Real Time Predictive Maintenance of Tugboat Engine Using Fuzzy Logic Approach

A Case study of Dar Es Salaam Port at Mv Kiboko

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ABSTRACT

Tugboat engines are subjected to demanding operational conditions that require high reliability and minimal downtime. Conventional maintenance strategies often result in either unnecessary maintenance or unexpected failures, leading to increased costs and safety risks. This research investigates a real-time predictive maintenance framework for tugboat engines using a fuzzy logic approach. The system identifies the key factors that influence the health status of tugboat engine by collects real-time data from engine sensors including Engine temperature, Lube oil Pressure, Vibration level, fuel consumption rate, Engine load conditions and Exhaust Gas Emissions. Fuzzy logic is designed to handle uncertainties and imprecise data in engine condition assessment and providing a robust decision-making mechanism, The fuzzy inference system evaluates the health state of the engine, predicts possible faults, and estimates the remaining useful life (RUL). By integrating fuzzy logic with predictive analytics, the proposed model offers accurate, flexible, and adaptive maintenance recommendations. The outcomes of this study include improved fault detection, optimized maintenance scheduling, reduced downtime, and cost savings. The findings demonstrate that fuzzy logic-based predictive maintenance is a viable solution for enhancing the reliability and efficiency of tugboat operations within the maritime industry

Keywords: Fuzzy Logic, Tugboat Engine, Predictive Maintenance, Real-Time Monitoring, MATLAB

INTRODUCTION

Marine vessel engine and auxiliary system are essential elements that guarantee dependable and effective maritime operations (Sardar, 2024). Advanced problem detection and predictive maintenance procedures are required to prevent costly downtimes and catastrophic failures in modern marine engines, which are becoming increasingly complicated (Daya, 2024). Traditional maintenance procedures, such as corrective and preventive maintenance, are frequently reactive and inefficient, resulting in high operational costs, unscheduled repair tasks, and significant safety issues. (West et al., 2024). Fuzzy logic has emerged as a promising method for improving fault diagnosis and predictive maintenance for marine engines, as artificial intelligence (AI) and computational intelligence have advanced. (Velasco-Gallego et al., 2023).

Marine engines operate under harsh and dynamic conditions, making fault detection and maintenance planning challenging

(Xu et al., 2021). The stochastic nature of engine failures and the variability in operational parameters demand a robust diagnostic system capable of handling uncertainties and imprecisions. According to a report by the International Maritime Organization (IMO) in 2022,

The adoption of fuzzy logic for diagnosing faults in marine engines has become more popular because it can handle uncertain and incomplete information (Gharib & Kovács, 2024). Marine engines generate significant amounts of sensor data about temperature, pressure, vibration, fuel economy, and exhaust pollution (Stoumpos & Theotokatos, 2022).

Statement of the Problem

Predictive maintenance has recently gained popularity as a technique for enhancing marine engine dependability by combining real-time sensor data and previous performance patterns (Mohamed Almazrouei et al., 2023). However, the unclear, imprecise, and partial data that are frequently found in actual marine environments are difficult for traditional predictive models, such as threshold-based and statistical techniques, to handle (Yang et al., 2024).

Fuzzy logic offers a promising solution by effectively modelling uncertainty and incorporating expert knowledge into decision-making (Tang & Ahmad, 2024). Unlike rigid binary classification systems, fuzzy logic-based fault diagnosis allows for nuanced interpretations of sensor data, enabling early fault detection and improved maintenance scheduling (Hedayati et al., 2024).

Objective of the study

Main Objectives of the Study

The main objective of this study is real time predictive maintenance of tugboat engine using fuzzy logic approach.

Specific Objectives

i. To identify the key factors that affect the performance of tugboat engine.

ii. To design a fuzzy logic model for real predictive maintenance of tugboat engine

iii. To evaluate the performance of fuzzy logic model on its accuracy and effectiveness in predicting maintenance of tugboat engine

Research Questions

i. What are the key factors that affects the performance of tugboat engine.

ii. Can a fuzzy logic model be used for real time predictive maintenance of tugboat engine?

iii. How to evaluate the performance of fuzzy logic model on its accuracy and effectiveness in predicting maintenance of tugboat engine

LITERATURE REVIEW

This chapter identifies research needs and advocates for the implementation of real time predictive maintenance of tug boat engine operating at Dar es Salaam Port by using fuzzy logic approach. It also provides a comprehensive overview of the existing literature on marine engine problem detection and predictive maintenance, with a focus on fuzzy logic applications. The chapter discusses factors and defect detection approaches, predictive maintenance tactics, and the importance of fuzzy logic in managing uncertainty in marine engine monitoring.

The literature study is organized as follows: an introduction of tugboat engine faults detection, predictive maintenance tactics, design of fuzzy logic and identification of research gaps. By reviewing current research, this chapter establishes the framework for constructing a better fault diagnostic model that improves engine dependability, lowers downtime, and optimizes maintenance efficiency in marine operations.

Conceptual Framework

According to Luft et al., (2022) conceptual framework of this study outlines the relationship between the key variables involved in fuzzy-enhanced engine fault diagnosis and predictive maintenance for marine vessels. It visually represents how fuzzy logic can be integrated into the maintenance management systems to improve engine reliability, reduce downtime, and optimize operational costs in the maritime industry, particularly in marine Vessel.

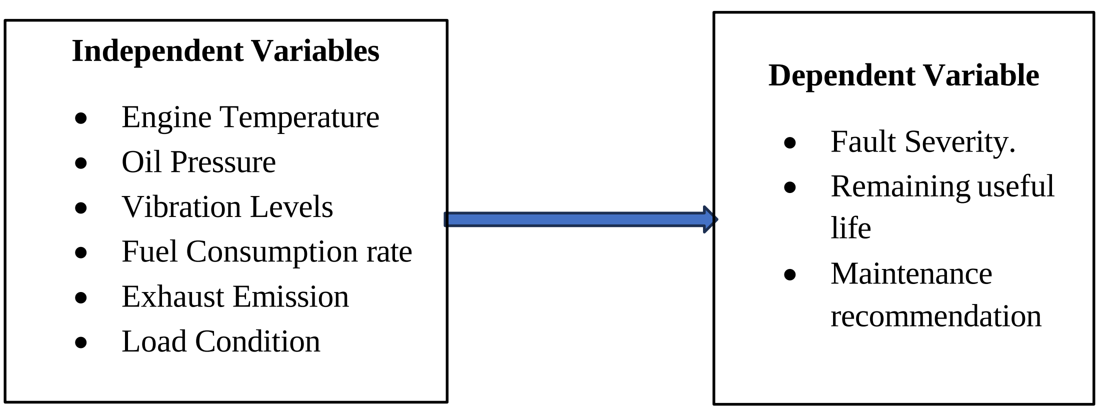

Figure1.*Conceptual Framework indicating the relationship of Dependent and Independent Data*

METHODOLOGY

This chapter presented the research methodology that was employed to achieve the objectives of the study. It described the research design, study area, target population, sampling procedures, methods of data collection, data analysis techniques, and ethical considerations.

Primary data were collected through structured questionnaires, interviews, and field observations from engine room personnel, marine engineers, and maintenance supervisors. Secondary data were obtained from official maintenance records, equipment manuals, logbooks, and relevant literature in marine engineering and artificial intelligence.

Research Design, in this study, an applied research design was employed to develop and evaluate a fuzzy logic-enhanced fault diagnosis and predictive maintenance model for marine vessels. The fuzzy logic model was designed using the Mamdani-type Fuzzy Inference System (FIS) in MATLAB and Simulink. The model incorporated six key input variables representing real-time operational parameters of the tugboat engine: Engine temperature, Lubricating oil pressure, Vibration levels, Exhaust gas characteristics Fuel consumption rate and Load condition

Each input was defined using fuzzy sets with appropriate linguistic terms (e.g., *Low*, *Normal*, *High*) and corresponding membership functions. The output variable was defined as engine health status, expressed in terms of fault severity levels (*Normal*, *Warning*, *Critical*).

Area of Study, The study was conducted in MV Kiboko at Dar es Salaam Port Location of 1 Nelson Mandela Road, Kurasini, Temeke District, Dar es Salaam, Tanzania Coordinates 6°50′6.40″S 39°17′37.65″E

Study Population, The study population consisted of marine engineers, engine room technicians, maintenance supervisors, and technical officers from the port's mechanical and marine operations departments.

Sample Size, A total of 32 respondents selected proportionally from the target population. The sample size was determined based on the availability of personnel, their level of involvement with MV Kiboko, and the need to represent each operational role fairly.

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RESULTS AND DISCUSSION

Model Development Process

The model was developed utilizing key engine performance parameters identified during the initial phase of the research. These parameters included engine temperature, lubricating oil pressure, vibration levels, exhaust gas emissions, fuel consumption rate, and load conditions.

The design process was implemented using MATLAB and Simulink software environments to facilitate model development, simulation, and validation.

Fig.2 MATLAB CMMS Fuzzy Logic Designer

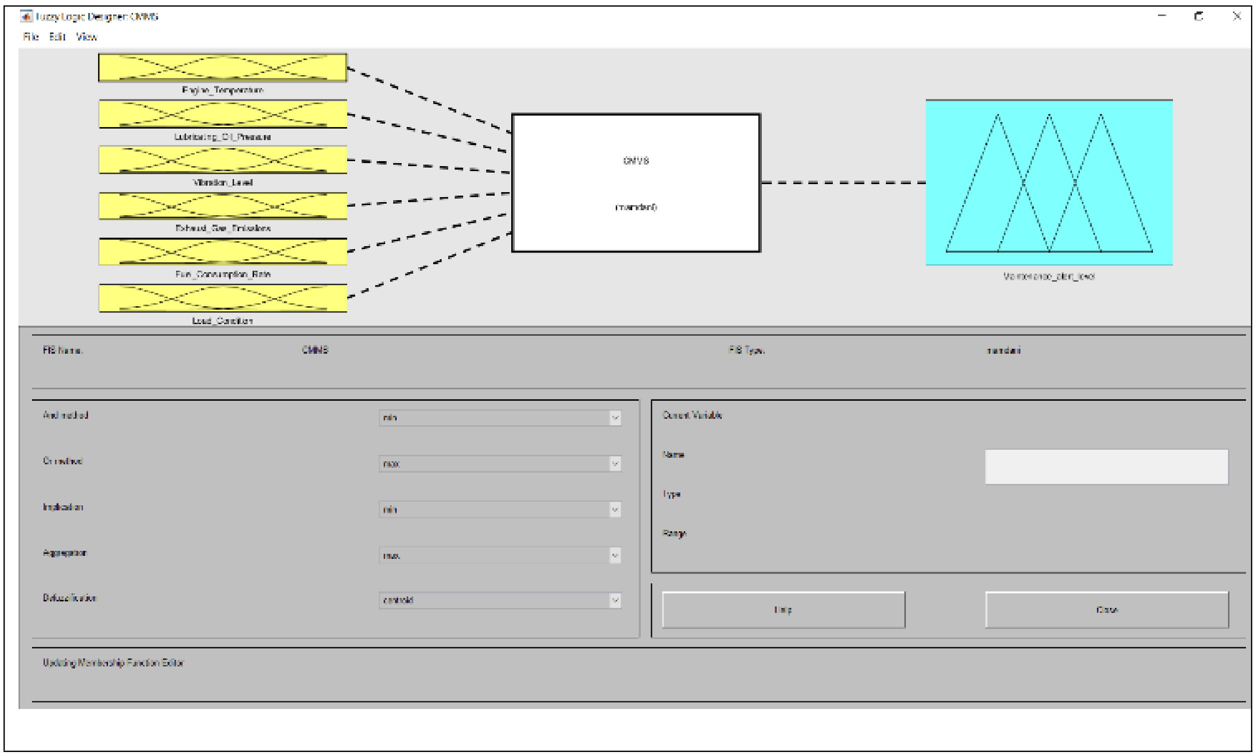

Figure 3, The block diagram included the following major components:- Input Blocks: Simulated sensor data (using Constant, Signal Generator, or From Workspace blocks), Fuzzy Logic Controller (Implemented using the “Fuzzy Logic Controller” block from the Fuzzy Logic Toolbox, connected to a .Fis file) Scope and Display Blocks (Used to visualize the output like maintenance alert level in real-time) and Data Logging Blocks (For exporting simulation results for further analysis)

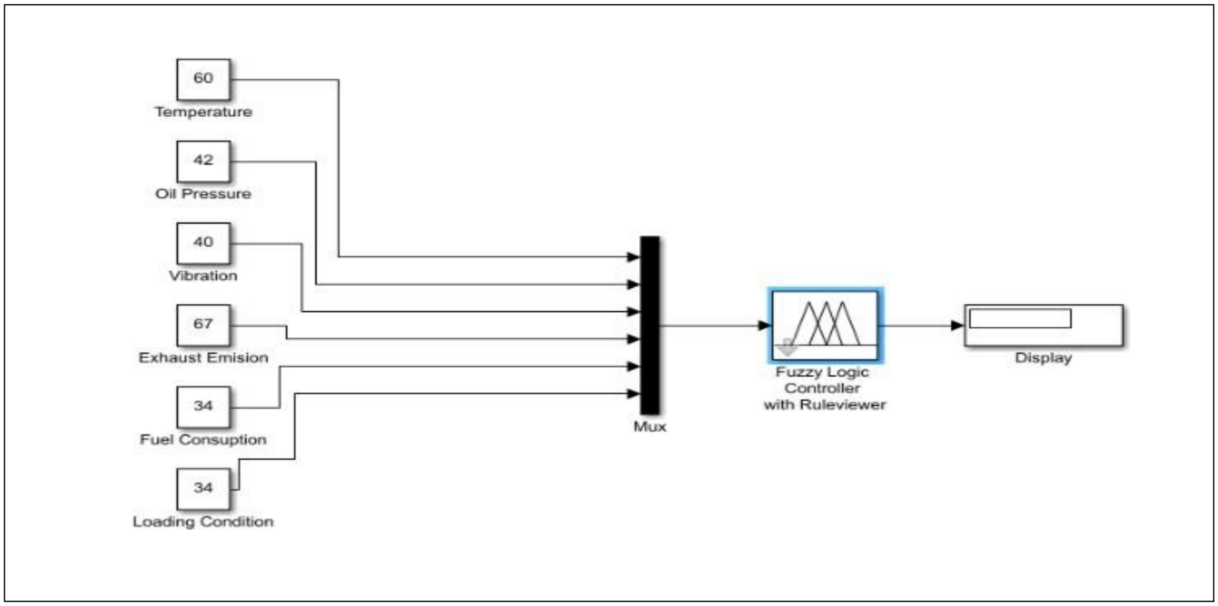

Fig.3: Simulink Block Diagram to Simulate CMMS model

Rule Base

In In total, 20 fuzzy rules were created to cover various combinations of engine conditions. The rules were encoded in MATLAB's Fuzzy Logic Designer interface using a Mamdani-type inference system, which is well-suited for control and decision-making application

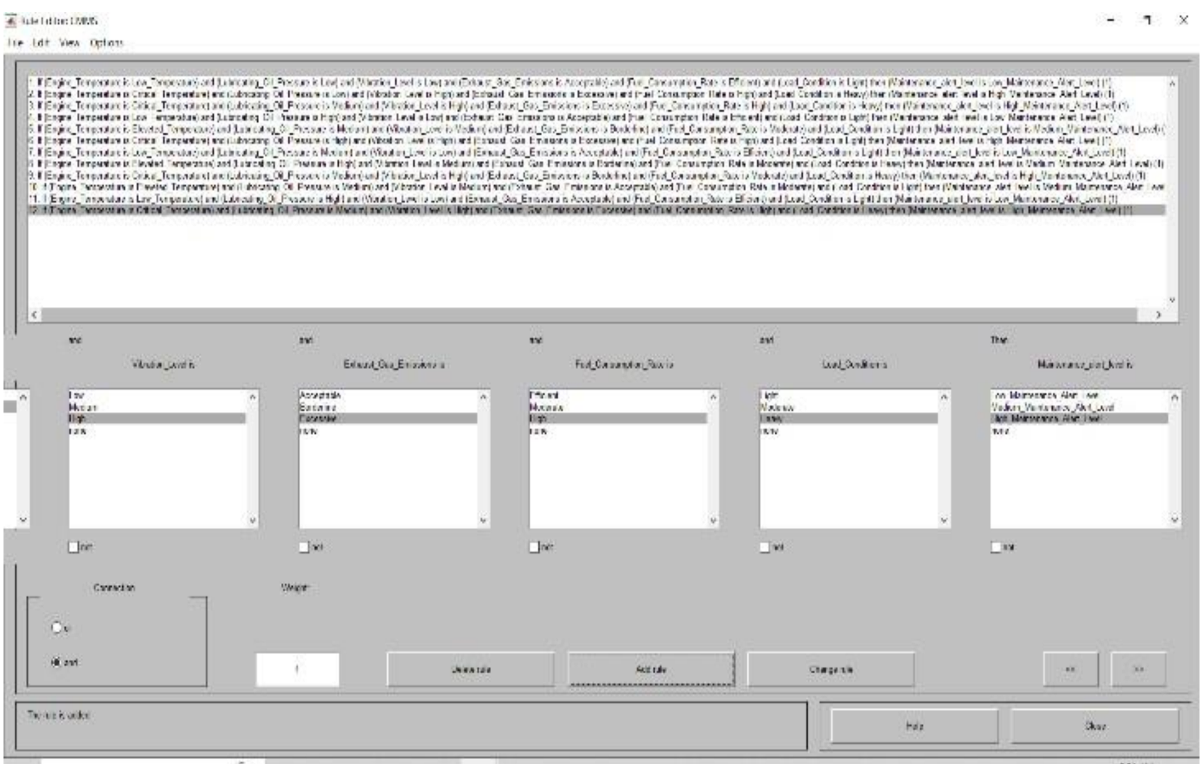

***Fig. 4*:** MATLAB Rule Editor for CMMS

This rule base forms the "knowledge engine" of the system, enabling it to assess complex interactions between inputs and determine when preventive action is needed, even in the absence of precise thresholds. This approach significantly enhances early fault detection capabilities and reduces the reliance on manual diagnostics.

Simulation-Based Evaluation

The fuzzy logic model was tested in MATLAB/Simulink using historical operational data collected from the MV Kiboko, which included recorded engine temperature, oil pressure, vibration levels, and other performance indicators.

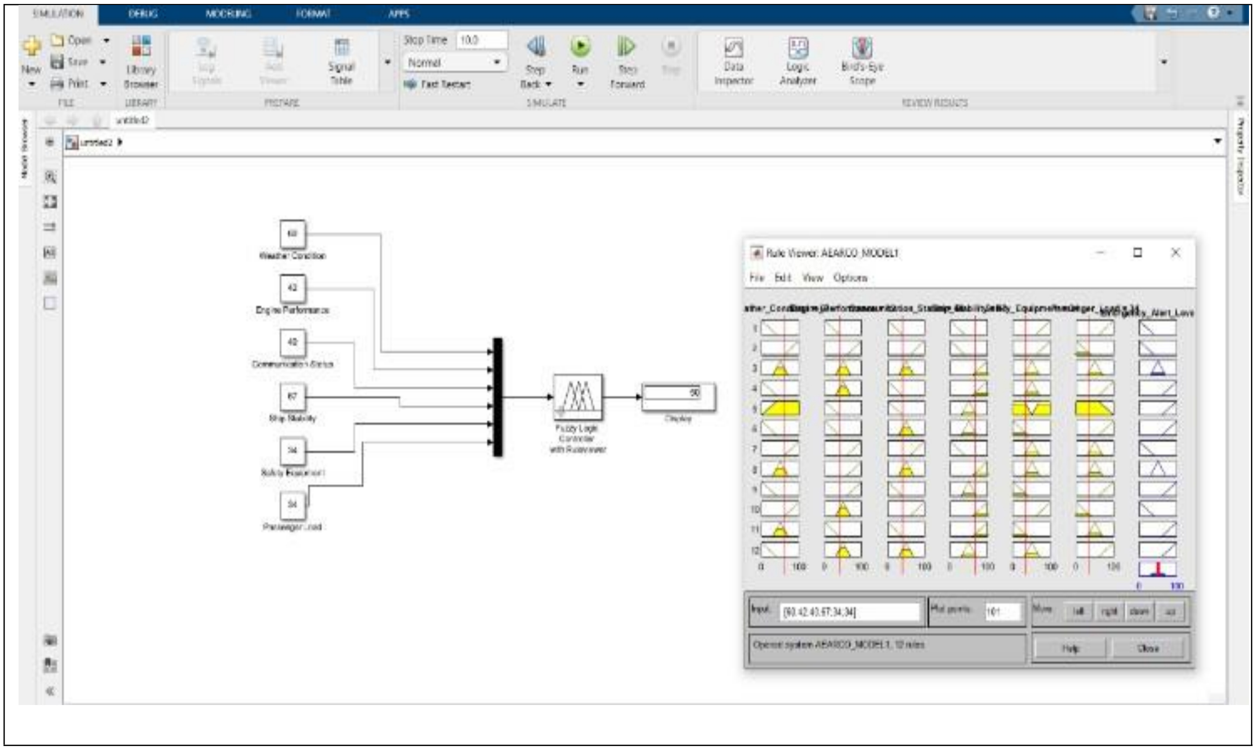

Fig. 5: Model Simulation in Simulink Environment

The model's output was compared against actual maintenance events and technician reports to measure predictive alignment.

CONCLUSION

The study focuses on designing a fuzzy logic model for real-time predictive maintenance of the tugboat engine on the MV Kiboko. This objective was achieved through the systematic development and simulation of a fuzzy inference system using MATLAB and Simulink (Malyszko, 2021).

The design process began by identifying six critical input variables: engine temperature, oil pressure, vibration levels, exhaust gas emissions, fuel consumption rate, and load conditions. These variables were chosen based on empirical data and expert opinions (Malkoç & Oskar Eikenbroek ir Eric van Berkum, 2023).

These parameters were then converted into fuzzy linguistic variables through a process called fuzzification. This approach allowed continuous sensor data to be expressed in descriptive terms such as "Low," "Medium," and "High," thereby addressing the uncertainty and imprecision typical of marine engine monitoring systems (Gharib & Kovács, 2024).

Using input from experts, a set of fuzzy rules was formulated to link combinations of input conditions with appropriate maintenance alert levels.

While this study successfully developed and evaluated a fuzzy logic model for real-time predictive maintenance of the MV Kiboko tugboat engine, several important areas for future research could further advance this field. One key area is the need for long-term field validation and deployment of the model in actual vessel operations (HONGJUAN, 2023). Continuous use in real-world scenarios will yield valuable data on the model's robustness, adaptability to varying conditions, and its impact on reducing engine failures and maintenance costs over time (Pratiwi, 2020).

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