Data-Driven Maintenance Prioritisation and Scheduling for Industrial Equipment

Degree project report in Production Engineering

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Cover: Visualisation of a smart manufacturing environment with real-time maintenance data and robotic automation.

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Abstract

Effective maintenance planning is essential for sustaining productivity, improving equipment reliability, and maintaining cost-efficiency in modern manufacturing environments. As production systems grow in complexity, the reliance on data has become more crucial for informed, timely, and scalable maintenance decisions. Traditional rule-based approaches often fail to account for the dynamic nature of operational data such as technician availability, machine utilisation, failure history, and cost trends, which limits their effectiveness in real-world industrial settings.. This thesis responds to these challenges by developing a tailored decision support system, integrating a hybrid multi-criteria decision-making model with constraint programming.

The proposed Decision Support System combines the Analytic Hierarchy Process and the Technique for Order Preference by Similarity to Ideal Solution to prioritise maintenance tasks based on costs, estimated downtime and risk priorities. These maintenance tasks are ranked and subsequently fed into a Constraint Programming model that generates an optimised maintenance schedule that accounts for technician availability, shift structures, and other production constraints. The complete system is implemented within an interactive dashboard, replacing traditional manual planning methods with a scalable, data-driven solution. This research demonstrates how hybrid decision-making techniques, when coupled with constraint-aware optimisation, can bridge the gap between expert-driven maintenance strategies and real-time operational planning. The resulting approach provides a replicable and adaptable methodology for proactive, optimised maintenance scheduling in industrial settings. Unlike the existing literature addressing Multi Criteria Decision Making and optimisation techniques individually, this thesis addresses combines a hybrid framework, through AHP and TOPSIS, with Constraint Programming into a unified and deployable framework designed to handle real world constraints in a dynamic manufacturing environment.

Keywords: Maintenance, Maintenance prioritisation, Maintenance Scheduling, MCDM, AHP, TOPSIS, Constraint Programming

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Akshay Bhat Vishwas Aravind
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List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

MCDM	Multi-Criteria Decision Method
AHP	Analytical Hierarchy Process
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
CM	Corrective Maintenance
PM	Preventive Maintenance
CBM	Condition Based Maintenance
PdM	Predictive Maintenance
TPM	Total Preventive Maintenance
TPdM	Total Predictive Maintenance
DSS	Decision Support system
CP	Constraint programming
CR	Consistency Ratio
OEE	Overall Equipment Effectiveness
MTTR	Mean Time to Repair
MTTF	Mean Time to Failure
MTBF	Mean Time to Between Failure
IoT	Internet of Things
ERP	Enterprise Resource Planning
Z3	Microsoft Z3 Theorem Solver
CBR	Case Based Reasoning
PROMETHEE	Preference Ranking Organisation Method for Enrichment of Evaluations
JIT	Just in Time
CMMS	Computerised Maintenance Management System
KPI	Key Performance Indicators
S	Severity
D	Detection
O	Occurence

Nomenclature

Below is the nomenclature of indices, sets, parameters, and variables that have been used throughout this thesis.

AHP and TOPSIS Variables

a_{ii}	Diagonal elements of the AHP pairwise matrix, always equal to 1
$a_{ji} = \frac{1}{a_{ij}}$	Reciprocal property of the AHP pairwise matrix when $i \neq j$
w	Priority vector of criteria derived from normalized AHP matrix
$\lambda_{\max}$	Principal eigenvalue of the pairwise comparison matrix
CI	Consistency Index in AHP
RI	Random Index based on matrix size
CR	Consistency Ratio, computed as $CR = \frac{CI}{RI}$
$D = [x_{ij}]_{m \times n}$	Decision matrix with m tasks and n criteria
r_{ij}	Normalized value for task i under criterion j
v_{ij}	Weighted normalized value for task i under criterion j
v^+, v^-	Ideal and negative-ideal solution vectors in TOPSIS
S_i^+, S_i^-	Distances of alternative i from ideal and negative-ideal solutions
C_i^*	Relative closeness of alternative i to the ideal solution

Weighted Average Formula

x_i	Downtime or cost value
w_i	Assigned weight based on event severity

Cost and Penalty Parameters

x_{ij}	Binary variable: 1 if task i is assigned to shift j, else 0
N, T	Total number of tasks and shifts respectively
C_i	Base cost associated with performing task i (e.g., part/labour cost)
H_i	Estimated downtime duration (in hours) for task i
$\alpha \cdot H_i$	Downtime penalty based on duration
R_j	Hourly rate for shift j (regular or night/weekend)
R_{ot}	Overtime rate applied to hours beyond 8
$\min(H_i, 8)$, $\max(0, H_i - 8)$	Splits total hours into regular and overtime portions
$\gamma \cdot \delta_{j \in \text{Peak}}$	Penalty for assigning tasks during high-production shifts
$\lambda \cdot \max(0, w_j - d_i)$	Escalating penalty for exceeding task deadline d_i in week w_j
$\beta \cdot \delta_{j \in \text{Early}}$	Incentive (bonus) for scheduling task early in the week

Scheduling and Model Parameters

m	Total number of maintenance tasks
n	Number of criteria
s_i	Scheduled shift index of task i
d_i	Deadline (target week) for task i
w_j	Calendar week of shift j
$\delta_{\text{condition}}$	Indicator function (1 if true, 0 if false)
W_w	Set of all shifts in week w
M, E	Sets of tasks requiring Mechanical or Electrical technicians
M_j, E_j	Technician capacity (Mechanical, Electrical) in shift j
Δ_g	Maximum allowed shift gap for grouping
Machine(i)	Machine to which task i belongs

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1

Introduction

This section provides a brief background and motivation for the thesis, and outlines its aim, research questions, as well as its scope and limitations.

1.1 Background

Efficient maintenance management has become increasingly critical in the current manufacturing landscape. With industries moving towards becoming more sustainable and efficient, the demand placed on machines and equipment continues to grow. As a result, traditional maintenance strategies often fall short in meeting the evolving needs of modern manufacturing. Increasing digitalisation and complexity in industrial operations are pushing companies to adopt smarter and more analytical approaches to maintenance management and planning. Maintenance departments are striving to adopt digital technologies to increase equipment availability, reduce downtime, and improve cost-effectiveness, while also investing in new technologies and upskilling their workforce [4]. Despite these efforts, machine failures remain inevitable, and effective maintenance remains essential to ensure reliability and minimise disruptions [12].

Maintenance plays a vital role in sustaining productivity in any manufacturing company that produces components. As the push for sustainability increases and becomes a regulatory requirement, the demand for high-performing machinery increases, putting additional strain on existing systems. Traditional maintenance practices are no longer efficient for supporting this shift. Production systems have become more complex and data-driven, requiring industries to adapt accordingly.

Manufacturing industries have become highly competitive, forcing organisations to digitally transform their operations to stay competitive. Maintenance functions have responded by enhancing equipment availability, increasing productivity, and investing in skill development and advanced tools [4]. However, failures are still unavoidable, regardless of technological advancements [12]. Maintenance is therefore critical in ensuring that systems remain operable, reliable, and profitable. Poorly executed or deferred maintenance can result in costly disruptions, delayed product delivery, and increased production expenses [18]. At the same time, manufacturers seek stable and predictable production flows, yet are confronted with highly volatile market demands. These demands, particularly for high-volume and mixed-product outputs, lead to complex scheduling scenarios [16]. As such, maintenance and production scheduling, often treated as separate processes, tend to compete with one another [28]. Nonetheless, consistent production cannot be achieved without reliable maintenance. With increasing demand and product variety, more companies are now turning to automation and integrated planning systems to align maintenance strategies with operational goals.

At the moment, maintenance is currently managed through two ways: Preventive Maintenance (PM) and Corrective Maintenance (CM). PM is scheduled at regular intervals based on the OEM recommendations. For example, the machines undergo PM tasks after every 2,000 operating hours to prevent failures and maintain optimal functionality.

CM, on the other hand, is performed reactively, triggered by equipment breakdowns or any issues on the shop floor. In such cases, work orders are generated, and maintenance tasks are planned up to three weeks in advance. This lead time allows the production team to align operational activities and minimise disruptions. One thing to note, most machines within the partner company are flexible and can handle similar operations with minor parameter adjustments. This flexibility enables production continuity even when individual machines fail. However, as production volumes increase in the future, this buffer will shrink, and the need for proactive, well-planned maintenance will become significantly more important.

Despite having access to work order logs and breakdown histories, current task prioritisation is carried out manually, relying heavily on technician experience and recent failure patterns. Maintenance and production are managed in traditional systems. These challenges underline the need for a structured, centralised, and data-driven maintenance planning framework, one that integrates operational constraints, failure risk indicators, and resource availability into a coordinated strategy. The framework proposed in this thesis is designed to address precisely this gap. By combining expert judgement with data-driven methods, it offers a tailored solution that reflects the industry's specific operational conditions and future scalability needs.

Our study addresses this gap by proposing an analytical framework for maintenance prioritisation and scheduling tailored for industrial equipment planning. The solution is specifically tailored to the industry's maintenance environment. The proposed framework incorporates various Multi-Criteria Decision Method (MCDM) techniques alongside constraint programming (CP) to improve transparency, responsiveness, and planning efficiency in maintenance operations.

1.2 Motivation

Modern manufacturing environments face increasing complexity, tighter production deadlines, more product variants, and less resource availability. As companies move toward higher levels of automation and demand responsiveness, maintenance becomes a critical enabler of operational stability. Traditionally seen as a cost centre, maintenance is now recognised as a strategic function that directly impacts productivity and profitability. Dunn [10], estimates that maintenance costs account for 15–40% of total production expenditure, emphasising the importance of making maintenance both effective and efficient. Without structured prioritisation and dynamic scheduling, maintenance tasks tend to be delayed, poorly aligned with production cycles, or inadequately tracked. This reactive approach leads to inefficiencies, escalated costs, and risks of unplanned downtime, especially in environments where equipment is shared or reconfigurable.

This thesis is motivated by the need for:

- A systematic, multi-criteria method to prioritise maintenance tasks based on objective factors such as risk, downtime impact, and cost.

- An interactive decision-support system that dynamically schedules tasks based on technician availability, machine utilisation, and production demands.

- By addressing these challenges, the proposed approach contributes to transform maintenance from a reactive function to a proactive and strategic component of production planning.

1.3 Aim

This thesis aims to establish a framework that, through a combination of frameworks, enables the integration of a Decision Support System (DSS) into its existing system to prioritise industrial machine components and plan maintenance operations accordingly. This study also discusses and provides practical insights and solutions for maintenance task prioritising and scheduling.

1.4 Objectives

To achieve this, the research focuses on three key objectives:

1. Develop a prioritisation model using the Analytical Hierarchy Process (AHP) – Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) hybrid MCDM approach to rank maintenance tasks based on multiple risk and operational factors.

2. Optimise the scheduling of maintenance tasks by applying constraint programming techniques that consider labour personnel, skills and production planning.

3. Design and build a DSS in the form of an interactive dashboard, thereby enabling real-time maintenance planning and enhanced user interaction.

1.5 Research Questions

The research is guided by the following questions:

1. How can industrial maintenance task be prioritised based on multiple conflicting criteria?

2. How can prioritised maintenance tasks be integrated into a decision support system to enable tracking, visualisation, and scheduling of maintenance tasks?

This research will provide both theoretical and practical contributions, offering valuable insights into optimising maintenance scheduling along with designing the dashboard for data driven decision making.

1.6 Scope and Limitations

This research is conducted within the context a real world production environment, focusing on a manufacturing cell consisting of eight machines to develop a DSS for prioritising and scheduling maintenance tasks. The proposed hybrid approach combines both AHP-TOPSIS and CP to align maintenance decisions with production demands. The DSS developed was based on historical data and expert judegments rather than real-time data. This was due to a lack of data availability for this particular manufacturing cell. The model assumes the availability of expert judgements at the component level for AHP comparisons to make pairwise comparisons, as well as complete datasets for downtime, cost, and technician categories per subcomponent. The model also assumes that, except for specified holiday weeks, the scheduling logic is designed to represent a set three-shift work schedule during the week and a single shift on the weekends.

The boundaries were defined to keep the scope narrow and ensure feasibility within the thesis time frame, operational constraints and current data maturity. Real-time machine data, inventory level intergration and system-wide automation were excluded as they require different data sets, infrastructure and logic. This thesis makes a notable contribution despite these limitations by showing how constraint-based scheduling and structured prioritisation logic may be used together in a real industrial context. The resulting DSS fills the gap between maintenance decision-making and operational planning by providing a transparent, scalable, and adaptive framework that may grow with future digitalisation initiatives like and Predictive Maintenance (PdM).

1.7 Thesis Structure

This thesis is organised into five chapters:

Chapter 1 provides an introduction to the research, including its context, motivation, objectives, and research questions.

Chapter 2 presents the theoretical framework and reviews relevant literature on maintenance prioritisation, MCDM methods, and constraint-based scheduling approaches.

Chapter 3 details the research methodology, covering data collection procedures, the AHP–TOPSIS prioritisation framework, and the integration of constraint programming for scheduling.

Chapter 4 showcases the results obtained from the implemented decision-support system and provides an in-depth discussion of its performance.

Chapter 5 reflects on the findings, discusses limitations, and outlines directions for future research.

Chapter 6 concludes the thesis by summarising key contributions and implications of the study.

2

Theoretical Background

This chapter provides the framework for the research through studying fundamental concepts in decision making, prioritisation, and maintenance scheduling. It begins by reviewing the role of maintenance in various factories and sectors before discussing the theoretical foundations of the prioritisation and scheduling methodologies employed in this research. Together, these topics provide the context for understanding how the suggested framework enables improved planning and decision-making in a manufacturing environment.

2.1 Maintenance in Industrial Context

Maintenance is an important aspect of keeping any industrial operation functioning smoothly. It ensures that equipment and systems continue to be safe, effective, and operational throughout time. Maintenance is now viewed as a strategic function rather than merely a technical task in modern manufacturing environments, where even a short interruption can result in large costs. Maintenance must be proactive, carefully thought out, and in line with production targets and resource availability, as manufacturing becomes increasingly automated and interconnected.

2.1.1 Definition and Types of Maintenance

Maintenance is defined as the "combination of all technical, administrative, and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function", according to European standard EN 13306. [34]. Maintenance is the set of tasks/activities performed to restore the functional state of equipment, machinery and systems [20]. Maintenance activities play a critical role in any industrial environment that directly influences factors like operational efficiency, safety, product quality and overall throughput.

Maintenance strategies can broadly be categorised into:

1. **CM:** This type of maintenance is carried out when a failure has already occurred and the machine is being restored to operational condition. Since it's reactive in nature, it is also known as reactive maintenance.

2. **PM:** Scheduled at regular intervals in order to extend asset life and prevent

failures. These predefined intervals can be time- or usage-based.

3. **Condition-Based Maintenance (CBM):** CBM involves monitoring the condition of machinery to determine the requirement for maintenance interventions.

4. **PdM and Total Predictive Maintenance (TPdM):** PdM is an advanced strategy that addresses shortcomings of time-based preventive maintenance by leveraging real-time data to forecast equipment failure. TPdM extends PdM further by incorporating operational data, production dynamics, and organisational constraints to make maintenance decisions more intelligent and aligned with business objectives [22]. TPdM not only predicts failure but also decides when and which maintenance tasks should be prioritised, considering factors such as maintenance history, resource availability, cost and downtime risks, equipment criticality, and production schedule constraints.

There is a noticeable shift from CM to data-driven methods, such PdM and Total Preventive Maintenance (TPM). The advancement in technologies, such as the use of sensors, digital twins, and artificial intelligence leading to use shift in maintenance paradigms [39].

2.1.2 Strategic Importance of Maintenance in Manufacturing

In recent years maintenance is recognised as in today's manufacturing world as a strategic enabler of operational efficiency rather than just mere a cost centre or support function. The influence of maintenance is across aspects such as safety, productivity, cost-effectiveness and Overall Equipment Effectiveness (OEE). In the literature Muchiri et al. 2011 [21] mentions that maintenance directly contributes to company strategy by having noticeable effects on key performance measures such as availability, reliability, and product quality.

A comprehensive maintenance plan can provide noticeable benefits by:

- Improving machine availability and reducing unplanned downtime.
- Lowering energy consumption and increase in throughput.
- Increasing equipment lifespan and thereby deferring new investment of new machinery.
- Increase safety and minimise environmental risks.

This strategic integration has become increasingly important in the context of Just in Time (JIT) production and complex system interdependencies, where any slight disruptions will result in significant delays, quality difficulties, and financial losses [18].

The conceptual model in the below 2.1 illustrates the link between maintenance objectives and corporate strategies. In line with business and production objectives, this figure highlights how maintenance supports important areas such plant operation, safety, and cost-effectiveness.

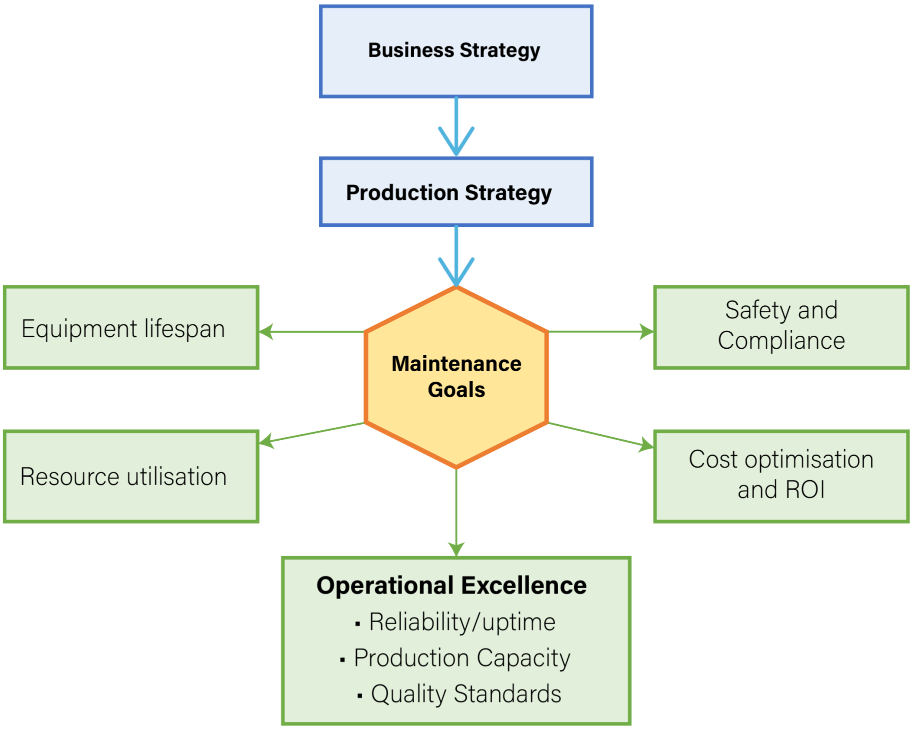


Figure 2.1: A summary of maintenance objectives for a maintenance department adopted from [21].

2.1.3 Maintenance Maturity Models and Best Practices

Different maintenance maturity models have been researched to facilitate planned and structured improvements. These models evaluate the level of complexity of maintenance tasks in various areas such as strategic integration, planning, execution, and monitoring. Notably, the multi-criteria hierarchical performance model developed by Parida and Chattopadhyay [25] divides performance indicators into strategic, tactical, and operational levels, making it easier to match maintenance choices with organisational objectives [21].

The following are considered best practices in maintenance management:

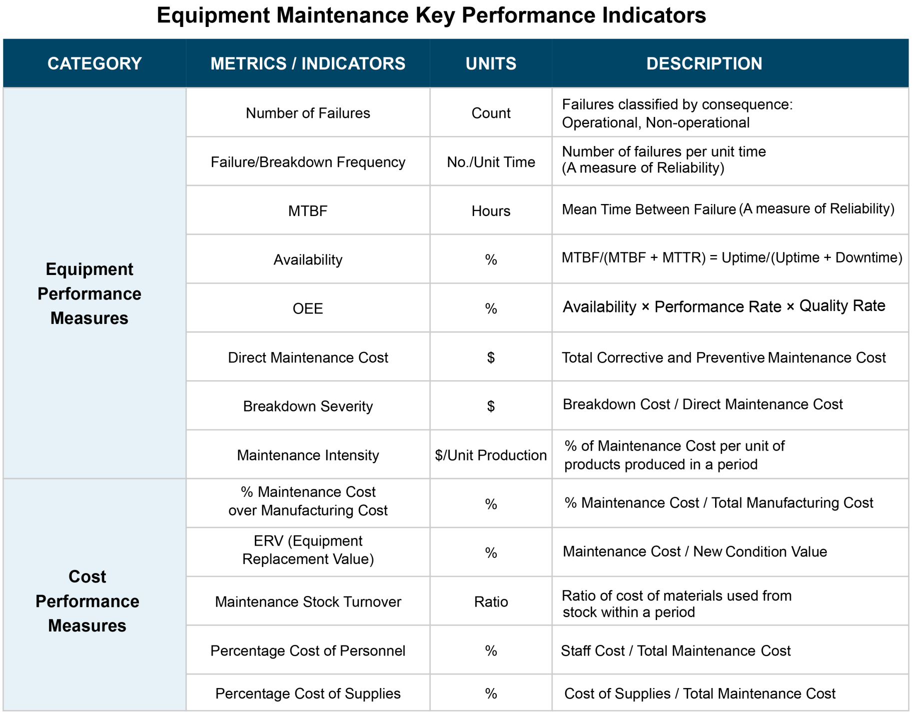
1. Adoption of Computerised Maintenance Management System (CMMS) to systematically track work orders, tasks, failures, and the logistics of replacement parts.

2. Inclusion of KPIs such as OEE, Mean Time to Repair (MTTR), Mean Time to Failure (MTTF), and Mean Time to Between Failure (MTBF) [27].

3. Implementation of TPM and Lean approaches, including autonomous maintenance and specialised improvement projects.

To facilitate these approaches, numerous technologies integrated with maintenance platforms are often linked to Internet of Things (IoT) and Enterprise Resource Planning (ERP) systems. This enables for real-time tracking and decision-making, historical data analysis, resource optimisation and collaboration between various departments [27].

In general, lagging performance indicators are used to assess the efficiency of maintenance. These metrics track factors like maintenance costs, failure rates, and downtime. Figure 2.2 shows a summary of the important lagging indicators that are vital to assessing performance and continuous improvement [21].



Equipment Maintenance Key Performance Indicators

CATEGORY	METRICS / INDICATORS	UNITS	DESCRIPTION
Equipment Performance Measures	Number of Failures	Count	Failures classified by consequence: Operational, Non-operational
	Failure/Breakdown Frequency	No./Unit Time	Number of failures per unit time (A measure of Reliability)
	MTBF	Hours	Mean Time Between Failure (A measure of Reliability)
	Availability	%	MTBF/(MTBF + MTTR) = Uptime/(Uptime + Downtime)
	OEE	%	Availability × Performance Rate × Quality Rate
	Direct Maintenance Cost	$	Total Corrective and Preventive Maintenance Cost
	Breakdown Severity	$	Breakdown Cost / Direct Maintenance Cost
	Maintenance Intensity	$/Unit Production	% of Maintenance Cost per unit of products produced in a period
Cost Performance Measures	% Maintenance Cost over Manufacturing Cost	%	% Maintenance Cost / Total Manufacturing Cost
	ERV (Equipment Replacement Value)	%	Maintenance Cost / New Condition Value
	Maintenance Stock Turnover	Ratio	Ratio of cost of materials used from stock within a period
	Percentage Cost of Personnel	%	Staff Cost / Total Maintenance Cost
	Percentage Cost of Supplies	%	Cost of Supplies / Total Maintenance Cost

Figure 2.2: A summary of lagging maintenance Key Performance Indicators (KPI), adopted from [21].

2.1.4 Challenges in Maintenance Planning and Execution

Even though we understand the need of maintenance, several challenges hinder it from being planned and carried out effectively. A few of the factors are listed below.

1. **Complex Machine Designs:** Modern industrial machines are highly complex, requiring coordinated scheduling, since failure in one subsystem can affect others [38].

2. **Unknown Failure Modes and Lack of Data Collection:** Legacy systems

often lack documented failure patterns, making PM less reliable [41].

3. **Resource Constraints:** Limited spare parts, skilled personnel, and access windows complicate scheduling [21].

4. **Non-alignment with Business Goals:** Maintenance metrics often overlook strategic KPIs such as cost per unit [40].

5. **Change Resistance and Organisational Culture:** Moving to predictive models demands cultural and procedural changes [40].

6. **Dynamic Operating Conditions:** Fluctuating production demands necessitate flexible planning strategies [21].

The OEE framework is widely regarded as one of the most effective methods for visualising the performance impact of maintenance. Equipment performance is broken down into three categories: availability, performance rate, and quality rate. And all of these are impacted by maintenance strategies. Figure 2.3 shows the various metrics such as MTTR, MTTF, planned and unplanned downtimes are directly related to maintenance performance [21].

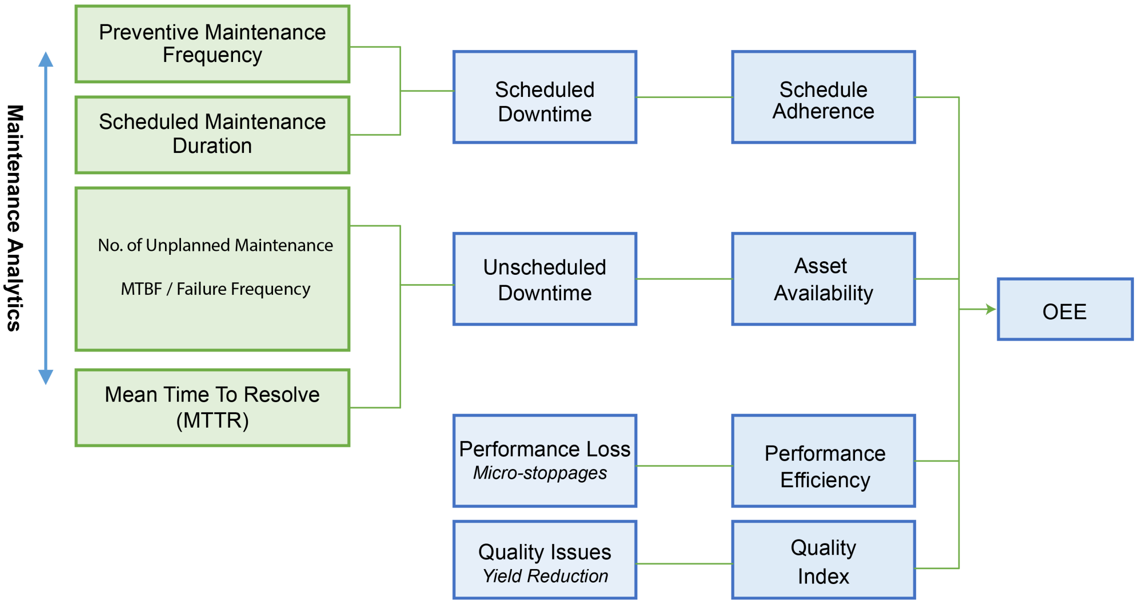


Figure 2.3: Important maintenance performance indicators in the OEE metric, adopted from [21].

2.2 Maintenance Task Prioritisation

In today’s industrial environments, it is difficult to balance maintenance tasks in any dynamic manufacturing environment. Resolving every possible problem at once is not practical, given the restricted resources of time, money, and manpower. This is where prioritising comes into play; by identifying the most important tasks first, businesses can control risk, reduce downtime, and make better use of their resources. The subsections that follow aim to discuss why prioritising is important and how various strategies are used to support it.

2.2.1 The Need for Prioritisation in Maintenance Management

In any manufacturing industry, regular and timely maintenance operations are critical for reducing production downtime, increasing machine availability, and ensuring safe working conditions. In most cases, with limited resources and complex production schedules, it may not be possible to address every potential issue right away. As a result, the ability to identify and prioritise maintenance tasks becomes critical, ensuring that the most critical and urgent maintenance tasks are completed first.

According to Chong et al. [6], organisations are often constrained by old and ageing infrastructure, limited budgets, increasing production costs, and the requirement of higher production efficiency standards, which are limiting many businesses. Prioritising maintenance becomes a critical for decision-making process in these situations, organisations often allocating limited resources to the most important projects. Additionally, organisations that lack a prioritisation approach risk allocating funds to low-impact maintenance tasks while ignoring parts that pose a serious threat to equipment operationality and safety.

Maintenance issues are the most common reason for production stoppages in any manufacturing industry. According to Soares Ito et al. [33], many organisations encounter hundreds of disruptions per day. This makes it nearly impossible to address all these issues solely through root cause analysis or CM. As a result, proper prioritisation is required to determine which maintenance tasks would benefit the whole system when accomplished within tight deadlines.

Furthermore, modern maintenance techniques such as TPM and PdM rely on real-time data to detect possible breakdowns. Even though it detects, it does not automatically provide decision logic for which components should be addressed first, especially when multiple warnings are generated at the same time. This reinforces the need for structured prioritisation frameworks that convert unstructured diagnostic data into useful judgements. Unplanned downtime has a ripple effect throughout the value chain in high-mix, high-volume manufacturing environments. Prioritisation frameworks in these conditions must consider operational, financial, and human factors in addition to technical urgency. Considering multi-faceted nature required in maintenance decision-making, MCDM frameworks are ideal for prioritising in these circumstances [25].

2.2.2 Key Factors Influencing Maintenance Prioritisation

Maintenance prioritisation is based on:

- **Severity (S):** Severity measures the potential impact of a failure of safety, production, or quality. A safety risk is caused by a complete halt in production or poses a safety risk that is rated higher than minor consequences. Severity drives urgency in a risk assessment model [17].

- **Occurrence (O):** Refers to the likelihood that a particular failure event is expected to occur. Higher scores are given to the components that fail more frequently. [6].

- **Detection (D):** Refers to the likelihood of how easily a failure event can be identified before it poses significant risks or downtime. The easier it is to detect a failure, the lower the risk [6].

- **Cost:** This includes the direct costs of labour, resources such as spare parts and materials and any tools that may be required for the task as well as indirect overhead costs associated with production, downtime or quality loss through rework. Costs are a critical parameter in MCDM frameworks [37].

- **Downtime:** Expected machine downtimes during maintenance tasks. Activities that may take more time or are more complex can be scheduled with a higher priority [42].

- **MTTR and MTTF:** Refers to the average operational time for a component that is likely to fail, and the average time taken to repair the equipment. The more complex the tasks are, the longer they need to repair and justify prioritising components for PM [1].

Task priority evaluation is influenced by severity, occurrence, detection, cost, downtime, and reliability measures like MTTR and MTTF, as shown in Table 2.1. The overall impact and necessity of the maintenance action are influenced differently by each of these factors.

Table 2.1: Summary Table: Key Factors Influencing Maintenance Prioritisation

Category	**Examples of Key Factors**
Technical	Severity, Occurrence, Detectability, Criticality
Operational	Downtime impact, Maintenance windows, Utilisation
Economic	Maintenance cost, Failure cost, Resource constraints
Organisational	Safety, Strategic value, Past data, Compliance

2.2.3 MCDM in Maintenance

In many cases, maintenance planning requires considering multiple conflicting criteria, such as cost, downtime, safety, failure risk and resource availability. To incorporate all these different criteria into decision-making, researchers and industries have used MCDM approaches. MCDM models provide maintenance planners with structured methods to evaluate these multifaceted complex scenarios using both qualitative and quantitative data, allowing them to make informed decisions [13, 24].

2.2.3.1 Overview of MCDM Approaches in Maintenance

In maintenance decision-making, selecting the most appropriate tasks to prioritise or the best strategy to follow is rarely straightforward. With multiple factors involved - such as cost, risk, downtime, and resource availability, organisations increasingly turn MCDM methods to structure their choices. Over the years, several MCDM techniques have gained traction in maintenance research and industrial applications. Each method offers its own benefits and drawbacks, depending on the context, the type of data available, and the level of subjectivity involved.

One of the most widely used methods is the AHP. AHP is particularly useful when expert judgement plays a significant role, as it allows decision-makers to express their preferences through pairwise comparisons. These comparisons are then used to calculate relative weights for each criterion. AHP is simple to apply and easy to understand, which makes it especially popular in industry-focused studies. For instance, Maletic et al. [18], used AHP in a Slovenian paper mill to assess different maintenance policies, while other researchers have applied it for ranking machine criticality or allocating resources under budget constraints [24].

However, AHP does come with limitations. It assumes that all criteria are independent of one another, which is not always the case in complex systems. Additionally, when the number of criteria increases, the number of pairwise comparisons grows rapidly, making the process more time-consuming and prone to inconsistency in judgement. Despite these challenges, AHP remains a valuable tool for structuring expert opinions in a systematic way.

Another well-regarded method is the TOPSIS. Unlike AHP, TOPSIS does not rely on pairwise comparisons. Instead, it evaluates each alternative based on its distance from an ideal solution (one that performs best on all criteria) and a negative-ideal solution (one that performs worst). The alternative closest to the ideal and furthest from the negative ideal is considered the most favourable. This approach is intuitive and easy to compute, especially when the criteria weights are already known, which is why it is often used in combination with AHP.

TOPSIS has been successfully applied in maintenance prioritisation problems, including spare parts ranking, equipment criticality assessment, and even the selection of vendors or contractors. Its main drawback lies in its sensitivity to how the data is normalised, and in some cases, results can be skewed if the scales of input values are inconsistent or poorly defined. Nonetheless, its clarity and ability to produce a full ranking of alternatives make it highly attractive for real-world use [31, 36].

Case-Based Reasoning (CBR) is another MCDM technique that has been used in maintenance, but to a lesser extent. The principle behind CBR is simple: past decisions and cases are stored and reused to inform future problems. For instance, if a similar component previously failed and required urgent maintenance under specific operating conditions, that case can guide the current prioritisation decision. CBR is especially useful when historical maintenance data is rich and well-documented. It supports learning over time and can adapt as more cases are added. However, its effectiveness is heavily dependent on the quality and completeness of the case base. Moreover, it may not perform well in entirely new scenarios where no similar case exists, making it more of a complementary tool than a standalone method in many settings [6, 8].

PROMETHEE, which stands for Preference Ranking Organisation Method for Enrichment of Evaluations, is an important method to be aware of. PROMETHEE is based on the concept of outranking, where each alternative is compared to the others across all criteria, and a preference index is calculated. One of PROMETHEE's strengths is its flexibility: it can handle both quantitative and qualitative data and can incorporate preference functions that reflect decision-maker behaviour more realistically. This makes it especially useful in stakeholder-heavy environments, such as in large public infrastructure projects or multi-site maintenance strategy selection. However, PROMETHEE is computationally intensive and may be harder to explain to non-technical stakeholders. Its use in industrial maintenance is promising but still limited due to these barriers [24].

Lastly, Fuzzy MCDM approaches have become increasingly popular for dealing with uncertainty and vagueness in decision-making. In practice, not all criteria can be expressed in precise numerical terms. For example, "likelihood of failure" might be better described as "high", "medium", or "low". Fuzzy logic allows for these kinds of linguistic inputs to be translated into mathematical models. Techniques like Fuzzy AHP and Fuzzy TOPSIS have been applied in maintenance environments where data is incomplete or where expert judgement is inherently imprecise. For example, Shyjith et al. [31], demonstrated the use of a fuzzy hybrid AHP–TOPSIS model to select maintenance policies for thermal power plants. These approaches are highly adaptable but do require a good understanding of fuzzy set theory, which may be a barrier for adoption in some industrial settings.

2.2.3.2 Why AHP–TOPSIS?

When making maintenance decisions, several factors such as cost, risk, downtime, severity, occurrence and operational impact often compete for consideration. Organisations make use of these MCDM methods to manage these complexities, thereby facilitating data-driven decision making based on quantitative, qualitative and expert judgements.

In order to address these challenges a hybrid methodology combining both AHP and TOPSIS was developed. This is because:

AHP: Expert knowledge is used to make pairwise comparisons and determine weights for prediction. In addition, domain expertise makes it easier to convert subjective evaluations into a consistent numerical scale [18].

TOPSIS: Once weights are established, TOPSIS is a very useful method for ranking alternatives. It compares each alternative's distance to both an ideal and a negative-ideal solution, which is both computationally efficient and comprehensible [5].

Several studies have demonstrated the benefits of this hybrid approach.

- Maletic et al. [18] - Used AHP at a Slovenian paper mill to determine an effective maintenance approach while balancing hierarchical and conflicting criteria.

- Al-Najjar and Alsyouf [2] - Demonstrated the importance of TOPSIS in ranking maintenance activities to maximise operational efficiency and cost effectiveness.

- Shyjith et al. [31] - Introduced an integrated fuzzy AHP-TOPSIS model for policy selection in thermal power plants, which produced more consistent and logical results than independent methods.

- Maletic et al. [18] - found that AHP-TOPSIS is more effective than traditional ranking methods for maintenance prioritisation due to improved traceability and justifiability of outcomes.

- Özcan et al. [24] used a mixed Goal Programming–AHP model with TOPSIS to identify the best maintenance plans for hydroelectric power facilities, showing how hybrid approaches improve operational efficiency and strategic alignment.

Using the TOPSIS method, maintenance planners can also evaluate rankings in relation to an ideal distance from the solution while taking into account the combined impact of RPN score, cost, and downtime. These characteristics make it appropriate for complex industrial problems in which no trade-off between these factors is possible and no single solution exists that fulfils all criteria.

2.2.4 AHP

The AHP is a structured MCDM method developed by Saaty [29] in the 1970s. This method is often employed when both quantitative data and subjective expert judgements are involved. It enables decision-makers to model complex problems using a hierarchy and derive ratio-scale weights through pairwise comparisons. In this thesis, AHP is employed to determine the weights of criteria for cost, downtime and risk, which are subsequently used in the TOPSIS analysis [24].

Hierarchy Structure: AHP breaks down a complex decision problem into a hierarchy consisting of:

- Goal (Top level) – the primary objective of the decision problem. - The prioritisation of maintenance tasks.
- Criteria (Middle level) – the parameters or factors to evaluate alternatives, in our case, it is risk, cost and downtime.
- Alternatives (Bottom level) – the individual machine components that require maintenance.

Pairwise Comparison Matrix: To create a pairwise comparison matrix, each criterion is compared to the others using Saaty's fundamental 1-9 scale (see table Table 2.2 [29]:

Table 2.2: Scale of relative preference for pair-wise comparison [18]

Value	**Interpretation**
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values

The comparisons are recorded in a reciprocal matrix:

- For all diagonal elements: $a_{ii} = 1 \quad \forall i \in \{1, 2, \ldots, n\}$

This equation expresses every criterion equally when compared with itself.

- Reciprocal Properties:

$$a_{ji} = \frac{1}{a_{ij}} \quad \text{for all } i \neq j$$

Calculation of Priority Vector: The weights (priority vector) are computed using matrix normalisation:

- Each column of the matrix is summed.
- Each entry is divided by the sum of its respective columns.

- The average of each row determines the relative weight W_i, of each criterion.

- To obtain more precise results, consider computing the principal right eigenvector of matrix A.

Consistency Ratio (CR): To ensure consistency in expert judgments, the CR is computed:

$$\mathrm{CR} = \frac{CI}{RI}$$

where

$$\mathrm{CR} = \frac{\lambda_{\max} - n}{(n-1) \cdot RI}$$

- Acceptable if CR < 0.1
- RI from standard table
- n - Number of criteria
- RI - Random Index (depends on n, typically from a table)
- A CR < 0.10 indicates acceptable consistency.

2.2.4.1 Steps Involved in AHP

1. **Define the Hierarchical Structure:** The hierarchy is constructed with the goal at the top (e.g. optimal maintenance prioritisation), followed by the criteria and sub-criteria levels, and finally the alternatives at the bottom for policy selection.

2. **Pairwise Comparison of Criteria:** Each pair of criteria is compared with respect to their relative importance using a 1–9 scale.

3. **Normalise the Comparison Matrix:** Each element is divided by the sum of its column, and the average of the rows is calculated to get the priority vector w, representing the weights of the criteria.

4. **Check CR:** AHP includes a consistency check to ensure logical consistency in judgments using

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}$$

5. **Finalise Criteria Weights:** If the CR is within an acceptable range, the derived priority vector is used as the criteria weights for TOPSIS. Otherwise, the comparisons must be revised.

Strengths of AHP: First is transparency. This method clearly shows how weights are determined, making it easy to understand. The second is flexibility, as it accommodates both qualitative and quantitative factors with ease. Lastly, consistency is ensured through the built-in CR computation, which verifies the logical coherence of expert inputs.

2.2.4.2 Applications in Maintenance Context

Due to its structured approach to handling complex multi-criteria decision problems, AHP has often been applied in the field of maintenance engineering. It enables high-level maintenance goals to be broken down into measurable criteria, allowing decision-makers to incorporate both expert judgement and quantitative data [18]. A primary application is in equipment criticality assessment. When planning maintenance, it is often necessary to prioritise certain machines during periods of higher operational risk, limited resource availability, or when specific components significantly impact downtime and throughput. In such cases, AHP supports quantitative prioritisation using criteria such as failure risk, cost, and expected downtime to ensure that critical equipment is proactively maintained [31].

Another important application of AHP is in resource allocation, especially in environments with constrained budgets, limited technician availability, or short maintenance windows. Through pairwise comparisons, it allows planners to assess the relative urgency and impact of competing tasks, ensuring justifiable and auditable maintenance decisions [6]. When AHP is used in combination with other methods like TOPSIS, it enhances the robustness of maintenance task evaluation. This hybrid approach simplifies complex prioritisation decisions by transforming them into a structured set of pairwise comparisons, improving transparency and interpretability.

2.2.5 TOPSIS

TOPSIS, introduced by Tzeng and Huang [36], is a widely used MCDM method that resolves trade-offs between conflicting objectives by measuring geometric distances to ideal solutions. Its adoption for maintenance scheduling is justified by three factors [24]:

- **Robustness to Scale:** Normalisation ensures fair comparison of criteria with distinctive units (e.g., RPN vs. repair costs).
- **Transparency:** Provides a clear ranking mechanism, critical for justifying maintenance decisions to stakeholders.
- **Adaptability:** Accommodates dynamic changes in constraints (e.g., sudden resource shortages) through real-time matrix updates.

Key Assumptions: TOPSIS is based on three key assumptions. First, it assumes monotonicity, where all criteria must be either strictly increasing (benefit-type) or strictly decreasing (cost-type). Second, it relies on linear compensation, meaning that poor performance in one criterion can be offset by strong performance in another. Third, the method assumes independence among criteria, implying that each criterion influences the decision independently and does not interact with others.

2.2.5.1 Steps Involved in TOPSIS

Step 1: Construct the Decision Matrix

Purpose: Capture quantitative performance of maintenance tasks across all criteria.

$$D = [x_{ij}]_{m\times n}, \text{ where:}$$

- m: Number of maintenance tasks
- n: Criteria
- x_{ij}: Score of task i for criterion j

Step 2: Construct a normalised decision matrix.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

Step 3: Calculate the weighted decision matrix.

$$v_{ij} = r_{ij} \cdot w_j \quad \text{where } \sum_{j=1}^{n} w_j = 1$$

Step 4: Determine Ideal and Negative-Ideal Solutions

$$v^+ = (\max v_{ij}), \quad v^- = (\min v_{ij})$$

Step 5: Calculate the separation distance of each competitive alternative from the ideal and negative ideal solution

$$S_i^+ = \sqrt{\sum (v_{ij} - v_j^+)^2}, \quad S_i^- = \sqrt{\sum (v_{ij} - v_j^-)^2}$$

Step 6: Calculate Relative Closeness

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-}$$

Step 7: Ranking the alternatives

Tasks are ranked by $\boldsymbol{C_i^*}$

2.2.5.2 Advantages of TOPSIS

TOPSIS offers several advantages that make it well-suited for industrial decision-making scenarios. It is easy to interpret, as alternatives are ranked based on their relative closeness to an ideal solution, providing intuitive and actionable results. The method also provides a complete ranking, offering a clear numerical order of alternatives rather than grouped or binary outcomes. Additionally, TOPSIS is computationally efficient, making it suitable for real-time decision environments and dashboard implementations where rapid evaluation is required. Its compensatory framework allows trade-offs between criteria, which is particularly important in maintenance planning where decisions must often balance cost, risk, and resource limitations [6].

2.2.5.3 Relevance in Maintenance Decision-Making

In the context of this study, TOPSIS is used to support the ranking and prioritisation of maintenance tasks. It enables the evaluation of equipment and components based on criticality, integrating various decision factors such as cost, downtime, and FMEA-derived risk scores. By applying AHP-derived weights to these criteria, TOPSIS produces a structured and transparent prioritisation of maintenance actions. This ranked output helps planners focus on tasks that have the greatest operational impact, ensuring that limited resources are allocated effectively and that decisions are aligned with production objectives.

2.3 Maintenance Scheduling in Industrial Settings

Maintenance scheduling is the structured planning and scheduling of maintenance activities to ensure they are executed at the right time to reduce machine downtime and any disruption, An effective maintenance strategy is essential in maintaining equipment reliability.

Maintenance prioritisation is a method in which maintenance tasks are prioritised based on factors such as risks and urgency, determining the circumstances under which each maintenance task should be executed ideally. Whereas in scheduling, the maintenance tasks are not only prioritised but are strategically planned to depend on resource availability, conditions and other priorities all while ensuring there is no decline in throughput [25]. To setup an ideal maintenance schedule, industries must first understand their constraints and priorities, such as costs, downtime, risks, resources and other predetermined factors, while continuing to push for reliability and efficiency in their operations [37].

2.3.1 Importance of Efficient Scheduling in Maintenance

In the real world, maintenance scheduling is executed under the complex network of constraints. These constraints can broadly be classified into:

1. **Human resource constraints (Technician availability and skill sets):** A major limitation in maintenance scheduling is the availability of human resources, i.e. technicians, operators and other maintenance personnel often trained and skilled that are available.

   Technician availability: Scheduling must account for work shifts, leave periods and overtime policies.

   Skills: Specific maintenance tasks require skills and personnel to be trained, particularly or who have certifications to perform those tasks. Allocating unskilled or underqualified personnel to maintenance activities would simply increase repair time or cause concerns for safety.

   Task restrictions: A technician cannot perform multiple tasks simultaneously and thus cannot have overlapped schedules.

   A larger organisation may have a dedicated maintenance team that is shared across departments, which may further increase complexity in scheduling maintenance tasks across the organisation [20].

2. **Machine availability and production cycles:** Maintenance activities depend heavily on machine availability, which is often constrained by production schedules and operating cycles. In most industrial settings, maintenance cannot be performed while machines are active, unless prompted by an unexpected failure, leading to unplanned downtime and disrupted production targets. Peak production periods leave little to no room for maintenance interventions. Whereas downtime for machines can be planned along with the production schedule to conduct PM or CM tasks. Scheduling these maintenance tasks is aimed at reducing unnecessary machine downtime and keeping throughput at maximum [32].

3. **Shift patterns and downtime windows:** Industries often deploy various shift patterns that are designed to meet their specific production demands. Heavier industries, such as the steel manufacturing industry, are required to keep their machines constantly functioning, reducing the maintenance window unless required for urgent maintenance.

   Additionally, labour regulations mandate working hours, overtime and mandatory rest periods for the employees, restricting the technician's availability to perform maintenance if the need arises outside their shift. Failure to align maintenance efforts with established patterns and downtime periods resulted in higher labour costs and resource conflicts. In some cases, it even led to forced shutdowns due to machine or equipment failure, affecting both production efficiency and overall equipment availability. Various industries employ different shift schedules that suit their production demands best. For example, chemical and steel industries generally have their machines active for longer durations, hence reducing the maintenance window. Strict labour regulations imply limited working hours for the employees, including the maintenance personnel, complicating maintenance tasks [19].

4. **Spare parts and tooling limitations:** Spare parts are a necessary consideration in scheduling maintenance tasks, despite all other resources being available. It simply would not be effective if the waiting period for parts to arrive is long and the machine is idle for that duration, the industry would be losing considerable value in machine downtime and at the same time increase stress on the remaining machines.

   Factors such as inventory levels, lead times, tool sharing and other factors must be integrated to allow for an ideal maintenance scheduling solution, avoiding last-minute delays due to unavailability of spare parts [30].

2.3.1 Traditional vs. Optimised Scheduling

Scheduling strategies have evolved considerable over the years in industries to intelligent data-driven systems from manual rule-based heuristic approaches. Traditionally, scheduling has often been dependent on expertise on when maintenance must be performed. As straightforward as it may seem, it reflects reactive maintenance and is inefficient and cannot be deployed in a dynamic environment [20].

Optimised scheduling employs automation and data-driven techniques along with decision support tools to plan maintenance activities effectively. Algorithmic approaches like Genetic algorithms and CP allow dynamic changes to be made in scheduling maintenance tasks based on real-time data like machine conditions, resource availability and production requirements [7, 11]. Modern techniques such as these algorithms enable organisations to respond more effectively to changing conditions and resource availability, integrating PdM insights for pre-emptive action.

The objectives of scheduling maintenance tasks are to remain consistent, extend tool life and ensure work is distributed evenly among the resources available [14]. These goals are achieved through optimised methods which are better equipped, particularly in systems with complex interdependencies and stringent resource constraints. A scheduling framework can outperform a traditional scheduling system by integrating factors such as throughput, resource availability, and failure risk, among others. By incorporating these techniques, industries can significantly reduce the total downtime and improve equipment and tool reliability and lifespan, especially when combined with predictive analysis and real-time data monitoring [35].

2.4 Constraint Programming for Maintenance Scheduling

As industrial systems become more complex and resource-intensive, traditional rule-based scheduling methods fall short unable to deal with the dynamically changing operational constraints. In such contexts, algorithms such as CP is an ideal model that can solve combinations of scheduling issues. CP is a declarative algorithm, constraints are expressed as the relationship between variables and the objective it to find feasible solutions that satisfy all specified conditions [11].

CP excels at scheduling maintenance in highly dynamic environments in industries where multiple variables interact under operational limits. CP enables data driven decision making by explicitly defining the relation between constraints, such as resource availability and operational limits, before identifying feasible solutions through the algorithm. In contrast to heuristic approaches, before approaching maintenance tasks, CP provides the decision makers with the options of a feasible solution with increased flexibility in adapting to the dynamic nature of manufacturing settings [7].

2.4.1 Key benefits using CP algorithms

Using CP has several advantages in maintenance scheduling. It allows for the integration of a wide variety of constraints within a single framework, enabling the model to replicate complex real-world scenarios. The constraints in this algorithm are flexible and can be dynamically adjusted based on changing operational conditions. Furthermore, the model can be tailored to focus on specific objectives, such as minimising cost, reducing downtime, or addressing high-risk components, depending on the organisations priorities. Finally, CP supports proactive planning by integrating with PdM indicators, making it a suitable approach for dynamic maintenance environments.

2.4.2 Possible constraints in maintenance

In an industrial environment, typical constraints that should be considered are:

- **Schedule window:** Maintenance tasks can ideally be performed when the machine or tool is idle, leaving us with specific windows of downtime in the production schedule to perform these tasks [23].

- **Resource availability:** The availability of spare parts, technicians, tools and other resources could often be limited and must be considered during planning a maintenance schedule and does not exceed the available capacity during any given period [14].

- **Interdependencies:** Some tasks may sometimes depend on other tasks to be performed beforehand, and the duration of these tasks may also vary depending on other constraints and increasing complexity.

- **Distribution of work:** Distributing maintenance tasks across available timeframes ensures that technicians or shifts are overworked, reducing stress on technicians and improving resource utilisation.

2.4.3 Popular tools and solvers for CP

To run CP algorithms effectively in industrial solutions, there exists a plethora of powerful tools and environments, such as:

- **Google OR-Tools:** An open-source suite by Google that supports CP, linear programming and other algorithms. It is widely used for production maintenance scheduling problems due its scalability and flexibility [26].

- **IBM CP Optimiser:** A commercial-grade solver that offers powerful features for modelling time-based constraints and optimising complex scheduling scenarios [15].

- **Microsoft Z3 Theorem Solver (Z3):** Developed by Microsoft Research, it is a high-performance theorem solver used for comparatively more formal verification tasks but adaptable for scheduling problems in specialised scenarios [9].

3

Methods

This chapter outlines the methodological framework adopted to develop a DSS for maintenance task prioritisation and scheduling. The methodology is built upon a hybrid approach, integrating MCDM techniques with constraint programming to address the multifaceted challenges of maintenance planning. Specifically, the AHP and the TOPSIS are employed to rank maintenance tasks based on criticality [3, 31]. These rankings are then utilised within a constraint-based scheduling model developed using the Z3 solver. By blending expert judgement with quantitative analysis, the proposed methodology ensures that the maintenance planning process is structured, scalable, and aligned with the operational constraints. Figure 3.1, represents the framework and working of the DSS that was developed.

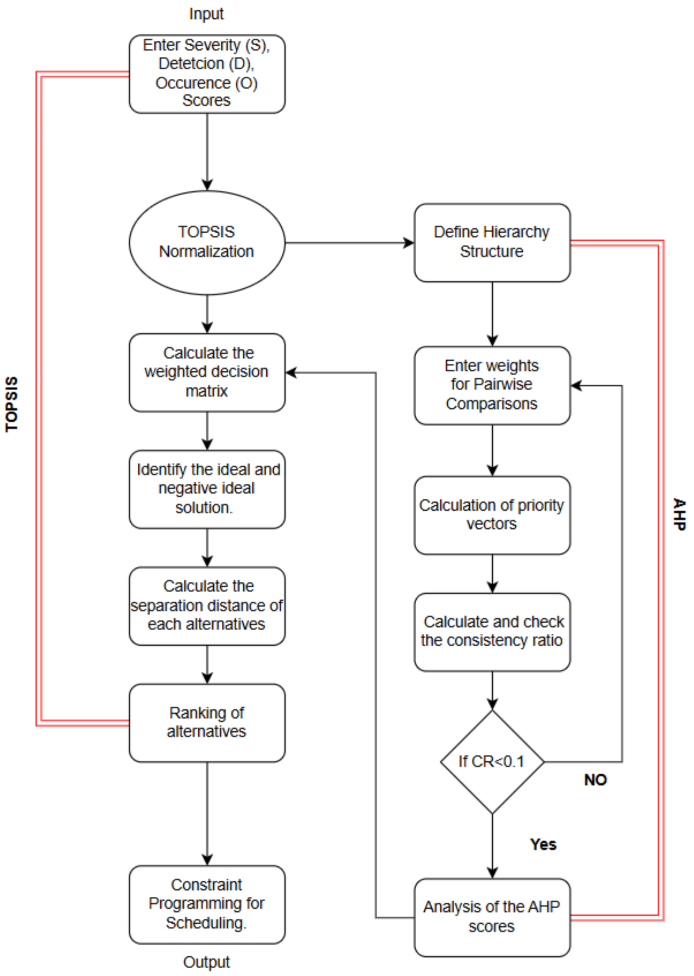


Figure 3.1: Methodological framework of the developed DSS

3.1 Data Collection and Assumptions

Data were collected directly from the case company's operations in order to develop a realistic and context-specific framework. This section outlines the information sources that underpin the scheduling logic and the prioritisation model, as well as the basic assumptions that impacted the framework's design and functionality.

3.1.1 Data Sources

The study focused on a single manufacturing cell comprising eight interdependent machines. To ensure that the prioritisation and scheduling models reflected the actual operational context [21], data were collected from multiple sources:

Firstly, interviews were conducted with maintenance engineers. These sessions provided valuable insights into machine functionality, failure modes, and the significance of various components within the production- flow. Follow-up meetings were held weekly to clarify operational procedures and validate preliminary findings.

Secondly, historical work orders and maintenance logs were examined. These documents offered detailed records of past maintenance activities, including part replacements,downtime, task frequencies, and downtime durations. Analysing this data allowed for the estimation of average downtime associated with specific component failures.

Thirdly, component-level cost data were obtained from the company's procurement and inventory systems. These included the cost of spare parts and, in some cases, estimated labour requirements. The cost information was essential in assessing the economic implications of maintenance scheduling decisions.

3.1.2 Manual Inputs

Although many input parameters were derived from historical records, certain risk-related values, specifically the S, O and D scores used in RPN calculations were left to be entered manually by the user. These fields are editable within the dashboard, allowing maintenance experts to apply their professional judgement in real-time. This flexibility ensures that the risk evaluation remains dynamic and responsive to situational nuances that static data may overlook.

3.1.3 Modelling Assumptions

Several assumptions were made to simplify the modelling process while preserving practical relevance:

- Task durations were considered fixed for each component, irrespective of the technician assigned or the shift timing.
- Technicians were categorised into two skill groups: Electrical and Mechanical. Each maintenance task required a match with at least one of these groups.
- Labour costs were assumed to be different across different shift timings. Specifically, night and weekend shifts incurred higher rates to reflect overtime and extra hours.
- The production calendar was assumed to be predefined, with designated peak and off-peak periods affecting scheduling preferences.
- It was also assumed that only one maintenance task could be executed at a given time to reflect technician and machine availability constraints.

These assumptions were validated and approved by the internal maintenance team at the partner company, although there is scope for refinement in future iterations of the DSS.

3.1.4 Component Hierarchy and Subcomponent Grouping

To enable structured and scalable prioritisation, all subcomponents were mapped and categorised to a high level component category. This grouping was necessary to simplify and aggregate the sub-components while maintaining clarity in the maintenance plan.

The classification was based on several factors, including the terminology in part descriptions, the functional role of the subcomponent, and common industry references. Subcomponents sharing similar roles or failure behaviours were grouped under the same functional category. Table 3.1 illustrates an example of this approach.

Table 3.1: Keyword Mapping of Subcomponents to L2 Categories

Keyword or Model	**Mapped to Component Category**	**Reason**
“Filter", “Air"	Filters & Pneumatics	Air/oil filter maintenance class
“RKP", “pump"	Hydraulic System	Known hydraulic components
“MGB-H-AA1A1"	Safety & Locking Hardware	Safety lock module from Euchner
“ZB4-BZ101"	Control & Interface System	Schneider control switch
“ET 200S"	Control & Interface System	Siemens I/O or interface module
“minicoder"	Sensing & Feedback Devices	Position/rotation sensor
“Bus module"	Connector & Cable System	Industrial communication hardware

3.1.5 Downtime and Cost Aggregation Strategy

Given that downtime was the primary factor influencing task prioritisation in this study, a structured categorisation of downtime events was essential. The categorisation was performed inductively based on historical logs, followed by validation through internal expert discussions. The aim was to convert qualitative downtime severity into a weighted numerical format suitable for prioritisation in the DSS.

Weighted Average =

$$\frac{\sum(x_i \cdot w_i)}{\sum w_i}$$

Where:

- x_i: downtime or cost value

- w_i: assigned weight based on event severity

Downtime categories and weights:

- Minor stoppage (< 2 hours): weight $= 3$
- Major downtime (2–5 hours): weight $= 6$
- Critical downtime (> 5 hours): weight $= 8$

The weights 3,6,8 were chosen based on the following criteria:

- **Fairness:** To ensure that each severity category contributes properly to the total priority score, avoiding overemphasis on uncommon but severe occurrences.
- **Interpretability:** Is consistent with how technicians and planners immediately understand the severity of downtime.
- **Responsiveness:** Keeps the scale from becoming too complicated while giving the model enough refinement to differentiate between tasks of varying degrees of complexity.

During expert evaluations, alternate schemes such 1–4–7 and 3–6–12 were discussed. However, they were either excessively aggressive, which caused rare critical events to be overprioritized, or too flat, which made mid-severity events unreliable. Using component failure reports from the past, the selected 3–6–8 model provided a workable compromise.

Cost aggregation was conducted using the available part-level data, applying a similar structured approach as with downtime classification. COst was treated as a supporting factor and separate or additional weights were assigned. It is recommended that future DSS iterations further refine the cost modelling to reflect dynamic pricing, criticality, or stock availability where applicable.

3.2 Prioritisation Framework: AHP–TOPSIS

To facilitate data-driven maintenance task prioritisation, a hybrid MCDM framework that combines TOPSIS and AHP was developed. AHP was utilised to generate consistent criteria weights using expert-driven pairwise comparisons, ensuring that failure risk, downtime, and cost were all proportionally reflected. Using vector normalisation and Euclidean distance metrics, these weights were then used in the TOPSIS model to evaluate each maintenance component to an ideal solution. This integration ensures that task rankings are both analytically sound and practically understandable.

3.2.1 AHP

AHP was utilised to generate consistent criteria weights using expert-driven pairwise comparisons, ensuring that failure risk, downtime, and cost were all proportionally reflected. Using vector normalisation and Euclidean distance metrics, these weights were then used in the TOPSIS model to evaluate each maintenance component against an ideal solution. This integration ensures that task rankings are both analytically sound and practically understandable [24].

- Failure Risk, quantified through the RPN, which incorporates estimates of occurrence, severity, and detection. incorporating severity, occurrence, detection.

- Production Impact, assessed through the anticipated downtime in hours if a specific component were to fail.

- Maintenance Cost, evaluated by considering the cost of necessary spare parts and labour effort.

Experts were prompted to provide pairwise comparisons of these criteria using a structured matrix within the dashboard. The geometric mean method was used to compute weights, and a CR was automatically calculated to ensure logical consistency. The system was designed to enforce a CR below 0.1, in accordance with Saaty's guidelines [18]. The implementation logic was robust enough to prevent the entry of inconsistently weighted judgements, thereby removing the need for manual correction.

3.2.2 TOPSIS Ranking

The TOPSIS method was then employed to translate these weighted criteria into a ranked list of maintenance components. This involved several computational steps [24, 31] :

First, the raw decision matrix was normalised using vector normalisation. This step ensured that the values across different units (e.g. hours, SEK, RPN) were rendered comparable. Next, the normalised values were multiplied by the respective AHP-derived weights, generating a weighted matrix.

For each alternative, the Euclidean distance to both the ideal solution (representing the lowest values for all criteria) and the anti-ideal solution (the highest values) was calculated. A closeness coefficient was then computed, indicating how near each component was to the ideal point. Components with higher coefficients were ranked as higher priority.

All criteria were treated as cost-type, meaning lower values were deemed preferable. This approach ensured that components contributing most to risk, cost, or disruption were addressed with higher urgency.

3.3 Constraint-Based Scheduling Using Z3

To translate prioritisation into schedules, a constraint programming model was developed using the Z3 solver [7, 11]. The objective is to generate optimal maintenance plans that simultaneously respect resource limitations, production throughput requirements and cost-minimisation goals.Table 3.2 lists the set of real-world constraints encoded in our model, based on the available data.

Table 3.2: Scheduling Constraints

Constraint	**Description**
Task Concurrency	Only one maintenance task can start at a time.
Task Limit per Week	A maximum of 4 tasks are allowed per week.
Skill Matching	Technician skills must match the task requirement.
Shift Costing	Night and weekend shifts incur higher cost.
Production Penalty	Maintenance during production peaks is penalised.
Grouping Preference	Tasks on the same machine or close in rank are grouped.
Deadline Penalties	Missed deadlines incur escalating costs.
Fairness	Tasks are spread evenly to avoid workload clustering.

Mathematical Constraints

Below are the key scheduling constraints implemented in the model:

Constraint 1: Task Concurrency

Each task must be scheduled exactly once.

$$\sum_{j=1}^{T} x_{ij} = 1 \quad \forall i \in \{1, \ldots, N\}$$

Constraint 2: Weekly Task Limit

No more than 4 maintenance tasks can be scheduled in any calendar week.

$$\sum_{i=1}^{N} \sum_{j \in W_w} x_{ij} \leq 4 \quad \forall w \in \{1, \ldots, 52\}$$

Constraint 3: Technician Skill Matching

The number of Mechanical or Electrical tasks in a shift must not exceed available technicians.

$$\sum_{i \in M} x_{ij} \leq M_j \quad ; \quad \sum_{i \in E} x_{ij} \leq E_j \quad \forall j$$

Constraint 4: Rank-Based Ordering

Tasks with a higher priority rank (lower rank number) must be scheduled no later than lower-priority tasks.

$$r_i < r_k \Rightarrow s_i \leq s_k \quad \forall i, k$$

Constraint 5: Grouping Preference

Tasks on the same machine (or similar in rank) should be scheduled close together.

$$|s_i - s_k| \leq \Delta_g \quad \text{if Machine}(i) = \text{Machine}(k)$$

Together, these constraints ensure that the maintenance scheduling model remains practical, cost-efficient, and implementable in real industrial settings. They account for resource availability, technician expertise, workload balancing, and operational requirements such as production peaks and incentive policies. By enforcing these rules, the model aims to generate a schedule that is both feasible and aligned with the strategic maintenance goals of the case company. While the current model uses a fixed cost framework, future enhancements could incorporate variables such as technician fatigue, skill-based wage tiers, or stochastic task durations.

3.4 Objective Function

The optimisation objective was to minimise the total maintenance cost [23]. This cost function aggregated various elements:

- Technician labour cost per assigned shift.
- Penalties for performing maintenance during high-production periods.
- Overtime charges for weekend and night work.
- Escalation costs for tasks that exceeded their deadlines.

The below is the mathematical representation of the objective function:

$$\begin{aligned}\min \sum_{i=1}^{N} \sum_{j=1}^{T} x_{ij} \cdot \Big(& C_i + \alpha \cdot H_i + R_j \cdot \min(H_i, 8) + R_{ot} \cdot \max(0, H_i - 8) \\ & + \gamma \cdot \delta_{j \in \text{Peak}} + \lambda \cdot \max(0, w_j - d_i) - \beta \cdot \delta_{j \in \text{Early}} \Big)\end{aligned}$$

Where:

- C_i, H_i, R_j, and R_{ot} represent the base cost, downtime duration, regular shift cost, and overtime penalty respectively.
- γ, λ, and β are cost multipliers for peak shifts, missed deadlines, and early-week incentives.
- $\delta_{j\in\text{Peak}}$, $\delta_{j\in\text{Early}}$ are indicator functions (1 if condition true, else 0).

(Refer to the Nomenclature section for the complete list of symbols.)

3.5 Output Format

The output of the scheduling model was a structured maintenance plan specifying the machine name, component, week, day, and shift during which each task should be performed. This output was formatted as a table and directly visualised within the dashboard. Users could export the data for reporting or integration into existing planning systems.

3.5.1 Trial - 1

This trial was conducted to demonstrate the practical application and how the dashboard functioned as a DSS. For this run, we used the Frech DAK 720 Die Casting Machine and the Reis SEP 10-30 Dialogue III Shaving Press. These machines were chosen because they had the largest dataset of spare-part, downtime, and cost data. These machines also have a number of similar components, which were chosen to demonstrate the model's ability to handle them. The goal was to assess the entire system using our AHP-TOPSIS-CP prioritisation and scheduling framework. They were chosen to mimic real-world scenarios based on the available data.

The first step was to make a pairwise comparison to evaluate the relative comparison across three criteria: i.e. downtime, cost and risk. The data for AHP pairwise was manually filled, and downtime was chosen as primary in this experiment. A score of 8 was given for downtime vs risk and 4 was given for downtime vs cost.The third value for CR was automatically calculated from the code to ensure CR will remain less than 0.1, thereby giving consistent pairwise comparisons. The system automatically calculated the geometric mean, normalised the weights, and checked the consistency of the input. In this case the CR was 0.0462 and was acceptable according to the literature[24].

Gathering expert input at the component level was the second phase. For each of the selected machines Severity, Occurrence and Detection score were manually entered into the dashboard. In the die casting machine, for instance, the connector and cable system was classified as "Rare" for occurrence, "High" for severity, and "Unlikely" for detection. Because of the manual input, the framework was able to incorporate latent risk and current operational problems that might not have been included in prior data. Using these expert-driven S, O, D scores, a total of five shaving press components and nine die casting machine components were configured.

Once the weights were assigned, TOPSIS was applied for priori station to give the final ranks. The model calculated each component's Euclidean distance from the ideal and negative-ideal solutions using the normalised and weighted criteria. As a result, each component was assigned a closeness coefficient that represented its relative importance. Because of its higher cost, downtime, and criticality, components like the electrical modules and hydraulic system were placed higher. The results were displayed as a dynamic ranking table on the dashboard, making them easily interpretable for maintenance planners.

The simulated experiments are closely related to the maintenance environment, where maintenance tasks must be scheduled ahead of time while taking into account the urgency of each component and task, technician availability, and financial constraints. This trial demonstrates how the system can convert theoretical models into workable plans by combining real component data, expert-configured scores, and flexible scheduling rules.

The output ranks from AHP-TOPSIS was then passed into Z3 constraint solver for scheduling. The 52-week planning horizon was used for scheduling, excluding the c holiday weeks (Weeks 1, 28–31, and 52). On weekdays, the scheduling model supported a typical three shift arrangement, on weekends and holidays, it supported a single shift. For morning and afternoon hours, there were eight mechanical and seven electrical technicians available, and for night shifts, weekends, and holidays, there were two technicians.

To guide the Z3 solver in making optimal scheduling decisions, a cost focused objective function was defined as mentioned in section 3.4. This function included various penalties reflecting the operational preferences as described in section 3.3. Shift-related rates were set and additional penalty weights included: 50 points for scheduling during night or holiday shifts, a rank penalty of 5 to discourage delay of high-priority tasks, and a group penalty of 10 to incentivise scheduling tasks from the same machine within close proximity. These penalty values were chosen based on a balance between operational reality and model responsiveness. Higher night and holiday rates were set to reflect overtime wages and reduced staff availability. The rank penalty prioritises urgency, while the group penalty improves scheduling efficiency by clustering similar tasks, reducing changeover and technician setup time.

This trial scenario closely reflects the industry's maintenance context, where tasks must be planned in advance while balancing technician availability, cost constraints, and the urgency of each task. By using real component data, expert-configured scores, and flexible scheduling rules, the trial offers a comprehensive demonstration of how the system can translate theoretical models into actionable plans.

The full list of scheduled tasks, along with their assigned machine, component, week, day, and shift, was generated as a final output. These outputs were reviewed for validity and cross-checked against expectations set by maintenance engineers.

3.6 Decision Support Dashboard

A user-friendly dashboard was developed using the Streamlit framework in Visual Studio Code. This dashboard served as the central interface through which maintenance engineers and planners could interact with the prioritisation and scheduling models.

3.6.1 Key Features

The decision-support dashboard developed in this study integrates all analytical components into a cohesive user interface. Its primary function is to serve as a bridge between the technical logic underpinning prioritisation and scheduling and the real-world decisions made by maintenance planners. The dashboard includes a pairwise comparison interface for AHP inputs [6], allowing users to enter their judgements directly into a matrix. This interface instantly computes priority weights and checks for consistency using Saaty's CR metric [24], providing feedback if the inputs deviate from acceptable thresholds. This ensures that users maintain logical coherence in their decision-making without needing to recalculate manually. Another notable feature is the risk input interface, which lets users manually enter S, O and D values that contribute to the overall RPN score. By doing so, the system accommodates expert judgement and context-specific insights, enabling risk evaluations to reflect current operational realities rather than static historical data.

Once the weights for AHP are calculated, the component rankings via TOPSIS are generated and the dashboard presents a ranked list of components in a dynamic table. This list provides full visibility into how each component scored against all criteria, and users can explore which factors influenced a component's prioritisation. For scheduling, the dashboard integrates a backend call to the Z3 solver. Upon initiating the scheduling process, users receive a detailed output specifying which tasks are scheduled in which week, day, and shift. These outputs are clearly formatted and easy to interpret, aiding maintenance planning at the tactical level. Finally, the dashboard features several visualisation tools, including bar charts and summary tables. These visuals enhance user understanding of scheduling patterns, technician distribution, and overall task criticality, supporting faster and more informed decision-making.

The dashboard is designed primarily for internal maintenance planners and operations engineers. By integrating multiple decision layers into a single tool, it enhances transparency, reduces manual planning errors, and supports timely, data-driven decisions. The entire process is displayed in an intuitive dashboard that is tailored to partner company's needs.

4

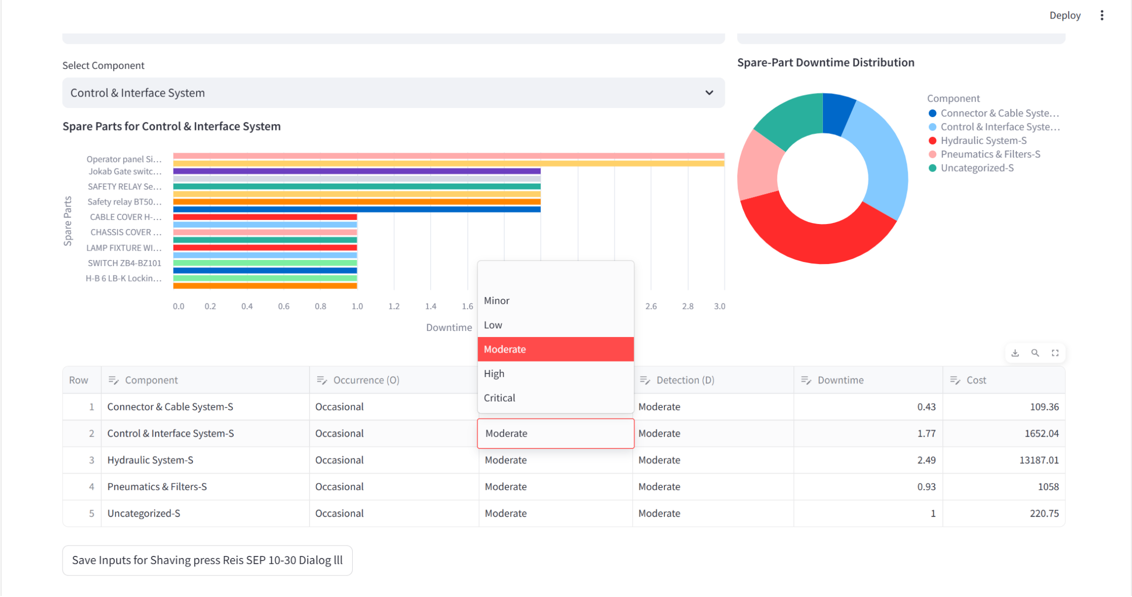
Results

This chapter presents the outcomes of the developed DSS, focusing on its functionality and deployment within a real-world industrial setting. It demonstrates how AHP–TOPSIS ranking and constraint-based scheduling were implemented through an intuitive dashboard. Key findings from the study are presented to evaluate the system's practical effectiveness.

4.1 Results from the developed DSS

One of the key objectives of this thesis was the development of a web application-based DSS in the form of a dashboard. The goal was to translate technical data from machines to a practical interface to be used in different scopes in the industry. Built using the Streamlit library, the dashboard is an interface where the users can input the data for the algorithm to analyse, rank and schedule the maintenance tasks. It was designed keeping in mind the requirements of the stakeholders. These include management teams, repair technicians, and production staff, all of whom can interact effectively with the dashboard despite differing technical backgrounds.

Upon launching the web application as shown in Figure 4.1, the user is greeted with a simple dropdown menu to select a 'Global Primary Criterion' to choose between 'Risk', 'Downtime' and 'Cost' depending on the background of the user. This forms the initial basis for how weights are assigned during the AHP pairwise comparison.



Select Component

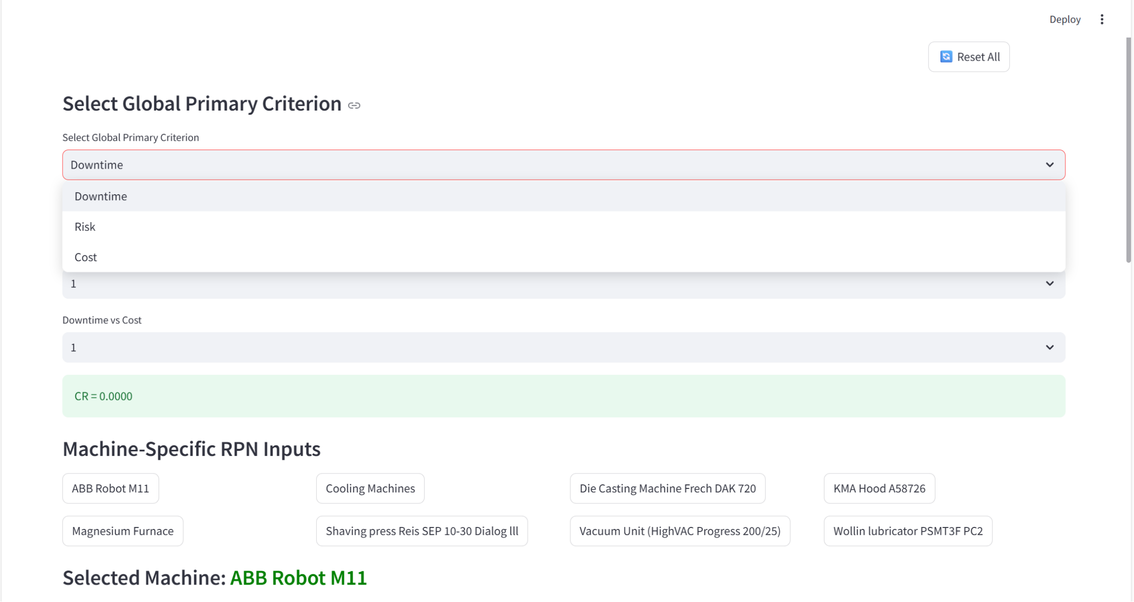
Control & Interface System

Spare Parts for Control & Interface System

Row	Component	Occurrence (O)		Detection (D)	Downtime	Cost
1	Connector & Cable System-S	Occasional		Moderate	0.43	109.36
2	Control & Interface System-S	Occasional	Moderate	Moderate	1.77	1652.04
3	Hydraulic System-S	Occasional	Moderate	Moderate	2.49	13187.01
4	Pneumatics & Filters-S	Occasional	Moderate	Moderate	0.93	1058
5	Uncategorized-S	Occasional	Moderate	Moderate	1	220.75

Figure 4.1: A view of the dashboard.

In the 'Pairwise Comparison' section, the users input their expertise about relative importance of these criteria Figure 4.2. The dashboard dynamically generates additional comparison drop-downs based on the prioritisation values assigned by the user as shown in 4.3, while ensuring the resulting 'CR' remains below 10% or 0.10. Following the guidelines by Maletic et al., Saaty [18, 29], which ensure that the expert input remains consistent. The automatic generation of comparisons removes the burden on users to perform complex calculations to ensure CR < 0.10.



Select Global Primary Criterion

Select Global Primary Criterion

Downtime

1

Downtime vs Cost

1

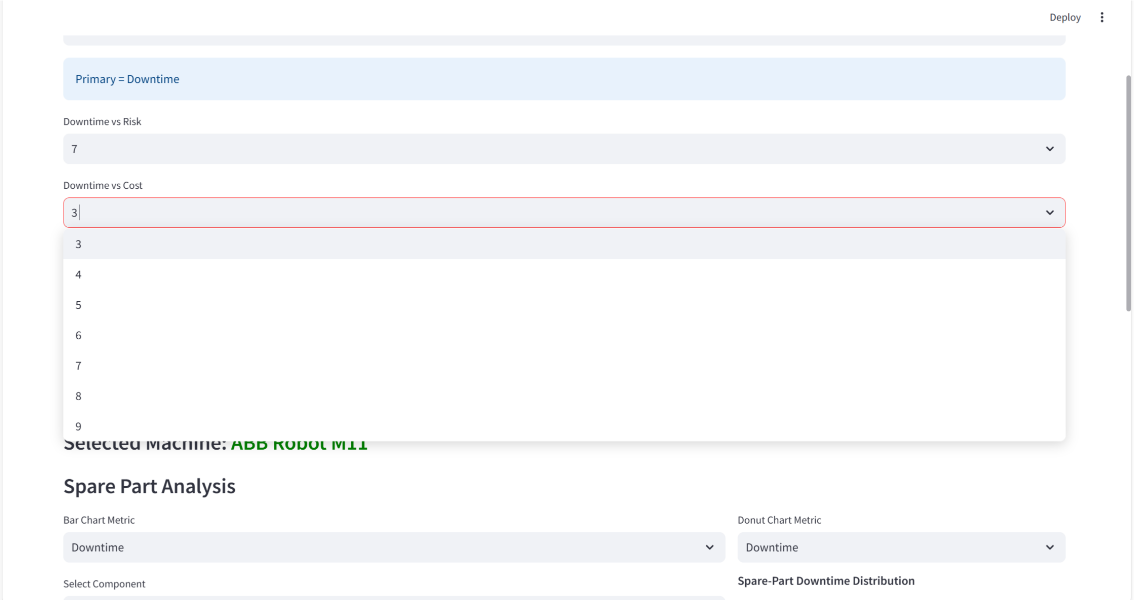
CR = 0.0000

Machine-Specific RPN Inputs

Selected Machine: ABB Robot M11

Figure 4.2: Selecting a Global Primary Criterion based on user input and priorities for scheduling maintenance.

When the dashboard initially runs, it summarises relevant historical data such as costs, overall downtime, and failure patterns across machines and components Figure 4.4. The user can also select a particular machine to view subcomponent-level data. This visual representation enables users to explore historical downtime and understand maintenance history in a component-wise manner.



Primary = Downtime

Downtime vs Risk: 7

Downtime vs Cost: 3

3
4
5
6
7
8
9

Selected Machine: ABB Robot M11

Spare Part Analysis

Bar Chart Metric: Downtime

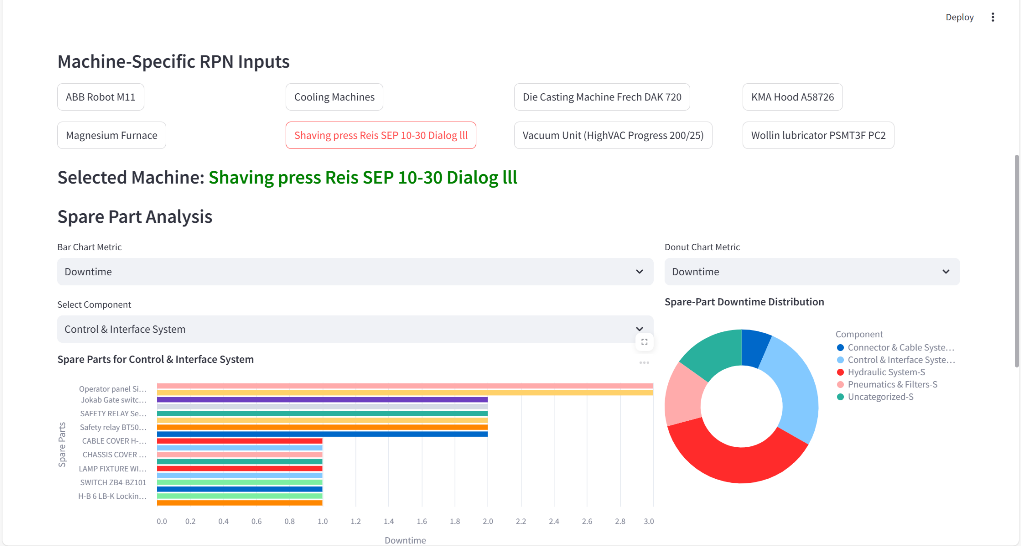
Donut Chart Metric: Downtime

Select Component

Spare-Part Downtime Distribution

Figure 4.3: Pairwise comparison based on user input.

The risk scoring module is a key feature where users can customise S, O and D levels for each machine. These values are used in RPN calculations and can be adjusted on a scale from ‘Minor’ to ‘Critical’, enabling flexible evaluation of operational risks as shown in Figure 4.5. Once RPN scores are finalised, users can trigger the TOPSIS algorithm. The algorithm ranks subcomponents based on criticality and presents a sorted list with closeness coefficients, offering transparency on how each component performed across the criteria.



Machine-Specific RPN Inputs

ABB Robot M11 | Cooling Machines | Die Casting Machine Frech DAK 720 | KMA Hood A58726 | Magnesium Furnace | Shaving press Reis SEP 10-30 Dialog lll | Vacuum Unit (HighVAC Progress 200/25) | Wollin lubricator PSMT3F PC2

Selected Machine: Shaving press Reis SEP 10-30 Dialog lll

Spare Part Analysis

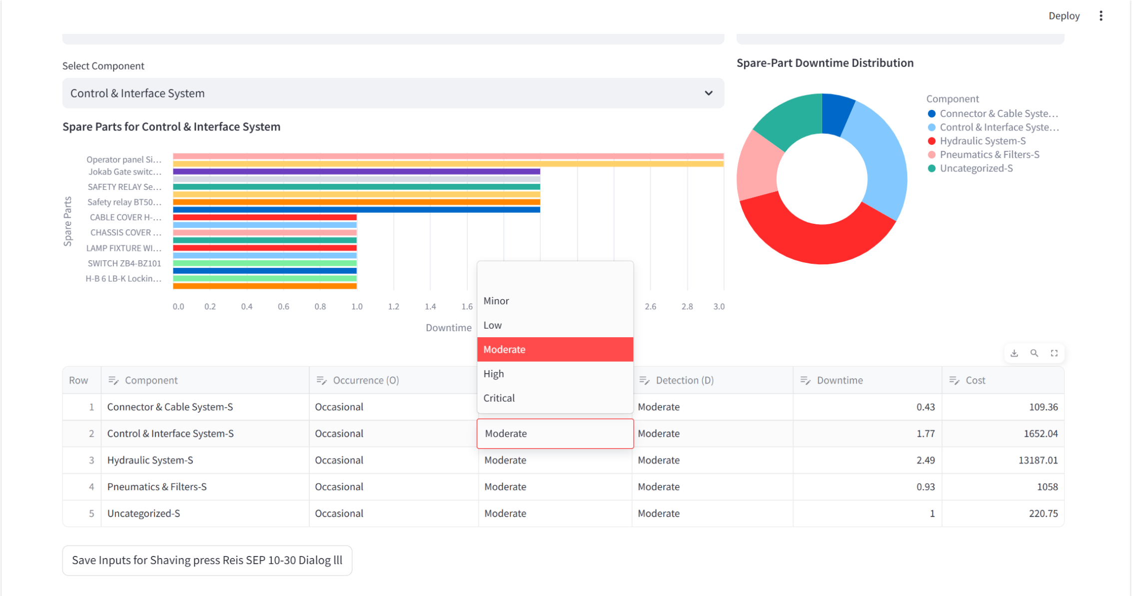
Bar Chart Metric: Downtime

Donut Chart Metric: Downtime

Select Component: Control & Interface System

Spare Parts for Control & Interface System

Figure 4.4: Intuitive design consolidating quantitative data into graphs for better insight



Select Component: Control & Interface System

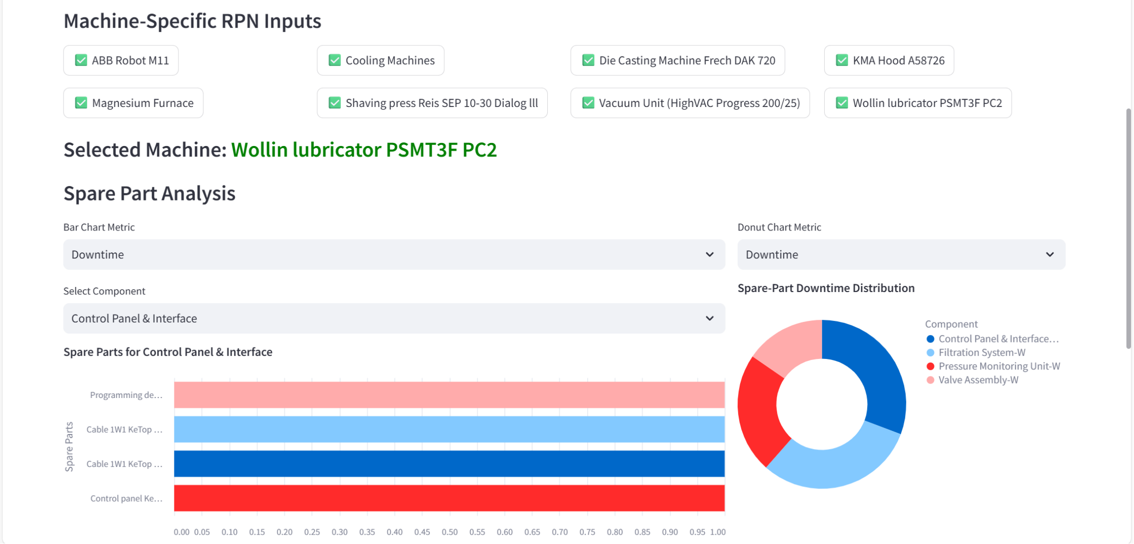
Spare Parts for Control & Interface System

Row	Component	Occurrence (O)		Detection (D)	Downtime	Cost
1	Connector & Cable System-S	Occasional		Moderate	0.43	109.36
2	Control & Interface System-S	Occasional	Moderate	Moderate	1.77	1652.04
3	Hydraulic System-S	Occasional	Moderate	Moderate	2.49	13187.01
4	Pneumatics & Filters-S	Occasional	Moderate	Moderate	0.93	1058
5	Uncategorized-S	Occasional	Moderate	Moderate	1	220.75

Save Inputs for Shaving press Reis SEP 10-30 Dialog lll

Figure 4.5: Manual input of S, O, D scores.

This implementation brings the hybrid AHP–TOPSIS model into a real-time Decision Support System that encourages data-driven maintenance planning. As Chong et al. [6] emphasise, MCDM methods act as bridges between domain knowledge and quantitative logic. This dashboard embodies those principles through a robust, transparent, and scalable tool for modern industrial maintenance planning Figure 4.6.



Machine-Specific RPN Inputs

☑ ABB Robot M11 ☑ Cooling Machines ☑ Die Casting Machine Frech DAK 720 ☑ KMA Hood A58726
☑ Magnesium Furnace ☑ Shaving press Reis SEP 10-30 Dialog lll ☑ Vacuum Unit (HighVAC Progress 200/25) ☑ Wollin lubricator PSMT3F PC2

Selected Machine: Wollin lubricator PSMT3F PC2

Spare Part Analysis

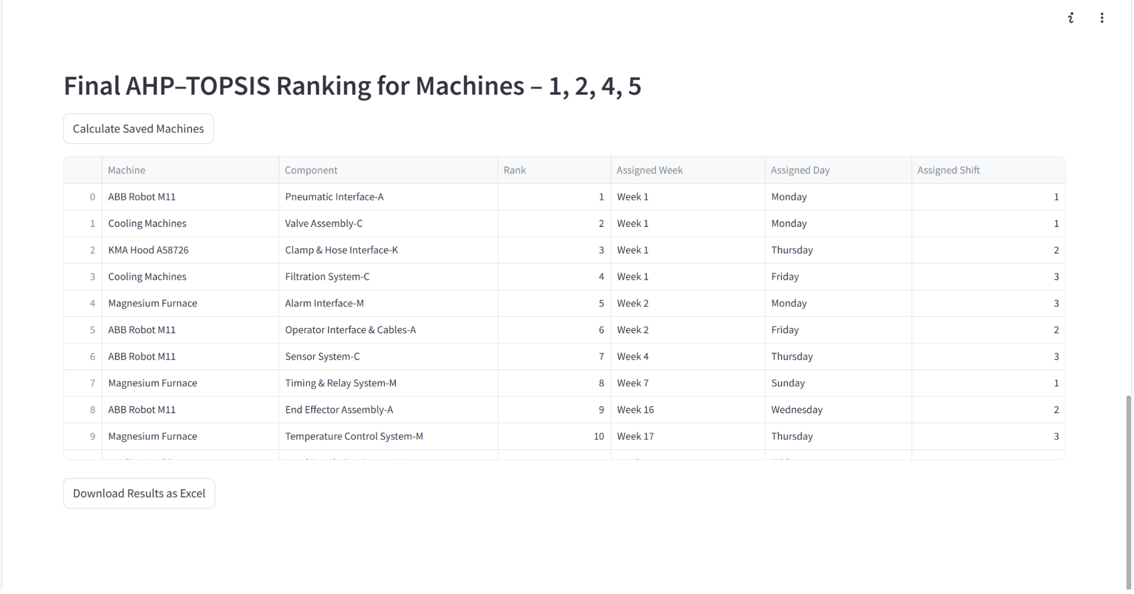
Bar Chart Metric: Downtime

Donut Chart Metric: Downtime

Select Component: Control Panel & Interface

Figure 4.6: Selecting machines to schedule for maintenance.

The dashboard integrates a backend Z3-based constraint programming algorithm that converts prioritised tasks into a feasible maintenance schedule aligned with production constraints. Upon clicking ‘Calculate’, the model evaluates multiple parameters, such as shifts, holiday periods, technician availability, downtime windows, production load, and other constraints described in Section 3.3—to generate an optimised task schedule organised by component, day, shift, and technician as shown in Figure 4.7.



Final AHP–TOPSIS Ranking for Machines – 1, 2, 4, 5

	Machine	Component	Rank	Assigned Week	Assigned Day	Assigned Shift
0	ABB Robot M11	Pneumatic Interface-A	1	Week 1	Monday	1
1	Cooling Machines	Valve Assembly-C	2	Week 1	Monday	1
2	KMA Hood A58726	Clamp & Hose Interface-K	3	Week 1	Thursday	2
3	Cooling Machines	Filtration System-C	4	Week 1	Friday	3
4	Magnesium Furnace	Alarm Interface-M	5	Week 2	Monday	3
5	ABB Robot M11	Operator Interface & Cables-A	6	Week 2	Friday	2
6	ABB Robot M11	Sensor System-C	7	Week 4	Thursday	3
7	Magnesium Furnace	Timing & Relay System-M	8	Week 7	Sunday	1
8	ABB Robot M11	End Effector Assembly-A	9	Week 16	Wednesday	2
9	Magnesium Furnace	Temperature Control System-M	10	Week 17	Thursday	3

Figure 4.7: Maintenance tasks are now scheduled.

4.2 Results from Trial-1

The model produces a complete schedule of all the prioritised tasks across the planned window. Maintenance components are distributed from Week 2 to Week 46. Since the objective function was cost-based, these maintenance tasks were scheduled mainly to minimise the cost while balancing risk and priorities. In some cases, tasks were scheduled during the 3rd shift when the model determined that the urgency and priority of the task justified the associated penalty. For example, the Control and Interface System for the Die Casting machine was scheduled for week 27 in the 3rd shift, while the Safety and Locking Hardware was scheduled for week 35 in the 3rd shift. This indicates that for certain high-priority tasks, the cost of delaying maintenance further exceeded the trade-off cost of scheduling during less preferred shifts. Such decisions highlight the model's ability to balance operational urgency, scheduling penalties, and maintenance priorities within an optimised framework.

In another instance, the Hydraulic System, despite being the most expensive (21,786 SEK) and having the highest downtime (4.22 hours), was scheduled in Week 46, suggesting that the model considered resource availability constraints in earlier weeks. This displays the ability of the model to balance costs, components and workloads to make decisions enabling operational feasibility. Multiple components from the Die Casting machine such as the electrical Modules, Safety Hardware and Motion Guidance were all scheduled within a few weeks of each other demonstrating that the group penalty was successful in pooling relative tasks together in the schedule, thereby improving efficiency and reducing time taken to switch tools as shown in Table 4.1.

Machine	Component	Rank	Assigned Week	Assigned Day	Assigned Shift
Die Casting Machine Frech DAK 720	Filters & Pneumatics-D	1	Week 2	Monday	1
Shaving press Reis SEP 10-30	Connector & Cable System-S	2	Week 4	Wednesday	2
Shaving press Reis SEP 10-30	Pneumatics & Filters-S	3	Week 7	Sunday	1
Shaving press Reis SEP 10-30	Uncategorized-S	4	Week 11	Wednesday	2
Die Casting Machine Frech DAK 720	Sensing & Feedback Devices-D	5	Week 14	Data	3

Table 4.1: Trial 1 Output – Scheduled Maintenance Plan

(Note: Only top 5 rows shown. Full schedule includes 14 tasks)

5

Discussions

The study set out to address how MCDM algorithm can be implemented through a DSS framework at a dynamic manufacturing environment to help schedule maintenance tasks. The findings display a strong alignment with the goals of reducing downtime and facilitating data-driven decision-making. A systematic and scalable way to maximise maintenance activities is to prioritise them based on criticality, which was made possible by the hybrid MCDM algorithm. The methodology enabled the prioritisation of components based on failure risk, downtime impact, costs, and labour requirements, using pairwise comparison and TOPSIS. Once the weights are established from AHP, TOPSIS algorithm computes the closeness coefficient of each component, maintenance task to an ideal solution. These ratings are then presented in a ranked format that enables the user to identify critical components and areas that require immediate attention. This demonstrates that MCDM techniques can support structured and informed decision-making in maintenance planning. While prior studies have individually applied and discussed AHP or TOPSIS as maintenance prioritisation techniques, this thesis presents a novel integration with a CP algorithm. This hybrid combination not only allows for a nuanced task ranking but also translates this ranking into realistic operationally feasible scheduling, helping in data-driven decision making, bridging the gap in existing literature.

Additionally, a user-friendly DSS framework was developed as an interactive dashboard built using Streamlit. The dashboard integrates Z3 based constraint programming algorithm that logically prioritises, and schedules maintenance tasks based on real world constraints such as shift limits, overtime, resource availability, costs, downtime and production schedule. The dashboard also translates historical data into interactive graphs, allowing users to identify trends. After expert inputs are provided, the dashboard generates an optimised schedule at the click of a button, ensuring that user intuition is included in a structured decision-making process as recommended by Chong et al. [6]. The model shows how a hybrid MCDM model, along with CP scheduling [11, 18, 31], to improve both strategic and operational aspects of scheduling maintenance activities in a dynamic environment. The future scope for research in this field could aim to focus on automating input and data collection process using IoT and other industry 4.0 practices and data pipelines that would make maintenance predictions and tool/equipment monitoring real-time and improve model responsiveness.

This outcome directly contributes to answering the two research questions by showing how prioritised tasks can be optimally scheduled within a real-time, constraint-aware decision-support system.

5.1 Maintenance Scheduling Output

The interpretation of a Z3 based constraint programming model represents a significant improvement in creating feasible schedules from maintenance priorities. Frost and Dechter [11], emphasised the importance of encoding real-world constraints such as resource availability, throughput, downtime, and risks. Our model reflects these conditions by ensuring structured and realistic planning. One of the model's advantages is that it inherently distributes workload evenly, relieving equipment and technicians from overburdening. It enforces shift and resource constraints while prioritising high-importance maintenance tasks. Similar strengths were demonstrated in Da Col and Teppan [7], where proactive scheduling led to a measurable reduction in maintenance backlog and labour overtime.

Additionally, penalties for scheduling tasks during night shifts or holidays guided the model to schedule most activities during regular shifts unless high risk justified the trade-off. This aligns with Niu et al. [23], that constraint-based models can simulate intelligent behaviour under multi-faceted conditions, implying that our results become more accurate as we increase the number of constraints for the algorithm to fulfil.

5.2 Visual Interpretation

The dashboard was developed to meet the operator's practical needs, including ease of use, clear visual representation of data, and a simple layout. Visual tools such as donut and bar charts to summarise the breakdowns of costs, downtime and other information were implemented along with a simple design. Simplified input options reduce cognitive load for operators working in dynamic environments. Recognising that operators may come from diverse backgrounds, the input process was made intuitive and adaptable to various user requirements. Instead of requiring standard numeric weights for AHP, operators select from qualitative options that are internally mapped to value ranges allowing experience-based inputs without the need for manual calculations.

As recommended by Chong et al. [6], when deploying the MCDM, it was considered that the visuals serve as communication between the algorithm and the operators, combining their heuristic inputs and data into reliable optimised intuitive format of a maintenance schedule.

5.3 Reflections on Trial 1

The success of the hybrid MCDM and CP framework in a real-world industry setting is illustrated by the trial. Manually adjustable S, O, D scores and weighted prioritisation provide the rankings that closely align with the expectations of the maintenance teams. They acknowledged that certain components, such as the Electrical Modules and Hydraulic System were ranked appropriately due to their effect on cost and downtimes. However, certain tasks were assigned during the night shift despite being technically optimal under the model's function. The stakeholders at the partner company also preferred to avoid any activities to done during the night shift. These cases suggest revising penalties or adding hard constraints for shift preferences.

While the resulting scheduled tasks met the maintenance team's expectations, a few discrepancies were noted. For example, the Control Interface System had no historical failure data and yet was prioritised in the maintenance schedule. This was mainly due to the grouping logic that is used by the model. The maintenance team noted that while these components may not have a history of failure. But it does not rule out potential failures that may occur in the future. The model doesn't predict failures at the part level due to data limitations, but it identifies high-risk areas on machines. This insight is useful for planners, even if not part-specific. Yet, the trial confirms the framework can support informed decision-making and resource allocations under these limitations.

Furthermore, the maintenance team recognised the visual transparency and clarity that the dashboard provides in the decision-making process. The component rankings and schedule breakdowns help cross-functional teams to easily collaborate, improving optimisation across departments and building confidence in the tool by enabling optimisation in maintenance without a necessary background. Importantly, the trial displays the competing operational goals, such as minimising costs, managing resources and risks can be handled in a transparent and traceable way. In general, the trial displays the real-world application and operational feasibility of expert judgement through AHP, risk and performance-based rankings through TOPSIS, and the CP model using Z3 that schedules the tasks based on flexible constraints. This trial is a strong validation of the DSS and sets the stage for future scope, like real-time data integration. PM and more effective rollout across different machines and production areas.

5.4 Deviations and Unexpected Results

The existing maintenance approach, despite being effective, is mostly informal and reactive. Any maintenance that is scheduled is periodic and preventive type maintenance, whereas most of the other maintenance that is carried out is reactive, since the partner company has a flexible production and maintenance schedule.

Comparatively, the AHP–TOPSIS based DSS developed in the project, aims to integrate a data-driven methodology for planning and maintenance. Expert opinion is effectively captured in AHP through pairwise comparison, transparent weightage for decision criteria such as failure risk, downtime and cost. Integrating TOPSIS enhanced the process by converting the weighted evaluations into a quantitative ranking of various tasks based on a closeness score with respect to an ideal solution calculated by the algorithm [3, 18]. The scheduling is handled by a Z3-based CP model that simulates real-world constraints during operation, such as resource availability, shift preferences, downtimes and costs of resources and shifts. This model generates a production schedule automatically, optimising the balance between these constraints and operational efficiency. The approach is consistent with the findings from Da Col and Teppan, Frost and Dechter [7, 11], which highlight the ability of the algorithms to solve such complex resource-constrained scheduling problems effectively.

Additionally, transitioning from reactive-based maintenance to a model-based planning could further expand scope to Industry 4.0 paradigms [14, 23], supporting predictive/proactive maintenance strategies. The model proposed in this project ensures traceability, consistency and supports decision making. Although the MCDM framework performed as expected, a few deviations were observed during result interpretation. These findings reveal the sensitivity of the model to specific constraints and highlight areas of improvement for the future.

Components with low RPN scores but higher spare parts costs were ranked unexpectedly high in the TOPSIS closeness scores. This phenomenon highlights the significance that even the moderately rated weighted criteria can impact the final ranking of maintenance tasks. A similar sensitivity was noticed by Maletic et al. [18], where it was found that the hybrid model could influence the pairwise comparison input quality, particularly when the relationship between costs and risk were not defined clearly.

Furthermore, the model sometimes clustered tasks with similar priorities, causing temporary workload spikes. Penalising clustering or enforcing strict load-balancing could mitigate this. Overall, the model followed hard constraints and delivered feasible solutions, indicating reliability despite areas for improvement.

5.5 Limitations

A handful of assumptions shaped the project throughout; since the maintenance team operates within a relatively flexible production environment, certain tasks can be performed without causing major disruptions. This creates variable constraints that are difficult to encode. The algorithm assumes that most maintenance tasks must be conducted during the day shift and excludes holidays. Additionally, most PM tasks are typically carried out during the summer, when production activity is reduced, allowing greater access to machines and equipment for maintenance.

Due to the large nature of the algorithm and current physical limitations, the computing time taken by the algorithm may be longer than expected, depending on the number of machines and schedules calculated. Optimising the algorithm and deployment at the production systems could potentially improve performance and reduce the time taken to calculate.

Additionally, cost and downtime data were simplified and not necessarily accurate. One important thing to note about this framework is that it doesn't point out the exact component that needs maintenance. Instead, it helps maintenance planners identify which machines or general areas are more likely to require attention. This gives them a clear starting point, but it doesn't go as far as identifying the exact component that needs to be fixed. The main reason for this limitation is the lack of detailed historical failure data and real-time monitoring information. We don't have enough past records or sensor data to confidently say "this component will fail soon." As a result, the system highlights where risk appears higher, but leaves the final judgement to the experience of the maintenance team.

5.6 Recommendations and Future Scope

The current system provides a strong foundation in maintenance planning, but offers several areas for future research in the field. A key recommendation is to is to integrate the framework with the TPdM initiative that allows for real-time PdM, reducing manual data input and increasing automation capabilities. Real-time data from machines can be leveraged by the dashboard to continuously update task priorities based on actual operating conditions and performance trends.

Improving the reliability and accuracy of the data collection with CMMS is also a major scope of improvement. The reliability of prioritisation inputs reduce with inconsistent logging of maintenance tasks. Ensuring robust data collection would provide a solid foundation for machine learning models in the future. Once CMMS data can be consistently captured, it could be seamlessly integrated with machine-learning algorithms that automate the DSS. For instance, historical patterns could be used to automatically populate RPN scores and ratings within AHP framework, improving responsiveness. The dashboard could potentially be transformed from a static input interface to a more and adaptive system.

Furthermore, the existing framework could potentially be integrated with an ERP system that could increase the operational awareness of the system. Crucial data such as resource availability, costs and production schedules could be directly fed to the CP algorithm to generate an operationally feasible maintenance schedule. For instance, if there is a critical component that might be out of stock to conduct maintenance activities, the algorithm could potentially have the ability to reschedule maintenance tasks automatically with minimal human interaction.

Long term scope would be for the system to be validated and stabilised in its current state and scaled to support the entire production line, including managing maintenance tasks across departments and coordinating operations, enabling centralised planning and organisation-level maintenance planning.

Combining predictive capabilities and system level integration, the proposed DSS can evolve into a fully autonomous, intelligent maintenance planning framework that is capable of adapting to dynamic environments like a manufacturing industry.

6

Conclusion

This thesis presents a comprehensive DSS for scheduling and prioritising maintenance tasks in a real-world manufacturing environment at a Swedish manufacturing company. The proposed framework, has been able to integrate a distinct hybrid MCDM process by combining both AHP and TOPSIS methods with CP algorithms to enable maintenance tasks to be scheduled as per operational feasibility. The DSS assists in planning and scheduling maintenance tasks based on both inputs from the user and quantitative data from the machines, enabling the maintenance team to make informed decisions considering factors such as risk, costs, technician availability and production cycles. In moving away from predominantly reactive-based maintenance. The system improves transparency and a prioritisation process that reflects both technical criticality and operational feasibility. AHP enables the operator to capture their knowledge and preferences through weights and structured pairwise comparisons, while TOPSIS converts those preferences and weights to a ranking list of tasks based on closeness to an ideal solution. The CP algorithm ensures that the resulting ranked maintenance priorities from TOPSIS are scheduled into feasible actionable maintenance schedules, keeping in mind downtime windows, technician and resource availability, costs, among other constraints.

Theoretically, this project emphasises on the importance of the unique hybrid MCDM approach to strategic scheduling and planning. Further expanding on existing literature, the model exhibits the advantages of decision-making methods can be operationalised into daily workflows, transforming how maintenance is planned. Thereby bridging the gap between strategy and execution that aligns with industry requirements. Practically, the DSS was designed for scalability and ease of use. The real-world use in an operational production facility like a Swedish manufacturing company demonstrates the model's potential to be extended across the facility with similar maintenance constraints. Furthermore, the integration of a dashboard interface allows for intuitive interaction with both, technical and non-technical users, empowering maintenance teams to make timely, data-informed decisions.

The trial results confirmed that the proposed DSS system can effectively integrates prioritisation and scheduling in a complex industrial environment. The use of real component data, expert inputs and configurable optimisation parameters results in a schedule that is both cost-effective and operationally feasible. Importantly, the model demonstrated flexibility in balancing trade-offs and adapting to stakeholder feedback.

In our context, the unique hybrid MCDM framework paired with CP algorithm results in a DSS that represents a step towards a more intelligent, proactive and strategically aligned maintenance planning system in modern manufacturing environments.

Bibliography

[1] Jose Ignacio Aizpurua, Victoria M Catterson, Ferdinando Chiacchio, and Diego D'Urso. A cost-benefit approach for the evaluation of prognostics-updated maintenance strategies in complex dynamic systems. In *Risk, Reliability and Safety: Innovating Theory and Practice: Proceedings of ESREL 2016 (Glasgow, Scotland, 25-29 September 2016)*. 2016.

[2] Basim Al-Najjar and Imad Alsyouf. Enhancing a company's profitability and competitiveness using integrated vibration-based maintenance: A case study. *European journal of operational research*, 157(3):643–657, 2004.

[3] Maurizio Bevilacqua and Marcello Braglia. The analytic hierarchy process applied to maintenance strategy selection. *Reliability Engineering & System Safety*, 70(1):71–83, 2000.

[4] Jon Bokrantz, Anders Skoogh, Cecilia Berlin, Thorsten Wuest, and Johan Stahre. Smart maintenance: a research agenda for industrial maintenance management. *International journal of production economics*, 224:107547, 2020.

[5] Yakup Çelikbilek and Fatih Tüysüz. An in-depth review of theory of the topsis method: An experimental analysis. *Journal of Management Analytics*, 7(2): 281–300, 2020.

[6] Alan Kim Wing Chong, Abdul Hakim Mohammed, Mat Naim Abdullah, and Mohd Shahril Abdul Rahman. Maintenance prioritization–a review on factors and methods. *Journal of Facilities Management*, 17(1):18–39, 2018.

[7] Giacomo Da Col and Erich C Teppan. Industrial-size job shop scheduling with constraint programming. *Operations Research Perspectives*, 9:100249, 2022.

[8] Jirapun Daengdej, Dickson Lukose, and Robert Murison. Using statistical models and case-based reasoning in claims prediction: experience from a real-world problem. In *Applications and Innovations in Expert Systems VI: Proceedings of ES98, the Eighteenth Annual International Conference of the British Computer Society Specialist Group on Expert Systems, Cambridge, December 1998*, pages 217–229. Springer, 1999.

[9] Leonardo De Moura and N Bjørner. International conference on tools and algorithms for the construction and analysis of systems. In *International conference on Tools and Algorithms for the Construction and Analysis of Systems*, pages 337–340, 2008.

[10] RL Dunn. Advanced maintenance technologies. *Plant Engineering*, 41(12): 80–93, 1987.

[11] Daniel Frost and Rina Dechter. Optimizing with constraints: A case study in scheduling maintenance of electric power units. In *CP*, page 469, 1998.

[12] Maheshwaran Gopalakrishnan. *Data-driven decision support for maintenance prioritisation: connecting maintenance to productivity.* Chalmers Tekniska Hogskola (Sweden), 2018.

[13] Narges Hemmati, Masoud Rahiminezhad Galankashi, DM Imani, and Farimah Mokhatab Rafiei. An integrated fuzzy-ahp and topsis approach for maintenance policy selection. *International Journal of Quality & Reliability Management*, 37(9/10):1275–1299, 2020.

[14] Andrew KS Jardine, Daming Lin, and Dragan Banjevic. A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical systems and signal processing*, 20(7):1483–1510, 2006.

[15] Philippe Laborie, Jérôme Rogerie, Paul Shaw, and Petr Vilím. Ibm ilog cp optimizer for scheduling: 20+ years of scheduling with constraints at ibm/ilog. *Constraints*, 23:210–250, 2018.

[16] Hans Löfsten. Management of industrial maintenance–economic evaluation of maintenance policies. *International Journal of Operations & Production Management*, 19(7):716–737, 1999.

[17] Isabel da Silva Lopes, Manuel Figueiredo, and Vera Sá. Criticality evaluation to support maintenance management of manufacturing systems. 2020.

[18] Damjan Maletic, Matjaz Maletic, Viktor Lovrencic, Basim Al-Najjar, and Bostjan Gomiscek. An application of analytic hierarchy process (ahp) and sensitivity analysis for maintenance policy selection. *Organizacija*, 47(3):177, 2014.

[19] Hossein Mirzaee, B Naderi, and Seyed Hamid Reza Pasandideh. A preemptive fuzzy goal programming model for generalized supplier selection and order allocation with incremental discount. *Computers & Industrial Engineering*, 122: 292–302, 2018.

[20] R Keith Mobley. *An introduction to predictive maintenance.* Elsevier, 2002.

[21] Peter Muchiri, Liliane Pintelon, Ludo Gelders, and Harry Martin. Development of maintenance function performance measurement framework and indicators. *International Journal of Production Economics*, 131(1):295–302, 2011.

[22] S. Nakajima. *Introduction to TPM: Total Productive Maintenance.* Preventative Maintenance Series. Productivity Press, 1988. ISBN 9780915299232. URL `https://books.google.se/books?id=XKc28H3JeUUC`.

[23] Gang Niu, Bo-Suk Yang, and Michael Pecht. Development of an optimized condition-based maintenance system by data fusion and reliability-centered maintenance. *Reliability engineering & system safety*, 95(7):786–796, 2010.

[24] Evren Can Özcan, Sultan Ünlüsoy, and Tamer Eren. A combined goal programming–ahp approach supported with topsis for maintenance strategy selection in hydroelectric power plants. *Renewable and Sustainable Energy Reviews*, 78:1410–1423, 2017.

[25] Aditya Parida and Gopi Chattopadhyay. Development of a multi-criteria hierarchical framework for maintenance performance measurement (mpm). *Journal of Quality in maintenance Engineering*, 13(3):241–258, 2007.

[26] Laurent Perron and Vincent Furnon. Or-tools. *Google.[Online]. Available: https://developers. google. com/optimization*, 2019.

[27] Ali Rastegari and Mohammadsadegh Mobin. Maintenance decision making, supported by computerized maintenance management system. In *2016 annual reliability and maintainability symposium (RAMS)*, pages 1–8. IEEE, 2016.

[28] Tracy D Rishel and DP Christy. Incorporating maintenance activities into production planning; integration at the master schedule versus material requirements level. *International Journal of Production Research*, 34(2):421–446, 1996.

[29] Thomas L Saaty. Decision making with the analytic hierarchy process. *International journal of services sciences*, 1(1):83–98, 2008.

[30] Lana MR Santos, Pedro Munari, Alysson M Costa, and Ricardo HS Santos. A branch-price-and-cut method for the vegetable crop rotation scheduling problem with minimal plot sizes. *European Journal of Operational Research*, 245 (2):581–590, 2015.

[31] Kailas Shyjith, Maari Ilangkumaran, and Sabhya Kumanan. Multi-criteria decision-making approach to evaluate optimum maintenance strategy in textile industry. *Journal of Quality in Maintenance Engineering*, 14(4):375–386, 2008.

[32] LIISA Sirkka and J Jämsä. Future trends in process automation. *Annual Reviews in Control*, 31(2):211–220, 2007.

[33] Adriana Soares Ito, Torbjörn Ylipää, Per Gullander, Jon Bokrantz, and Anders Skoogh. Prioritisation of root cause analysis in production disturbance management. *International Journal of Quality & Reliability Management*, 39(5): 1133–1150, 2022.

[34] Swedish Standards Institute. SS-EN 13306:2010 Maintenance – Maintenance terminology. Standard, SIS Förlag AB, 2010. Stockholm, Sweden.

[35] Albert HC Tsang. Strategic dimensions of maintenance management. *Journal of Quality in maintenance Engineering*, 8(1):7–39, 2002.

[36] Gwo-Hshiung Tzeng and Jih-Jeng Huang. *Multiple attribute decision making: methods and applications.* CRC press, 2011.

[37] Adriaan Van Horenbeek and Liliane Pintelon. Development of a maintenance performance measurement framework—using the analytic network pro-

cess (anp) for maintenance performance indicator selection. *Omega*, 42(1): 33–46, 2014.

[38] Hai Canh Vu, Phuc Do, Anne Barros, and Christophe Bérenguer. Maintenance grouping strategy for multi-component systems with dynamic contexts. *Reliability Engineering & System Safety*, 132:233–249, 2014.

[39] Geert Waeyenbergh and Liliane Pintelon. A framework for maintenance concept development. *International journal of production economics*, 77(3):299–313, 2002.

[40] Geert Waeyenbergh and Liliane Pintelon. Maintenance concept development: a case study. *International journal of production economics*, 89(3):395–405, 2004.

[41] Hongzhou Wang. *European journal of operational research*, 139(3):469–489, 2002.

[42] Lei Xiao, Sanling Song, Xiaohui Chen, and David W Coit. Joint optimization of production scheduling and machine group preventive maintenance. *Reliability Engineering & System Safety*, 146:68–78, 2016.

A

Appendix 1

Declaration of Generative AI and AI-Assisted Technologies in writing process:

During the writing of this thesis work, the authors have used various models of OpenAI's Chaptgpt to support proofreading, improve readability and assist in structring the content.Additonaly ChaptGPT was used to generate Phyton codes for the building and developing the Decision-support dashboard. All outputs were thoroughly verified and reviewved by authors, who take full responsibility for the final content and implementation.

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