DYNAMIC PREVENTIVE MAINTENANCE SCHEDULE BASED ON USAGE RATE FOR MEDICAL DEVICES: AN AHP AND IOT APPROACH WITH MAGNETOMETER SENSOR

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ABSTRACT

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DYNAMIC PREVENTIVE MAINTENANCE SCHEDULE BASED ON USAGE RATE FOR MEDICAL DEVICES: AN AHP AND IoT APPROACH WITH MAGNETOMETER SENSOR

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The management of medical equipment in hospitals directly affects treatment processes, healthcare service quality, and the satisfaction of patients and healthcare professionals. Proper planning can reduce the emergency priority failure rate in hospitals and ensure suitable treatment methods are used for more patients. Biomedical units in hospitals commonly use various types of software to manage this process because of the wide range of medical devices available. Managing this process poses several challenges, given the critical importance of medical devices in failures, maintenance, calibration process, medical devices cost and, idle time.

This thesis focuses on utilizing Internet of Things (IoT) technology and sensors to enhance the planning process of medical device maintenance. The magnetometer sensor is integrated with hospital data to establish a dynamic preventive maintenance schedule. The objective is to identify medical devices usage rates, optimize maintenance programs, and offer recommendations to improve hospital resource management.

In this thesis, we analyzed sensor data using the K-means clustering method to measure the usage rate of selected medical devices. The information gathered from the hospital and the utilization data measured by magnetometer sensor were used in the Analytic Hierarchy Process (AHP) to prioritize medical devices based on objective criteria. Our findings revealed that the dynamic measurement of usage data resulted in changes to the prioritization order.

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Key Words: Analytical Hierarchy Process (AHP), Internet of Things (IOT), Magnetometer Sensor, Preventive Maintenance, Prioritization of Medical Devices, Utilization Rate of Medical Devices

ÖZET

Yüksek Lisans Tezi

TIBBI CIHAZLARIN KULLANIM ORANINA DAYALI DINAMIK ÖNLEYICI BAKIM TAKVIMI: MANYETOMETRE SENSÖRÜ ILE AHP VE IOT YAKLAŞIMI

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Hastanelerde medikal cihazların yönetimi, tedavi süreçlerini, sağlık hizmetlerinin kalitesini, hasta ve sağlık çalışanlarının memnuniyetini doğrudan etkiler. Bu sürecin doğru planlanması, hastanede acil öncelikli arıza oranının azalmasını sağlanmasını ve daha fazla hastanın doğru methodlar ile tedavi olmasına olumlu etki eder. Çoğunlukla, hastanelerin biyomedikal birimleri medikal cihazların çeşitliliği nedeniyle bu süreci yönetmek için çeşitli yazılımlar kullanmayı tercih eder. Bu sürecin yönetimi, tıbbi cihazların sahip olduğu arıza, bakım, kalibrasyon süreçleri, maliyetleri ve kullanılmadıkları süreler gibi kritik önem taşıyan özelliklerinden dolayı birkaç zorluğu beraberinde getirir.

Bu tezde, tıbbi cihaz bakım planlama sürecini geliştirmek için Nesnelerin İnterneti (IoT) teknolojisi ve sensör kullanımına odaklanılmıştır. Manyetometre sensörü dinamik bir önleyici bakım takvimi oluşturmak için hastane verileri ile entegre edilmiştir. Amaç, tıbbi cihazların kullanım oranlarını belirlemek, bakım programlarını optimize etmek ve hastane kaynak yönetimini iyileştirebilecek bir öneri sunmaktır.

Bu tez çalışmasında, seçilen tıbbi cihazların kullanım oranını ölçmek için sensörlerden elde edilen verileri K-means kümeleme yöntemini kullanarak analiz ettik. Hastaneden toplanan bilgiler ve manyetometre sensorü ile ölçülen kullanım verileri Analitik Hiyerarşi Süreci'nde (AHP) kullanılarak tıbbi cihazların objektif kriterlere göre önceliklendirilmesi sağlandı. Bulgularımız, kullanım verilerinin dinamik ölçümünün önceliklendirme sırasında değişikliklere yol açtığını ortaya koydu.

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Anahtar kelimeler: Analitik Hiyerarşi Süreci (AHP), Nesnelerin İnterneti (IOT), Manyetometre Sensörü, Önleyici Bakım, Medikal Cihazların Önceliklendirilmesi, Tıbbi Cihazların Kullanım Oranı

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ABBREVIATIONS

AHP	Analytic Hierarchy Process
AIC	The Akaike Information Criterion
BIC	Bayesian Information Criterion
CMMS	Computerized Maintenance Management System
CBM	Condition Based Maintenance
ECG	Electrocardiogram
EM	Equipment Management
GA	Genetic Algorithm
Hz	Hertz
IoT	Internet of Things
mG	Milligauss
MSV	Minimum Score Value
MRI	Magnetic Image Resonance
MTBF	Mean Time Between Failure
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
NST	Non-stress Test
OEM	Original Equipment Manufacturer
PM	Preventive Maintenance
PdM	Predictive Maintenance
RFID	Radio Frequency Identification
Sec	Second
SMDP	Semi-Markov Decision Process
SVM	Support Vector Machine
TS	Total Score
TSV	Transformed Score Value
TTR	Time to Repair
USG	Ultrasound
V	Volt

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1. INTRODUCTION

Technologies that combine and transmit data on all metrics related to hospital organization and patient information are crucial to the future of healthcare services and the management of medical device resources in hospitals. Medical device management is a crucial metric that must be carefully monitored. It involves keeping track of the physical assets and their specifications within hospitals. It can directly affect treatment processes, healthcare service quality, and the satisfaction of both patients and healthcare workers.

Medium-sized to large-sized hospitals contain around 10,000 distinct types of medical equipment (Ramezani et al., 2016). Standards have been established for tracking all devices and managing medical device maintenance, calibration, and failure processes. All medical devices must comply with a complex set of safety regulations. Too many patients die each year from preventable medical errors due to malfunctioning medical monitoring equipment and inaccurate diagnoses (Yang et al., 2019).

Inaccurate diagnoses can have several causes:

- The patient ignores the diagnosis, does not follow up, or postpones necessary medical tests,
- Failed medical referrals,
- Medical equipment failures,
- Inaccuracy of the initial diagnosis.

In addition, under inadequate quality control procedures, non-standard medical equipment is produced and causes inaccurate diagnoses. For this reason, clinical and biomedical engineering departments have started to use more effective maintenance techniques for asset management (Taghipour et al., 2011).

In the ever-evolving healthcare landscape, the efficient management and maintenance of medical equipment are paramount. By digitalizing the healthcare environment, tools like the Computerized Maintenance Management System (CMMS) are critical in ensuring that medical devices have high availability.

CMMS software helps schedule maintenance, track work orders, monitor and report maintenance tasks. This software can be used for healthcare organizations in efficient management, including maintenance planning, calibration planning, and failure processes of medical equipment. CMMS software aids in the streamlining of equipment maintenance processes, monitoring inventory, ensuring compliance with regulatory standards, and minimizing downtime (CRAM, 1998).

CMMS software, its integration with Internet of Things (IoT) technology, and the potential offered by Radio Frequency Identification (RFID) technology, shedding light on how these innovations collectively contribute to the enhancement of patient care, safety, and overall operational efficiency in healthcare organizations.

IoT technology and the use of sensors support maintenance methods have enabled work to be carried out. IoT technology integration improves the monitoring, maintenance, and performance of medical devices in the healthcare sector, enhancing patient care and safety (Maktoubian & Ansari, 2019). IoT applications related to healthcare are expected to increase by an estimated 17.8% in the next five years (IoT Healthcare Market Size, Statistics, Growth Analysis & Trends (2030), n.d.). The market will be propelled by the need to automate several healthcare procedures to streamline operations, cut costs, and boost efficiency (Ltd, n.d.).

With RFID technology within the scope of IoT, integration of the sensors, which are used to track and monitor the real-time location of medical devices, can offer various opportunities to biomedical and clinical departments in hospitals, allowing them to provide a wealth of information related to medical devices. Additionally, temperature, humidity, and pressure sensors have been preferred to determine if the device functions correctly and establish traceable processes (Maktoubian & Ansari, 2019).

In hospitals, implementing fixed maintenance and calibration schedules that are not sensitive to changes and not supported by real-time data causes excellent inefficiency (Alkanat et al., 2021). Since device status is not monitored instantaneously, it causes disruptions in planning and results in a decrease in service quality. This study proposes a dynamic maintenance schedule based on a AHP model using real-time data from sensors via RFID to eliminate inefficiencies and improve service quality.

This thesis aims to develop a comprehensive strategy that evaluates the application of AHP and RFID technologies in combination with magnetometer sensors for medical devices. The objective is to determine usage rates for medical devices by attaching a tag to them, without any intervention. Subsequently, a dynamic schedule will be created based on this information. With this study, the maintenance schedule will regulate device control and idle time frequency.

As will be seen in literature review section, prior research has used historical data and device-specific information for predictive maintenance, or employed sensors for condition-based preventive maintenance. However, all sensors are not suitable for measurements in medical devices. Presenting a dynamic preventive maintenance schedule approach using a magnetometer sensor, in conjunction with actual hospital data, is the main aim of the thesis.

The main maintenance methods and their characteristics are covered in detail in literature review section. The preventive maintenance method, which is the method analyzed and selected in this thesis, is discussed in detail. The other two main steps of the thesis, RFID technology, and sensors are examined. Methodologies section explains the implementation of RFID technology with magnetometer sensors, which is one of the methods employed in this thesis. The acquired data is integrated into the AHP method, one of the multi-stage decision making methods. As a result, the impact of "utilization" data on the maintenance schedule of medical devices is analyzed.

2. LITERATURE REVIEW

This chapter explores various methods that play a critical role in maintenance management. This thesis examines three fundamental approaches to improve and optimize maintenance management: Preventive Maintenance, RFID Technology, and Sensor Technology. Each of them offers unique advantages that assist businesses in improving operational efficiency. By thoroughly examining these three maintenance approaches, this thesis aims to assist businesses in understanding their potential to enhance maintenance management and select the most appropriate strategies.

2.1 Main Maintenance Methods

Maintenance aims to extend the life, ensure the safety, enhance the efficiency, and prevent unexpected failures and downtime of the object, machine, or system. (Liao et al., 2021). Maintenance encompasses all regular and special activities required to ensure that an object, machine, or system can normally function and achieve optimum performance at the beginning of 1960 (Barlow & Hunter, 1960). According to the study conducted by Barlow and Hunter, non-periodic maintenance was usually conducted in response to failures or unexpected downtime. These maintenance activities are event-based tasks not part of a regular program. After a while, all biomedical devices were subjected to routine inspections and preventive maintenance procedures in the 1970s. “The more, the better” became the governing philosophy in many situations. It became apparent in the 1980s that many of these initiatives wasted money and significantly raised the mission risk for equipment management (EM) (Rice, 2007).

$$EM = Function + Physical\ Risk + Required\ Maintenance$$

The formula above, proposed by Rice in 2007, highlights the relationship between maintenance strategies and three essential components: function, physical risk, and required maintenance. Briefly,

- The function component represents the intended purpose or role of the equipment within a system. Maintenance strategies should align with the desired function and consider the criticality of the equipment's role.
- The physical risk component considers the likelihood and impact of equipment failures, including factors such as failure probability, consequences, safety, and environmental risks. Maintenance strategies need to address the level of physical risk associated with the equipment.
- The required maintenance component encompasses the maintenance activities necessary to ensure reliability, availability, and performance. It includes both preventive and corrective tasks based on equipment specifications, manufacturer recommendations, industry standards, and regulations.

By incorporating these three components into maintenance planning and decision-making, organizations can develop effective strategies to optimize equipment reliability, mitigate risks, and achieve the desired function.

Equipment management, asset management, or both take a more comprehensive and holistic view by considering all types of assets and their interdependencies. Equipment management, also termed asset management, is a systematic organizational effort to realize the value of assets including maintenance management according to ISO 55000,2014 (Gao et al., 2021). This approach aims to extend the lifespan of the device and lower maintenance and optimization costs (Maktoubian & Ansari, 2019). In order to obtain the best results, including higher productivity, decreased expenses, increased income, and improved return on investment (ROI), assets must be carefully managed and used. Utilization, maintenance, lifecycle management, risk assessment, and financial considerations are just a few variables considered. Asset management provides the overarching framework and strategic direction for managing assets across their lifecycle.

An asset system is a collection of procedures designed to manage and preserve an organization's assets. This system includes all the elements, processes, and resources needed to efficiently manage assets throughout their lifecycle. In the context of systems or equipment, the following are key terms related to their life cycle:

Mean Time to Failure (MTTF): MTTF is a measurement of the mean time elapsed between two component failures. It is a measure of reliability and is typically calculated based on statistical analysis or historical data. MTTF is often used for non-repairable systems or components replaced rather than repaired after failure.

Mean Time Between Failures (MTBF): MTBF is similar to MTTF, but it applies to repairable systems or components. MTBF is a measurement of the mean time between two consecutive failures, and it includes the time required to repair the system to its operational state. It is a means of estimating the expected reliability of a system.

$$MTBF = \frac{Total\ Uptime}{Number\ of\ Breakdowns}$$

Mean Time to Repair or Restore (MTTR): MTTR is a measurement of the mean time to repair a failed system or component to operating state. It includes the time spent diagnosing the problem, acquiring the necessary resources or spare parts, and performing the repair or restoration. MTTR is a measure of maintainability and is crucial in determining system availability.

$$MTTR = \frac{Total\ Downtime}{Number\ of\ Breakdowns}$$

Availability: Availability is a measurement that describes the operational time of a system or equipment. It is commonly expressed as a percentage and is calculated using the following formula:

$$Availability = \frac{MTBF}{MTBF+MTTR} * 100$$

Higher availability indicates better system reliability and maintainability.

These metrics assess systems and equipment's performance, reliability, and maintainability throughout their life cycle. By monitoring and optimizing these factors, organizations can improve system uptime, reduce downtime, and enhance overall operational efficiency. The operational viewpoint is the maintenance procedures for a system to continue performing its defined function at the expected capacity (Basri et al., 2017). Identifying the system and the units is necessary to determine its capacity. A unit or component is a part of a system that requires maintenance. There are no sub-units require maintenance (Nardo et al., 2021).

The system state is divided into two categories: single-unit and multi-unit systems. A single-unit system consists of either one or multiple components. On the other hand, multi-unit systems consist of several system units with several components (de Jonge & Scarf, 2020). In a study, the system state has been described as follows: considering a system's status is to depict it as either functioning normally, malfunctioning, or entirely failing (Basri et al., 2017). Two basic categories of operating or failing are thought to accurately reflect the system's state in the approach of another study (Lie & Chun, 1986). Considering a system's state allows us to depict it as being in one of three states: normal, operation and breakdown mode. As a result, decision-making according to preventive maintenance planning is based on the analyzing the system's state and function (Yang et al., 2019).

A repairable system is typically monitored periodically and non-periodically throughout its life cycle. A repairable system can be restored to its initial condition after failure without the need replacing the whole system (Maktoubian & Ansari, 2019).

Preventive replacement is necessary when the system's age, the number of failures, or the total damage amount surpasses certain limits. Healthcare facilities can manage the timing of repairs and replacements to reduce costs and increase operational efficiency by implementing a well-designed policy (van Staden & Boute, 2021).

A study on repair and replacement decisions was conducted in the scope of healthcare facilities. The age-old issue of repair vs replacement choices, which dates back to the 1960s and is still prevalent in many industries, was examined. In terms of modeling, replacing or repairing a portion of a multi-unit system is always possible (de Jonge & Scarf, 2020).

The delay time model refers to a state between the functioning and the failed state. (de Jonge & Scarf, 2020). The time between the first moment when a fault is detected and the occurrence of the fault is called delay time in a system. In the delay-time model, states can generally be described as good, faulty, and fail (Maktoubian & Ansari, 2019).

In general, a piece of equipment can malfunction in one of two ways (Rice, 2007):

1. By producing readings that are not accurate or calibrated,
2. The machinery breaks down.

Failures might be silent or hidden, or they can be self-announcing, meaning that no research is necessary to find them (Maktoubian & Ansari, 2019). A failure mode's importance or criticality depends on the interactions of some variables, including severity, probability, detectability, cost, and time (Rice, 2007).

It entails taking preventative action to avoid breakdowns, increase equipment uptime, and use maintenance resources best. Reactive maintenance, referred to as “breakdown maintenance” or “run-to-failure,” entails taking care of maintenance concerns and fixing equipment only after a failure or breakdown occurs. Instead of aggressively preventing problems, this strategy relies on responding to them as they occur. On the other hand, a proactive maintenance strategy tries to identify and address possible issues before they have a significant impact or cause considerable damage (Basri et al., 2017). By implementing proactive maintenance measures, organizations can enhance their assets' reliability, availability, performance, minimizing unexpected downtime and optimizing overall operational efficiency.

As shown in Figure 2.1, maintenance approaches can be classified into reactive, semi-proactive, and proactive maintenance. Preventive maintenance is performed regularly based on scheduled time, independent of the equipment's condition. However, predictive maintenance is performed when needed, not based on a specific time.

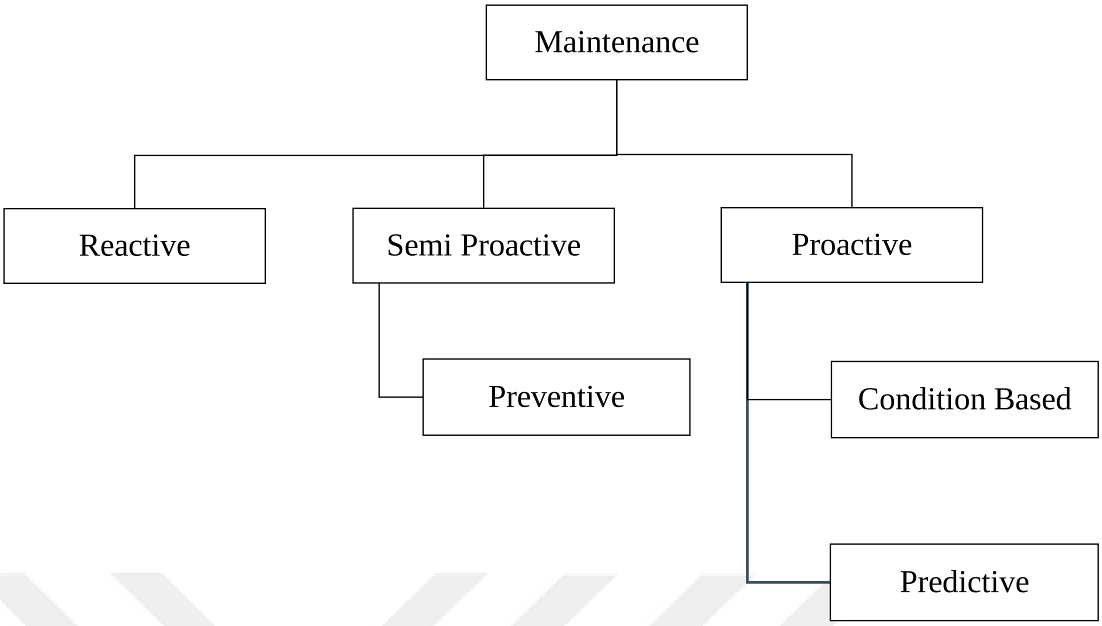

Figure 2.1 Classification maintenance approaches

Table 2.1 provides a foundational overview to compare and contrast the distinctive characteristics of each maintenance strategy, offering a starting point for understanding maintenance strategy attributes and benefits.

Table 2.1 Comparison of main maintenance approaches and properties

Method / Properties	Reactive Maintenance	Proactive Maintenance		
		Preventive Maintenance	**Condition-Based Maintenance**	**Predictive Maintenance**
Subcategories of Planning	Failure-based planning	Time-based planning, Cost-based planning, Failure-based planning	Failure-based planning	Failure-based planning, Cost-based planning
Proactiveness	Not proactive	Semi-proactive	Proactive	Proactive
Timing	After failure occurrences	Scheduled intervals	Real-time monitoring	Predictive models and real-time
Data utilization	Failure occurrence data	Historical maintenance data and schedules	Real-time data analysis and condition monitoring	Real-time data analysis
Focus	Fixing failures as they occur	Preventing failures through inspections	Monitoring specific indicators or conditions	Predicting failures before they occur
Repair or replace decision	Based on the nature and cost of failure	Based on condition assessment and cost	Based on condition monitoring and cost	Based on predictive analytics and cost
Decision-making	Reactive approach, decisions made after failures occur.	Scheduled maintenance based on predefined criteria, may involve repair or replacement decisions.	Maintenance decisions based on real-time monitoring and condition analysis.	Maintenance decisions based on predictive models and real-time data analysis.
Inadequate repairs	May lead to inadequate repairs	May address issues before they become inadequate repairs	May prevent inadequate repairs through continuous monitoring	May prevent inadequate repairs through early detection
Delayed replacements	May result in delayed replacements	May help identify the need for timely replacements	May prevent delayed replacements by monitoring asset conditions	May prevent delayed replacements through predictive insights
Objectives	Responding to equipment failures and minimizing downtime	Scheduled maintenance to minimize the risk of failures	Monitoring and addressing specific condition indicators	Anticipating and preventing failures through data analysis

2.2 Preventive Maintenance

Any maintenance performed while the system is in use is preventive maintenance (Lie & Chun, 1986). Actions for preventive maintenance should be scheduled or initiated, for example, depending on data about the time, age, usage, or condition.

The three aspects of the PM planning are:

- Determining the objectives or purpose,
- Providing descriptions of the system's state in terms of both its importance and functions,
- Categorizing the methods that aid in identifying the best solutions for the highlighted issues.

There are three strategies of planning-based PM: time-based, cost-based and failure-based planning (Basri et al., 2017). Table 2.2 provides detailed information about these strategies and the studies carried out explained in detail below.

a) Time-based Preventive Maintenance

The preventive maintenance approach based on time schedules maintenance activities at set intervals. Various names may be used to refer to this approach in studies:

- Calendar-based preventive maintenance
- Scheduled preventive maintenance
- Fixed-time preventive maintenance
- Time-dependent preventive maintenance

Time-based maintenance can be considered for devices with an average criticality score (Taghipour et al., 2011). A study considers age-based maintenance for a unit with a failure rate that increases over time. The Poisson process models the number of events that occur in a given time, such as equipment failure.

Table 2.2 Preventive maintenance strategy comparison: time-based, cost-based and failure-based

Parameters	Time-Based PM	Cost-Based PM	Failure-Based PM
Definition	A planning-based approach that schedules maintenance based on fixed time intervals.	A planning-based approach that aims to minimize maintenance costs while meeting availability requirements.	A maintenance strategy that monitors the actual condition of an asset and performs maintenance based on indicators.
Objective	Schedule maintenance activities at fixed time intervals.	Minimize overall maintenance costs.	Perform maintenance when specific indicators show decreasing performance or upcoming failure.
Approach/model example	Age-based maintenance policies for a finite time horizon.	Genetic algorithm (GA) to optimize PM schedules.	Semi-Markov decision process (SMDP) to minimize expected cost over a planning horizon.
Benefits	Suitable for devices with average criticality score.	Significant cost savings	Prevents unnecessary maintenance and reduces the risk of unexpected failures.
Considerations	Known model parameters or uncertain lifetime distribution.	Timing and frequency of PM activities.	Monitoring actual condition and specific indicators for maintenance decision-making.
Key metrics	Time intervals for maintenance activities.	Cost of failure, cost of preventive maintenance.	Indicators showing decreasing performance or upcoming failure.
Results	Improved system availability	Decrease in overall maintenance costs.	Reduced total expected cost of the system.
Comparison with other	Considers age-based maintenance policies and failure rate over time.	Outperforms conventional approaches to PM schedule optimization.	Outperforms other CBM policies for balanced systems.

These failures occur randomly throughout the lifespan of a given product and are therefore used in age-based replacement models to optimize preventive maintenance strategies. (Cha et al., 2017).

Another study aims to determine the structural outcomes of the most effective usage-based approaches. The study investigates schedules that can be amended based on corrective maintenance or maintained regardless of the number of failures between routine maintenance procedures. The research aims to analyze the data using various probability distributions to model the number of failures, time to repair (TTR), and the number of failures within a 72-hour period. The frequency analysis results demonstrate the most common reasons for infusion pump failures in the existing dataset, such as “No Problem Found,” “Physical Damage,” and “Random Failure.” The sensitivity analysis results demonstrate that the daily operating revenue and warranty duration impact the decision to repair or replace (Liao et al., 2021).

In a study, usage intensity, also can be called as utilization, was defined as the relationship between average consumption and the number of patients seen per hour (Taghipour et al., 2011). A device often used may become worn out and damaged, requiring more frequent maintenance. On the other hand, a low utilization rate brought on by prolonged inactivity may result in problems and damage to specific components. Therefore, frequent periodic maintenance is required for all devices, including those with moderate usage rates.

Another paper introduces a model for prioritizing medical equipment preventive maintenance schedules using an alternative methodology. The criteria and sub-criteria employed in the study include function, age, maintenance requirements, utilization level, and failure rate. The model has been tested on 200 units of medical equipment, encompassing 70 distinct device types. The results of the research suggest that there is a need for urgent preventive maintenance for 15% of the cases, while a higher priority should be given to 19%. Furthermore, 30% of the cases require medium priority, whereas 27% need low priority, and 9% necessitate the least priority for preventive maintenance (Saleh et al., 2015).

b) Cost-based Preventive Maintenance

Cost-based preventive maintenance is a planning-based approach that aims to minimize maintenance costs while meeting availability requirements. This approach may be referred to by various names in studies:

- Risk-based preventive maintenance
- Economical preventive maintenance
- Cost-effective preventive maintenance

A study presents a novel approach to improving the series-parallel systems' preventive maintenance (PM) schedule. The proposed method utilizes a genetic algorithm (GA) to reduced PM cost, maintaining the system's availability at prescribed criteria. The GA computes the optimum PM time vector to optimize the PM timing for each system segment. The outcome is a meaningful reduction in the total maintenance expenses. Furthermore, the study demonstrated that the GA-based PM schedule optimization outperformed conventional techniques. By identifying more effective PM schedules in terms of timing and frequency of activities, this approach can potentially reduce overall maintenance costs by up to 20% (Samrout et al., 2005).

c) Failure-based Preventive Maintenance

Failure-Based Preventive Maintenance is an approach to maintenance whereby the present condition of an asset is observed and maintenance is then performed according to particular indications or signs of likely failure. This approach may be referred to by various names in studies:

- Condition based preventive maintenance
- Condition-sensitive preventive maintenance
- Failure-predictive preventive maintenance

Condition-based maintenance (CBM) is a strategy that objectively analyzes an asset's current state to determine necessary maintenance. Maintenance should only be conducted under specific indicators showing decreased performance or impending failure, according to CBM principles. Prior implementation of CBM requires condition monitoring, an intervention that partially determines the unit's status (Maktoubian & Ansari, 2019).

CBM allows for real-time component monitoring, which assists in determining whether to repair or replace a component. Since it has been shown that some medical equipment, such as scanners and radiation equipment, is malfunctioning, preventive maintenance programs and real-time monitoring systems can be useful (Williamson Sr., 2014).

In a study, a system becomes imbalanced once a specific component's deterioration level reaches a critical point or when there is a certain threshold exceeded in the difference between the deterioration levels of two symmetric components (Wang et al., 2021). The study illustrates both failure-based and cost-based preventive maintenance. PM thresholds are determined by minimizing system maintenance costs in a Semi-Markov Decision Process (SMDP) to prevent such failures (Wang et al., 2021). An SMDP is a stochastic model that enables decision-making under uncertainty. In the context of CBM, the SMDP model takes into account the following variables:

- Availability: The probability that a system will be able to perform its required function at a given time.
- Reliability: The likelihood that a system will not fail within a specific time frame.
- Cost of failure: The cost of a system failure, including the cost of lost production, the cost of repairs, and the cost of safety incidents.
- Cost of preventive maintenance: The cost of inspecting and maintaining a system, including the cost of labor, materials, and downtime.

The objective of the SMDP model is to minimize the total expected cost of the system over a finite planning horizon. The SMDP model is solved using a dynamic programming algorithm. The dynamic programming algorithm works by iteratively solving a series of subproblems. Each subproblem considers the possible deterioration levels of the components in the system and the possible maintenance actions that can be taken.

Another study focused on evaluating the performance of a maintenance model using data from an original equipment manufacturer (OEM). The researchers wanted to determine whether deviating from the approved periodic maintenance schedule was necessary based on their findings. The study used a Poisson generalized linear model and aggregated data from different machine classes to improve predictions of machine failure behavior when historical data is unavailable. The researchers found that their proposed strategies were, on average, 5% more effective than existing strategies (Van Staden et al., 2022). Previously, a study showed that recent machine failures increase the probability of subsequent problems. Therefore, the availability of historical failure and maintenance data is critical. The study concentrated on collecting prescriptions for unscheduled preventive maintenance and accelerating regular periodic maintenance procedures (Deprez et al., 2020).

After analyzing the potential usefulness of such data, the study provided policy recommendations for different combinations of machine classes and usage intensities. In addition, the suggested policies could identify underperforming or frequently failing equipment, allowing for proactive maintenance. This approach could save up to 44% over relying solely on scheduled periodic maintenance.

The results from various studies underscore the need for a customized and comprehensive approach, as evidenced by the identification of specific devices requiring varying levels of priority in preventive maintenance efforts. These findings contribute to the ongoing efforts to enhance reliability, extend equipment lifespan, and optimize resource allocation in the maintenance of medical equipment.

2.3 Preventive Maintenance with RFID

RFID technology is based on the use of wireless communication technology to unique identify objects or people using tags. Its foundation is built on radio signals and radar technology, with its first prominent usage dating back to World War II. The RFID system consists of three crucial parts: a tag, a reader, and a controller system.

The U.S. Food and Drug Administration (FDA) advises against using wireless devices without a license in some frequency ranges, including the Industrial, Scientific, and Medical bands (Lie & Chun, 1986). Bluetooth Low Energy technology is one of these bands (Williamson Sr, A. 2014). Briefly stated,

- The RFID tag: An RFID tag, also called a transponder, consists of a semiconductor chip, antenna, and battery, depending on the tag type. An RFID tag with a battery or an internal power source is classified as an active tag. The tag uses the power source to obtain the necessary power to transmit data to the reader when data needs to be transmitted. Active tags can communicate with readers over long distances and send data (de Jonge & Scarf, 2020).
- The RFID reader: RFID reader consists of an antenna, a radio frequency electrical element, and a control electronics element. A reader can communicate with multiple tags and can repeatedly scan information on multiple products.
- The RFID controller: RFID controller consists of a computer workstation with a database and management software. When an object with an RFID tag goes into the communication area of the reader, the reader tells the tag to send the stored data. After the reader accumulates the data from the tag, the reader sends the data to the RFID controller by a network connection.

The RFID tag and reader use a specific radio frequency to communicate. In the healthcare industry, passive RFID tags typically operate at 13.56 Hz, while active or passive tags use the 900 MHz ultra-high frequency band.

RFID technology offers advantages such as a broad reading range, effortless data transmission between a receiver and transmitter, secure data storage, and cost and time efficiency. RFID provides a higher rate of process automation with better data integrity and accuracy, enabling real-time response capabilities.

The use of RFID is subject to some limitations. One of these limitations is reader interference, which occurs when several readers are used simultaneously and causes signal interference and decreased tag identification accuracy. Environmental variables can also impact RFID system performance, including electromagnetic interference and physical obstructions that interfere with communication between the reader and the tags. The positioning of the tags about the reader might affect the signal strength and readability since tags that are too close or far away from the reader may have trouble transmitting data. The read range and effectiveness of the RFID system can also be impacted by the separation between the reader and the tags and the reader's power level. These limits must be considered and efficiently addressed to enable trustworthy and precise tag detection in RFID systems.

Most RFID applications in healthcare are centered on locating and monitoring healthcare supplies, equipment, and personnel. The primary goal of these applications is to digitize the manual process. RFID technology tracks and monitors medical assets, preventing theft and equipment loss (Williamson Sr, A. 2014).

For the past 18 years, RFID has generated interest in healthcare due to its ability to simplify the identification process, track and manage medical resources, improve their utilization, and reduce annual costs by preventing the purchase of unnecessary equipment (Williamson, n.d.).

Additionally, doctors and nurses can access equipment more quickly and efficiently to treat patients by tracking medical equipment. The result is increased staff productivity and treatment of more patients. Also, small hospitals can save up to one million dollars annually (de Jonge & Scarf, 2020).

Effective monitoring of medical equipment requires the capacity to make decisions in real time. Nowadays, all healthcare disciplines have new chances to improve data gathering. Data can be collected from medical device sensors to ensure the accuracy and reliability of medical devices and to identify device-related hazards. The monitoring of devices depend on real-time data processing. Implementing an autonomous integrity monitoring system with IoT capabilities can significantly improve these procedures.

Failure analysis requires the real-time detection of appropriate parameters using IoT technology and machine learning techniques to predict and categorize healthy and failing equipment conditions (Rice, 2007).

According to a study conducted in 2020, the use of predictive maintenance was expected to increase to 83% with the adoption of IoT (Shamayleh et al., 2020). Additionally, PdM is expected to decrease costs by 12%, increase uptime by 9%, reduce threats to safety, health, environment, and quality by 14%, and extend asset lifetime by 20% (Williamson Sr., 2014).

Predictive maintenance management of medical equipment depends on collecting relevant parameters in real-time using IoT technology and machine learning tools, like Support Vector Machine (SVM), to estimate and classify equipment status as healthy or faulty.

2.4 Medical Equipment Maintenance with Sensor

Medical equipment's dependability and accuracy are crucial for providing high-quality care. Sensor technology has improved the maintenance of these vital components by offering real-time monitoring, diagnostics, and adaptive capabilities. This section examines sensors' crucial role in maintaining medical equipment, emphasizing some examples and the radical changes they have made to medical procedures.

In a study, a sensor-based system for computing maintenance costs and residual value of medical equipment was built to improve the efficacy and financial success of medical equipment recycling. This system aims to precisely predict maintenance costs and residual value, enabling recycling businesses to make well-informed decisions regarding the acquisition and disposal of equipment using information from sensors attached to medical equipment (Williamson Sr, A. 2014).

Vibration, sound pressure, motor current, magnetic field, and temperature variables are mostly measured for predicted maintenance applications. Examples of potential sensors are barometers, light sensors, magnetometers, moisture sensors, proximity sensors, and thermometers (Liu, 2017).

According to the results of a study, most of the devices examined in a study of over 150 anesthetic machines and auxiliary monitors across 45 hospitals had significant problems that could result in severe accidents. Information on current, humidity, light, pressure, temperature, and vibration can be continuously collected from the equipment using self-monitoring technology. There is an example of the usage of magnetometer sensors with infusion pump. The infusion rate set to the medical device is expected to affect the measured waveform from the magnetometer sensor. As the infusion rate increases, motor's speed increases (Engku Ariff et al., 2021). The magnetometer sensor is expected to monitor the strength of the magnetic field produced by the motor at varied infusion rates. Although the magnetic flux strength fluctuation is not perfect, it can be used as a general measure of how well a medical device is being used (Shamayleh et al., 2020). The outcome shows that a magnetometer sensor can track the degree of usage of the understudied infusion pumps.

Parameters like current, vibrations or voltage are measured to collect relevant data for predictive maintenance. Signal processing techniques, such as filtering, amplification, correlation, and compression, minimize artifacts and noise levels to ensure high-quality signals. Commonly used filtering techniques, such as wavelet and Fourier transformation, are used to reduce noise and enhance signal characteristics. The SVM prediction model and ROC curve analysis is commonly employed in predictive maintenance to classify equipment status and assess the model's performance.

In a thesis, the magnetic field sensors are used specifically for magnetic resonance imaging (MRI) machines. These sensors were used to determine the strength of the magnetic field. Based on sensor data, the K-nearest neighbor (k-NN) technique and the multiple linear regression approach were used to anticipate maintenance costs and residual values (Yang et al., 2019).

3. METHODOLOGIES

Chapter 3 presents the time-based dynamic preventive maintenance schedule specifically designed for medical devices. To achieve this, we harnessed the capabilities of a magnetometer sensor and integrated it with an active tag. We used an active tag with a battery and RFID technology capable of continuously transmitting data to the signal receiver. The steps we followed are presented in the flowchart in Figure 3.1.

As seen in Figure 3.1, data collected from some medical devices conducted in a hospital was analyzed, and it was determined that utilization data for selected medical devices could be extracted. The recorded data was segmented into 24-hour sets and analyzed. As a result of this, K-means clustering method as a machine learning model was identified, and it was used to make predictions for subsequent days.

The obtained utilization data was used in the analytic hierarchy process method, which is frequently used in prioritization studies of medical devices, to ensure that the thesis is dynamic. It is suggested that the maintenance plan of the medical device can be brought forward, carried out as planned or postponed with the Transformed Score Value (TSV) calculated as a result of the AHP method. Literature TSV score ranges were adjusted for this thesis study to classify when maintenance is necessary. (Taghipour et al., 2011).

The characteristics of the sensor and the specification of the tag used in this thesis are examined in Section 3.1. Section 3.2 mentions the K-means clustering method used to analyze the data. Section 3.3 includes a detailed discussion of AHP methods. As a result of AHP methods, TSV scores were calculated according to the features of the medical device that were selected for the thesis. Also, we calculated all possibilities according to the parameters of medical devices, described in Appendix B Table 4.4, and recommended updating the medical device maintenance schedule.

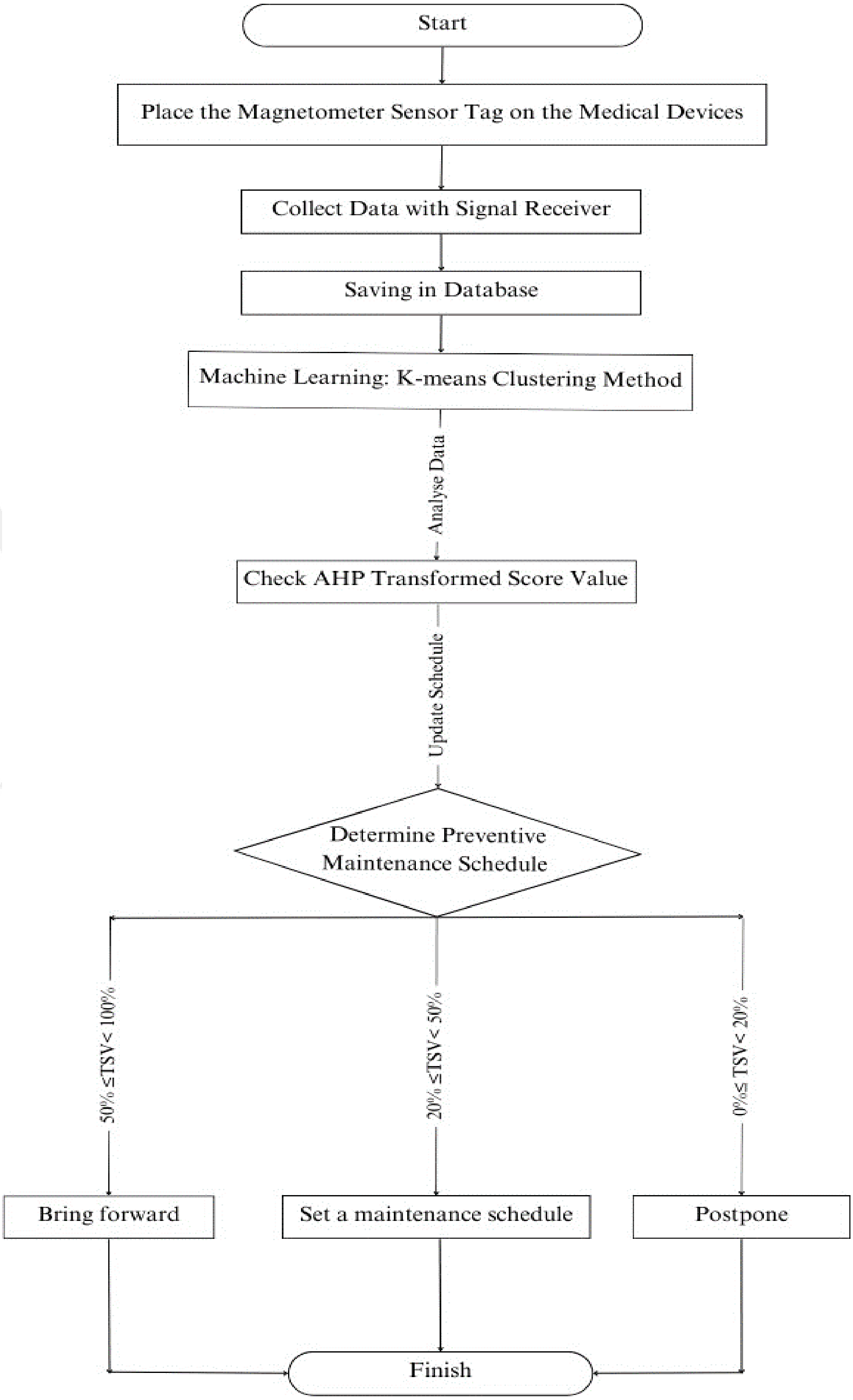

Figure 3.1 Flowchart of dynamic preventive maintenance schedule development process

3.1 Material Information

At the beginning of this section, some background information is provided on the magnetometer sensor as a main material, followed by an explanation of its area of usage. The main focus of this investigation was the IIS2MDC, which is a magnetometer sensor code and a three-axis digital magnetic sensor with outstanding accuracy and extremely low power consumption. The features include three magnetic field channels, a dynamic range of about 50 gauss, and 16-bit data output for accurate readings. This sensor is built for a variety of applications. Anti-tampering systems, positioning sensors, presence detection, magnetic switches, and changeable magnetic field monitoring are just a few of the sectors it finds use in (IIS2MDC - STMicroelectronics, n.d.)

The IIS2MDC offers versatility in power supply and operates within a voltage range of 1.71V to 3.6V. It can attain sampling speeds of up to 150 Hz in single-measurement mode. Hard-iron adjustment, a programmable interrupt generator, self-test capability, and an inbuilt temperature sensor enhance its performance and versatility. The IIS2MDC, housed in a plastic Land Grid Array (LGA) package, functions effectively throughout a broad temperature range of -40 °C to +85 °C. Accuracy of the sensor is ±7 mG/ Least Significant Bit (LSB). "±7mG/LSB" indicates that for each LSB change in the sensor's digital output, the magnetic field sensitivity or resolution is approximately seven mG. The tag, enabling real-time asset tracking, broadcasts the Bluetooth 5.1 compatible beacons.

The IIS2MDC magnetometer sensor also has applications in magnetic field-based detecting systems in the medical industry. This sensor is employed in medical applications, aiding in stroke rehabilitation, and developing real-time monitoring systems (Gao et al., 2021). In assistive technology, the sensor is utilized for indoor navigation systems, which is particularly beneficial for individuals with visual impairments (Ivanov, 2010). These studies aim to enhance medical diagnostics, patient monitoring, and accessibility for individuals with specific needs highlighting the sensor's versatility and significance in these domains.

The primary reason for selecting this sensor is that it does not affect the medical devices in any way. For this reason, it was analyzed with a magnetometer sensor to determine whether the magnetic field change that the medical device would create while running could be detected.

Another point to explain in this section is the tag's properties on which the magnetometer sensor is placed. A magnetometer sensor has been positioned within a tag connected to the signal receiver via Bluetooth. Figure 3.2 shows the microscope image of the magnetometer sensor placed in the tag.

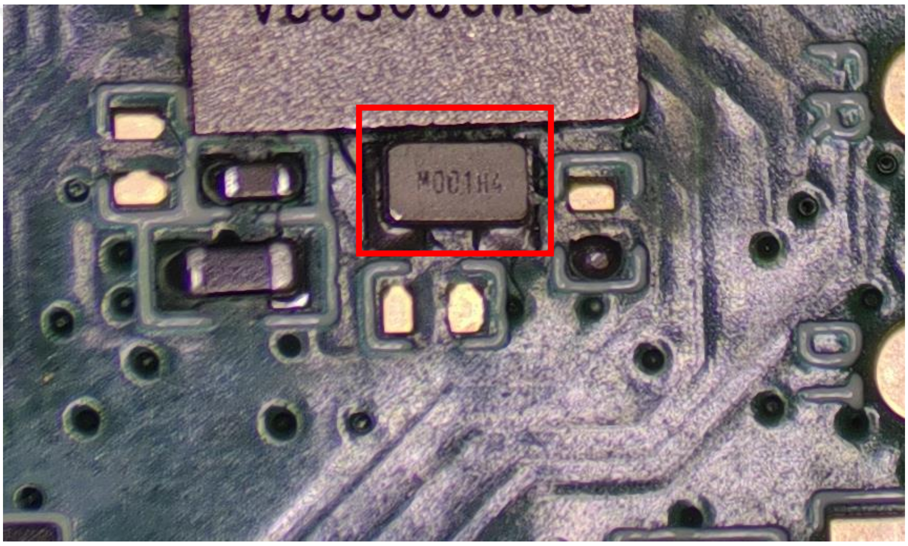

Figure 3.2 Image of the magnetometer sensor placed inside the tag

The tag can be affixed to assets using double-sided tape. Remote firmware and configuration updates are also capabilities of the tag. The tag's specifications for assets designed specifically for healthcare are shown in Table 3.1. The tag was placed in designated positions on selected medical devices with double-sided tape, and a tag code was determined for each tag to avoid confusion. The tags attached to the Electrocardiogram (ECG) and infusion pump are shown in Appendix C, Figure C.1 as an example. The frequencies of the tags are 1 Hz and labeled as follows: A1A5A6, A2A5A6, E0AAB2, E0AAF5, E0AB44. When the preliminary studies were completed, tags were fixed to medical devices for long-term data collection. The tag A1A5A6 is fixed to the ECG device, A2A5A6 is fixed to the infusion pump, E0AAB2 is fixed to the Non-Stress

Test (NST) device, E0AB44 is fixed to the defibrillator device, and finally, the device E0AAF5 is fixed to the Ultrasound (USG) device. The database records every bit of information the tag delivers to the signal receiver. Appendix C, Figure C.2, shows the signal receiver used. After the tests were completed, these tags were fixed to the selected medical devices, and long-term data was taken.

Table 3.1 Tag’s key elements and specifications information

Key Elements	Specifications
Outer Dimension	40 mm width, 35.5 mm height, 14.50 mm thickness
Weight	17.2 gram
Material	Polycarbonate.
Battery Voltage	3V
Frequency Range	2400-2480 Hz.
Sensitivity	-98.6 dBm
Maximum Indoor Range	30 meters

The data recorded from the sensor contains timestamp information. Also, the magnetometer sensor receives three data: Field X, Field Y, and Field Z. Field X represent the intensity information of the magnetic field measured on the x-axis, Field Y from the y-axis, and Field Z from the z-axis. Recorded data from the sensor can be positive or negative and it represent directional information. Attention has been paid to placing the tag in the area closest to the engine the device has.

3.2 The K-means Clustering Method

In this section, we present the findings derived from the tests conducted at the hospital as a preliminary studies and explain why the K-means clustering method was used. The data obtained from the sensor must be processed with a method and must be estimated. Because of environmental factors in the hospital, an approach such as the devices running at a constant value only based on actual data has not been made. In line with the tests performed, it was decided to use the K-means clustering method by using the standard deviation values of the data. K-means clustering is a unsupervised machine learning approach that divides objects into K classes based on a set of attributes. The goal of K-means clustering is to group similar data points while minimizing the variance within each cluster (Javidan et al., 2023).

The following steps can explain the K-means clustering algorithm:

a) Data points are assigned to clusters that minimize the distance between the cluster centers and the data points within the cluster,

b) The cluster centers are computed by averaging all data points within the cluster,

c) The cluster centers are computed again,

d) Steps b and c are repeated until convergence is achieved.

In the following, the tests performed in the hospital environment are described in detail. The K-means clustering algorithm result, which was applied to the test data, was compared with the actual data to evaluate its accuracy. The K-means clustering method was then applied to all of the acquired data, and examined.

After placing tags on the selected medical devices, the data was observed during dependent real-time tests. Dependent real-time test means instantaneous observation of the incoming data by operating the device in the hospital environment and recording the “running” and “non-running” situations with timestamps. A control panel was developed to view data at that moment. The results of the two tests performed are shown in detail as examples. The first test was performed on the NST device. Timestamp and status information for the test are shown in Table 3.2.

Table 3.2 Test times and conditions performed on the NST device on 03.10.2023 by using the A1A5A6 tag

Test Time	State
15.00:00	Tag was placed
15:03:20	NST was run
15:08:00	NST was closed
15:10:08	Tag was removed

Figure 3.3 illustrates the standard deviation of actual data obtained as a result of these tests. The standard deviation of the data collected from tag A1A5A6 is calculated using a rolling window of size 10 for this dependent test. This rolling process allows you to observe variations and trends in the standard deviation across the entire dataset.

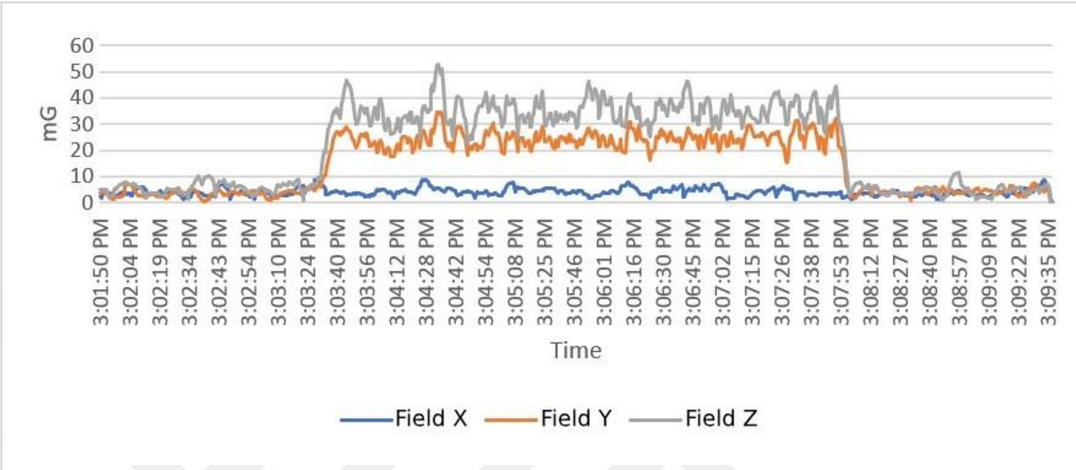

Figure 3.3 Standard deviation data obtained from the sensor during the test performed on the NST device on 03.10.2023 using the tag A1A5A6

Figure 3.4 shows K-means clustering result graphs. In Figure 3.4:

- Std. Dev. of Field X, Std. Dev. of Field Y, and Std. Dev. of Field Z shows the standard deviation change in the respective axes of the actual data from the sensor,
- Operation Status shows the moments when the device is running as a result of K-means clustering,
- Arranged Opr. Status shows the corrected version of the operation status with Algorithm 1, which will be discussed.

Inaccurate data can come from sensors that are affected by the conditions of the hospital and the environmental. Due to these erroneous data, the standard deviation values may increase momentarily. Therefore, K-means may cluster these data as "running". "Algorithm-1" was used to correct this erroneous behavior. A pseudocode, "Algorithm-1" is developed to correct this erroneous behavior, the detail given below. It is aimed to prevent a false-positive situation that may occur when instantaneous standard deviation changes are encountered. As a result, the runtime of the device is calculated more accurately.

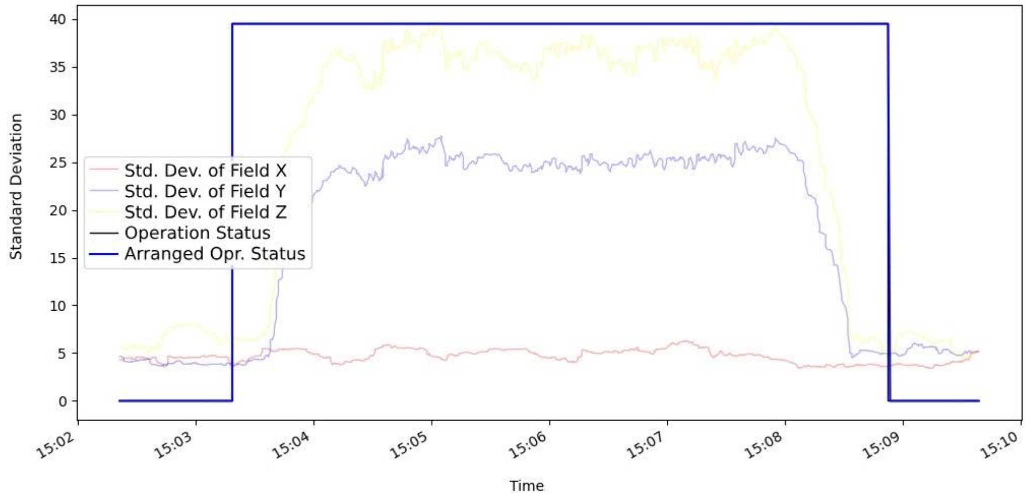

Figure 3.4 K-means analysis result of the test performed on the NST device on 03.10.2023 using the tag A1A5A6

In Figure 3.4, the Arranged Opr. Status is shown in dark blue, and as can be seen from the figure, the area labeled as device "running" between 15:03 and 15:09 is framed. This test is a dependent test, and the result is consistent with the times recorded in Table 3.2. The same dependent test was performed for the infusion pump. Timestamps and status information of the test are shown in Table 3.3.

Table 3.3 Test times and conditions performed on the infusion pump device on 03.29.2023 using the tag E0AAB2

Test Time	State
19:33:00	Tag was placed
19:35:00	Infusion Pump was run
19:37:30	Infusion Pump was closed
19:39:50	Infusion Pump was run
19:45:10	Infusion Pump was closed
19:47:32	Tag was removed

Figure 3.5 illustrates the standard deviation of actual data obtained as a result of these tests. The standard deviation of the data collected from tag E0AAB2 is calculated using a rolling window of size 10 for this dependent test. Figure 3.6 shows K-means clustering result graphs. In Figure 3.6, the device was found to be “running” between 19:35 and 19:43, and its area is indicated by the frame. The result is consistent with the times recorded in Table 3.3 and Figure 3.5.

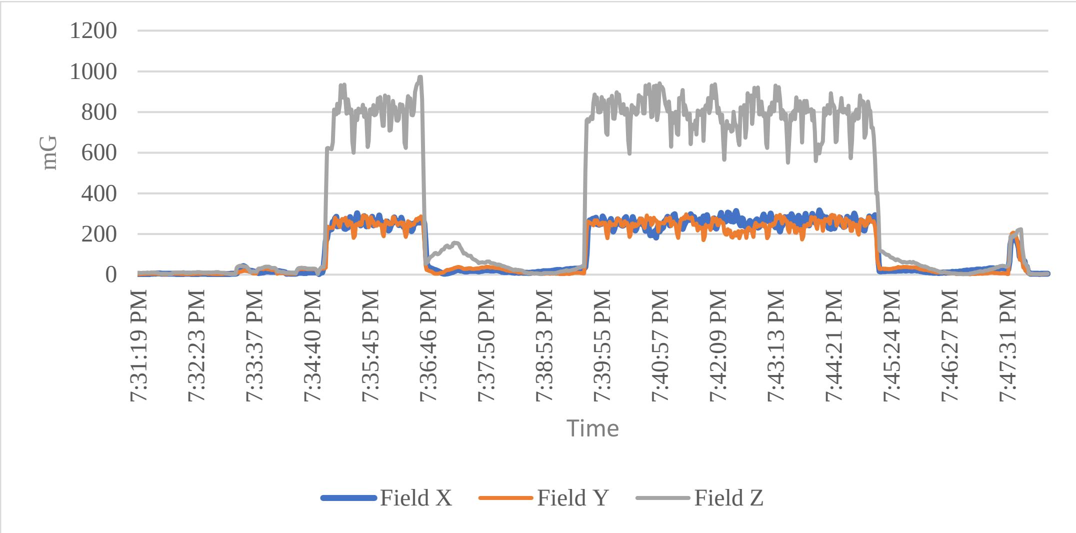

Figure 3.1 Standard deviation data obtained from the sensor during the test performed on the infusion pump device on 03.29.2023 using the tag E0AAB2

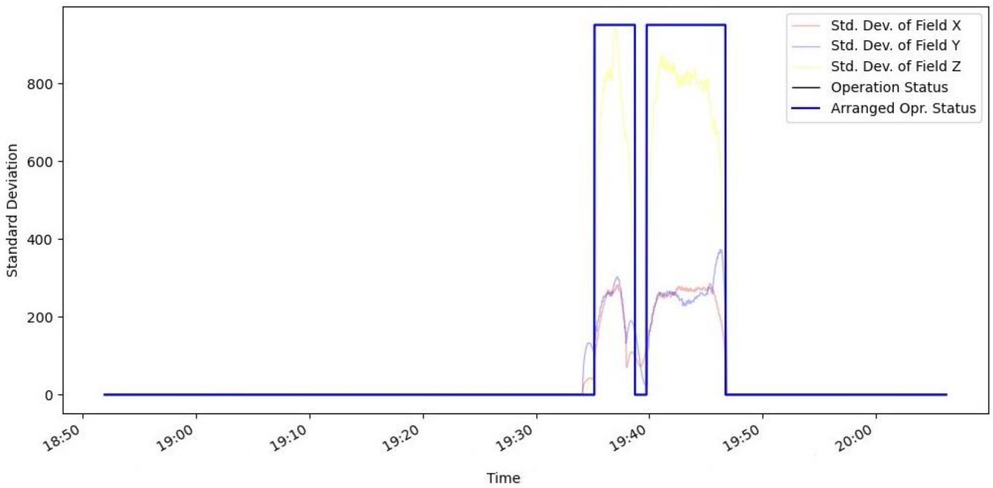

Figure 3.2 K-means analysis result of the test performed on the infusion pump device on 03.29.2023 using the tag E0AAB2

During the conducted dependent tests, while medical devices were running (not just plugged in or powered on, but actively performing functions) in the same environment, any variations in the data received from the sensors were monitored. As a result of these observations, it was noted that the frequency of data transmissions increased, and deviations became more pronounced during the moments when the tested medical devices were running. This observation highlights that these deviations were not merely tied to the devices being plugged in or turned on but were specifically associated with their active operational states.

All data recorded in a database. The standard deviation of the data collected from each tag is calculated using a rolling window of size 1000. This means, for example, when calculating the standard deviation in actual data, the first data is calculated with the formula for the standard deviation of data between 1-1000, then the second data is calculated with the formula for the standard deviation of data between 2-1001, and the resulting number of standard deviation data is 1000 less than the number of actual data. Then, these standard deviation values are clustered using the K-means clustering method. In the above dependent tests, we determine the rolling window of size as 10 because the test duration was short and the amount of data was, therefore, low.

The K-Means algorithm can group these examples based on Euclidean distance, which is calculated using the equation one (Leskovec et al., 2014):

$$Distance = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2} \qquad 1$$

The collected data was analyzed based on standard deviation values due to the high variability introduced by the hospital environment and device mobility. This approach was adopted due to the dynamic nature of the hospital setting and the device operations.

As previously stated, there may be inaccuracies in K-Means clustering result due to environmental factors. To avoid these, a corrective algorithm has been created as a solution. The pseudocode of the algorithm is given in detail in "Algorithm-1". The algorithm takes the output from K-Means clustering and two required thresholds. The required thresholds are: first, average utilization time of a device per a patient, called "thWorking", and second, the minimum amount of time each machine has to go between two working processes, called "thMin".

When the algorithm starts, it first examines the start and end times of the running times in the loop. If the time between the end time of run t and the start time of run t+1 is less than "thMin", then runs t and t+1 is combined, and the loop is examined again. During merging, the start time of run t and the end time of run t+1 are taken and merged. The run time is recalculated. The running times are then analyzed. If the working time is less than "thWorking", it is marked as an anomaly and removed from the output.

"thWorking" time default value is five minutes. However, "thWorking" time was determined specifically for each device, according to the function of each device and by obtaining information from nurses. This time was determined as five minutes for ECG, 25 minutes for infusion pump, 15 minutes for NST, a minute for defibrillator, and five minutes for ultrasound.

In the K-means clustering method, a specific reference day is required to predict how much the device is running every day, taking data from the sensor. The results of the K-means clustering method were compared with the data obtained from the hospital, and reference days were determined. The following is the reference date selected for each medical device in Table 3.4 and the result obtained when the devices were running. Table 3.4 can be explained as follows: The ECG device with tag code A1A5A6 was running on 05.10.2023. The standard deviation value resulting from the K-means clustering of the 24-hour data on this date is a maximum of 159.35 mG on field Z.

The data shown in Table 3.4 are the standard deviation values of the data obtained on days when the devices are known to be operating. When the devices are running, the standard deviation data increases for a long time and the data oscillates. Table 3.4 shows the maximum and minimum points during this oscillation. "Mean" column shows the average of all data obtained on the specified date.

Algorithm 1 Pseudocode for MergeAlgorithm

```
Input:
    - outputData: The output data obtained from the K-Means algorithm shows the intervals in which the machine runs.
    - thMin: The minimum time expected to elapse between two run times (The default is 10 minutes)
    - thWorking: The minimum working time in minutes for each machine (The default is 5 minutes)

Output:
    - outputData: The output data after processing in the algorithm.

procedure MergeAlgorithm(outputData, thMin, thWorking)
    change ← 0

    while change = 0 do
        change ← 1
        sorted_keys ← SortKeys(outputData)
        delete_keys ← []
        i ← 0

        for k in sorted_keys[: −1] do
            e ← ParseDateTime(outputData[k]['end_time'])
            q ← sorted_keys[i + 1]
            s ← ParseDateTime(outputData[q]['start_time'])
            if (s − e) then ≤ thMin
                change ← 0
                outputData[k]['end_time'] ← outputData[q]['end_time']
                delete_keys.append(q)
            i ← i + 1

        for k in delete_keys do
            DeleteKey(outputData, k)
    delete_list ← []

    for k, v in Iterate(outputData) do
        e ← ParseDateTime(v['end_time'])
        s ← ParseDateTime(v['start_time'])
        if (e − s) < thWorking then
            delete_list.append(k)

    for k in delete_list do
        DeleteKey(outputData, k)
    j ← 0

    for k in Sort(outputData) do
        if j ≠ k then
            Set(outputData, i, outputData[k])
            DeleteKey(outputData, k)
        j ← j + 1
    return outputData
```

Table 3.4 “Reference data” standard deviation rates in mG

Device Name	Tag	Date	Field X			Field Y			Field Z		
			Max.	Min.	Mean	Max.	Min.	Mean	Max.	Min.	Mean
ECG	A1A5A6	05.10.23	139.16	2.69	15.45	159.35	2.63	15.79	159.35	2.79	18.33
Infusion Pump	A2A5A6	05.02.23	65.69	2.62	7.44	39.27	3.09	5.95	39.27	2.76	10.25
NST	E0AAB2	07.06.23	156.21	3.52	11.27	76.92	2.96	10.75	76.92	9.33	21.04
Ultrasound	E0AAF5	07.11.23	135.29	2.50	13.00	119.70	2.44	13.07	119.70	2.45	20.93
Defibrillator	E0AB44	06.15.23	5.72	3.13	4.31	8.71	2.19	3.68	52.07	2.28	6.85

Table 3.5 was calculated by subtracting the background data specified below from the actual data. So, the actual data, which occurred when the devices were running on the reference day, was filtered from noisy data.

Table 3.5 “Reference data” filtered from background noisy data in mG

Device Name	Tag	Date	Field X		Field Y		Field Z	
			Max.	Min.	Max.	Min.	Max.	Min.
ECG	A1A5A6	05.10.23	421.62	-8.63	363.45	-171.05	337.30	-193.20
Infusion Pump	A2A5A6	05.02.23	195.61	-53.89	87.14	-29.36	118.02	-286.98
NST	E0AAB2	07.06.23	-264.17	-468.84	-35.43	-185.10	130.99	-273.68
Ultrasound	E0AAF5	07.11.23	101.50	-316.00	248.07	-195.43	457.82	-239.68
Defibrillator	E0AB44	06.15.23	-34.34	-61.34	12.12	-33.88	-165.59	-305.59

When the device is not running, stored data is called background data, including environmental conditions. Days when the device is not running, are confirmed by consulting with the hospital and defined as background reference data. Table 3.6 and Table 3.7 are based on an analysis of 24-hour data obtained from the hospital by selecting days when the devices were never running. Table 3.6 is the standard deviation data for the days when the selected devices were not running for 24 hours. Table 3.7 is the average of actual data on Field X, Field Y, Field Z for the days when the selected devices were not running for 24 hours.

Table 3.6 shows the average of the standard deviation values of all data received on the specified days. When the medical device is not working, very small oscillations occur and the standard deviation values are small. Table 3.6 shows that the reference standard deviation values are greater than the standard deviation values on days when the devices defined as background reference standard deviation data are not working.

Table 3.6 “Background reference data” standard deviation rates in mG

Device Name	Tag	Date	Background Standard Deviation		
			Field X	Field Y	Field Z
ECG	A1A5A6	05.28.2023	6.66	9.04	14.92
Infusion Pump	A2A5A6	05.03.2023	13.00	6.10	10.70
NST	E0AAB2	07.15.2023	9.38	5.10	13.58
Ultrasound	E0AAF5	07.30.2023	3.60	3.69	3.89
Defibrillator	E0AB44	07.18.2023	4.92	3.86	3.22

Table 3.7 “Background reference data” filtered from background noisy data in mG

Device Name	Tag	Date	Background Actual Data		
			Field X	Field Y	Field Z
ECG	A1A5A6	05.28.2023	1140.13	34.05	1119.70
Infusion Pump	A2A5A6	05.03.2023	557.39	-401.64	1271.48
NST	E0AAB2	07.15.2023	-15931.60	-5753.26	-11923.32
Ultrasound	E0AAF5	07.30.2023	921.50	-310.57	-1169.32
Defibrillator	E0AB44	07.18.2023	39.34	-280.12	-1544.41

The data stored in Table 3.4 was used as reference points, and all other data was loaded and analyzed using the K-means clustering algorithm. As a result of the K-means cluster analysis method, a graph and report are obtained. The information contained in the report is as follows:

- Duration information on which the device operates,

- Start and end times of maximum and minimum points occurring during the device running in the x, y, and z fields,
- Range value representing the difference between the maximum and minimum points

For example, Table 3.8 shows the K-means clustering output report obtained from the data received on 05.02.2023 from the tag A2A5A6 installed on the infusion pump.

Table 3.8 shows the actual data at the time of device operation. The infusion pump ran twice on the specified date as seen in the Table 3.8. In the "Duration" column, the running time is indicated in seconds. The maximum and minimum points that occur during the oscillation of the device and the range value expressing the difference between them are given in the table.

Table 3.8 K-means clustering results for infusion pump with tag A2A5A6 on 05.02.2023 in mG

Start time	End time	Duration (sec)	Field X			Field Y			Field Z		
			Max.	Min.	Range	Max.	Min.	Range	Max.	Min.	Range
2:54:51 PM	3:30:36 PM	2145	864	455	409	-253	-422	169	1481	1109	372
11:11:32 PM	11:50:05 PM	2313	642	552	90	-376	-440	64	1298	860	438

Figure 3.7 shows that the standard deviation data increase six times during the day. Since four of these increases lasted less than 25 minutes with the algorithm used, they can be considered as deviations due to environmental. As a result of K-means clustering, two of these data increase do not belong to the "running" category. The accuracy of this output was confirmed by the nurse working in the service and using the device.

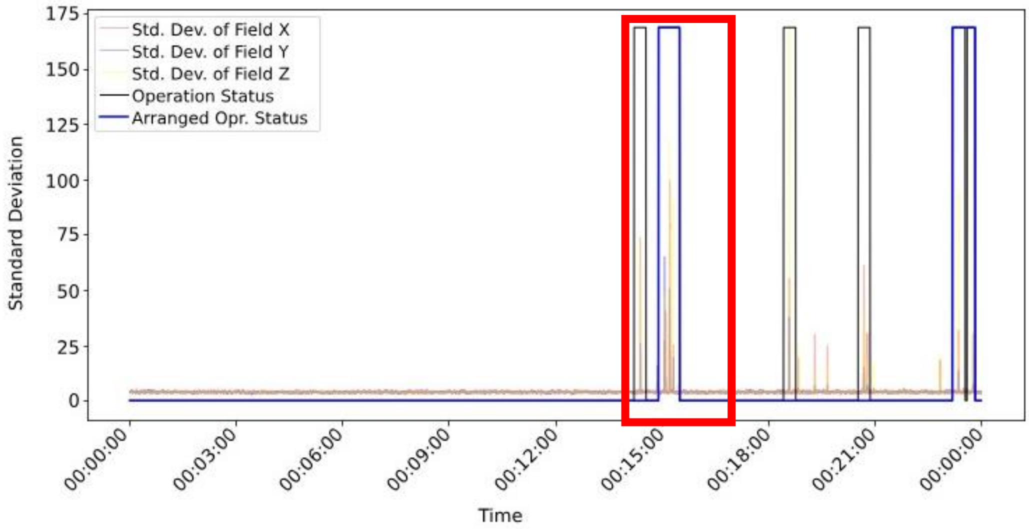

Figure 3.3 Standard deviation of K-means clustering results of infusion pump with tag A2A5A6 on 05.02.2023

In this thesis, since the data was measured in real time from the hospital, the actual data from the sensor was not sufficient for decision making. For example, location, phone call, and other factors may affect the actual data coming from the sensor and the actual data may increase or decrease momentarily. This change increases the standard deviation only momentarily and Algorithm-1 was used for these reasons. The accuracy of measurements made using actual data on stationary devices may be high, but it is correct to use standard deviation data across all devices. Figure 3.7 is an example of why standard deviation data is used in this thesis because actual data is insufficient for decision-making due to the variation of actual data according to the surrounding conditions.

3.2.1 An Illustrative Example

An illustrative example based on the tests mentioned previously has been presented in order to support the method utilized in this section. A specific time was examined as an example and compared to the actual data obtained to verify the K-means clustering results. The first row in Table 3.8 has been examined, and the examined section area is indicated by the red frame in Figure 3.7. If the K-means clustering result shows that the device is running, when the actual data of fields x, y, and z are displayed on the graph, the range between the data is expected to be significant. Because the standard deviation increases while devices are running. The accuracy can be observed by comparing the actual data graph with the K-means clustering result graphs.

In this illustrative example, as a result of K-means clustering from actual data, 1000 rows-data were selected from the time interval in which the device was running. Due to the high standard deviation in the selected interval, it is aimed to observe the change.

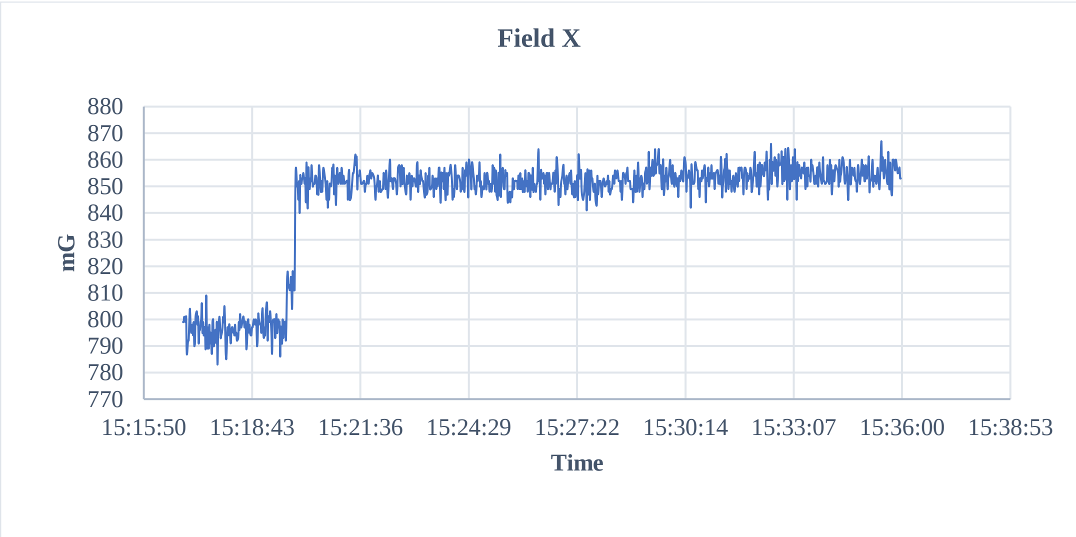

Figure 3.4 Data on the field X in the section determined as "running" and sampled as a result of K-means clustering results for infusion pump with tag A2A5A6 on 05.02.2023

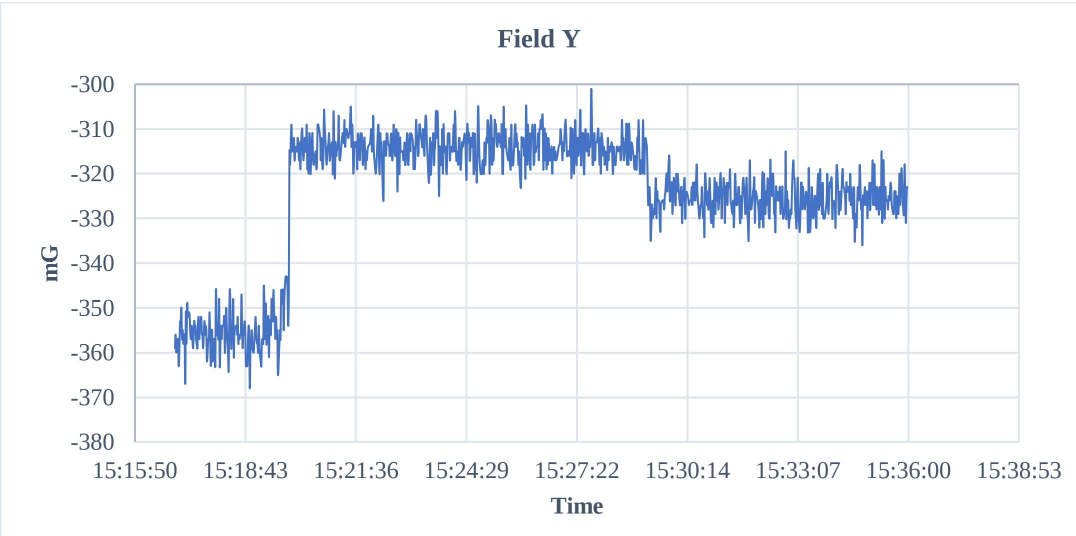

Figure 3.5 Data on the field Y in the section determined as "running" and sampled as a result of K-means clustering results for infusion pump with tag A2A5A6 on 05.02.2023

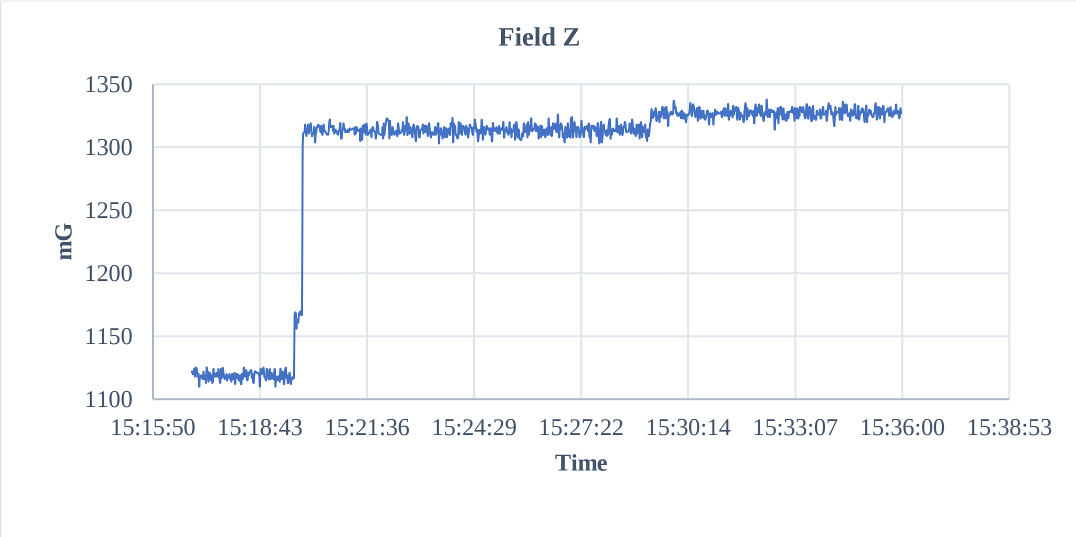

Figure 3. 6 Data on the field Z in the section determined as “running” and sampled as a result of K-means clustering results for infusion pump with tag A2A5A6 on 05.02.2023

The reason why the graph reads negative data on the field y is that no offset value is added in the sensor software. For this reason, negative values were recorded in the actual data. In addition, observed a change in the y and z axes but not in the x axis at 15:30. Since the standard deviation data is grouped according to the Euclidean distance formula in the K-means clustering method, it does not affect the result.

Because of the dependent tests that called preliminary study, it was decided that the K-means clustering method is suitable for estimating the operating status of the devices for independent tests planned to be performed with long-term data. By processing the data obtained from the tags attached to the device with the K-means clustering method, it was determined how long the devices worked on which day, and the results are examined in result and discussion section.

3.3 Analytic Hierarchy Process (AHP)

In this section, we describe the AHP model which is used to create a dynamic maintenance schedule by prioritizing the devices using utilization data as a result of K-means clustering method.

The Analytic Hierarchy Process is a decision-making method developed by Thomas L. Saaty (Saaty, 1990). It is a structured and systematic approach used to solve complex decision-making problems where multiple criteria and alternatives need to be considered.

The application steps of the AHP method can be summarized in four steps:

a. Criteria Identification

- *Problem Definition:* The decision problem to be addressed using AHP is defined. The main objective and criteria contributing to achieving that objective are identified.
- *Hierarchical Structure:* The criteria are organized into a hierarchical structure. The top level is occupied by the main objective, followed by intermediate levels for primary criteria, secondary criteria, and so forth. This hierarchical arrangement aids in the breakdown of the complex decisions into manageable components.

b. Comparison and Scoring

- *Comparison Matrices:* Matrices are created for each level of criteria to facilitate the comparison of the importance of each criteria in relation to others. Preference values are assigned to each comparison using Saaty's scale. Appendix B Table B.1 defines the Saaty's scale. (Saaty, 2008).
- *Eigenvalue Calculation:* Normalized eigenvectors for each matrix are calculated. This step entails the calculation of the average of each column in the matrix, followed by normalization to ensure a sum of one. The eigenvector denotes the relative importance of criteria within each level.

c. Synthesis and Weight Calculation

- *Sub-criteria Synthesis:* Similar to criteria, comparison matrices are formed for sub-criteria, and their normalized eigenvectors are calculated.

- *Aggregation:* The criteria eigenvector is multiplied by the sub-criteria normalized eigenvectors, producing aggregated weights for each sub-criteria.
- *Alternative Evaluation:* Matrices are devised to assess alternatives concerning each sub-criteria, yielding weighted scores for alternatives based on aggregated sub-criteria weights.

d. Consistency Check

- *Consistency Ratio (CR):* CR is calculated for each comparison matrix to assess judgment reliability. Decisions may need to be revised if the CR exceeds a predefined level (typically 0.1).

By adhering to these steps, criteria, sub-criteria, and alternatives are systematically evaluated, incorporating the preferences and intensity assessments of experts. The AHP process culminates in weighted scores for alternatives that guide the decision-making process. In this thesis, these four criteria have been applied step by step in the following part.

3.3.1 Application of AHP

Generally, maintenance and calibration schedules of medical devices cannot be arranged and prioritized according to their status. In accordance with this problem, the AHP method was used to prioritize medical devices.

a. Criteria Identification

First of all, the main criteria and sub-criteria determined to establish the hierarchy structure are shown in Table 3.9. Table 3.9 lists the criteria and sub-criteria determined by obtaining information from the hospital where the tests were performed.

Table 3.9 Main criteria and sub-criteria for priorization of medical devices

Main criteria and Subcriteria for Priorization of Medical Devices	Function	
	Age	
	Maintenance Requirement	
	Functionality	Utilization
		Alternative Device
	Total Risk	Failure Frequency
		Detectability
		Failure Consequence

Main criteria, sub-criteria, and their categories are detailed in Appendix B Table B.4. The parameters shown in Table B.4 are used to prioritize medical devices. Main criteria and Sub-criteria are as follows:

Function: The functions of the medical devices used are the categories currently used by the hospital. Medical devices are categorized based on their existing functions within the treatment process.

Age: It is the duration elapsed since the purchase date of the devices. The biomedical department of hospitals indicates that after five years, devices tend to generate more malfunctions, requiring more maintenance tasks such as battery replacements

Maintenance Requirement: Some medical devices require daily checks and maintenance. For instance, the defibrillator device used in this thesis is intended for emergency situations and needs to be inspected daily. Nurses perform these checks twice a day, and their monitoring is ensured.

Functionality: The functionality has been analyzed in two categories: utilization and the number of alternative devices. In this thesis, utilization is dynamically calculated using the employed sensor. The count of alternative devices represents the devices present in the hospital and ready for use at any time. Some of these devices can be kept in stock, but it is essential to manage this process carefully. It is crucial for utilization values to be balanced for each device. For example, if one device is heavily utilized on one floor while another device on a different floor is never used, adjustments can be made according to the needs.

Total Risk: In this thesis, the total risk of a device is analyzed in three contexts. Failure frequency answers the question of how often a device fails. This provides a prediction for the number of failures that may occur in the future. Detectability answers whether the device warns when a malfunction occurs or is observable in advance. Most medical devices generate these alerts and signals, and users should pay careful consideration to them. Failure consequences answer how long the device remains unusable when it fails. In this thesis, information was obtained from the hospital about the number of failures and the cause of the failure of the devices of the same type as those tested.

Briefly, we identified the criteria used to prioritize medical devices when creating their maintenance and calibration schedules in this section. Section two determines the significance of these criteria and the extent to which changes in device condition affect their prioritization rate. The degree of significance indicates how much a medical device's prioritization rate will alter over time in response to changes in condition.

b. Comparison and Scoring

We created comparison matrices for all main criteria, sub-criteria and their categories identified in section a. The importance levels of the criteria in the comparison matrices were determined according to the Saaty scale defined in Appendix B Table B.1 (Saaty, 2008).

Table 3.10 is an illustrative example to showcase the implementation of AHP and shows the comparison matrix created for the main criteria. The equations used are explained through this example for AHP analysis. Table 3.10 is based on the opinions of individuals working in the biomedical field. This provides a relative measure of the importance or intensity of the element in comparison to the others.

Table 3.10 Main criteria comparison matrix *A*

Main Criteria	Function	Functionality	Age	Total Risk	Maintenance Requirement
Function	1	2	3	6	5
Functionality	1/2	1	4	7	8
Age	1/3	1/4	1	4	3
Total Risk	1/6	1/7	1/4	1	2
Maintenance Requirement	1/5	1/8	1/3	1/2	1

The reciprocal main criteria value in the columns and rows listed in Table 3.10 are one, because the same criteria have equal priority over each other. Another example, the value of the function criteria in the row corresponding to the age criterion is three. This means that in the maintenance calendar created for medical devices, the function criterion of the devices is moderate importance according to the age criterion, and this corresponds to three points in the Saaty scale (Saaty, 2008).

The consistency of the comparison matrix is evaluated by calculating the consistency ratio defined in the fourth step of the AHP application process. The formulas for computing the consistency ratio are described step by step and applied to the comparison matrix generated for the main criteria indicated in Table 3.10.

- The matrix A is a square matrix that compares the main criteria and is shown by a matrix equation. The matrix entry a_{ij} refers to the relative importance or preference of element i over element j.

$$A=\begin{bmatrix} 1 & 2 & 3 & 6 & 5 \\ 1/2 & 1 & 4 & 7 & 8 \\ 1/3 & 1/4 & 1 & 4 & 3 \\ 1/6 & 1/7 & 1/4 & 1 & 2 \\ 1/5 & 1/8 & 1/3 & 1/2 & 1 \end{bmatrix}$$

- For every column j, the elements $a_{ij'}$ are acquired by dividing each element a_{ij} by the sum of the elements present in the same column.

$$a_{ij'} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \qquad 2$$

The normalized matrix A_1 is then computed.

$$A_1=\begin{bmatrix} 0.45 & 0.57 & 0.35 & 0.32 & 0.26 \\ 0.23 & 0.28 & 0.47 & 0.38 & 0.42 \\ 0.15 & 0.07 & 0.12 & 0.22 & 0.16 \\ 0.07 & 0.04 & 0.03 & 0.05 & 0.10 \\ 0.09 & 0.04 & 0.04 & 0.03 & 0.05 \end{bmatrix}$$

c. **Synthesis and Weight Calculation**

- The total of every row in matrix A_1 is divided by n, representing the number of criteria. The result is the eigenvector w_i.

$$w_i = \frac{\sum_{i=1}^{n} a_{ij'}}{n} \qquad 3$$

$$w_i=\begin{bmatrix} 0.39 \\ 0.36 \\ 0.14 \\ 0.06 \\ 0.05 \end{bmatrix}$$

- Multiply the original matrix A by the eigenvector w_i to obtain the eigenvalue. Eigen Value = $w' = Aw_i$

$$A=\begin{bmatrix} 1 & 2 & 3 & 6 & 5 \\ 1/2 & 1 & 4 & 7 & 8 \\ 1/3 & 1/4 & 1 & 4 & 3 \\ 1/6 & 1/7 & 1/4 & 1 & 2 \\ 1/5 & 1/8 & 1/3 & 1/2 & 1 \end{bmatrix}, \ w_i=\begin{bmatrix} 0.39 \\ 0.36 \\ 0.14 \\ 0.06 \\ 0.05 \end{bmatrix}, w'=\begin{bmatrix} 2.14 \\ 1.94 \\ 0.75 \\ 0.31 \\ 0.25 \end{bmatrix}$$

Table 3.11 displays the eigenvalue and eigenvector ratio calculations for each criteria in the decision matrix.

Table 3.11 Calculation of eigen values and eigenvector ratios

Main Criteria	$\boldsymbol{w_i}$	$\boldsymbol{w'}$	$\boldsymbol{w' / w_i}$
Function	0.39	2.14	5.46
Functionality	0.36	1.94	5.46
Age	0.14	0.75	5.27
Total Risk	0.06	0.31	5.09
Maintenance Requirement	0.05	0.25	5.10
Sum	1.00	5.39	26.39

d. Consistency Check

The λ_{max} formula calculates the maximum eigenvalue. It's the average of the ratio of each eigenvalue to its corresponding eigenvector value.

$$\lambda_{max} = \frac{1}{n}(\frac{w_1'}{w_1} + \frac{w_2'}{w_2} + \cdots \ldots \ldots \frac{w_n'}{w_n}) \qquad 4$$

The Consistency Index (CI) provides a measure of how consistent the matrix is.

$$CI = \frac{\lambda_{max} - n}{n-1} \qquad 5$$

The Random Index (RI) is a constant that depends on the order of the matrix (the number of criteria). It is pre-determined and based on the size of the matrix (Saaty, 2004).

The Consistency Ratio (CR) is the ratio of the consistency index to the random index. It is used to assess the consistency of the decision matrix. If CR is close to 0, it indicates good consistency; otherwise, it suggests that the decision matrix may be too inconsistent.

Table 3.12 Consistency analysis with λ and RI

λ max	**Consistency Index**	**RI**	**CR**
5.27	0.067	1.12	0.060

Table 3.12 shows that the consistency check score of this comparison matrix is 6%, and the maximum lambda value is 5.27. If the calculated consistency ratio values are less than 0.10, the comparison is consistent, and accordingly, the comparison matrix in Table 3.10 is consistent (Saaty, 2004). These steps were applied to all the comparison matrices we created for the main criteria, sub-criteria and their categories. All comparison matrices we create are consistent.

Using these comparison matrices, a transformed score value (TSV) is calculated to prioritize medical devices. This calculation is calculated using the following equations. (Taghipour et al., 2011). The equations mentioned below are applied to all comparison matrices. Explained the application of these equations for the main criteria comparison matrix as an example.

The weight (v) of main criteria comparison matrix's grades (a_{ij}) can be obtained as follows:

$$v = \frac{\left(\Pi_{j=1}^{5} a_{ij}\right)^{1/5}}{\sum_{i=1}^{5}\left(\Pi_{j=1}^{5} a_{ij}\right)^{1/5}} \quad i = 1 \dots ,5, j = 1 \dots 5 \qquad 6$$

The Intensity (I) of main criteria comparison matrix's grades can be obtained as follows:

$$I = \frac{v_i}{max(v_i)} \quad i = 1 \dots ,5 \qquad 7$$

To calculate the TSV score, it is necessary to first calculate the Minimum Total Score (MTS) value and the MTS value is a constant metric. MTS is calculated as a weighed sum of minimum intensity values of the main criteria. In the same vein, minimum intensity values of the main criteria are calculated as the weighed sum of their sub criteria, if there are any. The calculated values of the main criteria and sub-criteria are shown in Table 4.8. This process can be expressed with the formulas (8) and (9):

$$MTS = \sum_{i=1}^{5} v_i x_i \tag{8}$$

$$x_i = \sum_{k=1}^{M} \beta_k y_k \tag{9}$$

Here, x_i represents minimum intensity of each one of the 5 different main criteria (i.e. function, mission critically, age, total risk and maintenance requirement values) and v_i is the corresponding weight values. And if any of the main criteria x_i has sub-criteria, y_k represent each one of those M sub-criteria with β_k being the corresponding weight value.

The Total Score (TS) is a measure that may be compared to the established thresholds to determine which category the item belongs in. Total score is the weighted sum of the all-possible intensity values of the main criteria. If main criteria have sub-criteria, intensity of the main criteria is, again, the weighted sum of their intensities.

$$TS = \sum_{i}^{5} v_i I_i \tag{10}$$

In equation 10, v_i is the weight value for each intensity value I_i. The calculated total scores can be transformed to percentage values using the following equation:

$$TSV = \frac{TS - MTS}{1 - MTS} \tag{11}$$

The TSV score is created for combinations of all parameters, for the main criterion, sub-criteria and their categories. In other words, a TSV score was obtained for all states of a medical device.

To sum up, the application steps of the AHP method and the method of using the criteria and sub-criteria used in AHP are evaluated together. The results of equation 11, as presented in chapter 4, play a crucial role in determining the category of medical devices for preventive maintenance.

4. RESULT AND DISCUSSION

Chapter 4 gives a thorough examination of two essential components of our research: the results of K-means clustering and the outcomes provided by the AHP. The application of these analytical techniques plays an integral role in our effort to unveil and interpret complex data patterns and relationships. The K-means clustering results reveal how our data naturally segregates into distinct clusters. Similarly, the AHP results provide a robust framework for decision-making, enabling the establishment of priorities and preferences within a complex hierarchy of criteria and alternatives. This chapter represents the findings generated by these two methodologies are analyzed, discussed, and interpreted.

4.1 Analysis of K-means Clustering Results

In this section, the results obtained as a result of K-means clustering of all data are analyzed in detail. As a result of K-means clustering model, the total duration of running for the tested medical devices was determined in seconds throughout the entire period. For the analysis of these values obtained using the K-means clustering method, the average of the values obtained during the entire period was taken.

The advantages of knowing utilization time of medical devices are as follows:

1. The Biomedical Department of the hospital can organize and control procurement requests and analyze the distribution of device numbers on a floor-by-floor basis within the hospital.
2. User-based malfunctions can be prevented through frequent checks of frequently used devices, and assessments can be made for electronic and mechanical failures.
3. Unused or forgotten devices in large hospitals can be identified, delivered to a suitable floor, or stored as backups for future use in case of malfunctions with other devices.
4. The device's location can be determined based on the data received from the data collection point.

Table 4.1 shows the category of the selected devices, the code of tag which sends data, the number of days data was received, the total utilization time calculated during this period, and the average daily utilization data. Actually, table 4.1 summarizes the functions of the medical devices used and their respective running durations. According to the usage data provided, the ranking of the most to least used devices during the testing process is as follows:

- Infusion pump > NST > Ultrasound > Defibrillator > ECG

Table 4.1 Utilization time and device information measured on selected devices

Device Category	Device Name	Tag	Day	Total Utilization Time (Sec.)	Daily Average Utilization Time
Life Support and Treatment	Infusion Pump	A2A5A6	107	2684718.91	6:58:10
Physiological Signal Monitoring Devices	NST	E0AAB2	75	867308.72	3:12:44
Imaging and Radiology Devices	Ultrasound	E0AAF5	63	158376.44	0:41:54
Physiological Signal Monitoring Devices	ECG	A1A5A6	86	84186.16	0:16:19
Life Support and Treatment	Defibrillator	E0AB44	50	58236.58	0:19:25

Table 4.2 shows the average actual data during the running of medical devices. Data specified in Table 4.2 was calculated by averaging the data obtained from the K-means clustering method when the selected devices ran throughout the entire period.

Table 4.2 “Average actual data’ during medical devices running in mG

Tag	Field X			Field Y			Field Z		
	Max.	Min.	Range	Max.	Min.	Range	Max.	Min.	Range
A1A5A6	1227.49	721.39	506.10	842.30	311.96	530.35	2535.30	1950.03	585.27
A2A5A6	-660	-1446	786	1396	750	646	7	-1252	1259
E0AAB2	-12529.6	-14633.6	2104.01	-5286.45	-6396.83	1110.38	-6931.52	-9097.14	2165.62
E0AAF5	151.86	-252.41	404.28	-608.59	-932.81	324.21	-1080.37	-1727.81	647.43
E0AB44	40.31	-6.15	46.46	-260.01	-364.09	104.08	-1547.92	-1758.84	210.92

Table 4.3 shows the average standard deviation when the medical device is running for the number of days data is collected. The time of medical devices running is the result of the K-means clustering on the data collected over 24 hours and recorded daily.

Table 4.3 “Average standard deviation data” during medical devices running in mG

Tag	Field X			Field Y			Field Z		
	Max.	Min.	Mean	Max.	Min.	Mean	Max.	Min.	Mean
A1A5A6	151.85	2.55	15.78	155.81	2.55	15.61	164.06	2.71	18.63
A2A5A6	231.43	2.88	126.59	213.64	3.06	133.22	398.83	2.83	235.05
E0AAB2	679.02	3.27	22.37	331.20	3.24	18.16	618.99	9.86	53.15
E0AAF5	135.13	2.60	13.80	95.70	2.65	11.16	203.30	2.90	19.84
EOAB44	9.32	2.97	4.48	18.04	2.17	4.12	59.53	2.21	7.37

Table 4.3 shows that the standard deviation of the defibrillator data is lower than that of the other devices. The reason is that the defibrillator device is checked twice daily by the nurse at 8 a.m. and 8 p.m. by opening the defibrillator and checking it according to the specified procedures. At the same time, defibrillators with self-control features can do this once a day on their own. Figure 4.1 shows the example of K-means clustering result for defibrillator on 06.17.2023. Controls and self-control were detected in the defibrillator.

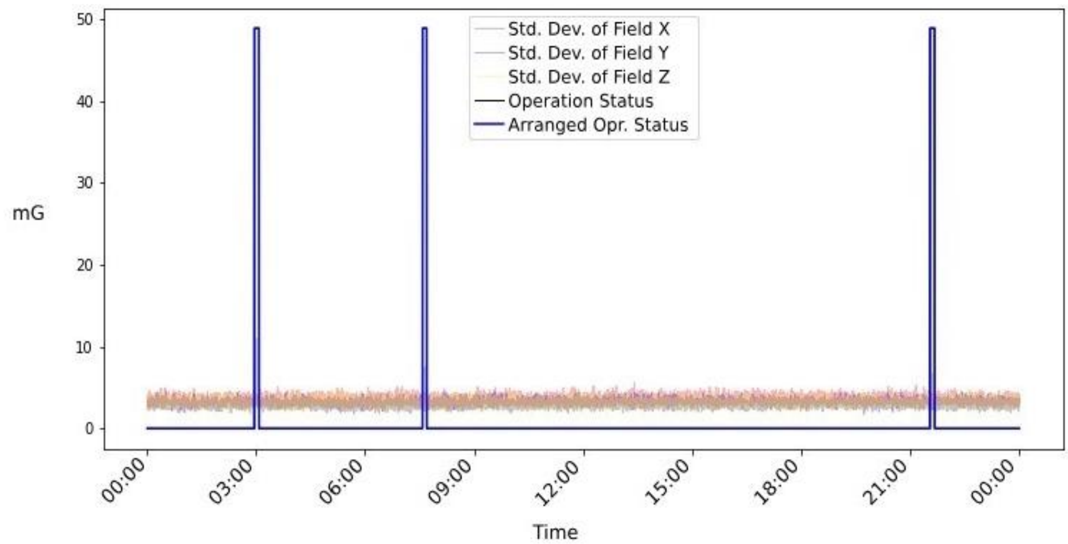

Figure 4.1 Standard deviation of K-means clustering results of tag E0AB44 on 06.17.2023

Table 4.4 shows the actual data without background data calculated by averaging long-term data. While the device is running, data oscillates due to the increase in standard deviation. The average maximum minimum data and the difference values obtained when the device is running are given in Table 4.4

Table 4.4 "Average actual data" filtered from background noisy data during medical devices running in mG

Tag	Field X			Field Y			Field Z		
	Max.	**Min.**	**Range**	**Max.**	**Min.**	**Range**	**Max.**	**Min.**	**Range**
A1A5A6	87.35	-418.74	506.09	808.25	277.90	530.34	1415.60	830.32	585.27
A2A5A6	-1205.55	-1986.07	780.52	1762.27	1122.94	639.33	-1277.35	-2527.81	1250.46
E0AAB2	3407.66	1256.25	2151.41	485.25	-655.66	1140.91	4928.61	2705.22	2223.38
E0AAF5	-769.63	-1173.91	404.28	-298.03	-622.25	324.21	88.9408	-558.49	647.43
E0AB44	0.89	-45.85	46.75	18.58	-86.20	104.78	-17.19	-229.06	211.86

As a result, utilization data was calculated with K-means clustering method and the data obtained from the sensor was analyzed. To conduct an evaluation in accordance with the AHP criteria and sub-criteria definitions, information about the medical devices used in the hospital where the test was conducted was collected in addition to utilization data. The hospital has 150 beds, eight operating theatres, 48 clinics, and is accredited by the Joint Commission International. The data received is from a software used and includes the information entered by the users, but there may be missing information due to the user or the system.

In addition to utilization data, the number of hospital devices in each category and the failure rates of these devices for the last two years were analyzed to determine the failure frequency. In 2022, two malfunction records for the tested USG and ECG devices were due to electronic malfunctions. The USG device malfunctioned on March 3, 2022, and the ECG device malfunctioned on January 19, 2022. In Table 4.5, the "Total Device" column indicates the total number of the respective medical devices in the hospital. The "Number of Failures" column represents the known number of failures in those medical devices. The "Number of Failures (%)" column indicates the ratio of the occurred failures to the total number of devices. The breakdown rates for the selected devices category in the years 2022 and 2023 are presented in Figure 4.2 and Figure 4.3. Table 4.5 shows that when the number of devices in the same category is small, properly and timely maintenance must be in place to avoid recurrence of failures.

Table 4.5 Number of devices in the hospital with the same device category as the selected devices, total number of failures in 2022 and 2023 and percentage of failures

Device Category Name	Total Device	Number of Failures	Number of Failures (%)
Infusion Pump	116	22	18%
NST	10	5	50%
Ultrasound	16	20	125%
ECG	16	7	43%
Defibrillator	30	5	16%

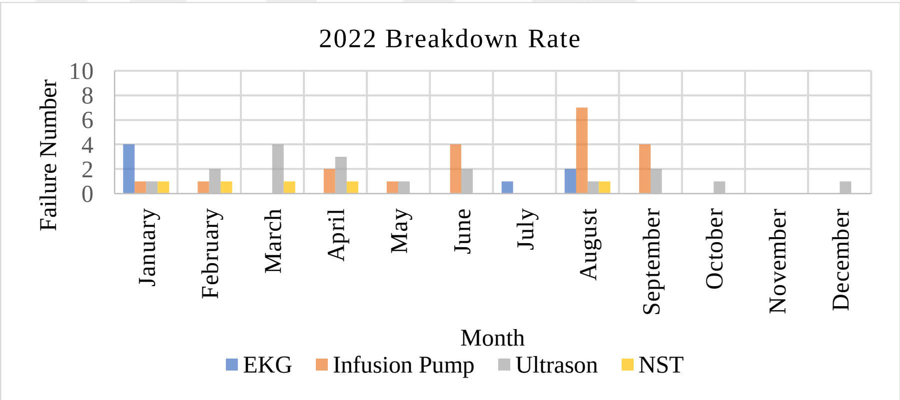

Figure 4.2 Failure rates of selected medical device category in 2022

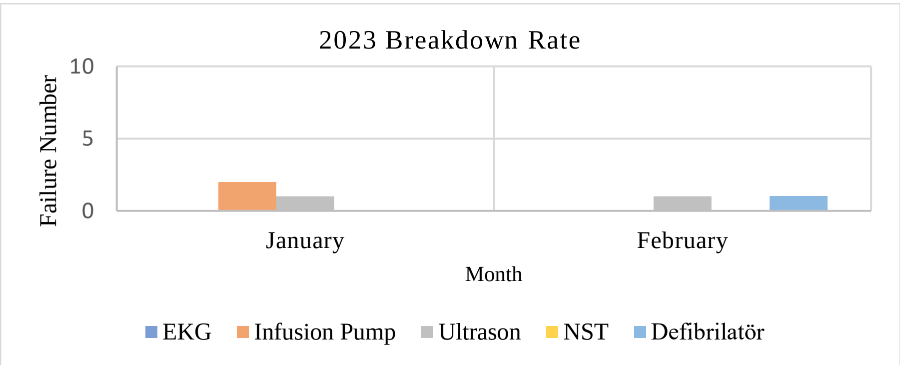

Figure 4.3 Failure rates of selected medical device category in 2023

The calculations of accessible and operational devices based on the device quantities are provided in Table 4.6. Table 4.6 calculates according to the ratio of the total number of defective devices to the total number of devices in the same category. For example, 25% of the total number of ECG devices failed in January 2022. Hospitals need to check and track failure data regularly. How often the device fails, for what reasons, the cause of the failure, and the downtime due to this failure are essential for resource and time management.

Table 4.6 Monthly failure rate of medical devices in the same category

Year	Month	ECG	Infusion Pump	Ultrasound	NST	Defibrillator
2022	January	25%	1%	6%	10%	3%
	February	0%	1%	13%	10%	7%
	March	0%	0%	25%	10%	3%
	April	0%	2%	19%	10%	0%
	May	0%	1%	6%	0%	0%
	June	0%	3%	13%	0%	0%
	July	6%	0%	0%	0%	0%
	August	13%	6%	6%	10%	0%
	September	0%	3%	13%	0%	0%
	October	0%	0%	6%	0%	0%
	November	0%	0%	0%	0%	0%
	December	0%	0%	6%	0%	0%
2023	January	0%	2%	6%	0%	0%
	February	0%	0%	6%	0%	3%
	March	0%	0%	0%	0%	0%
	April	0%	0%	0%	0%	0%
	May	0%	0%	0%	0%	0%
	June	0%	0%	0%	0%	0%

Table 4.7 presents data sourced from the software employed for fault analysis in the hospital. It details the priority status assigned to user-entered faults and the causes for their occurrence. 27% of these failures are urgent-priority failures of selected devices. Two of the urgent-priority failures have the highest importance and are caused by the user. As one of the objectives of the thesis, it is expected that these failures will decrease due to regular follow-up with the maintenance schedules to be created.

Table 4.7 Failure causes and priority status

Reason / **Device Category Name**	**Electronic**				**User Base**		**Mechanical**		**Others**			
	U[1]	H[2]	M[3]	L[4]	U	L	U	L	U	H	M	L
Defibrillator		4		1								
ECG	1			1				2			1	1
Infusion Pump			1	5						2	6	3
NST		1	1	1	1		1					
Ultrasound		2	2	8	1	1			1	2		1
Total	1	7	4	16	2	1	1	2	1	4	7	5

[1]Urgent, [2]High, [3]Medium, [4]Low

These data were used to decide which class the selected devices belong to in the maintenance schedule created according to the definitions specified in the AHP and are explained in the next section.

4.2 Analyzing the Analytic Hierarchy Process Results

The AHP method serves as a crucial tool in the selection process of medical devices. In this section, we will present the results and discussion of applying the AHP method in prioritizing medical devices using the methodology in chapter 3. The weight and intensity values shown in Table 4.8 were calculated using equation six and equation seven from the comparison matrices created for main criteria and sub-criteria.

Table 4.8 Determining weights and intensities of criteria, sub-criteria and their categories in AHP analysis

Main Criteria and Sub-criteria	$\pi_{j=1}^{5} a_{ij}$	$\left(\pi_{j=1}^{5} a_{ij}\right)^{1/5}$	Weight	Intensity
1. Function	180.000	2.825	0.396	1.000
1.1 Life Support and Treatment	336.000	3.201	0.458	1.000
1.2 Auxiliary Hospital Equipment	0.005	0.349	0.050	0.108
1.3 Physiological Signal Monitoring Devices	22.500	1.864	0.267	0.582
1.4 Imaging and Radiology Devices	2.178	1.168	0.167	0.365
1.5 Sterilization Devices	0.011	0.407	0.058	0.127
2. Functionality	112.000	2.569	0.360	0.909
2.1 Utilization	3.000	1.732	0.75	1.000
2.1.1 High	6.000	1.817	0.673	1.000
2.1.2 Medium	0.167	0.550	0.204	0.303
2.1.3 Low	0.037	0.333	0.123	0.183
2.2 Alternative Device	0.333	0.577	0.25	0.333
2.2.1 Low	54.000	3.780	0.770	1.000
2.2.2 Medium	0.500	0.794	0.162	0.210
2.2.3 High	0.037	0.333	0.068	0.088
3. Age	1.000	1.000	0.140	0.354
3.1 Old	315.000	4.213	0.510	1.000
3.2 Almost Old	12.000	1.861	0.225	0.442
3.3 Average	2.000	1.189	0.144	0.282
3.4 New	1.000	1.000	0.121	0.237
4. Total Risk	0.001	0.412	0.057	0.145
4.1 Failure Frequency	15.000	2.466	0.637	1.000
4.1.1 High	32.000	3.175	0.717	1.000
4.1.2 Medium	0.750	0.909	0.205	0.286
4.1.3 Low	0.042	0.347	0.078	0.109
4.2 Detectability	0.067	0.405	0.105	0.164
4.2.1 Low	32.000	3.175	0.717	1.000

Table 4.9 Determining weights and intensities of criteria, sub-criteria and their categories in AHP analysis

Main Criteria and Sub-criteria	$\pi_{j=1}^{5} a_{ij}$	$\left(\pi_{j=1}^{5} a_{ij}\right)^{1/5}$	Weight	Intensity
4.2.2 Medium	0.750	0.909	0.205	0.286
4.2.3 High	0.042	0.347	0.078	0.109
4.3 Failure Consequences	1.000	1.000	0.258	0.405
4.3.1 High	32.000	3.175	0.716	1.000
4.3.2 Medium	0.750	0.909	0.205	0.286
4.3.3 Low	0.042	0.347	0.078	0.109
5. Maintenance Requirement	0.004	0.334	0.047	0.118
5.1 High	54.000	3.780	0.770	1.000
5.2 Medium	0.500	0.794	0.162	0.210
5.3 Low	0.037	0.333	0.068	0.088

Table 4.9 shows the weight values calculated for each category and subcategory and the minimum weight value to be used to calculate the total score. Considering these values, function is the most prioritized feature used in the comparison matrices when creating a preventive maintenance schedule.The total score value specified in equation five was obtained and used in equation six for calculating the TSV score.

When all of these conditions are listed, there are a total of 2916 possibilities for each device and a total of 14580 rows. The list, containing probabilities calculated for each tested category of medical device, is sorted from the highest to the lowest based on the TSV score. In total, there are 14580 rows in the list.

Table 4.10 Weight values determined by AHP comparison matrix and calculated minimum density values for main criteria and sub-criteria

Main Criteria and Sub Criteria	Weight	Minimum Intensity
Function	0.396	0.108
Functionality	0.355	0.159
Utilization	0.750	0.183
Alternative Device	0.250	0.088
Age	0.143	0.237
Total Risk	0.061	0.107
Failure Frequency	0.633	0.109
Detectability	0.106	0.109
Failure Consequences	0.260	0.109
Maintenance Req.	0.049	0.088
Minimum Total Score		**0.144**

In Figure 4.4, a section has been selected from the list of all possibilities as an example. For example, under certain conditions, the TSV score of some devices may exceed 50%, even if they are not life support devices, and should be prioritized in the maintenance schedule.

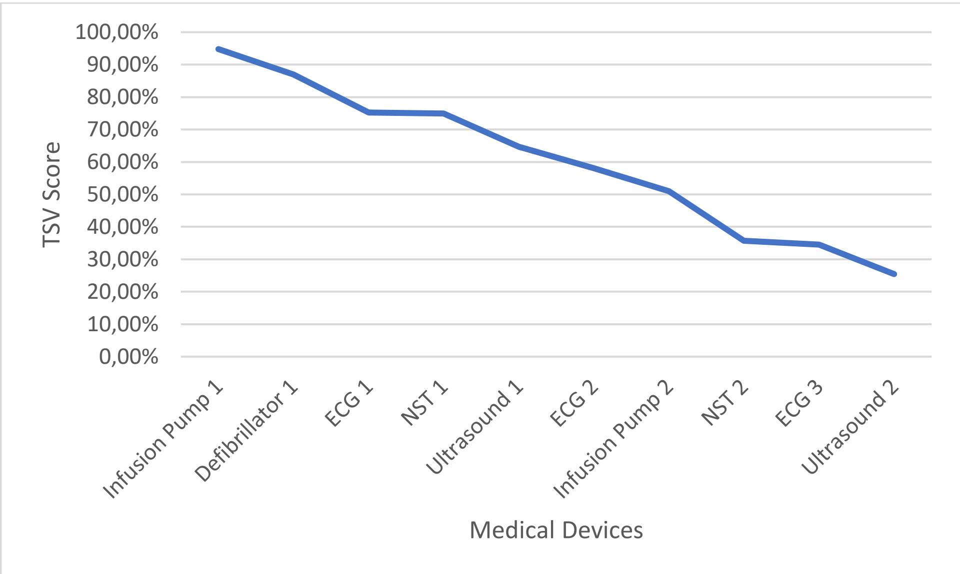

Figure 4.4 TSV score result graph from all decision definition possibilities

Table 4.11 TSV scores calculated according to conditions selected as examples in the dynamically created preventive maintenance schedule model

No	Function	Utilization	Alternative Devices	Age	Failure Frequency	Detectability	Failure Consequences	Maintenance Requirement	TSV Score
Infusion Pump 1	Life Support and Treatment	High	Low	Old	High	Low	High	Low	94.78 %
Defibrillator 1	Life Support and Treatment	High	Low	Almost Old	Medium	Medium	High	High	86.91%
ECG 1	Physiological Signal Monitoring Devices	High	Low	Old	Low	Low	Low	High	75.19%
NST 1	Physiological Signal Monitoring Devices	High	Low	Old	High	High	High	Low	74.97%
Ultrasound 1	Imaging and Radiology Devices	High	Low	Old	Low	Medium	Low	High	64.70%
ECG 2	Physiological Signal Monitoring Devices	High	Medium	New	High	Medium	Medium	High	58.06%
Infusion Pump 2	Life Support and Treatment	Low	Low	New	Low	High	Low	Medium	50.97%
NST 2	Physiological Signal Monitoring Devices	Low	High	Old	Medium	Medium	Medium	Low	35.69%
ECG 3	Physiological Signal Monitoring Devices	Low	Low	Almost Old	Low	High	Low	Low	34.56%
Ultrasound 2	Imaging and Radiology Devices	Low	Low	Almost Old	Low	Medium	Low	Medium	25.44%

Table 4.10 displays the category in which the devices chosen from Figure 4.4 are situated within the main and sub-criteria. For example, suppose the usage rate of an infusion pump device is high, the number of alternative devices is low, age is high, failure frequency is increased, failure detectability rate is low, failure consequences rate is high, and maintenance need is low. The TSV score of this device is 94.78%, and maintenance should be prioritized. The values specified in this section as High, Low, Medium, and Almost Old are defined in Table B.3 in Appendix B. The categorizations and classifications identified in this thesis can vary based on hospital management and requirements. The crucial aspect is measuring medical device usage status through this method, in turn, enhancing patient well-being and care management by organizing the maintenance and calibration of frequently employed devices. The proposed method serves as a stimulus to recognize high-usage devices that necessitate maintenance and calibration.

Table 4.11 shows the minimum and maximum TSV scores calculated for each device category for these possibilities.

Table 4.12 Minimum and maximum TSV score as a result of AHP

Device Name	**Min. TSV Score**	**Max. TSV Score**
Infusion pump	41%	100%
NST	22%	81%
Ultrasound	12%	71%
Defibrillator	41%	100%
ECG	22%	81%

Table 4.12 shows the number of possibilities in the group determined according to the classification in Table B.3 as a percentage. For example, Table 4.12 shows that a device in the defibrillator and infusion pump category cannot be included in the “Postpone” class under any circumstances. That is, its maintenance must be completed on time.

Table 4.13 Distribution of maintenance recommendations based on AHP results

TSV Score	Defibrillator	ECG	Infusion Pump	NST	Ultrasound	Total
50% ≤ TSV ≤ 100%	16.41%	6.91%	16.41%	6.91%	3.12%	49.76%
20% ≤ TSV < 50%	3.52%	13.09%	3.59%	13.09%	13.77%	47.06%
0% ≤ TSV < 20%	0%	0%	0%	0%	3.11%	3.11%

As a result, there is a 47.06% probability that the maintenance date should not be delayed, and it is in the "set a maintenance schedule" class. 49.76% of the devices are in the "bring forward" class.

Among all probabilities, probabilities with "high" utilisation data were filtered and shown in Table 4.13.

Table 4.14 Distribution of maintenance recommendations based on AHP results for high utilization category

TSV Score	Defibrillator	ECG	Infusion Pump	NST	Ultrasound	Total
50% ≤ TSV ≤ 100%	6.67%	6.26%	6.67%	6.26%	3.12%	28.96%
20% ≤ TSV < 50%	0%	0.41%	0%	0.41%	3.55%	4.37%
Total	6.67%	6.26%	6.67%	6.26%	3.12%	28.96%

When the AHP results are evaluated based on the utilization value for devices with the Life Support and Treatment function, where the score value is above 50%, and the utilization rate is high, the percentage of devices requiring maintenance is 28.96%. Among all functions, devices with the Life Support and Treatment function require maintenance with a priority of 32.82%. Physiological Signal Monitoring Devices constitute 13.82%, while Imaging and Radiology Devices comprise 3.12%.

Based on the intervals defined in Appendix B Table B.3, it is recommended to prioritize the maintenance plan of the defibrillator and infusion pump as a result of the TSV score in Table 4.14. The categorization of the devices into low, medium, or high conditions for their criteria and sub-criteria is by the definitions provided in Table B.4. This classification is derived from the utilization values and failure data calculated in the thesis. Results have been drawn from the TSV score calculated for each condition of these devices.

Table 4.15 TSV scores calculated for devices tested in a dynamically generated preventive maintenance schedule model

Device Name	Utilization	Alternative Device	Age	Failure Frequency	Detectability	Failure Consequences	Maintenance Requirement	TSV
Infusion Pump	High	High	Medium	Medium	Medium	Low	High	73.13%
Defibrillator	Low	High	Medium	Medium	High	High	High	47.92%
NST	Medium	Medium	Medium	High	Low	High	Low	33.77%
ECG	Low	High	Medium	High	Low	High	Low	28.79%
Ultrasound	Low	High	Medium	High	Low	Medium	Medium	18.20%

For example, an infusion pump is a life support device. It works for an average of seven hours a day. Since the utilization data of devices working 24 hours a week is defined as high, it is a device with high utilization. In addition, there are 116 infusion pumps in the hospital, and the alternate device ratio is high. Since there has been no known malfunction in the last year, the frequency of malfunction is average. Since the infusion pump comes into contact with liquid medicines, its sensors may give a warning, and the failure detection is average. When it malfunctions, repair time is short. Due to contact with liquid, maintenance is required every day regarding device cleaning. In line with these rates, the infusion pump should be prioritized.

5. CONCLUSIONS

In this thesis, a dynamic preventive maintenance schedule strategy based on the usage rates of medical devices have been developed to improve the medical devices management process in the biomedical department of hospitals. Managing medical device maintenance, calibration, and failure processes has become increasingly challenging with the growth of hospital capacities. The maintenance of these devices directly affects patient health and treatment processes. Many CMMS programs have been developed for this process, and hospitals use these programs to manage the process digitally. Keeping records of historical data is essential for tracking the history of any medical device.

The identified problem stems from the large number of hospital devices, which leads to extended maintenance and calibration processes and makes tracking difficult. Some medical devices have spare parts. These spare parts need to be replaced after a certain period, especially after the device's warranty has expired. The procurement process for these spare parts can be lengthy due to logistics and purchasing procedures. Non-original parts may be preferred to shorten this process. It is essential to know how long each device is used in which service to plan these processes correctly.

IoT technology, which has become widespread and integrated into the healthcare field, is explored in addition to using sensors in RFID tags to obtain information about how much time medical devices are used. For this thesis, we conducted trials using appropriate equipment at the chosen hospital and collected data from the identified medical devices around the clock. Care was taken to select devices that are actively used and have different functions.

As a result of the tests:

1. When the device is plugged in, there is no change in the data from the sensor.
2. When the device is turned on, there is no change in the data from the sensor.
3. When the device starts to operate, especially near the device's motor, changes are observed in the data from the sensor.

Based on these tests, it is observed that usage data of the device can be obtained from the sensor. The tests conducted in the hospital determined how long the device operates every 24 hours using the K-Means clustering method on data from other days. The obtained data was integrated into the existing AHP model, a ranking method, to propose a maintenance schedule.

Based on the characteristics of the selected devices, the results indicate that the maintenance schedule for the infusion pump device should be rescheduled to an earlier time than currently planned. The advantage of using this schedule is that it will facilitate process planning and help prevent high-priority and urgent breakdowns from occurring. It will also make it easier to track maintenance and calibration. Additionally, through collaboration between the biomedical department and users, continuous monitoring and maintenance will reduce user-based failure rates. Criteria, sub-criteria, and decision definitions, which may vary for each hospital, can be changed and integrated into the software used in the hospital.

5.1 Proposal

In the realm of healthcare, the reliability and optimal functioning of medical devices are of paramount importance, as they directly impact patient care and safety. The concept of dynamic preventive maintenance, particularly when based on the usage rate, has gained prominence as a proactive strategy for ensuring the continuous availability and efficiency of these devices. This thesis has explored the application of an innovative approach, combining Analytical Hierarchy Process (AHP) and Internet of Things (IoT) technologies, with a focus on magnetometer sensors. The utilization of these sensor technologies for real-time monitoring of medical device conditions has shown significant promise in enhancing preventive maintenance schedules.

The research findings indicate that the AHP-based decision-making framework enables a systematic and comprehensive evaluation of maintenance priorities, considering multiple criteria and their relative importance. Incorporating IoT technology has provided real-time data monitoring capabilities, which enable predictive maintenance and reduce the likelihood of unexpected device failures.

Building on the research conducted in this thesis, there are several areas for future investigation and development:

Battery Life Enhancement: In the thesis, the battery of tags was replaced 3-4 months after the independent tests started. Prior to this study, no battery life optimization study had been conducted considering the sensor frequency or any other factor. Conducting this research is fundamental to the practical implementation of the thesis.

Machine Learning Models: Different machine learning methods other than the K-means method can be used to make decisions with the data obtained from sensors.

Alternative Sensor Technologies: In addition to magnetometer sensors, the incorporation of supplementary sensor technologies can offer a more complete perspective of the health status of medical devices. Vibration sensors, temperature and humidity sensors can be providing monitoring environmental conditions can be critical for the longevity of certain medical devices.

Real-World Implementation and Validation: Longer independent tests can be conducted to evaluate its practicality and effectiveness. By including different medical devices, data can be collected, especially on whether a device's malfunction can be detected in advance. Collaboration with healthcare institutions and medical device manufacturers can provide valuable insight and validation of system performance. The software can be used to monitor the process and make the right decisions by analyzing the correct data.

In conclusion, this thesis lays a strong foundation for a dynamic preventive maintenance system based on usage rate, AHP, and IoT with magnetometer sensors for medical devices. Further research and development in the aforementioned areas can lead to the creation of more advanced, efficient, and reliable maintenance strategies, ultimately benefiting both healthcare providers and patients by ensuring the continuous availability of critical medical equipment.

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APPENDIX A

Table A.1 shows the long-term independent test dates performed using the magnetometer sensor and the running time in seconds on those dates. The "-" sign in the Table A.1 indicates that no data was received from the sensor that day.

Table A.1 Measured running times of medical devices as a result of K-means clustering

Date	ECG	Infusion Pump	NST	Ultrasound	Defibrillator
	A1A5A6	A2A5A6	E0AAB2	E0AAF5	E0AB44
4/11/2023	-	8032.78	7568.56	-	-
4/12/2023	-	6550.08	27358.79	-	-
4/13/2023	-	0.00	18077.585	-	-
4/14/2023	-	6083.60	6819.96	-	-
4/15/2023	-	9137.76	2596.68	-	-
4/16/2023	-	0.00	4091.62	-	-
4/17/2023	-	5588.27	0.00	-	-
4/18/2023	-	0.00	0.00	-	-
4/19/2023	-	1955.99	6964.80	-	-
4/20/2023	-	12927.38	5740.48	-	-
4/21/2023	-	5201.02	-	-	-
4/22/2023	-	0.00	-	-	-
4/23/2023	916.23	0.00	-	-	-
4/24/2023	0.00	0.00	-	-	-
4/25/2023	0.00	5454.34	-	-	-
4/26/2023	3166.65	0.00	-	-	-
4/27/2023	4449.45	0.00	-	-	-
4/28/2023	0.00	0.00	-	-	-
4/29/2023	1343.65	0.00	-	-	-
4/30/2023	1145.62	0.00	-	-	-
5/1/2023	1493.54	0.00	-	-	-
5/2/2023	1851.19	4458.24	-	-	-
5/3/2023	751.258	0.00	-	-	-

Date	ECG	Infusion Pump	NST	Ultrasound	Defibrillator
	A1A5A6	A2A5A6	E0AAB2	E0AAF5	E0AB44
5/4/2023	0.00	2119.48	-	-	-
5/5/2023	3623.71	0.00	-	-	-
5/6/2023	1651.10	0.00	-	-	-
5/7/2023	622.239	0.00	-	-	-
5/8/2023	1017.646	0.00	-	-	-
5/9/2023	1634.05	0.00	-	-	-
5/10/2023	3218.90	0.00	-	-	-
5/11/2023	2833.07	0.00	-	-	-
5/12/2023	0.00	8546.11	-	-	-
5/13/2023	0.00	37207.00	-	-	-
5/14/2023	0.00	63360.71	-	-	-
5/15/2023	657.31	6023.85	-	-	-
5/16/2023	893.80	0.00	-	-	-
5/17/2023	577.224	16745.25	-	-	-
5/18/2023	1018.371	5603.13	-	-	-
5/19/2023	0.00	2032.00	-	-	-
5/20/2023	1578.31	3884.14	-	-	-
5/21/2023	0.00	17411.42	-	-	-
5/22/2023	2995.57	64706.61	-	-	-
5/23/2023	1203.842	57456.40	-	-	-
5/24/2023	0.00	50513.24	-	-	-
5/25/2023	901.128	62989.42	-	-	-
5/26/2023	1558.09	65084.37	-	-	-
5/27/2023	914.33	73326.69	-	-	-
5/28/2023	0.00	71823.40	-	-	-
5/29/2023	1037.29	70196.02	0.00	-	-
5/30/2023	1228.24	77732.59	3281.873	8062.26	-
5/31/2023	-	74801.43	22265.63	3142.85	-
6/1/2023	-	28549.44	12757.21	0.00	-

Date	ECG	Infusion Pump	NST	Ultrasound	Defibrillator
	A1A5A6	A2A5A6	E0AAB2	E0AAF5	E0AB44
6/2/2023	-	62018.00	9822.70	0.00	-
6/3/2023	-	1893.84	4722.01	12233.90	-
6/4/2023	-	-	20268.17	0.00	-
6/5/2023	-	-	29522.14	0.00	-
6/6/2023	-	0.00	14785.06	9380.76	-
6/7/2023	-	0.00	0.00	0.00	-
6/8/2023	-	2418.446	5703.11	0.00	-
6/9/2023	-	-	0.00	14811.97	-
6/10/2023	-	-	0.00	0.00	-
6/11/2023	-	-	0.00	0.00	-
6/12/2023	-	-	0.00	8722.96	-
6/13/2023	-	-	5305.73	4121.71	-
6/14/2023	356.89	1809.01	6523.19	712.3	1367.32
6/15/2023	848.61	2293.93	0.00	0.00	385.41
6/16/2023	906.474	21427.37	1598.78	0.00	450.85
6/17/2023	697.149	7889.17	11782.22	0.00	918.89
6/18/2023	1012.04	3885.93	1099.57	4078.39	1329.75
6/19/2023	0.00	12290.89	0.00	5011.68	889.91
6/20/2023	543.03	6667.47	8573.66	5011.68	1548.97
6/21/2023	914.71	32848.13	10696.92	2385.45	871.76
6/22/2023	0.00	40718.87	4969.99	1958.55	1249.48
6/23/2023	0.00	9813.85	5745.56	7665.06	1319.64
6/24/2023	0.00	21853.63	2301.98	2989.46	1667.15
6/25/2023	620.476	0.00	0.00	0.00	1126.75
6/26/2023	1523.65	35382.58	8591.41	0.00	1203.17
6/27/2023	811.21	69303.00	0.00	6432.50	1233.80
6/28/2023	0.00	81579.95	9072.01	4695.82	742.71
6/29/2023	938.108	55597.50	0.00	0.00	1184.91
6/30/2023	550.21	24093.36	0.00	0.00	1171.15

Date	ECG	Infusion Pump	NST	Ultrasound	Defibrillator
	A1A5A6	A2A5A6	E0AAB2	E0AAF5	E0AB44
7/1/2023	0.00	15098.86	2154.85	0.00	1213.34
7/2/2023	0.00	8320.03	9139.03	1356.62	1054.84
7/3/2023	0.00	24424.25	2876.09	0.00	1298.06
7/4/2023	0.00	69251.13	1595.92	0.00	1679.54
7/5/2023	684.50	6844.94	1207.37	4455.51	1205.74
7/6/2023	2601.18	0.00	11416.37	3045.74	1968.74
7/7/2023	644.057	0.00	4715.33	0.00	1692.43
7/8/2023	907.031	0.00	15502.49	2283.70	1105.00
7/9/2023	0.00	0.00	85975.00	0.00	613.24
7/10/2023	0.00	0.00	33488.21	885.01	1254.90
7/11/2023	1425.46	0.00	7397.63	2310.20	953.00
7/12/2023	3312.24	1590.19	21692.19	0.00	1287.16
7/13/2023	1857.76	1617.91	0.00	4884.76	1100.80
7/14/2023	3686.80	0.00	4216.28	0.00	920.82
7/15/2023	0.00	0.00	0.00	0.00	974.54
7/16/2023	0.00	0.00	0.00	0.00	974.12
7/17/2023	0.00	32616.25	2896.64	0.00	1019.35
7/18/2023	1279.34	68210.67	0.00	0.00	0.00
7/19/2023	829.78	74508.09	3101.87	5717.02	1753.93
7/20/2023	0.00	69390.79	1535.04	7529.95	1259.41
7/21/2023	0.00	62129.73	3635.17	0.00	835.78
7/22/2023	781.172	74511.23	0.00	0.00	1305.02
7/23/2023	1345.34	72981.14	13573.176	0.00	1178.62
7/24/2023	996.357	54426.35	5126.76	3283.31	1360.50
7/25/2023	1565.39	79818.09	0.00	5663.54	815.44
7/26/2023	3342.58	81134.12	19241.85	4227.17	1430.53
7/27/2023	719.305	81931.37	41647.27	4303.69	1331.44
7/28/2023	1644.53	81547.58	85727.526	1494.62	1314.04
7/29/2023	377.46	83723.78	75623.623	1646.65	1384.24

Date	ECG	Infusion Pump	NST	Ultrasound	Defibrillator
	A1A5A6	**A2A5A6**	**E0AAB2**	**E0AAF5**	**E0AB44**
7/30/2023	0.00	69725.29	44490.90	0.00	1338.33
7/31/2023	2181.52	53013.88	52356.34	3871.65	1028.33
8/1/2023	787.29	52747.24	38368.41	1496.71	1378.13
8/2/2023	3208.661	45868.96	0.00	5792.51	1545.67
8/3/2023	446.02	42710.76	7155.21	0.00	1325.26
8/4/2023	0.00	6370.90	2792.96	4096.12	1541.68
8/5/2023	2426.52	0.00	0.00	4691.54	1283.37
8/6/2023	1538.11	1606.05	11817.80	0.00	1277.88
8/7/2023	5575.47	2531.95	8707.78	3151.08	1404.60
Sum	84186.16	2684718.91	867308.72	158376.44	58236.58
Number of Data	86.00	107.00	75.00	63.00	50.00

APPENDIX B

Table B.1 The essential absolute number scale (Saaty, 2008).

Intensity of Importance	Definition	Explanation
1	Equal Importance	Two activities contribute equally to the objective
2	Weak or slight	-
3	Moderate importance	Experience and judgement slightly favour one activity over another
4	Moderate Plus	-
5	Strong importance	Experience and judgement strongly favour one activity over another
6	Strong plus	-
7	Very strong or demonstrated importance	An activity is favoured very strongly over another; its dominance demonstrated in practice
8	Very very strong	-
9	Extreme importance	The evidence favouring on activity over another is of the highest possible order of affirmation

Table B.2 Random Index (Saaty, 2004).

n^5	1	2	3	4	5	6	7	8	9	10
Random	0	0	0.52	0.89	1.12	1.25	1.35	1.40	1.45	1.49

n^5= number of criteria

Table B.3 The decision definitions based on the specified TSV score intervals.

TSV Score Range	Action
50%≤TSV≤100%	Bring Forward
20%≤TSV<50%	Set a Maintenance Schedule
0%≤TSV<20%	Postpone

Table B.4 The decision parameters corresponding to the intensity values calculated with comparison matrices for the specified main criteria, sub-criteria and their categories.

Main Criteria and Sub criteria	Description	Intensity
1. Function	Evaluates the primary purpose of medical devices	1.000
1.1 Life Support and Treatment	Devices related to sustaining life and medical treatment.	1.000
1.2 Auxiliary Hospital Equipment	Equipment that supports hospital operations.	0.109
1.3 Physiological Signal Monitoring Devices	Devices for monitoring vital signs.	0.582
1.4 Imaging and Radiology Devices	Equipment for medical imaging and radiology.	0.365
1.5 Sterilization Devices	Devices used for sterilization in healthcare settings.	0.127
2. Functionality	Assesses how effectively devices serve their intended purpose	0.909
2.1 Utilization	Assessing how often and how extensively a medical device is used in healthcare settings.	1.000
2.1.1 High	Devices that are used intensively, with more than 24 hours of usage per week.	1.000
2.1.2 Medium	Devices that see moderate usage, with 12 to 24 hours of weekly operation.	0.303
2.1.3 Low	Devices with limited usage, operating less than 12 hours per week.	0.183
2.2 Alternative Device	Evaluating the availability of substitute devices or options to replace the primary medical device.	0.333
2.2.1 Low	Devices in this category have very limited or less than one alternative options available	1.000
2.2.2 Medium	These devices have one to four alternative options, allowing for some flexibility and potential substitution.	0.210
2.2.3 High	These devices have over four available alternatives, reducing dependence on a specific model or brand.	0.088
3. Age	Considers the age of devices in use	0.354

Main Criteria and Sub criteria	Description	Intensity
3.1 Old	Devices that have been in use for over a decade.	1.000
3.2 Almost Old	Devices that are between 5 and 10 years old, approaching the “old” category.	0.442
3.3 Average	Devices with a standard age of 3 to 5 years since their introduction or purchase.	0.282
3.4 New	Devices that are relatively new, having been used for less than 3 years.	0.237
4. Total Risk	Examines the overall risk associated with device usage	0.145
4.1 Failure Frequency	Examining how often a medical device experiences malfunctions or failures during its operation.	1.000
4.1.1 High	Likely to occur (several occurrences in 1 year)	1.000
4.1.2 Medium	Several occurrences in 1–2 years) 0.33 Uncommon Possible to occur (one occurrence in 2–5 years)	0.286
4.1.3 Low	Unlikely occur (1-10 years)	0.109
4.2 Detectability	Determining how easily and promptly failures or malfunctions in a medical device can be identified or detected.	0.164
4.2.1 Low	Not detected by regular inspection	1.000
4.2.2 Medium	Visible by naked eye	0.286
4.2.3 High	Self-announcing	0.109
4.3 Failure Consequences	Assessing the impact and severity of potential consequences when a medical device malfunctions or fails.	0.405
4.3.1 High	Extended periods of non-operation with downtime exceeding 24 hours.	1.000
4.3.2 Medium	Brief non-operational periods with downtime less than 24 hours.	0.264
4.3.3 Low	Devices that remain functional without significant downtime	0.101

Main Criteria and Sub criteria	Description	Intensity
5. Maintenance Requirement	Focuses on the level of maintenance needed for proper device operation	0.118
5.1 High	Maintenance involves shift test, auto test, and user test, indicating more frequent and comprehensive maintenance procedures.	1.000
5.2 Medium	Maintenance primarily includes user test, suggesting moderate maintenance requirements.	0.210
5.3 Low	Maintenance is simplified and mainly involves auto Test, indicating minimal maintenance needs.	0.088

APPENDIX C

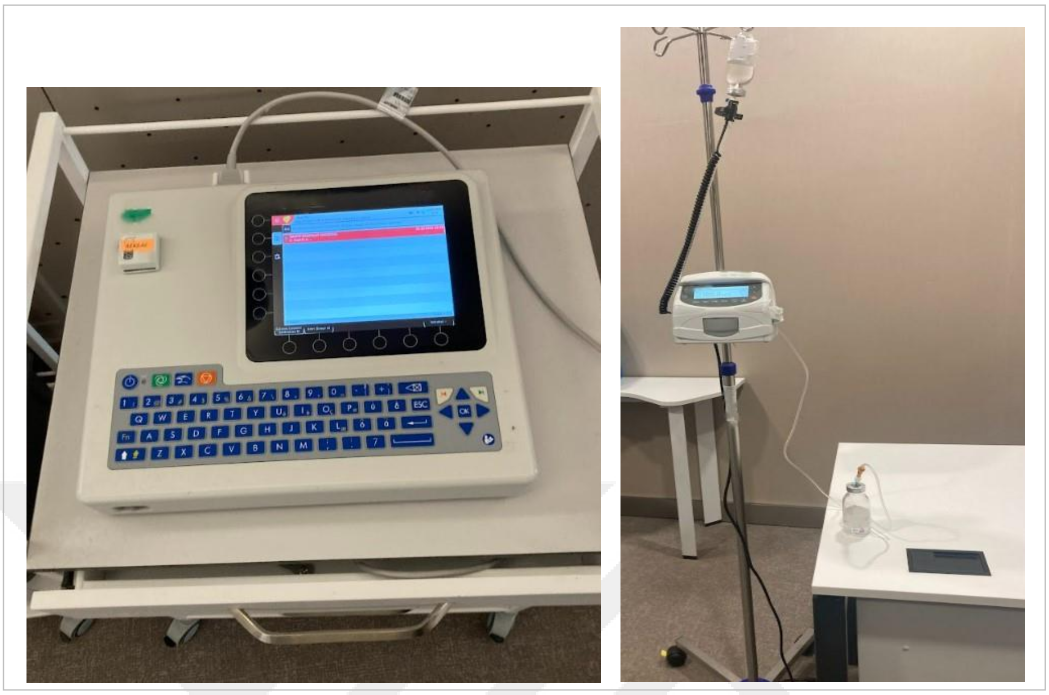

Figure C.1 The ECG and A1A5A6 tag used are shown on the left, and the infusion pump and the A2A5A6 tag attached to its side are shown on the right.

Figure C.2 The signal receiver used data from the tag with RFID technology.