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ORIGINAL ARTICLE

Precision fault diagnosis in screw compressors using ANN

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Abstract

Screw compressors are critical assets in petroleum and chemical industries, where the ineffectiveness in the functioning may result in the considerable financial losses. The study introduces an effective fault diagnosis model, which is founded on the Artificial Neural Networks (ANNs) technology to distinguish between the malfunctions of the major compressor subsystems: engine, compressor block (CB), cooling system, and oil control circuit. Custodial ANN were trained on large industrial datasets, and attained high classification accuracy: 100% in the engine (3-12-7-3, MSE: 3.47e-17), 100% in the CB (2-13-8-5-3, MSE: 4.76e-18), 99.4% in the cooling system (2-11-6-3, MSE: 6.76e-14), and 100% in The system proved to be capable of working in severe operational conditions, such as high vibration (RMS 5.1 mm/s, gA 6 mm/s^2) and high temperatures (up to 130 °C), which was tested extensively. The findings support the argument that the suggested ANN-based solution is a scalable, high-fault diagnosis, and real-time solution, which is significantly superior to the traditional methods in order to minimize maintenance expenses and maximize operational efficiency of industrial screw compressors.

Keywords Screw compressor · Fault · Monitoring · Diagnosis · Neural network

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Nomenclatures

ANN	Artificial Neural Network
CB	Compressor Block
MSE	Mean Square Error
RMS	Root Mean Square
gA	Acceleration due to vibration (mm/s²)
T	Temperature (°C)
VSD	Variable Speed Drive
tansig	Hyperbolic tangent sigmoid activation function
logsig	Logistic sigmoid activation function
AFNOR	French standardization association (used for parameter thresholds)
TCR	True Classification Rate
LSTM	Long Short-Term Memory
GAN	Generative Adversarial Networks

1 Introduction

Industrial sector has experienced an unprecedented installation and use of automation and higher order intelligence systems that has seen the need to have efficient and reliable machinery in different industries. On the one hand, screw compressors as the significant elements of the manufacturing activities associated with refrigeration and pneumatic systems, are the assets of the industrial processes whose performance directly impacts production efficiency and safety [1]. The shift toward Industry 4.0 has required the development of more sophisticated diagnostic systems that allow predicting possible failures and thus reducing unscheduled downtime and the optimization of maintenance solutions. In this regard, precision fault diagnosis has been identified as a key technology with the potential to change traditional reactive maintenance paradigms to proactive data-driven schemes, given their high complexity under artificial intelligence methods [2].

Screw compressors work by making two helical rotors to interact inside very carefully manufactured housing that forms compression chambers that sequentially diminish in size as the rod passes through discharge port and suction port. These machines are easily prone to most of the failure modes, such as bearing degradation, rotor wear, seal degradation, and thermals [3]. Conventional methods of diagnosis are mostly time based which implies regular maintenance or corrective action after the major failures giving rise to a huge loss to the economy in terms of monetary losses as well as downtime of the operations. The requirement for screw compressor systems to operate continuously demands, requires advanced monitoring and diagnostic capabilities that have the ability to accurately detect incipient faults and also differentiate the usual changes in the operations of the system and the actual anomalies [4].

There has been a remarkable evolution of machine learning in the diagnosis of machinery fault where machine learning was originally applied using the traditional statistical approach, which has evolved to the use of sophisticated deep learning structures. Initial methods relied mainly on the use of support vector machines and simple neural nets as ways of recognizing beats in a collection of vibrations. Nevertheless, the shortcomings of the traditional machine learning techniques on the extraction of complex, multi-dimensional information in industrial systems has propelled scientists to seek better solutions whose understanding is better as well. Training of physics-informed neural networks has become one of the promising avenues where knowledge about the domain is combined with data-driven machine learning to make the diagnostic more accurate and reliable [5, 6].

Newer generations of fault diagnosis techniques make use of deep learning designs that are able to automatically find interesting ways of varying sensor input. Convolutional neural networks, recurrent neural networks, and their hybrid mixes have been reported to carry better performance to detect complex pattern faults in rotating machines [7, 8]. The emergence of sophisticated architectures namely Long Short-Term Memory (LSTM) based models in specific has demonstrated potential towards modeling temporal relationships within data on the condition of machines, to achieve prognostic capabilities with greater accuracy [9, 10].

Along with the machine learning applications, there are daunting challenges that remain inherent in the machinery fault diagnosis. The imbalance of data also constitutes a considerable challenge because the number of healthy operating data is overwhelming compared to the samples of fault conditions in most industrial contexts [11]. This skewed trend may create biased performances of the models, which in case of diagnostic systems, makes them proficient at detecting normal conditions but incompetent identifying the rare but vital fault conditions. Generative adversarial networks are being considered as one of the solutions to the data imbalance problem that can be solved by generating a fake realistic sample of fault data to be used to supplement training datasets [12–14].

The modern industrial systems are complex and this poses other complexities that revolve around data fusion and multi-modal sensor integration. The various data streams provided by machinery systems through accelerometers, temperature sensors, pressure transducers, and acoustic emission sensors are diverse and will need cutting edge techniques of fusion to intelligently merge the different complementary sources of information. These data streams are heterogeneous, and due to different sampling rates and uncertainties of measurements, this makes it hard to form single diagnostic frameworks [15].

The industrial Internet of Things era has provided new paradigms to deploy diagnosis systems, especially via the use of federated learning that facilitates distributed model training without violating data privacy and minimizes the communication requirement [16]. Federated learning models enable decentralized training of diagnostics by separate machines or even facilities without sharing the centralized data which is why this method has no issues with proprietary information safety and bandwidth constraints [17, 18].

Recent trends in learning-based methods with federations in case of machinery fault detection have shown encouraging findings in circumstances where data is decentralized, and communication channels possess faults [19]. Such strategies will allow creating strong diagnostic systems that will be able to utilize group know-how without compromising operational autonomy, especially useful in the context of screw compressors in distributed industrial plants.

Not much fault related data is recorded in industrial application and this has necessitated an enormous amount of research being conducted towards the use of data augmentation to specifically fault diagnose machinery. Conventional data augmentation methods such as noise addition and signal operation have not been effective to provide feasible fault signature simulation outputs. This has been achieved owing to several recent developments of advanced generative models, especially Wasserstein Generative Adversarial Networks (GANs) and their derivatives that are more powerful at generating high-quality fault data with the statistical properties of the actual fault scenario perfectly retained [20–22].

The compressed sensing methods have also shown to be useful in improving data augmentation of fault data especially when applied to cases where highly-representative fault samples are in short supply. The approaches make use of the sparsity of the fault signatures in transformed spaces to obtain full patterns of faults given incomplete measurements [23]. The combination of deep learning architecture and compressed sensing has shown to have potential towards the realization of a solid diagnostic structure that could be operated effectively when data on faults are limited.

The peculiar causes of rarity of fault events in systems that are not undergoing any industrial degradation has contributed to the work of anomaly detection strategies that mostly train models based on normal operating properties. Generative adversarial networks especially in the format of anomalous GAN like AnoGAN and f-AnoGAN have proven useful in finding minute anomalies in normal operating processes without the use of huge fault databases [24–27].

Auto encoder architectures is another type of unsupervised learning technique which has performed well in the diagnosis of machinery faults. Locally the networks learn encoding of the normal operation patterns in a compressed representation and during operation, anomalies are detected by checking the reconstruction errors [28, 29]. The additional capability of this type of auto encoder in being able to denoise the data it is dealing with also improves its resistance to measurement noise and other types of disturbances that occur in industrial environments.

Changes in the industrial process and variations in the trend of degradation of the machines systems have been a driving force towards an adaptive method of diagnosis based on reinforcement learning principles [30]. Those methods can make diagnostic systems continually learn and acclimatize to varying conditions of operation as well as fault patterns as they arise over time without having to re-train using historical data [31, 32].

Another bit of flexibility comes in the form of weakly supervised learning techniques, when specific labeling of faults is either unknown or uncertain [33]. These techniques have the potential to exploit partial labeling (information) or expert advice to come up with diagnostics without having complete fault databases, which are especially practical in complex systems such as screw compressors where the characterization of the fault may be problematic.

Integration of numerous deep learning models has also resulted in hybrid models that utilize the advantages of distinct models towards optimizing performance in their diagnostic capabilities. CNN-LSTM models have proven especially useful to accommodate spatial patterns in sensor measurements as well as time-dependent fault progress [34]. Such combinations of methods allow the thorough analysis of machinery status data, including instantaneous measurements and historical changes to increase the accuracy of diagnosis.

Bidirectional LSTM models have been useful when need to analyze both forward and backward temporal patterns in order to detect gradual degradation processes and sudden faults occurrence [35, 36]. These techniques of Bayesian optimization, in conjunction with deep learning structures, also improve model performance by automatically optimizing hyperparameters and quantifying uncertainties [37].

This work presents a novel Artificial Neural Network (ANN)-based fault diagnosis and identification system specially designed to have the highest classification accuracy (up to 100%) ever reached to correct components such as engine, compression block, cooling system and the oil circuit in screw compressors. The substantial improvement is in: (1) custom-designed ANN architectures (e.g., 3–12-7-3 of the engine) trained on industrial datasets comprising 25,000 or more samples, (2) an inclusion of vibration (RMS, gA) and thermal parameters that are incorporated into an integrated diagnostics framework, and (3) having nearly zero error rates (MSE as low as 3.47e-17), which is much higher than traditional methods. Using available tansig/logsig activation functions and a proper validation, the system provides real time solution scalable to reduce downtime and maintenance cost in an industrial scenario, which is a considerable enhancement of old-style fault detection methods.

2 Artificial neural network (ANN)

Artificial neural networks (ANNs) are computer models inspired by the human brain, widely used in artificial intelligence for classification, prediction, and pattern recognition [38]. Their main advantage lies in their ability to model nonlinear relationships between data. However, for linear relationships, classical statistical methods are often more appropriate. It is therefore recommended to combine the two approaches for better data interpretation [39].

Figure 1 displays the design of artificial neural network (ANN), which is made up of connected layers of neurons. Initial data is received at the input layer and transferred to the hidden layers, in which majority of the calculations take place and define the complexity of the network. The outermost layer is the output layer which gives the final result and the neurons are those related to the expected output values or classes. The weighted interconnections between the neurons in this layered structure allows ANNs to capture non-linear relationships in data and hence are useful in such tasks as classification, prediction, and pattern recognition. The diagram will indicate the flow of information between the inputs and the outputs with the aspect of learning and adaptation through training of the network.

The model of Artificial Neural Network (ANN) used in this paper is a feedforward multi-layer perceptron (MLP). A mathematical description can be used to describe the mathematical process of a single neuron in an output or hidden layer.

First, the net input $z_j^{[l]}$ for the *j*-th neuron in layer *l* is computed as the weighted sum of the outputs from the previous layer plus a bias term:

$$z_j^{[l]} = \sum{}_{i=1}^{n} (w_{ji}^{[l]} . a_i^{[l-1]}) + b_j^{[l]} \tag{1}$$

Where:

- $w_{ji}^{[l]}$ is the weight connecting the i-th neuron in layer l−1 to the j-th neuron in layer *l*,
- $a_i^{[l-1]}$ is the output (activation) of the i-th neuron from the previous layer l−1,
- $b_j^{[l]}$ is the bias term for the j-th neuron in layer l,
- n is the total number of neurons in layer l−1.

The output $a_j^{[l]}$ of this neuron is then obtained by applying a non-linear activation function f to the net input:

$$a_j^{[l]} = f\left(z_j^{[l]}\right) \tag{2}$$

Two activation functions were critically chosen in this work, which were first tested:

The hidden layers made use of the hyperbolic tangent sigmoid (tansig):

$$f(z) = \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \tag{3}$$

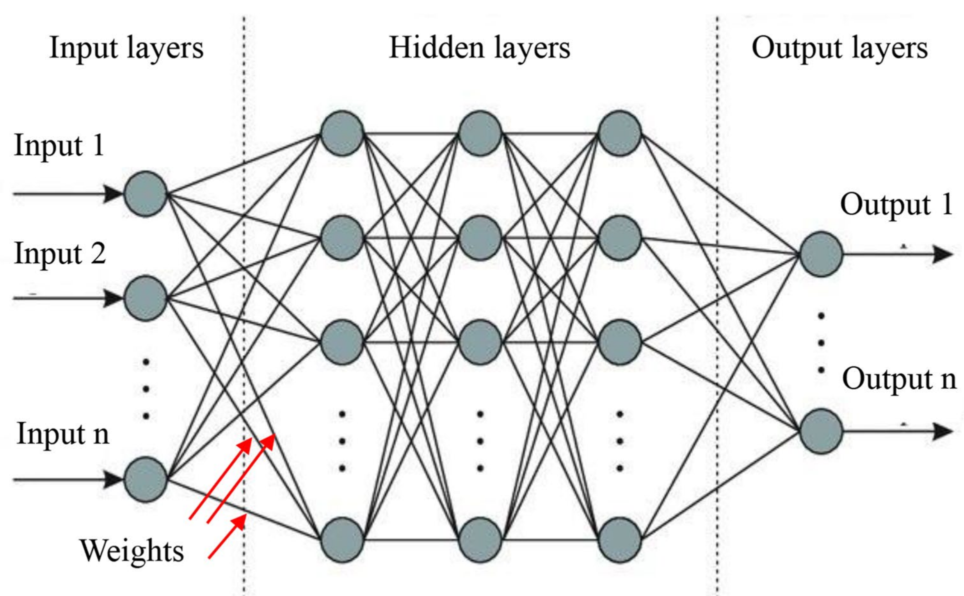

Fig. 1 Artificial neural network architecture

In the output layer, the logistic sigmoid (logsig) was used to squash the results into a [0, 1] space, which is appropriate to be used in classification:

$$f(z) = \frac{1}{1+e^{-z}} \tag{4}$$

The overall goal of the training process was to minimize the Mean Square Error (MSE) between the network's predicted outputs $\widehat{y}_k$and the actual target values y_k. The MSE for a dataset with m samples and K output neurons is defined as:

$$MSE = \frac{1}{m}\sum_{k=1}^{m}\sum_{j=1}^{k}\left(y_{kj} - \widehat{y}_{kj}\right)^2 \tag{5}$$

The backpropagation algorithm was used to train the network, to repeatedly optimize the weights and biases, with the aim of obtaining the MSE to the very low values reported (e.g., 3.47e-17), thus resulting in the high levels of classification accuracy shown in the results.

3 Compressor description

The research is made on Atlas Copco ZT75 screw compressor that is oil-free and air-cooled compressor used in industry where high purity demands are applied to air. The most prominent characteristics are compact in size, the variable speed drive (VSD) technology used to ensure energy efficiency, and the quality components that provide reliability and the ability to meet the high standards of quality. The visual descriptions are offered in Figs. 2 and 3 which present a half-sectional view of the compressor and Figs. 2 and 3 the view of the inside part of the compressor respectively.

Fig. 2 The real photo Atlas Copco ZT75 screw compressor unit

This is an excellent compressor in an environment sensitive to the performance, energy savings and uncontaminated air.

The Atlas Copco ZT75 is an air-cooled screw compressor designed to be used in applications where high-purity air is needed, and is oil-free, with important operational characteristics including a 7.2 to 8.5 bar range of operating pressure, discharge air temperatures of between 40 °C and 140 °C, and important vibration limits indicated by an RMS velocity up to 5.1 mm/s and a peak acceleration (gA) up to 6 mm/s^2. Its on-board Variable Speed Drive (VSD) technology maximizes energy savings by varying the speed of the motor to the air demand needs, and its durable mechanical engineering can maintain its performance under the demanding standards of industry condition monitoring, like those of AFNOR E 90–300, on which the fault classification criteria in this study are based.

4 Implementation of ANN for air compressor unit fault classification

4.1 Dataset description

The data set will be sensor measurements on the Atlas Copco ZT75 compressor during steady-state and transient operation to cover the faults thoroughly. A total of 25,000 samples were obtained per subsystem and they were spread in fault classes as below: engine (8,334 per class: Good, Alarm, Fault), compressor block (8,334 per class), cooling system (8332 per class), and oil circuit (8,334 per class) with an approximate ratio of 60% healthy (Good) to 40% fault (Alarm/Fault) samples overall. PCB Piezotronics 352C33 accelerometers (±0.5% uncertainty) were used to measure vibration data at 10 kHz and K-type thermocouples were used to measure temperature (error of ±0.5%). This step-by-step description guarantees the reproducibility and reliability of the ANN based fault diagnosis findings in this paper.

4.2 Initial network parameters

The paper used neural modeling such as multi-layer perceptron (MLP) and a total of 70-percent data was used to train the model, 15-percent was used to evaluate the model and 15-percent as a test. The training process used two stopping criteria: a maximum of 1000 iterations or a minimum root mean square error of 1e-20. Activation functions were critically chosen and the choice of activation function in the hidden layers was in the form of tansig (hyperbolic tangent sigmoid) which has proved to run through the non-linear patterns and logsig (logistic sigmoid) in the output layer due to the effectiveness of these forms in the preliminary tests. In this study, the implementation was

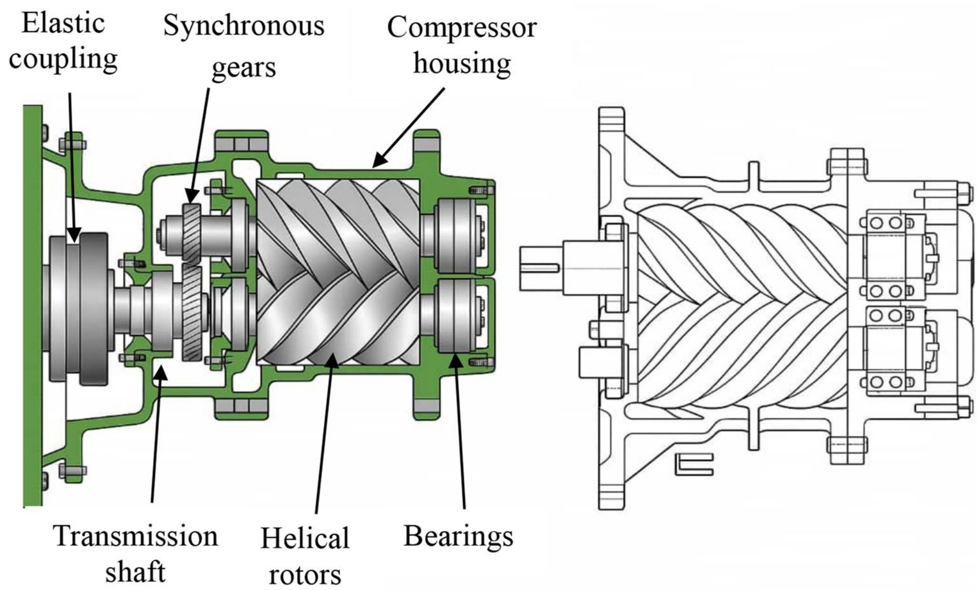

Fig. 3 The sectional view of the compressor and its internal components

undertaken in the MATLAB platform as shown in Fig. 4, whereby similar parameters were applied to all the five neural systems in order to be reproducible and reliable in classifying the faults.

Figure 5 illustrates in a concise manner all the steps in the process of modeling and evaluating the artificial neural network.

4.3 Implementation of ANN for engine fault classification

Selection of architecture The choice of the best ANN construction was made to use two main criteria: the root mean square error (RMSE), which determines the accuracy prediction of the network and the correct classification rate based on confusion matrices to determine the correct identification level of the ANN network to categorize the type of fault. They were referred to the AFNOR E 90–300 standard that establishes engine parameter thresholds (e.g., vibration, temperature) to determine the engine operational states as follows: Good, Alarm, Fault. Since RMSE was minimal and classification accuracy was maximized, the selected architecture (e.g., 3–12-7-3 in the case of the engine) guaranteed that the results of the fault detection process were reliable and that they could meet the industrial requirements (performance was nearly perfect, achieving 100% accuracy for the engine). This was an intense method of designing in in-between accuracy and practicality in compressor monitoring. The Table 1 is admissible standards of the different engine parameters before the AFNOR E 90–300 standard [40] (Table 2).

The chosen ANN architecture, that is, 3–12-7-3, performed best in fault classification with a very low mean square error (3.47 e −17) and optimal correct classification (100% on any of the datasets, that is, training, validation, and test sets). Figure 6 demonstrates this optimal accuracy: they are all classified correctly with no misclassifications, which proves that the model has a notably high generalization ability with unfamiliar data. The hidden layers (12 and 7 neurons) are well-tuned and hence capture effectively the non-linearities inherent in the fault data generated in compressors and assure robust and reliable diagnostics of faults in a compressor. The findings affirm that ANN is suitable in industry fault detection in which accuracy is essential.

The performance curve of the Engine ANN is shown in Fig. 7 which demonstrates the training process of the network by recording the error (more likely the Mean Squared Error, MSE) against the epochs. The curve curves steeply down at initial training periods indicating these high levels of reduction in the number of errors then reaches a near-zero error value very quickly, showing highly-effective learning. The tiny end error shows that the ANN is highly accurate in classification of faults with the accuracy of correctly classifying faults supported by the confusion matrices whose accuracy was 100 this is crucial. This has highlighted the effectiveness of the selected architecture (3–12-7-3), and training parameters so that the specified parameters can cause the high and exact fault detection of the compressor system.

4.4 ANN implementation for compressor block (CB) defect classification

Choice of architecture The operational parameters and the fault classification criteria of the CB are described in Table 3 and the conditions are broken down into good, alarm, and

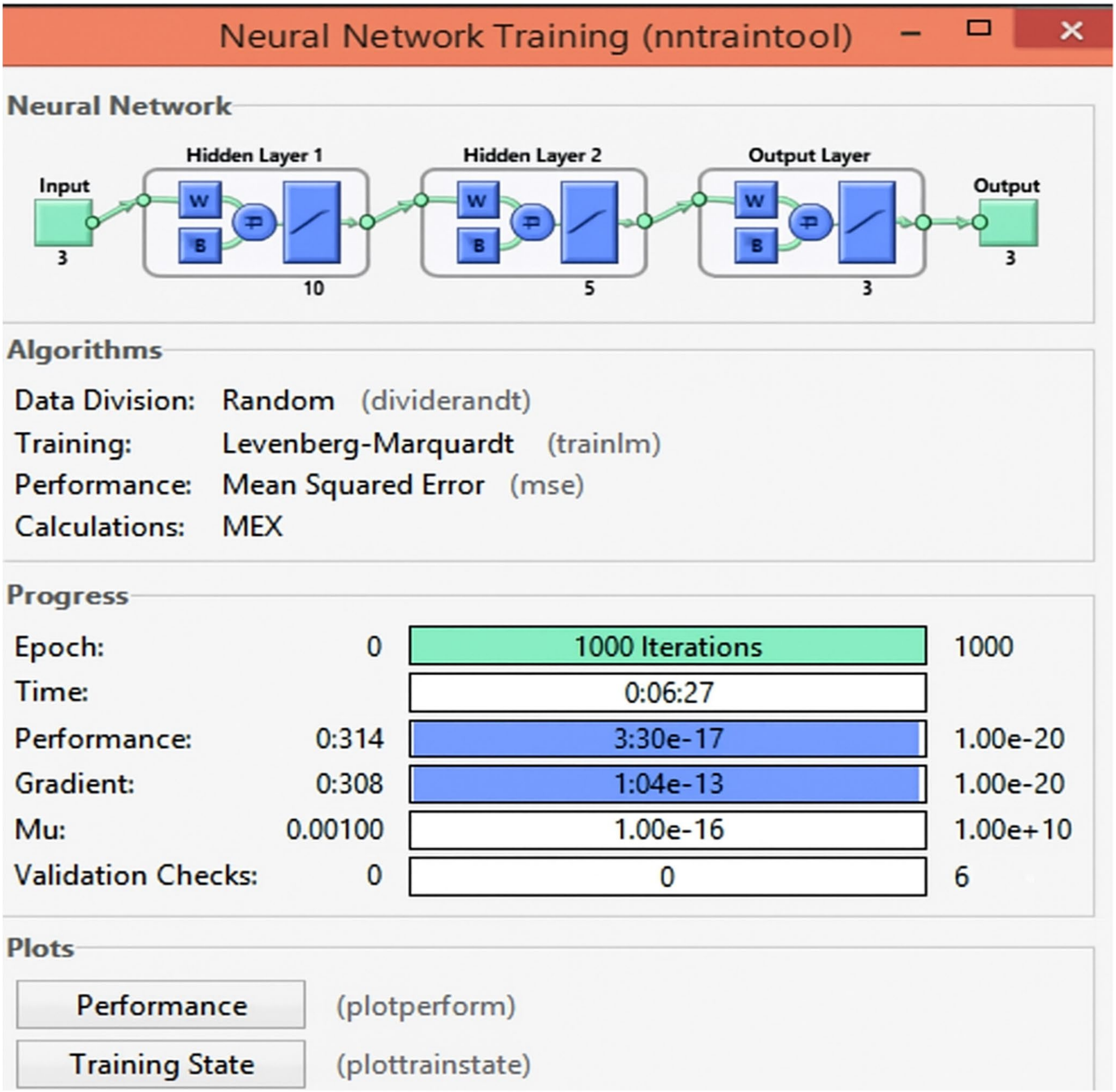

Fig. 4 Overview of the Proposed Framework

default (fault) states. Its parameters have specific thresholds (air temperature and air pressure at the outlets of the compression block). The criteria for choosing the best structure are the mean square error and the correct classification rate presented in the confusion matrices. We used a training database of over 1,000 samples to train our ANN.

The confusion matrices of the BCA (Block Compressor Air) ANN were shown in Fig. 8, where the outputs of the classification of the training, validation, test and overall dataset were provided. The values of the matrices represent that the percentages of correct classifications are large (100% in training set and validation, and 99.4% in a test set and total sets) and the occurrences of misclassifications are minimal. The green diagonal cells are those which have been predicted correctly, the red off-diagonal cells are the errors which are not significant. It illustrates the strength of the said ANN structure (2–13-8-5-3) used in classifying faults that is informed by its minimal mean square error (4.76 e-18) and reliability in application in the real world scenario.

The illustration shown in Fig. 9 is the performance curve of the ANN (Artificial Neural Network) of the compressor

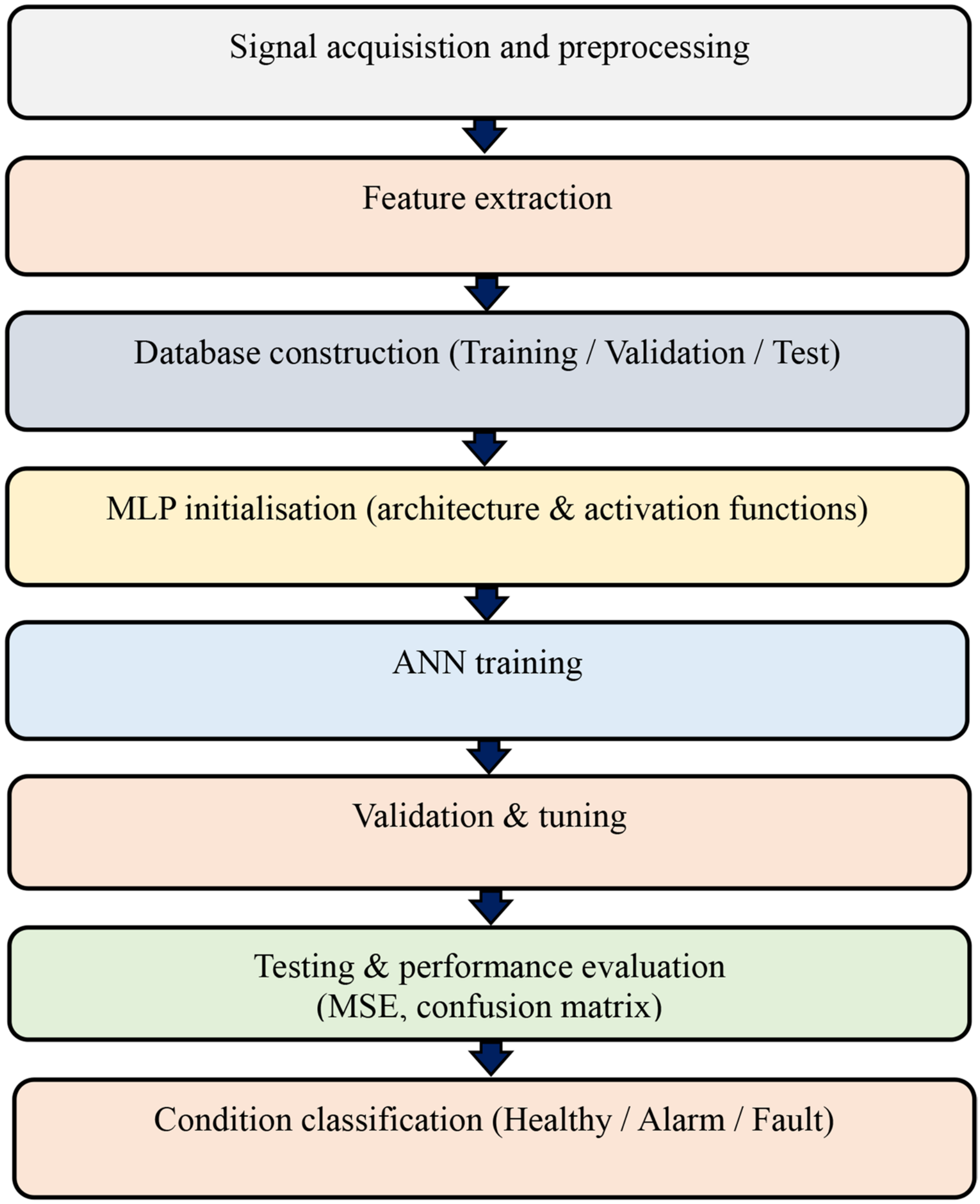

Fig. 5 Global ANN-based methodology flowchart

Table 1 Engine parameters

Engine parameters		Good			Alarm			Default		
La codification		1	0	0	0	1	0	0	0	1
Vibration parameter	RMS (mm/s)	0–2.82.82			2.83–4.46			4.47 ou plus		
	gA (mm/s²)	0–4.42.42			4.43–7.01			7.02 ou plus		
Temperature (°C)		40–120			120.1–140			140.1 ou plus		

Table 2 Engine test results

Architecture	Correct answers (%)				MSE
	Learning	Validation	Test	Total	
3–10-5-3	99.9	100	99.9	99.9	0.000120
3–12-7-3	100	100	100	100	3.47 e-17
3–9-4-3	100	100	100	100	4.67 e-6
3–14-9-3	100	100	100	100	6.8 e-5

block in training, validation and testing mode. As the epochs increase, seen in the graph, there is a steep decrease in error (most probably Mean Squared Error, MSE), which means that the learning process is rapid and effective. The error level oscillates to an extremely low value (4.76 e −18), which demonstrates the superior accuracy of the network in the classification of fault in the air compression block.

Fig. 6 Confusion matrices of the engine's ANN

The performance of this model together with the fact that the confusion matrices accuracy was 100% proves the effectiveness of the selected architecture (2–13-8-5-3) when it comes to identifying faults in the compressor system.

Table 4 shows the various tests that were performed to determine the number of hidden layers and the number of hidden layer neurons.

4.5 ANN implementation for cooling system fault classification

Architecture selection Operational limits of the air cooling system have been described in Table 5 where conditions are represented by the group of Good, Alarm and Default ranges of temperatures and pressures. Concerning temperature, the Good arguments are 40–60 °C, the alert arguments are 35–39 °C or 61–64 °C and the Fault warns less than 35 °C or over 64 °C. In the same manner, pressure is categorized as Good 6.15–6.25 bar, Alarm 5.8–6.14 bar or 6.26–7.41 bar and Fault when the value is out of the range. Such thresholds provide accurate fault detection and identification using the ANN thus ensuring early maintenance and reliability of the system.

Table 6 detailed the findings of several tests that were implemented to determine the best ANN architecture to use in the cooling system on different hidden layer configuration and number of neurons in the layer. The most successful structure 2–11-6-3 reported a good level of correct classification (99.4% total samples) and of mean squared error (6.76 e-4), which represents high levels of accuracy in identifying faults. Those other tested architectures that were 2–10-5-3, 2–10-15-3, and so on, revealed slightly lower performance as well, which once again emphasizes the point that depending on the complexity of the network, highly

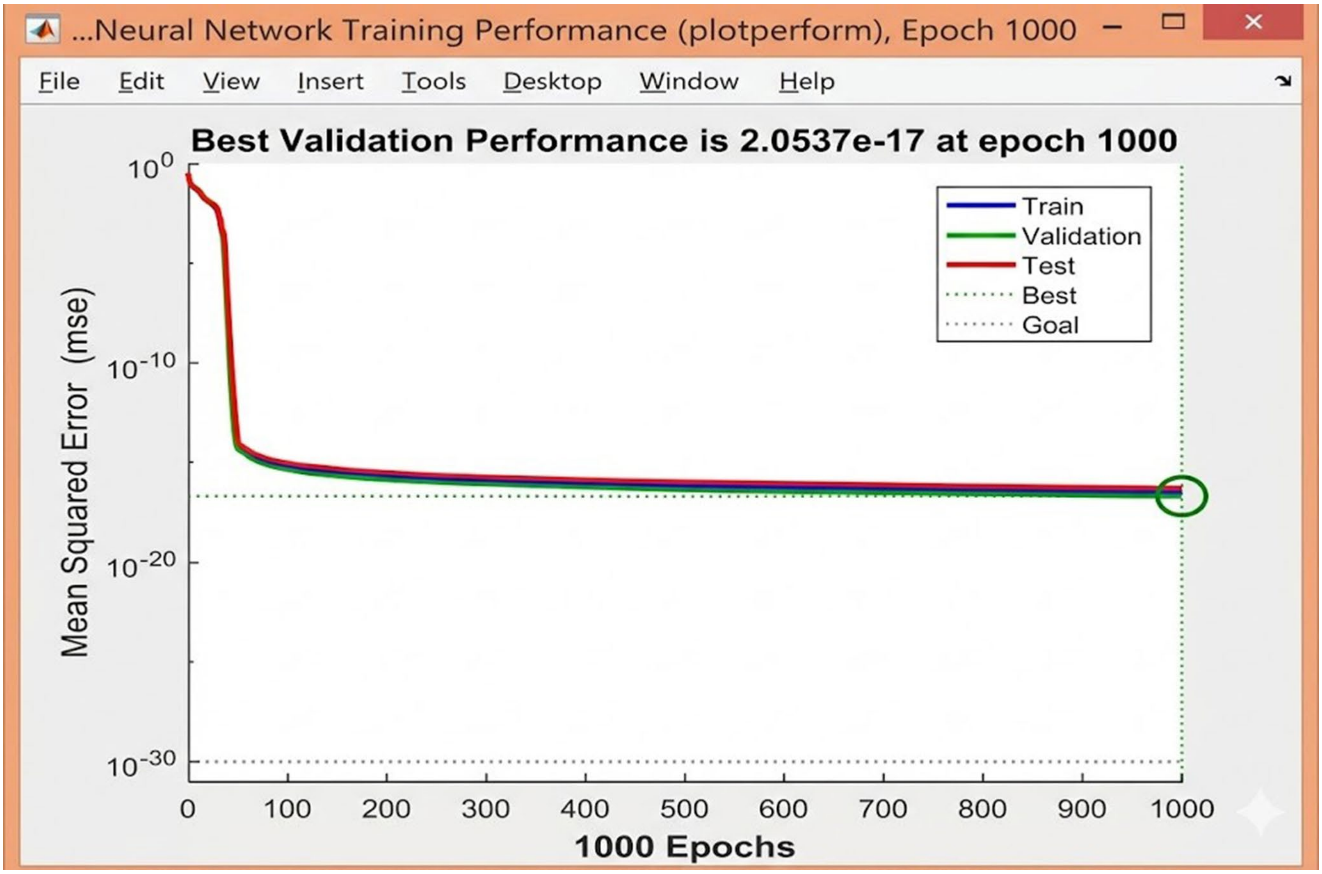

Fig. 7 Performance of the ANN of the engine's

Table 3 CB parameters

Engine parameters	Good			Alarm			Default		
Classification	1	0	0	0	1	0	0	0	1
Air temperature at the outlet of the compression block (°C)	65–100			3–65			Less than 3		
				100–110			More than 110		
Air pressure at the outlet of the compression block (bar)	7.5–7.8			7.2–7.5			Less than 7.2		
				7.8–8.5			More than 8.5		

effective outcomes can be achieved. The table has reflected that the process of ANN parameter refinement is an iterative one aimed at maximizing reliability in classifying the faults.

Figure 10 shows the artificial neural network (ANN) confusion matrices to categorise the cooling system faults. The matrices indicate the accuracy of the classification of training, validation, test and all data sets with the correct classification proposed to be 100% on the class 1, 98% on the class 2 and 99.9% on the class 3. The correctly classified cases are under the green cells whereas misclassifications are covered under the red cells. The rate of accuracy and low error proves the efficiency of ANN in diagnosing the error resulting in the cooling system, and provides reliable monitoring and maintaining the compressor.

4.6 Implementation of ANN for the classification of oil circuit faults

Structure choice Parameters and the classification range of oil circuit in the screw compressor are listed in Table 7 with differentiation between Good, Alarm, Default states depending on the values of temperature and pressure. Good (40–70 °C), alarm (20–39 °C or 71–90 °C) and default (below 20 °C or above 90 °C) are established as the temperature ranges. In the same way, the pressure will be good (6.4 to 6.99 bar), alarm (5.8 to 6.39 bar or 7 to 7.39 bar), and default less than 5.79 bar or more than 7.4 bar. These parameters are essential to observe the health conditions of the oil circuit to make a timely detection and classification of

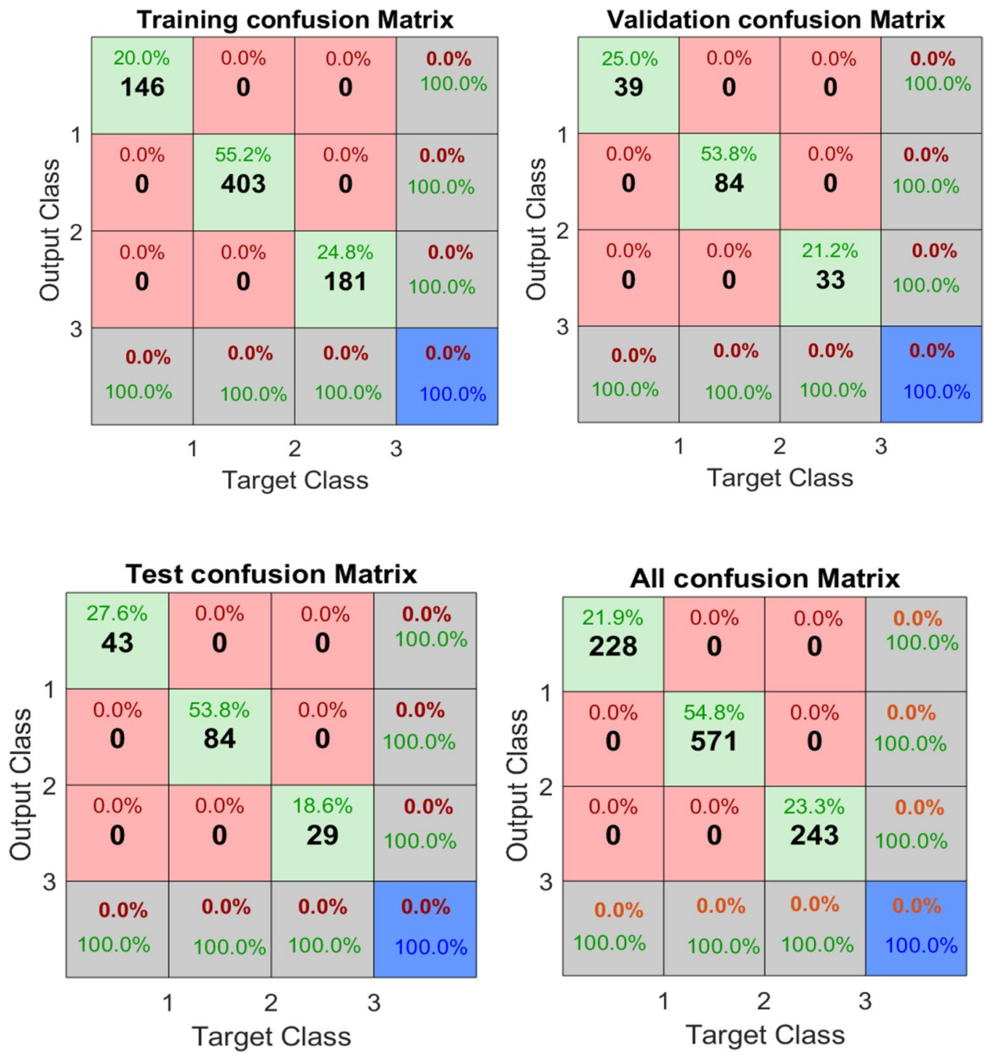

Fig. 8 Confusion matrices of the ANN of the engine

the faults according to the ANN-based system that reached 100% accuracy at testing.

The results of the test to classify the oil circuit fault with artificial neural networks (ANNs) are described in Table 8. Architecture 2–10-10-3 is the best one by performance as it performed with 100% accuracy in classification errors on the learning, validation, and test sets, and the root mean square error (MSE) was minimal at 7.03e-13. Additional architectures, 2–13-8-3 and 2–15-12-7-3, were also good in performance reaching an accuracy of 98.8% and 99.5% with an increased MSE value of 6.82 and 0.50 respectively. These findings reflect the efficiency of the selected ANN architecture in the precise classification of the oil circuit faults, which could be used as an efficient industrial diagnostic.

The efficiency test of the engine network was conducted in Table 9 which explains that the ANN can classify between the faults well by taking parameters such as temperature (T), vibration (gA), and root mean square (RMS) as parameters. The table reflects the calculated outputs and network outputs against each other portraying 100% accuracy of all the tested samples. The fact that the ANN has successfully classified samples as good, alarm, or default also proves the resilience of the architecture (3–12-7-3) as well as its applicability to a screw compressor real-life fault diagnosis scenario and is evident by each row (3–12-7-3).

Figure 11 shows the oil circuit ANN confusion matrices and demonstrates how the model performs in categorizing the faults as being within the classes of Good, Alarm and Default. The matrices are highly accurate with a 100% correct classification rates on training, validation and test sets as shown by the green cells in the diagonal representing correct classification of the samples. The small number of red squares in its diagonal cells and the small root mean square error (7.03 e-13) proves the ability of ANN in identifying faults and thus far the effectiveness in doing so as well in monitoring and maintaining the oil part of the compressor system [39].

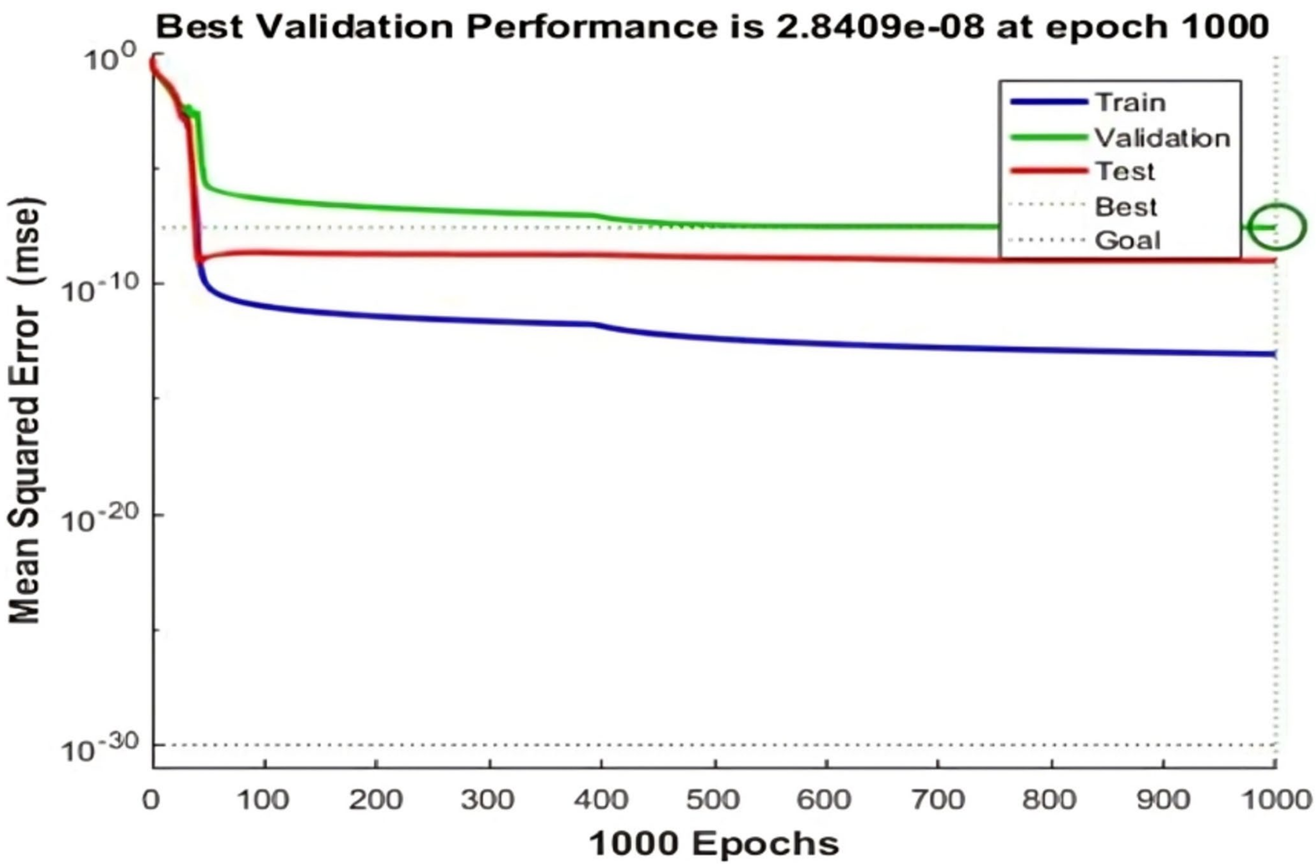

Fig. 9 Performance curve of the ANN of the CB

Table 4 Test results for CB

Architecture	Correct answers (%)				MSE
	Learning	Validation	Test	Total	
2–15-10-5-3	100	99.4	99.4	99.8	7.03 e-13
2–13-8-5-3	100	100	98.1	99.7	4.76 e-18
2–14-10-6-3	100	98.7	98.1	99.5	7.14 e-13
2–12-7-3-3	100	98.7	99.4	99.7	2.31 e-9
2–12-7-5-3	100	100	100	100	9.13 e-14

5 Conclusion

This paper demonstrates that the suggested Artificial Neural Network (ANN) based fault-classification system on screw compressors shows outstanding correctness and reliability in identifying faults in different elements of the compressor such as the engine, compression block (BC), cooling, and oil circuit. Through careful architecture design it has been demonstrated that ANN can be used to model nonlinear relationships between faults with optimal performance in classifying faults (engine: 3–12-7-3, 100% accuracy, MSE = 3.47e-17; BC: 2–13-8-5-3, 100% accuracy, MSE = 4.76e-18; cooling system: 2–11-6-3, 99.4 fellowship, MSE = 6.76e-4; The system is also proven to be effective; not only through simple testing but also by rigorous testing where the engine network was able to correctly label the samples accurately, even in cases such as severe vibration (RMS 5.1, gA 6) and high temperatures (130 °C). Such findings demonstrate the ANN capability to reduce maintenance expenses, improve the efficiency of the processes, and provide fault detection in time, which is a solid

Table 5 Cooling system parameters

Classe	Good			Alarm			Default		
The codifications	1	0	0	0	1	0	0	0	1
The temperature (°C)	[40, 60]			[35, 39]			Under 35		
				[61, 64]			More than 64		
Pressure (bar)	[6.15, 6.25]			[5.8, 6.14]			Less than 5.8		
				[6.26, 7.41]			More than 7.41		

Table 6 Test results for the cooling system

Architecture	Correct answers (%)				MSE
	Learning	Validation	Test	Total	
2–11-6-3	99.9	98.7	98.1	99.4	6.76 e-4
2–10-5-3	99	98.1	97.4	98.6	0.00712
2–10-15-3	99.4	99.4	96.8	99	0.00446

alternative to the existing diagnostic methods. The combination of such big amounts of data (e.g. 25,000 + engine training samples) and use of more powerful activation functions (tansig, logsig) also emphasises the scalability and accuracy of the system. Although the proposed ANN system proves to be highly accurate and strong within the confines of the conditions tested, there are certain limitations of this work, such as the use of data related to a particular compressor model and working setting, which may impact the generalizability. Moreover, the quality and labelling of historical data used to train the evaluation might not be as good in the industrial case. It is planned that the system will be tested on other types of compressors and

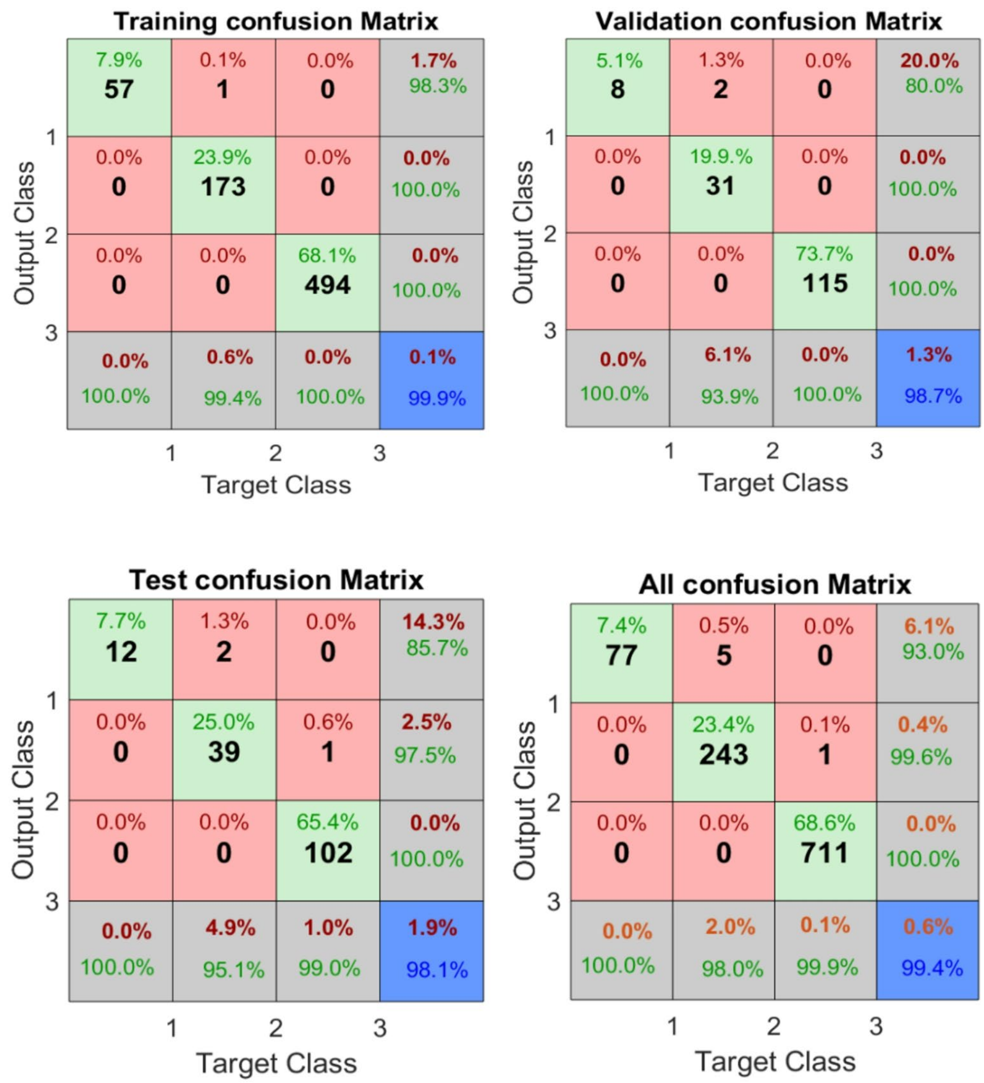

Fig. 10 Confusion matrices of the cooling system

Table 7 Oil circuit parameters

Class	Good			Alarm			Default		
The codifications	1	0	0	0	1	0	0	0	1
Temperature (°C)	[40, 70]			[20, 39]			Less than 20		
				[71, 90]			More than 90		
Pressure (bar)	[6.4, 6.99]			[5.8, 6.39]			Less than 5.79		
				[7, 7.39]			More than 7.4		

Table 8 Test results for the oil circuit

Architecture	Correct answers (%)				MSE
	Learning	Validation	Test	Total	
2–10-10-3	100	100	100	100	7.03 e-13
2–13-8-3	100	99.1	93.2	98.8	0.000381
2–15-12-7-3	100	99.1	97.4	99.5	2.97 e-4

various operating regimes to validate the system and applying adaptive learning methods to adapt to changing fault modes and insufficient data, and real-time deployment of the system in distributed industrial networks will be investigated to make the system more practical and resilient.

Table 9 Engine network effectiveness test results

Sample [T; gA; RMS]	The desired outputs			Network exits			Answers
[50;3.2;1.9]	1	0	0	1	0	0	TRUE
[60;4;1]	1	0	0	1	0	0	TRUE
[95;6;5.1]	0	0	1	0	0	0.999	TRUE
[105;0.5;2.5]	1	0	0	1	0	0	TRUE
[110;5;3.8]	0	1	0	0	1	0	TRUE
[130;6.3;5.5]	0	0	1	0	0	1	TRUE
[115;3;4.8]	0	0	1	0	0	1	TRUE
[86;4;6.6]	0	0	1	0	1	0	TRUE

Fig. 11 Confusion matrices of the ANN of the oil circuit

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Declarations

Conflict of interest The authors declare no competing interests.

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