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A dynamic maintenance planning methodology for HVAC systems based on Fuzzy-TOPSIS and failure mode and Effect Analysis

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ABSTRACT

Maintenance is critical to the efficiency of Heating, Ventilation, and Air Conditioning (HVAC) systems in buildings. The conventional maintenance methods are planned for ideal situations and cannot easily be adapted to prevailing management/operational conditions, resulting in increased use of resources and energy. This study developed a dynamic maintenance planning framework for HVAC systems employing Fuzzy-TOPSIS and FMEA and aimed at reducing and stabilising maintenance costs while enhancing system reliability. Fuzzy-TOPSIS technique was used to establish maintenance priorities based on a carefully identified set of criteria, including the risk priority number (RPN), which is adaptable to changing conditions and ensures continuous monitoring. This is a novel application to HVAC systems. A real-world implementation in an HVAC company involving data collection, fuzzification of expert evaluations, priority ranking of components, and development of maintenance ranking validated the framework's efficiency. The running conditions of the HVAC system under the new approach, expressed by the air quality and air leakages (by extension energy saving), showed a significant improvement at the various test points in the 600-h running. The results demonstrated significant cost savings, enhanced system reliability, improved energy efficiency, and better indoor air quality. This dynamic maintenance planning framework offers a concise and adaptable solution for optimising HVAC maintenance operations.

1. Introduction

Heating Ventilation and Air conditioning systems (HVAC) are integral to modern buildings and provide and maintain a conducive or suitable environment for the occupants or the process being conducted. The primary goals of any HVAC system are to control the ambient temperature, keep humidity levels in check, and ensure optimal air quality inside the building. HVAC systems, being one of the most energy-intensive components in buildings, contribute to almost half the total energy consumption within structures [1]. Consequently, implementing energy-efficient strategies to enhance HVAC operations can be a practical means to move closer to achieving net-zero energy consumption goals [2]. HVAC system operation efficiency directly relates to reduced energy consumption and carbon emissions. Studies have shown that effective maintenance is instrumental to achieving more energy-efficient and

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environmentally friendlier operations. Effective maintenance of the HVAC systems is essential for so many reasons. Apart from the compelling need to comply with health and safety and environmental legislation, it is also a critical driver of competitiveness and profitability across industry sectors. As organisations increasingly recognise the strategic importance of maintenance management within the broader context of physical asset management, there is a heightened emphasis on improving maintenance performance to achieve greater productivity and minimise waste, enhancing competitiveness.

Most HVAC system maintenance strategies stem from corporate policies and prescribe actions that need to be performed during the life cycle of a system or plant equipment to uphold or restore it to defined operating conditions. Over time, it has been noted that such an approach lacks adaptability and often results in poor Maintenance Performance Levels Luo et al. [3], Chaudhary & Meshram [4], and Hedjazi [5] concluded that organisations prioritise maintenance tasks during resource constraints by employing various strategies and models that balance resource availability with maintenance needs to optimise performance and reliability, as many governments have reviewed subsidies and other intervention policies leaving companies to face the realities of the post-COVID economy. A fixed/static maintenance schedule for HVAC systems could lead to increased energy consumption and suboptimal component performance. Besides, alternative maintenance sites do not contribute equally toward organisation objectives. Also, the variables and parameters of the failure modes [6,7] vary in levels and must be considered in determining the priority amongst alternative maintenance locations. In this context, the prioritising maintenance locations can be seen from the dynamic maintenance point of view.

Dynamic maintenance strategies consider the actual conditions and needs described as variables and levels of parameters of the system, such as age and degradation levels, to determine the optimal maintenance intervention actions, thereby minimising the long-run cost rate and improving system reliability[8]. Recently, this has been ensured through advanced predictive models and optimisation algorithms. For instance, a deep neural network model based on Just-in-Time learning with hyperparameter R (RJITL) has been shown to improve prediction accuracy by 5.17 % and speed by 41.72 %, enabling real-time energy consumption predictions and adaptive updates to the system, which enhances the overall efficiency [9]. Additionally, optimisation algorithms such as the Firefly Algorithm have demonstrated the potential to reduce energy consumption by nearly half, from around 508003 kWh to a range of 20000–25500 kWh, by optimising damper settings in HVAC systems [10]. Though these methods have shown to be largely successful under controlled conditions, they suffer low implementation levels in practical terms due to the high skill required for their implementation. The critical skill level of maintenance personnel significantly impacts the effectiveness of maintenance implementation [11,12]. Optimal maintenance is achievable when maintenance workers are skilled enough to handle strategies efficiently. These studies underscore the need for more straightforward, effective HVAC systems maintenance models.

Building HVAC systems often face challenges related to design flaws, equipment functionality, and control system errors, leading to inefficient energy use. Common issues include mechanical problems such as stuck dampers, leaking valves, sensor inaccuracies, and improper user interventions. Addressing these issues early can save significant energy. The problems are generally categorised into two types: degradation faults, which slowly worsen over time and are typically unnoticed until they become severe and abrupt failure faults, which cause sudden equipment breakdowns and total system failures [13].

Unanticipated equipment failures can result in significant financial burdens, disrupt production, and present safety and environmental risks. Therefore, a well-suited maintenance strategy is imperative across various industries to mitigate these adverse consequences. Such a strategy reduces the likelihood of equipment breakdowns and improves asset conditions, leading to cost savings and improved product quality. Quantifying maintenance performance is paramount as it equips maintenance managers with valuable insights to attain maintenance objectives and enhance operational results. This performance evaluation is critical for assessing both effectiveness in minimising the impact of equipment performance decline and efficiency in reducing maintenance expenses [14].

Various simple techniques, such as machine components, have been proposed for evaluating and ranking alternatives. Criticality analysis [15,16], and Failure Mode and Effect Analysis (FMEA) [17–20] have been proposed. The strength of these methods lies in using a set of criteria to articulate the divergent conditions of the components and support the maintenance decisions. However, they are criticised mainly due to the poor handling of a diverse array of occasionally conflicting criteria, uncertainty, and imprecisions associated with the conditions of the structures. More so, it is contended that relying solely on the FMEA's output, known as RPN, is insufficient for comprehensively assessing maintenance priorities.

Fuzzy TOPSIS, a widely utilised multi-criteria technique, stands out for its clear methodology and easily programmable computation process. The methodology consists of sequential steps that maintenance managers can easily replicate, facilitating understanding and application without extensive technical knowledge. Its ability to adeptly handle imprecise and uncertain data through fuzzy logic makes it well-suited for addressing the intricate challenges presented by maintenance decision-making. Fuzzy TOPSIS offers a systematic framework for assessing and ranking maintenance alternatives, enabling decision-makers to discern optimal solutions from many influencing factors. It also operates as a compromise model, acknowledging that while an ideal solution may be elusive, achieving a solution with optimal values across all criteria is still possible [21].

This study presents a comprehensive yet simplified maintenance strategy targeting twelve critical components of HVAC systems. The approach integrates the qualitative assessment power of Failure Mode and Effects Analysis (FMEA) with the flexibility and precision of the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (Fuzzy-TOPSIS). By leveraging FMEA's straightforward identification and ranking of potential failure modes and coupling it with the nuanced decision-making capabilities of Fuzzy-TOPSIS, the framework effectively captures the HVAC system components' real-world operational conditions and performance data. This synergy enables a more accurate identification of maintenance needs and establishes a clear, data-driven prioritisation for maintenance activities. The proposed methodology addresses the complexity associated with traditional maintenance planning. It provides a dynamic, adaptable model that aligns with the ever-changing conditions of HVAC systems, ensuring optimised operational efficiency and prolonged equipment lifespan. The study further recognised scope limitations, such as data constraints. It highlighted the significance of the study in the context of HVAC maintenance, emphasising potential impacts on system performance, energy efficiency, and cost reduction.

2. The framework

The framework has three parts: i) information gathering and documentation, ii) formulation of maintenance priority criteria, and iii) evaluation aggregation. These are depicted in Fig. 1 and discussed in the following subsections.

2.1. Information gathering and documentation

HVAC domain data collection is of paramount importance as it forms the bedrock upon which the creation of a dynamic maintenance planning framework is built. The data were collected from both primary and secondary sources. For instance, an extensive literature review was conducted to identify potential criteria relevant to the maintenance context. The HVAC historical maintenance record sheets and manufacturers' guides/manuals were further used to contextualise the identified criteria to industry/organization-specific during close interactions with HVAC engineers and maintenance technicians. Thus, Historical maintenance records, HVAC experts' views (from questionnaires and surveys), and manufacturer specifications were integrated into formulating decision support for HVAC maintenance planning. HVAC maintenance records were collected from a distinct HVAC company, offering great insights into past maintenance practices and component failures. The expert views, as contained in the questionnaires, provided current industry perspectives. The HVAC equipment manufacturer data ensures accuracy and aligns maintenance practices with industry standards. These sources contribute to a comprehensive and robust maintenance framework for HVAC systems. Plate 1 shows the maintenance records collected from the HVAC equipment from a distinct company.

2.2. Formulating maintenance criteria

This step integrates an intensive literature review, historical real-time operation data, and stakeholder perspectives to reveal the aspects of the organization-wide objectives that would be primarily affected should any of the components break down. The exercise tends to answer the question, "What would distinguish between the HVAC components as a preferred first choice of maintenance." Given that suitable experience resides within the decision-making team, the members role-played the positions of key interest groups in a simulated experiment to answer the question, ensuring that their perspectives were not overlooked in deriving the criteria [22]. Based on this perspective of criteria, it is logical that they cannot be equally important: some criteria will relate more to achieving the aim than others. This difference is usually established in MCDM through weighting-describing a situation where the DM assesses criteria with unique perspective enhancing model robustness and flexibility [23]. Weights are critical to the outcome of the MCDM process, and variation across case studies or HVAC types could challenge the model's generalisability. To address this, DMs must understand the MCDM process's aim and how the criteria collectively achieve this aim. There are many ways to accomplish this: the subjective, objective, and the mixed method [24,25]. These methods tend to determine trade-offs between the number of units of one criterion that the DMs are willing to give up improving the performance of another criterion by unit categories. In so doing, hidden predicaments behind several mutually exclusive alternatives evaluated across multiple criteria could be highlighted, making DMs aware of their choice's potential gains and losses. Weighting methods based on pairwise comparison, like the Analytical Hierarchical Process (AHP) and Best-Worst Method (BWM), have demonstrated better prospects at addressing equalising bias [26] and are also suitable for individual decision-making processes [27]. In contrast, the Level-Based Weight Assessment model (LBWA) [28] does the same with minimal comparisons and provides flexibility for sensitivity analysis. The DM must know the strengths and weaknesses of the various techniques before settling on the method to use.

In addition, FMEA was conducted to provide additional insight into conceivable failure scenarios and their respective risk levels based on the Risk Priority Number (RPN): a measure derived by integrating severity, occurrence, and detectability of the components of the HVAC system on a multiplicative scale [29]. A notable characteristic of the framework is the integration of RPN into the Criteria. More so, the Delphi method, characterised by multiple rounds of surveys, is adopted to allow experts to review and refine their responses based on collective feedback, leading to a consensus on the most critical criteria.

2.3. Failure mode and Effect Analysis (FMEA) method

The primary purpose of using FMEA in this research is to pinpoint conceivable failure scenarios of HVAC components, evaluate their consequences, and establish a hierarchy of actions to reduce the potential failure risk in the HVAC system. The evaluation of

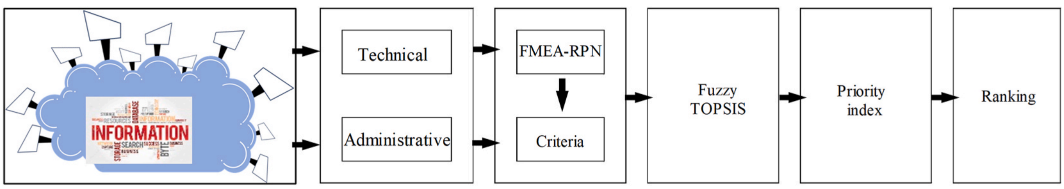
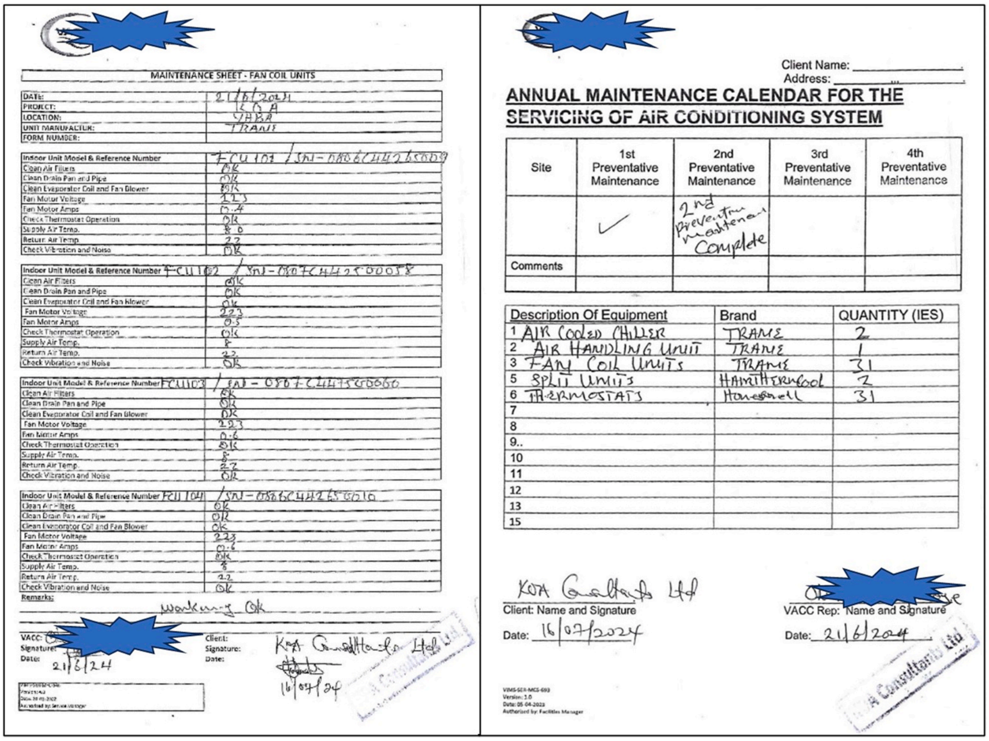


Fig. 1. The methodology framework.



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MAINTENANCE SHEET - FAN COIL UNITS

DATE:	21/6/2024
PROJECT:	KOA
LOCATION:	YABA
UNIT MANUFACTUR:	TRANE
FORM NUMBER:	

Indoor Unit Model & Reference Number	FCU 101 / SN-0806C44265009
Clean Air Filters	OK
Clean Drain Pan and Pipe	OK
Clean Evaporator Coil and Fan Blower	OK
Fan Motor Voltage	223
Fan Motor Amps	0.4
Check Thermostat Operation	OK
Supply Air Temp.	8.0
Return Air Temp.	22
Check Vibration and Noise	OK

Indoor Unit Model & Reference Number	FCU 102 / SN-0807C44250005 8
Clean Air Filters	OK
Clean Drain Pan and Pipe	OK
Clean Evaporator Coil and Fan Blower	OK
Fan Motor Voltage	223
Fan Motor Amps	0.5
Check Thermostat Operation	OK
Supply Air Temp.	8
Return Air Temp.	22
Check Vibration and Noise	OK

Indoor Unit Model & Reference Number	FCU103 / SN-0807C44750060
Clean Air Filters	OK
Clean Drain Pan and Pipe	OK
Clean Evaporator Coil and Fan Blower	OK
Fan Motor Voltage	223
Fan Motor Amps	0.6
Check Thermostat Operation	OK
Supply Air Temp.	8
Return Air Temp.	22
Check Vibration and Noise	OK

Indoor Unit Model & Reference Number	FCU 104 / SN-0806C44265010
Clean Air Filters	OK
Clean Drain Pan and Pipe	OK
Clean Evaporator Coil and Fan Blower	OK
Fan Motor Voltage	223
Fan Motor Amps	0.6
Check Thermostat Operation	OK
Supply Air Temp.	8
Return Air Temp.	22
Check Vibration and Noise	OK

Remarks: Working Ok

VACC: [redacted]
Signature:
Date: 21/6/24

Client: KOA Consultants Ltd
Signature:
Date: 16/07/24

[redacted]

Client Name:
Address:

ANNUAL MAINTENANCE CALENDAR FOR THE SERVICING OF AIR CONDITIONING SYSTEM

Site	1st Preventative Maintenance	2nd Preventative Maintenance	3rd Preventative Maintenance	4th Preventative Maintenance
	✓	2nd preventive maintenance Complete		
Comments				

Description Of Equipment	Brand	QUANTITY (IES)
1 AIR COOLED CHILLER	TRANE	2
2 AIR HANDLING UNIT	TRANE	1
3 FAN COIL UNITS	TRANE	31
5 SPLIT UNITS	HAMITHERMCOOL	2
6 THERMOSTATS	Honeywell	31
7		
8		
9..		
10		
11		
12		
13		
15		

KOA Consultants Ltd
Client: Name and Signature
Date: 16/07/2024

[redacted]
VACC Rep: Name and Signature
Date: 21/6/2024

Plate 1. Historical data: sample of HVAC Maintenance Record sheet.

failure risks involves the examination of three key criteria: severity, occurrence, and detection. Severity pertains to the scale of the ultimate impact of a system failure. A more substantial consequence corresponds to a higher severity rating assigned to that effect. On the other hand, occurrence relates to how often the underlying cause is anticipated to materialise, expressed qualitatively as terms like

Table 1
Ranking system for occurrence, severity and detection.

	Occurrence		Severity		Detection	
#	Probability	Rate	Effect	Criteria	Likelihood of Detection	
1	Remote: Unlikely	*<1/ 1500000*	None	*No Effect*	Almost certain	*chance that a control will detect a potential cause of failure or subsequent failure mode*
2	Very minor failures	*1/15000*	Very minor	*Fit & finish or squeak & rattle items do not conform -discriminating customers notice defect*	Very high	
3	Low: Relatively few failures	*1/15000*	Minor	*Fit & finish or squeak and rattle items do not conform - average customers notice defect*	High	
4	Low to very low	*January 2000*	Very low	*Fit & finish or squeak and rattle items do not conform - most customers notice defect*	Moderately high	
5		*1/400*	Low	*Product is operable, but comfort or convenience items operate at reduced level of performance*	Moderate	
6	Moderate: Occasional failures	*1/80*	Moderate	*Product is operable, but comfort or convenience items are inoperable*	Low	
7	High: Repeated	*1/20*	High	*Product is operable, but at reduced level of performance*	Very low	
8	failures	*1/8*	Very high	*Product is inoperable with loss of primary function.*	Remote	
9	Hazardous With warning	*1/3*	Hazardous w/ warning	*Failure affects safe product operation or involves noncompliance with government regulation w/warning*	Very remote	
10	Very high: Failure almost inevitable	*>1/2*	Hazardous w/ o warning	*Failure affects safe product operation or involves noncompliance with government regulation w/o warning*	Absolutely uncertain	*Uncertain that a control will detect a potential cause of failure or subsequent failure mode; or there is no control*

"remote" or "occasional" rather than in specific time intervals. Detection, in this context, refers to the probability of identifying the root cause before it leads to a failure event.

The risk priority is critical to the FMEA. It is a quantitative measure of the risk inherent in the failure event of the HVAC component. It is given by (1), where S is the Severity rating corresponding to an assessment of the effect of the potential failure on the next component, subsystem, or system. Scored on a 10-point scale, a low severity score of "1" is read as "None" and indicates a No effect of the failure on the next component in line. Likewise, a high score of "10" indicates a "Hazardous w/o warning", meaning that Failure affects safe product operation or involves noncompliance with government regulation without warning. O is the Occurrence rating, i. e., the likelihood of a specific potential failure. Like the severity, it is scored on a 10-point scale, too, where a low score of "1" indicates "Remote: Unlikely" (one in one million, five hundredth thousand chances of occurring). Likewise, a high score of "10" indicates a "very high" chance of occurring or almost an inevitable failure (one-and-a-half chance of occurring). D is the detection rating, which is the probability of a failure arising from a cause being detected before the consequence of the effect is realised. The scoring too is done on a 10-point scale in which the lowest score of "1" indicates "almost certain detection", and the highest score of "10" indicates "no known means of detection". Usually, scales link the indices (1–10) to specific classes of O, S, and D. An example is shown in Table 1 [30,31].

Using the available HVAC data collected from technical experts, maintenance records, questionnaires, and a deep understanding of the components of the system, the potential failure mode of HVAC components and their corresponding effect was evaluated based on severity, occurrence, and detection. These factors were assessed on a scale of 1–10, encompassing a spectrum from low to high. To compute the Risk Priority Number (RPN) for each potential failure mode and its associated effect, the numerical ratings for these three factors were multiplied together, as shown below in Equation (1).

$$\text{RPN} = \text{Severity (S)} \times \text{Occurrence (O)} \times \text{Detection (D)} \tag{1}$$

Thus, the FMEA analysis of the critical HVAC component is presented in Table 2.

2.4. Fuzzy TOPSIS method

Maintenance decision-making is essential in ensuring the efficiency, reliability, and longevity of systems/assets. In practice, decision-makers often grapple with various occasionally conflicting criteria. Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) has proven to be one of the most powerful multi-criteria decision-making tools, especially in maintenance, due to its capacity to manage uncertain and imprecise data using fuzzy logic. It provides a structured approach for evaluating and ranking maintenance options, helping decision-makers identify the most important option based on multiple influencing factors. This article reports experience a real case of the application of Fuzzy TOPSIS in maintenance decision-making, highlighting its principles and methodology. It demonstrates how Fuzzy TOPSIS can improve maintenance strategies and enhance system performance and reliability. The article also underscores the critical importance of maintenance in ensuring system availability, reliability, product quality, and safety despite historically receiving less focus than production and manufacturing concerns [32].

This research used a triangular Fuzzy number to express the linguistic judgments of decision-makers (HVAC Evaluators) and the distance between two fuzzy ideal solutions in multi-criteria decision-making for HVAC maintenance prioritisation. Using linguistic

Table 2
Failure mode and effect analysis.

HVAC Components	Potential Failure Mode	Effects of the Failure	SEV	Potential Cause	OCR	Current Controls	DET	RPN
Evaporation coil	Refrigeration leakage	Loss of cooling	7	Corrosion over time	4	Conduct leak detection tests during routine maintenance	7	196
Condenser coil	Corrosion	Reduces heat dissipation	6	Exposure to moisture	6	Regular Cleaning	5	180
Compressor	Mechanical failure (broken piston, bearings wear)	Loss of cooling capacity	9	Overheating	5	Regular inspection and Servicing	6	270
Expansion Valve	Blockage	Ineffective cooling	5	Accumulation of foreign particles	3	Regular Inspection/Filter Drying	6	90
Blower fan	Motor failure		8	Overheating	4	Regular lubrication	5	160
Thermostat	faulty wiring	Inaccurate temperature control	4	connection/ calibration issues	5	Wiring Inspection	4	80
Air Filter	Clogging with dirt	Poor air quality	6	Dust Accumulation	7	Regular replacement	4	168
Control panel	faulty switches or button	Affect setting adjustment	4	damage of internet wiring	4	Routine Inspection	6	96
Cooling housing	Corrosion	Exposure of internal component and can damage the housing	5	Exposure to weather elements	6	Coating/Shelter	6	180
Draining system	Corrosion/Blockage	water leakages	2	Accumulation of dirt/Exposure	5	Regular Cleaning	7	70
power cord	wiring/plug issues	Loss of power	7	Bending, crushing and exposure	4	Periodic Inspection	5	140
Exhaust fan	Motor failure	Poor IAQ and comfort	6	Overheating	3	Lubricate Regularly	5	90

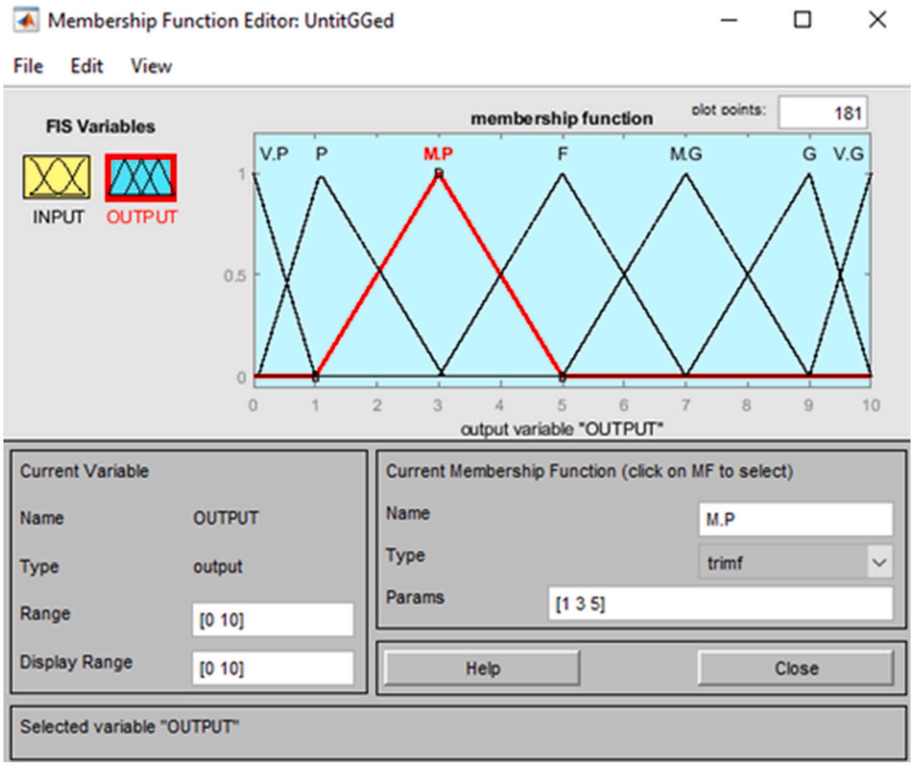

Fig. 2. Triangular membership function.

variables in experts' evaluation allows the experts to express their feelings in easily relatable languages. These linguistic variables defined the membership functions and were implemented using MATLAB, as shown in Fig. 2. This resulted in linguistic variables for rating alternatives and for the weighting of each criterion, as presented in Tables 3 and 4.

3. Maintenance framework implementation

The study developed a dynamic maintenance planning method that combined fuzzy TOPSIS and FMEA to aid in the maintenance decisions for selected HVAC components. It is dynamic in that the outcome evolves continuously as inputs change. Precisely, as the likelihood of the failure modes of the component changes (due to maintenance intervention), the Risk Priority Number (RPN) also shifts, leading to variations in the maintenance ranking of the components. While FMEA is currently employed to determine maintenance priorities for these components, it is contended that relying solely on the FMEA's output, known as Risk Prioritisation Number (RPN), is insufficient for comprehensively assessing maintenance priorities. Therefore, to establish a more effective maintenance strategy, criteria related to the HVAC components, including reliability improvement (REL), energy efficiency (EEF), Indoor air quality (IAQ) enhancement, cost constraint (CRS), and environmental impact (EMI), were incorporated for the Fuzzy TOPSIS analysis.

The evaluation was carried out by a team of three experts in the HVAC sector selected from the networks of the American Society of Heating, Refrigerating, and Air Conditioning Engineers (ASHRAE) communities. These experts represent the three units: Heating, Ventilation and Air-conditioning. They have brought insights from a broader panel (consisting of plant operators and foremen) harnessed in preliminary studies and fashioned by tacit experiences in the HVAC industry, as captured in Fig. 3. The authors make a case for the validity of judgement from three experts given that the decision context is well-defined, and the experts share a common

Table 3
Linguistic variable for rating alternatives.

Linguistic variable	Fuzzy number
Very Poor	(0,0,1)
Poor	(0,1,3)
Medium-Poor	(1,3,5)
Fair	(3,5,7)
Medium good	(5,7,9)
Good	(7,9,10)
Very good	(9,10,10)

Table 4
Linguistic variables for the weighting of each criterion.

Linguistic variable	Fuzzy number
Very low	(0,0,0.1)
Low	(0,0.1,0.3)
Medium-low	(0.1,0.3,0.5)
Medium	(0.3,0.5,0.7)
Medium-high	(0.5,0.7,0.9)
High	(0.7,0.9,1.0)
Very high	(0.9,1.0,1.0)

understanding of the problem [33,34]. The number of experts considered enough for logical judgment often arouses debate among researchers and could vary depending on the decision context. However, previous studies [35–37] have argued that a small panel of experts (n\le 5) could leverage easily verified accuracy and trust to maximise the probability of making sound judgments. Each of the 12 HVAC components was assessed under the parameters, and scores were assigned to them as provided by the evaluation scale.

The expert's evaluation is illustrated in Tables 5 and 6.

The scores ascribed by each evaluator for each component against the criteria and weighting scores of the criteria were fuzzified using the fuzzy scale outlined in Table 3, preparing data for the Fuzzy TOPSIS Analysis. Based on the data in Table 6, the weighting scores for each criterion assigned by experts A, B, and C for the 12 selected components were fuzzified. The result of the fuzzification is presented in Tables 7–9, respectively.

Furthermore, fuzzy decision matrix and aggregate fuzzy weight vector were obtained using Equations 2 and 3

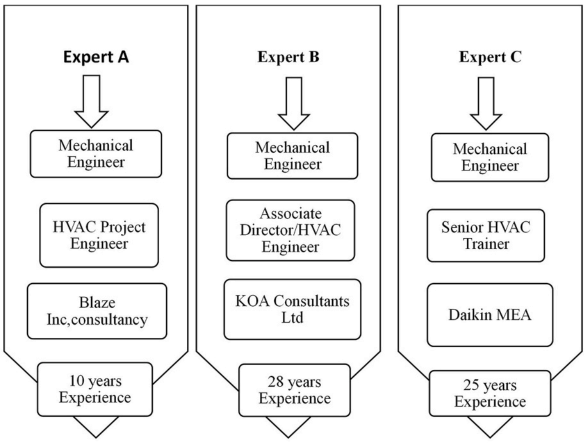

Fig. 3. Decision Maker/HVAC experts.

Table 5
Expert rating scores for components.

S/N	Components	Expert A					Expert B					Expert C				
		REL	EFF	IAQ	EMI	**CSR**	**REL**	**EFF**	**IAQ**	**EMI**	**CSR**	**REL**	**EFF**	**IAQ**	**EMI**	**CSR**
1	Evaporator coil	VG	MG	G	G	F	G	G	G	G	G	VG	G	G	G	VG
2	Condenser coil	VG	G	VG	G	G	G	MG	G	MG	G	VG	VG	M	G	VG
3	Compressor	G	VG	VG	G	VG	MG	G	G	G	MG	G	VG	M	VG	VG
4	Expansion valve	F	MG	MG	F	MG	MG	G	MG	G	MG	G	G	M	M	MG
5	Blower fan	F	MG	MG	MG	F	VG	VG	G	VG	VG	G	VG	MG	M	VG
6	Thermostat	F	P	P	P	P	F	MG	MG	MG	MG	G	MG	P	P	G
7	Air filter	G	MG	G	VG	F	MG	MG	MG	G	G	VG	G	VG	M	VG
8	Control panel	F	F	F	F	G	G	G	G	G	MG	F	M	G	MG	G
9	Cooling house	F	P	F	F	M	MG	MG	MG	MG	M	M	VP	F	M	M
10	Draining system	P	P	P	P	P	G	G	G	G	G	F	P	P	P	P
11	Power cord	P	P	P	P	P	G	G	G	G	G	F	VG	VG	VG	P
12	Exhaust fan	MG	G	F	VG	MG	G	G	G	G	G	MG	G	VG	F	G

Table 6
Expert weighting score for each criterion.

Evaluator	RPN	REL	EFF	IAQ	EMI	CSR
A	H	H	VH	H	H	M
B	VH	H	VH	VH	H	VH
C	M	M	VH	H	MH	H

Table 7
Expert (A) data fuzzification.

S/N	HVAC Component	REL	EEF	IAQ	EMI	CSR
1	Evaporator coil	(9,10,10)	(5,7,9)	(7,9,10)	(7,9,10)	(3,5,7)
2	Condenser coil	(9,10,10)	(7,9,10)	(9,10,10)	(7,9,10)	(7,9,10)
3	Compressor	(7,9,10)	(9,10,10)	(9,10,10)	(7,9,10)	(9,10,10)
4	Expansion valve	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)
5	Blower fan	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)
6	Thermostat	(3,5,7)	(0,1,3)	(0,1,3)	(0,1,3)	(0,1,3)
7	Air filter	(7,9,10)	(5,7,9)	(7,9,10)	(7,9,10)	(3,5,7)
8	Control panel	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(9,10,10)
9	Cooling house	(3,5,7)	(0,1,3)	(3,5,7)	(3,5,7)	(1,3,5)
10	Draining system	(0,1,3)	(0,1,3)	(0,1,3)	(0,1,3)	(0,1,3)
11	Power cord	(0,1,3)	(0,1,3)	(0,1,3)	(0,1,3)	(0,1,3)
12	Exhaust fan	(5,7,9)	(7,9,10)	(3,5,7)	(7,9,10)	(5,7,9)

Table 8
Expert (B) data fuzzification.

S/N	HVAC Component	REL	EEF	IAQ	EMI	CSR
1	Evaporator coil	(7,9,10)	(7,9,10)	(7,9,10)	(7,9,10)	(7,9,10)
2	Condenser coil	(7,9,10)	(5,7,9)	(7,9,10)	(5,7,9)	(7,9,10)
3	Compressor	(5,7,9)	(7,9,10)	(7,9,10)	(7,9,10)	(5,7,9)
4	Expansion valve	(5,7,9)	(7,9,10)	(5,7,9)	(7,9,10)	(5,7,9)
4	Blower fan	(9,10,10)	(9,10,10)	(9,10,10)	(9,10,10)	(9,10,10)
6	Thermostat	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)
7	Air filter	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,10)	(7,9,10)
8	Control panel	(7,9,10)	(7,9,10)	(7,9,10)	(7,9,10)	(5,7,9)
9	Cooling house	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(1,3,5)
10	Draining system	(7,9,10)	(7,9,10)	(7,9,10)	(7,9,10)	(7,9,10)
11	Power cord	(7,9,10)	(7,9,10)	(7,9,10)	(7,9,10)	(7,9,10)
12	Exhaust fan	(7,9,10)	(7,9,10)	(7,9,10)	(7,9,10)	(7,9,10)

$$a_{i,j^1} = \min\left(a_{ij^1}\right), b_{ij^2} = \frac{1}{k}\sum_{k=1}^{k} b_{ij^2}, c_{ij^3} = \max\left(c_{ij^3}\right) \tag{2}$$

$$w_{i,j^1} = \min\left(w_{ij^1}\right), w_{ij^2} = \frac{1}{k}\sum_{k=1}^{k} w_{ij^2}, w_{ij^3} = \max\left(w_{ij^3}\right) \tag{3}$$

The resulting fuzzy weight vector and fuzzy decision matrix are presented in Tables 9 and 10, respectively.

As presented in Table 11, the RPN for each HVAC component retrieved from FMEA analysis were integrated into the fuzzy decision matrix. Hence, the Normalized fuzzy decision matrix was calculated using equations (4) and (5):

$$r_{ij} = \left(\frac{a_{ij}}{C_j^*}, \frac{b_{ij}}{C_j^*}, \frac{c_{ij}}{C_j^*}\right), \mathrm{J} \in \mathrm{B} \tag{4}$$

$$r_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \mathrm{J} \in \mathrm{C} \tag{5}$$

where:

$$c_j^* = \max\left(c_{ij}\right), if = \mathrm{J} \in \mathrm{B}\ (\text{benefit criteria})$$

$$a_j^- = \min\left(a_{ij}\right), if = \mathrm{J} \in \mathrm{C}\ (\text{cost criteria})$$

Table 9
Expert (C) data fuzzification.

S/N	HVAC Component	REL	EEF	IAQ	EMI	CSR
1	Evaporator coil	(9,10,10)	(7,9,10)	(7,9,10)	(7,9,10)	(9,10,10)
2	Condenser coil	(9,10,10)	(9,10,10)	(1,3,5)	(7,9,10)	(9,10,10)
3	Compressor	(7,9,10)	(9,10,10)	(1,3,5)	(9,10,10)	(9,10,10)
4	Expansion valve	(7,9,10)	(7,9,10)	(1,3,5)	(1,3,5)	(5,7,9)
4	Blower fan	(7,9,10)	(9,10,10)	(5,7,9)	(1,3,5)	(9,10,10)
6	Thermostat	(7,9,10)	(5,7,9)	(0,1,3)	(0,1,3)	(7,9,10)
7	Air filter	(9,10,10)	(7,9,10)	(9,10,10)	(1,3,5)	(9,10,10)
8	Control panel	(3,5,7)	(1,3,5)	(5,7,9)	(5,7,9)	(7,9,10)
9	Cooling house	(1,3,5)	(0,0,1)	(3,5,7)	(1,3,5)	(1,3,5)
10	Draining system	(3,5,7)	(0,1,3)	(0,1,3)	(0,1,3)	(0,1,3)
11	Power cord	(3,5,7)	(9,10,10)	(9,10,10)	(9,10,10)	(0,1,3)
12	Exhaust fan	(5,7,9)	(7,9,10)	(9,10,10)	(3,5,7)	(7,9,10)

In the decision-making and analysis, "cost" and "benefit" refer to the positive or negative effects of various factors or criteria. Although these terms are commonly linked to financial considerations, they can encompass a range of elements such as time, resources, and other pertinent considerations. In this context, RPN, cost constraint, and environmental impact were categorised as cost criteria as maximising this criterion will have a negative impact on the HVAC system; thereby, it will be minimised. Reliability improvement, IAQ enhancement, and energy efficiency were categorised as benefit criteria, as maximising these criteria positively affect the system. The normalized fuzzy decision matrix is presented in Table 12.

After normalising the fuzzy decision matrix, a weighted fuzzy decision matrix was created, denoted as $\tilde{V} = [\tilde{v}_{ij}]_{m \times n}$, with elements $\tilde{v}_{ij}$ determined as the product of the normalized value r_{ij} and the weight w_j. Table 13 shows the result of the weighted normalized decision matrix.

3.1. Determination of maintenance priority ranking by fuzzy TOPSIS

In this stage, the fuzzy TOPSIS technique was utilised to establish the maintenance priority ranking of the components based on the closeness coefficient. When the closeness coefficient approaches 1, an option is deemed to be closer to the fuzzy positive ideal solution and farther away from the fuzzy negative ideal solution.

Subsequently, the fuzzy positive ideal solution A* and the fuzzy negative ideal solution as A^- were defined in Equations in (6) and (7).

$$A^* = \left(V_1^*, V_2^*, \dots V_n^*\right) \tag{6}$$

$$A^- = \left(V_1^-, V_2^-, \dots V_n^-\right) \tag{7}$$

Distances between each alternative, from the ideal positive (i.e., A^*) and the ideal negative (i.e., A^-) were calculated using equations (8) and (9), and the results are presented in Tables 17 and 18.

$$d_i^* = \sum_{j=1}^{n} d\left(V_{ij}, V_j^*\right), i = 1, 2, \dots, m \tag{8}$$

$$d_i^- = \sum_{j=1}^{n} d\left(V_{ij}, V_j^-\right), i = 1, 2, \dots, m \tag{9}$$

where d (.,.) is the distance between two fuzzy numbers and calculated using Equation (10) as follows:

$$d(x, y) = \sqrt{\left[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2\right]} \tag{10}$$

where (a_1, b_1, c_1) and (a_2, b_2, c_2) are triangular fuzzy numbers. Closeness coefficient (CC_i) determine the ranking order of all alternatives was calculated based on Equation (11):

Table 10
Fuzzy weight vector.

Experts	RPN	REL	EFF	IAQ	EMI	CSR
A	(0.7,0.9,1)	(0.7,0.9,1)	(0.9,1,1)	(0.7,0.9,1)	(0.7,0.9,1)	(0.3,0.5,0.7)
B	(0.9,1,1)	(0.7,0.9,1)	(0.9,1,1)	(0.9,1,1)	(0.7,0.9,1)	(0.9,1,1)
C	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.9,1,1)	(0.7,0.9,1)	(0.5,0.7,0.9)	(0.7,0.9,1)
Weights	(0.3,0.8,1.0)	(0.3,0.77,1.0)	(0.9,1.0,1.0)	(0.7,0.93,1)	(0.5,0.83.1.0)	(0.3,0.8,1.0)

Table 11
Fuzzy Decision matrix.

S/N	HVAC Component	RPN	REL	EEF	IAQ	EMI	CSR
1	Evaporator coil	(5,7,9)	(7,9.7,10)	(5,8.3,10)	(7,9,10)	(7,9,10)	(3,8,10)
2	Condenser coil	(3,5,7)	(7,9.7,10)	(5,8.7,10)	(1,7.3,10)	(1,8.3,10)	(7,9.3,10)
3	Compressor	(9,10,10)	(5,8.3,10)	(7,9.7,10)	(1,7.3,10)	(7,9.3,10)	(5,9,10)
4	Expansion valve	(0,1,1)	(3,7,10)	(5,8.3,10)	(1,5.7,9)	(1,5.6,10)	(5,7,9)
4	Blower fan	(3,5,7)	(3,8,10)	(9,10,10)	(5,7.7,10)	(1,6.7,10)	(3,8.3,10)
6	Thermostat	(0,1,1)	(3,7,10)	(5,9,10)	(0,3,9)	(1.7,3,9)	(4,8.3,10)
7	Air filter	(3,5,7)	(5,8.7,10)	(0,5,9)	(5,8.9,10)	(1,7,10)	(3,8,10)
8	Control panel	(0,1,1)	(3,6.3,10	(5,7.8,10)	(3,7,10)	(3,7,10)	(5,8.7,10)
9	Cooling house	(3,5,7)	(1,5,9)	(3,5.7,10)	(3,5.7,9)	(3,5,9)	(1,3,5)
10	Draining system	(1,3,5)	(0,5,10)	(0,3.7,10)	(0,3.7,10)	(2.3.7,10)	(2.3,3.7,10)
11	Power cord	(0,1,1)	(0,5,10)	(0,6.7,10)	(0,6.7,10)	(5.3,6.7,10)	(2.3,3.7,10)
12	Exhaust fan	(0,1,1)	(5,7.8,9)	(7,9,10)	(3,8,10)	(3,7.7,10)	(5,8.3,10)

Table 12
Normalized fuzzy decision matrix.

S/N	HVAC Component	RPN	REL	EEF	IAQ	EMI	CSR
1	Evaporator coil	(0.5,0.3,0.1)	(0.7,1,1)	(0.5,0.8,1)	(0.7,0.9,1)	(0.1,0.1,0.1)	(0.3,0.1,0.1)
2	Condenser coil	(0.7,0.5,0.3)	(0.7,1,1)	(0.5,0.9,1)	(0.1,0.7,1)	(1,0.1,0.1)	(0.1,0.1,0.1)
3	Compressor	(0.1,0,0)	(0.5,0.8,1)	(0.7,1,1)	(0.1,0.7,1)	(0.1,0.1,0.01)	(0.2,0.1,0.1)
4	Expansion valve	(1,1,0.9)	(0.3,0.7,1)	(0.5,0.8,1)	(0.1,0.6,0.9)	(1,0.2,0.1)	(0.2,0.1,0.1)
5	Blower fan	(0.7,0.5,0.3)	(0.3,0.8,1)	(0.5,0.9,1)	(0.5,0.8,1)	(1,0.2,0.1)	(0.3,0.1,0.1)
6	Thermostat	(1,1,0.9)	(0.3,0.7,1)	(0,0.5,0.9)	(0,0.3,0.9)	(0.6,0.3,0.01	(0.3,0.2,0.1)
7	Air filter	(0.7,0.5,0.3)	(0.5,0.9,1)	(0.5,0.8,1)	(0.5,0.9,1)	(1,0.1,0.1)	(0.3,0.1,0.1)
8	Control panel	(1,0.9,0.9)	(0.3,0.6,1)	(0.3,0.6,1)	(0.3,0.7,1)	(0.3,0.1,0.1)	(0.2,0.1,0.1)
9	Cooling house	(0.7,0.5,0.3)	(0.1,0.5,0.9)	(0,0.3,0.9)	(0.3,0.6,0.9)	(0.3,0.2,0.1)	(1,0.3,0.2)
10	Draining system	(0.9,0.7,0.5)	(0,0.5,1)	(0,0.4,1)	(0,0.4,1)	(0.4,0.3,0.1)	(0.4,0.3,0.1)
11	Power cord	(1,1,0.9)	(0,0.5,1)	(0,0.7,1)	(0,0.7,1)	(0.2,0.2,0.1)	(0.4,0.2,0.1)
12	Exhaust fan	(1,1,0.9)	(0.5,0.8,1)	(0.7,0.9,1)	(0.3,0.8,1)	(0.3,0.1,0.01)	(0.2,0.1,0.1)

Table 13
Weighted normalized fuzzy decision matrix.

S/N	HVAC Component	RPN	REL	EEF	IAQ	EMI	CSR
1	Evaporator coil	(0.2,0.2,0.1)	(0.2,0.7,1)	(0.5,0.8,1)	(0.5,0.8,1)	(0.1,0.1,0.01)	(0.1,0.1,0.1)
2	Condenser coil	(0.2,0.4,0.3)	(0.2,0.7,1)	(0.5,0.9,1)	(0.1,0.7,1)	(0.5,0.1,0.01)	(0.04,0.1,0.1)
3	Compressor	(0.03,0,0)	(0.2,0.6,1)	(0.6,0.9,1)	(0.1,0.7,1)	(0.1,0.1,0.01)	(0.1,0.1,0.1)
4	Expansion valve	(0.3,0.8,0.9)	(0.1,0.5,1)	(0.5,0.8,1)	(0.1,0.5,0.9)	(0.5,0.1,0.01)	(0.1,0.1,0.1)
5	Blower fan	(0.2,0.4,0.3)	(0.1,0.6,1)	(0.5,0.9,1)	(0.4,0.7,1)	(0.5,0.1,0.01)	(0.1,0.1,0.1)
6	Thermostat	(0.3,0.8,0.9)	(0.1,0.5,1)	(0,0.5,0.9)	(0,0.3,0.9)	(0.3,0.3,0.01	(0.1,0.1,0.1)
7	Air filter	(0.2,0.4,0.3)	(0.2,0.7,1)	(0.5,0.8,1)	(0.4,0.8,1)	(0.5,0.1,0.01)	(0.1,0.1,0.1)
8	Control panel	(0.3,0.7,0.9)	(0.1,0.5,1)	(0.3,0.6,1)	(0.2,0.7,1)	(0.2,0.1,0.01)	(0.1,0.1,0.1)
9	Cooling house	(0.2,0.4,0.3)	(0.03,0.4,1)	(0,0.3,0.9)	(0.2,0.5,0.9)	(0.2,0.2,0.01)	(0.3,0.3,0.2)
10	Draining system	(0.3,0.6,0.5)	(0,0.4,1)	(0,0.4,1)	(0,3.7,10)	(0.2,0.2,0.01)	(0.1,0.2,0.1)
11	Power cord	(0.3,0.8,0.9)	(0,0.4,1)	(0,0.4,1)	(0,0.3,1)	(0.1,0.1,0.01)	(0.1,0.2,0.1)
12	Exhaust fan	(0.3,0.8,0.9)	(0.2,0.6,1)	(0.6,0.9,1)	(0.2,0.7,1)	(0.2,0.1,0.01)	(0.1,0.1,0.1)

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-} \quad i = 1, 2, \ldots, m \tag{11}$$

The component that becomes closer to the positive ideal solution (A*) and moves further from the Negative ideal solution (A^-) as the closeness coefficient (CC_i) approaches 1. Hence, the ranking for the maintenance HVAC component was established using the closeness coefficient and the most suitable option from the 12 selected feasible components to the priority.

4. Results

The HVAC data on the rating of the selected component with respect to the three dimensions of potential failure mode, i.e., severity (SEV), occurrence(OCR), and detection(DET), were fed into the model to derive the RPN based on equation (1). The outcome is presented in Table 14.

As shown in Table 14, the RPNs for HVAC components were categorised into seven classes for evaluation using the fuzzy scale outlined in Table 15.

The resulting fuzzy RPNs for the components are presented in Table 16.

Table 14
Calculation results for FMEA.

HVAC Components	SEV	OCR	DET	RPN
Evaporation coil	7	4	7	196
Condenser coil	6	6	5	180
Compressor	9	5	6	270
Expansion Valve	5	3	6	90
Blower fan	8	4	5	160
Thermostat	4	5	4	80
Air Filter	6	7	4	168
Control panel	4	4	6	96
Cooling housing	5	6	6	180
Draining system	2	5	7	70
Power cord	7	4	5	140
Exhaust fan	6	3	5	90

4.1. Maintenance planning framework

Tables 17 and 18 present the computational outcomes derived from Equations (8) and (9) based on the steps detailed in the preceding sections.

After completing the steps detailed in the preceding sections and inserting data from Tables 17 and 18 into Equation (11), the computational outcomes derived from the proposed method are presented in Table 19.

4.2. Discussion of results

Analysis of the FMEA RPN result: Based on the result presented in Table 19, the following can be inferred from the component's RPN presented in Table 16.

i. The RPN values provide a quantitative assessment of the risk associated with each HVAC component. Notably, the compressor exhibits the highest risk with an RPN of 270, warranting close attention and potential preventive/predictive measures.
ii. Components, such as the evaporator coil, condenser coil, and cooling unit, also show significant RPN values, suggesting a need for prioritised maintenance to mitigate potential failures and ensure the system's reliability.
iii. Components with lower RPN values, like the Drain pan, exhaust fan and thermostat sensor, still require attention but may pose comparatively lower risks to the overall system.

The comparative analysis of Table 15 becomes clearer when presented in the FMEA pareto plot of Fig. 4.

Analysis Results from Maintenance Priority by Fuzzy TOPSIS: The RPN scores were incorporated as a criterion in evaluating the priority indices based on fuzzy TOPSIS. The overall ranking is presented in Fig. 5.

The maintenance priority ranking for HVAC components is detailed in Table 19 and Fig. 5. The result reflects the maintenance need of the components based on the prevailing conditions and is pivotal in guiding a focused and efficient maintenance strategies framework. With a closeness coefficient of 0.74227, the air filter claims the top priority, underscoring its critical role in system functionality. The blower fan closely follows with a second rank of priority and a coefficient of 0.7235, emphasising its significance. The exhaust fan, condenser coil, and expansion valve round out the top five, each with varying urgency. Notably, the draining system, with the lowest closeness coefficient at 0.37032, emerges as the lowest priority for maintenance. These rankings provide a deep understanding of component criticality, allowing for targeted interventions to enhance the overall reliability and performance of the HVAC system.

Assessment for the Maintenance Priority Ranking: In this phase, a detailed report and outcomes of the analysis were communicated to HVAC maintenance managers as decision support in the evaluation and assessment of the robustness, feasibility, and practicality of the maintenance prioritisation outcome. It is worth noting that the HVAC experts' evaluators also double as the HVAC maintenance specialists and have four experienced HVAC Professionals and one random expert with minimal experience. The assessment covers the feasibility of the results and comparison with tacit field knowledge. The highlight of the evaluations is the

Table 15
Fuzzification of risk priority numbers (RPNs).

Linguistic variable	Fuzzy number	RPN
Very low	(0,0,1)	70–99
Poor	(0,1,3)	99–127
Medium-poor	(1,3,5)	127–156
Fair	(3,5,7)	156–184
Medium good	(5,7,9)	184–213
Good	(7,9,10)	213–242
Very good	(9,10,10)	242–270

Table 16
Fuzzification of the RPN values.

HVAC Components	RPN	Fuzzy RPN
Evaporator Coil	196	(5,7,9)
Condenser Coil	180	(3,5,7)
Compressor	270	(9,10,10)
Expansion Valve	90	(0,0,1)
Blower Fan	160	(3,5,7)
Thermostat	80	(0,0,1)
Air Filter	168	(3,5,7)
Control Panel	96	(0,1,1)
Cooling Unit	180	(3,5,7)
Drainage system	70	(0,0,1)
Power Cord	140	(1,3,5)
Exhaust Fan	90	(0,0,1)

Table 17
Distance from positive ideal solution.

Components	RPN	REL	EEF	IAQ	EMI	CSR	d^*
Evaporator coil	0.526	0.098	0.146	0.000	0.430	0.279	1.479
Condenser coil	0.263	0.098	0.183	0.448	0.025	0.330	1.346
Compressor	0.788	0.026	0.067	0.448	0.430	0.315	2.073
Expansion valve	0.467	0.142	0.192	0.532	0.022	0.298	1.652
Blower fan	0.263	0.079	0.180	0.187	0.000	0.281	0.990
Thermostat	0.467	0.142	0.753	0.749	0.251	0.276	2.639
Air filter	0.263	0.000	0.224	0.143	0.006	0.279	0.915
Control panel	0.432	0.189	0.491	0.336	0.333	0.313	2.094
Cooling house	0.263	0.323	0.876	0.430	0.336	0.000	2.227
Draining system	0.000	0.320	0.825	0.697	0.303	0.204	2.350
Power cord	0.467	0.320	0.672	0.536	0.406	0.204	2.605
Exhaust Fan	0.467	0.077	0.000	0.295	0.334	0.311	1.484

Table 18
Distance from negative ideal solution.

Components	RPN	REL	EEF	IAQ	EMI	CSR	d^-
Evaporator coil	0.286	0.416	0.738	0.749	0.003	0.059	2.252
Condenser coil	0.531	0.416	0.730	0.421	0.429	0.000	2.528
Compressor	0.000	0.297	0.923	0.421	0.000	0.017	1.658
Expansion valve	1.234	0.178	0.705	0.258	0.432	0.035	2.843
Blower fan	0.531	0.248	0.757	0.567	0.430	0.058	2.591
Thermostat	1.234	0.178	0.200	0.000	0.296	0.064	1.972
Air filter	0.531	0.320	0.656	0.640	0.430	0.059	2.636
Control panel	1.184	0.137	0.392	0.439	0.100	0.018	2.270
Cooling house	0.531	0.104	0.000	0.325	0.123	0.330	1.413
Draining system	0.788	0.000	0.120	0.118	0.198	0.158	1.382
Power cord	1.234	0.000	0.380	0.355	0.042	0.158	2.169
Exhaust Fan	1.234	0.254	0.876	0.520	0.097	0.020	3.001

Table 19
The maintenance priority ranking of the HVAC components.

Components	CC_i	Rank
Evaporator coil	0.60366	6
Condenser coil	0.6525	4
Compressor	0.44443	9
Expansion valve	0.63239	5
Blower fan	0.7235	2
Thermostat	0.42771	10
Air filter	0.74227	1
Control panel	0.52006	7
Cooling house	0.38824	11
Draining system	0.37032	12
Power cord	0.45433	8
Exhaust Fan	0.6691	3

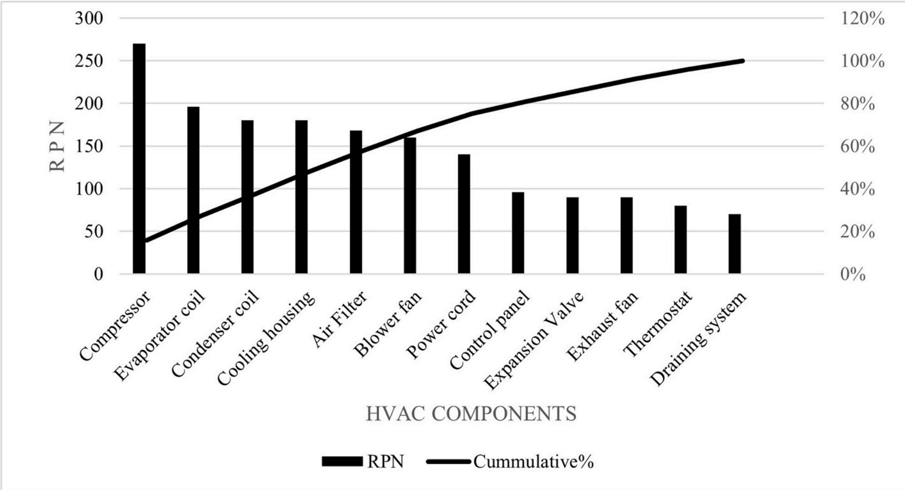

Fig. 4. FMEA Pareto plot.

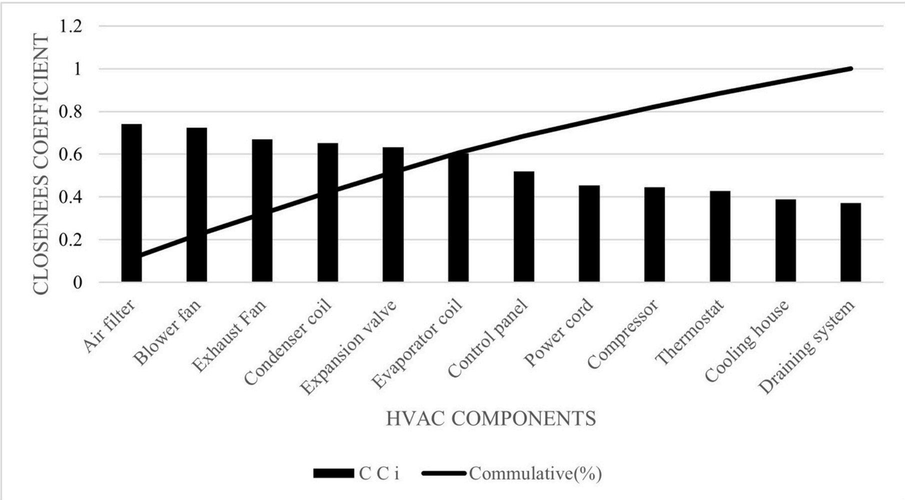

Fig. 5. Maintenance Priority Ranking chart.

valuable feedback and approval from the maintenance managers for potential improvements.

Managers expressed valuable insights into the practicality of the proposed dynamic maintenance framework. Their observations highlighted several key considerations for real-world application. For instance, Manager A emphasised the correlation of the methodology with practical applications. “To achieve the low-budget objective, prioritising the upkeep of power fuses, fans, and air filters should be considered. Meanwhile, the compressors and coils generally demand less maintenance. Power fuse issues often stem from unstable power or lack of stabilisers, aligning with the correlation in the results of the proposed model. Well done on your analysis!”

Similarly, Manager B acknowledged that results have great potential for achieving the intended objectives.

Manager C also gave feedback: “From what I have observed in the field, the air filter is the first thing to take care of after a proper installation. This makes your analysis unique and acceptable as it also accords the air filter the highest maintenance priority.”

Manger D: “This is cool, and I strongly agree with your maintenance ranking results; it is feasible.”[sic].

***Performance Analysis of the maintenance plan*:** To further consolidate the expert’s validation of the proposed HVAC maintenance approach, the direct and indirect running conditions data from key components under the proposed HVAC maintenance strategy was compared with the previous practices. Firstly, the mean time to failures for the components improved significantly. Secondly, the air quality in the fraction of time the blower fan operates [38] expressed by the air temperature in the blower fan, was analysed for 600 h (in line with the company’s policy). Thirdly, and aligning with the ASHRAE 215 procedure [39] of assessing air leakages in HVAC systems, the company takes record of the flow rates at different pressures with closed terminal dampers using the Shut-Off Method. This ventilation-related energy consumption is used to model the energy-saving capability of the proposed HVAC maintenance approach.

If the performance aligns with expectations, the framework can be utilised with regular reviews; otherwise, adjustments are necessary to address issues. The maintenance plan represents the prioritisation of maintenance tasks. It is a methodology that identifies component criticality, helping to determine which components should be prioritised for maintenance over others. The proposed maintenance planning framework seamlessly combines the benefits of FMEA and fuzzy TOPSIS techniques, efficiently managing inherent uncertainties in maintenance decisions. It offers a clear and understandable concept with high computational efficiency, enhancing reliability by incorporating additional criteria beyond RPN. The system is efficient because the analysis dynamically updates in response to changes in ratings. For example, if a component's rating score changes, the Risk Priority Number (RPN) will adjust accordingly based on the current status of the HVAC component. Even minor changes in the component's condition can affect the results, thereby altering the maintenance priority of each component. Moreover, the framework provides a realistic and dynamic maintenance planning tool, considering up-to-date data and ensuring continuous performance monitoring. These advantages make the proposed framework appealing to maintenance managers for implementation in solving maintenance planning challenges. Its dynamic nature lies in the fact that the results can continuously evolve as inputs change. Specifically, as the failure modes of each component adjust due to ongoing maintenance, the Risk Priority Number (RPN) also shifts, leading to variations in the maintenance ranking of the components. The direct and indirect conditioning runtimes methods showed a significant improvement of 36.77 % and 28.4 %, respectively, at the various stages of tests in the 600-h running. However, the detailed data on these tests cannot be published due to the company's internal policies. The performance of the proposed HVAC maintenance method aligns with expectations and so can be utilised with regular reviews.

5. Conclusion and recommendation

In conclusion, the goal of creating a simplified maintenance methodology for 12 specific HVAC components has been achieved. This methodology represents a significant step in improving maintenance strategies, offering a systematic and proactive approach tailored to each component's unique characteristics and criticality. The comprehensive collection of HVAC systems data has played a crucial role in ensuring that maintenance decisions are well-informed and have accurate information. The combination of Failure Mode and Effects Analysis (FMEA) has successfully identified and prioritised critical components, providing a proactive understanding of potential failure modes. Additionally, incorporating FMEA into the Fuzzy TOPSIS assessment has improved the precision of maintenance prioritisation by considering both criticality and performance criteria. Overall, this research has far-reaching implications for HVAC maintenance, presenting a refined and adaptable framework aligned with industry best practices. The framework accommodates changes in system configurations and ensures responsiveness to evolving maintenance needs.

The conclusion of this study paves the way for further exploration and highlights the necessity of proposing enhancements for future research.

a. A continuous monitoring system should be set up for HVAC data to keep the maintenance framework updated. The dataset should be regularly adjusted to reflect changes in system behaviour and component performance.
b. Basic training for staff involved in maintenance decision-making is recommended for a smooth transition to the new framework. Resources and guidance should also be provided to improve their skills in using fuzzy TOPSIS and interpreting FMEA analysis results. This recommendation suggests that if all maintenance staff are trained to interpret the analysis, equipment breakdowns will be minimised, as they will be able to maintain components based on their condition and maintenance prioritisation
c. Expand research efforts to apply the maintenance framework in various industries or with different HVAC system complexities. This will enhance understanding of its versatility.

The authors acknowledge that data inaccuracies can affect reliability. However, as pointed out by Ref. [21], the fuzzy approach was adopted to minimise the effect of impressions and inaccuracies associated with the expert's evaluation, thereby enhancing the decision-making process. Additionally, more experts can be involved in the assessments to further reduce biases. The model allows for iterative refinement as more accurate data becomes available. These strategies will help ensure the methodology remains effective under varying data quality conditions.

CRediT authorship contribution statement

Uzoma G. Okoro: Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Abdullahi Mubaraq:** Writing – original draft, Software, Methodology, Investigation, Conceptualization. **Ezutah Udoncy Olugu:** Writing – review & editing, Validation, Supervision, Software, Methodology, Investigation, Formal analysis. **Sunday A. Lawal:** Writing – review & editing, Supervision, Software. **Kuan Yew Wong:** Writing – review & editing, Conceptualization, Methodology, Investigation, Formal analysis, Supervision.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Sci Space to find relevant literature. After using this tool/service, the author (s) reviewed and edited the content as needed and took (s) full responsibility for the content of the published article.

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Data availability

Data will be made available on request.

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