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CIRCULAR ECONOMY APPROACH FOR HVAC MAINTENANCE

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Abstract

The maintenance processes plays a crucial role in assuring sustainable energy supply in the air conditioning system which should be managed for the optimization of expenses includes the consumption of material and labour involved. In this study, the maintenance activity is planned for the machine in such a manner that the criticality level is maintained at higher stage . In the initial stage, the criteria for evaluation which is designed by key people in that area is checked by the AHP. To estimate the criticality levels of the machine MTBF is evaluated,. The planning activity for executing maintenance is done during MTBF.For evaluating the maintenance activity ANN model is developed. The activities that are necessary in the maintenance area are planned to be completed before onset of any breakdowns so that economic life of equipment can be extended.

Keywords: ANN,AHP,MTBF,

1. Introduction

The Circular Economy promotes a model which is economic in nature in which manufacturing and utilization systems are organized in a structured way, emphasizing competitiveness and innovation. This concept goes beyond simple waste management and recycling, focusing instead on the efficient use and optimization of all available resources. Maintenance activities such as **repair**, **reuse**, **maintenance**, and **life extension** play an important role in achieving the goals of the Circular Economy. The application of maintenance techniques like **Condition-Based Maintenance)**, in support of **Total Productive Maintenance** and **Reliability-Centered Maintenance** strategies, along with

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predictive analytics, helps increase system availability and prevent failures with significant consequences.

In today's competitive landscape, organizations must improve their economic performance to sustain their operations and implement plans that reduce the total costs associated with these activities. Within the scope of the Circular Economy, it is crucial that all machinery, in production facilities should work without any failure reliably, consistently, and with high quality, fulfilling their intended functions without delays or interruptions.

Optimizing maintenance expenses in accordance with operational conditions is essential, as these costs can represent **15% to 70% of total production expenses**, depending on the type of operation (Wang, Z. and Srinivasan, R.S. [1]).. A key focus should be placed on **monitoring, inspection, and follow-up processes**, using performance metrics such as **MTBF**, **Failure Stop Rate**, and **Fault Repair Time** to evaluate and improve maintenance effectiveness.

The influence of machine on sustainable energy consumption—particularly in air conditioning systems—can be evaluated based on the **criticality level** or **risk level** of the equipment. **Prioritizing maintenance activities** according to these criticality levels helps ensure that air conditioning systems stay aligned with **sustainable energy consumption goals**. The main objective of execution of maintenance activities is to prolong **the duration of healthy condition in the equipment operation**. This can be achieved most effectively and **cost-efficiently** by performing maintenance **before potential failures occur**. Furthermore, **maintenance performance indicators** contribute to the improvement of **environmentally friendly electricity generation**.

Initially, the criteria influencing the problematic stage of HVAC machines are **weighted using AHP**. These weights are then utilized in the **TOPSIS algorithm** to determine the harmful **levels** of each piece of machine in relation to **energy supply which is in accordance to sustainable condition**. This methodology supports improved **efficiency**,

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prolongs the economic lifespan of air conditioning systems, **reduces operational costs**, and **maximizes system availability**.

Study Motivation: HVAC systems are a primary focus in implementing **circular economy strategies**, as they contribute significantly to **reducing overall energy consumption**.

Study Objective: This paper aims to evaluate the effectiveness of **artificial intelligence-driven maintenance techniques which are predictive in nature** in HVAC systems, with a particular focus on **minimizing machine non working time**.

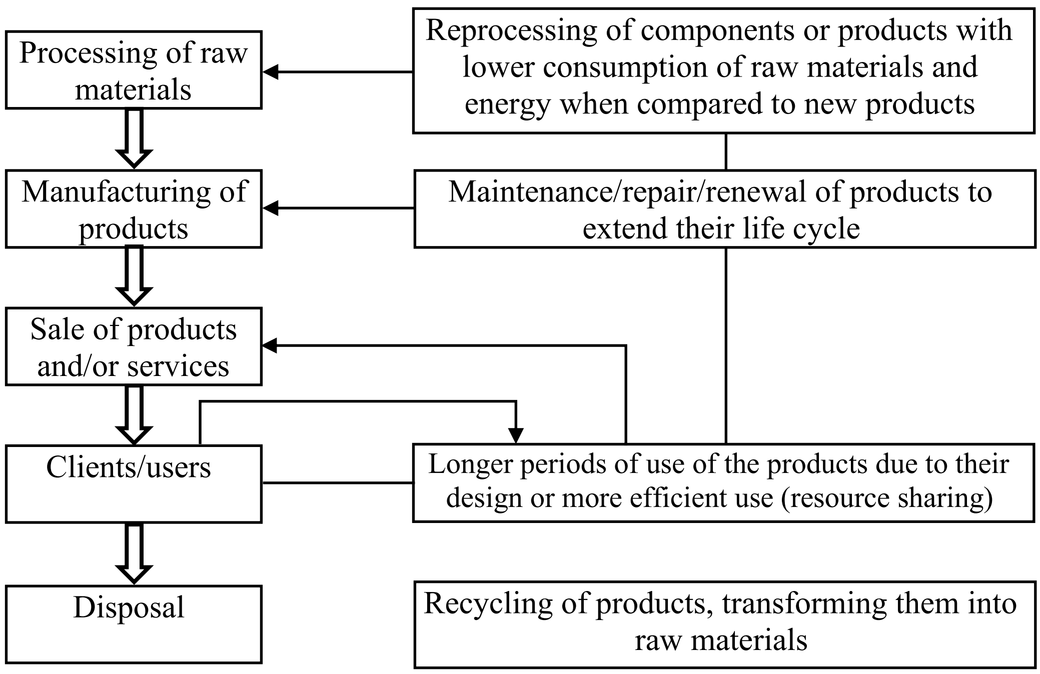

Fig. 1: Potential economic gains of the circular economy

2. Literature Review

MCDM is an effective approach for improving decision-making in situations where multiple, often conflicting qualitative and quantitative criteria must be considered simultaneously (Hwang, C.-L., & Yoon, K. [2]). The ability of MCDM to integrate diverse types of parameters makes it a practical and robust evaluation tool for complex problems.

Due to its versatility, a variety methods—like the **AHP**, **ANP**, **TOPSIS**, **ELECTRE**, **PROMETHEE**, and **VIKOR**—have been widely applied across domains including **site selection, project evaluation, personnel recruitment, supply chain management, strategic planning**, and **healthcare**. Decision-making in energy systems, including air conditioning, also inherently involves multiple criteria, making MCDM especially relevant.

Research by Zyoud and Fuchs-Hanusch [3] showed that integrating **AHP and TOPSIS** yields more accurate and reliable results than using either method individually. In this study, AHP is used initially to reduce subjectivity, ensure ease of implementation, and provide flexibility for integration with other numerical approaches such as linear programming. **TOPSIS** is employed afterward for its straightforward and effective method of ranking alternatives based on proximity to an ideal solution.

Furthermore, **Artificial Neural Networks (ANNs)** have become prominent among AI tools such as **fuzzy logic** and **genetic algorithms**, particularly in applications involving **diagnostics and energy forecasting** (Al-Shayea Q.K. [4]; Kalogirou S.A. [5]). Yohannes et al. [6] proposed a evaluation framework which is having multi-criteria in nature to defend arrive at a conclusion by combining environmental, economic, social, legal, technical, and business criteria—while incorporating circular economy (CE) indicators. This framework can also be adapted for component-level analysis in various industries.

Authors Kirchherr, J., and Rizos, V. [7,8] emphasized the importance of recognizing the **barriers and challenges** that organizations encounter in implementing circular economy models. Kristensen, H.S., and Mosgaard, M.A. [9] highlighted the urgent need for **decision-support tools, performance metrics**, and **methodologies** to facilitate the adoption of circular strategies across industries. In today's highly dynamic and competitive market, industries must constantly evolve and respond to change to maintain their competitive edge.

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As noted by Mounia Achouch et al. [10], companies must adopt continuous improvement practices to remain responsive, increase both production volume and quality, meet customer expectations, and reduce production costs. **Artificial Neural Networks** are particularly advantageous in these contexts due to their ability to detect **complex, relation existing between** input and output parameters which is nonlinear in nature., without necessitating complete information about system in advance. Le, X.H. [11].

A study by Mohammed Alkahtani et al. [12] investigated the **reverse logistics** process involved in remanufacturing used window air conditioners (ACs) under uncertain demand and production conditions. The system includes **collection, remanufacturing, recycling, supplier coordination**, and **distribution**, with each function operating independently while pursuing its own objectives. With input from both industry and academia, a **simulation model** was designed to maximize inventory which is average and reduce unmet demand—significantly improving collection system efficiency.

Effective maintenance is essential for reliable operations. However, as H. Kamel [13] pointed out, in today's competitive environment, maintenance activities must be **optimized and condition-based**, ensuring that they are performed only when necessary to avoid unnecessary costs and resource waste—aligned with **predictive maintenance** and **Industry 4.0 principles**.

Finally, Numfor et al. [14] described how **end-of-life vehicles** are disassembled into key components such as engines, transmissions, and chassis through manual or automated methods. These components are then sorted by material type—such as metals and plastics using methods such as shredding and melting for reuse.

Altaf Hossain Mollaa [15] has developed to enhance the management extension of life which is termed as End of life (ELV) in the transportation and related sectors. He addressed gaps in current practices and also in the quality assessment systems, with an objective to guarantee the qualitative aspects , safety aspects and sustainability related issues of recycled products.

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Product recovery at the EOL phase is increasingly recognized as a promising strategy to enhance economic value while minimizing environmental impact. Yicong Gao [16] introduced a MCDM approach to manage uncertainties in EOL product recovery processes.

Mallika Kliangkhlao et al. [17] developed a causal machine learning model for the early-stage failure detection of HVAC systems. The model captures system behavior by analyzing random variables influenced by indoor ambiance, outdoor environment, and HVAC operational patterns, with a particular emphasis on air conditioning units.

Hamza et al. [18] proposed an integrated decision-making framework combining two s—Best-Worst Method and TOPSIS—to estimate and rank HVAC systems for optimal selection in designing sustainable office buildings.

Artificial Neural Networks (ANNs) have demonstrated high efficacy in solving complex problems, particularly those with sufficient available data (White, H. [19]). ANN models are notably effective in energy forecasting, a domain often characterized by complexity (Wang and Srinivasan [1]). ANNs also support process automation by reducing reliance on human intervention in tasks such as maintenance planning, aligning with circular economy principles in the energy sector.

ANN models can incorporate both environmental variables (e.g., external temperature, solar radiation) and internal condition data (e.g., equipment temperature at different operational intervals). This enables early fault detection and supports quantitative risk assessment. For instance, Schlechtingen and Santos [20] utilized SCADA data for offshore wind turbine maintenance planning using ANN and ANFIS approaches. Their work exemplifies how fault prediction using ANN is prevalent across various sectors.

Braglia et al. [21] introduced a multivariate statistical method for classifying mechanical components based on Mean Time Between Failures (MTBF). Their approach identifies variations in MTBF linked to differing operational parameters. Similarly, Liu et al. [22]

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applied MTBF for assessing CNC grinder reliability, while Yang et al. [23] focused on failure repair time as a key maintenance parameter.

Key insights include:

Various AI methods are used in maintenance planning, with MTBF being a foundational parameter for early fault detection.

The incorporation of AHP enhances analytical rigor in the evaluation process, distinguishing this study and contributing meaningfully to the literature.

Identified Literature Gaps:

Future research should apply the proposed evaluation methodology to a broader range of products, services, and industrial sectors

Another opportunity lies in extending the framework to include the **pre-use and use phases**, focusing on production-related energy efficiency measures.

Currently, few evaluation methods assess circularity strategies at the **product level**, a gap noted by Saidani et al. [24].

To address HVAC failures, particularly those caused by mechanical components such as valves and temperature sensors, a machine learning model has been developed to forecast the residual working period of compressors. This model utilizes time-series data collected from real-time sensors. Key recommendations for further improvement include:

Training the model with new datasets to enhance prediction accuracy.

Applying Principal Component Analysis (PCA) to reduce variable dimensionality.

Deploying the model through a web-based platform for real-time compressor failure prediction.

However, incorporating damper behavior into the causal model remains a significant challenge, as noted by Mallika Kliangkhlao [17], and is recommended for future investigation.

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3. Methods

3.1 Importance of Maintenance

Maintenance is essential to ensure that assets operate near their original condition and fulfill their intended function.

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3.2 ANN application in predictive maintenance

Multi-Layer Perceptrons (MLP) is applied to for diagnosing the faults in bearings, induction motors,. A non-destructive estimation of check valve performance and its path of degradation is attempted.

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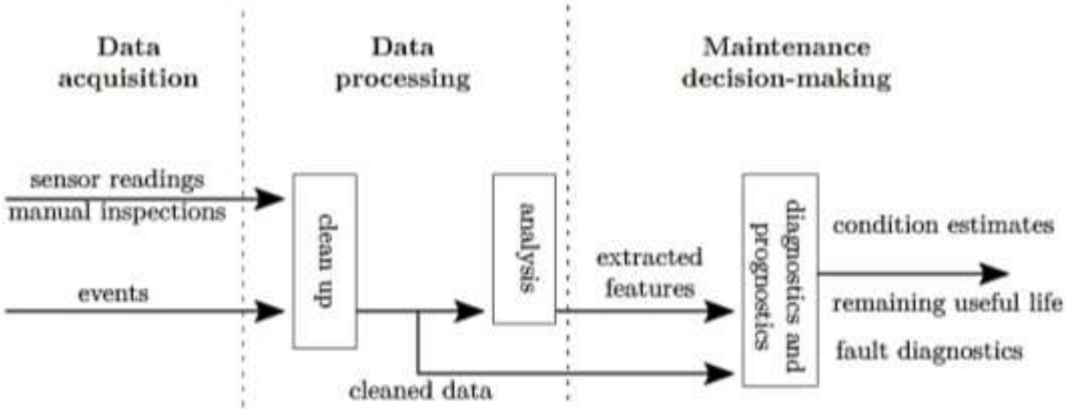

Fig. 4: Maintenance activities as defined in EN 13306

4. Methodology

4.1 Data collection

a) Sources of data

Data acquisition is going to be the most important step in implementing AI-based predictive maintenance. In HVAC systems, data is collected from various components, including sensors, devices, maintenance logs, and operational records. Typical parameters include temperature, humidity, vibration, and airflow rates, among others. This data is gathered continuously and stored in the company's database, often in the form of logbooks, for future analysis and use.

b) Data preprocessing

In this study, data pre processing involved cleaning and formatting the raw data to make it suitable for analysis. This step addressed common issues such as missing values,

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outliers, normalization, and feature extraction. For instance, sensor data containing noise had to be filtered, while categorical information from maintenance logs required encoding to be properly interpreted by analytical models

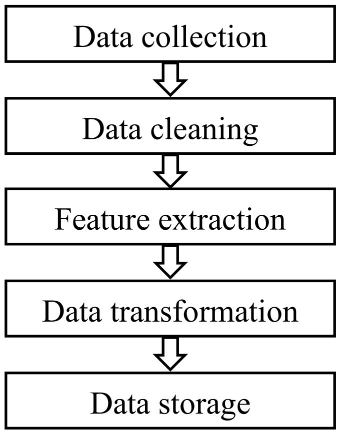

Fig. 6: Data preprocessing workflow

4.2 AI and ML models adopted

The data acquired is to be applied in the flow chart shown below.

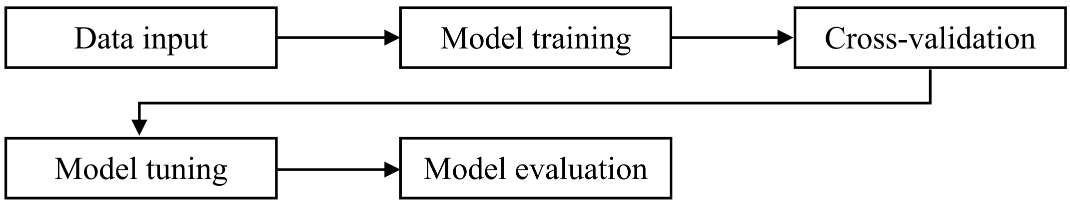

Fig. 7: Model training process

4.3 Incorporation of predictive maintenance activities to be used

a) Application of predictive maintenance activities *with HVAC systems*

The existing HVAC related equipment will be adapted to incorporate trained predictive maintenance models. This adaptation includes establishing real-time data flow from the exisisting from system meters into the **predictive maintenance** models, allowing for continuous monitoring and automated maintenance recommendations based on sensor input.

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The diagram below illustrates a Predictive Maintenance System infrastructure specifically planned for HVAC systems. This infrastructure combines observing activities occurring in real time while the artificial intelligence is able to monitor to deliver timely and efficient maintenance. At the core are the HVAC components—heating, ventilation, and air conditioning—which continuously generate operational data through sensors monitoring parameters such as temperature, pressure, and vibration.

This data acquired through the sensors flows into the **Data Pipeline**, which consists of multiple stages of analysis. The **Data Collection** module gathers real-time data, followed by **Data Preprocessing**, where the raw data—often noisy or incomplete—is cleaned, filtered, and transformed to ensure high-quality inputs for analysis.

Next, the refined data is processed by the **Predictive Maintenance Engine**, where a **Trained AI Model** analyzes it for early signs of system failure. These models, built on historical datasets, are capable of identifying patterns that indicate potential breakdowns. The **Predictive Analytics** component then enables proactive scheduling of maintenance tasks before a critical failure occurs, significantly reducing emergency repairs.

Maintenance recommendations are generated and relayed to technicians, while real-time alerts notify teams of urgent issues. These insights are also displayed on a centralized **dashboard**, providing a comprehensive view of the system's health and actionable guidance.Additionally, the AI engine is based on a **neural network model** comprising inputs, weights, an aggregation function, an activation function, and an output. Inputs consist of numerical values from sensors or preceding neurons. Weights determine the influence of each input. The aggregation function combines inputs into a net signal, which is then processed by a non-linear **activation function** to produce the final output—representing the AI's decision structure.

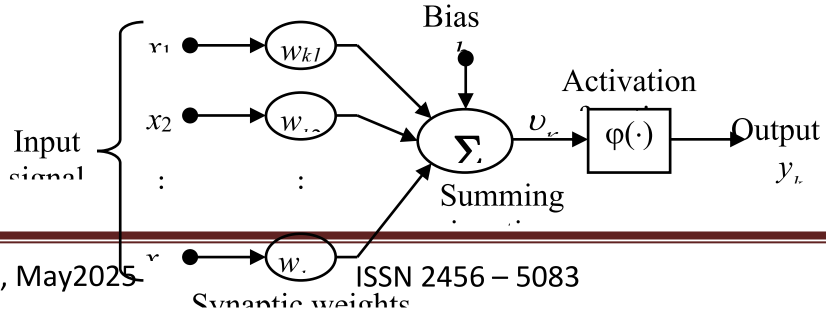

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Fig. 8: A simple ANN structure

b) Monitoring and alerts

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Table-4: Example of alarms given by predictive maintenance system

Machine element	The issue which is detected	Non working time estimated	Remedy advocated
Compressor	Any anomaly in Vibration	24 hours	Replacement
Air filter	Reduction in Airflow	15 days	Either Cleaning or replacement
Heat exchanger	A rise in Temperature	12hours	Identification of any blockage

4.4 Key performance indicators considered

MTBF ,MTTR and Energy Efficiency Improvement are taken as performance indicators

a) Flow chart:

The model is detailed in figure:

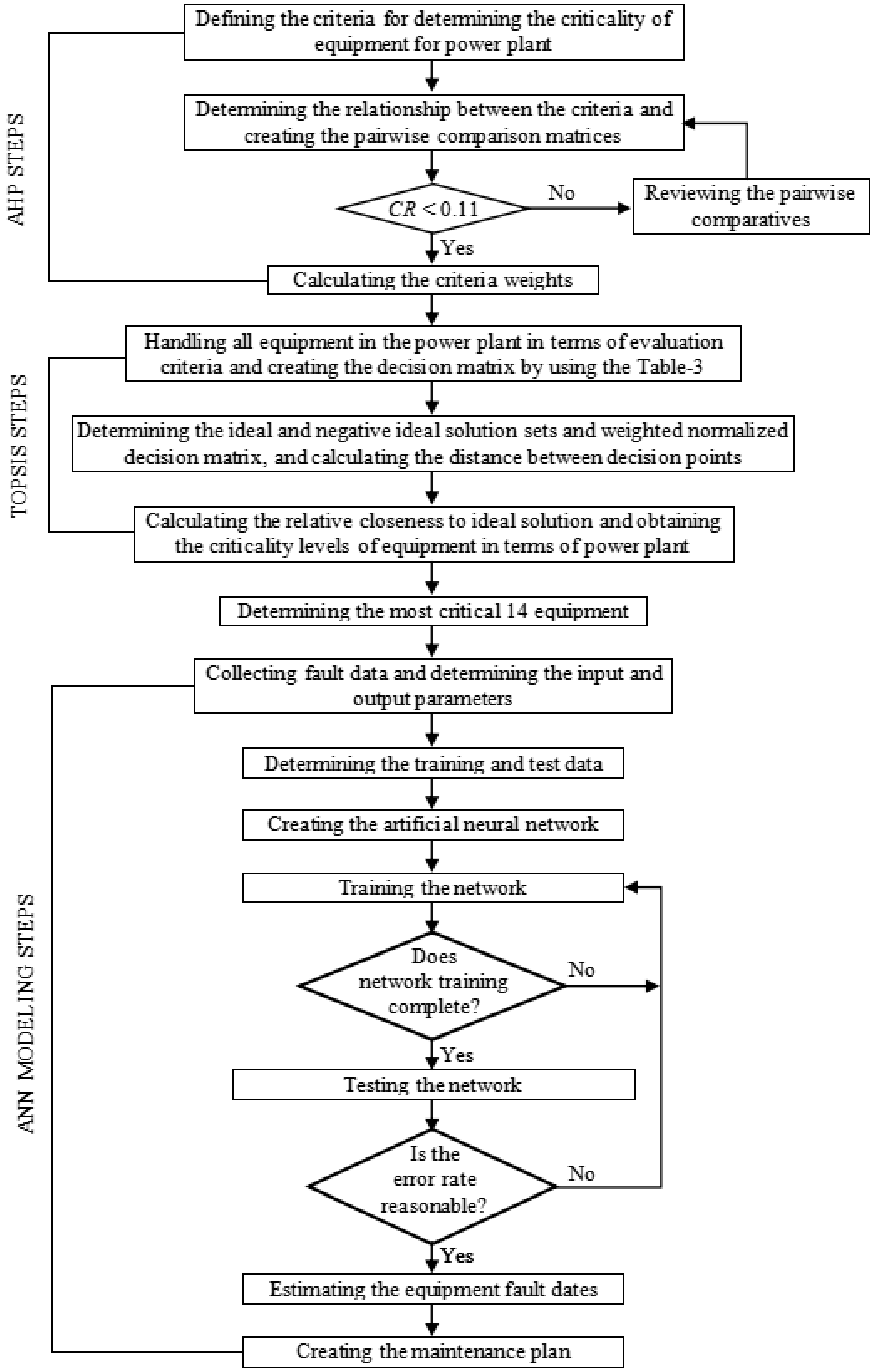
AHP STEPS
Defining the criteria for determining the criticality of equipment for power plant
Determining the relationship between the criteria and creating the pairwise comparison matrices
CR < 0.11
No
Reviewing the pairwise comparatives
Yes
Calculating the criteria weights
TOPSIS STEPS
Handling all equipment in the power plant in terms of evaluation criteria and creating the decision matrix by using the Table-3
Determining the ideal and negative ideal solution sets and weighted normalized decision matrix, and calculating the distance between decision points
Calculating the relative closeness to ideal solution and obtaining the criticality levels of equipment in terms of power plant
Determining the most critical 14 equipment
ANN MODELING STEPS
Collecting fault data and determining the input and output parameters
Determining the training and test data
Creating the artificial neural network
Training the network
Does network training complete?
No
Yes
Testing the network
Is the error rate reasonable?
No
Yes
Estimating the equipment fault dates
Creating the maintenance plan

Fig. 9: Flow chart

4.5 Implementation Details

a) Data Integration

Sensor Data Collection: The system continuously receives data from multiple sensors that monitor parameters like temperature, humidity, vibration, and energy consumption. This data which is related to activities of real-time is grasped for the predictive maintenance model.

Data Preprocessing: Before analysis, raw data undergoes cleaning procedures such as filtering and normalization to enhance its quality and ensure consistency. This step improves the model's performance by eliminating noise and formatting discrepancies.

Predictive Model Analysis: Once preprocessed, the data is fed into a predictive model powered by machine learning algorithms. The model identifies patterns or anomalies that suggest early signs of system degradation or potential failure.

Maintenance Decision Output: Based on the predictive analysis, the system generates actionable maintenance alerts. These alerts specify which component is at the brink of failure , and the kind of failure to be happen, and a corrective maintenance related action to be undertaken.

Job Initiated: The generated alarms are sent to the maintenance team, who then carry out the suggested actions. This proactive approach reduces the equipment downtime and improves overall system performance.

b) Anomaly Detection and Predictive Alerts

The predictive maintenance system continuously monitors operational parameters and compares them against baseline values. When deviations are detected, the model flags potential issues:

For instance, a sudden rise in temperature in an air conditioning unit may indicate a blocked airflow or malfunctioning cooling coil.

Unusual vibration levels could signify bearing wear in a chiller, potentially leading to failure if left unattended.

c) Maintenance Execution

Upon receiving predictive alerts, the maintenance team follows a structured process to address the identified issues. The AI model recommends only the most valuable actions, ensuring that maintenance efforts are timely and effective.

Proactive Repairs: For example, lubricating chiller bearings before they fail avoids unscheduled downtime and eliminates the need for emergency repairs.

Cost Efficiency: Addressing problems proactively during scheduled maintenance significantly reduces repair costs and extends equipment life.

4.6 AHP-TOPSIS Combination

To identify and prioritize the most critical equipment affecting HVAC system reliability, a combined AHP-TOPSIS approach is applied:

First, critical equipment groups—those whose failure would lead to a shutdown or significant degradation of HVAC performance—are identified using AHP (Analytic Hierarchy Process) and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution).

Based on this prioritization, an **Artificial Neural Network (ANN)** model is proposed for predictive maintenance planning of the most critical equipment. Maintenance actions are scheduled in advance of predicted failure dates, reducing downtime and enhancing operational continuity.

The overall implementation process is illustrated in **Figure 3**.

The TOPSIS methodology involves the following steps:

Evaluation Criteria Definition: The relevant criteria affecting the criticality of each equipment group are defined based on expert input and operational experience (as outlined in Table 3).

Scoring Equipment: Each piece of equipment is assigned a qualitative score for each criterion, based on parameters listed in Table 2. These scores are then translated into numerical values (on a scale from 0 to 10) for use in the TOPSIS analysis

The highest score (10) is given to criteria with a direct and critical impact on system performance (e.g., complete unit shutdown). Other parameters are scored relative to this benchmark, taking into account their influence on system reliability and energy generation.

This structured decision-making framework ensures that maintenance planning is both data-driven and aligned with system priorities.

Table-5: Criteria need for estimation

Nature of Job	Job related activities	Representation of activities in numerical form
Cl spares backup	Never	3
	occasionally	2
	every time	1
C2 Maintenance pre-conditions	Non working condition	7
	Stopped by instruction	6
	Periodic shutdown	5

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Nature of Job	Job related activities	Representation of activities in numerical form
	Maintenance with zero option	2
	Activity executed in non stop condition	1
C3 Additional work requirement	needed	5
	Not required	1
C4 Failure period	Month wise	8
	Every quarter	5
	Every six months	3
	Yearly once	2
	Long term	1
	Unknown	1
C5 Possible results	Unit non working condition	10
	Disruption in urgent situation	9
	Drop in load	8
	Running without back up	7
	Equipment stopped on instruction	6
	Security issue	6
	Deficient issue	2
	Damage noticed on equipment	2
	Problem noticed	1
	Increase in liquid use	1
C6 Readiness of measuring equipment	Equipment is in working condition	3
	Equipment is not in working condition	1
C7 Static, dynamic or electrical property of equipment	Dynamic spare issue	2
	Static spare issue	1
	Electrical	1
	I&C	1
C8 Fault occurring time	Weekly once	9
	Exceeding 24 hours	3
	Unknown	3
	2-6 hours	2
	Less than 2 hours	1
C9 Capacity to detect failure	With great pain	3
	Easily traceble	1

The action which indicate separation are estimated for every machine using Eq. (5) and Eq. (6).Ultimately, machine levels which indicate priority (C_i^*), every equipment is estimated by using Eq. (7)

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The levels of priority of the machine is estimated using TOPSIS. Its value in case of the most crucial machine in terms of air conditioning is 0.837 C_i^* . The estimation criteria weights are evaluated with AHP in case of airconditioning. The value of CR according to AHP process is found to be as 0.051. which indicates the matrix used is satisfactory. The Criteria weights are presented in Table -6

Table-6: The weights of Criteria

Criteria		Weights
C1	spares abundant	0.051
C2	conditions before execution of maintenance acitivity	0.241
C3	requirement of extra work	0.029
C4	period in failed condition	0.071
C5	Possible scenario"s	0.400
C6	Presence of measuring equipment	0.062
C7	Dual mechanical or electrical parameter' of equipment	0.055
C8	Fault sorting time	0.029
C9	Ability to trace failure	0.062

Table-7: Scores

Rank	Equipment	Score
1	Compressor	80
2	Fan	75
3	Refrigerant	100
4	Pump	98
5	Butterfly valve	98
6	Power transformer	97.5
7	Tripping system	97.5
8	Compressed oil tank	96.9
9	Cooling water structure	96.9
10	Valves	96.8
11	Relay	96.7
12	Excitation transformer	96.7
13	Pump	95.9

The score which is above 95 is considered as good.

ANN

The application data which is numerical in nature in the ANN models has a positive impact on the network,

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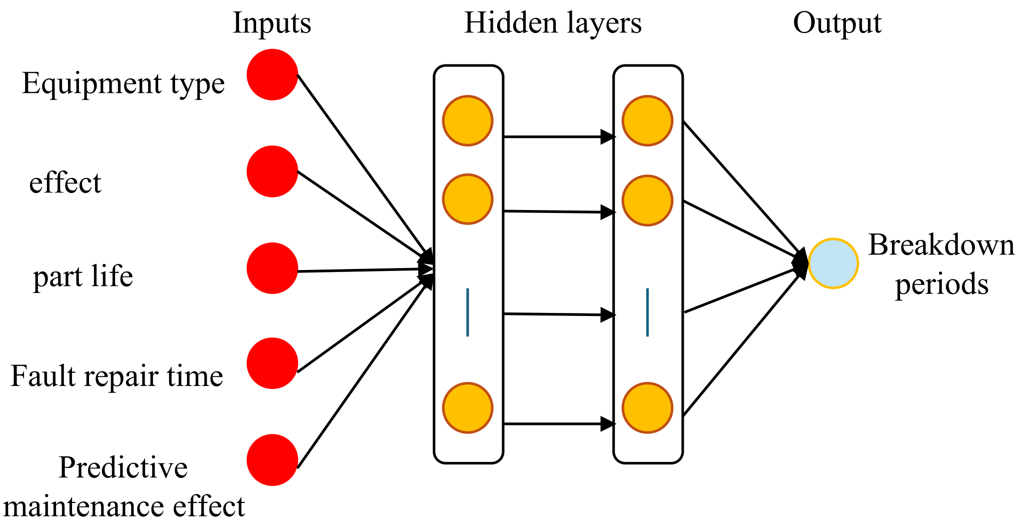

Fig. 10: ANN chart

Fig. 10 shows the ANN network with purelin and tansig functions are used as transfer functions respectively, and learngdm is used as a learning function. Levenberg- Marquardt algorithm is applied in the training of the network. The number of neurons in the hidden layers are 20 and 10. respectively. The other parameters of net work are Epoch = 1000", "performance goal = 0", "learning rate = 0.01", "momentum constant = 0.9" and "maximum validation failures = 6" were taken as stopping criteria.

Table-8: Fault period

Sno	Component used	Non working period (minutes)
1	Compressor	1,056
2	Fan	1,055
3	Refrigerant	753
4	Pump	750
5	Butterfly valve	201
6	Power transformer	1,091
7	Tripping system	751
8	Compressed oil tank	357
9	Cooling water structure	366
10	Valves	1,557
11	Relay	1,461
12	Excitation transformer	762
13	Pump	362

14	Thermos stat	730

The Mean Absolute Percentage Error and R^2 values are found as 0.03 and 0.92

5. Results and Conclusions

a) The increase in the Performance;

The application of the model has witnessed many differences which are positive in nature in the HVAC system's performance. The prominent performance Indicators are as following

MTBF: Its value is increased 200% and hence the system condition is precarious if monitoring is reduced.

- MTTR: The time taken to repair the system also reduced which indicated speedy implementation of maintenance practices.
- Energy Efficiency: Driving energy efficiency is also increased by 2% which led to drop in the operation costs..
- System Downtime: The system non operatable hours also reduced drastically in a month which made the building working constant operating conditions.

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Table-9: Variation of key parameters before and after application of new model

parameter	Prior to application	Results after application	Enhancement (%)
MTBF	250 hours	350 hours	60%
MTTR	6 hours	5hours	16%
Efficiency of Energy used	88%	90%	2%
Non operating time of System	15 hours / month	14hours / month	6%

b) Effectiveness of ANN

Table-10: The opinion of user on New improved system

parameter	Rating (1-5)	Opinion of user
System alertness with user	4.6	Timely and efficient alerts received
Ability to operate	4.1	System is operatable at ease
Implementable changes	4.5	Repairs are with clarity and clear
Dependability of system	4.5	Less false positive, dependable alerts

c) The capacity to forecast the Failure

It is presented in the Table-11 below

Table-11: New model performance indicators

Metric	Value
Precision	0.91
Recall	0.85
F1 score	0.83

f) New model and old model variation

Integration with legacy systems is an aspect studied and implemented in a reasonable period.

HVAC systems are essential for ensuring a sustainable energy supply and are built on principles of continuity, reliability, efficiency, cost-effectiveness, and environmental responsibility. Achieving these goals requires strict adherence to operational protocols set by HVAC manufacturers, along with the implementation of well-managed and systematic maintenance processes. Given the complexity of HVAC systems—comprising thousands

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of interconnected components—effective maintenance planning is crucial and forms the foundation of system management.

This integrated method represents a novel contribution to the literature, being the first to utilize these three techniques collectively to generate a maintenance schedule based on MTBF (Mean Time Between Failures) estimations in HVAC systems. Incorporation of the new integrated approach within the scope of this study has led to notable improvements, including increased operational efficiency, extended equipment lifespan, reduced maintenance and operational costs, and a higher overall system availability rate.

Table-13: Comparing the current planning with the proposed planning

	Energy consumption	**Number of**	**Average time**	**Uninterrupted**
Proposed maintenance planning	6.432.274	8.866.	146	%87
Current maintenance planning	6.429.558	8.424	162	%45

A machine learning model has been designedto estimate the residual healthy working period of machinery by leveraging algorithms trained on time-series data collected from online sensor measurements.

Future Scope of Study:

To enhance the model's performance and accuracy, the following improvements are considered:

Model Optimization: Continuously updating the model with new data to refine its predictive capability.

Dimensionality Reduction: Applying Principal Component Analysis to reduce the number of input variables, thereby simplifying the model and improving computational efficiency.

References

1. Wang Z, Srinivasan RS. A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models. Renewable and Sustainable Energy Reviews 2017
2. Hwang C-L, Yoon K. Methods for multiple attribute decision making. Multiple Attribute Decision Making 1981: 58-191, https://doi. org/10.1007/978-3-642-483189_3.
3. Zyoud SH, Fuchs-Hanusch D. A bibliometric-based survey on AHP and TOPSIS techniques. Expert Systems with Applications 2017; 78:158-181, https://doi.org/10.1016/j.eswa.2017.02.016.
4. Al-Shayea QK. Artificial neural networks in medical diagnosis. International Journal of Computer Science Issues 2011; 8: 150-154.
5. Kalogirou SA. Artificial neural networks in renewable energy systems applications: a review. Renewable and Sustainable Energy Reviews 2001; 5: 373-401, https://doi.org/10.1016/S1364-0321(01)00006-5.
6. Yohannes A. Alamerew, Marianna Lena Kambanou, Tomohiko Sakao and Daniel Brissaud, A Multi-Criteria Evaluation Method of Product-Level Circularity Strategies, Sustainability 2020, 12, 5129; doi:10.3390/su12125129, www.mdpi.com/journal/sustainability.
7. Kirchherr, J.; Piscicelli, L.; Bour, R.; Kostense-Smit, E.; Muller, J.; Huibrechtse-Truijens, A.; Hekkert, M. Barriers to the circular economy: Evidence from the European Union (EU). Ecol. Econ. 2018, 150, 264–272. [CrossRef]
8. Rizos, V.; Behrens, A.; van der Gaast, W.; Hofman, E.; Ioannou, A.; Kafyeke, T.; Flamos, A.; Rinaldi, R.; Papadelis, S.; Hirschnitz-Garbers, M.; Implementation of circular economy business models by small and medium-sized enterprises (SMEs): Barriers and enablers. Sustainability 2016, 8, 1212. [CrossRef]
9. Kristensen, H.S.; Mosgaard, M.A. A review of micro level indicators for a circular economy—Moving away from the three dimensions of sustainability? J. Clean. Prod. 2020, 243, 118531. [CrossRef]
10. Mounia Achouch, Mariya Dimitrova, Rizck Dhouib, Hussein Ibrahim, Mehdi Adda, Sasan Sattarpanah Karganroudi, Khaled Ziane and Ahmad Aminzadeh, Predictive Maintenance and Fault Monitoring Enabled by Machine Learning: Experimental Analysis of a TA-48 Multistage Centrifugal Plant Compressor, *Appl. Sci.* 2023, *13*(3), 1790; https://doi.org/10.3390/app13031790.
11. Le, X.H.; Ho, H.V.; Lee, G.; Jung, S. Application of Long Short-Term Memory (LSTM) Neural Network for Flood Forecasting', *Water* 2019, *11*, 1387. https://doi.org/10.3390/w11071387.
12. Mohammed Alkahtani, Bashir Salah, Aiman Ziout, and Moath Alatefi, Collection System of Air Conditioners Remanufacturing: Development and Optimization under Probabilistic Uncertainty, Mathematical Problems in Engineering, Vol. 2022, Article ID 3428247 2022.

13. H. Kamel, Artificial intelligence for predictive maintenance Journal of Physics: Conference Series (2022)
14. Numfor, S. A., Takahashi, Y., & Matsubae, K. (2022). Energy recovery from end-of-life vehicle recycling in Cameroon: A system dynamics approach. *Journal of Cleaner Production*, *361*, 132090. https://doi.org/10.1016/J.JCLEPRO.2022.132090
15. Altaf Hossain Mollaa, Saeed H. Moghtaderia, Zambri Haruna, Alias Jedia,b and Nallapaneni Manoj Kumarc Insights into end-of-life vehicle recycling and its quality assessment systems in Malaysia reveals the need for a new stakeholder-centric approach for vehicle waste management, Production & Manufacturing Research 2023, VOL. 11, NO. 1, 2236676 https://doi.org/10.1080/21693277.2023.2236676
16. Yicong Gao, Yixiong Feng, Qirui Wang, Hao Zheng, Jianrong Tan A multi-objective decision making approach for dealing with uncertainty in EOL product recovery Journal of Cleaner Production Journal of Cleaner Production 204 (2018) 712-725
17. Mallika Kliangkhlao, Kanjana Haruehansapong, Kirttayoth Yeranee and Bukhoree Sahoh Causal Artificial Intelligence–Driven Approach for HVAC Preventive Maintenance Explanation ieee access 2024 *DOI 10.1109/ACCESS.2024.345241*
18. Hamza, M.; Bafail, O.; Alidrisi, H. HVAC Systems Evaluation and Selection for Sustainable Office Buildings: An Integrated MCDM Approach. Buildings 2023, 13, 1847. https://doi.org/10.3390/buildings13071847
19. White H., Learning in artificial neural networks: A statistical perspective. Neural Computation 1989; 1: 425-464, https://doi.org/10.1162/ neco.1989.1.4.425.
20. Schlechtingen M, Santos IF. Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 2: Application examples. Applied Soft Computing 2014; 14: 447-460, https://doi.org/10.1016/j.asoc.2013.09.016.
21. Braglia M, Carmignani G. Frosolini M, Zammori F. Data classification and MTBF prediction with a multivariate analysis approach. Reliability Engineering & System Safety 2012; 97: 27-35. https://doi.Org/10.1016/j.ress.2011.09.010.
22. Liu Y, Fan J, Li Y. One system reliability assessment method for CNC grynder. Eksploatacja i Niezawodnosc - Maintenancen and Reliability 2014; 16(1): 97-104.
23. Yang Y, Lu Z, Luo X, Ge Z, Qian Y. Mean failure mass and mean failure repair time: parameters linking reliability, maintainability and supportability. Eksploatacja i Niezawodnosc - Maintenance and Reliability 2014;16(2): 307-312.
24. Saidani, M.; Yannou, B.; Leroy, Y.; Cluzel, F. How to assess product performance in the circular economy? Proposed requirements for the design of a circularity measurement framework. Recycling 2017, 2, 6. [CrossRef]
25. Saaty TL. The analytic hierarchy process: planning, priority setting, resource allocation. McGraw-Hill International Book Company; 1980.