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Artificial Neural Network for the Clustering of Vibration Signals for Condition Monitoring of Rotating Machines

Eyere EMAGBETERE[1], Samson UWATSE[1], Omonzokpia Goerge OKOIDIGUN[2]

[1]*Department of Mechanical Engineering, Federal University of Petroleum Resources, Effurun, 330102, Nigeria*
emagbetere.eyere@fupre.edu.ng/samsonuwatse@gmail.com

[2]*School of Information technology, University of the Cumberland, Kentucky, USA*
Ookoidigun20180@ucumberlands.edu

Corresponding Author: emagbetere.eyere@fupre.edu.ng, +2348057130590
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Abstract: *Vibration analysis is commonly used to provide valuable insights into the condition of a machine, which is crucial for ensuring reliability and reducing maintenance costs. However, analysis of vibration signals using artificial neural network (ANN) is mostly via development of classification models, which cannot be suitably applied to several varied machine types and specifications. This study investigates the use of ANN in the clustering of vibration signals for machine condition monitoring of several rotating machines. Data obtained from different rotating machines for 4 years was utilized for the study. The data contained values of vibration signals taken at 12 different pickup points, power ratings, year and equipment location. The obtained data was preprocessed and analyzed statistically. Then, silhouette scores and within-cluster sum of squares (WCSS) were used to obtain the optimum number of clusters for the analysis. Afterwards, different clusters were created using ANN, which were then explored to gain insights for potential applicability of the technique for assessment of the conditions of rotating machines. The result of ANOVA showed that there were significant variations between readings obtained from different pickup points and readings obtained from the different machines, with p-values far less than 0.05 for both cases. It was found via silhouette and WCSS that 9 was an optimum number of clusters for the analysis. Calculated mean of standardized values informs that 6 clusters contained machines with different forms of faults, having positive mean values far greater than 0. Also, there were 2 clusters with machines having good working conditions with negative mean values, while one cluster had machines that were moderately okay with mean values close to 0. The study has shown that ANN can effectively cluster a set of machines based on their conditions using vibration signals taken at different pick-up points. The developed framework is a suitable alternative to ANN-based classification methods which have limited applicability.*

Keywords: *ANN, Data Mining, Unsupervised Learning, Data Clustering, Predictive Maintenance*

1. INTRODUCTION

Rotating machines are extensively utilized for various applications in industries. For better productivity and profitability, the conditions of these machines need to be monitored to ensure that they operate effectively without unexpected breakdown. Several factors including environment, aging, wear, fatigue and design and operating conditions can lead to various mechanical faults [1]. These mechanical faults can cause unplanned downtime if not detected early leading to negative economic consequences [2, 3]. Traditional condition monitoring techniques are limited by high costs and inefficiencies [4]. There is thus a critical need for efficient techniques for monitoring the condition of rotating machines, to swiftly detect emerging faults and reduce financial losses that could result from unexpected breakdowns.

Faults and failures in machines have been linked with recognizable patterns of vibration signals [5]. These recognizable vibration patterns can provide insights into the condition of the machine and help to identify existing faults [6, 7]. Vibration signals are generally utilized for monitoring the condition of machines by exploring the patterns of the signals to using suitable algorithms. This task of analyzing and interpreting vibration signals is, however, not an easy task because of the nonlinear dynamic nature of machines and several influencing factors. Notwithstanding, vibration analysis is well dated and has evolved over the years, and currently, it is commonly applied for monitoring the condition of rotating machines [8], [9], [10].

Continued improvements in artificial intelligence and machine learning algorithm has made it possible to explore new ways of machine condition monitoring using vibration signals. ML algorithms, specifically ANN that models the neural network of the human brain, have proven themselves to have high potential in learning and understanding the pattern of data. From available studies it was evident that the use of ANN outperformed the earlier conventional methods in efficiency of fault detection by a significantly high percentage [9, 11, 12]. Furthermore, it can be understood that ANN may improve fault diagnosis performance and decrease false alarms originating from diverse rotating machines compared to conventional approaches [13], which suggested that ANN has good potentials for application in machine condition monitoring systems.

From the several review journals [9, 14, 15, 16], ANN-based research pertaining to the use of vibration signals for machine condition monitoring have mainly focused on the methodology of developing and applying ANN-based classification models, which grossly depends on learning from labelled dataset. These classification algorithms have some drawbacks like poor performance on an imbalanced data set or where in the dataset had fewer rates of fault or fails to include some fault types [17]. Also, the models are prone to overfitting which means that their predictions might be off in some unfamiliar cases [18]. There is still a notable gap in the literature regarding implementation of ANN for clustering vibration signals which can cater for the challenges associated with ANN-based classification models. The utilization of ANN for clustering vibration signals offers a promising approach to automate the identification of distinct patterns associated with different machine conditions. However, extensive analyses of the existing and potential methods of ANN-based clustering are still scarce, indicating that further studies should be conducted in order to adequately assess potential of this approach for fault diagnosis of the rotating machines.

This study aims to develop and evaluate an ANN-based framework for clustering vibration signals for machine condition monitoring of a set of rotating machines with different specifications. Our goal is to address the limitations associated with the use of ANN-based classification models by investigating a novel approach of ANN-based clustering method for monitoring the condition of rotating machines, which will ultimately lead to more effective maintenance procedures and decreased equipment downtime.

The collection of vibration signals has become easier by the use of advanced sensor technologies [19]. The complexity and amount of data created by these signals often proves tedious to analyze using for traditional methods [20, 21], whereas other advanced ANN-based classification techniques have limitations [18]. The findings from this work has potentials of use for real-time machine condition monitoring of several rotation machines with varied speciation within a complex or organization, as it can effectively group machines based on the similarities in the patterns of vibration signals and detect anomaly. This can potentially save cost, reduce false alarm, and improve accuracy of fault detection.

2. METHODOLOGY

2.1 Data Collection /Acquisition of Vibration Signal Datasets

The data utilized for this study consists of vibration signals collected at the Warri Refining and Petrochemicals Company (WRPC) Limited, Ekpan-Warri, Delta State. The vibration signals were measured from the different centrifugal pumps located within different departments at the refinery. The machines considered were motors, pump, compressors and turbines. It covered a span of 4 years (2015 -2018). During the data collection process, experts were utilized throughout. The vibration signals were collected using a IRD digital vibrometer shown in Figure 1. It is known for its accuracy and reliability in capturing dynamic vibrations. The instrument features frequency range of 100 – 1000 Hz, velocity range of 0-1000 mm/sec, making it suitable for a wide range of industrial applications.

The vibrometer was strategically placed at 6 different points to capture vibration signals representative of various components and potential fault zones. To collect the vibration signal, the pickup-cable was attached to the end of the vibrometer's receptacle point. Then the other end of the pickup-cable is positioned at the most suitable position for collecting the most useful vibration signals. Vibration readings were taken at the inboard and outboard of the machines. The device then measures vibration velocity in the direction or the axis in which the device is placed. Values taken at the horizontal, vertical and axial directions were recorded for each procedure. The positioning of the pickup-cable to get horizontal, vertical and axial readings is shown in Figure 2.

All necessary details were included during data gathering, including machine specifications described by their tags, date, power of machine, and pickup point. Obtained values of vibration signals were in two categories, which are in-board and out-board signals. The readings were taken twice for each pickup point of for the three (3) different directions (horizontal, vertical and axial). The data was labelled as H, V and A for horizontal, vertical and axial readings, respectively, and it is accompanied with a number 1 or 2 which indicates the reading as 1^{st} or second, at the in-board or out-board, respectively. For instance, H1 means horizontal in-board reading.

2.2 Preprocessing of Vibration Data

The raw vibration data was subjected to pre-processing steps to enhance signal quality. This included cleaning to remove wrong data and missing values as well as normalization for consistency across datasets. Also, all evident data errors or outliers that could skew the analysis's findings was removed or corrected. A simple formula shown in Equations 1 and 2 that computes outliers were used to calculate and remove all outliers from the readings. Vibration signals greater than the upper limit or lesser than the lower limit were then removed.

$$Lower\ limit = Q1 - 1.5 * IQR \tag{1}$$

$$Upper\ Limit = Q3 + 1.5 * IQR \tag{2}$$

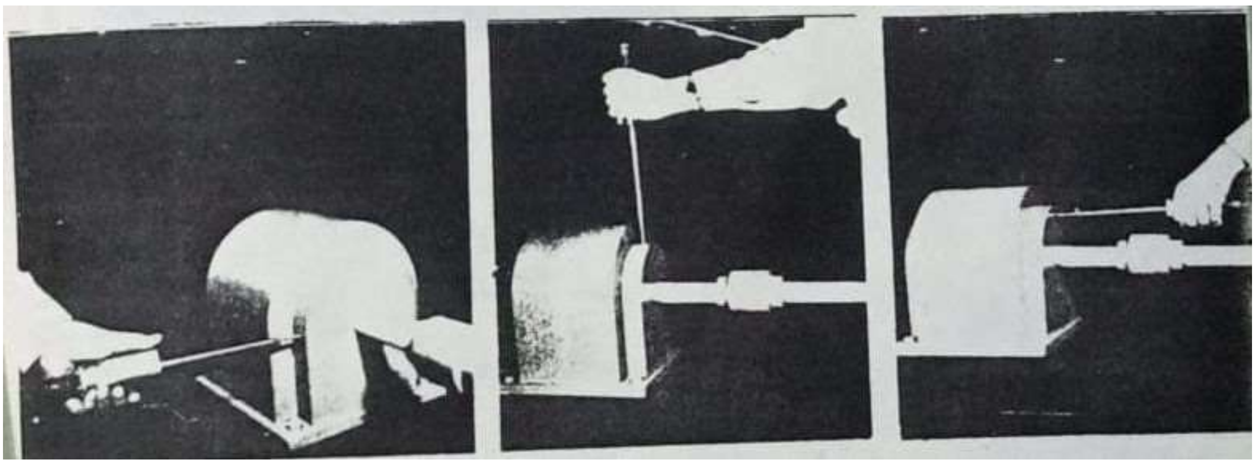
Q1 is first quartile, IQR is the interquartile range, Q3 is the third quartile

At the end, the data was reduced to a total of 374 samples, and was statistically analyzed. To address issues of differing scaling, all the measured variables were transformed by calculating their z-scores using Equation 3. This helps in preventing bias toward variables with higher magnitudes. Calculated Z-scores are known effective way of scaling data.

$$z = \frac{x-\mu}{\sigma} \tag{3}$$

Z is the z-score
X is the measure signal being transformed
μ is the mean
σ is the standard deviation

Figure 1: Equipment used for taking vibration readings



Horizontal (H) Vertical (V) Axial (A)

Figure 2: Positioning the device for taking vibration readings

2.3 Cluster Analysis

Two approaches were used to determine the number of clusters suitable for the analysis. They are the elbow method and the silhouette plot techniques. The first procedure involves plotting the cost function or the within-cluster sum of squares (WCSS) versus the number of clusters. The second method, which was the silhouette analysis, calculates an object's degree of similarity to its own cluster in relation to other clusters. Every data point generates a silhouette score, and the average score over all points was used to determine the ideal number of clusters.

The ANN clusters observations in two basic stages to address clustering difficulties. In the first, the network was trained for a particular data set using the pre-determined learning rule. This phase is referred to as training or learning. The second step, often referred to as the recall stage, is classifying the observations. In summary, the ANN is divided into layers: output and input layers. The nodes used to input data are located in the input layer. The output layer produced the user's readable and understandable output. There may exist other levels or hidden strata beyond these two. As seen in Figure 3, the output of each layer becomes the input of the following layer until the signal reaches the output layers.

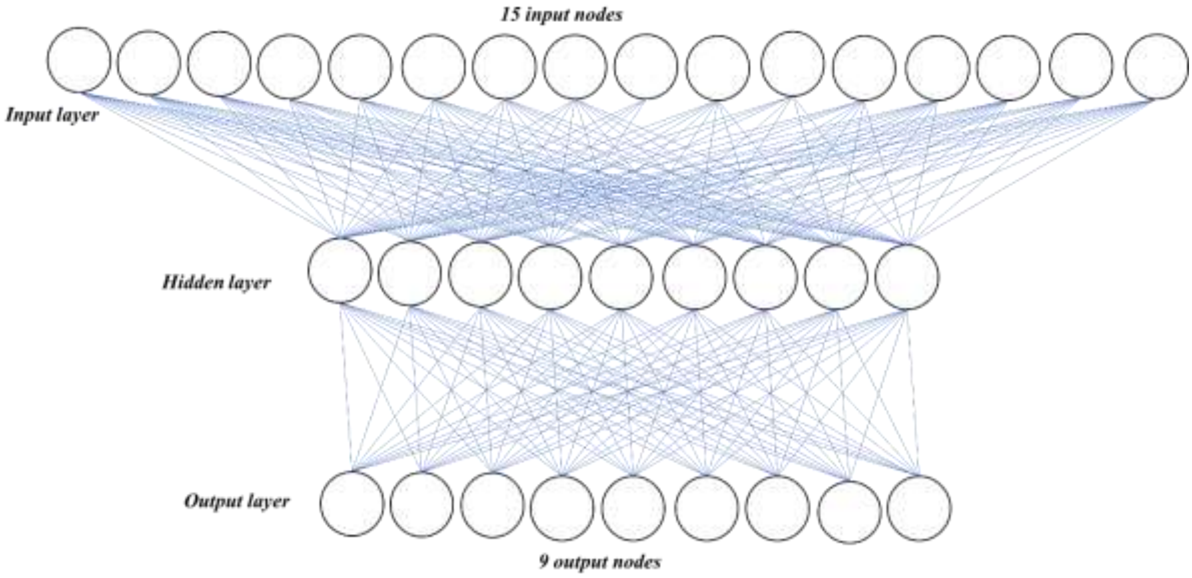


Figure 3: Illustration of the neural network for clustering

This study utilized the Kohonen's Self-Organization Map, which is one of the most well-known ANNs algorithm for data clustering [22]. The netwmingork is made up of two layers which are the input layer and the Kohonen layer, which transform n-dimensional input to two dimensions by typically arranging neurons in a two-dimensional layout. In essence, it is a mapping that preserves topology between the input space and the clusters that a self-organizing competitive network provides. The weight vector associated with the node l is given by Equation 4

$$w_l = \left(w_{1l} w_{l2} \dots w_{lp}\right)' \tag{4}$$

where w_{lj} indicates the weight assigned to input x_j to the node l, k is the number of nodes (cluster seeds), and p is the number of variables.

$x = \left(x_1 x_2 \dots x_p\right)'$ is the mathematical representation of the input vector (training case).

The network picks each object in the training data set at random. An imbedded process known as Kohonen's learning law locates the node that is most similar to each training example, and uses that information to shift the "winning" node closer to the training case. A portion of their distance is used to displace the node and training case apart. The learning rate specifies the fraction.

The distance di between the weight vector and the input signal is calculated for each object i in the training data set. The node with the lowest di wins when the tournament begins. A learning rule is then applied to modify the weights of the winning node. The non-winning nodes' weights remain unchanged. To compare each node with each object, the Euclidean distance is usually used, though any other metric could be chosen. The Euclidean distance between an item with the weight vector $w_l = \left(w_{1l} w_{l2} \dots w_{lp}\right)'$ and the observed vector $x = \left(x_1 x_2 \dots x_p\right)'$. is given by Equation 5.

$$d(x, w_i) = \left[\sum_{j=1}^{p} (x_j - w_{ij})\text{^}2\right]^{1/2} \tag{5}$$

Let Xi be the input vector for the ith training case, be the learning rate for the sth step, and wsl be the weight vector for the lth node on the sth step of the algorithm. A training case (Xi) is chosen at each stage, and the index q of the cluster that wins is ascertained Equation 6.

$$q = \arg_l \min \left|\left|w_l^q - X_i\right|\right| \tag{6}$$

For the winning node, the Kohonen update rule is provided by equation 7.

$$w_q^{s+1} = w_q^s(1-\alpha^2) + X_i\alpha^s = w_q^s + \alpha^s(X_i - w_q^q) \quad (7)$$

Where $w_q^{s+1} = w_l^s$ for each node that is unsuccessful. The literature on neural networks and machine learning has created a plethora of alternative techniques. It is also possible to employ neural networks that modify the weights of the victorious node and the nodes in its predetermined neighborhood [23].

2.4 Implementation of the neural network

The neural network for the clustering of vibration signals was implemented in MATLAB, and it involves several steps, which are development of the network architecture design, training, and evaluation. The preprocessed data, a total of 374 samples, was loaded into the MATLAB workspace, and then split into 70%, 15% and 15% for training, validation, and testing sets, respectively.

The architecture of the neural network includes the number of 3 layers (input layer, a SOM layer or hidden layer and the output layer), nodes in each layer, and the activation functions. The network had 15 input layers, based on the 15 input variables of the data collected as discussed in section 2.1, 9 SOM layers based on the predetermined number of clusters suitable for the analysis as discussed in section 2.3, and 9 output layers which constitute the number of clusters to be determined.

The training process was completed in less than a minute, and three major checkpoints to evaluate the model performance were included while saving the results intermittently. The ANN model passed through 200 iterations during the training phase. The learning rate which controls the step size of weight adjustments during training was initially set to 0.1, and it usually decreases over as raining progresses.

The Artificial Neural Network (ANN) was trained on a system with the following specifications:
Processor: Intel® Core™ i7-12700K (12 cores, 3.6 GHz base frequency)
Memory: 32 GB DDR4 RAM
Graphics Processing Unit (GPU): NVIDIA® GeForce RTX 3060 (12 GB GDDR6 memory)
Operating System: Windows 11 Professional (64-bit)

The default topology function, "hextop" (Equations 8 and 9), was used in the study based on its popularity and reliability.

$$x = i.d \quad (8)$$

$$y = j * d * \frac{\sqrt{3}}{2} + (i \; mod \; 2) * d * \frac{\sqrt{3}}{4} \quad (9)$$

Where d is the distance between adjacent nodes; i, j are the grid indices of the node;
The term $(i \; mod \; 2)$ is used to alternate the vertical position of nodes in every other column, creating the characteristic staggered rows of a hexagonal grid. It is 0 if i is even and 1 if i is odd. It is determined using Equation 10

$$(i \; mod \; 2) = \frac{1-(-1)^i}{2} \quad (10)$$

The distance function measures the topological distance between neurons during training based on their topology. The default distance function, which is the "linkdist" function (Equation 11) was utilized for this study.

$$linkdist\big((i_1, j_1), (i_2, j_2)\big) = \max(|q_1 - q_2|, |r_1 - r_2|, |s_1 - s_2|) \quad (11)$$

Where (i, j) are the cartesian grid coordinates of the neurons in the SOM; q, r, s) are the coordinates of the hexagonal grid.

3. RESULTS AND DISCUSSION

3.1 Statistical Description of the Data Set

The mean and maximum values for the readings taken at 12 different pickup points is estimated and shown in Figure 4. As can be observed, there are variations in the maximum and average values, with axial outboard reading taken at point 1 (A1) being the minimum. Also, the average vertical outboard reading taken at point 4 is low. Point A3 (axial reading at point 3) recorded the highest average vibration level, indicating a potential hotspot for fault investigations. On the other hand, point H3 (horizontal pickup point) recorded the highest maximum vibration level, suggesting occasional spikes in vibration at such locations that may need attention. The high average vibration at point A3 could be due to its proximity to a rotating component or a fault, likewise other areas with high vibration levels.

In this study, a two-way analysis of variance (ANOVA) was performed on the vibration signals collected from 12 pickup points of the rotating machines. The results of the ANOVA test are summarized in Table 1. The table shows the values of F-statistic, p-value, and F-crit. The p-value is less than 0.05 when different vibration reading taken at different location of sensors were compared, indicating that the vibration reading measured at different pickup points differ significantly. This variation in vibration levels across different points is in-line with previous studies in which vibration level varies significantly from one point to another of a machine [24, 25]. Thus, it is important to consider recording vibration signals at several different points for a more accurate result when adopting vibration signals for machine condition monitoring of rotating machines. Furthermore, the there is a significant difference in vibration levels across readings taken at different times. This could be as a result of varied factors like operating conditions or presence of a fault [26, 27]. Further analysis was thus conducted to determine the specific differences between these points and their implications for the machine's health and performance.

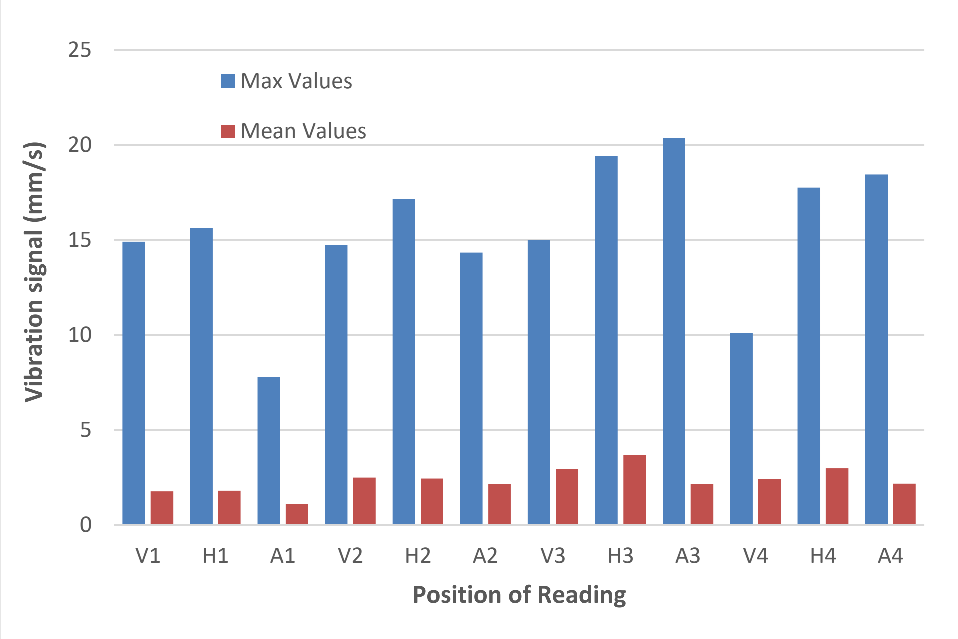


Figure 4: Average and maximum values of vibration signals for readings taken at different points and positions

Table 1: Analysis of variance for the vibration signals

ANOVA

Source of Variation	*SS*	*Df*	*MS*	*F*	*P-value*	*F crit*
Different Readings	9999.533	373	26.8084	7.055636	2.4E-235	1.130512
Location of sensor	1684.38	10	168.438	44.33078	7.22E-84	1.833234
Error	14172.4	3730	3.799572			
Total	25856.32	4113				

3.2 Optimum Number of Clusters

In this study, the silhouette plot and within-cluster sum of squares (WCSS) were used to identify the optimum number of clusters for our dataset. Starting from 3 to 10 clusters, the silhouette score and WCSS was determined for each clustering. While WCSS gauges the clusters' compactness, the silhouette score assesses how similar each element is to its own cluster in relation to other clusters [28]. The silhouette scores and WCSS values were plotted against the number of clusters and shown in Figure 5. The silhouette plot reveals that the optimum number of clusters was k = 7 with an approximate silhouette coefficient of 0.69. Similarly, the WCSS plot shows a significant drop in WCSS score when the number of cluster equals 7, beyond which the drop in values of WCSS score become less pronounced. It is thus, an indication that clustering the data into 7 clusters would be very effective. However, for clustering with ANN, only perfect squares can be used as the number of clusters because the technique creates clusters by dividing into square planes with equal number of horizontal and vertical rows [23]. Hence nine clusters is utilized for this study being the smallest perfect square number close to 7.

3.3 Results of ANN Cluster Analysis using Self-Organizing MAP

During the network training, each neuron's weight vector moves to become the hub of a cluster of input vectors. ANN training for clustering uses Self-organizing Map (SOM) that aids the visualization of a high-dimensional input space in the two dimensions of the network topology. There are nine neurons in this network, and the topology of nine self-organizing neurons arranged in a three-by-three hexagonal grid was mapped. Every neuron has acquired the ability to represent a distinct class of each machine, with neighboring neurons generally representing classes that are comparable. Figure 6 displays a SOM layer with neurons represented as gray-blue patches and red lines indicating their immediate neighbors.

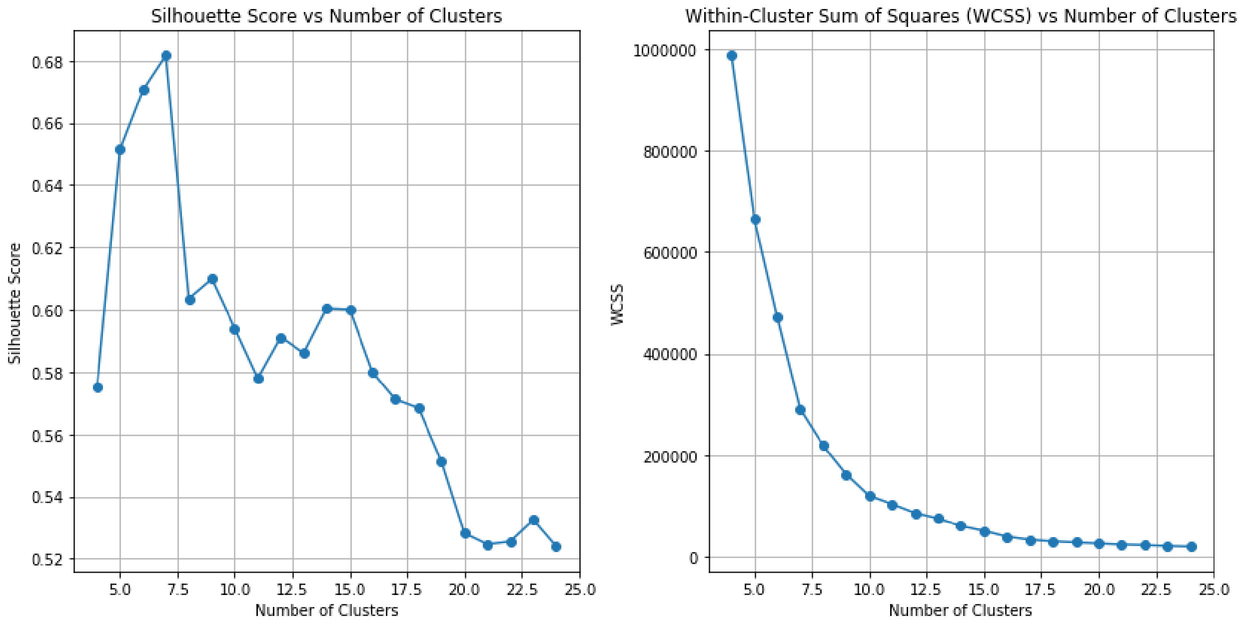


Figure 5: Silhouette scores and WCSS values versus number of clusters

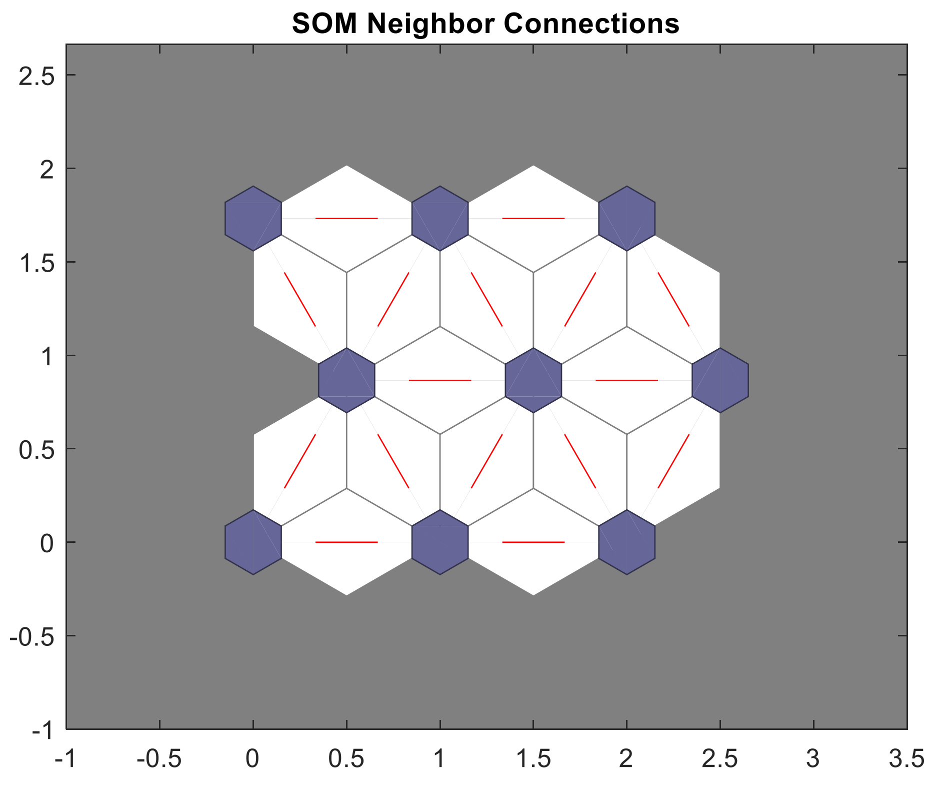


Figure 6: 2D diagram showing the SOM neighbor connections

The SOM neighbor distances or U-matrix, which shows the distance, expressed in Euclidian units, between the class of each neuron and its neighbors, is shown in Figure 7. The blue hexagons stand in for the neurons. The red lines link neighboring neurons. The colors in the regions with red lines indicate the distances between the neurons. Darker colors indicate greater distances, whereas lighter colors indicate smaller distances. This implies that bright connections represent parts of the input space with substantial connectedness. Conversely, dark links show classes corresponding to remote, sparsely populated feature space locations. With extended borders of black connections dividing major portions of the input space, the classes on either side of the boundary show machines with very different features. A band of black segments extends from the lower-left corner to the centre. The SOM network appears to have divided the machine readings into several distinct groups.

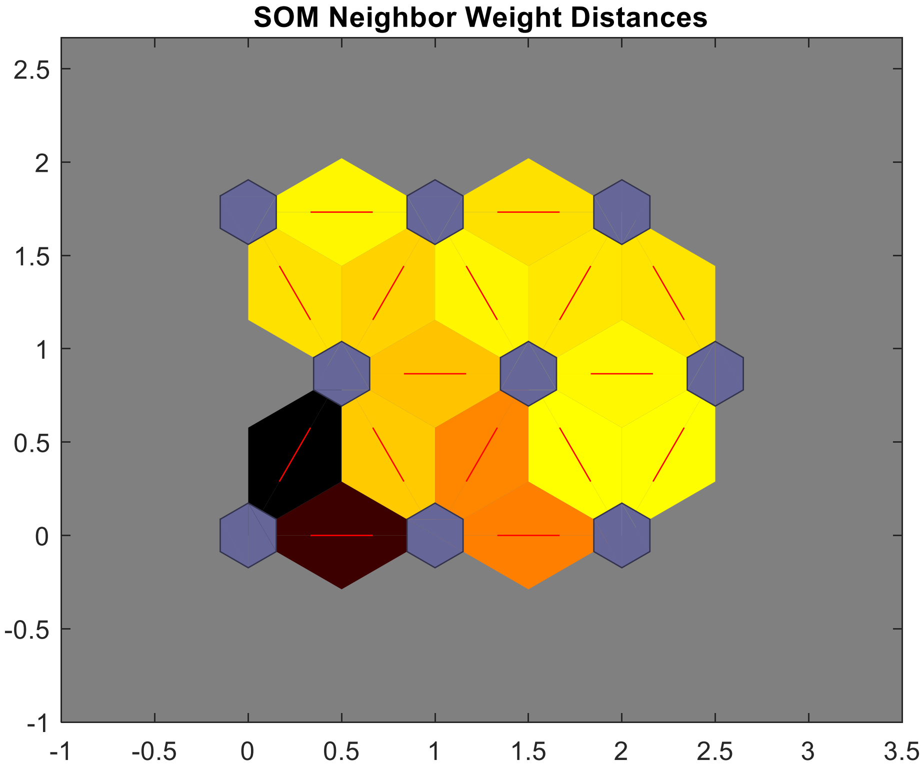


Figure 7: SOM neighbour weight distances

Figure 8 shows a weight plane for each of the fifteen input qualities, which are representations of the weights connecting each of the nine neurons to each of the inputs in the 3x3 hexagonal grid. Each ith subplot shows the weights from the ith input (variable utilized in the study) to the layer's neurons; these are grouped according to the machine's power rating to the 12 separate pickup locations, then by year and equipment location. Darker colors correspond to larger weights, while input variables with similar colour gradients show a high correlation between them. Red indicates the strongest positive connections, blue indicates the majority of negative connections, and black indicates zero or no connections. It is evident that features 1 (power rating) and 15 (equipment location) have a high proportion of black color, implying that these two variables had minimum or no influence in grouping the data set into distinct clusters. This finding suggests that the condition of machines with different power ratings and at different location can be assessed simultaneously using ANN-based clustering technique since they have minimum effect on how they are grouped. Expectedly, a machine's functionality shouldn't be impacted by its location unless there are differences in the operators and maintenance staff and procedures. This effect would not likely affect how they are clustered using ANN because the algorithm would likely group machines with similar characteristics regardless of their conditions. This means that a set of machines with related vibration signals would likely be in the same groups.

During SOM training, the weight vector of each neuron migrates to become the center of a cluster of input vectors. Each of these hits has a cluster label that has been determined and plotted, as seen in Figure 9. The fewest machines were found in cluster 1 and the greatest number in cluster 6. The smallest numbering cluster contained two machines, while the largest cluster contained 100 machines. Neurons with high hit counts—100, 58, and 68 machines, indicating classes with comparable densely populated regions of the feature space. On the other hand, classes with few hits indicate sparsely populated sections of the feature space.

3.4 Statistical Analysis of Standardized Values of Each Cluster

Analyzing the mean values of the scaled dataset can provide useful insights as to how each cluster deviates from the overall mean value of the dataset. This can provide suggestive information as to which clusters have machines that could be faulty due to higher vibration signals relative to the mean of the overall data set. Thus, the data were scaled, and then the mean of the different readings at different pickup points were determined for all machines in different clusters identified through Self-Organizing Maps (SOM) analysis. This analysis provides a comprehensive view of the vibration patterns exhibited by different clusters of machines, aiding in the identification of potential issues and the formulation of targeted maintenance strategies.

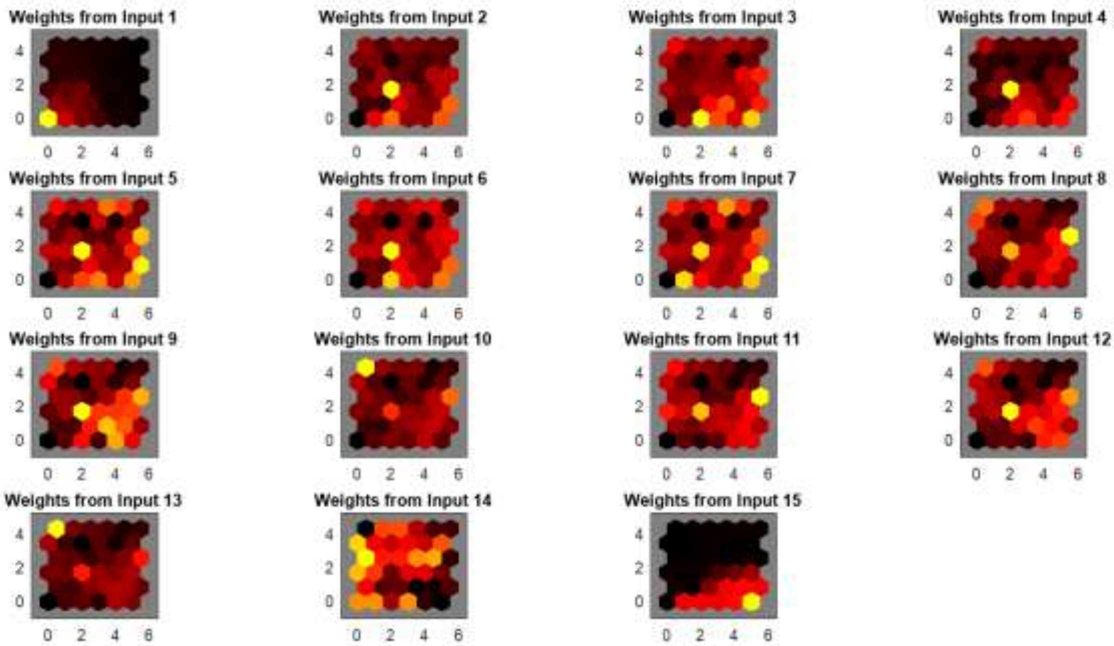


Figure 8: Weight plane for the different features

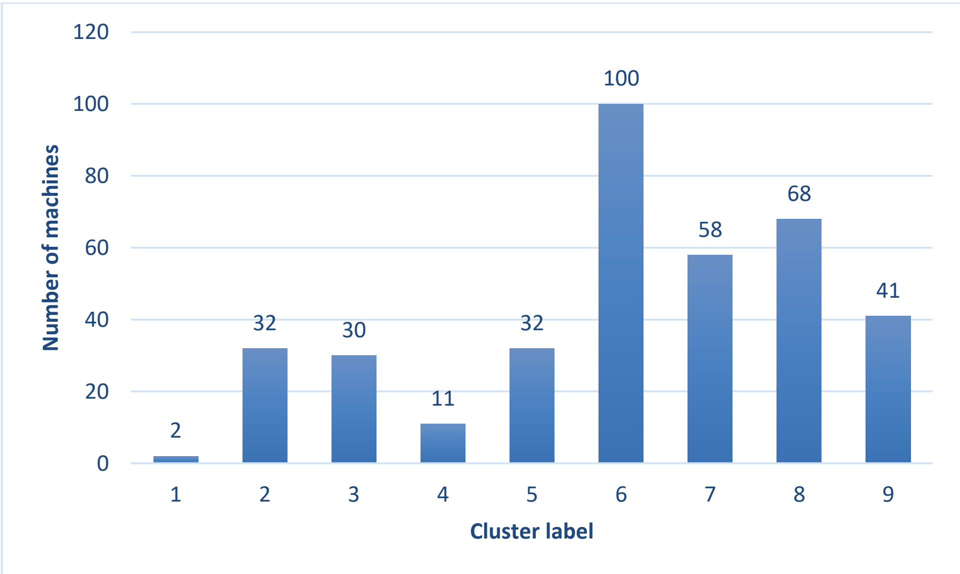


Figure 9: Cluster labels and the number of machines in each cluster

The average standardized mean values of inboard and outboard readings for the nine different clusters are shown in Figures 10 and 11, respectively, while those for each pickup point is shown in Tables 2 and 3 for inboard and outboard readings respectively.

As can be observed, the 1st and 3rd Clusters had very low standardized average mean values for outboard and inboard readings compared to the overall mean of the dataset, and the average vibrations signals are less than zero for all pickup points. The 9th cluster had machines with overall standardized average mean for inboard and outboard readings as well as standardized average values at all pickup points far greater than zero. This suggests that machines grouped in the 1st and 3rd clusters are operating under normal conditions with minimal vibrations, while those grouped in the 9th clusters are in a very critical conditions because machines with minimal vibrations are likely to be less defective and in good working condition [29]. This could be indicative of various issues such as misalignment, unbalanced components, or bearing faults [30, 31], which are commonly associated with increased vibration levels. The total number of machines in this group are 105

The set of machines in the 2nd and 5th Clusters 2 and 5 have standardized mean values greater than zero for of inboard readings and less than zero for outboard readings. This is an indication that the machines in these categories have defects which are related to inboard components. Conversely, machines in cluster 7 had overall standardized average values of outboard readings greater than zero for while that of inboard readings is less than zero. This suggest that these machines may be having issues related to outboard components [25]. The significance of this finding is that a more reliable recommendation can be made regarding the machines for proper inspection and fault diagnoses.

Machines in the 4th, 6th and 8th clusters had overall mean values that are close to 0. This indicates that these machines are somewhat similar to the overall average of readings from all machines put together. These clusters of machines demonstrate moderate mean vibration readings, indicating a potential for vibration-related issues that may require attention. The moderate values are suggestive of issues that are not yet critical but may require attention. Machines in these clusters may benefit from further physical inspection to identify and address any underlying causes of vibration patterns that are a bit higher than normal.

Overall, the cluster analysis based on inboard readings provides valuable insights into the vibration characteristics of the machines, enabling maintenance teams to prioritize their efforts effectively. Machines in clusters with higher vibration levels may require immediate attention to prevent further damage, while those in clusters with lower vibration levels may benefit from routine maintenance to ensure continued optimal performance. The standardized average values at the different pickup points can serve as a pointer to the location of the element within the machine that may be bad.

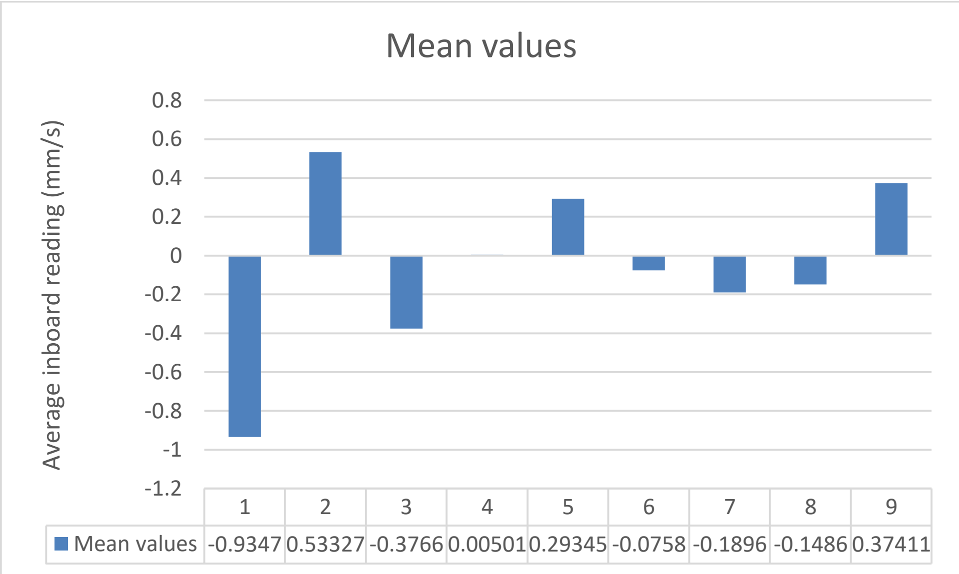


Figure 10: Average inboard reading for the different clusters

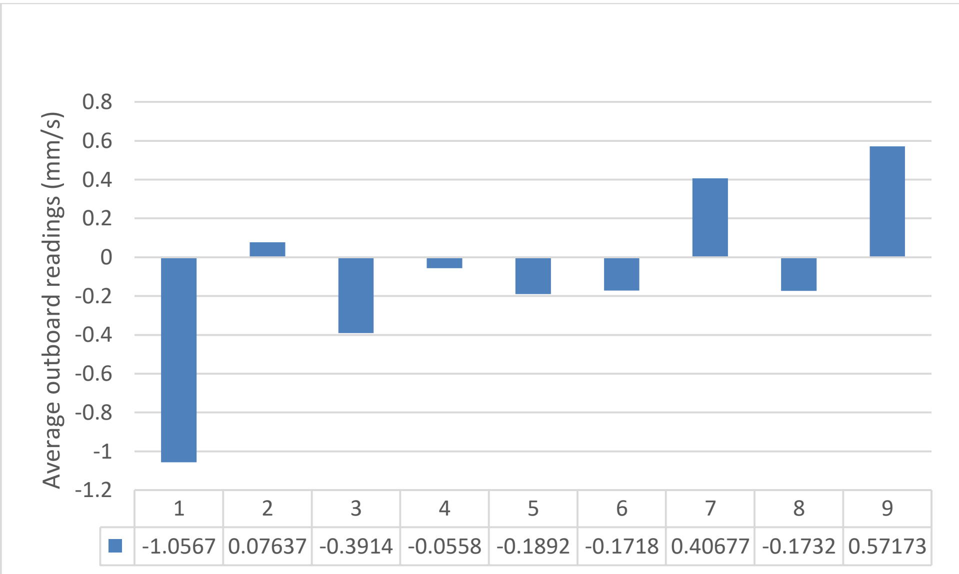


Figure 11: Average out-board reading for the different clusters

Table 2: Scaled data mean values for inboard readings of the different clusters

Cluster label	V1	H1	A1	V2	H2	A2
1	-0.88647504	-1.05167	-0.88882	-0.88807	-1.05016	-0.84277
2	0.79928739	0.480295	0.839877	0.267203	0.686705	0.126237
3	-0.28714876	-0.28548	-0.50823	-0.4208	-0.42445	-0.33333
4	-0.18151984	0.128635	0.055069	0.073087	0.107659	-0.15288
5	-0.06183528	0.109336	-0.09864	0.815965	0.186504	0.809344
6	-0.15666571	-0.10664	-0.13057	-0.03205	-0.01603	-0.01281
7	-0.06762657	-0.06388	-0.24248	-0.28458	-0.2323	-0.24667
8	-0.13691017	-0.17349	-0.14215	-0.16976	-0.12404	-0.1454
9	0.43132847	0.403686	0.719168	0.248504	0.224832	0.217153

Table 3: Scaled data mean values for outboard readings of the different clusters

Cluster label	V3	H3	A3	V4	H4	A4
1	-1.20739138	-1.09555	-0.9263	-1.11345	-1.04326	-0.9543
2	0.09147964	0.194174	-0.12088	0.132472	0.134851	0.026146
3	-0.41677722	-0.2759	-0.33749	-0.5447	-0.39492	-0.3787
4	-0.22082412	-0.54305	-0.11965	0.725376	-0.09074	-0.08601
5	-0.19501331	-0.136	0.034205	-0.30285	-0.35602	-0.17945
6	-0.18975193	-0.20635	-0.18915	-0.11263	-0.15761	-0.17526
7	0.61369442	0.179655	0.526454	0.245439	0.310865	0.564504
8	-0.21053339	-0.23245	-0.10228	-0.14506	-0.19273	-0.1559
9	0.44774219	0.990266	0.278111	0.559323	0.801121	0.353845

4. CONCLUSION

This research has examined the application of Artificial Neural Network (ANN) clustering technique for condition monitoring of rotating machines via the clustering of vibration signals to address the problems associated with the ANN-based classification models. ANN clustering capability of accurately clustering vibration patterns for capturing the performance characteristics of group of rotating machines with different specifications have been established. It could be applied in real-time condition monitoring in industrial environments. Additionally, for the design of ANN models that used self-organizing map, the identifying of the right number of clusters in which the rotating machines can be grouped was done effectively by silhouette score and Within-the-cluster-sun-of-squares. The computational analysis yields insights that can be used to identify the best setup for vibration signal analysis. The study's findings can be useful for various industries that utilize several rotating machines. Application of ANN clustering approaches for condition monitoring of rotating machines may cut downtime, enhance maintenance planning, and eventually extend the life of equipment. This can make it possible to experience major cost savings and improvement of operational efficiency. By demonstrating that it is possible to perform ANNs clustering for the analysis of vibration signals of rotary machines, this work contributes to the field of machine condition monitoring. The findings underscore the relevance of applying machine learning strategies to enhance the reliability and efficiency of protecting machinery maintenance practices amid increasing costs and optimal performance of industrial systems.

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