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DEVELOPMENT OF AN ENDURANCE TEST RIG FOR CABIN CONTROL VALVE IN COMMERCIAL VEHICLE SYSTEM

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ABSTRACT:
Endurance test kit aims to address the common failures in Cabin Control Valves (CCVs) used in heavy vehicles and designed to simulate 100,000 operational cycles. Key issues include difficulty in identifying failure modes such as cam splitting, wear and tear of components, and failures in the plunger assembly and challenges related to material selection and environmental controls. Through a comprehensive methodology, including a broad literature review and industry-focused research, significant progress has been made in calculating force and area requirements, designing a pneumatic circuit, developing a custom fixture and also in developing the test kit for optimal performance and reliability.
A detailed Failure Mode and Effects Analysis (FMEA) was used to identify 10 failure modes, with top three Risk Priority Number of 280, 252, 240 for pressure fluctuations, solenoid valve failure and FRL failure respectively. The Quality Function Deployment (QFD) matrix translated 8 customer needs into 9 technical requirements, with scores assigned using a 1–5 importance scale and 9–3–1 relationship weights. Post-test inspections assess wear in critical valve components. Advanced predictive techniques, including K-Nearest Neighbours (KNN) and Artificial Neural Networks (ANN), were applied to forecast potential failures. KNN performed best at K = 11, while ANN showed higher accuracy with 16 hidden neurons. The endurance test kit enables the validation of valve performance, helping reduce product failure rates and improve overall reliability in real-world applications.
Keywords
Cabin Control valve, 1,00,000 cycles, cam splitting, wear and tear, FMEA, QFD, Prediction analysis.

INTRODUCTION:
Automation has long been regarded as a pivotal factor in improving manufacturing processes, especially in sectors where precision, speed, and efficiency are essential, such as the automotive industry. The assembly of direction control valves (DCVs), particularly for pneumatic systems like cabin control valves, is one such area where automation can play a transformative role. Traditionally, many of the sub-processes involved in assembling these valves have been done manually. While this ensures a degree of flexibility, it also introduces inefficiencies, particularly in terms of time, labour, and quality control.
The pneumatic systems operates based on air pressure, which are common in hydraulic systems. In pneumatic systems, air pressure is used to actuate various components, particularly in industrial vehicles or large transportation units that rely on compressed air for multiple functions. The pneumatically operated system that relies on the coordinated use of pneumatic pressure to manage the flow of hydraulic fluid. This system integrates both pneumatics and hydraulics, leveraging the advantages of each for efficient control and power transmission.

CABIN CONTROL VALVE :

A cabin control valve is a specialized pneumatic valve used primarily in the automotive and heavy machinery sectors. It is a critical component that controls various cabin functions, such as the movement of seats, opening and closing of doors, steering adjustments, and other cabin-related pneumatic systems. Cabin control valves regulate the flow and direction of compressed air in a vehicle's cabin control system, ensuring that mechanical parts operate smoothly.

Figure 1: Cabin Control Valve

(Source www.shutterstock.com)

In vehicles like trucks, buses, and construction equipment, where air systems are commonly used for automation, the cabin control valve is integral to controlling the movement of the driver's seat, adjusting the cabin tilt, and managing air suspension systems. These valves are designed for durability, precision, and long-term reliability due to the demanding nature of their operational environment.

METHODOLOGY

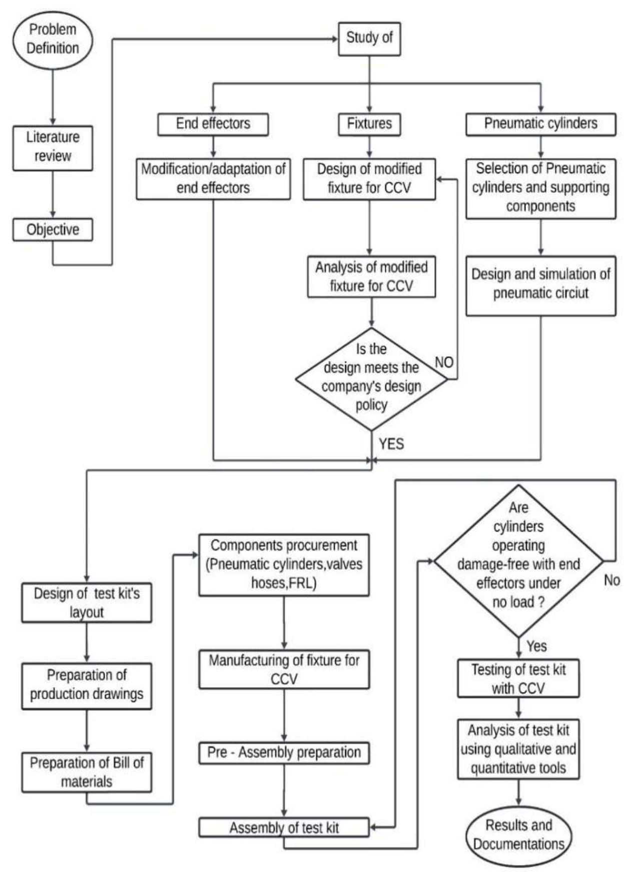


Figure 2: Methodology

PNEUMATIC CIRCUIT DESIGN :

The pneumatic circuit was designed by using Festo FluidSIM software, demonstrating the capabilities of this powerful tool in creating efficient pneumatic systems. The circuit comprises four cylinders, strategically configured to showcase various operational principles without the need for complex class based structures. This design emphasizes the flexibility and functionality of pneumatic circuits, illustrating how each cylinder can be controlled to perform specific tasks within the system.

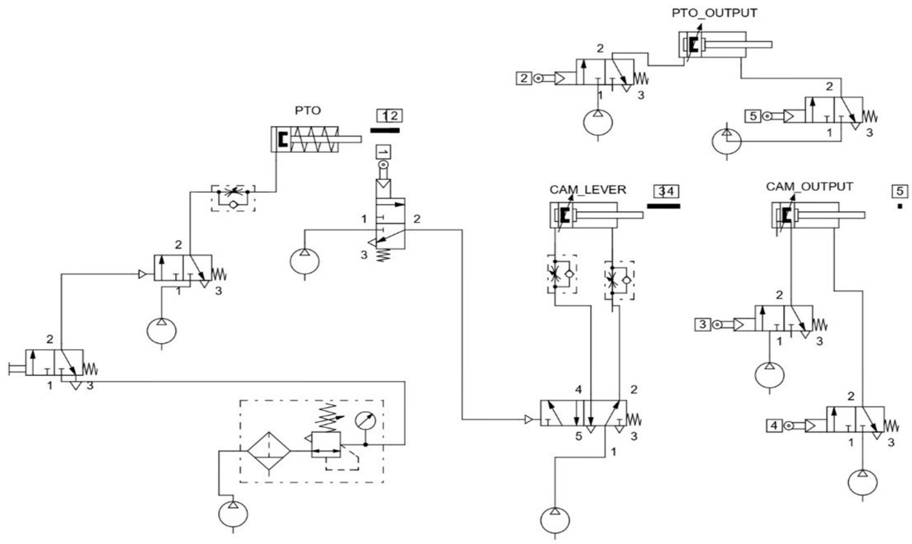


Figure 3: Pneumatic circuit design

DESIGN CALCULATIONS

To determine the force required for actuating these components, a trial and error method was employed, using a spring scale to take precise measurements. During this process, a range for force readings for actuation had been done. This method enabled us to identify the specific force necessary for optimal performance under different conditions.

Force (PTO Switch) = 50N
For (CAM lever) = 100N
Pressure = 6 Bar
Solution

PTO Switch:

Area $= \frac{\textbf{Force}}{\textbf{Pressure}}$

$83.3333 = \frac{50}{0.6}$

Area $= \boldsymbol{\pi r^2}$

$83.333 = \pi r^2$

$R_1 = 5.19$ mm

D_1 = 10.38 mm

Standard diameter = 12mm

CAM Lever

Area $= \frac{\textbf{Force}}{\textbf{Pressure}}$

$166.667 = \frac{100}{0.6}$

Area $= \boldsymbol{\pi r^2}$

$166.667 = \boldsymbol{\pi r^2}$

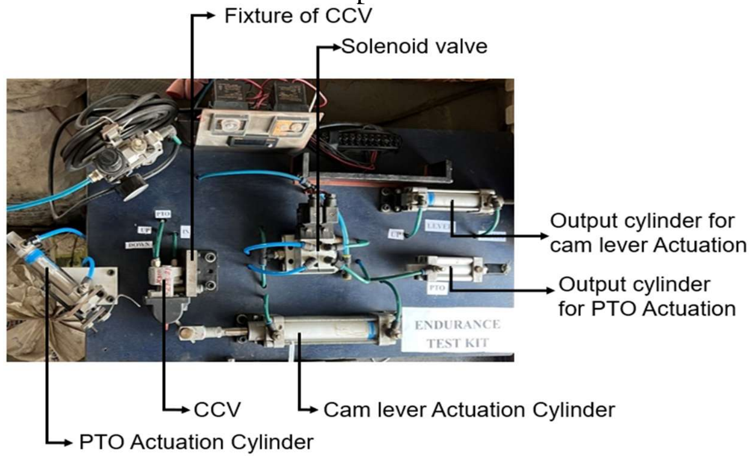
$R_2 = 7.285$ mm

D_2 = 14.57 mm

Standard diameter = 16 mm

FABRICATION OF ENDURANCE TEST RIG :

The final integration phase involves assembling all the pneumatic, electrical, and mechanical components onto the wooden base to form a complete functional endurance test kit. This step brings



together previously fabricated and prepared elements such as cylinders, solenoid valves, the test fixture, regulators, relay modules, and wiring systems. Once all components are mounted, electrical connections are established for the control system, including powering the solenoids and relay modules. The pneumatic lines are connected and checked for any leaks or pressure drops. A series of dry runs are then performed to verify the functionality of the entire system and to ensure that the CCV is actuated correctly and consistently.

Figure 4: Final test kit assembly

ANALYSIS AND INSIGHTS

FMEA

To evaluate the criticality of potential issues in the system, a Failure Mode and Effects Analysis (FMEA) was performed using RPN. In this process, 10 failure modes were identified based on system behaviour, maintenance history, and industry input. Each failure mode was then assessed using three key factors Severity (S), Occurrence (O), and Detection (D) which has a scale factor from 1 to 10.
Risk Priority Number (RPN) is a quantitative metric used in Failure Mode Effects Analysis to evaluate and prioritize potential failure modes in a system and it is calculated using

$$RPN = Severity \times Occurance \times Detection$$

Table 1: FMEA Analysis of Identified Failure Modes Based on RPN

S.No	Failure mode	Severity (S)	Occurance (O)	Detection (D)	RPN
1	Pneumatic Cylinder failure	7	6	5	210
2	Cam splitting	8	5	4	160
3	Solenoid Valve Failure	7	6	6	252
4	Fixture Misalignment	6	5	5	150
5	Extreme wear of valve body, PTO & cam	6	7	4	168
6	O-ring Fatigue	5	7	5	175
7	Improper signals from timer and counters	5	4	3	60
8	Pressure fluctuations	7	8	5	280

9	Failure of FRL	8	5	6	240
10	Leakage of air in entire rig	7	6	5	210

S.No.	**Failure mode**	**RT (S)**	**FF**	**OC**	**DTF**
1	Pneumatic Cylinder failure (seal problem)	88	0.67	2.1	124
2	Cam splitting	128	0.67	1.6	137
3	Solenoid Valve Failure	107	0.67	2.52	181
4	Fixture Misalignment	94	1.33	1.5	188
5	Extreme wear of valve body, PTO& cam	132	0.67	1.68	149
6	O-ring Fatigue	88	1.33	1.75	205
7	Improper signals from timer and counters	65	0.67	0.6	26
8	Pressure Fluctuations	97	1.33	2.8	361
9	Failure of FRL	63	0.67	2.4	101
10	Leakage of air in entire kit	136	3	2.1	857

From the table 1, it is evident that the Risk Priority Number (RPN) values vary significantly for different failure modes. These values help prioritize which failure modes require immediate attention. The top three failure modes with the highest RPN values are:

1. Pressure Fluctuations = 280
2. Solenoid Valve Failure = 252
3. Failure of FRL = 240

DOWN TIME FACTOR :

Down Time Factor (DTF) is a critical metric used to quantify the impact of equipment failures on overall system availability. It combines three key parameters: Repair Time (RT), Failure Frequency (FF), and Operational Criticality (OC).

Down Time Factor = Repair Time X Failure Frequency X Operational Criticality

Operational Criticality = $\frac{\text{RPN}}{\text{Max of RPN}}$ X 10 = $\frac{\text{RPN}}{1000}$ X 10 = $\frac{\text{RPN}}{100}$

Table 2: Calculation of Down Time Factor

RT – Repair Time in seconds; FF – Failure Frequency;
OC – Operational Criticality; DTF – Down Time Factor in sec/month

For the same 10 failure modes the Down Time Factor had been calculated using the above formulae which is shown in table 2

The top three failure modes with the highest DTF values are:

1. Leakage of air in entire kit = 857 seconds/month
2. Pressure Fluctuations = 361 seconds/month
3. O-ring Fatigue = 205 seconds/month

These failure modes are responsible for the most significant downtime and should give a corrective action.

Maintenance Priority Index:

The Maintenance Priority Index (MPI) is a metric used to prioritize maintenance activities based on both the risk associated with a failure mode and its impact on operational downtime. MPI is used to prioritize failure modes based on their risk and downtime impact and ensure that maintenance efforts focus on issues that are high.

$$\text{Maintenance Priority Index} = \frac{\text{Risk Priority Number}}{\text{Down Time Factor}}$$

For the same 10 failure modes the Maintenance Priority Index had been calculated using the above formula which is shown in table 3

Table 3: Calculation of MPI

S.No.	Failure mode	RPN	DTF	MPI
1	Pneumatic Cylinder failure (seal problem)	210	124	1.69
2	Cam splitting	160	137	1.17
3	Solenoid Valve Failure	252	181	1.39
4	Fixture Misalignment	150	188	0.80
5	Extreme wear of valve body, PTO& cam	168	149	1.13
6	O-ring Fatigue	175	205	0.85
7	Improper signals from timer and counters	60	26	2.31
8	Pressure Fluctuations	280	361	0.78
9	Failure of FRL	240	101	2.38
10	Leakage of air in entire kit	210	857	0.25

From the table 3, These values help determine which failures pose the greatest maintenance priority when considering both risk and downtime impact.

The top three failure modes with the highest MPI values are:

1. Failure of FRL = 2.38
2. Improper signals from timer and counters = 2.39
3. Pneumatic Cylinder failure (seal problem) = 1.69

These failure modes indicate a high maintenance priority and should be addressed through targeted actions such as preventive maintenance, system redesign, or improved.

Quality Function Deployment

Quality Function Deployment (QFD) is a qualitative tool used to transform voice of the customer (customer needs) into technical requirements and design specifications. It ensures that customer expectations are considered throughout the product development or service design process.

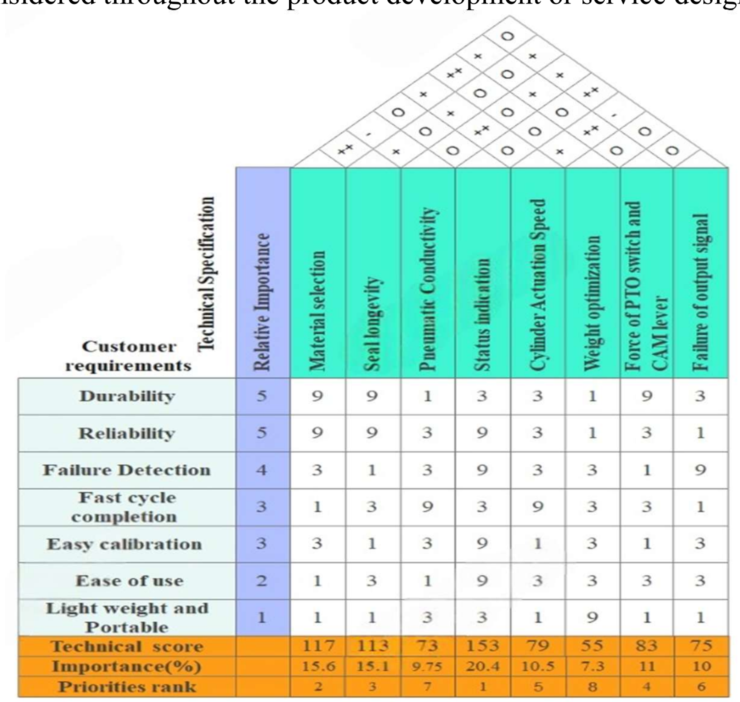


Figure 5 Matrix of QFD

CALCULATION OF PRIORITY RANK:

Technical important score:

In order to determine which technical specifications have the greatest impact on fulfilling customer requirements, a technical importance score was calculated for each specification. It is calculated using the formula ∑(Importance Rating X Relationship value).

Material selection = (5×9) + (5×9) + (4×3) + (3×1) + (3×3) + (2×1) + (1×1)
= 117

Seal Longevity = (5×9) + (5×9) + (4×1) + (3×3) + (3×1) + (2×3) + (1×1)
= 113

Status Indication = (5×3) + (5×9) + (4×9) + (3×3) + (3×9) + (2×9) + (1×3)
= 153

Pneumatic Conductivity = (5×1) + (5×3) + (4×3) + (3×9) + (3×3) + (2×1) + (1×3)
= 73

Cylinder Actuation Speed = (5×3) + (5×3) + (4×3) + (3×9) + (3×1) + (2×3) + (1×1)
= 79

Weight Optimization = (5×1) + (5×1) + (4×3) + (3×3) + (3×3) + (2×3) + (1×9)
= 55

Force of PTO switch and cam lever = (5×9) + (5×3) + (4×1) + (3×3) + (3×1) + (2×3) + (1×1)
= 83

Failure of Output Signal = (5×3) + (5×1) + (4×9) + (3×1) + (3×3) + (2×3) + (1×1)
= 75

Total importance score = 117 + 113 + 153 + 73 + 79 + 55 + 83 + 75
= 748

Priority rank of technical importance score

Table 4: Calculation of priority ranks

S.No	Technical specification	Technical importance score	Importance (%)	Priority rank
1	Material selection	117	15.6	2
2	Seal Longevity	113	15.1	3
3	Status Indication	153	20.4	1
4	Pneumatic Conductivity	73	9.75	7
5	Cylinder Actuation Speed	79	10.5	5
6	Weight Optimization	55	7.3	8
7	Force of PTO switch and cam lever	83	11	4
8	Failure of Output Signal	75	10	6

Status Indication was the top priority (score: 153, 20.4% contribution), followed by Material Selection (117) and Seal Longevity (113). Future improvements should focus on these three areas to maximize customer satisfaction and system reliability.

POST VALVE INSPECTION:

The goal is to identify wear, deformation, failure in any part of the valve due to fatigue, material weakness, or design flaws. It is carried out using digital vernier caliper. Valve is inspected every 20000 cycles for upto 100000 cycles. The inspection activities includes visual examination, dimensional inspection and functional testing. The inspection takes place in the features and components like big plunger bore, small plunger bore(up), small plunger bore (PTO), big plunger O ring, small plunger O ring(up), small plunger (PTO), cam and PTO switch.

After every 20000 test cycles, the data of wear rate from valve are measured and tabulated separately.

Table 5: Inspection of big plunger bore

Part name	**Description**	**Cycle count**					
Big plunger bore		**0**	**18869**	**41628**	**60429**	**82198**	**105268**
	Observed data	18.029	18.030	18.033	18.035	18.039	18.044
Specification = 18±0.05	**Remarks**	Ok	Ok	Ok	Ok	Ok	Ok

Note: All dimensions are in mm.

Table 6: Inspection of small plunger bore (up)

Part name	**Description**	**Cycle count**					
SMALL PLUNGER BORE(UP)		**0**	**18869**	**41628**	**60429**	**82198**	**105268**
	Observed data	8.200	8.201	8.204	8.209	8.214	8.220
Specification = 8.20±0.05	**Remarks**	Ok	Ok	Ok	Ok	Ok	Ok

Note: All dimensions are in mm.

Table 7: Inspection of small plunger bore (PTO)

Part name	**Description**	**Cycle count**					
SMALL PLUNGER BORE(PTO)		**0**	**18869**	**41628**	**60429**	**82198**	**105268**
	Observed data	8.200	8.200	8.200	8.201	8.201	8.202
Specification = 8.20±0.05	**Remarks**	Ok	Ok	Ok	Ok	Ok	Ok

Note: All dimensions are in mm.

Table 8: Inspection of big plunger O ring

Part name	**Description**	**Cycle count**					
		0	**18869**	**41628**	**60429**	**82198**	**105268**

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BIG PLUNGER O RING	**Observed data**	18.27	18.26	18.24	18.23	18.22	18.20
	Remarks	Ok	Ok	Ok	Light scratches are found	Surface becomes rough	Small holes are found

Note: All dimensions are in mm.

Table 9: Inspection of small plunger O ring (up)

Part name	**Description**	**Cycle count**					
		0	**18869**	**41628**	**60429**	**82198**	**105268**
SMALL PLUNGER O RING (UP)	**Observed data**	8.52	8.51	8.50	8.49	8.48	8.46
	Remarks	Ok	Ok	Ok	Ok	Light scratches are found	Light scratches are found

Note: All dimensions are in mm.

Table 10: Inspection of small plunger O ring (PTO)

Part name	**Description**	**Cycle count**					
		0	**18869**	**41628**	**60429**	**82198**	**105268**
SMALL PLUNGER O RING (PTO)	**Observed data**	8.53	8.52	8.52	8.51	8.51	8.50
	Remarks	Ok	Ok	Ok	Ok	Ok	Ok

Note: All dimensions are in mm.

Table 11: Inspection of cam and PTO switch

Part name - cam and PTO switch		
Cycle count	**Observed**	**Remarks**
0	Fitted in good condition	Ok
18869	No aesthetic deviations are observed	Ok
41628	No aesthetic deviations are observed	Ok
60429	No aesthetic deviations are observed	Ok
82198	Light scratches are found in contact area	Ok
105268	Surface becomes rough	Ok

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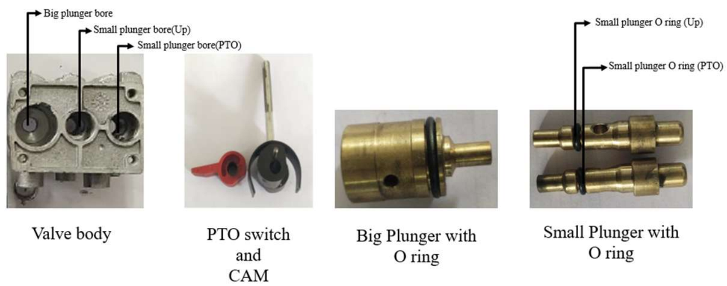

Figure 6: Inspection of features and components of CCV

PREDICTION ANALYSIS:

K-Nearest Neighbours(KNN) :

Prediction analysis involves the process collecting and analyzing historical data, statistical techniques, and machine learning models to forecast future outcomes or identify that can help predict future occurrences. Among the machine learning models, K-Nearest Neighbours (KNN) and Artificial Neural Networks (ANN) are used for making predictions, based on the similarities of current data points with historical failure cases. In the context of endurance test rig, prediction analysis helps in estimating potential failure point (wear rate) of CCV.

The K-Nearest Neighbour model is developed using C++ to predict the wear percentage of valves based on their cycle count. The process to predict wear percentage starts by declaring the valve dataset and reading the cycle count given by user along with the value of K = 11, which represents the number of nearest neighbours to consider.

A loop is then used to calculate the Euclidean distance between the input cycle count and all existing data points in the training dataset. After loading and sorting the dataset based on these distances, the algorithm identifies the K closest entries and calculates the wear percentage from them. This wear percentage serves as the predicted condition of the valve.

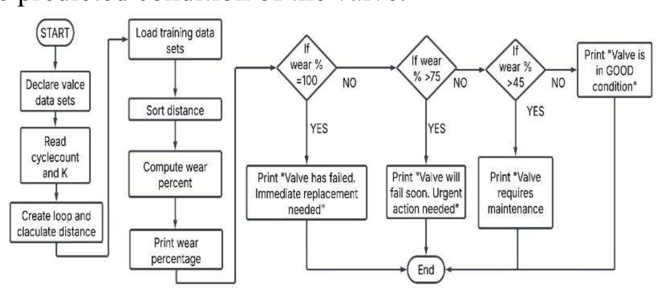

Figure 7: Flowchart of KNN predictive modelling

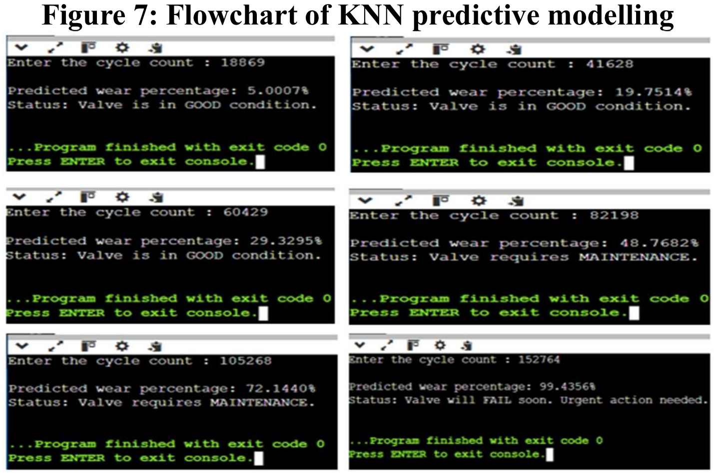

Figure 8: Output of wear prediction using KNN predictive modelling

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As shown in figure 5.7, based on the computed wear value a decision-making process classifies the valve's condition into different categories. If the wear percentage is exactly 100%, it indicates that the valve has completely failed and requires immediate replacement. If the wear is greater than 75%, the valve is predicted to fail soon, and urgent action is recommended.
If the wear percentage is greater than 45% suggests that the valve needs maintenance. If the wear is 45% or below, the valve is considered to be in good condition.

ARTIFICIAL NEURAL NETWORK (ANN) :

An Artificial Neural Network (ANN) model is developed using C++ to predict the wear percentage of valves based on their cycle count. The process begins with the initialization of the ANN model, including the random initialization of weights and biases. A loop is created to continuously adjust these values during the training process. The system then loads the training dataset and takes the current cycle count as user input, which is normalized to ensure effective learning and consistent scale.
Using this input, the ANN performs a forward pass to generate a prediction and a backward pass to adjust weights by calculating errors and gradients. Once the network is trained, it computes the wear percentage of the valve for the given cycle input. given cycle input.

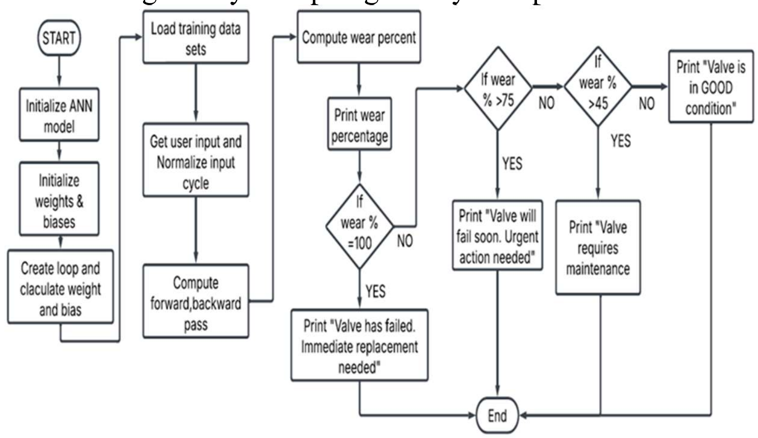

Figure 9: Flowchart of ANN predictive modelling

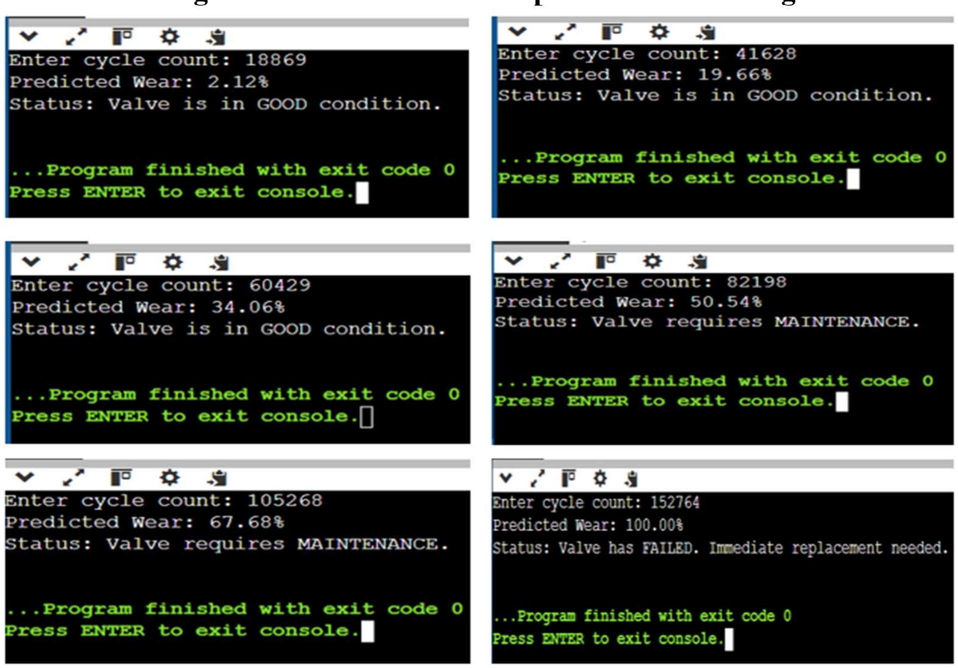

Figure 10: Output of wear prediction using ANN predictive modelling

The predicted wear value is then used in a decision-making system similar to the one used in the KNN model. As shown in figure 5.8, if the wear percentage is exactly 100%, the program indicates that the valve has failed and needs immediate replacement. If it is greater than 75%, it warns that the valve is close to failure and urgent attention is required. A wear percentage greater than 45% suggests that the valve requires maintenance, while values below or equal to 45% indicate that the valve is in good condition. This ANN based model enables accurate and intelligent maintenance planning, reducing downtime and preventing unexpected equipment failure.

COMPARATIVE ANALYSIS OF KNN, ANN AND ACTUAL WEAR RATE :

After 1,00,000 cycles of testing, wear rate data was collected manually using a Vernier caliper at different cycle intervals to serve as the baseline. To evaluate the effectiveness of models in predicting wear behaviour, two techniques KNN and ANN were employed.

The primary objective of this analysis is to determine which of the two models offers the best prediction accuracy when compared to actual wear rate data. By evaluating the predicted wear rates against experimentally observed values at different cycle counts, the performance of each model can be assessed in terms of its ability to capture the wear progression accurately.

Table 5.14 summarizes the comparative results of actual measurements and the predictions obtained from KNN and ANN across various cycle counts.

Table 12: Wear Rate Comparison

Analysis type	Cycle count				
	18869	41628	60429	82198	105268
Actual wear rate	4.76	19	28.57	47.61	71.42
KNN	5	19.75	29.32	48.76	71.14
ANN	2.12	19.66	34.06	50.54	67.68

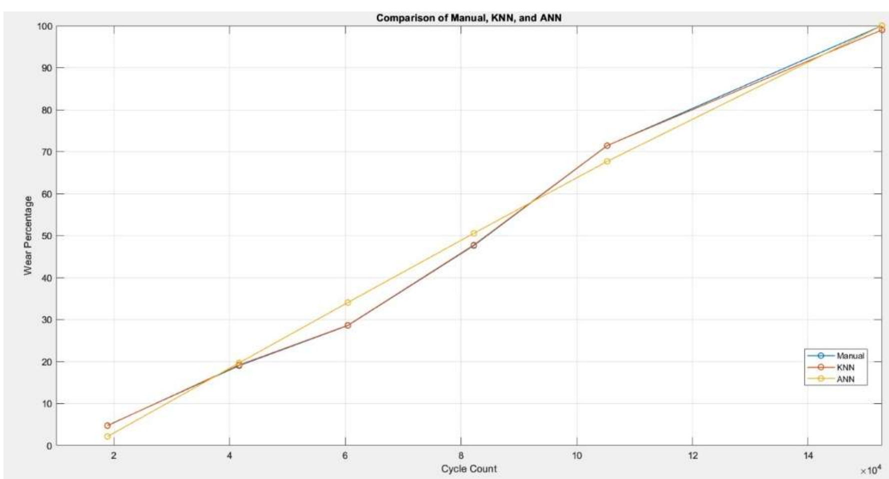

Figure 11: Graphical comparison of wear rate

Based on the comparative analysis presented in the table and the corresponding graphical representation plotted using MATLAB, it is evident that the KNN model demonstrates a higher level of accuracy in predicting valve wear rate when compared to the ANN model. In contrast, the ANN model exhibits slightly larger discrepancies from the actual wear values, particularly at certain cycle counts, indicating reduced predictive precision in those regions. Given this observation, it can be concluded that the KNN model provides a more reliable and accurate estimation of wear progression under the tested conditions. Therefore, KNN stands out as the more suitable model for wear rate prediction in this application.

FUTURE SCOPE :

In the future, the project can be significantly enhanced by integrating real-time monitoring through IoT-based sensors, enabling live tracking of valve wear and automated data logging. The Artificial Neural Network (ANN) model can be expanded by using advanced techniques like Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) to improve prediction accuracy and handle complex failure behaviours. By increasing the size and diversity of the dataset, the model's robustness can be further enhanced for different operating conditions. The endurance test rig can also be optimized for multi-valve testing and adaptive load conditions, while developing a user-friendly software interface for input, visualization, and reporting will make the system more practical for industrial use. Moreover, integrating predictive analytics with Failure Mode and Effects Analysis (FMEA) and Risk Priority Number (RPN) can help create a comprehensive predictive maintenance system. In the long term, industrial-scale deployment and lifecycle management of cabin control valves can be achieved, making the system highly valuable for commercial vehicle manufacturers and service providers.

CONCLUSION:

The development of an endurance test rig for Cabin Control Valves in commercial vehicle system plays a vital role in enhancing the reliability and durability of PTO switch and CAM lever. By subjecting the CCVs to 100,000 operational cycles, the test kit allows for early identification of potential failure points, leading to valuable insights for improving their design and maintenance. The findings from this project are expected to benefit both manufacturers and operators, contributing to more efficient and long lasting cabin control systems, ultimately improving CCV performance and reducing downtime.

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