09:24:14 | 208.58 | 32.08 | 54.42 |
| **130134** | 2020-02-07 09:24:41 | 208.58 | 32.02 | 57.36 |
| **130135** | 2020-02-07 09:25:15 | 306.64 | 31.66 | 59.34 |
| **130136** | 2020-02-07 09:25:48 | 226.11 | 32.82 | 62.53 |
| **130137** | 2020-02-07 09:26:15 | 208.58 | 32.32 | 64.75 |
| **130138** | 2020-02-07 09:26:46 | 208.58 | 32.20 | 67.17 |
| **130139** | 2020-02-07 09:27:18 | 306.64 | 32.57 | 69.29 |

Figure 3.13. Imported Data presentation in Python.

The LSTM performance depends on the hyperparameters turning. To find the optimal parameter values for a minimum model loss and improved model efficiency from overfitting phenomena, at the end of each model hyperparameter turning, the created model is evaluated on both the train and test datasets. The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are calculated using Equations (9) and (10), respectively, and the values are saved.

$$\mathrm{MAE} = \sum_{\mathrm{t}=1}^{\mathrm{n}} \frac{1}{\mathrm{n}} |\mathrm{y_t} - \hat{\mathrm{y}}_\mathrm{t}| \tag{9}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}[(y_1 - \hat{y}_1)^2 + (y_2 - \hat{y}_2)^2 + \ (y_3 - \hat{y}_3)^2 \ + \cdots + \ (y_n - \hat{y}_\mathrm{n})^2]} \tag{10}$$

Where $y_t$ and $\hat{y}_t$ are respectively the actual and the predicted value by the model corresponding to $y_t$ at time step t, n is the total number of steps of the test set.

To evaluate the model, we iterate the turning different parameters to different values and save the MAE and RMSE scores. By comparing the obtained errors, the minimum model loss that is attained on the hyperparameters values is shown in Table 3.1.

Table 3.1. Model parameters optimal values in experiment.

| **Parameters** | **Optimal model values for heaters dataset** | **Optimal model values for pump dataset** |
|---|---|---|
| Train dataset | 80% | 80% |
| Test data set | 20% | 20% |
| Input layer | 1 | 1 |
| LSTM Cells/ Units per each activation | 2 cells / 50 units per each | 1 cell/ 100 units |
| Activation | Rectified Linear Unit (ReLu) | Rectified Linear Unit (ReLu) |
| Dropout wrapper | 0.2 | 0.2 |
| Dense layer | 1 | 1 |
| Optimizer | Adam | dam |
| Epoch | 20 | 20 |
| Batch sizer | 70 | 70 |
| Look back window | 30 | 30 |
| Loss function | Mean Squared Error (MSE) | Mean Squared Error (MSE) |

Table 3.2 presents the minimum error values as well as model performance accuracy. The test mean absolute error is less than that of training, which is the best for our model.

Table 3.2. Model performance evaluation values.

| **Evaluation Factor** | **First model for Heaters** | **Second model for Pumps** |
|---|---|---|
| Train Mean Absolute Error | 19.699 | 1.624 |
| Train Root Mean Squared Error | 24.895 | 2.830 |
| Test Mean Absolute Error | 17.968 | 1.598 |
| Test Root Mean Squared Error | 22.894 | 2.900 |

| | | |
|---|---|---|
| Coefficient of determination ($R^2$) | 0.755 | 0.963 |
| Total error loss | 0.096 | 0.04 |
| Accuracy | 90.432 % | 96.0% |

Figure 3.14 shows the training and test loss of our LSTM model at optimal parameter values. We can see that the train and test losses decrease for larger epoch values and that train and test losses both stabilize at closer points. The loss instability in the pump model resulted from data complexity due to the continuous changes of equipment health status.

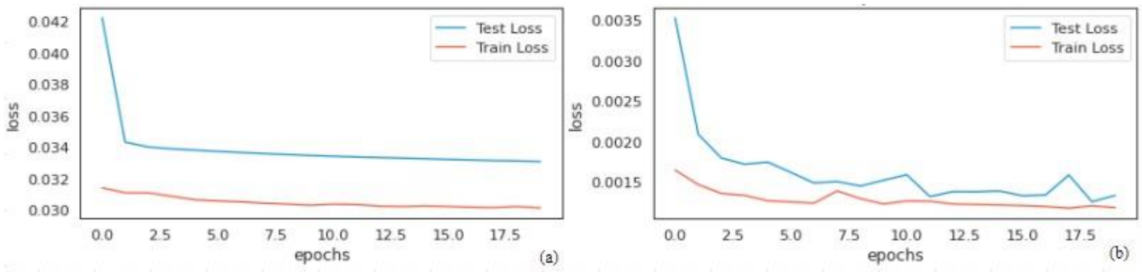

Figure 3.14. Model loss for (a): heaters and (b): pump models.

Figure 3.15 shows the actual and predicted results for both the train and test data. For pumps, the actual and predicted results are closer. A slight fluctuation between the actual and predicted values on pump train data is caused by the dropout regularization that is used to reduce the overfitting phenomenon and prediction error to unseen data. The heaters' dispersion results between actual and predicted points are explained by the higher fluctuations of the real data from component.

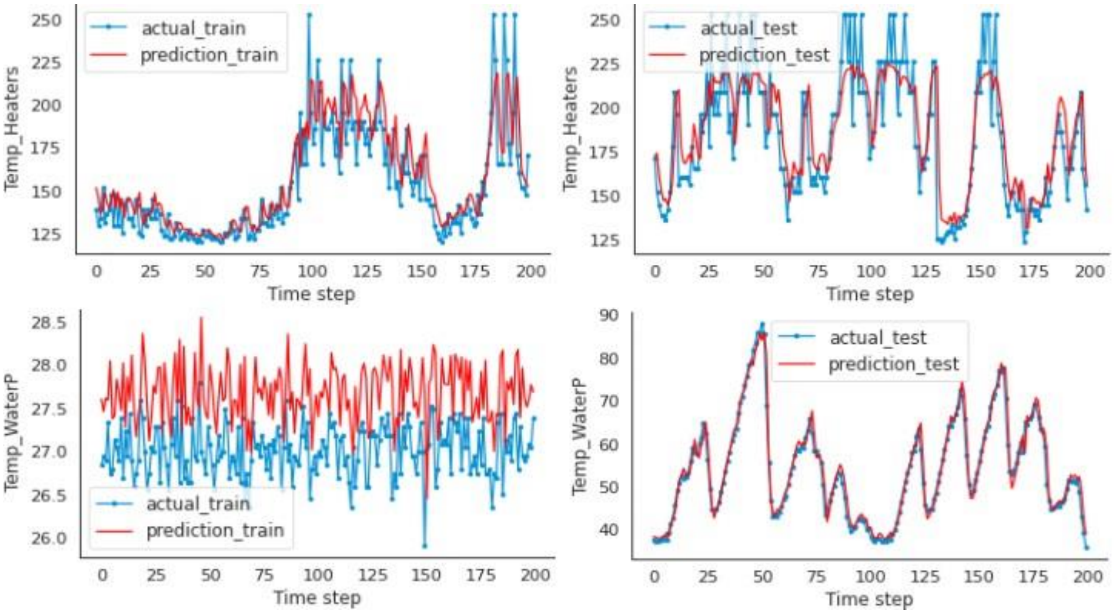

Figure 3.15. Actual and predicted results for heaters and pumps models.

### 3.6.3 Discussion and future work

The experimental results show that meaningful real data could only be gathered when equipment operates.

We used our real-time data to execute our LSTM algorithm. Based on the calculated performance accuracy with a low training and test MAE and RMSE, as Table 3.2,

- Our models' accuracies are 90% and 96% on predicting the component temperature.
- Our models do not overfit, and the loss is less. We naively conclude that their prediction accuracies are good.
- We recommend LSTM model to be used as mono-variate predictive model in proposed structure.

Classification of components health status should be done after investigating their operational principles and observing their generated data versus their health change.

Based on the pump’s operational specification, past maintenance history, as well as the experimental observation on the machine fluctuation versus the changes in pump's temperature, the temperature working performance range was sub-categorized, relating to correlated operational health status.

The temperature from steam is irregular time series, due to the fact that it is usually affected by the normal operation of the machine, such as adding cold water into steam generator and automatic regulated heating grasp during operation. Nevertheless, its output temperature may rise and fall in some range during the operation period. In addition, because the change in temperature of steam relates to the temperature change in sterilization room, we have observed 100 sterilization cycles for classifying the range of desirable temperature of the steam. Table 3.3 illustrates the operational performance classes with their related temperature range.

Table 3.3: Component health status thresholds for both pumps and heaters.

| Component Health Status | Temperature range for Pumps | Temperature range for heaters |
|---|---|---|
| Healthy | Below 40°C | Above 150°C |
| Alerting | 41 to 70°C | 141 to 150°C |
| Going to collapse | Above 70°C | Below 140 °C |

Based on the highlighted equipment' components health category boundaries, Figure 3.16 shows the process of achieving the final stage of predictive maintenance.

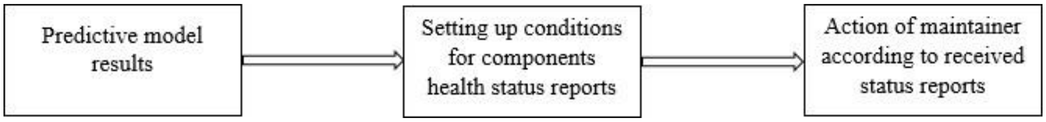

Figure 3.16. Process to maintenance actions.

On the top of the output layer, every output at current time step will be fed to the defined conditional function with if, elseif, and else condition to read the output and decide based on settled thresholds with the purpose of classifying three health states' labels of the component as Healthy, Alerting, or Going to collapse.

For the alerting system, it is found that, for heaters, temperatures below 150°C are only occurring in preheating time that only takes up to five minutes; since the data readings are two per minute, the maximum readings below 150°C could not go beyond 10 along the whole sterilization cycle. Similarly for pumps, occurrence beyond a healthy status is a good indicator of defect. The maintenance team needs to be ready and take actions for maintenance activities, since the 'Alerting' reading is reported, and it performs activities as soon as 'Going to collapse' status is reported.

Because a complete sterilization cycle may vary from 45 to 55 min, depending on the load in chamber, the function is defined to conclude the component status after each operation cycle, which is averaged to 50 min. The maintenance team will get an alerting message since the concluded status is alerted to get ready for the next repair state.

For future work in this field, we note that there are many components on single equipment and different physical parameters on each component that could be assessed to create full operation status monitoring of the equipment. Additional works would consider multivariable monitoring that combines different component physical parameters. The second aspect would be to create a platform that may compile the health status from different components, learn them, and then provide which maintenance activities is sensitive than others as input to the predictive model as well as the equipment's overall summarized results to the end users.

## 3.7 Conclusion

The maintenance of mechanical equipment is a vital aspect in the overall performance of hospitals. Regarding the significance of their availability to the healthcare services in Rwanda, mechanical equipment that is used in hospital requires a real-time monitoring system where the health of the equipment is continuously observed and maintained before failure occurs.

In this respect, the structure of PdM Using IoT is proposed. Real-time data were collected while using a developed IoT device from autoclave equipment three components, of which two are similar at King Faisal Hospital. Prediction was done while using LSTM and performed with an accuracy of 90% and 96% with respect to the components. The prediction of future physical parameters will improve the equipment reliability, availability and reduce downtime.

The scope of this chapter does not include the maintenance actions priority that may reduce numbers of different predictive analytics models from different components and scheduling system. Consequently, the study's purpose of creating an intelligent architecture of IoT based PdM structure is attained, and it shall be a suitable offer for maintainers' satisfaction and system reliability.

The proposed PdM structure using IoT may also be employed to other industrial equipment with similar physical performance parameters. It can be also customized to all industrial equipment through building of suitable model to available performance parameters' data.

# Chapter 4:

## Prologue to second article

### 4.1 Article details

Irene N.M., Zennaro M., Uwitonze A., “Enhancing the priority for the maintenance activities of the hospitals’ mechanical equipment using the fuzzy expert system”, in International Conference on E-Infrastructure and e-Services for Developing Countries. pp 170–181, 2022 - Springer; https://doi.org/10.1007/978-3-031-06374-9_11.

### 4.2 Personal contribution

With the purpose to enhance the decision making on maintenance priority, this work proposes the Fuzzy logic based expert system for small and medium sized hospitals. It considers the expertise of maintainers in faults detection and classification through the various monitoring of the physical condition parameters from equipment's components. Parameters' condition severity in respect of the total equipment downtime are considered to suggest maintenance activities priority. This conference proceeding was done with the guidance of Zenarro M., and Uwitonze A.

### 4.3 Context

Decision making has been highlighted important in asset management. Various generic decision-making models were proposed and highlight the necessity for continuous autonomous suggestion of actions. On the side of Maintenance activities priority for complex equipment, maintainers are manually deciding on crucial action to be performed prior to others. We claim that the integration of knowledge based expert system might support an effective predictive maintenance through accurate maintenance priorities.

### 4.4 Contributions

The proposed system is evaluated using random data in respect with the operating parameters' values range and the results show that the created Fuzzy expert system is capable to provide the maintenance activities priority by evaluating the inputted variables.

### 4.5 Recent developments

**S**ince the publication of this article, it was considered by one researcher under name of Mezhuyev Vitaliy [167], to support his/her work entitled “Development of an Expert System to Support the Decision-Making Process on the Shop Floor”.

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# Chapter 5:

## Enhancing the priority for the maintenance activities of the hospitals' mechanical equipment using the fuzzy expert system

### 5.1 Introduction

Within the scope of industry 4.0, the Internet of Things (IoT) based predictive maintenance techniques through continuous real-time monitoring may lead to failure prediction ahead of time. This shall increase the equipment availability, decrease the unnecessary preventive maintenance as well as allied cost, and improve the business reliability.

Till now, small, and medium companies including hospitals conduct the regular preventive maintenance including costly periodical profession inspections to identify the exhausted components and servicing. This does not guarantee the full availability of the equipment and cannot avoid unplanned downtime of the equipment [168] as it may not be done in right time of an equipment deficit. However, as maintenance technologies are evolving, they need to adopt a systematic approach to proper predictive maintenance with capability of proactive activities prioritization [169].

Different research works [170] emphasized on predictions and related decision support using prognostic models to process, analyze data and then to provide recommendations. However, referring to the main parameters of decision-making process [171], deciding on the urgency maintenance activity among others is still a challenging task. There is therefore an interest in real-time activities prioritization methods.

Previous studies in this area summarized in Table 5.1, considered single critical component such as rotating elements as whole and simple equipment which is different for complex equipment.

Table 5.1. Some work in predictive maintenance decision making.

| Study | Description |
|---|---|
| [19] | Adding to the literature that considered current signal to diagnostic signal for electrical machine failures, authors reviewed possible patterns of vibration signal of the motor' parts as key fault for such machines |
| [20] | After reviewing the various failure and their root causes for electrical machine from literatures, they proposed an impedance based diagnostic model using the voltages and currents signals of an induction machine |

|  |  |
|---|---|
| [172]–[176] | By vibration conditions monitoring of the rotating part of the machine and using a fuzzy system, authors presented the maintenance decision making tools for different type of machines. |

Contrary to single crucial component like in Table 5.1, for a complex equipment, different components may lead to an abrupt failure of the entire equipment.

Currently, especially in hospitals, the maintenance decisions and scheduling are made thanks to the knowledge of maintainers on the equipment's operating manual together with various working condition parameters as well as impact severity of each component to the overall performance scenarios.

Hence, maintenance experts' knowledge could be converted into knowledge base system that may facilitate them to fully monitor their assets in real-time, and to prioritize the maintenance plan of activities depending on the health condition of different components as well as their impact to the total downtime of the equipment. The Fuzzy logic system [177] which is based on human experts' opinions shall be helpful. It is reasonably simple to build as it does not require a prevailing theoretical model to rely upon. It shall only require a few sensors to get conditional parameters together with a thin, affordable and energy efficient computer such as Raspberry Pi to host fuzzy inference.

With purpose to reduce number of sequential models from different parts of the equipment to one model with summated information from all parts, this chapter discusses a knowledge based expert system using a fuzzy logic approach to provide an enhanced means of maintenance activities priority for hospitals' equipment. Powered by IoT based predictive maintenance capabilities, the real-time data can be fed to the expert system and continuously provide insights to both users and Predictive analytical model. The presented expert system may also be adopted for all small and medium-sized companies.

The rest of this work presents the reviewed literature on decision making and Fuzzy logic utilization in predictive maintenance in Section 5.2. In the Section 5.3, a methodological review of Fuzzy expert system is described. Basing on the real-time data analytics, maintainers expertise as well as impact of each parameter to the total downtime of the equipment, an expert and robust Fuzzy system to prioritize the predictive maintenance activities is proposed in Section 5.4. Section 5.5 discusses the results, whereas Section 5.6 concludes the work and suggests the future research works.

## 5.2 Review of Decision making and Fuzzy logic application in predictive maintenance

Since the manufacturing and market requirements have been evolved from one level to another, maintenance techniques have also advanced from reactive approach to proactive maintenance. Similarly, Techniques may vary from one another depending on the technology in place, available infrastructures, monitoring techniques and capabilities.

Motivated by dynamic recommendations from literature on maintenance activities to be performed prior failure, authors identified gaps and put a call to the further research including the dynamic decision making.

Authors [75], [77] have reviewed the contributions of efficient maintenance toward a business sustainability and sustainable manufacturing. [178] highlighted limitations from the conducted research under decision making in predictive maintenance, [179], [180] reviewed maintenance decision and priority making techniques and models in last decade maintenance.

Researchers in [84], [181], [182] mostly considered historical data, administrative as well logistic processes and respectively have come up with a decision-making framework.

Though, all works recommend further research to mature the predictive maintenance especially by empowering the continuous monitoring, exploring real-time data and maintainers knowledge.

Among developed decision-making systems, fuzzy logic has been employed in predictive maintenance into different industries as knowledge based expert system that may combine available information to provide accurate predictions, suggestions, and scheduling.

A fuzzy logic system that was introduced among others by Zadeh [177] was proven to be useful in monitoring of uncertain and vagueness systems. Fuzzy logic has been deployed in maintenance decision making process to select a favorable maintenance approach [183], [184], activities planning [103], [168], [172], [173] as well as risks level computation [185].

From literature, a single component was considered as the only one crucial for an equipment failure. Yet for complex equipment: the working deficit from each among different components can lead to total downtime of the whole equipment. And the deficit from one component may affect the working status of another component. Thus, different parameters from each component can lead to make a priority on critical needed maintenance activities to be performed.

We noticed that real faults detection and linked decision on activities priority are at their infant stage. There is no universal or specific approach to adopt. Consequently, there is a gap especially when it comes to real-time decision making intended from the asset real-time data captured through sensors.

Furthermore, an autonomous decision making in maintenance mainly concentrated to the administrative and logistic process but did not reflect on expertise of the maintainers to detect and resolve faults. To enhance the maintenance priority decision making based on an equipment health state, this research contributes by proposing a real-time data based fuzzy expert system, whose inference designed referring to maintainers' expertise. This shall provide real-time commendations on the crucial activities to be prioritized while planning for maintenance execution.

## 5.3 Methodology for maintenance activities priority expert system

In a maintenance field, maintainers use their knowledge and tools to monitor the working status of their equipment and to fix them either when they are malfunctioning or they break. Even though different mechanical equipment presents the common parameters [19], [20] such as temperature, vibration, noise, oil level, power consumption, pressure, dust, etc.; their condition parameters for early faults detection may differ from one equipment to another due to its structure and assembled components.

The standards, maintenance historical data, literature, and maintainers' expertise shall be used to assign a divergence severity of each parameter based on its associated failure and effect to the whole equipment. Table 5.2 summarizes the methodological steps followed to accomplish this work.

Table 5.2. Methodology used to create a Fuzzy Expert system.

| | |
|---|---|
| Step 1: **Define** | i. Investigating the maintenance practices in place, assess the frequent failures and their root causes.<br>ii. Basing to assessed failure root causes, select an equipment as case study, identify crucial equipment physical performance condition parameters to be monitored.<br>iii. Classifying the value of physical condition parameters according to the working status of component. |
| Step 2: **Compiling the expert database.** | i. Sorting the condition parameters severity according to the threat that may cause to the overall equipment performance.<br>ii. Elaborating possible scenarios of matching different condition parameters at their different levels to create rules.<br>iii. Elaborating the maintenance priorities file. |
| Step 3: **Create the fuzzy expert system.** | i. Create an expert system linguistic variables and database by considering the technical requirements, literature, as well as maintainers' expertise and judgements.<br>ii. Create rules based to deficit threshold limit and associated responses or actions. |
| Step 4: **Results** | i. Simulate<br>ii. Discuss the results. |

## 5.4 Fuzzy expert system for the predictive maintenance activities priority.

### 5.4.1 Defining the Expert System requirements

Following to the methodological steps in Table 5.2, with regards to maintainers' expertise and available historical data, considering that the equipment lifetime is extended depending on the applied maintenance strategies and inspectors' knowledge, also that the maintenance activities priority depends on the components' condition divergence severity's impact to the overall performance of an equipment:

To understand the maintenance activities, procedures, applied techniques and to define the process for this work, four professionally trained and experienced maintainers from three hospitals in Kigali were repetitively visited to collect general information on their mechanical equipment, their healthy monitoring techniques, continuous monitoring tools, monitored conditional parameters, and maintenance practices in place.

Using the information and data from experts, we propose the maintainers' knowledge based expert system capable of diagnosing faults and to reduce the ambiguity in the severity sorting by providing recommendation on proactive maintenance activities priority.

### 5.4.2 Fuzzy Expert System

The acquired knowledge from maintenance experts, literature and component marked industrial thresholds are arranged into knowledge base consisting of formed rules and consequents to be generated by various variables mapping. The rules are created using IF-AND or OR-THEN syntax to associate more antecedents with consequents. Consequences in knowledge base might be generated in view of the threat to equipment that may be caused by the physical condition parameters' set.

The fuzzy inference engine shall be encrypted in appropriate setup to judge the inputs using rules and consequents, then to generate desired conclusion. Using the data collector described in Chapter 3.5.1[186], real-time data can be gathered from different components and being fed to the fuzzy expert system for judgment.

To reduce the additional cost that may be brought by the application of this fuzzy expert system, instead of using large computer, we recommend the hospitals to use of Raspberry Pi, which is capable to perform things like other computer, yet is low cost, very small in size, and lower power device [187], [188]. It is also flexible to be incorporated in any embedded system such developed IoT device.

Referring to the diagram of the fuzzy inference system in [189], Figure 5.1 illustrates the fuzzy expert system that can help maintainers to quickly decide on which part in critical condition than others depending on their working conditions, so that to prioritize critical maintenance activities among others.

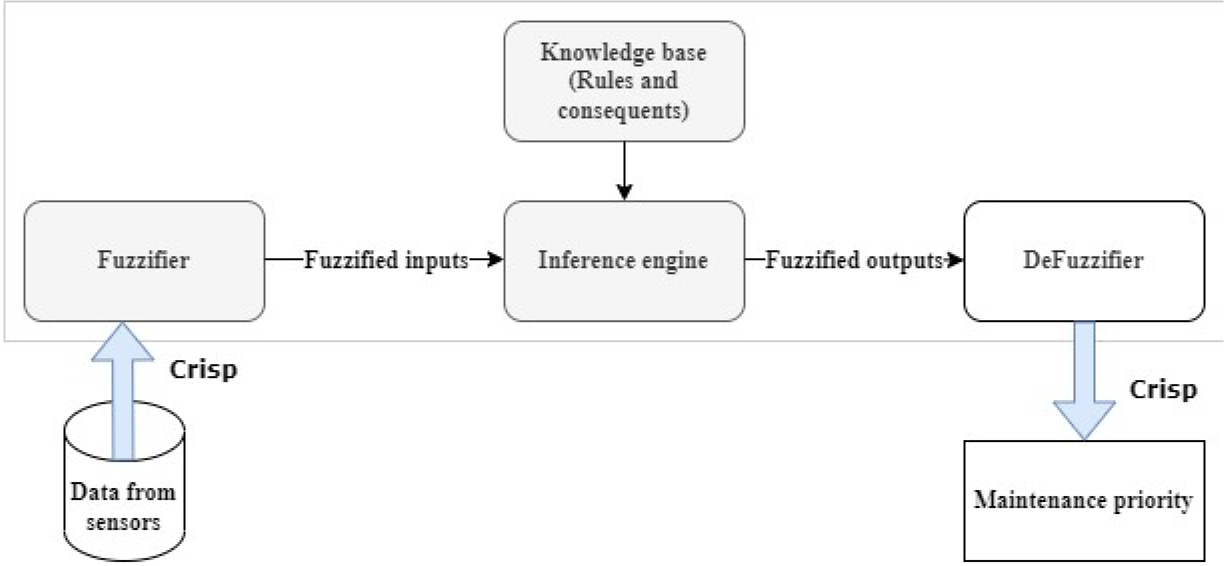


Figure 5.1. Diagram for created Fuzzy expert system.

The system working procedures are classified into three main activities:

1st: The data from sensors which are condition parameters to define the equipment working status shall be captured using sensors, fed to the fuzzifier to be converted into fuzzy input sets with some extent of membership varying in the interval of [0, 1]. Each value in the [0, 1] interval denotes the degree of ambiguity in the set. 0 means that the value does not fit the fuzzy set; 1 represents a peak value in the set.

2nd: Fuzzified data are applied to the rules in knowledge base to be evaluated using fuzzy operators. The fuzzy inference engine also aggregates the rules outputs.

3rd: Fuzzified output from inference engine are defuzzified and transformed into real world readable output.

To make the expert system more relevant, we considered common physical condition parameters to mechanical equipment that were underlined from literature [19], [20] and by maintainers. The list of parameters and their severity grades may vary due to the nature of equipment and their frequency of occurrence, but the most common parameters are Temperature, Pressure, Vibration, Lubricant, Power consumption, Noise and Dust.

### 5.4.3 Case Study: Customized Fuzzy Expert System

For our experiment, the steam sterilizer autoclave is considered as mechanical and critical equipment for all sized hospitals. It is used to sterilize surgical instruments, clothes, and dressing materials. It is a must for infection control.

Thanks to King Faisal Hospital-Kigali and Teaching University Hospital of Kigali to allow the conduction of special discussions based to the questions posed on maintenance procedures, fault detection techniques as well as maintenance decision making procedures with respective two and one expert maintainers on the steam sterilizer autoclave working principles. We highlight its main critical components and the available empirically based thresholds of physical condition parameters. Only four metrics (Temperature (TE), Vibration (VI), Pump (PU) and Boiler (BO) power consumption) are then considered in building our fuzzy expert system to prioritize maintenance activities.

Table 5.3 and Table 5.4 respectively show the input variables and parameters healthy range, whereas

Table 5.5 shows output variables and priority classification range.

Table 5.3. Input variables and nature of defect to be discovered.

| Input variables | Notation | Nature of defect to be detected |
|---|---|---|
| Temperature | TE | Flow normality in pumping system and Working stress (gap, misalignment, or failure) of coupled motor. |
| Vibration velocity | VI | working stress (gap, misalignment, or failure) for integrated pumping system motor. |
| Pump Power consumption | PU | Normality of current flow. |
| Boiler Power consumption | BO | Healthy status of heaters. |

Table 5.4. Input variables healthy ranges.

| Temperature (Celsius degree: $^{o}$C) | Vibration (mm/s) | Pump power consumption (KW) | Boiler power consumption (KW) | Linguistic variables | Notation |
|---|---|---|---|---|---|
| 40 and below | 2.8 and below | 0.25 to 0.44 | 9 to 13.5 | Normal | NO |
| 30 to 70 | 2.3 to 4.5 | 0.38 to 0.56 | 12.0 to 16.5 | Slightly strange | SS |
| 60 to 100 | 3.5 to 10 | 0.5 to 1 | 15.0 to 20 | Very strange | VS |

Table 5.5. Output variable ranges.

| Maintenance priority variables | Notation | Range |
|---|---|---|
| Low | LO | 0 to 30 |
| Moderate | MO | 20 to 60 |
| High | HI | 50 to 80 |
| Very High | VH | 70 to 100 |

Even though the data collector was developed in Chapter 3.5.1 [186] and previously used to collect some real-time data, the recent real data for all parameters in this work were not collected due to COVID-19 restrictions. Hence, the values range that reflect to the fault severity levels in Table 5.4 and maintenance priority indices in

Table 5.5 are classified by considering previously available data recorded during regular inspections by maintainers on time basis, experiments, standards in literature, operating thresholds as well as experts' judgments which are also referred to historical data and knowledge from professional training and long experience. We note that the power consumption thresholds are calculated by averaging the sterilization cycle to 50 minutes and considering the averaged time for power consumption of pumping as well as heating along the sterilization cycle.

The inputs and outputs linguistic variables are defined based on the grade of parameter indicators and the effect that could be caused by a certain indicated level. Our input Linguistic variables are notated as NO, SS and VS, whereas output maintenance priorities are notated as LO, MO, HI and VH.

Maintenance priorities are related to the urgency level to perform maintenance activity. Low (LO) indicates no action is required, Moderate (MO) requires close monitoring, High (H) recommends maintenance in the near future and Very High (VH) calls for immediate action.

The system is designed using Simpful library [190] in Python. Simpful was chosen because of its simplicity, richness and friendly usage while implementing any fuzzy membership function. We realize membership functions using trapezoidal function.

Figure 5.2 illustrates inputs and output variables membership depending on the range of values that classify the component health status.

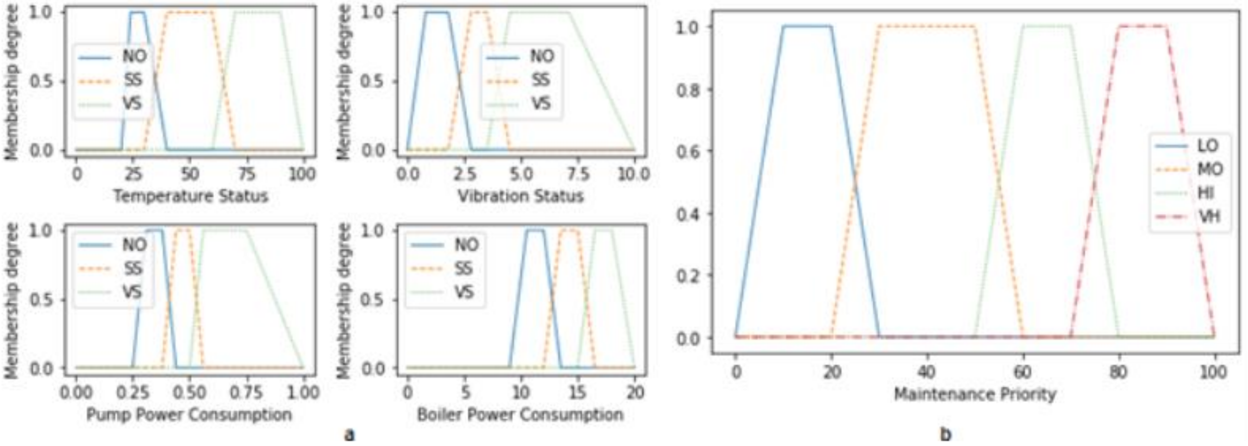
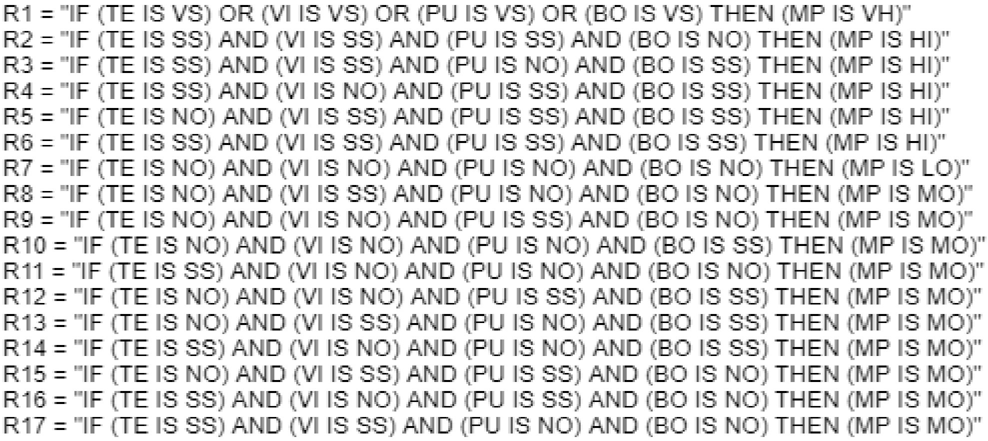


Figure 5.2. Membership functions for (a): inputs and (b): output variables.

## 5.5 Results discussion

Basing on the data and information from expertise maintainers, for four selected inputs with three variables each, 81 rules are possible using ‘AND’ operator. In our case, rules have been created using both ‘OR’ and ‘AND’ operators, whereby only 17 seizures all possibilities. The Figure 5.3 that shows created rules is taken from our created expert system.



```
R1 = "IF (TE IS VS) OR (VI IS VS) OR (PU IS VS) OR (BO IS VS) THEN (MP IS VH)"
R2 = "IF (TE IS SS) AND (VI IS SS) AND (PU IS SS) AND (BO IS NO) THEN (MP IS HI)"
R3 = "IF (TE IS SS) AND (VI IS SS) AND (PU IS NO) AND (BO IS SS) THEN (MP IS HI)"
R4 = "IF (TE IS SS) AND (VI IS NO) AND (PU IS SS) AND (BO IS SS) THEN (MP IS HI)"
R5 = "IF (TE IS NO) AND (VI IS SS) AND (PU IS SS) AND (BO IS SS) THEN (MP IS HI)"
R6 = "IF (TE IS SS) AND (VI IS SS) AND (PU IS SS) AND (BO IS SS) THEN (MP IS HI)"
R7 = "IF (TE IS NO) AND (VI IS NO) AND (PU IS NO) AND (BO IS NO) THEN (MP IS LO)"
R8 = "IF (TE IS NO) AND (VI IS SS) AND (PU IS NO) AND (BO IS NO) THEN (MP IS MO)"
R9 = "IF (TE IS NO) AND (VI IS NO) AND (PU IS SS) AND (BO IS NO) THEN (MP IS MO)"
R10 = "IF (TE IS NO) AND (VI IS NO) AND (PU IS NO) AND (BO IS SS) THEN (MP IS MO)"
R11 = "IF (TE IS SS) AND (VI IS NO) AND (PU IS NO) AND (BO IS NO) THEN (MP IS MO)"
R12 = "IF (TE IS NO) AND (VI IS NO) AND (PU IS SS) AND (BO IS SS) THEN (MP IS MO)"
R13 = "IF (TE IS NO) AND (VI IS SS) AND (PU IS NO) AND (BO IS SS) THEN (MP IS MO)"
R14 = "IF (TE IS SS) AND (VI IS NO) AND (PU IS NO) AND (BO IS SS) THEN (MP IS MO)"
R15 = "IF (TE IS NO) AND (VI IS SS) AND (PU IS SS) AND (BO IS NO) THEN (MP IS MO)"
R16 = "IF (TE IS SS) AND (VI IS NO) AND (PU IS SS) AND (BO IS NO) THEN (MP IS MO)"
R17 = "IF (TE IS SS) AND (VI IS SS) AND (PU IS NO) AND (BO IS NO) THEN (MP IS MO)"
```

Figure 5.3. Created rules.

Bearing in mind that real-time data may change over time due to the working environment of the component, the possible operating universe of discourse for real values from each parameter and their significance to the health status of the component are defined in Table 5.4. Our expert system is therefore evaluated using random values in the defined range for each variable.

Rules and their evaluation were presented to expert maintainers for their assessment and approval. Table 5.6 shows some variables' values and predicted maintenance priorities between consecutive readings. The used data were not recorded with respect to time interval; thus, the timestamp is not shown.

We conclude that the created Fuzzy expert system can evaluate the input variables to produce the maintenance activities priority (M P) for mechanical equipment, thus, to enhance the existing prioritization method. In addition, for complex equipment with various physical condition parameters, to minimize number of predictive models, priorities could be served as overall input to the advanced predictive analytics model for the overall predictions.

Table 5.6. Evaluation using random data.

| **TE** | **VI** | **PU** | **B0** | **M_P** | **Priority level** |
|---|---|---|---|---|---|
| 37 | 4.00 | 0.57 | 13.64 | 0.85 | Very High |
| 59 | 2.00 | 0.29 | 9.09 | 0.40 | Moderate |
| 29 | 1.33 | 0.29 | 12.73 | 0.29 | Low |
| 98 | 1.33 | 0.71 | 8.18 | 0.50 | Moderate |
| 27 | 6.00 | 0.14 | 16.36 | 0.50 | Moderate |
| 61 | 1.33 | 0.43 | 14.55 | 0.61 | High |
| 85 | 6.00 | 0.57 | 10.00 | 0.85 | Very High |
| 39 | 4.00 | 0.43 | 14.55 | 0.70 | High |

## 5.6 Conclusion and future work

Mechanical equipment is generally a complex system made up of different components and each component may present various physical condition parameters. The information from a single component does not summarize the health status of the whole complex equipment. As a result, the full monitoring and control of an equipment’s overall performance is influenced by many features depending on its components’ condition parameter levels and level of hazards that may cause. To save time used by maintainers to diagnose fault and to avoid unplanned prompt downtime, also benefiting from the simplicity of fuzzy logic, an expert system was developed to enhance the maintenance activities prioritization in relation with the working status of equipment’s components.

Priority is classified as Normal whereby there is no need of maintenance, Moderate, High and Very High that appeals respectively for close monitoring, to perform the maintenance within few days and for immediate or closer maintenance intervention. We expect that this system will provide support to the maintainers in continuous monitoring of their equipment, early fault detection as well as in enhancing the priority making of critical maintenance activities among others. The maintenance priority shall be also fed to the predictive analytics model for further prediction as summed input from different components of the equipment.

For future work, the real-time data from operating equipment for longtime, preferably till failure will be collected and being used to determine the remaining useful life (RUL) of the whole equipment basing on their components operational health status and to provide proactive suggestions to each component of the equipment.

# Chapter 6:

## Prologue to 3rd article

### 6.1 Article details

Irene N.M., Zennaro M., Uwitonze A., Rwigema J., Rovai M., “On- Device IoT-Based Predictive Maintenance Analytics Model: Comparing TinyLSTM and TinyModel from Edge Impulse”, in Sensors 2022, 22, 5174. https://doi.org/10.3390/s22145174

### 6.2 Personal contribution

We presented the ability of the two real-time tiny predictive analytics models: tiny long short-term memory (TinyLSTM) and sequential dense neural network (DNN). The equipment degradation insights were assessed through the real-time data gathered from operating equipment. To label our dataset, fuzzy logic based on the maintainer’s expertise is used to generate maintenance priorities, which are later used to compute the actual remaining useful life. The article composition was done under the guidance of Zennaro M., and Uwitonze A. Thanks goes to Zennaro M. for the idea of using TinyML.

### 6.3 Context

A precise prediction of the health status of industrial equipment is significant to determine its reliability and lifespan. This prediction provides users information that is useful in determining when to service, repair, or replace unhealthy equipment’s components. In the last decades, many works have been conducted on data-driven prognostic models to estimate the asset’s remaining useful life. These models require updates on the novel happenings from regular diagnostics, otherwise, failure may happen before the estimated time due to different facts that may oblige rapid maintenance actions, including unexpected replacement. Adding to offline prognostic models, the continuous monitoring and prediction of remaining useful life can prevent failures, increase the useful lifespan through on-time maintenance actions, and reduce the unnecessary preventive maintenance and associated costs.

### 6.4 Contributions

The predictive analytic models were developed and performed well, with an evaluation loss of 0.01 and 0.11, respectively, for the LSTM and model from Edge Impulse. Both models were converted into TinyModels for on-device deployment. Unseen data were used to simulate the deployment of both TinyModels. Conferring to the evaluation and deployment results, both TinyLSTM and TinyModel from Edge Impulse are powerful in real-time predictive maintenance, but the model from Edge Impulse is much easier in terms of development, conversion to tiny version, and deployment.

## 6.5 Recent developments

This article has been recognized by

Yunfei Yan [191] into his/her work with title of “ Dynamic QoS Prediction Algorithm Based on Kalman Filter Modification”,

Ernia Susana [192] into her research entitled “Edge Classification of Non-Invasive Blood Glucose Levels Based on Photoplethysmography Signals”, and

Muhammad Faris [193], into the work titled “Improved Real-Time House Fire Detection System Performance with Image Classification Using Mobilenetv2 Model”.

# Chapter 7:

## On- Device IoT-Based Predictive Maintenance Analytics Model: Comparing TinyLSTM and TinyModel from Edge Impulse

### 7.1 Introduction

In today's maintenance, the early fault detection and prediction is mainly centered on the maintainer's experience and their familiarity with the equipment. Due to the development in engineering and the complexity of equipment, human judgment is not sufficient to prematurely predict and continuously oversee the status of assets.

As result, over recent decades, machine learning models have been highlighted as meaningful tools in predictive maintenance, especially in prognostic and asset health management [46]. Different prognostic algorithms and models [194] have been developed using simulated [195] and/or offline data sets [196]–[199] to estimate the asset's remaining useful life (RUL), which is based on the targeted values function.

There is no universal model due to different systems, type and quality of data, different performance conditions, and working principles; therefore, the construction of a life degradation model up to total failure is mainly performed for the projection of maintenance actions, especially to keep spare inventory on track ahead of time, and it is based on subjective choice [195], such as asset state, age, usage load, deterioration curve, rate or patterns, failure types, and conducted maintenance history parameters.

In addition, most of the RUL models for traditional regression problems do not operate in real-time; thus, they must be updated by new findings from the regular preventive maintenance [200]. They also mainly rely on the logistical, managerial, and decision support processes to procure the spares regarding the estimated lifetime, rather than the continuous fault diagnostics that may fortify the powerful prediction.

Among others, traditional models, such as random forest and XGBoost [201], Seasonal Autoregressive Integrated Moving Average (SARIMA) [202], Support Vector Machine (SVM) [203]–[205] , a stochastic model such as Hidden Markov Model (HMM) [206], and fuzzy neural network [207] have demonstrated efficient predictions on real-time data, but with some limitations based on manual data processing and expertise of the developer [197], [208]. Deep learning has shown admirable performance in the prognosis of a high amount of data [208]. Among the popular deep prognostic models there are Convolutional Neural Network (CNN) [197]–[199], [203] and Recurrent neural network particularly its long short-term memory [196], [209]–[212] version.

In the predictive maintenance domain, the equipment degradation recalls the long- term chronological beliefs from its real-time physical performance data. Thus, the long short-term memory (LSTM) variant has been appreciated and adopted in the literature to provide better performance for time series data [201], [211], [212] due to its capability to preserve information for long periods.

These asynchronous predictive models do not provide a full availability of the equipment's health state. Consequently, prompt downtime may occur between two consecutive prediction periods. Afterwards, maintainers claim to continuously oversee their asset's operating bulletin that may fall in different health states before reaching the failure point. There is also a claim on a continuous and autonomous prediction of the RUL of their equipment.

To overcome this deficiency, through the steady novelties in technology, such as the Internet of Things (IoT), the real-time state of the equipment can be observed continuously on edge by employing different sensors to acquire different health information and the analytics predictive model in real-time on edge devices. The IoT-based predictive maintenance [213] may enable users to obtain autonomous real-time updates of their equipment health conditions for timely accurate decision making on maintenance actions.

Adding to the real-time LSTM on edge (TinyLSTM), the Edge Impulse [25] is recently being developed and deployed as a leading Artificial Intelligence (AI) platform that simplifies the development and deployment of machine learning models on the Tiny embedded devices (at the edge) with a possibility of ultra-low power consumption (TinyML).

Driven by the claims on extended up-time and lifespan of equipment, to minimize unplanned downtime and unnecessary preventive maintenance as well as to reduce the frequency of component replacement, along with this work, we comparatively assessed the development and deployment of TinyLSTM and TinyModel from Edge Impulse performances on the real-time data collected from different components of operating equipment with a purpose to advise the best on edge predictive maintenance analytics model. Both have been built and evaluated using Keras library [166]. Later, they are transformed into the TinyModel version for their deployment on the IoT device installed on the monitored equipment.

Adding to existing offline sequential predictive maintenance models, the TinyModel proposed in this work provides real-time updates on the RUL of the running equipment and reduces the maintenance time as well as cost through performing only the necessary maintenance activities in a convenient time; therefore, the model will be continuously running, and the device on the edge will also require a close degradation monitoring for all its parts.By considering the maintainers' expertise, the gathered real-time data were preprocessed using the fuzzy expert system to find the diagnostic facts to label the maintenance actions priority, from which the actual remaining useful life could be calculated depending on the conditional status of each component.

The major contributions of this part are the following:

- For real-time application, the real-time performance data to develop the analytics model were gathered using an IoT device installed on the equipment.
- For multi-conditional parameters that may separately affect the equipment life and to reduce the number of mono-variate analytics models, different variables' data are labeled using the fuzzy expert system based on the maintainers' expertise.
- To predict an equipment's remaining useful life depending on equipment's component's status, the IoT-based real-time predictive analytics models: LSTM and Model from Edge Impulse are developed and compared.
- For the fault prediction and early notification on maintenance priority suggestions, each model is converted to TinyModel, and its deployment onto an IoT device for continuous real-time health monitoring is simulated.

The results show the prediction ability is good with a low mean squared error (MSE) of 0.01and 0.11 for LSTM and the model from Edge Impulse, respectively. The $R^2$ for LSTM is 77% whereas the accuracy is 99.87% for the model from Edge Impulse. We compared the process from model creation up to deployment simulation and we concluded by proposing the TinyModel from Edge Impulse platform to be a suitable and easy model for real-time edge application.

The remainder of this part is organized as follows: we introduce the data gathering and processing in Section 7.2. Section 7.3 describes and discusses results for selected models; Section 7.4 describes the compression of regular to TinyModel (TinyML), whereas the two models comparison is presented in Section 7.6. Finally, Section 7.7 concludes the work and suggests future works.

## 7.2 Data Gathering and Processing

Following the defined steps to develop and deploy a predictive TinyModel, as shown in Figure 7.1, the main Predictive Maintenance (PdM) engine is the data and the way they are preprocessed. The type and quality of data determine the prediction accuracy that reflects the correctness of decisions on maintenance actions to be taken. For better precision in prediction, two types of data are needed: historical and real-time data. Historical data helps to understand the operation of the equipment and to select the critical physical condition parameters to be monitored in a real-time manner. They are recorded by the experts in maintenance who also help to determine the necessary parameters to monitor. The real-time data from the specified equipment shall provide clear insights into its real health status. This also requires vigorously observing any change from the real-time data against the behaviors of the equipment operating status.

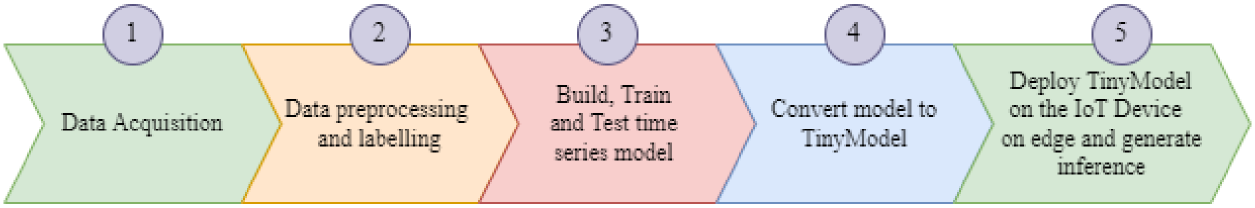


Figure 7.1. Strategic steps to build an Analytics TinyModel.

### 7.2.1 Data Acquisition

The process to collect the real-time data starts by choosing the equipment, under- standing its operational procedures, learning its diagnostics from the maintenance history, and highlighting the major detected faults, their causes, and their impact on the overall equipment life. From the acquired evidence, we highlight the critical components, their conditional parameters to be intelligently observed, as well as the required materials.

In line with the PdM claim, the longtime real-time data that may provide different scenarios of the equipment's health status were collected using the data collector developed in Chapter 3.5.1 [186]. The data collection processes shown in Figure 7.2 are used in this work to collect and save data before being processed and used to build the predictive model.

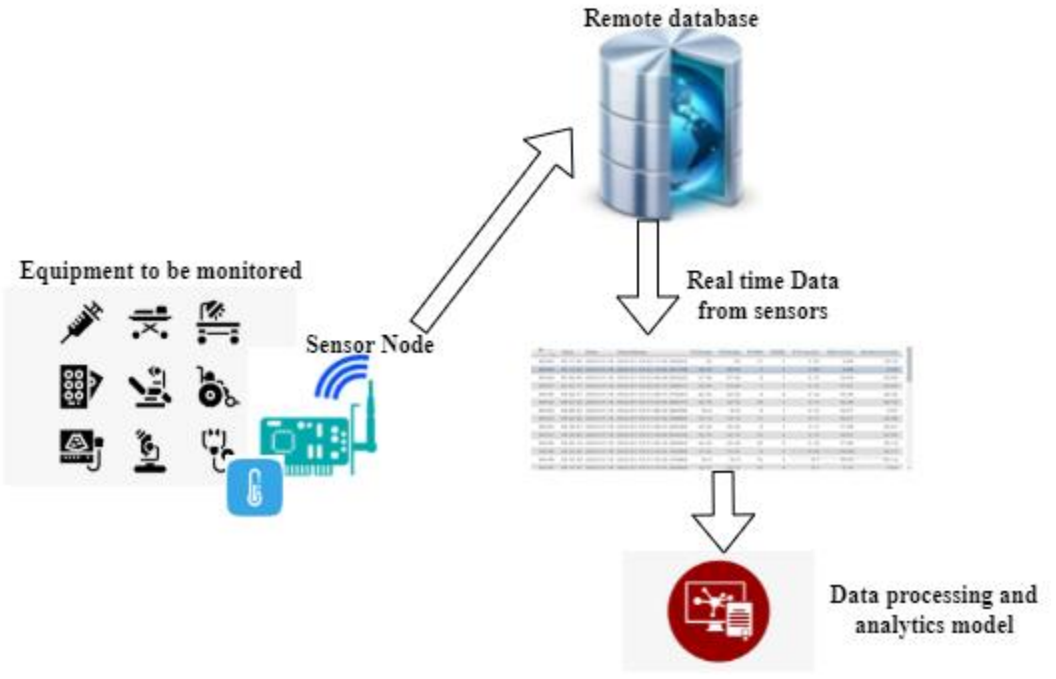


Figure 7.2. Data acquisition process.

The defined sensors according to the critical health condition parameters were installed on different critical components of the selected equipment (autoclave sterilizer) and timestamped data were sent to the virtual database via the General Packed Radio Service(GPRS) communication device as it was the easiest method to continuously observe the data flow by means of an internet connection without frequent visits to the equipment.

The real-time data have been collected from three different critical components (two pumps and steam generator) to compare the overall performance of the autoclave. Even though, two pumps serve different activities, they presented similar physical performance parameters with almost the same indicators. Thus, during our experiment, we have considered data from one pump and from a steam generator. The four variables' dataset from which a short sample is shown in Table 7.1 consists of Temperature (Temp.), Vibration (Vibr.), and two Current (Curr.) flows from the different sources (A and B), which is considered to build our models.

Table 7.1. Dataset sample presentation.

| **Temp. (°C )** | **Vib. (mm/s)** | **Curr. A (mA)** | **Curr. B (mA)** |
|---|---|---|---|
| 33.44 | 48 | 0.12 | 0.12 |
| 33.88 | 46 | 0.08 | 17.53 |
| 30.56 | 16 | 2.72 | 0.10 |
| 32.50 | 11 | 0.03 | 0.12 |
| 35.56 | 7 | 0.01 | 0.12 |
| 35.88 | 47 | 0.01 | 0.10 |
| 43.63 | 47 | 0.06 | 0.12 |

Since the equipment does not operate all the time, the data was only gathered during operation times.

### 7.2.2 Data Preprocessing and Labeling Using Fuzzy Expert System

For the PdM precision and decision making on maintenance activities, the supervised predictive analytics tools are quite helpful. This requires the preprocessed data [214]such as cleaned, prepared, and labeled data.

#### 7.2.2.1 Data Preprocessing

Since for real-time application at the edge, the raw data from the sensors are fed immediately to the predictive analytics model on the device at edge for processing and analytics, every step performed in the data preprocessing phase has to be captured and coded in the program running onto the microcontroller to be executed before data are able to be supplied to the TinyModel. As a result, it is necessary to maintain the originality of the data, so that the data processing may not require more cleanup. Only missing data and data normalization are taken into consideration.

#### 7.2.2.2 Recall of Fuzzy Expert System in Predictive Maintenance

Considering that all decisions on maintenance activities are taken via the maintainer's expertise, there is not a single way to assume the health status of the equipment without assessing each part of it. In additional the shortage of any component may affect the overall performance of the equipment or cause a failure. As a result, we needed to use a tool that may put together different health status from different critical components of a single piece of equipment to determine the maintenance priorities.

Fuzzy logic, an artificial intelligence software proposed by Zadeh (1965) [177], which is also customized to our predictive maintenance application in Chapter 5.4, is adopted as a tool to facilitate the transformation of the maintainers' expertise into an automated expert system that will provide a continuous observation of the equipment state and accordingly plan and prioritize maintenance activities before any unplanned downtime can occur.

For complex industrial equipment with many components, including uncertain and imprecise behavior, there is a risk that unplanned downtime may occur for the whole system. To address this problem, fuzzy logic is a powerful tool for modeling and controlling this type of equipment [215]. Referring to the literature [168], [172], [173], [183]–[185], fuzzy logic has been used in maintenance as a decision-making, scheduling, and hazard-level reckoning tool.

Based on the maintainers' expertise as well as long-time continuous monitoring of the equipment and their components' health status vis a vis their physical conditions and associated performance, we labeled our conditional data from sensors using the Fuzzy Expert System, which is simple to learn and use, as it does not require a speculative model.

With the Fuzzy Expert System, the fuzzified inputs set values (F(i)) are computed using a sigmoid function in Equation (11). The function presents the symmetry property described in Equations (12) and (13), whereby the Equation (13) extends Equation (12) for multiple variables n.

$$\mathrm{F(i)} = \frac{1}{1 + \mathrm{e}^{-\mathrm{i}}} \tag{11}$$

$$\mathrm{F(i)} + \mathrm{F(-i)} = 1 \tag{12}$$

$$\left(\mathrm{F}(i_1) + \mathrm{F}(-i_1)\right) \times \left(\mathrm{F}(i_2) + \mathrm{F}(-i_2)\right) \times \ldots\ldots\ldots\ldots\ldots\ldots \times \left(\mathrm{F}(i_n) + \mathrm{F}(-i_n)\right) = 1 \tag{13}$$

The fuzzified input set is directed to the Mamdan inference engine [216] to be weighed by mapping the defined fuzzy sets, which are well-matched to experienced human operators that map precedent rules and consequences in a knowledge base. The fuzzy set (X) is presented as a group of tidy pairs, as shown in Equation (14) and the mapping function (M(i)) in Equation (15). The inference aggregates the output (crisp value), which is transformed into a real-world output by the defuziffier.

$$\mathrm{X} = \{(\mathrm{i}, \mathrm{M}(\mathrm{i})), \mathrm{i} \varepsilon \mathrm{I}\} \tag{14}$$

$$\mathrm{M}(\mathrm{i}) = \mathrm{I} \rightarrow [0,1] \tag{15}$$

Where X is fuzzy set, F(i): Input set values, M(i): Membership function, i: element belongs in universe of discourse, n: number of variables, and I: universe of discourse.

#### 7.2.2.3 Data Labeling (RUL) Using a Fuzzy Expert System

Considering that preventive maintenance is regularly conducted to keep up the equipment, reaching the downtime state of the equipment is not feasible; thus, the remaining useful time is defined as the remaining time to reach the very-high maintenance priority zone and the remaining lifetime is calculated in terms of days.

The possible scenarios from input variables membership to create fuzzy rules are assessed in order to build a fuzzy system that can figure out the maintenance activities priority liable to the health status of different components of the equipment. The maintenance priorities are then used to compute the remaining useful life (RUL) of the entire equipment. The arithmetical functions in Python are used to determine the RUL at each row of data by considering a current datapoint to compute the remaining time until the data point which belongs to the very- high maintenance priority zone.

To label our data, we reflected on the fact that each component may push the equipment to downtime. Based on the historical methods used to detect errors during regular preventive maintenance and expert inspections as well as their results, we have classified the health status into the Fuzzy Expert System’s linguistic variables of each component versus the value range of its working condition parameters as Normal, Slightly Strange, and Very Strange.

The output variable (maintenance action priority) zones shall depend on the fuzzy membership functions of status from the four variables. By means of the triangular membership function, using the real data from operating equipment, Figure 7.3-Figure 7.6 show the linguistic variable as the health status ranges (on the X-axes) of different parameters. Figure 7.7 summarizes the maintenance priority output. The X-axes and Y-axes present the ranges of maintenance priority and the degree of priority, respectively.

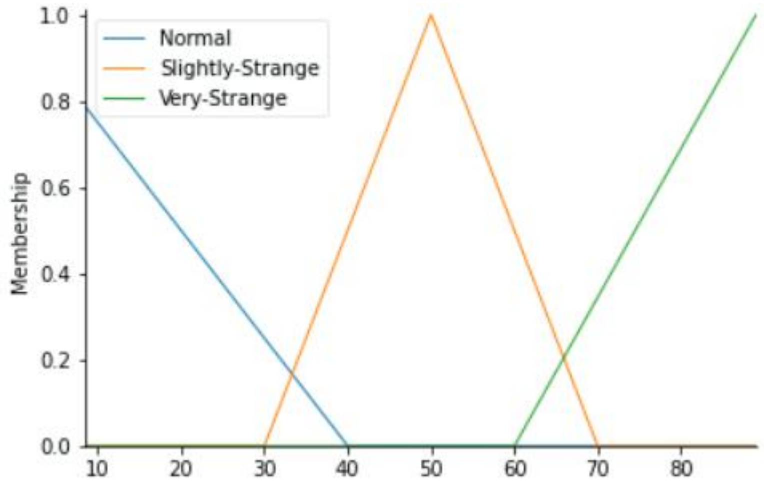


Figure 7.3. Temperature variable.

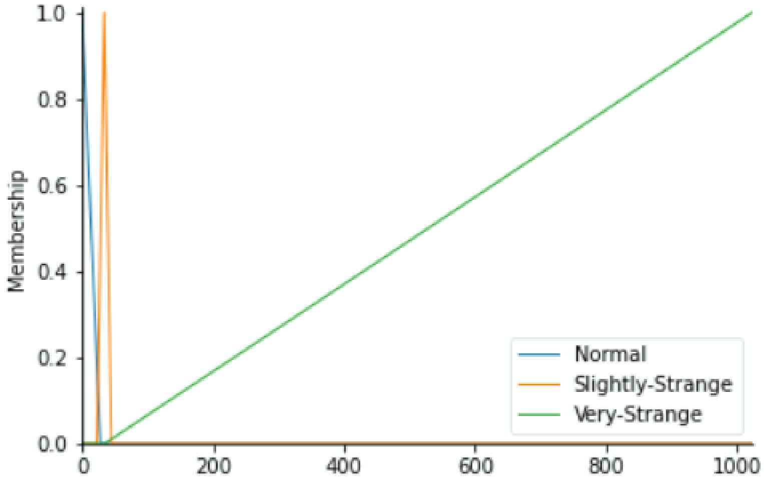


Figure 7.4. Vibration variable.

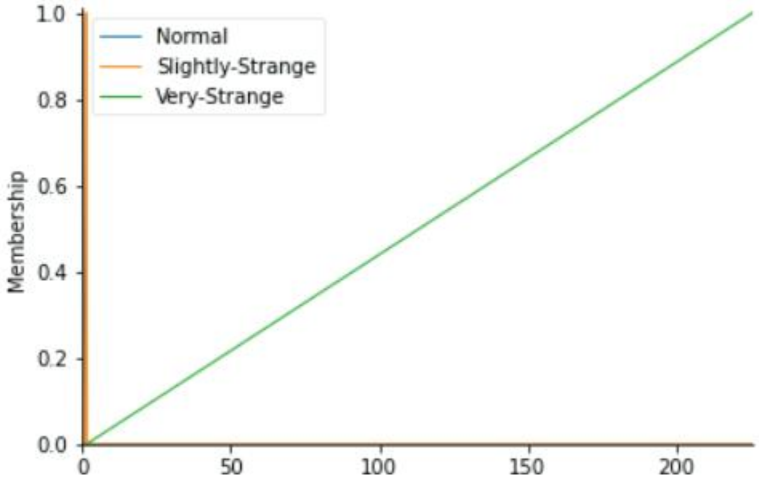


Figure 7.5. Current (A) variable.

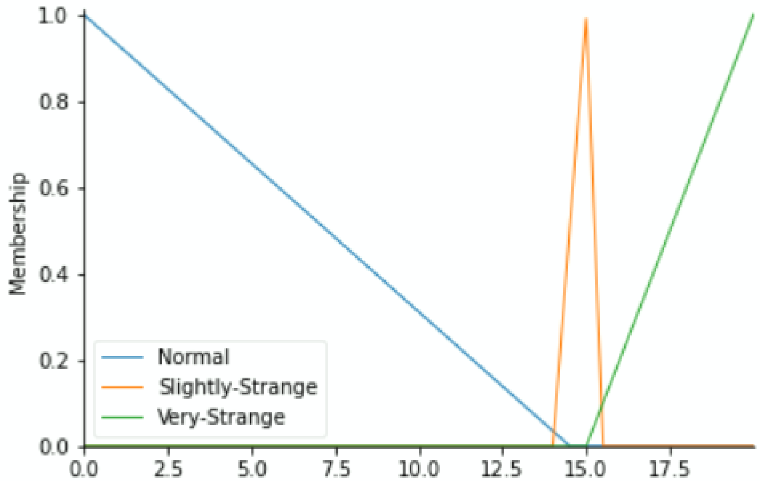


Figure 7.6. Current (B) variable.

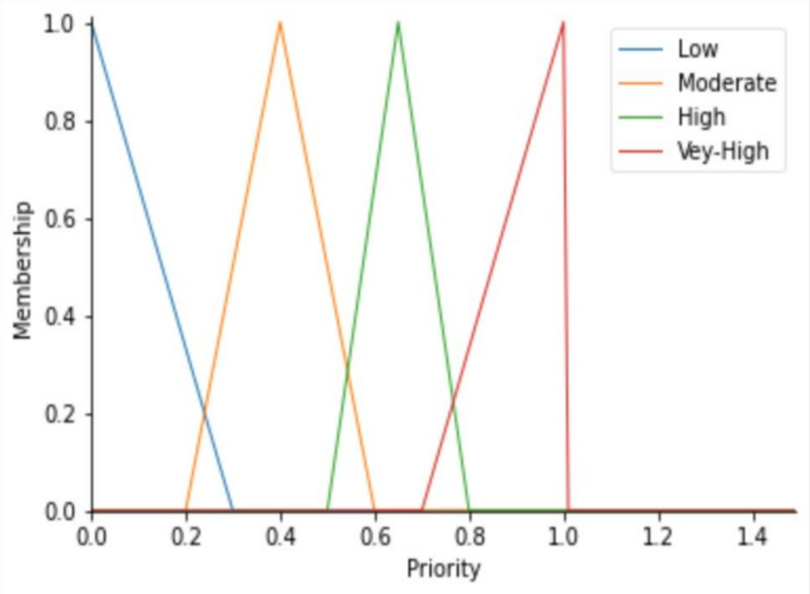


Figure 7.7. Maintenance priority variables.

As defined in Chapter 5, the maintenance priority linguistic variables recall the urgency levels as either low, moderate, high, or very high, which designate the need for maintenance action as either no action, far future, near future, or immediate maintenance action, respectively.

From the maintenance priority calculated by the Fuzzy Expert System, we labeled our dataset by computing the remaining useful life (RUL). The RUL is calculated using functions in Python that consider the current state and compute the probable time to attain the neighbor data point belonging in the risky zone, which is indicated by very-high priority. The RUL is calculated in terms of the number of days remaining for the equipment to operate continuously before entering the risky zone. Adding to the raw data in Table 7.1, Table 7.2 shows randomly picked rows from the dataset with two added columns consisting of maintenance priority (M. Priority) generated through fuzzy and different values of calculated RUL as a label of our dataset. The priority varies in a normal fuzzy output range of [0, 1], whereas the obtained maximum RUL of our equipment could be 22 days without any maintenance.

Table 7.2. Labeled dataset.

| **Temp. (°C)** | **Vib. (mm/s)** | **Cur. A (mA)** | **Cur. B (mA)** | **M. Priority (0 to 1)** | **RUL (Days)** |
|---|---|---|---|---|---|
| 89 | 12 | 2.53 | 17.65 | 0.9 | 1 |
| 47 | 6 | 6.07 | 0.01 | 0.86 | 2 |
| 34.81 | 12 | 4.89 | 0.12 | 0.86 | 3 |
| 44.88 | 6 | 2.79 | 0.03 | 0.86 | 4 |
| 31.44 | 9 | 5.21 | 0.15 | 0.86 | 5 |
| 33.75 | 0 | 3.56 | 0.11 | 0.86 | 6 |
| 26.87 | 0 | 0.1 | 15.45 | 0.89 | 7 |
| 28.25 | 50 | 0.13 | 0.05 | 0.86 | 8 |
| 38 | 7 | 0.13 | 0.12 | 0.38 | 9 |
| 34 | 6 | 0.11 | 0.11 | 0.31 | 10 |
| 37.88 | 8 | 0.1 | 0.12 | 0.38 | 11 |
| 30.31 | 0 | 0.1 | 0.12 | 0.15 | 12 |
| 30.31 | 10 | 0.1 | 0.12 | 0.15 | 13 |
| 29.25 | 0 | 0.08 | 0.12 | 0.13 | 14 |
| 29.25 | 0 | 0.08 | 0.11 | 0.13 | 15 |
| 29.25 | 0 | 0.13 | 0.1 | 0.13 | 16 |
| 28.44 | 0 | 0.1 | 0.11 | 0.13 | 17 |
| 25 | 0 | 0.13 | 0.33 | 0.12 | 18 |
| 28.5 | 0 | 0.03 | 0.32 | 0.13 | 19 |
| 28.5 | 0 | 0.13 | 0.11 | 0.13 | 20 |
| 30.19 | 10 | 0.1 | 0.11 | 0.15 | 21 |
| 30.18 | 9 | 0.11 | 18.2 | 0.89 | 22 |

## 7.3 Predictive Analytics Models (LSTM and Model from Edge Impulse)

Replying to the shortage in continuous and real-time availability of industrial equipment health states with the purpose of providing predictive maintenance solutions at the edge in real-time, and by taking consideration of the LSTM model prediction performance on real and sequential data from the literature and the currently booming Edge Impulse platform that provides a single way to develop and deploy real solutions on the edge device, both LSTM and the model from Edge Impulse are assessed in this work.

### 7.3.1 Long Short-Term Memory (LSTM)

In the TensorFlow backend, using Python, data were preprocessed, labeled using fuzzy logic, as described in Section 5.4, and later through the Keras library [166], which was used to build the sequential long short-term memory (LSTM) model. The details on LSTM structure are provided in Section 3.4.3.

### 7.3.2 Predictive Analytics Model from Edge Impulse

Edge Impulse is the novel platform in the era of machine learning with the purpose of providing embedded machine learning solutions on edge applications [25]. Adding to other machine learning development platforms, Edge Impulse provides the simplest way to collect data using either built-in or outer sensors in smart devices, such as mobile and embedded devices. Edge Impulse also helps in analyzing the data, designing, and testing the model, as well as providing the deployable version of the model without much experience in coding. It also allows customized data and the ability to customize the model design.

### 7.3.3 Results and Discussion

The intention of this section is to build and compare the two competent sequential models that drive us to adopt a suitable predictive analytical model for IoT-based predictive maintenance real-time application. From the literature, LSTM was mainly used and performed well on time series data. LSTM was also proven to perform well on real-time data throughout this work. In contrast, the Edge Impulse platform has provided a simplified way to build and deploy a new model on edge applications. Consequently, both LSTM and model from Edge Impulse were designed, trained, and evaluated to learn multivariate real-time data collected from autoclave equipment for our experiment. Both models were then converted into TinyModel versions and deployed on the edge through simulation using unseen real-time data.

#### 7.3.3.1 LSTM Model Structure and Performance Metrics

Since the dataset is different to the one used to build LSTM in Chapter 3:, the LSTM has been redesigned. Thus, using the Keras deep learning library, which runs on the TensorFlow platform[163] in Python, we built the LSTM analytics predictive model. Our dataset contains a total of 126,333 data points taken with an equal interval of one minute between two data points.

As LSTM refers to the previous data to figure out the convenient function of new data, we set data to be sampled into a small sample of 60 data points, whereby LSTM shall learn before concluding on the next prediction point. The sample size was fixed based on the length of time used by the equipment to complete a single operation cycle and that the health status assessment could be summarized at least after each operation cycle.

To fit the LSTM structure, our data were arranged into a three-dimensional array format and split into two parts, the train and test datasets, with portions of 80% and 20%, respectively. The data format loaded into the LSTM to train and after to test is shown in Table 7.2, where the priority and RUL (two last columns, respectively) were used to build a predictive analytics model.

Since each model performs according to the applied hyperparameters, we iterate the training and testing phases using different parameters to obtain the best results evaluated by assessing loss and model performance accuracy through mean squared error (MSE) and coefficient of determination (R) metrics for both training and testing datasets.

The adopted model structure, hyperparameters, and performance result metrics' values at a minimum loss are presented in Table 7.3.

Table 7.3: Model structure metrics and performance values.

| Parameters | Optimum Metrics' Value |
|---|---|
| Model training dataset portion | 80% |
| Model evaluation dataset portion | 20% |
| Model Type | Sequential |
| LSTM layer | 32 neurons |
| Hidden Dense layer | 16 neurons |
| Dropout packaging | 0.2 |
| Output layer (Dense) | 1 neuron |
| Optimizer | Adam |
| Learning rate | 0.001 |
| Epoch | 5 |
| Performance metrics | MSE (Mean Square Error) and Coefficient of determination $R^2$ |
| Batch size | 16 |
| Time step window | 60 |
| Train MSE | 0.0295 |
| Test MSE | 0.01 |
| $R^2$ | 0.77 |

Our model fits the regression line at 77%, which is reasonably good since the data may vary from normal to worse values; we note that the far data from the regression line could not be considered as an outlier if it belongs to the equipment condition parameters' range.The total train loss of 0.029 and total test loss of 0.01 are small, which is good for the model's performance.

Figure 7.8 presents the model loss trend. To determine the best model performance values for minimum loss and overfitting, at each hyperparameter value, the model was tested on both datasets. It is seen that the losses for the test dataset are lower than that of the train dataset and overfitting was not present. In addition, both model training and testing losses are lower as the epochs increase and keep steady at closer points.

To evaluate the real and predicted RUL relationship, the test dataset was used. Figure 7.9 shows that both real and predicted RUL (on Y-axes) are reasonably closer when you keep rounding a float number to an integer. The RUL in our real data is rounded to the closer integer at each time point whereas the predicted results are kept in floats.

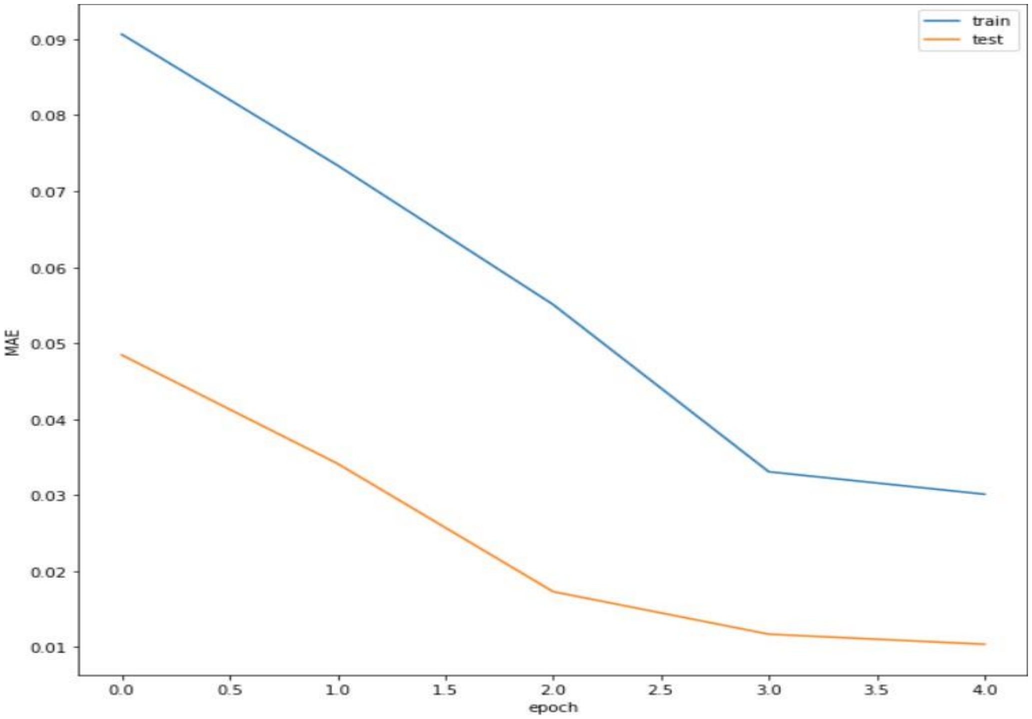


Figure 7.8. LSTM model loss.

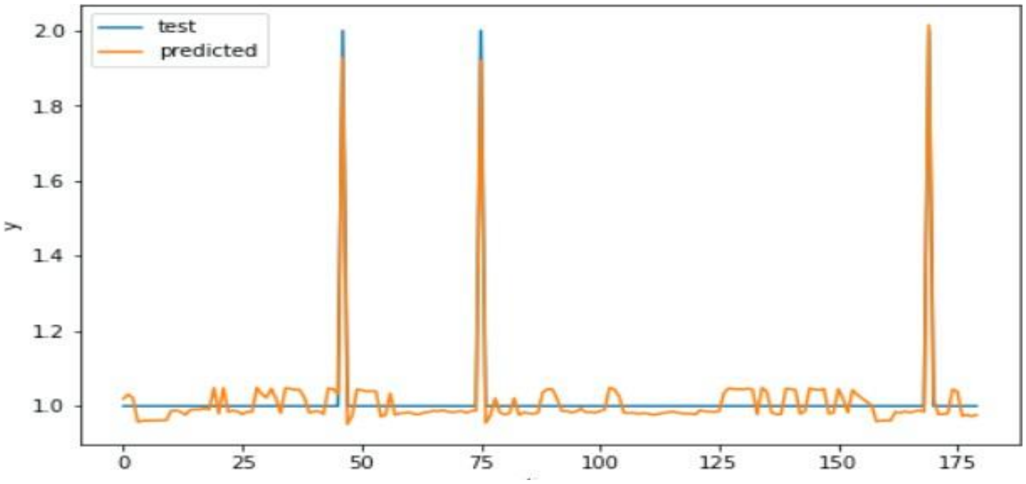


Figure 7.9**.** Actual versus predicted RUL.

### 7.3.3.2 Model from Edge Impulse Structure and Performance Metrics

The Edge Impulse platform provides a well-structured and simple step to build a model. It allows users to upload different types of preprocessed data.

For this experiment on a predictive model, the raw data were uploaded and indicated as time series data. Since our data were used for regression problems, the data upload technique may differ from the familiar classification method. The dataset structure requires separate files, each named under its label for all data points. Figure 7.10 presents a single sampled data point and its corresponding features as each data point of our dataset is made by four variables and named on its specific label.

Raw features

0.2702, 0.0039, 0.0004, 0.0055

DSP result

Processed features

0.2702, 0.0039, 0.0004, 0.0055

Figure 7.10**.** Data presentation in Edge Impulse.

Forwarding to the model building, we start with the default settings and built-in neural network (NN) architecture in Edge Impulse, and we keep tuning the settings and retraining to obtain a best model that may fit our data with the least amount of loss. Table 7.4 illustrates the adopted optimal prior model parameter settings and the architecture of theNN block.

Table 7.4: Model parameter settings and neural network block architecture.

| Parameters | Specifications |
|---|---|
| Training cycles | 10 cycles |
| Training dataset | 80% of the entire dataset |
| Validation and testing dataset (to be used during training) | 20% of the entire dataset |
| Learning rate | 0.005 |
| Activation | ReLu |
| Batch size | 32 |
| Epoch | 10 |
| Loss function | Mean Squared Error (MSE) |
| Model type | Sequential |
| Input layer | 4 features |
| Hidden Dense layer at first level | 20 neurons |
| Hidden Dense layer at second level | 10 neurons |
| Output layer | 1 class (1 neuron, no activation) |

The hidden dense layers are fully connected. Within the current version of the developed Edge Impulse platform for regression problems, the model output always appears in classes. With the optimum specifications in Table 7.4, using the validation dataset, the achieved minimum loss reaches 0.11.

As the Edge Impulse is specifically designed to build models for real-time application on the edge, after each training and validation set, the built model summarizes the model performance on the device at the edge, as shown in Figure 7.11.

INFERENCING ...
1 ms.

PEAK RAM USA...
1.4K

FLASH USAGE
10.4K

Figure 7.11. On Device Performance.

Figure 7.12 shows the specification of the device at the edge to host the TinyModel. The model testing results show a good model performance of 99.87% and MSE of 0.11.

ACCURACY ⓘ
99.87%

MEAN SQUARED ERROR
0.11

Figure 7.12. Edge Impulse model testing results.

The results in Figure 7.13 show that most of the performance data from our equipment fall into class one of the RUL, which is similar to actual RUL from raw data.

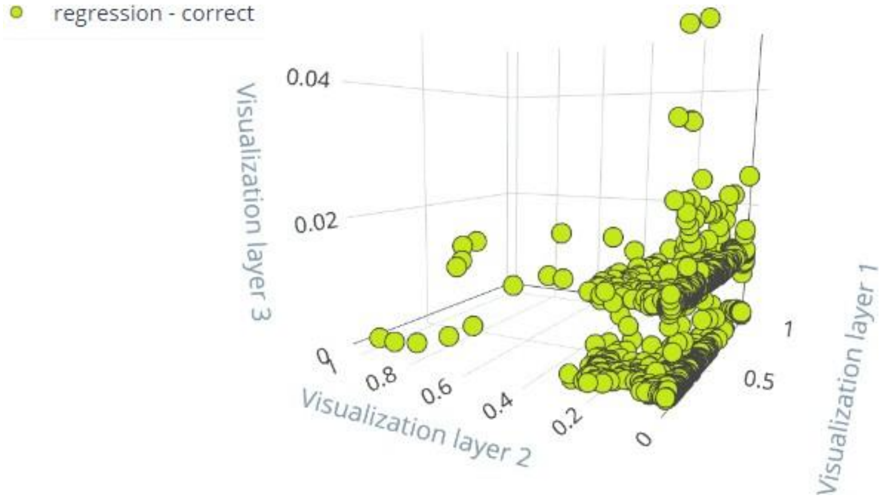


Figure 7.13. Evaluation data presentation.

## 7.4 TinyModel

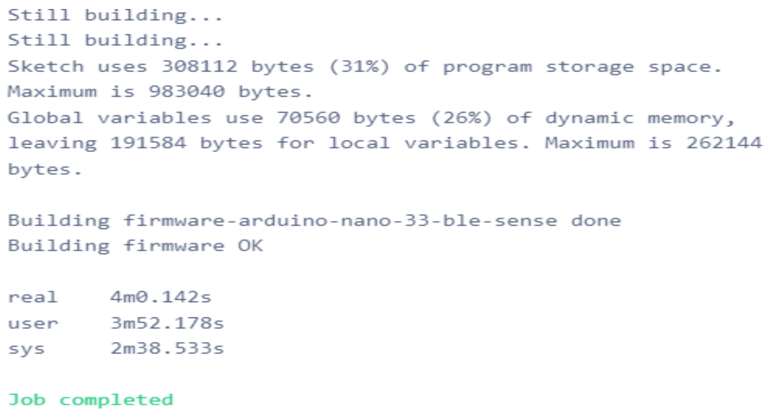
For both the LSTM model and model from Edge Impulse, the TinyModel is obtained by converting the ordinal neural-network-based model to TinyModel. From Edge Impulse, the conversion process is integrated into the platform. In contrast, for the LSTM model, we used the TensorFlow-Lite (TF-Lite) converter to convert the ordinary Keras LSTM to TF-LiteTinyLSTM.

Both conversions methods require specifying the type of device that will host the TinyModel. Considering the industrial constraint of energy consumption, we chose the Arduino Nano BLE Sense [217], which was purposely designed to have power saving features for IoT-based edge applications.

To learn more about the needed embedded device to host the model into Edge Impulse, we optimize and compile the model for deployment to check the final recommended specification of targeted embedded devices. Since TF-Lite does not provide the summary of the needed device specifications additional tools will be required to assume the needed deployment memory and possible latency.

Finally, the TinyModels for both LSTM and the model from Edge Impulse were built, and the source files were downloaded to be installed and deployed on the embedded device.

Figure 7.14 shows the TinyModel firmware for Arduino Nano BLE Sense built from Edge Impulse.



```
Still building...
Still building...
Sketch uses 308112 bytes (31%) of program storage space.
Maximum is 983040 bytes.
Global variables use 70560 bytes (26%) of dynamic memory,
leaving 191584 bytes for local variables. Maximum is 262144
bytes.

Building firmware-arduino-nano-33-ble-sense done
Building firmware OK

real    4m0.142s
user    3m52.178s
sys     2m38.533s

Job completed
```

Figure 7.14. TinyModel firmware for Arduino Nano BLE Sense.

## 7.5 Simulating the Deployment and Inference Creation

Both TinyModel's (TinyLSTM & TinyModel_EI) deployment were performed using unseen data gathered from the same equipment. Prior to feeding data to the simulator, all preprocessing activities performed on training and testing data were considered and must be coded into a program running onto the microcontroller to be processed before reaching the TinyModel. The obtained simulation results from both TinyModels are shown in Figure 7.15 and Figure 7.16 respectively, for TinyLSTM and TinyModel_EI.

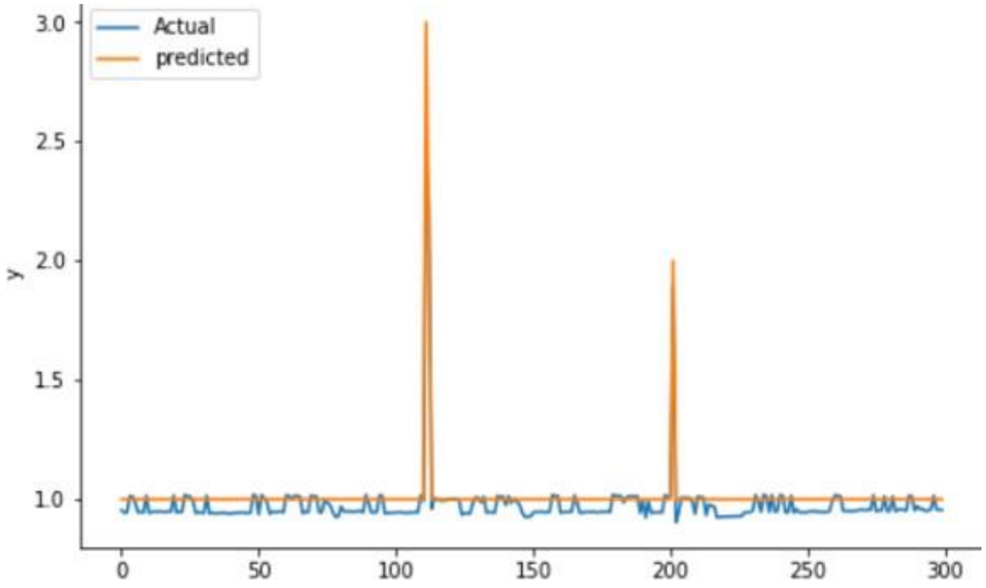


Figure 7.15. Deployment simulation results for TinyLSTM-Model.

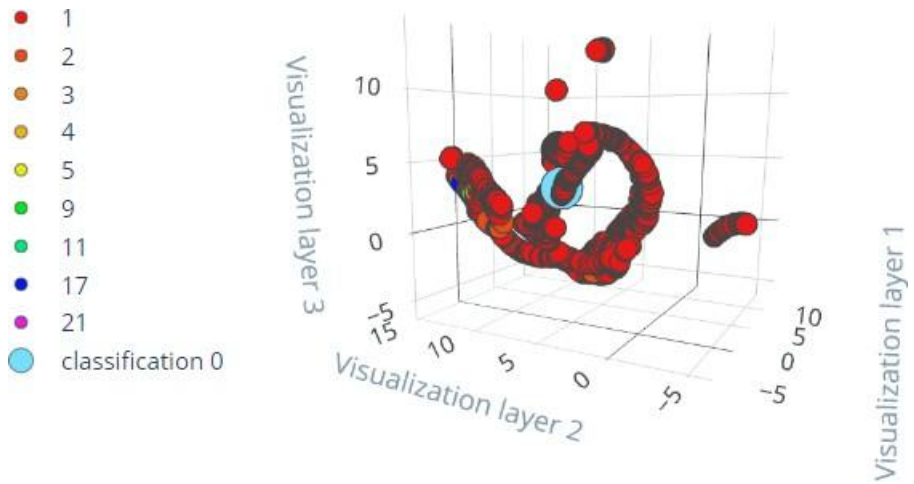


Figure 7.16. Deployment simulation results for TinyEI-Model.

Deployment simulation results were shown to have almost the same model performance as the results obtained when evaluating the models. To evaluate the similarities between actual and predicted outputs, we compared actual and predicted RUL and found no differences.

To facilitate the maintainers to observe the detailed condition status of their equipment,we must determine the critical status of the overall equipment. Adding to Figure 7.15 and Figure 7.16, Table 7.5 shows the real physical conditional values from the different components of the equipment and predicted RUL in order to determine the overall equipment status. The values from components that may cause the downtime and alerting RUL in the last column are highlighted in red.

Table 7.5: Real-time data and predicted RUL.

| Temp. ($^o$C) | Vib. (mm/s) | Curr. A (mA) | Curr. B (mA) | Actual RUL (Days) |
|---|---|---|---|---|
| 50.56 | 45 | 0.14 | 17.97 | 1 |
| 54.31 | 25 | 2.63 | 0.01 | 1 |
| 54.31 | 55 | 2.65 | 0 | 1 |
| 55.13 | 127 | 2.71 | 18.07 | 1 |
| 47.69 | 50 | 0.14 | 18.09 | 1 |
| 41.44 | 42 | 0.14 | 18.23 | 1 |
| 37.88 | 48 | 0.14 | 18.12 | 1 |
| 36 | 70 | 0.14 | 18.06 | 1 |

Depending on the maintainers' demand, physical conditional values in the same health status could be given the same color code to help them observe and fully explain the reason behind the predicted RUL.

## 7.6 Models' Comparison

The comparison consists of three main components, which are the coding platform and data processing in Table 7.6, model structure and performance metrics in

Table 7.7, and TinyModel conversion and deployment in Table 7.8.

Table 7.6: Coding platform and data processing for LSTM and Model from EI.

| Element | For LSTM Model | For Model from Edge Impulse |
|---|---|---|
| Model building platform | TensorFlow | Edge Impulse |
| Free version of platform | No limitation on data size and training time but keep confirming the work in progress. | Limited data size and training time |
| Library | Keras | Keras |
| Data preprocessing | In same platform | Out of Edge impulse |

Table 7.7: Model structure and performance metrics.

| Element | LSTM Model | Model from Edge Impulse |
|---|---|---|
| Data acquisition for regression model | Upload a whole dataset at once | Each data point as separate file |
| Model Type | Sequential | Sequential |
| Model structure | Based on Neural networks block | Based on Neural networks block |
| Models build up | Customized by a developer | There is a proposal of standardized inbuilt model which could be improved |
| Training time for same dataset | Long | Short |
| Regression performance metrics | To be defined by the developer | Defaulted as MSE |
| Outputs representation | Customized by the developer depending on the metrics to be presented | Defaulted and limited |

| | | |
|---|---|---|
| Activation | To be defined and mostly ReLu for regression model (Keras standardized) | Defaulted as ReLu |
| Ordinary model building simplicity | Depends on the experience of the developer | Standardized inbuilt model may perform well on the data and in case of improvement, it is easy even for less experienced developer |
| Regression output | Single Value | Class |
| Model Train loss (MSE) | 0.0295 | 0.11 |
| Model Test loss (MSE) | 0.0092 | 0.11 |
| Model performance | R2: 77% | Accuracy: 99.87% |

Table 7.8: TinyModel conversion and deployment

| **Element** | **TinyLSTM** | **TinyModel from Edge Impulse** |
|---|---|---|
| Converting the ordinary model to TinyModel | Using TensorFlow Lite | Inbuilt conversion |
| TinyML device required memory | Not assumed | Both Read only memory (ROM) and flask memory are automatically assumed. |
| Latency of the TinyModel on TinyML device | Not assumed | Automatically assumed by Edge Impulse platform. Latency equals to1ms in our case |
| Microcontroller for edge deployment | On Choice: in this case Arduino Nano BLE Sense is chosen | On Choice: in this case Arduino Nano BLE Sense is chosen |

Summarizing the comparisons in Table 7.6 to Table 7.8, both models performed well on data with minimum losses and a slight difference in losses from one model to another. In contrast, through comparing the models building up to TinyModel processes, LSTM requires significant experience in coding and requires much more training time than the Edge Impulse model. Edge Impulse limits the user to customizing their own detailed graphical presentations, but it is much more user friendly and easier for people with limited programming skills.

Coming to the deployment on edge, Edge Impulse provides some estimated information, such as required device memory and processing latency, which is not given by the TensorFlow Lite platform. From the deployment simulation, referring to the latency factor, LSTM may also reflect the higher power consumption than TinyModel_EI. Hence, TinyModel_EI is much easier to develop and a more suitable real-time model for deployment than TinyLSTM

## 7.7 Conclusion and Future works

The RNN models, specifically its LSTM, have been appreciated in the literature based on their ability to perform well on sequential problems. Looking to the RUL in the era of IoT-based predictive maintenance on the edge, LSTM development until its TinyModel deployment on the edge is compared to the new vibrant model from Edge Impulse designed to support the machine learning model on the edge. Both models are designed, trained, and tested using the real-time data collected from industrial complex equipment with the purpose to assess and adopt a suitable and easiest model for real-time predictive maintenance applications on edge.

Considering the impact of each component of the equipment on the overall health of complex equipment, the Fuzzy Logic Expert System, which is based on human expertise, is utilized to mark the maintenance priority level of the equipment by combining different states from its different components and predefined rules to detect its different health levels. The fuzzy output is used to compute the actual RUL for model training and testing.

The evaluation and deployment simulation results from both models proved good performance with slight regression loss of 0.01 and 0.11, respectively, for the LSTM and the model from Edge Impulse. Since both models perform well on real-time data, the adoption of the best model is based on the overall process from model build-up, up to its deployment on the edge and information on TinyModel deployment. The deployment on the edge is much easier for the Edge Impulse platform compared to LSTM, as LSTM: is built using TensorFlow, requires an experienced developer, takes a significant amount of time to develop, and requires TensorFlow Lite for the conversion to a TinyModel version. Therefore, we recommend the adoption of TinyModel from Edge Impulse in the era of automated and continuous real-time predictive maintenance.

To extend this work, the various conditional parameters from different components of the equipment shall be observed to have fully continuous monitoring of the equipment RUL.

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# Chapter 8:

## General Conclusion

In the highly competitive corporate world of today, each sized industry needs to pay attention to even a single advantage to attain its functioning consistency and sustainability. Among many key success factors, industrial equipment play an important role to steady production so that to extend the profitability.

Looking at the need for healthy equipment in the healthcare sector, the maintenance of hospital equipment is a vital aspect in the overall performance of hospitals. Regarding the significance of their availability to the healthcare services in Rwanda, mechanical equipment used into hospital are archaically maintained though regular preventive maintenance techniques which is not effective to avoid unplanned failure of the equipment. With this technique, maintainers do not have any perception on the health status of the operating equipment unless they conduct a specific maintenance inspection using testing tools which also implicates additional cost.

This deficiency creates some uncertainties in decision making on necessary maintenance renovation, plan of activities, and the convincing statements to the sustainable and valuable maintenance practice. Hence, there is call for a real-time monitoring system where the health of the equipment and its degradation process are continuously observed and maintained before failure occurs.

## 8.1 Summative conclusion on completed works.

To reply to the highlighted shortage in maintenance, along this research, the IoT based real-time predictive maintenance architecture that will combine various actual sensors readings together with IoT solutions to perform powerful analytics on captured data using the Integrated Advanced Analytics (IAA) model is proposed. Three main works' phases were executed to achieve the results of this project:

1. The structure of PdM Using IoT is proposed. This structure illustrates different parts of the IoT based PdM platform from data collection on the equipment, data processing and analytics as well as data transmission to the end users (Maintainers). Considering that all prediction is based on data and analytics capabilities, the embedded device to collect and process real-time data for further analytics was developed and used to collect real-time data from autoclave equipment at King Faisal Hospital. The collected data were used to build the LSTM sequential models that could be used in predictions of maintenance activities.

Since the data from different components of the equipment are independent to push the equipment down, the dataset from each part was uniquely considered to build LSTM predictive analytics models. The LSTM models' performance results showed its effectiveness in predictive maintenance with an accuracy of 90% and 96% respecting to two selected components while data collection. The prediction of future physical parameters will improve the equipment reliability, availability and reduce downtime.

2. Considering that mechanical equipment is generally a complex system made up by different components and each component may present various independent physical condition parameters, the information from single component does not summarize the health status of the whole complex equipment. Yet, the developed LSTM models are separate from each component to another and do not summarize the overall life status of the complete equipment.

   With this regard, to monitor the entire equipment may require many different models which will also imply the maintainers or addition embedded systems to assess their results and more power consumption. In addition, the full monitoring and control of an equipment's overall performance is influenced by many features depending on its components' condition parameter levels and level of hazards that may cause.

As result, to reduce the number of LSTM models and to save time used by maintainers to diagnose various health status results from different parts of the equipment and to avoid unplanned prompt downtime, also benefiting from the simplicity of fuzzy logic, an expert system was developed to enhance the maintenance activities prioritization in relation with the working status of equipment's components. These maintenance priorities shall therefore feed to predictive model as combined health status of the whole equipment for further decisions. The maintenance priorities were classified as Normal that means no need of maintenance, Moderate, High and Very High that appeals respectively for close monitoring, to perform the maintenance within few days and for immediate or closer maintenance intervention.

3. From the labeled dataset with maintenance priorities, the remaining useful life (RUL) of the equipment was computed. RUL computation was based on the real-time sequential data from operating equipment and the taken time for the equipment's component to change from good to worse health states. With purpose of real-time predictive maintenance application on the edge, adding to LSTM, we also considered the current booming on edge application model from Edge Impulse platform. Therefore, using the real-time collected data, two models (TinyLSTM and TinyModel from Edge Impulse) were developed and comparatively analyzed up to their deployment on the edge, with the purpose to assess and adopt a suitable and easiest model for real-time predictive maintenance application on edge.

The evaluation and deployment simulation results from both models proved the good performance. Thus, the adoption of the best model to be integrated in proposed structure and developed IoT device by hospitals and any other industry shall base on the overall process from model build-up, up to its deployment on the edge and information on TinyModel deployment. Meanwhile, we recommend the adoption of the model from Edge Impulse platform as it is much easier than LSTM to be deployed in the era of automated and continuous real-time predictive maintenance.

To sum-up the works done, referring to the IoT based PdM structure developed into Chapter 3:, the heart of the predictive maintenance is its part named Data acquisition, processing, and analytics. Adding to the proposed structure and developed IoT device, the Figure *8.1* illustrates the proposed processing and analytics tools.

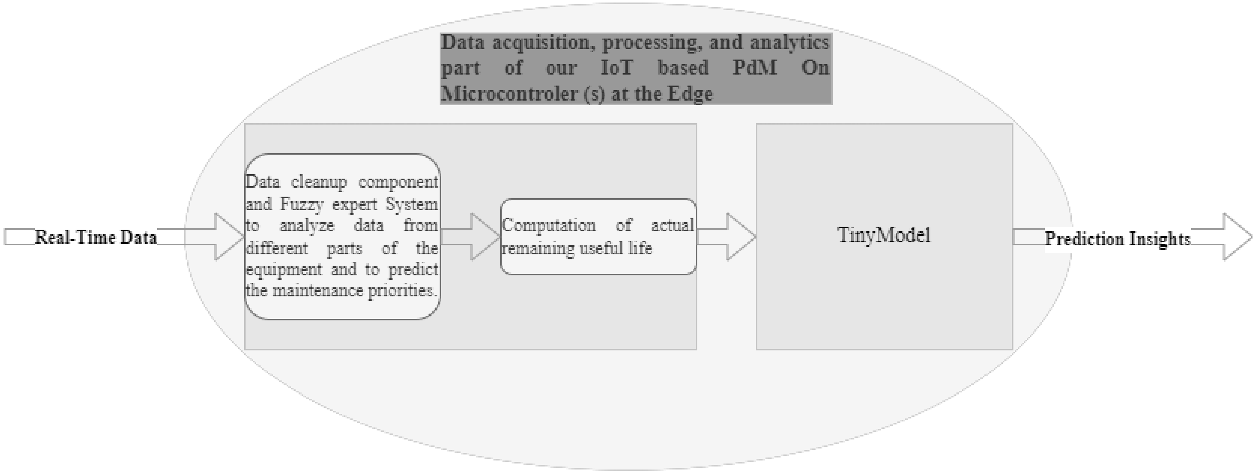

Figure 8.1. Proposed data processing and analytics tools.

We expect that this IoT based PdM with Integrated Advanced Analytics (IAA) model will support maintainers in continuous monitoring of their equipment, early fault detection, enhancing the priority making of critical maintenance activities among others, assuming RUL as well as reduce the maintenance cost through performing only needed activities with assurance on the fault causes.

Adding to this, even though this research was customized to hospitals mechanical equipment, The proposed platform is not limited only to investigated equipment; it can also be used to monitor any equipment in any hospital with similar physical condition parameters. Again, any other industry interested in real-time health status prediction of their equipment may adopt this proposed IoT based PdM structure with predictive Analytics Model. In this case, the data might be reinvested to update the analytics model for the best of RUL prediction.

## 8.2 Challenges and recommendations.

The new concept of IoT based Predictive Maintenance is new on the market. Its conceptual design requires to involve both beneficiaries and project implementers as its implementation may require setup capital. Due to this novelty, during this research, we have faced some challenges such as:

- **Beneficiary availability**: Hospitals personnel especially maintainers are always busy with regular maintenance and do not have time to learn about modern predictive maintenance practice.
- **Lack of historical maintenance data**: There are not enough records of historical maintenance performance data. Thus, the phase of such data collection phase took long waiting for the maintainers' availability for discussions on the functionality of the equipment and how they often detect faults. In addition, they don't provide full information on crucial parts of the equipment to be monitored. The researcher took time to assist maintainers' daily maintenance activities for being able to highlight and choose feasible condition parameters to be monitored.
- **Limitation of data**: The equipment owner and maintainers do not trust the researcher especially when it comes to the deployment of sensors. There are some parts of the equipment we were not allowed to access.
- **Deployment**: Due to the fact that the company intends to get the introduction on new maintenance techniques by the known outsources expert companies, there is always a lack of trust on the deployment feasibility by researcher. As a result, we were not able to test our prototype on the field.

Following the faced challenges, we recommend the university to work closely with stakeholders and to invest in their tangible practical projects that may create trust of the researcher. We also recommend hospitals and other interested companies to cooperate with researchers, together assess their project results, implementation impacts to the company and allow them to implement the research project of course with some evaluation conditions.

## 8.3 Research project deployment and extension

With the authorization of beneficiaries, to extend and implement this work, the various conditional parameters from different components of the equipment shall be observed to have fully continuous monitoring of the equipment RUL. The real-time data from operating equipment till failure shall be collected and used to determine the useful remaining time (URT) from one status to another and to provide proactive suggestions to each component of the equipment.

The structure may be adopted by other different industries with prerequisites to assess the type and nature of data to update the analytics model. The communication part could also be checked if GPRS is a good option in specific environments.

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# Appendix

## Publications

1. I. Niyonambaza, M. Zennaro, A. Uwitonze, “Predictive Maintenance (PdM) Structure Using Internet of Things (IoT) for Mechanical Equipment Used into Hospitals in Rwanda”, Future Internet 2020, 12(12), 224 – MDPI; https://doi.org/10.3390/fi12120224

2. Irene N.M., Zennaro M., Uwitonze A., Rwigema J., Rovai M., “On-Device IoT-Based Predictive Maintenance Analytics Model: Comparing TinyLSTM and TinyModel from Edge Impulse”, - Sensors, 2022, 22(14) - mdpi.com; https://doi.org/10.3390/s22145174

3. I.N. Mihigo, M. Zennaro, A. Uwitonze, “Enhancing the Priority for the Maintenance Activities of the Hospitals' Mechanical Equipment Using the Fuzzy Expert System”, International Conference on E-Infrastructure and e-Services for Developing Countries, 2022 – Springer; https://doi.org/10.1007/s41870-019-00384-w