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Fuzzy Logic-Based Decision Support System for Adoption of Industry 4.0 Predictive Maintenance by Manufacturing Industries

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ABSTRACT

In the context of Industry 4.0, predictive maintenance enhances operational efficiency by optimizing processes, minimizing downtime, and improving cost-effectiveness. However, implementing predictive maintenance requires a systematic approach due to its complexity. This study collected expert input from 15 food and beverage manufacturing industries located in Dar es Salaam, Tanzania, using a purposive sampling technique. Six representatives were selected from each industry, and their opinions were analyzed using MATLAB 7.6 through a fuzzy logic inference system. The analysis focused on key factors influencing Industry 4.0 technology adoption for predictive maintenance, including adoption intention (strategic decision, equipment data, perceived benefit) and perceived usefulness (organizational culture, risk perception, external pressure). The results indicate that when strategic decision-making (technical function) is at 20%, equipment data quality at 15%, and perceived benefit (flexibility) at 25%, the adoption intention of the technology drops to 10%. The fuzzy logic system used techniques such as fuzzification, inference, and aggregation to assess the feasibility of predictive maintenance adoption. The model was validated and refined to ensure accuracy and relevance, offering decision support for maintenance planning and resource allocation. This Fuzzy Logic-Based Decision Support System provides a structured approach to overcoming the complexities of adopting predictive maintenance in Industry 4.0, helping manufacturing industries improve their operational efficiency and competitiveness.

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INTRODUCTION

The history of industrial development has unfolded through successive stages, each marked by transformative technological shifts. The First Industrial Revolution introduced mechanized production systems powered by steam and water. This was followed by the Second Industrial Revolution, which brought about mass production through the use of electrical energy and assembly line methods. The Third Industrial Revolution marked the emergence of automation, facilitated by the integration of electronics, information technology, and programmable logic controllers (PLCs). Currently, the world is experiencing the Fourth Industrial Revolution (Industry 4.0) a paradigm characterized by the convergence of digital technologies such as cyber-physical systems, the Internet of Things (IoT), artificial intelligence (AI), big data, and advanced analytics. These technologies are deeply interlinked and are reshaping industrial operations by enabling smarter, real-time monitoring, predictive optimization, and autonomous decision-making in manufacturing environments (Kumar et al., 2020).

A central feature of Industry 4.0 is the application of Predictive Maintenance (PdM) an advanced maintenance strategy that leverages cutting-edge technologies to anticipate equipment malfunctions before they occur. Unlike conventional approaches such as reactive maintenance, which addresses failures post-occurrence, or preventive maintenance, which relies on scheduled interventions based on time or usage thresholds, PdM utilizes real-time data collected from IoT-enabled sensors, in combination with machine learning algorithms and big data analytics, to forecast potential faults. This predictive capability allows for timely and targeted maintenance actions, minimizing unexpected downtimes and optimizing operational efficiency and resource utilization (Couper, 2020).

Despite its potential benefits, the widespread adoption of PdM poses significant challenges for manufacturing enterprises. These include the technological complexity inherent in Industry 4.0 systems, the high capital investment required for infrastructure and skill development, and the organizational change necessary to integrate and sustain such technologies (Bosman et al., 2020). Moreover, industry leaders often face the daunting task of evaluating a broad spectrum of technological solutions, balancing cost-effectiveness, and managing the inherent uncertainties associated with dynamic production environments. In view of the complexities and implementation challenges surrounding predictive maintenance (PdM) in the Industry 4.0 environment, there is a clear and urgent need for a robust decision-making framework that can support manufacturers in addressing these barriers and unlocking the full benefits of PdM technologies. To this end, the present study proposes the development of a Fuzzy Logic-Based Decision Support System (DSS) specifically designed to facilitate the integration of predictive maintenance within smart manufacturing contexts.

Fuzzy logic, recognized for its ability to manage uncertainty and imprecise information, offers a structured methodology for assessing key performance indicators (KPIs), evaluating PdM feasibility, and supporting strategic decision-making throughout the adoption process. By incorporating fuzzy aggregation methods, rule-based reasoning, and linguistic variable models, the proposed DSS is capable of generating practical insights that enhance maintenance planning, resource allocation, and overall operational performance.

Drawing upon an extensive review of literature, conceptual models, and empirical case studies, this research investigates the effectiveness of fuzzy logic in predictive maintenance decision-making. The study contributes to the broader Industry 4.0 discourse by introducing a systematic tool for overcoming technical, organizational, and financial constraints, thereby enabling manufacturers to enhance productivity, operational resilience, and long-term competitiveness.

Decision Support Systems for Maintenance Optimization

The use of Decision Support Systems (DSS) for maintenance optimization has garnered significant attention, particularly in response to the increasing complexity and data intensity of contemporary manufacturing operations. DSS frameworks serve as valuable tools for assisting decision-makers in enhancing maintenance planning, reducing equipment downtime, and improving overall system reliability. Early implementations of these systems often relied on traditional statistical techniques and rule-based expert systems to guide maintenance-related decisions.

For example, Wang et al. (2018) introduced a machine learning-driven DSS capable of prioritizing maintenance activities and forecasting potential equipment failures. Although such systems demonstrated strong analytical capabilities and handled large-scale data efficiently, they frequently lacked consideration for important qualitative dimensions such as human expertise, operational context, and risk tolerance that are integral to sound maintenance decision-making. Addressing these limitations has become increasingly important in the design of next-generation DSS, particularly within the context of Industry 4.0 environments that require flexible, adaptive, and human-informed decision models.

Recent developments in decision support systems (DSS) have leveraged state-of-the-art technologies, including artificial intelligence (AI), the Internet of Things (IoT), and big data analytics, to enhance predictive maintenance (PdM) capabilities. Kothamasu et al. (2019) investigated the use of AI-driven analytics and real-time sensor data to forecast equipment failures and suggest optimal maintenance strategies. Despite these advancements, the management of diverse data from multiple sources presents a significant challenge. Fuzzy logic has emerged as an effective tool for handling uncertainties, as illustrated by Gupta et al. (2020), who developed a Fuzzy Logic-Based DSS that integrates both quantitative and qualitative data to offer contextually relevant recommendations. Furthermore, hybrid models, such as the one proposed by Rodríguez et al. (2021), which combine machine learning, fuzzy logic, and simulation models, have shown success in improving maintenance decision-making by addressing the random nature of equipment failures and the uncertainties surrounding resource availability.

Tanzania Manufacturing Industries

The manufacturing sector is a vital component of Tanzania's economy, contributing about 8% to the country's GDP according to recent data from the World Bank (2023). This sector is varied, including areas such as textiles, chemicals, construction materials, and food processing. Despite its potential, the sector's growth has been hindered by several challenges, such as inadequate infrastructure, unreliable power supply, and limited access to modern technology. A significant number of manufacturing industries in Tanzania continue to use outdated machinery, leading to operational inefficiencies and increased production costs (United Nations Industrial Development Organization, 2022). The adoption of Industry 4.0 technologies, including predictive maintenance, is deemed essential for enhancing the sector's competitiveness. However, many companies face difficulties due to the high initial costs of implementation and a lack of technical expertise (Mwangola et al., 2023).

Food and Beverage Manufacturing Industries

The food and beverage sector plays a substantial role within Tanzania’s manufacturing industry, largely driven by the country’s agricultural productivity. Together, these industries represent over half of the nation’s total manufacturing output and primarily focus on processing agricultural products such as cereals, dairy, and beverages (Tanzania Investment Centre, 2022). Nevertheless, they encounter distinct challenges, including seasonal variations in production and limited access to modern technologies necessary for maintaining consistent product quality. Although initiatives have been undertaken to introduce automation and predictive maintenance to boost operational efficiency, adoption has been gradual, hindered by high costs and a general lack of awareness about advanced technological solutions. Integrating Industry 4.0 technologies, particularly in predictive maintenance, offers promising prospects for reducing equipment downtime, enhancing reliability, and increasing overall productivity in this vital sector (Mbogoni et al., 2023).

Fuzzy Logic Applications in Decision Making

Fuzzy logic has gained prominence as an effective method for managing imprecise and uncertain data within decision-making contexts. Ottomanelli et al. (2005) contributed foundational theoretical insights into fuzzy logic applications, highlighting its capacity to emulate human reasoning and incorporate subjective judgments into analytical models. In the realm of maintenance decision-making, research by Aiello et al. (2021) has demonstrated the practical utility of fuzzy logic-based approaches in evaluating equipment reliability, prioritizing maintenance activities, and assessing associated risk factors. This body of work underscores fuzzy logic's relevance in enhancing decision quality under conditions of uncertainty.

Case Studies and Practical Applications

Multiple case studies and practical implementations have demonstrated the practical viability and advantages of fuzzy logic-based decision support systems (DSS) within manufacturing environments. For example, Dell'Orco et al. (2008) reported the successful deployment of a fuzzy logic-based DSS for maintenance scheduling and resource management at a semiconductor manufacturing plant, leading to notable cost reductions and enhanced operational performance.

Despite these advances, while the existing body of literature offers valuable insights into predictive maintenance, decision support systems, and the application of fuzzy logic—along with their integration into Industry 4.0 frameworks—there remains a significant research gap. Specifically, there is a need to develop comprehensive models that effectively navigate the complexities of maintenance decision-making in the highly dynamic and uncertain conditions of modern manufacturing settings (Vidanagamachchi et al., 2020).

This study aims to address this gap by proposing a novel fuzzy logic-based decision support system (DSS) explicitly designed to facilitate the adoption and implementation of predictive maintenance in Industry 4.0-enabled manufacturing sectors. The proposed framework seeks to enhance decision accuracy and operational efficiency amidst the evolving technological landscape.

Basics of Fuzzy logic

Fuzzy logic was first conceptualized by Lukasiewicz in the 1930s (Lau and Dwight, 2011). Its practical application in engineering began in the 1960s, initially through the development of fuzzy set theory, followed by the introduction of fuzzy algorithms in 1968. Since then, fuzzy logic has significantly contributed to engineering disciplines, primarily because of its ability to accommodate subjectivity and uncertainty during model development and problem-solving processes (Punniyamoorthy et al., 2011). Its importance becomes even more pronounced when modeling systems that are difficult to define with precision, such as the adoption of innovative technologies. This unique feature has empowered fuzzy logic to support research in production management, especially in environments where dynamic conditions hinder clear specification of objectives, constraints, and measurements.

The appeal of fuzzy logic has grown further due to its capacity to effectively describe problems involving both statistical vagueness and qualitative ambiguity. Its versatility is reflected across various domains within the supply chain, including production management, quality assurance, and cost-benefit analysis (Marzouk and Osama, 2017). The prevalence of imprecise and ambiguous information in these fields primarily drives the application of fuzzy set theory. Moreover, the scarcity of comprehensive knowledge, precise references, and reliable data accentuates the utility of fuzzy logic, as it provides a structured framework for tackling such uncertainties. In these contexts, scoring methods are often employed to handle the inherent ambiguities, making fuzzy logic an attractive approach to complex decision-making problems.

However, this method is not typically applied in decision-making related to the adoption of manufacturing industry (MI) technologies. As proposed in this paper, utilizing fuzzy inference techniques can significantly aid in making such complex decisions. Unlike traditional approaches like classical logic, fuzzy logic effectively manages systems characterized by ambiguity and uncertainty (Addabbo et al., 2004). In fuzzy set theory, a universe of discourse, or simply the universe, comprises the elements of a fuzzy set. By defining a membership function also known as a grade of membership over the interval [0, 1], fuzzy set theory encapsulates the imprecision associated with numerous variables.

Mathematically, consider a finite set of objects ($X = \{x\_1, x\_2, x\_3, ..., xn\}$), where each (x_i) is an element in (X). Each element (x_i) is associated with a membership function (u). A fuzzy set (A) can then be expressed as a collection of ordered pairs: ($A = \{(x1, u1(x1)), (x2, u\_2(x\_2)), ..., (xn, un(xn)\}$). The fuzzy rule base comprises a series of "if–then" (also called Antecedent–Consequent) rules, formulated based on domain knowledge derived from data samples. For instance, a rule might be: "If ($x1$) is (A) and ($x2$) is (B), then (y) is (C)," where ($x1$) and ($x2$) are input variables, (y) is the output or decision variable, and (A), (B), and (C) are fuzzy terms representing linguistic descriptions. This fuzzy rule structure enables effective modeling of complex, uncertain decision environments inherent in technology adoption processes.

MATERIALS AND METHODS

Design of fuzzy inference system model

In a fuzzy system, specific input data are fed into a set of rules tailored to the particular system being analyzed. These rules process the inputs through fuzzy logic mechanisms, producing fuzzy outputs. The final decision is then derived by defuzzifying and aggregating these outputs. The entire workflow of a typical fuzzy inference system is illustrated in Figure 1, providing a clear overview of how inputs are transformed into actionable decisions using fuzzy logic principles.

Data collection

The study population comprised 15 manufacturing industries in Tanzania (TMIs). Data collection was conducted through a structured questionnaire, developed based on existing measurement scales for the research constructs. To ensure content validity and clarity, a preliminary review was carried out involving 15 executives from different TMIs. Their feedback prompted several modifications, resulting in a questionnaire that was more meaningful and easier to understand for the targeted respondents. Particular attention was given to user-friendliness and ease of completion during this revision process.

The finalized questionnaire consisted of 90 items framed on a five-point Likert scale, where respondents from various TMIs were asked to evaluate their opinions regarding specific maintenance technologies or techniques. Responses were then transformed by multiplying the average scores of each variable by 20, changing the original scale from 1–5 to 1–100. This scaling adjustment aligns with the membership function scale used in the fuzzy inference modeling process.

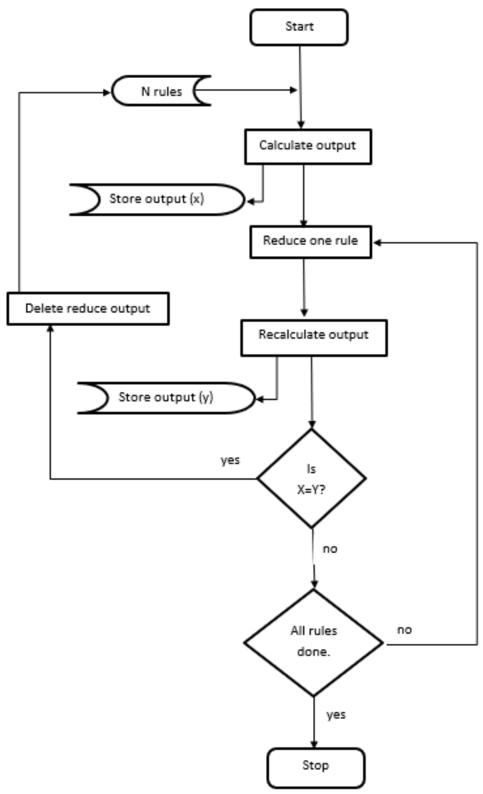

Figure 1: Fuzzy inference system process.

Although the constructs studied are primarily individual in nature, the research assumes that these perceptions reflect organizational roles and strategic perspectives, especially among key personnel responsible for maintenance management. Pre-testing revealed that individuals in strategic positions within organizations are more knowledgeable about inter-organizational relationships and exchanges, which supports the validity of gathering data at this level. Consequently, responses were collected from key informants within the maintenance departments of TMIs.

This approach aligns with established practices in strategic management research, where surveying senior executives to assess adoption factors of maintenance technologies like Predictive Maintenance 4.0 (PdM 4.0) is common. Respondents rated the importance of various factors influencing the adoption of such technologies using a five-point scale, with endpoints labeled 'least important' (=1) and 'most important' (=5). Factors with an average importance score below 2 were excluded from further analysis. The importance scores for the remaining factors are summarized in Figure 2.

Identification of input and output variable

The selected variables are: strategic decision (SD), perceived benefit (PD), equipment data (ED), Organizational culture (OC), external pressure (EP), risk perception (RP). The next part provides a detailed description of each variable and its matching membership function to help prevent confusion among the decision maker's decisions. From a mathematical perspective, the ultimate choice is a function, with a collection of the six variables listed above serving as its domain. These variables are assigned appropriate values based on how important they are for a particular manufacturing industry (MI). Therefore, the decision regarding the adoption of the manufacturing industry (MI) technology is, then $y = f(x_1, x_2, x_3, x_4, x_5, x_6)$. These six variables are categorized into two distinct groups based on their inherent nature, serving as intermediate variables. Each group is processed separately to produce a single output. The overall decision is then derived from a combined output, generated by using these two intermediate results as inputs, effectively transforming a multi-objective problem into a single decision-making process.

The characteristics of each group are detailed below. Group 1 includes variables directly related to the intention to adopt, which we refer to as "adoption characteristics." The inputs for this group are: SD (Strategic Decision), PB (Perceived

Benefit), and ED (Equipment Data). Its output is termed "Adoption Intention (AI)." roup 2 comprises variables directly linked to perceptions of the usefulness of PdM 4.0, with inputs: OC (Organizational Culture), EP (External Pressure), and RP (Risk Perception). This group's output is called "Perceived Usefulness (PU)."
The outputs from these two groups are then fed into a third process, which consolidates them into a single outcome, labeled "Actual Adoption (AA)." This modular framework effectively reduces the six variables into two, and subsequently condenses these into one final decision metric, represented as (c). If we denote the outputs of Group 1 and Group 2 as (a) and (b) respectively, the final output (c) is derived through a function shown in Equation 1.
Mathematically:
$a = f1(x_1, x_2, x_3)$, $b = f2(x_4, x_5, x_6)$, and $c = f3(f1(a), f2(b))$ ……………………… (1)

RESULTS AND DISCUSSION

Design of membership functions

A fuzzy inference system was developed using MATLAB software, with each of the six variables defined alongside their corresponding membership functions and universe of discourse. Gaussian and Bell membership functions were used to characterize the shape of both input and output variables in the system. For each set of input values (x1) through (x6), the vectors (a), (b), and (c) were computed to capture the respective fuzzy outputs.
To analyze vector (a), which involves two input variables and one output, the variables are characterized as follows:
SD (x1): Represents the strategic decision regarding technology adoption by manufacturing industries. It is classified into three categories low, medium, or high based on how it compares to the mean quality level of the technology available for predictive maintenance.
ED (x2): Reflects the manufacturing industry's capacity to collect and organize equipment data for predictive maintenance. This capability is categorized as Insignificant, some, or Considerable.

PB (x3): Encompasses the perceived benefits of using predictive maintenance, such as cost reductions and increased equipment uptime. As shown in Table 1, these benefits are divided into none, few, or many, according to membership function levels.
The output variable, Perceived Benefit, provides three possible evaluations regarding the suitability of a particular predictive maintenance approach, based on the aforementioned inputs. Similarly, vector (b) involves three input variables and one output:

OC (x4): Organizational culture, indicating the manufacturing firm’s ability to promote knowledge transfer, training, and sharing among employees concerning Industry 4.0 predictive maintenance. This is categorized as low, medium, or high, based on membership functions as per Table 2.

EP (x5): External pressure, measuring the company's ability to handle technological requirements and innovations, especially regarding emergency service responses from suppliers. It is classified as Insignificant, some, or Considerable.

RP (x6): Risk perception, or the perceived ability to absorb risks associated with adopting new technologies. It considers the potential reduction in severity and impact of such risks, categorized as Insignificant, some, or a lot.
The final variable, Actual Adoption, as detailed in Table 2, reflects three distinct outcomes based on the input combinations, representing different levels of adoption readiness as per real-world scenarios.

Design of rule base and rule viewers

Defining the rules that will regulate these variables comes after developing the membership functions for various input and output variables.

Table 1: Rules for group 1.

If X1(SD)	And X2(ED)	And (PB)	Then a(AI)
Low	Insignificant	None	Insignificant
Medium	Some	Few	Some
High	Considerable	Many	Considerable
High	Some	None	Some
Medium	Considerable	None	Some
Low	Some	Many	Some
Medium	Insignificant	Few	Some
Low	Considerable	Many	Considerable
Low	Insignificant	Few	Insignificant

When vector a had three inputs, there were originally 18 rules defined. Following several versions, the non-contributing rules were removed. Six regulations remained in the end. Table 1 displays these regulations. Rule viewers that display the values of the several inputs (SD, ED, and PB) to the model and the associated computed output (Adoption intention) are shown in Fig. 2. Following the similar approach, rules for vector b and c were defined. These are shown in Tables 1–3. Rule viewers and the corresponding computed outputs are shown in Figs. 2–4.

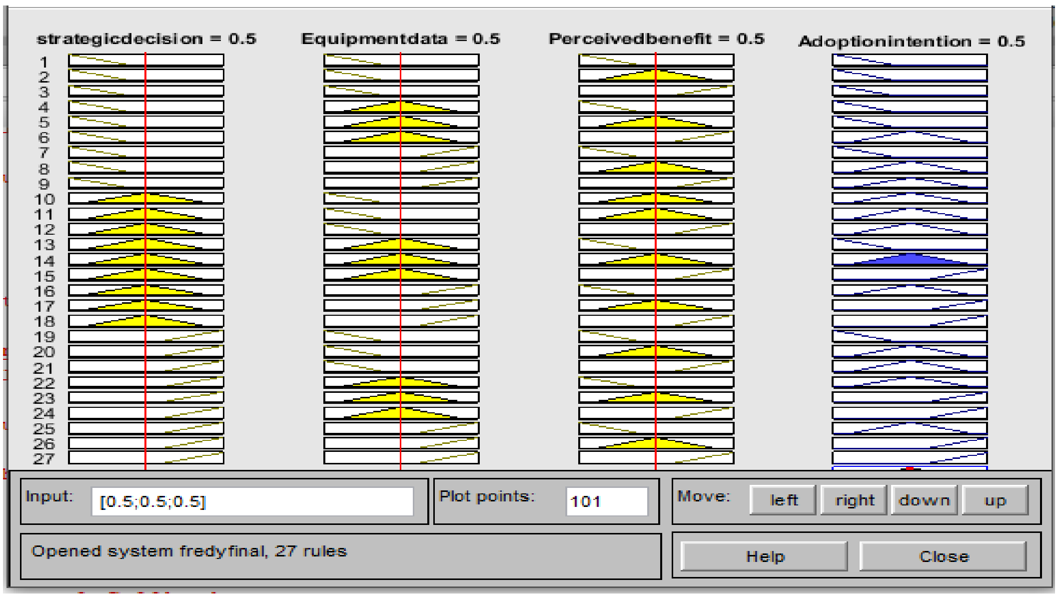

Figure 2: Fuzzy logic result for Adoption intention.

Table II: Rules for group 2

If X4(OC)	And X5(EP)	And X6(RP)	Then b(PU)
Low	Insignificant	Insignificant	Insignificant
Medium	Some	Some	To some extent
High	Considerable	A lot	Considerable
High	Some	A lot	Considerable
Medium	Some	A lot	Considerable
Low	Considerable	Some	To some extent

Medium	Considerable	Some	To some extent
Low	Some	A lot	To some extent

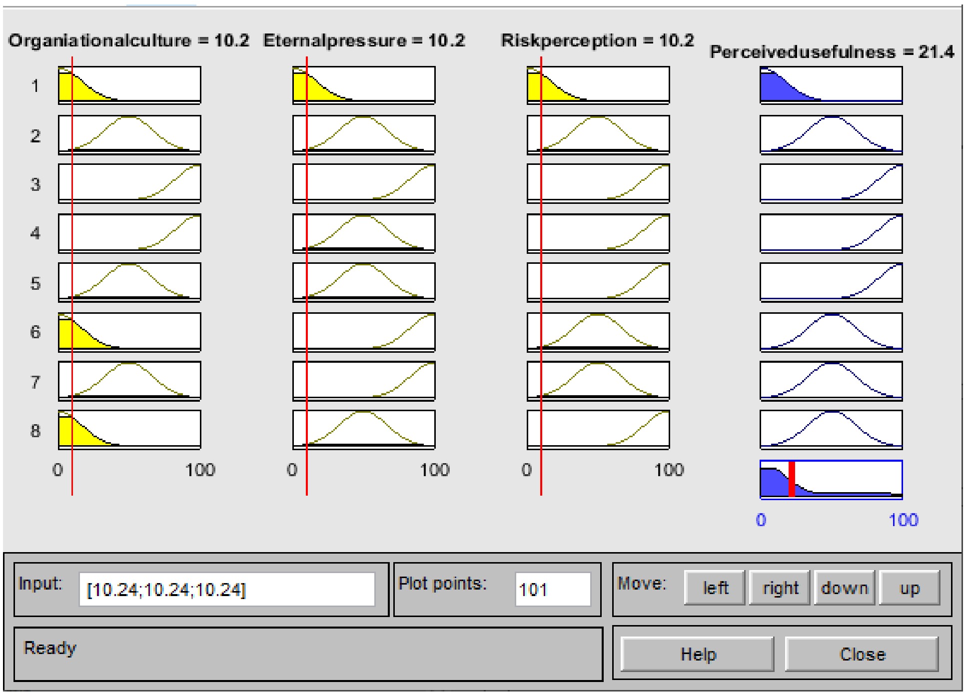

Figure 3. Fuzzy logic result for Perceived usefulness.

Table III: Rules for Actual Adoption

If a(AI)	**And b(PU)**	**Then c(AA)**
Insignificant	Insignificant	Insignificant
Some	To some extent	To some extent
Some	Some	To some extent
Considerable	Considerable	Considerable
Considerable	Considerable	Considerable
Some	Considerable	Considerable
Insignificant	To some extent	To some extent
Considerable	To some extent	To some extent

Table 4: Group 1 result

Inputs SD	**ED**	**PB**	**Output adoption intention**
Low (10)	Insignificant (10)	None (10)	Insignificant (9.56)
Medium (50)	Some (50)	Few (50)	Some (48)
High (90)	Considerable (90)	Many (95)	Considerable (93.5)

Table 5: Group 2 result

Inputs OC	**EP**	**RP**	**Output Perceive usefulness**
Low (10)	Insignificant (10)	Insignificant (10)	Insignificant (7.13)
Medium (55)	Some (50)	Some (50)	To some extent (48.4)
High (95)	Considerable (95)	A lot (95)	Considerable (93.7)

Testing of fuzzy inference system.

Every component of every vector can be thought of as a function of every component of the vector that came before it. Because most production systems involve multiple variables and can minimize these variables at each phase, the fuzzy inference approach is helpful in most of these systems, until actual adoption is achieved.

In any industry, for the technology adoption evaluation process is essential since adoption intention account for the majority of implementation costs. To guarantee that the approach selected is fully effective, decision makers must make these selections regularly. These kinds of domains are ideal for fuzzy inference systems. Such systems are beautiful because they can give a set of inputs, produce the same result that a decision maker would in any given circumstance.

In order to augment the dependability of the suggested system, multiple simulations were run in which one or more inputs were varied concurrently. Upon completion of the aforementioned simulations, multiple assessments were conducted at the ultimate phase of the suggested fuzzy inference systems. Using the previously established rules, a distinct value of x was assigned to each input in order to define the intermediate vectors. Every input's value was made sure to fluctuate between almost its lowest and highest values. To get the final output y in a wide range of values simplifies the working of the proposed system.

The multiple simulations are displayed below with varying input values. Tables 4–7 display the numerical and linguistic formats in which the system's results are displayed. These simulations show how the system functions as well as how the values obtained for intermediate vectors a and b vary. Values for vector c, or "actual adoption," were calculated using these intermediate vectors as inputs, as indicated in Table 6.

Table 6: Actual adoption group result

Inputs Adoption intention	Perceived Usefullness	Output Actual Adoption
Insiginificant (10)	Insiginificant (10)	Insiginificant (Level 1 maturity (14.1))
Some (40)	To some extent (40)	To some extent (Level 2 maturity (48.7))
Some (70)	To some extent (70)	Considerable (Adopt PdM 4.0 (70.8))
Considerable (95)	Considerable (95)	Level 3 maturity (91.6)

Table 7: Computed values for the various variables

Value of the Variables	Average value
X1 (SD)	80
X2(ED)	90
X3 (PB)	78.5
a (Adoption intention)	87.9
X4 (OC)	75.7
X5 (EP)	82.5
X6 (RP)	92.8
b (Perceived usefulness)	88.5
C (Actual adoption)	88.6

Illustrative example through a case study

Suggested case study used as an example to demonstrate the suggested paradigm. The obtained information from a reputable TMI manufacturer of cement (not included in the survey). To gather data for the model, managers, and engineers within the company (from the departments of production, stores, and Maintenance) were asked to fill out a questionnaire.

To make the terms used in the questionnaire clear to the respondents, details of definitions of terms were attached with the questionnaire. An average value of 28 responses collected.

The acquired values are utilized in Figures. 2, 3, and 4 to determine the values of "Perceived Usefulness" and "Adoption Intention," which come out to be 87.9, 88.5, and 92.5, respectively. By sliding the vertical lines in Fig. 4, these values were utilized to obtain the value for "Actual Adoption". The result for this value is 88.6. Therefore, the organization's true adoption. Table 7 and Figure 4 shows the computed values of the variables.

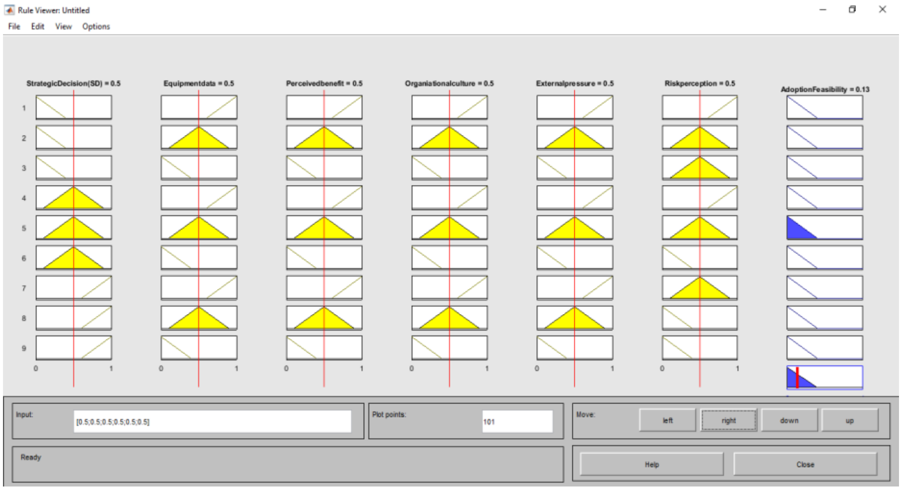

Figure 4: Fuzzy logic result for Adoption Feasibility.

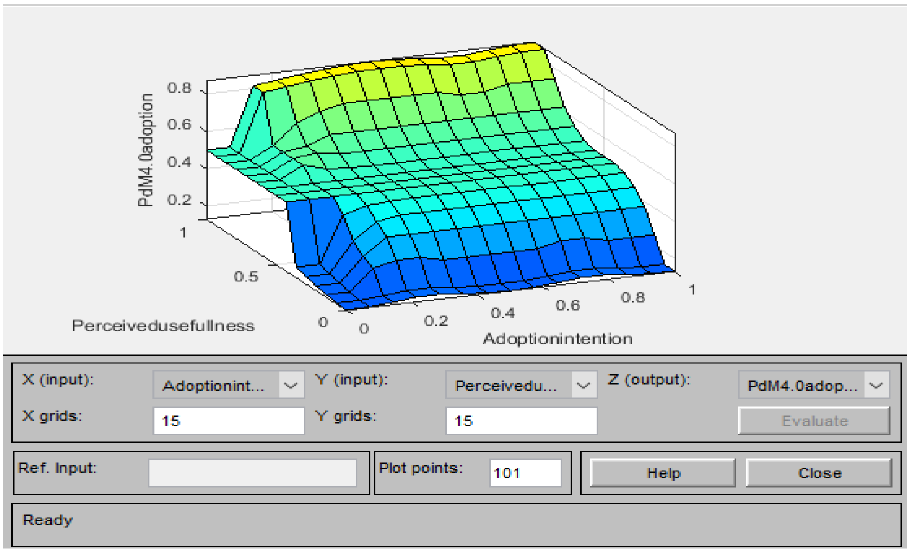

Figure 5: Surface view PdM 4.0 Adoption feasibility.

CONCLUSION AND RECOMMENDATION

This study presents a decision support system for adoption of industry 4.0 predictive maintenance by gathering information from a survey of fifteen manufacturing industries (MI) in Tanzania. The variables that these MIs take into account while assessing a certain industry 4.0 predictive maintenance have been ascertained through the use of a questionnaire. According to the respondents, a multi-input single output according to Lau and Dwight, (2011) Mamdani fuzzy inference system has been suggested for PdM 4.0 adoption , taking into account the six most significant parameters.

According to the literature, there is currently no rational process in place for the ongoing assessment of an industry 4.0 technologies that supports maintenance in the sector being examined (Bousdekis, Lepenioti, and Apostolou 2019). The suggested method can be highly beneficial to the businesses in helping them make judgments on technology evaluation, especially in light of the amount of maintenance costs associated with equipment maintenance. By simply altering the variables, the suggested methodology can be extended beyond technology evaluation and used to simulate the decision-making procedures for facility and service adoption.

As the aforementioned sections demonstrate, the suggested approach is highly user-friendly for engineers and managers in related sectors, and they will find it straightforward and appropriate to adopt this technique. The fuzzy logic scheme is not without its problems, just like any other system(Yahya et al. 2024). To create fuzzy rules that will make the system work, field specialists' experience, experimental findings, and theoretical derivation are needed. In certain instances, experts might even need to be dispatched to the scene to confirm features that could impact the entire system and to fine-tune the hazy regulations at the outset.

There's a chance that this activity will raise system development costs. Additionally, fuzzy reasoning lacks the concept of justification for fact, unlike rule-based systems, and trades some explanation for precision, reliability, and compactness. Using a certain sample population to create the model could be another way that this study endeavor is limited (Kafuku et al. 2016). The study perceives that, a diverse population of respondents from various sources can expand the model's breadth of generalizability, also the study suggests that this be taken into account in subsequent studies. The system has certain limitations, as mentioned above, but there is no question about the potential advantages of implementing the suggested approach in Tanzania manufacturing industries. It is questionable if the suggested method is an efficient way to practice the art of creating the ideal system. Future research should therefore focus on issues associated with these worries. This study represents a meager step in that direction.

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