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# Strategic Reliability Centered Maintenance Decision Analysis Model Using Fuzzy and Analytic Hierarchy Process for Refinery Valves

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**Abstract:** *Modern industries, particularly oil and gas, necessitate robust maintenance management and optimization for increased profits, plant availability, and maintenance cost reduction. The maintenance strategy is therefore crucial, especially under global economic pressures on equipment reliability. This study examines the present maintenance management practices for refinery valves, critical equipment whose failure can have severe consequences. Many existing models for selecting critical equipment in maintenance management face limitations due to inadequate decision analysis and exclusion of key criteria. This research proposes a strategy model, combining artificial intelligence and multi-criteria decision-making techniques like Fuzzy Logic and Analytical Hierarchy Process, to fill this gap and manage refinery valves' maintenance. Proven by case studies and interviews, the model improves safety, reliability, operational availability and enables operators to monitor their decision consequences. The model can convince asset managers to invest in maintenance initiatives.*

**Keywords**: Reliability Centred Maintenance (RCM), Strategic, Failure Mode & Effect Criticality Analysis (FMECA); maintenance strategy; fuzzy system; multi-criteria decision-making, Analytic Hierarchy Process (AHP), refinery valves

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## 1. Introduction

Fossil-based energy, crude oil-derived products like fuel oils, gasoline, and jet fuel, plays a key role in global energy supply, industry, and daily life. Crude oil is essential for the oil sector, from exploration to petrochemical production. Ensuring reliability and availability is crucial for cost-effective, sustainable manufacturing. Manufacturers must enhance plant performance, reliability, and regulatory compliance to manage costs. Therefore, optimizing maintenance to maintain reliability and performance is increasingly vital for refinery operators' survival (Dwi Prasetyo et al., 2020). Conventional maintenance methods primarily focus on severity and probability, lacking a comprehensive perspective. Criticality assessment must consider multiple factors, ranging from safety and environmental impact to financial aspects. Current maintenance decision-making often relies on qualitative assessments, which may introduce bias (Pride, 2010).

One of the important assessments in RCM is Failure Mode and Effect Criticality Analysis (FMECA) where each equipment item is evaluated in detail, considering various failure scenarios and corresponding maintenance strategies. This requires knowledgeable personnel. FMECA results in a ranking within a criticality hierarchy, guiding maintenance priorities (Ciliberti, 1998). However, some reports suggest that failures can occur in components initially deemed non-critical (Liu et al., 2013). Knowledge-based or expert systems, as discussed by Fasanghari et al. (2010), aim to provide expert-level decision support by accumulating specialized knowledge. Recent studies aim to improve critical assessment systems for more effective maintenance strategies. Researchers agree that the conventional method within the Reliability Centered Maintenance framework has debates, weaknesses, and lacks precision (Braglia et al., 2003a) due to lack a comprehensive perspective, leading to suboptimal strategies that can impact safety, environmental compliance, and operational costs. The challenge is to develop a strategic model that considers multiple risk factors and integrates fuzzy logic and Analytic Hierarchy Process (AHP) to improve the criticality assessment and maintenance strategy selection for refinery valves, ultimately optimizing their reliability and performance.

## 2. Literature Review

Petroleum refineries are essential for converting crude oil into fuels and chemicals. They have three main sections: separation, conversion, and finishing, which use temperature, pressure, and catalysts for different processes. These processes fall into separations, conversions, and blending, each with unique operations (Adendorf et al., 2012). Refineries strive for improved performance in risk management, reliability, and maintenance to remain competitive. The ultimate objectives of maintenance in refineries include increasing profit, reducing safety and environmental risks, enhancing equipment reliability, and improving production performance, efficiency, and product quality (SolomonAssociates, 2017). Valves are vital components in refinery operations, responsible for controlling parameters like flow, level, pressure, and temperature. They come in two main categories: linear and rotary valves, each with unique features suitable for specific applications. Valves serve essential functions, acting as control elements, safeguards for process safety, and contributors to mechanical integrity in refineries. Failures in valves can have severe consequences, including environmental incidents and safety hazards (Carneiro et al., 2014).

Assessing maintenance for thousands of plant valves is a significant task, but it's crucial due to potential safety and production impacts. Valve failures can lead to containing hazardous substances, safety risks, revenue loss, and more. Factors like process conditions, operational needs, and degradation contribute to failures. To prevent them, refineries use strategies like predictive, preventive, condition-based, or reactive maintenance, choosing based on cost and spare part availability for tasks like replacement, overhaul, modification, repair, or coatings maintenance. (Carneiro et al., 2014). Valve failures can have far-reaching consequences, making it imperative for refineries to adopt appropriate maintenance strategies based on their specific needs and the criticality of the valves in their processes. These strategies help prevent unexpected shutdowns, reduce repair costs, improve process performance, and ultimately increase profitability.

### 2.2 Overview of Maintenance Management

Maintenance management involves actions to maintain or restore equipment (Dhillon, 2002). Adebimpe et al. (2015) broaden this to include repair, preservation, and failure prevention, reducing losses and environmental impact which ultimately reduce production losses and environmental hazards. Maintenance management is a vital aspect of modern industrial operations, driven by various goals and objectives (Muchiri et al., 2011; Pintelon et al., 1992).

Maintenance management objectives include extending equipment lifespan through repair and replacement to avoid costly failures, minimizing service disruptions to ensure uninterrupted production or services, enhancing equipment and system reliability to reduce breakdowns, improving equipment capabilities for increased efficiency, and addressing safety, health, and environmental factors to enhance product quality and revenue. (Dwi Prasetyo et al., 2020). Maintenance management has become instrumental in maintaining intricate machinery and aligning with industry-specific targets, driven by the need for productivity, availability, quality, safety, and environmental considerations (Arunraj et al., 2007). Choosing the right maintenance management approach hinges on an organization's operational system, resources, and employee expertise. Maintenance management encompasses various facets, including setting objectives, defining strategies, and implementing means such as planning and control (Márquez, 2007).

### 2.2.1 Strategic Maintenance Management

Strategic Maintenance Management aligns activities with organizational goals, optimizing maintenance, reducing downtime, and costs (Pintelon et al., 1992). It fosters proactive maintenance, prioritizing based on criticality, and informed decisions on strategies, frequency, techniques (Murthy et al., 2002).. It integrates diverse perspectives - environmental, safety, cost-effectiveness, productivity, learning, and quality (Eti et al., 2006; Mather, 2005). Strategic management enhances resource optimization and overall performance. Industries adapt strategies to equipment, risk, and focus (Al-Shayea, 2012). Kermani (2016) introduced an AI-based decision model, harmonizing safety, financial, operational, and technical aspects, addressing critical equipment and strategies' selection limitations, offering a comprehensive approach.

## 2.3 Current RCM Implementation

Reliability-Centered Maintenance is a systematic asset management approach that balances proactive maintenance with potential reductions in an item's useful life to minimize life cycle costs (Afefy, 2010; Moubray, 1997). Originating from the aviation industry, RCM prioritizes safe, cost-effective, and long-lasting maintenance practices (Kullawong et al., 2015; Moubray, 1997). It allows for systematic functionality and cost-effectiveness of assets, ensuring they remain reliable over time (Campbell et al., 2015; Rastegari et al., 2016). There are many Industry-specific standards guide RCM (Rausand, 1998; Rausand et al., 2008). Critical success factors of RCM include improving maintenance programs and selecting critical equipment wisely (Zeinalnezhad et al., 2020).

In practice, Failure Mode Effects and Criticality Analysis is a qualitative reliability technique that systematically assesses potential failure modes, their probability of occurrence, and their effects. FMECA forms part of RCM and helps identify and mitigate potential failures. Maintenance task selection in RCM follows a logic path to determine the most appropriate strategy based on the consequences of failure modes, ensuring applicability and cost-effectiveness (Moubray, 1997). The goal is to maintain assets while minimizing life cycle costs and achieving safety, reliability, and environmental goals. Overall, RCM is a structured approach to asset management that has proven effective in various industries by enhancing reliability, safety, and cost-efficiency while minimizing maintenance expenses. It involves critical success factors, industry-specific guidelines, and methodologies like FMECA and maintenance task selection to ensure the continued functionality of critical assets.

### 2.3.1 Review on Current FMECA Method

RCM has limitations, including being time-consuming and resource-intensive for complex systems. It involves multiple experts and can be subjective in risk evaluation. Traditional RCM may not effectively prioritize equipment criticality, as it can produce the same Risk Priority Number for different scenarios. Therefore, researchers have explored alternative approaches to improve maintenance decision-making. Several studies proposed fuzzy logic-based methods to enhance RCM and FMECA. Bowles et al. (1995) introduced fuzzy logic to prioritize failures in FMECA but considered only standard factors which are Occurrence (O), Severity (S) and Detectability (D). Pillay et al. (2003) also used fuzzy rules but lacked consideration of additional risk factors. Braglia et al. (2003a) applied fuzzy RPN but focused on probability, severity, and detectability while Braglia et al. (2003b) introduced a multi-attribute approach using fuzzy TOPSIS. While innovative, these papers are considered improved in terms of methods but failed to consider non-conventional risk factors.

Bevilacqua et al. (2012) integrated traditional risk factors with non-conventional ones for equipment criticality assessment in an oil refinery. Their method included safety and environmental impact, corrosion sensitivity, and more. However, it still relied on RPN calculations. Qi et al. (2012) used fuzzy logic for criticality-based maintenance but considered only two risk factors: health and safety impact and shutdown impact. Wu et al. (2013) expanded the sub-factors under likelihood and severity for corrosion assessment. Gupta et al. (2017), Renjith et al. (2018), Gallab et al. (2019) and George et al. (2019) used fuzzy rule-based methods for risk analysis but limited they only focus to are Occurrence (O), Severity (S) and Detectability (D). Jaderi et al. (2019) used fuzzy rule-based inference but considered only frequency of failure and consequences. Petrović et al. (2020) considered more sub-factors under Severity but required precise data while Jasiulewicz-Kaczmarek et al. (2021) included ten non-conventional risk factors using Fuzzy Analytic Hierarchy Process (AHP) but faced complexity and subjectivity challenges. Shahri et al. (2021) proposed Pythagorean fuzzy method, which improved upon traditional FMECA but required complex algorithms to implement into real industry application. In summary, while various studies have proposed fuzzy logic and other methods to enhance RCM and FMECA, most still rely on conventional risk factors or introduce complexity and subjectivity. Future research should aim for more comprehensive and practical approaches to equipment criticality assessment in maintenance management.

### 2.3.2 Review on Current Maintenance Task Selection Method

The second major stage in RCM assessment involves selecting the appropriate maintenance strategy for components, equipment, or systems. Decision analysis techniques in operational research, particularly Multi-Criteria Decision Making (MCDM), play a vital role in this process. Alias et al. (2008) identified two main trends in MCDM: Artificial Intelligent (AI) approaches (AIMCDM) and Classical operational research techniques (CMCDM). AI approaches encompass techniques like Fuzzy Logic (FL), Genetic Algorithm (GA), Neural Network (NN), and Expert System (ES). On the other hand, Classical methods include Analytic Hierarchy Process (AHP), Elimination and Choice Expressing Reality (ELECTRE), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Technique for Order-Preference by Similarity Ideal Solution (TOPSIS), and Analytic Network Process (ANP) (Arjomandi et al., 2021). Within maintenance selection papers using MCDM, popular methods are Analytic Hierarchy Process (AHP), Technique for Order-Preference by Similarity Ideal Solution (TOPSIS), and Analytic Network Process (ANP), primarily applied in the field of management to select, rank, and evaluate maintenance alternatives.

Within maintenance selection papers using Multi-Criteria Decision Making (MCDM) popular methods are AHP, TOPSIS, and ANP, primarily applied in the field of management to select, rank, and evaluate maintenance alternatives. AHP was applied in various contexts. Many researchers used AHP as their based method for the Multi-Criteria Decision Making (MCDM) maintenance strategy selection such as Triantaphyllou et al. (1997), Labib (2004) , Bertolini et al. (2006), Lazakis et al. (2012), Goossens et al. (2015), Resobowo et al. (2014), Azadeh et al. (2016), Vishnu et al. (2016) and Panchal et al. (2018). Other methods, such as Fuzzy Analytic Network Process (FANP) and Fuzzy TOPSIS, have also been used in diverse contexts for maintenance strategy selection and long-term objectives, as highlighted in the paper's summary and comments such as Ighravwe et al. (2017), Hemmati et al. (2018), Hemmati et al. (2019), Aghaee et al. (2020), Kausar et al. (2020), Mathew et al. (2020) and Arjomandi et al. (2021) proposed their Multi-Criteria Decision Making (MCDM) methodology by using more complex techniques by combining methodologies such as decision-making trial and evaluation laboratory (DEMATEL), Analytic Network Process (ANP), and *VlseKriterijuska Optimizacija I Komoromisno Resenje* (VIKOR) for maintenance strategy selection, considering few risk perspectives. Table 1 summarized the findings and the critical comments of their research.

Various Multi-Criteria Decision Making (MCDM) techniques play a significant role in selecting optimal maintenance strategies across different industries, considering diverse criteria and perspectives. These methods enhance decision-making processes and contribute to improved maintenance practices. However, most researchers still considered limited consideration of risk factors and perspectives in maintenance decision-making. Many papers rely on conventional risk factors like occurrence, severity, and detectability (O, S, D) without exploring more comprehensive criteria. Furthermore, the lack of attention to strategic dimensions in maintenance management is noted. While research often addresses financial and technical aspects, the strategic perspective, including qualitative data analysis for continuous improvement, is often overlooked. This study aims to integrate strategic perspectives into the maintenance decision-making process.

The fuzzy-based method offers advantages such as handling qualitative and imprecise information, flexible combination of risk factors, customization based on process nature, and incorporation of expert knowledge (Liu et al., 2013). This research intends to leverage these advantages for assessing and prioritizing risks associated with refinery valves. Regarding maintenance task selection methods, there is a need for a model specifically tailored to refinery critical valves. While Analytic Hierarchy Process (AHP) is commonly used, complex methods like fuzzy set theory, mathematical programming, and AI approaches may be challenging to implement in industry. Addressing this gap requires simplifying and adapting these complex methods for practical use in maintenance decision-making.

## 3. Methodology

This research aims to develop an improved RCM decision-making framework for refinery valves. It begins with a literature review on the refinery industry and focuses on valves as the subject. The goal is to identify risk factors for valve maintenance decisions. The study draws from industrial standards, reports, manufacturer catalogs, academic research, and maintenance management frameworks. It then details the development of a strategic RCM model in two phases, first is to improved criticality assessment using fuzzy logic and secondly to improve maintenance strategy selection using AHP. The advantages and disadvantages of this approach are discussed. Case studies and expert interviews inform the model, with validation using real refinery data. Figure 1 shows the simplified version of RCM critical work process.

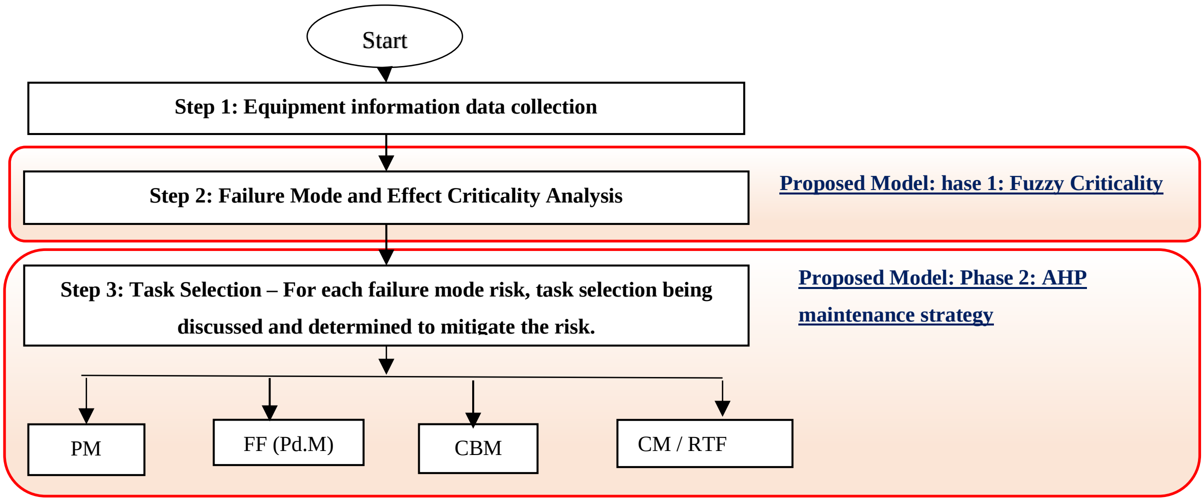


**Figure 1: Current practice of RCM critical work process**

### 3.1 Development of Strategic RCM Decision Making Model

RCM aids in identifying suitable maintenance tasks for known failure modes and is consistently applied throughout the equipment's lifespan, with ongoing adjustments based on operational experience. There are two phases in RCM decision making propose improvement, phase one creates a fuzzy model for better critical assessment, identifying key equipment functions, failure modes, causes, and assessing failure consequences. Phase two uses Multi-Criteria Decision Making (MCDM) which is Analytic Hierarchy Process (AHP) for maintenance task selection. These changes replace time-based maintenance with a proactive approach, boosting economic benefits and reducing equipment failure risks.

#### 3.1.1 Fuzzy Criticality Assessment

Fuzzy logic aids complex decision-making, offering nuanced degrees of truth, unlike Boolean logic's binary approach. It involves fuzzification, rule evaluation, and defuzzification for gray area outcomes (Liu et al., 2013). Useful when experts vary in perspective, fuzzy logic reduces uncertainty in maintenance decisions, accommodating human errors (Zadeh et al., 1992). Applied in RCM, it enhances criticality assessment and supports holistic maintenance improvement, optimizing practices, and reducing failure risks. In this research model, fuzzy logic is applied individually to various dimensions, each representing the viewpoint of one or two managers. These factors were determined through a survey involving experts from a refinery organization: Figure 1 illustrates the top factors grouped into Kermani (2016) structure strategic perspectives.

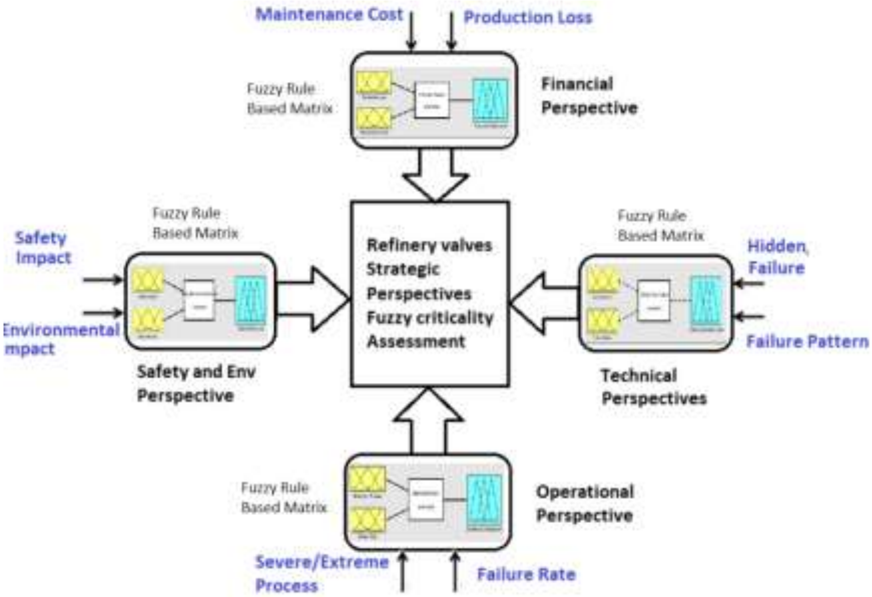


**Figure 2: Phase 1 Model with Selected Risk factor re-grouped into four main strategic perspectives adopted from Kermani (2016)**

The first step in defining a decision problem in fuzzy logic is known as fuzzification where it is necessary to define inputs that need to be considered as the basis of decision-making. The methodology used to create Tables 1 to 4 is a Fuzzy Criticality Assessment approach that evaluates various criteria from different perspectives (Safety and Environmental, Technical, Operational, and Financial) to determine the criticality level of a system or component. The provided information outlines a structured methodology for fuzzy criticality assessment from various perspectives: Safety and Environmental, Technical, Operational, and Financial. These perspectives help evaluate the criticality of systems or components based on specific criteria and linguistic terms. The matrix is then input into the MATLAB Fuzzy Toolbox utilizing the Mamdani Fuzzy method. Subsequently, the subsequent step involves the formulation of fuzzy rules for each input perspective.

**Table 1: Safety and Environmental Perspective Fuzzy Criticality Assessment Tools**

| Fuzzy Parameters | (2,3,4) | (4,5,6) | (6,7,8) |
|---|---|---|---|
| Linguistic Term | Low | Medium | High |
| Criteria (Impact on Safety) | Slightly Hazardous | Hazardous | Deadly Hazardous |
| Criteria (Impact on Environment) | Minor Pollution | Significant Pollution | Major Pollution |

| Safety Impact Level / Environment Impact | Deadly Hazardous (H) | Hazardous (M) | Slightly Hazardous (L) |
|---|---|---|---|
| Major Pollution (H) | Very High Critical | Very High Critical | High Critical |
| Significant Pollution (M) | Very High Critical | High Critical | Medium Critical |
| Minor Pollution (L) | High Critical | Medium Critical | Low Critical |

**Table 2: Technical Perspective Fuzzy Criticality Assessment Tools**

| Fuzzy Parameters | (0,4,6) | (4,6,10) |
|---|---|---|
| Linguistic Term | Low | High |
| Criteria (Failure Type) | Evident | Hidden |

| Fuzzy Parameters | (2,3,4) | (4,5,6) | (6,7,8) |
|---|---|---|---|
| Linguistic Term | Low | Medium | High |
| Criteria (Failure Pattern) | Infant Failure | Random Failure | Wear Out Failure |

| Failure Type / Failure Pattern | Hidden (H) | Evident (L) |
|---|---|---|
| Wear Out Failure (H) | Very High Critical | Medium Critical |
| Random Failure (M) | High Critical | Low Critical |
| Infant Failure (L) | Medium Critical | Low Critical |

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**Table 3: Operational Perspective Fuzzy Criticality Assessment Tools**

| **Fuzzy Parameters** | (2,3,4) | (4,5,6) | (6,7,8) |
|---|---|---|---|
| **Linguistic Term** | Low | Medium | High |
| **Criteria** (Servere Process Condition) | Normal Service | At least one severe service condition | More than one severe service condition |
| **Criteria (**Failure Rate**)** | Relatively few failures | Occasional failures | Repeated failures |

| Servere Process Condition / Failure Rate | More than one severe service condition (H) | At least one severe service condition (M) | Normal Service (L) |
|---|---|---|---|
| Repeated failures (H) | Very High Critical | High Critical | Medium Critical |
| Occasional failures (M) | High Critical | High Critical | Medium Critical |
| Relatively few failures (L) | MediumCritical | Medium Critical | Low Critical |

**Table 4: Financial Perspective Fuzzy Criticality Assessment Tools**

| **Fuzzy Parameters** | (2,3,4) | (4,5,6) | (6,7,8) |
|---|---|---|---|
| **Linguistic Term** | Low | Medium | High |
| **Criteria** (Production Loss) | Acceptable Production downtime | Major Production downtime | Prolonged Production downtime |
| **Criteria (**Maintenance Cost**)** | Low Cost | Medium Cost | High Cost |

| Production Loss / Maintenance Cost | Prolonged Production downtime (H) | Major Production downtime (M) | Acceptable Production downtime (L) |
|---|---|---|---|
| High Cost (H) | Very High Critical | High Critical | Medium Critical |
| Medium Cost (M) | High Critical | High Critical | Medium Critical |
| Low Cost (L) | Medium Critical | Medium Critical | Low Critical |

Each perspective is summarized as follows, with detailed information available in Tables 1 to 4. Its focuses on each perspective, using fuzzy parameters to evaluate them. Categories include Low, Medium, and High, assessing consequences levels to determine criticality levels, from Very High Critical to Low Critical.

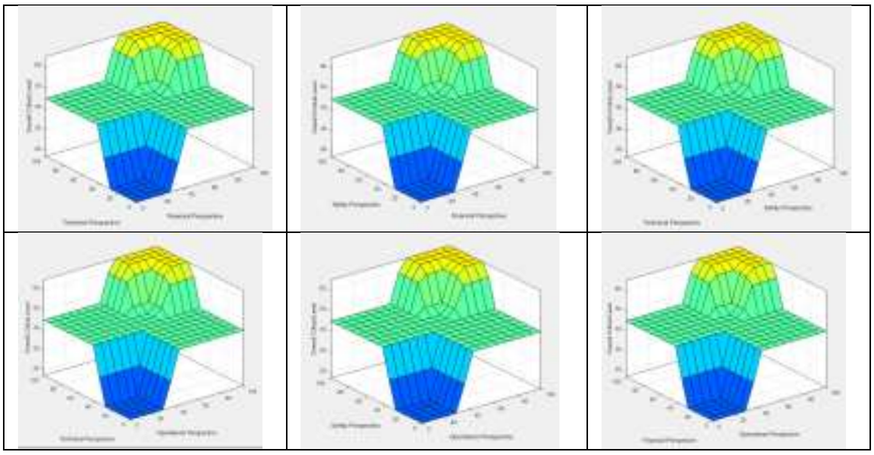

**Figure 3: The fuzzy logic toolbox inputs, Fuzzy crips and Fuzzy surface for overall criticality level, representing each main factor against every other risk factor.**

The overall fuzzy logic approach is employed to impartially consider all factors in determining the equipment's criticality. While some inputs rely on subjective judgments, introducing uncertainty within each factor and between the four dimensions, the concept of fuzzy logic is applied to address these uncertainties and interdependencies. The first phase of fuzzy logic involves merging the results from the de-fuzzification of the four criticality factors, and this outcome serves as an input to the model. Initially, there are four inputs, each representing the fuzzy logic outputs of a factor with four membership functions defin ed, resulting in a total of 250 rules. However, the increasing number of rules, coupled with subjective decision-making, can compromise result accuracy, and introduce uncertainty. To mitigate these concerns, a decision was made to reduce the number of rules. For instance, if three of the inputs are Very High Critical (VHC), then the output will be VHC, regardless of the fourth input.

**Table 5: Defined Rule for Criticality Output**

| *Category 1 – Very High Critical (VHC)* | *Category 2 - High Critical (HC)* |
|---|---|
| • Rule 1: If all and/or at least 3 out of 4 MFs are VHC, then the output membership functions would be VHC.<br>• Rule 2: If 2 MFs are VHC and the other 2 MFs are HC, then the output membership functions would be VHC.<br>• Rule 3: If 1 MFs are VHC and the other 3 MFs are HC, then the output membership functions would be VHC. | • Rule 4: If 2 out of 4 MFs are VHC then the output membership functions would be HC.<br>• Rule 5: If all and/or at least 3 out of 4 MFs are HC then the output membership functions would be HC.<br>• Rule 6: If 1 out of 4 MFs is VHC and at least the other 1 MFs are HC then output MF is High Critical (H.C). |
| ***Category 3 Medium Critical (MC)*** | ***Category 4 Low Critical (LC)*** |
| • Rule 7: If 1 MFs are VHC and no HC in the other MFS, then the output MF is MC.<br>• Rule 8: If 2 out of 4 MFs are HC and the other 2 is MC or LC, then the output MF is MC.<br>• Rule 9: If all and/or at least 3 out of 4 MFs are MC, then the output membership functions would be MC<br>• Rule 10: If 1 MFs are HC and 2 of Other MFs is MC, then the output membership functions would be MC. | • Rule 11: If all condition not fulfilled Rule 1 to Rule 10, then the output is LC or Non-Critical. |

Table 5 provides detailed rules for this reduction. The following categories have been proposed to guide the creation of rules: Very High Critical (VHC), High Critical (HC), Medium Critical (MC), and Low Critical (LC). These rules establish a methodology for decision-makers to generate rules efficiently. As presented in Figure 3, the range of values that has been considered for overall criticality membership functions in MATLAB Fuzzy Toolbox and 3D surface model shows no inconsistencies means the rules is equally and fairly generated between all four factors dimension.

### 3.1.2 AHP Based Maintenance Task Selection

Selecting maintenance strategies varies by industry due to differing priorities. Safety is crucial in nuclear plants, while oil platforms consider oil prices. Decision models balance criteria like cost, downtime, safety, and reliability. However, most models lack a strategic focus. This research uses AHP for its simplicity and alignment with decision-makers' views. It prioritizes strategies via pairwise criteria comparisons. AHP, by Saaty et al. (1980)s, aids multi-criteria decisions. It ranks criteria, streamlining complex choices. Steps include defining criteria, comparing them, assigning weights, and calculating scores. Experts' consensus involves averaging scores. AHP structures strategy selection hierarchically with levels: objective, criteria, sub-criteria, and strategies. Pairwise comparisons and numerical scales gauge criteria importance. It ranks alternatives for evaluation, merging qualitative and quantitative aspects(Saaty et al., 1980).

Figure 4 depicted the phase 2 model, considered eight (8) risk factors from strategic perspectives in phase one as selection criteria. The proposed AHP model features a four-level hierarchy, with the objective at the top. Criteria, sub-criteria, and alternatives are positioned at lower levels. Criteria and sub-criteria are derived from the Phase 1 model, focusing on valve maintenance risk factors and sub-risk factors. Main criteria include Safety Perspective (C1), Technical Perspective (C2), Operational Perspective (C3), and Financial Perspective (C4). Sub-criteria encompass Safety Impact (SC1), Environmental Impact (SC2), Hidden/Evident

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(SC3), Failure Pattern (SC4), Severe Extreme Process (SC5), Failure Rate (SC6), Production Loss (SC7), and Maintenance Cost (SC8).

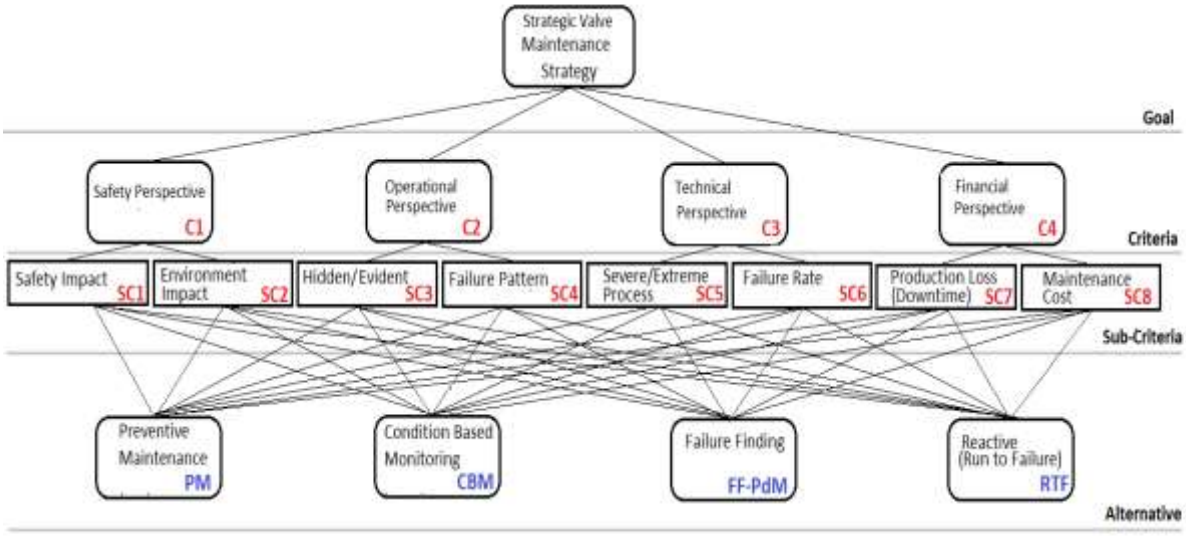


**Figure 4: Phase 2 model- AHP Hierarchy maintenance strategy selection**

**Table 6: The AHP results of the priority weights of criteria, sub-criteria and four maintenance strategies**

| | | | | | **Global priority of maintenance strategies** | | | |
|---|---|---|---|---|---|---|---|---|
| **Criteria** | **Weights of Criteria** | **Weights of Sub-criteria** | **Relative weight** | **Global weight** | **Preventive (PM)** | **Condition Based (CBM)** | **Failure Finding (FF-PdM)** | **Run to Failure (RTF)** |
| C1 Safety Perspective | **0.5597** | SC1 Safety Impact | 0.5803 | 0.3248 | 0.0778 | 0.0404 | **0.1923** | 0.0144 |
| | | SC2 Environment Impact | 0.4197 | 0.2349 | 0.0607 | 0.0261 | **0.1379** | 0.0102 |
| C2 Technical Perspective | **0.0634** | SC3Hidden/ Evident | 0.8458 | 0.0536 | 0.0097 | 0.0055 | **0.0362** | 0.0022 |
| | | SC4 Failure Pattern | 0.1545 | 0.0098 | 0.0028 | **0.0055** | 0.0009 | 0.0005 |
| C3 Operational Perspective | **0.1096** | SC5 Severe | 0.437 | 0.0479 | **0.029** | 0.0112 | 0.0056 | 0.0021 |
| | | SC6 Failure Rate | 0.5628 | 0.0617 | **0.0363** | 0.0149 | 0.0078 | 0.0027 |
| C4 Financial Perspective | **0.2673** | SC7 Prod. Loss | 0.8486 | 0.2268 | **0.1346** | 0.0577 | 0.0253 | 0.0092 |
| | | SC8 Maintenance Cost | 0.1513 | 0.0404 | **0.0178** | 0.0011 | 0.0058 | 0.0060 |
| | | | Ranking Value | | 0.3543 | 0.1707 | 0.4164 | 0.0586 |
| | | | Overall Ranking | | **2** | **3** | **1** | **4** |

The AHP model provides a structured approach for selecting maintenance strategies based on expert opinions, ensuring a comprehensive evaluation of criteria and alternatives. The decision-making process for selecting maintenance strategies involves constructing a pairwise comparison matrix using Saaty's scale. Experts' assessments result indicates consistency ratios of less than 0.1 for each expert, demonstrating acceptable pairwise comparisons. Safety Perspective (C1) receives the highest weight, aligning with industry and company safety and environmental policies. Financial Factors (C4) rank second, followed by Likelihood Factors (C3) and Failure Type factors (C2). Table 6 displays the relative weights and global priority weights for criteria and sub-criteria, calculated by multiplying relative weights for the criteria and sub-criteria. The AHP model's results, reveal the preferred maintenance strategy for each sub-criterion. Failure-Finding -Predictive Maintenance (FF-PdM) emerges as the most preferable strategy, followed by Preventive Maintenance (PM), Condition-Based Monitoring (CBM), and Run-to-Failure (RTF).

Failure Finding (FF-Pd.M.) maintenance strategy is the first rank alternative for Safety Factors (C1). Preventive Maintenance (PM) was found to be the most suitable for valve with high Financial Factors (C4) and high Likelihood of Failure (C3). While for Failure Factors (C2), the recommended maintenance strategy is different for sub-factors. As expected, hidden failure required Failure Finding (FF-Pd.M.) due to the nature of the failure required periodically testing. The failure pattern associate to wear out failure recommend using Condition Monitoring (CBM) as maintenance strategy. It was not a surprise that Failure-Finding -Predictive Maintenance (FF-Pd.M) is the most suitable for high critical valve. As they are very critical to the production, any type of valve unexpected failure cannot be tolerated and Failure-Finding -Predictive Maintenance (FF-PDM) is the only strategy that can predict the failures and prevent them. Also, the cost of planned repair or correction before failure for valve will not be costly, as the repair can be planned properly during any opportunity window such as turnaround or shutdown.

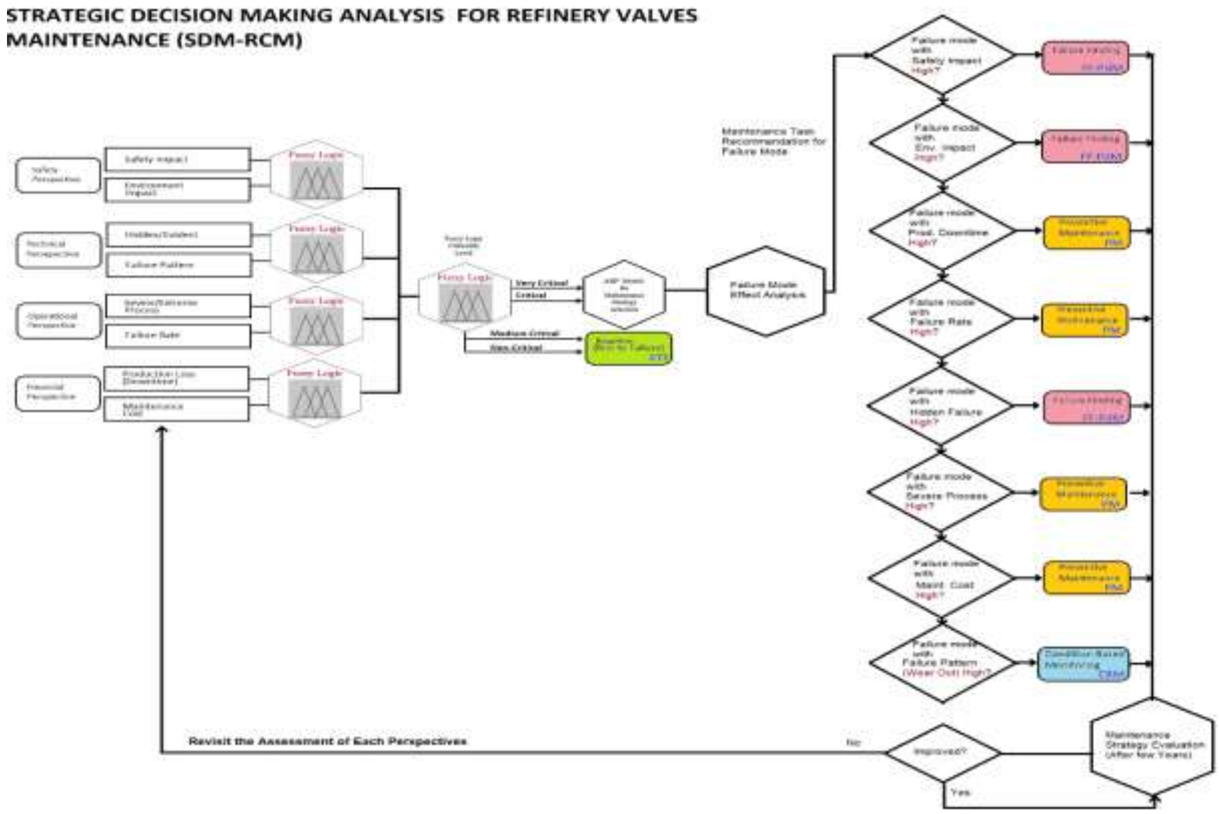


**Figure 5: Proposed Final SDM-RCM Model**

Based on the result from the Phase 1 and Phase 2 model development, a final model called Strategic Decision-Making Reliability Centred Maintenance (SDM-RCM) was developed to guide maintenance strategy selection for different risk factors associated with valves in the refinery. The model takes into consideration various the eight criticality factors which divides into four perspectives - safety, technical, financial, and likelihood of failure. The final SDM-RCM model, as depicted in Figure 5, integrates the results from Phase 1 and Phase 2. It guides maintenance strategy selection for valves in the refinery, considering eight criticality factors across four perspectives: safety, technical, financial, and likelihood of failure. The model emphasizes that Failure-Finding -Predictive Maintenance (FF-PDM) is the most suitable strategy for highly critical valves due to its ability to predict and prevent failures. The graphical flowchart aids in evaluating valves based on the weight of risk factors, ensuring a systematic approach to strategy selection. Overall, the final model provides a systematic approach for selecting maintenance strategies for different risk factors associated with valves in the refinery, considering their criticality levels and specific requirements.

## 4. Discussion and Conclusion

In summary, our study introduces the Strategic Decision-Making Reliability-Centered Maintenance (SDM-RCM) model, which offers an innovative approach to managing maintenance in the petroleum refining sector. This model combines fuzzy logic-based criticality assessment with the Analytic Hierarchy Process (AHP) for maintenance strategy selection. By considering safety, technical, financial, and likelihood of failure perspectives, the SDM-RCM model provides a holistic view of maintenance challenges. It emphasizes the importance of Failure-Finding -Predictive Maintenance (FF-PDM) for highly critical valves. This research contributes a practical framework for optimizing maintenance practices, enhancing safety, and improving profitability in refinery operations. Future research may explore the integration of advanced technologies like Artificial Intelligence (AI) and Machine Learning (ML) and extend the model's applicability to other industries. In essence, the SDM-RCM model offers a strategic and innovative solution to address maintenance issues in petroleum refining, benefiting decision-makers and ensuring the reliability of critical valves.

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