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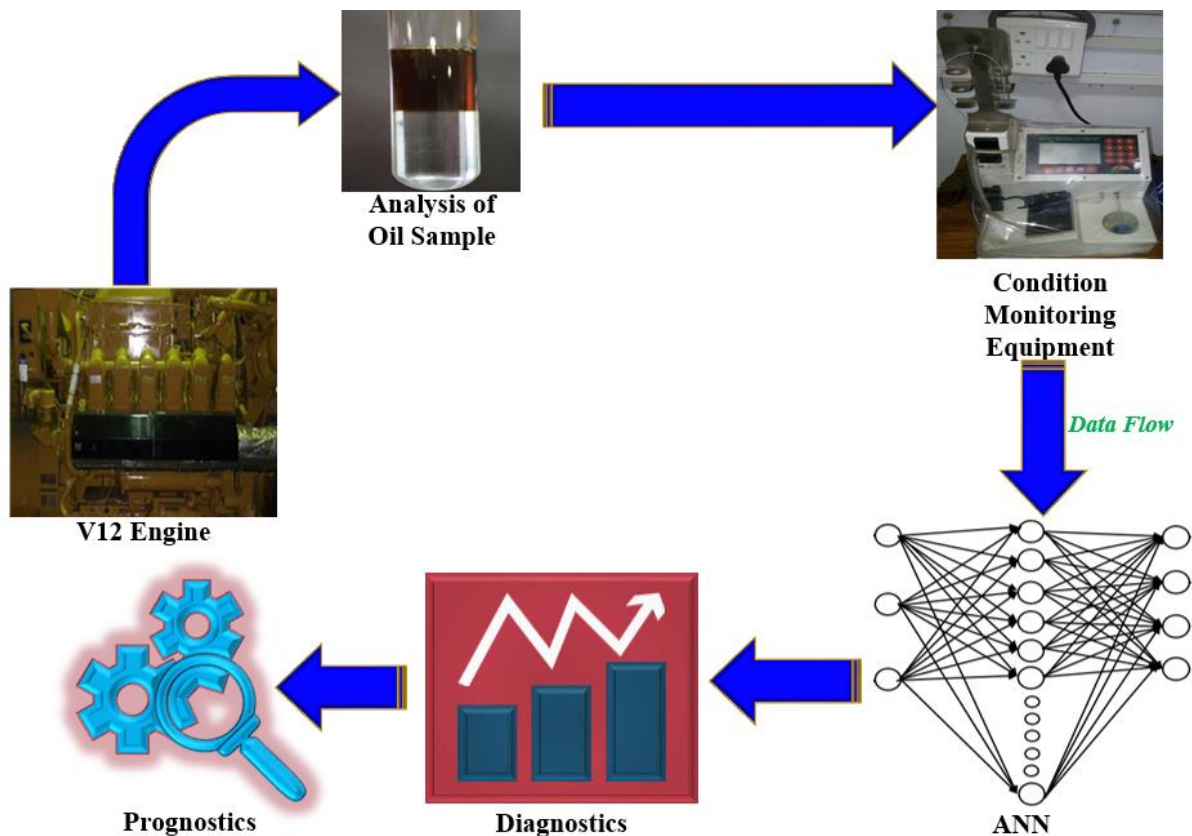
Artificial Neural Network coupled Condition Monitoring for advanced Fault Diagnosis of Engine

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Graphical Abstract



Abstract

This paper reflects on the use of the Artificial Neural Network (ANN) approach to diagnose and interpret engine failure behaviour. The current research focuses on the analysis of quantitative wear trend patterns through Condition Tracking (CM) and soft computational approaches. Oil analysis has been carried out to observe the engine failure trend. An ANN model using a Nonlinear Autoregressive with Exogenous Input (NARX) architecture has been employed to predict quantitative outputs such as Wear Particle Concentration (WPC), Wear Severity Index (WSI), Severity Index (SI) and Percentage of Large Particle (PLP) in connection with input functions of Engine Running Hours, RPM and oil temperature. Correlation function

and error similarity are statistically evaluated to represent the model's robustness and effectively chart the loss input-output sequence. The subsequent ANN model demonstrates the capabilities for advance diagnosis and better prediction of engine performance.

Keywords: CBM, Diagnosis, NARX, ANN, Fault, Wear, Prognostic.

1. Introduction

To produce a sustained power output, engine failure is not desirable and is an essential energy supply for both the automobile and industrial industries. A significant area of study is failure analysis. In this sense, and taking into account researchers conducted failure prediction by lubricating oil analysis through ferrography techniques that help to control the maintenance process until a failure occurs in case of engine run by alternative fuel. The root cause analysis of the failure of the outer ring fracturing of the four-row cylindrical roller bearing was done, and the visual inspection of the failed rolling surfaces was emphasised. [1]. Failure by overheating of the exhaust valve of the heavy-duty CNG engine. They researched and observed failure well faster than the predicted life span [2]. This research is also focusing on a heavy-duty CNG engine but in a different way. The aim is to increase availability, alarming wear tendency rate to prevented failure by locating the wear out equipment, which would effectively minimize repair costs and performance rate.

With this respect, maintenance contributes significantly to the life of the technology capital assets. It describes a combination of all administrative, technical, and sporting stuff to operate maintenance and other physical layouts in an attempt to re-establish appropriate working conditions [3]. Maintenance aims to keep the plant from being shut down by an uncontrollable operation [4 - 5]. The health of the rotating equipment should be maintained according to appropriate maintenance methods, such as condition-based maintenance, preventive maintenance, and break down maintenance. Each unit must be adequately operated to keep it secure, supposed with unconditioned operation [6-7]. The research was based on 50 samples of oil and tested over 250 straight hours in the engine. The result is that maintenance intervals can last longer, while maintenance costs increase at the same time [8]. Various wear-atlases have been issued since then, some of them having been distributed online. The correct sampling frequency must be specified in the vehicle's maintenance log. When potential problems are identified, the sampling frequency should be raised until the condition and operation of the machine is determined. To measure each lubrication parameter, set a constant range of operation of the test engine/lubricant over time [9]. Lubricant monitoring is useful for

all vital rotating machinery. The maintenance manager can collect essential data about the equipment's working conditions by doing the lubricant test. While the industry still relies primarily on a sequential, predictive maintenance strategy, growing uncertainty, enhanced demands and competitive criteria as to the availability, reliability of equipment and the effect of the data revolution on vessel operations, it prefers a better-organized Condition Based Maintenance (CBM) system [10].

CBM points not only on identifying and assessing device faults, but also on investigating, predicting, and monitoring faults compared to breakdowns and preventive maintenance [11]. Predictive maintenance relies on condition-based maintenance on the results of analysis and critical attenuation parameters [12]. Predictive maintenance is routine monitoring of the existing condition of rotating equipment, operational productivity and various parameters providing evidence to assess the optimum time between measures to minimise costs and to decrease the number of indefinite delays [13]. Increasing the availability of equipment not only involves reducing the amount of damage, but also the time needed for repair and inspection: insufficient stable equipment to reach high capability levels; similarly, significant is the optimum speed of repair, maintenance and inspection. To increase the performance of machinery and industrial wellbeing, all recognised failures with disastrous consequences must be avoided [14].

The core of the CBM is condition monitoring, which aims to collect data on equipment state and is performed by defining and predicting various measurable parameters using different instruments. This is an important predictive maintenance element. Condition monitoring techniques allow to identify the root source of failure and take precautionary measures before an error occurs. Information can contain the vibration, acoustic, thermal, oil and lubricant, and current signal measurements. Condition monitoring is the technique of a new method to scheduled maintenance focused on condition monitoring approaches using an assessment of the state of the equipment that arrived in the 1970s and 1980s. situation [15]. The basic requirement, i.e., human resource tools, skills, and knowledge, are used for implementing a condition monitoring technique. This technique allows the research, recording, and monitoring of data obtained using computer tools and the error trend curves [16]. When the condition is checked, if the reading exceeds the predetermined value, the monitoring equipment is declared faulty, and maintenance interference is activated. However, little thought was paid to how critical levels and monitoring gaps are determined in both practical and theory [17]. The purpose of general maintenance and machine condition monitoring is to predict the

degradation trend of the equipment performance, which tends to combine reliability and accessibility directly and indirectly at a minimal cost [18 - 22]. Recently, new approaches have been explored to improve equipment reliability, availability, and maintainability [23].

Preventive maintenance is a preferred choice for machinery operators and is actively monitored by predictive maintenance. Therefore, corrective maintenance structures and equipment adjustments are avoided, increasing reliability and overall availability. In addition, the transition to data from scheduled repairs will lead to more effective scheduled maintenance to enhance the cost reduction, increased use of equipment, and improved security. Therefore, the industry is looking for reliable, time-efficient and utmost operating performance as well as safe and stable operation in an unfavourable environment.

The oil analysis technique is a type of failure analysis technique, covering a wide range of topics, including oil corrosion analysis, physical, chemical and contamination detection. This analysis was done by various techniques like; ferrography analysis, magnetic plug analysis, Fourier transform infrared spectrum analysis, infrared spectrum analysis, Plasma Spectrometer Test (PST) and more [24 - 27]. Ferrography is an example of a prosperous oil analysis method capable of monitoring the wear of engineering systems. It is a technique of separation particle in glass based on the magnetic time interactions and flow of suspended particles in an external magnetic field [28 - 29]. This method was developed in the 1970s to study the occurrence of wear particles in lubricated dynamic components. New areas of research and practice have been opened in wear monitoring of mechanical equipment for the unique advantages of ferrographic analysis. As most mechanical instruments are made of iron and steel, the idea of using magnets to trap wear particles in lubricants is implemented. Many information is revealed as a result of repeated experiments and research, the development of ferrography, a new technique of oil analysis [30 - 34].

The ANN is capable of solving analytical modelling problems including non-traditional methods including physical, dynamic and energy transfer processes. Therefore, they can use pre-service approaches that can help decision-makers choice the suitable maintenance equipment for their appliances. The need for smart technology used as an adjunct to existing situational control programs in experiments and applications is emerging as one of the most successful technologies in this field [35]. ANN provides diagnostic tools to understand and interpret the external state of complex systems [36]. Based on the state of the system and its resistance parameters, data-based methods for diagnosing faults and predicting useful life are increasingly applied [37]. Unlike the classical model-based approach, ANN is a data-driven,

adaptive approach that has little resemblance to the model under study [38]. They learn from preceding examples and derive ambiguous functional relationships between data. Secondly, ANN has the potential to improve overall performance. After training in the presented data, ANNs were able to manage data they had never seen before correctly. Third, ANN is a more general and interactive global mathematical calculation than conventional computational and statistical approaches.

Monitor the status of accelerator alarms to facilitate the decision-making load on the accuracy of the system and equipment and apply ANN to the error class [39]. They used ANN to diagnose marine diesel engine failures associated with engine clearance and cylinder load fluctuations. Their research suggests that ANN is highly accurate in predicting the faults of a ship engine and can improve the reliability engine performance [40]. Also, a neural network is used to diagnose faults in the marine system that cause failure due to input and prediction data in the network[41]. ANN has applied for CBM in the engine of medium-speed diesel engine working on a case study of a fishing boat. ANN analyzes real-time controlled data to determine the status of a machine fault [42].

On the other hand, predicted its performance based on the ANN model of the marine diesel engine, based on input data, i.e. engine load and speed which operate with output data, i.e. braking power, specific brake fluid consumption and exhaust gas temperature. These results suggest that the ANN models predicted error is smaller than the experimental models [43]. Perform applications for the clustering and monitoring the data on marine diesel engine using self-organised map neural networks (SOM) [44]. Furthermore, scrutinize the performance based on the driven data model using CBM in a marine propulsion system. The results established that it is possible to use the CBM and machine learning technique; ANN typically performs best outcomes [45]. They Conducted several analyses using a multi-layer neural network to predict oil production from the Gulf of Mexico. Choosing the dimensions of serial data is difficult and time-consuming and requires further study [46]. Validation of the nonlinear system remains an active area of research. This journal publishes a collection of papers based on a set of nonlinear system identification benchmark problems [47-51].

Henceforth, it can be said that quantitative analysis of wear particle is a compelling way of deriving the key parameters required to diagnose and predict the failure of moving equipment. This can be gainfully applied to the prediction of failure of engine operated by unconventional fuel to prescribe an effective maintenance strategy which may not be in line with the standard practice of maintenance of the engine operated by conventional fossil fuel.

So, this paper focuses on combining the Condition Monitoring as a diagnostic approach with an ANN developed model based on NARX architecture. After testing over a large number of lubricant oil samples, an ANN diagnostic system has been designed at an optimal parameter setting to predict fault at an early stage. The predictive model developed from wear quantitative data sets can monitor the engine performance, help prevent maintenance and warn of any maintenance that results in requests for replacement or repair.

1.1 Significance and novelty of work

After deriving a holistic amount of information from the past literature survey, the present work has been aimed with the following objectives:

- a) To incorporate condition-based maintenance so that any interruption of power generation due to regular inspection and overhauling can be minimised. The failure of the components can be predicted in advance as well as the necessary repair or replacement works can be performed.
- b) To develop an intelligent fused system (Neural Network model) to predict the failure and provide proper diagnostic measurement before the actual failure of the system to reduce the generation of sudden power loss.

The primary novelty of this work is stated below

- a) Most of the literature is concerned with the investigation of understanding the maintenance strategy and behaviour of wear inquisition--- in the state of art literature; a minimal emphasis is given on identifying the probable cause of failure inside a system.
- b) The primary focus of our work was concerned in predicting the failure of a system, with a systematic combination of experimental results and soft computational work.
- c) This work is an integration of experimental, and soft computational study, which is a novelty in itself.

2. Methodology

The current work is separately split into two parts, respectively, experimental and soft computing. Both approaches are briefly defined in the following subsections.

2.1 Experimental Procedure

Experimental procedures consist of a series of samples of lube oil accompanied by an analysis of the quantity of wear debris with the samples carried out by ferrographic techniques. Those are briefly mentioned in the following section.

2.1.1 Oil analysis

Oil testing is quick to measure particles existence in the oil, which determines engine health. It is like a medical blood test that can diagnose our disease with our blood. In recent years, engine lubricants demand has been increasing, particularly in the energy generated sectors. This has contributed to the production of synthetic lubricants at a low risk that does not react at high temperatures. Synthetic oils are processed using sophisticated processing and modern formulas.

There resulting from PAO based synthetic compounds (polyolefin, polyester, polyglycol), non-synthetic PAO, esters, alkylated naphthalene, and alkylated benzene. It is becoming increasingly important to use synthetic oils where mineral oils do not meet the requirements. Improper combustion produces oxides and harmful particulates in the environment. Consequently, the process of accessories and lubricants are developing products with longer service life, which can reduce oil discharges during operation of the equipment. An essential feature of lubricants in relation to temperature increase is their behaviour. They are not used at room temperature; They usually increase in temperature and pressure.

To enhance the existing quality, chemicals are used to inform the unique properties of the oil, mainly when the lubricant is worked under extreme conditions. The degradation of lubricants is not a natural phenomenon-the weakening of their physical properties, corrosion over time and multiple-use during life. Degradation of the lubricant was due to oxidation; viscosity; contamination; lack of additives (anti-corrosion, anti-wear, dispersing agents, etc.). The present oil analysis was carried out, accompanied by a quantitative ferrographic method.

2.1.1.1 Sampling point

The sample collection for the present case study is done from four-stroke, twelve-cylinder vertical CNG engine from oil and natural gas industry. **Table 1** demonstrates the specifications of CNG engine. The working hours of the engine range from 17-18 hrs per day with an interval of 1-1.5 hrs following 6-7 hrs of steady running. The collection of lubricant samples from CNG engine was done under normal operating conditions. The thermal properties of oil range at an approx. Limit of 3000⁰F to 3200⁰F, and speed of engine maximum up to 1100 RPM. The capacity of the lubricating chamber was 350 litres with filter replacement within 800 hrs. Seven CNG engine lubricating oil samples were taken keeping a periodical interval of 800 hours from the start. Tetrachloroethylene (C₂Cl₄) was used as a cleaning solvent, and for preventing contamination, dry containers were used for safely preserving the lubricating oil samples. To retain the wear particles uniformly, the oil collection was done immediately after switching off the engine.

Table 1. Specifications of the CNG engine.

Particulars	Specifications
Engine Model	3412C TA, V-12, 4-Stroke Air-Cooled Diesel
Compression Ratio	13:0:1
Fuel System	Pump and Lines
Bore	137.22 mm
Displacement	27.02 L
Stroke	152.4 mm
Maximum power	800 kW (900 kVA)
Speed	1500 or 1800 RPM
Frequency	50 or 60 Hz

2.1.1.2 Feature of lubricant

- UHPDO (Ultra-High-Performance CNG Oil) is a synthetic multi-grade lubricant primarily developed for the lubrication of CNG engines of heavy-duty vehicles, either ambient or turbocharged, working in extreme environments. The utilisation of this kind of lubricant allows for a significant decrease in the consumption of natural gas and broad cycles of oil replacement. This item complies with the few parameters and has the properties shown in **Table 2** below.

- The robust stability of the lubricating film, which preserves its properties even under extreme pressure and temperature environments.
- Improved potential for detergent/dispersant, guaranteeing the engine's flawless cleaning by instigating a deposit forming.
- High consistency of alkaline reserve over the lifespan of the lubricant.
- Strong low-temperature flowability, enabling cold starts.

Source: Specific sheet of lubricant, supplier of lubricant.

Table 2. Properties of CNG Engine oil.

Properties	Test Method	Typical
SAE Viscosity Grade	J 300	15W-40
Viscosity @ 100 °C, mm ² /s	ASTM D445	15.5
Viscosity @ 40 °C, mm ² /s	ASTM D445	116.2
Viscosity Index	ASTM D2270	141
Density @ 15°C, kg/L	ASTM D4052	0.872
Total Base Number, mg KOH/g	ASTM D2896	7.9
Flash Point, °C	ASTM D92	228
Pour Point, °C	ASTM D5950	-36
Sulphated Ash, %mass	ASTM D874	0.97

2.1.1.3 Preparation of oil sample for testing

The magnetic settling of wear particles in lubricating oil starts directly after the sample is left waiting. The particles must be uniformly distributed to produce a sample size from a large sample size. The following technique is recommended for producing a homogenous mixture:

- To allow for the observation of the oil and significant particles, the oil should be in a clean vessel. Ensuring that the vessel is two-thirds full to allow agitation to blend the particles deeply into the oil, thereby giving a homogeneous mixture to the sample.
- Heat the oil to 55 ° C (approximately 131 ° F). This is to keep the particles suspended as long as possible, according to ASTM standard practice because of to remove the moisture.
- Take it from the source of heat and quake the bottle strenuously.

- Remove 1 ml of oil and dispense in a new sample vial with the pipettor and new pipette cap.
- Mix 1 or 2 ml of tetrachlorethylene in 1 ml of oil in the sample tube in the sample tube, the viscosity of the oil determines the quantity of tetrachloroethylene applied to the oil. To minimise the viscosity of high-viscosity fluids, add 2 ml of tetrachloroethylene. This will cause the viscous oil to flow at a comparable rate to lower viscosity fluids along the precipitator tube. 1 ml of tetrachloroethylene will be enough to enable fluid flow into the precipitator tube for low-viscosity fluids. It does not matter if 1 or 2 ml of tetrachloroethylene is used, as long as the required 1 ml of oil used for each test. Nevertheless, high viscous samples that pass too slowly will impact the particle deposition by increasing the volume of material accumulated on the DL versus the DS.
- The faster analyse a sample gives better results. It may contribute to assembling of particles from the precipitator tube by enabling the sample to settle on a test vial as much of the material is accumulated at the bottom of the vial and concentrated in the precipitator tube around the DL sensor. To prevent this, use the prepared sample or re-mix the sample before testing so that the wear particle is adequately dispersed.

2.1.1.4 Quantitative Ferrographic technique

Quantitative ferrography is useful for analysing the nature, magnitude and the trend of growth in wear rate by the particle size distribution of wear debris as shown in **fig.1(a)** and **fig.1(b)** shows the schematic diagram of DR-V ferrography. This characterises and distinguishes different wear situation. Oil samples, along with solvent tetrachloroethylene (C_2Cl_4) is shaken in a test tube to reduce the viscosity of the oil. This is made to flow through a precipitator tube under symphonic action. A magnet is placed beneath the glass tube.

The magnetic attraction arrests the ferrous particles. D_L (5 microns) are deposited at the entry while D_s (1-2 microns) are arranged away from the entry. The magnetic force is proportional to the volume of particle, whereas the viscous force resisting motion is proportional to the particle area. The motion downward through the glass tube is proportional to the effective particle diameter. Two light beams pass through the precipitator tube. The first beam is located at the vicinity of the tube entry where large (L) particles are deposited and the second beam crosses the tube where the smaller (S) particles are deposited. The number of particles deposited is measured by the attenuation of light from a light source, the light passing being detected by the photoelectric transducer. *WPC* (wear particle concentration), *WSI* (wear

severity index), *SI* (Severity Index) and *PLP* (Percentage of large particles) are subsequently measured, informing machine wear state and identify trend lines.

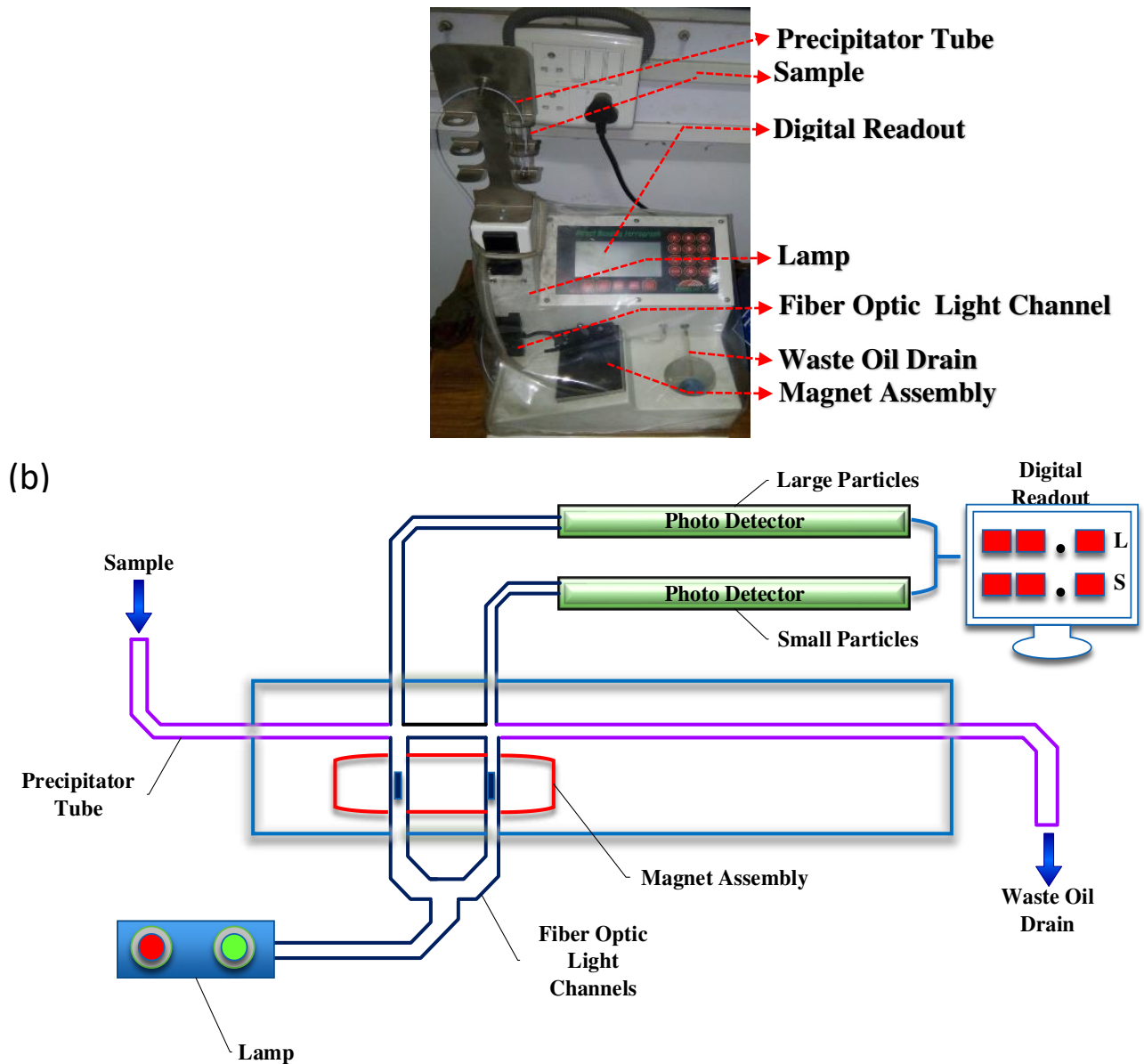


Fig.1 (a) DR-V Ferrograph and (b) Schematic diagram of DR-V Ferrograph.

2.2. Soft computing technique

In-depth wear particle analyses are very relevant to obtain various wear trend parameters that are useful for predicting the failure using the soft computational model. In the following sections, the soft computing approach, i.e. ANN (NARX) used for current research, is briefly discussed.

2.2.1. Construction of NARX model

The data-driven predictive diagnostic is more effective methods in CNG engine prognostic applications because of the simplicity in data finding and consistency in complex processes. They are also of particular importance because of the ability to integrate innovative and conventional approaches by generating inclusive diagnostic methods over a wide-ranging data series. One such technique for modelling multi-step prediction is NARX. NARX model is described as a time series recurrent neural system which can examine the condition-based maintenance of CNG engine. The diagnostic model based upon NARX was so designed to make the model learn from the current monitoring data and forecast condition of wear inside the engine system.

An ANN model using a Nonlinear Autoregressive with Exogenous input (NARX) plays a vital role in fault diagnosis. In NARX, the neural system of the cerebrum is very close to that in neurons. Within the neural network, there are three layers, i.e., input, hidden, and output layers. Inside the hidden layer, the neurons are modified repeatedly to capture the dynamic value and deliver an optimal output. A time series is a continuous data set that is typically measured at a straight point over the same time interval. A set of vectors $z(t)$, $t=0,1, 2, \dots, d$ where 't' signifies the elapsed time with a set of separate values $z_1, z_2, z_3, \dots, etc..$ The vector $z(t)$ is assumed to be a random variable, and occurrence calculations are performed in the proper order in the time series. In the NARX model, time series values $z(t)$ is calculated from the prior $z(t)$ and outer series $r(t)$. Thus, the NARX model can reflect as the exogenic inputs to predict $z(t)$ time series relative to nonlinear autoregressive (NAR) models and to detect model parameter changes based on exterior conditions which are shown in equation (1).

$$z(t) = f(r(t-1), \dots, r(t-d), z(t-1), \dots, z(t-d)) \quad (1)$$

Where $r(t)$ is the observation of an exogenic input at t (time).

In addition, the management of time series data is minimized over time, changing the opening mode for the network loop network response, input mode, and layer state. It allows configuring easily the original time series data in a network that consumes less time. The timeline is used to store the accumulated values (t) and $z(t)$. The graphical outline model of NARX is shown in **Fig. 2**.

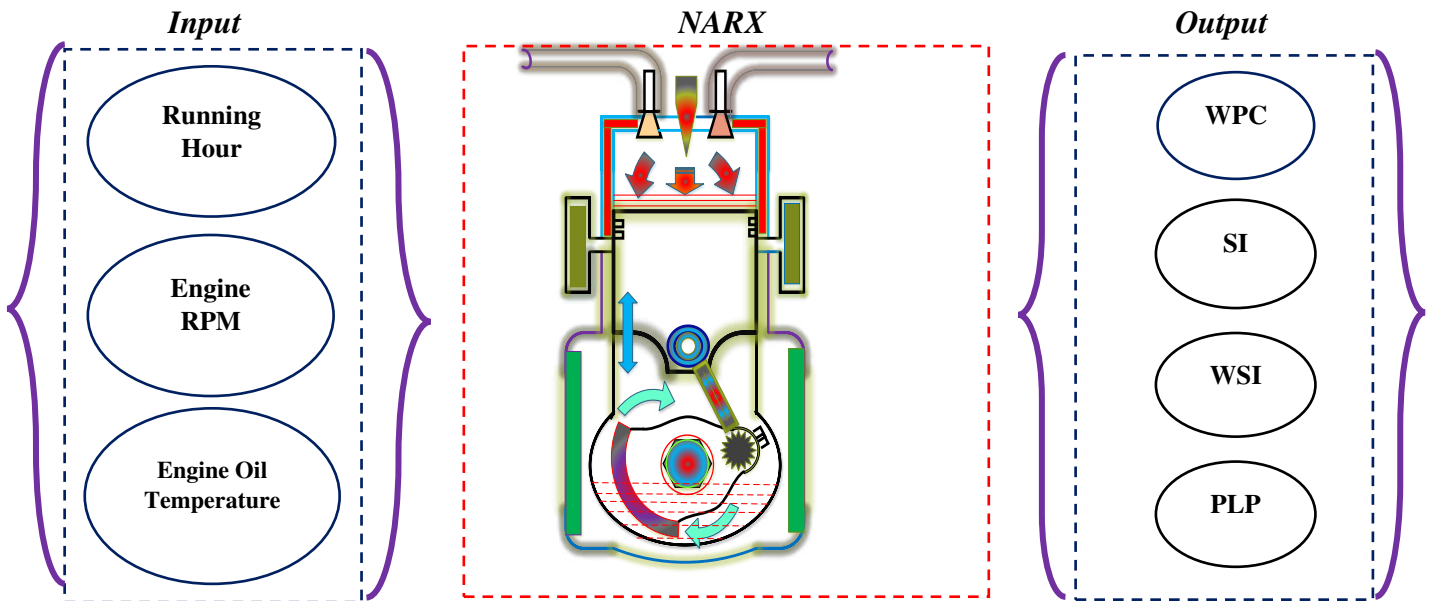


Fig. 2. Graphical outline model of NARX.

2.2.2. Determining input and output data

The normalised data was of direct use for training. It adapts to the outside of the neuron, transforming it into a range of network activity according to the needs of the network. Their results do not go beyond saturation. The current research studies, the model of Input targets as to engine parameters as Engine Running Hour, RPM and oil temperature and output targets as to wear quantitative parameters like wear particle concentration (WPC), wear severity index (WSI), Severity Index (SI) and Percentage of large particles (PLP). The data are processed and processed with minimum and maximum values of -1 to 1 in the ANN model for proper analysis and enhancement of network analysis by using the formula (2) where, W_k denotes the normalized estimation of P_k , $P_k \text{ max.}$, and $P_k \text{ min.}$ are experimental, maximum and minimum values.

$$W_k = -1 + \left\{ 2.0 \times \left(\frac{P_k - P_k \text{ min.}}{P_k \text{ max.} - P_k \text{ min.}} \right) \right\} \dots\dots\dots (2)$$

2.2.3 Decision of Dataset

The literature review shows that the NARX frame model can be correctly utilised for training and testing in different sections of the data collection. In this study, 75 per cent of the total data set was chosen to prepare the model for training, along with a 10-timesteps delay line. The cross-recognition and neural sample training were connected to a secondary collection

of results. A key reason for solving the over-fitting of the neural system is the selection of 20 percent of the cross-recognition database to prevent mistrust.

2.2.4 Determination of activation function

Transfer function primarily aimed at adjusting neuron level or activation node inputs for the NARX model. Also, the activation function provides details on non-linear regression between neuron patterns to create a correct relationship between the input and the output layer, weight and bias. A single hidden layer with tangent sigmoid activation function (*tansig*) was built to predict better output outcomes using the selected **formula (3)** to train the network, as it is differentiable, continuous and non-linear to predict a better outcome.

$$P(N)=\frac{2}{\left(1+e^{-2n}\right)-1} \dots\dots\dots(3)$$

2.2.5 Determination of training algorithm

The first NARX prototype was designed as a feed-forward backpropagation. During training, the weight and bias of the network are updated as all inputs and targets are presented to the network. The network is dynamic, and only the input, target, and external inputs are correct for the NARX model. The basic *trainlm* algorithm is often used for NARX network training. This algorithm upgrades the weight values and deviations according to the Levenberg-Marquardt optimization [52]. This class reduces the combination of error and weight and then sets the correct combination to create an excellent generalized network and avoid over-crowding. Network performance is evaluated with the sum of square error (MSE) and connection correspondence. ANNs are trained in an open-loop and transmitter network based on the above criteria.

2.2.6 Statistical estimation of output variables

Statistical estimation is conducted using multiple sets of statistical parameters to predict performance sets of data. The output of the ANN model was developed in the current study by evaluating some statistical output parameters with their importance and range of approximation are mentioned in **Table 3** below.

Table 3. Statistical evaluation of output parameters

	R	MSE	MAPE	MSRE
Statistical parameters	Correlation Coefficient	Mean Square Error	Mean Absolute Percentage Error	Mean Square Relative Error
Significance	Correlation between the experimental values and predicted outcomes.	Calculates the difference between the measured and predicted values.	Computes error in percentage of the predicted values.	Compute relative error between experimental values and predicted values.
Formula	$R = \sqrt{1 - \frac{\sum_{i=1}^n (a_i - b_i)^2}{\sum_{i=1}^n b_i^2}}$	$MSE = \frac{1}{N} \left[\sum_{i=1}^n (a_i - b_i)^2 \right]$	$MAPE = \left[\sum_{i=1}^n \left \frac{a_i - b_i}{a_i} \right \right] \times \frac{100\%}{n}$	$MSRE = \left \frac{1}{n} \left[\sum_{i=1}^n \left\{ \frac{(a_i - b_i)^2}{b_i^2} \right\} \right] \right $
Accuracy	>0.9	<0.001	<5%	-

Where,

n , a_i , and b_i = the total data, actual value and predicted value respectively.

3. Benchmark results and discussion

3.1. ANN (NARX architecture) modelling

The purpose of this analysis was to build the predictive model with at least no test variables and to compare with the outputs. The ANN model was constructed using NARX architecture which resembles a time series neural prediction system. In this study, there are three inputs concerning the engine parameters **fig.3.** shows the framework model. The flowchart of the

model is shown in **fig 4**. There are four sets of output (WPC, SI, WSI, PLP), and each set contains 30 data. The unit of each output is distinct from each other; thus, the output cannot be comparable. For this purpose, the data are normalised to make them identical.

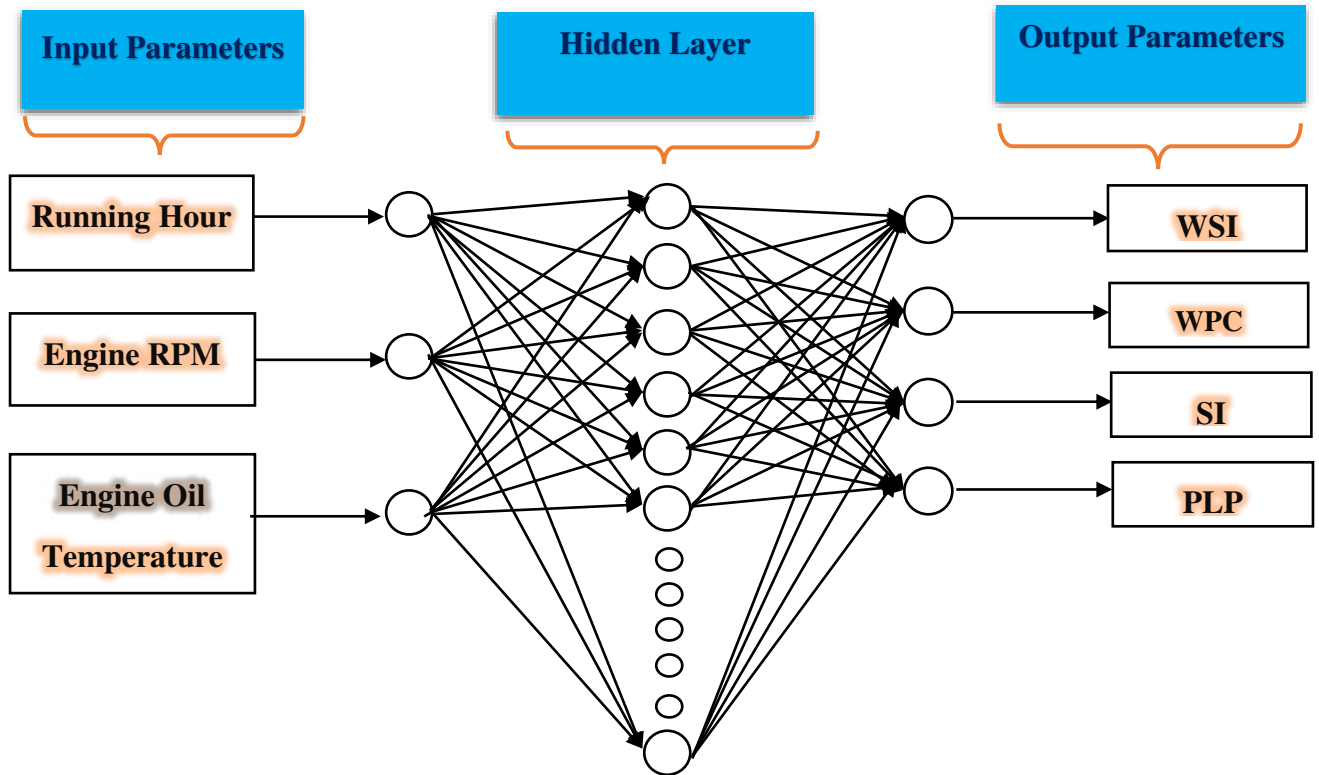


Fig. 3. General ANN model configuration.

In the next step, a multi-layer perceptron model was formed with NARX architecture having feed-forward error backpropagation and tapped delay lines to define the hidden relationship between input and output. The data were trained by comparing the engine parameter with the quantitative parameters derived from the observational investigation. **Fig 5.** shows the designed structure of the NARX model.

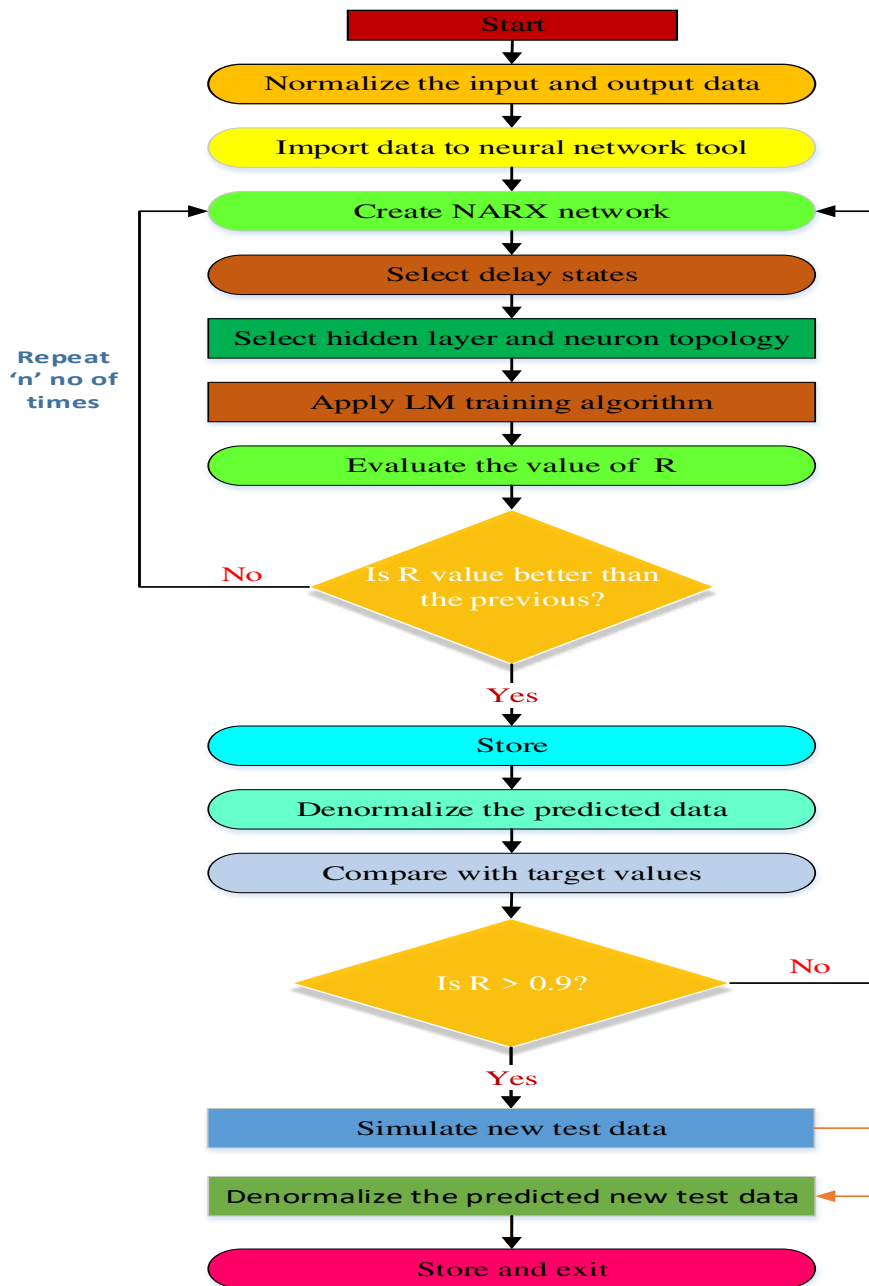


Fig 4. Flowchart of NARX model

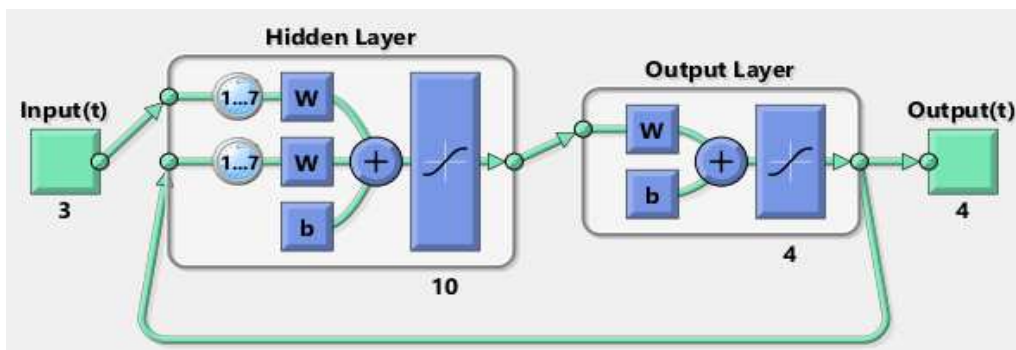


Fig. 5. Representation of NARX model.

3.2 Optimization of neuron topology

The NARX model testing was evaluated with six different algorithms, namely the quasi-Newton algorithm, Levenberg-Marquardt algorithm, scaled conjugate algorithm, resilient algorithm, gradient descent with momentum algorithm, gradient descent with adaptive learning rate algorithm. Tansig (tangent sigmoidal) activation function with one hidden layer is selected during the training session of the network. Before training, specific engine test parameters as engine running hours, RPM and oil temperature were put as input. For output parameters, WPC, WSI, SI, and PLP were selected. Variation of neurons from two to twenty were studied to evaluate the optimal network. The best ANN model was determined when the statistical error, i.e., MSE (mean square error) < 0.001 , MAPE (mean absolute percentage error) $< 5\%$ and R (regression coefficient) > 0.98 , was determined using a particular method as seen in **table 3**. The model input-output configuration is shown in fig 4. The normalization of data sets was done in between -1 to +1 using **formula (2)**. From the normalized data sets, selection of 70% random data was utilised in network training, 10% for network validation and 20% in network testing. The TRAINLM algorithm with a single hidden layer and the *tansig* transfer function produces an optimised collection of analyses with the lowest error rate after iteration with six separate algorithms. **Fig. 6** shows the variation of the number of neurons with the variation of MSE. From the graph, it is noticeable that *trainlm* has minimal MSE correlate with other training algorithms. For *trainlm*, the minimum MSE is taken at the number of neurons 10. The best results of the six training algorithms are shown in **Table 4**. It is made evident that, (3-10-4) topology with *trainlm* was established to be the optimal network. **Table 5** shows how the proposed model is optimally configured. **Table 6** illustrates the analysis of the amount of *trainlm* neurons. The overall mean value of R is 0.99459 (as seen in **Fig.7**), while it is 0.99645 for training, 0.98237 for testing, and 0.98411 for validation of the current ANN model. **Fig. 8** shows the autocorrelation error plot within 95% of the confidence limit, which informs about the minimal deviation of NARX predicted results from experimental outcomes.

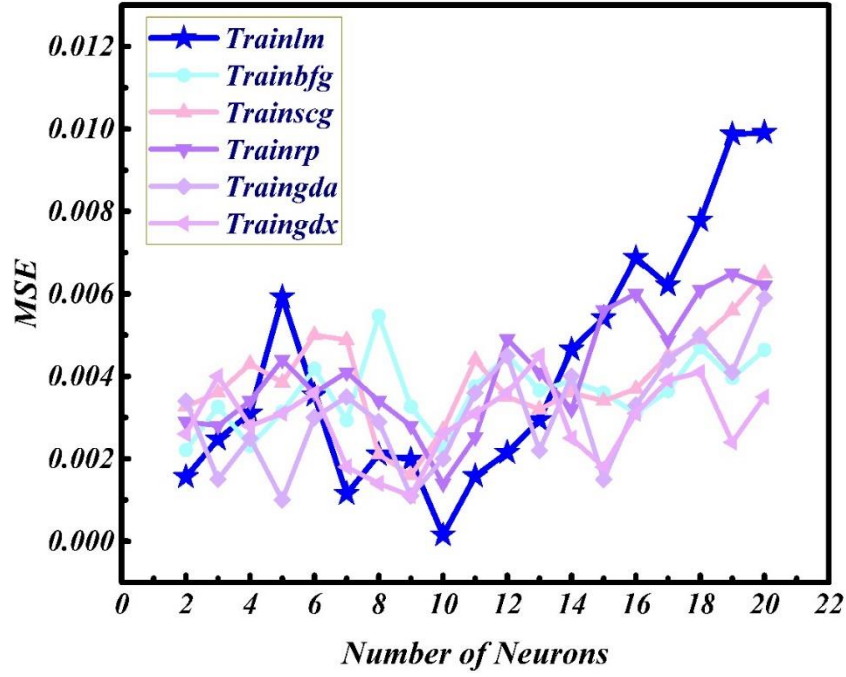


Fig. 6. Variation of Number of Neurons with MSE.

Table 4. Best results of the selected training algorithms.

Topology	Training algorithm	Regression Coefficient(R)				MSE	MAPE
		Training	Validation	Testing	Overall		
3-9-4	Trainbfg	0.85244	0.98756	0.99682	0.88125	0.00168	5.32
3-7-4	Trainscg	0.85051	0.98859	0.99196	0.87134	0.02536	7.13
3-15-4	Trainrp	0.85902	0.99901	0.97583	0.87498	0.00504	3.78
3-10-4	Trainlm	0.99645	0.98411	0.98237	0.99459	0.00019	1.67
3-17-4	Traingda	0.97973	0.99984	0.99896	0.98215	0.00245	5.71
3-5-4	Traingdx	0.93946	0.98963	0.99997	0.95304	0.00395	3.69

Bold indicates the optimal value.

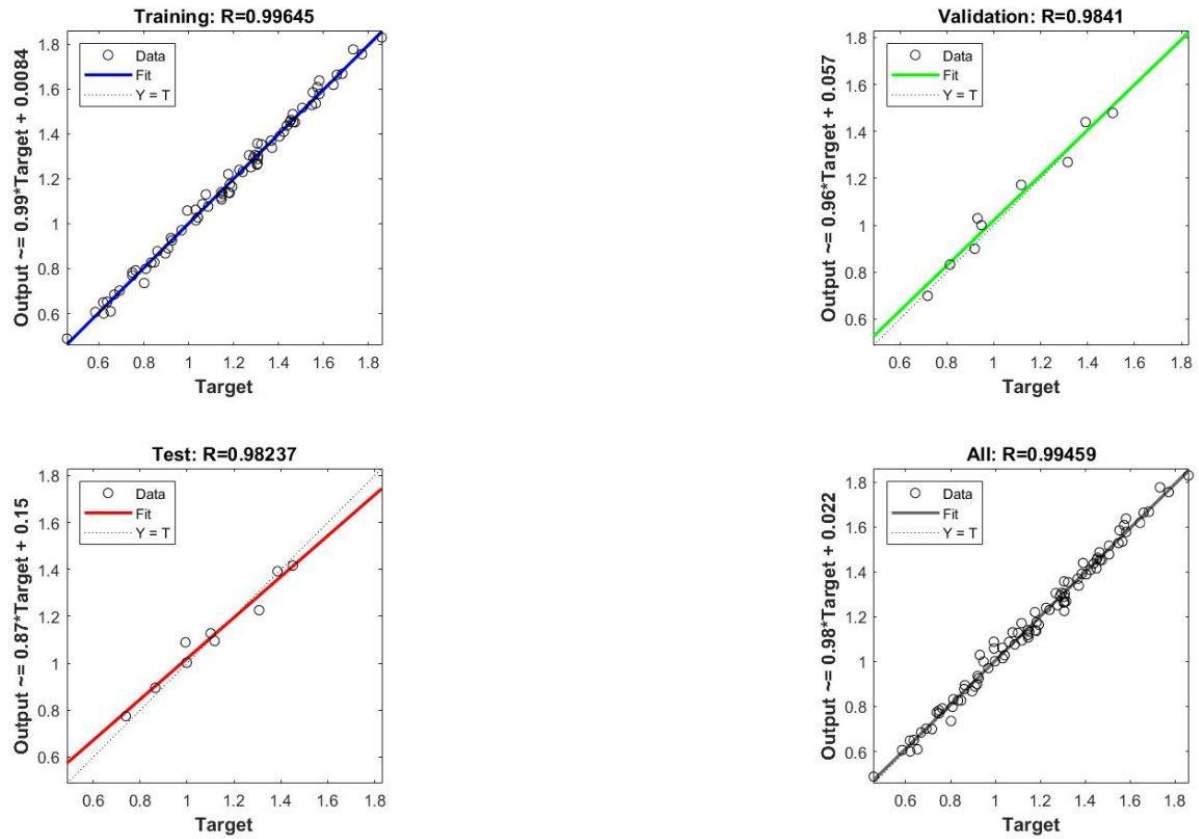


Fig. 7. Overall R values for the selected trainlm algorithms.

Table 5. Optimal training parameter setting

Training Conditions	Value	Description
Epochs	1000	Maximum epoch count
Goal	0	Performance goal
Lr	0.001	Learning rate
Maximum fail	1000	Maximum failures with validation
Minimum gradient	1E-10	validation failures
Param.time	Inf	time to train (seconds)
Activation function	tansig	Training algorithm
Function	MSE	Performance function
Divide function	Divide block	Dataset division
Parameter	70%-10%-20%	Training, validation, test data

Table 6. The output of the different number of neurons.

Neuron	Regression Coefficient(R)				MSE	MAPE
	Training	Validation	Testing	Overall		
2	0.86275	0.99372	0.98682	0.87315	0.00156	6.32
3	0.86015	0.97695	0.98927	0.88314	0.02476	6.31
4	0.88924	0.98324	0.98912	0.88498	0.00541	5.87
5	0.92665	0.97823	0.98951	0.9189	0.00592	7.05
6	0.97973	0.99842	0.98963	0.97215	0.00354	4.1
7	0.92956	0.99997	0.95423	0.94324	0.00375	2.86
8	0.92364	0.96279	0.99652	0.94684	0.00421	2.78
9	0.95302	0.98642	0.98456	0.96854	0.00798	2.08
10	0.99645	0.98411	0.98237	0.99459	0.00019	1.67
11	0.97456	0.98743	0.98457	0.98723	0.00158	2.86
12	0.89279	0.95677	0.96874	0.98926	0.00215	3.85
13	0.97576	0.97843	0.99456	0.91184	0.00194	3.56
14	0.94687	0.97631	0.98576	0.98042	0.00165	4.38
15	0.97456	0.93288	0.95358	0.97205	0.00241	3.77
16	0.94258	0.98376	0.94268	0.97162	0.00287	2.87
17	0.85289	0.97567	0.98594	0.91012	0.00421	4.09
18	0.85735	0.91947	0.97859	0.94964	0.00378	5.75
19	0.89231	0.90818	0.98740	0.99211	0.00287	4.13
20	0.9819	0.98769	0.99687	0.98684	0.00891	2.78

Bold indicates the optimal value

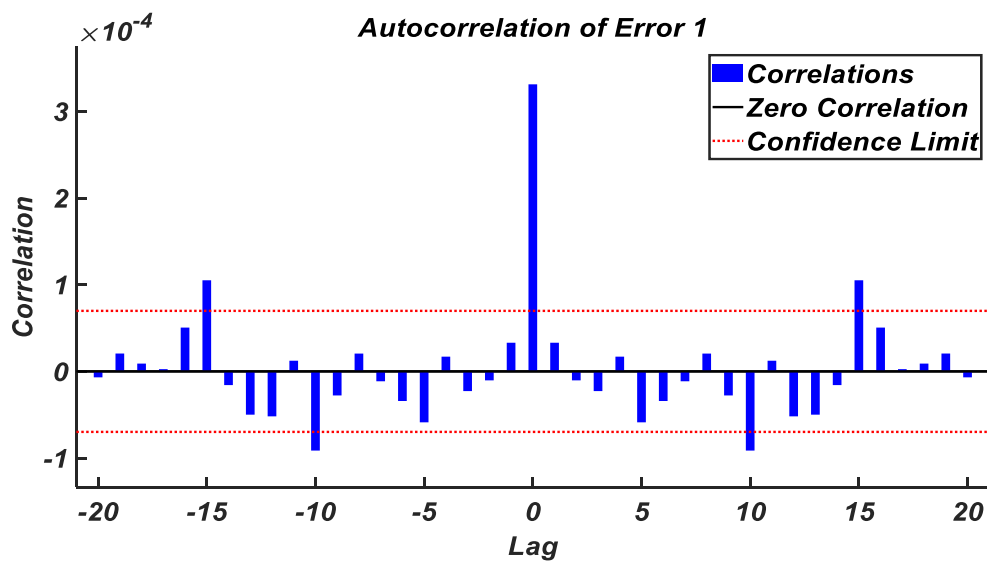


Fig.8. Correlation measurement for the optimized model.

3.3 NARX model validation

The objective of designing the NARX failure predictive model is to verify the output responses with the experimental outcomes. The quantitative parameters for CNG units are validated with NARX outcomes. **Fig. 9-13** shows the comparison of predicted results and actual machine results for each test case of the developed model (trainlm). This is the most consistent and accurate evidence between the predicted output and the actual output of each test case in the network. In **Fig. 9** (a and b) reflect WPC forecast by ANN toward experimental observations WPC. The predicted WPC model values (as shown in **Fig.13**) with MSE show the value of 0.000155, 0.000112 for MSRE, 3.1 % for MAPE and 0.99991 for R-value. Similarly, **Fig. 10** (a and b) illustrate the SI predicted by ANN against the SI calculated experimentally. The constructed model achieved MSE of 0.000089 with MSRE of 0.000154 with MAPE of 2.78 % and the R-value of 0.99894 in predicting SI (as shown in Fig.12). The predicted WSI value is correlated with the experimentally measured WSI values, as shown in **Fig. 11** (a and b) of 0.000128, 0.00074, 2.78 % and 0.99861 with MSE, MSRE, MAPE and R (as seen in **Fig.13**) respectively. Similarly, the experimentally measured PLP and ANN predicted PLP is shown in **Fig.12** (a and b). Comparison of error calculations (as seen in **Fig.13**) shows that MSE and MSRE scored 0.000213 and 0.00035 for PLP, with 3.39 % for MAPE and 0.99999 for R respectively. Hence, It is a prominent sign of the developed ANN (NARX) model as a robust detection in predicting the quantity of equipment output wear real-time property relations.

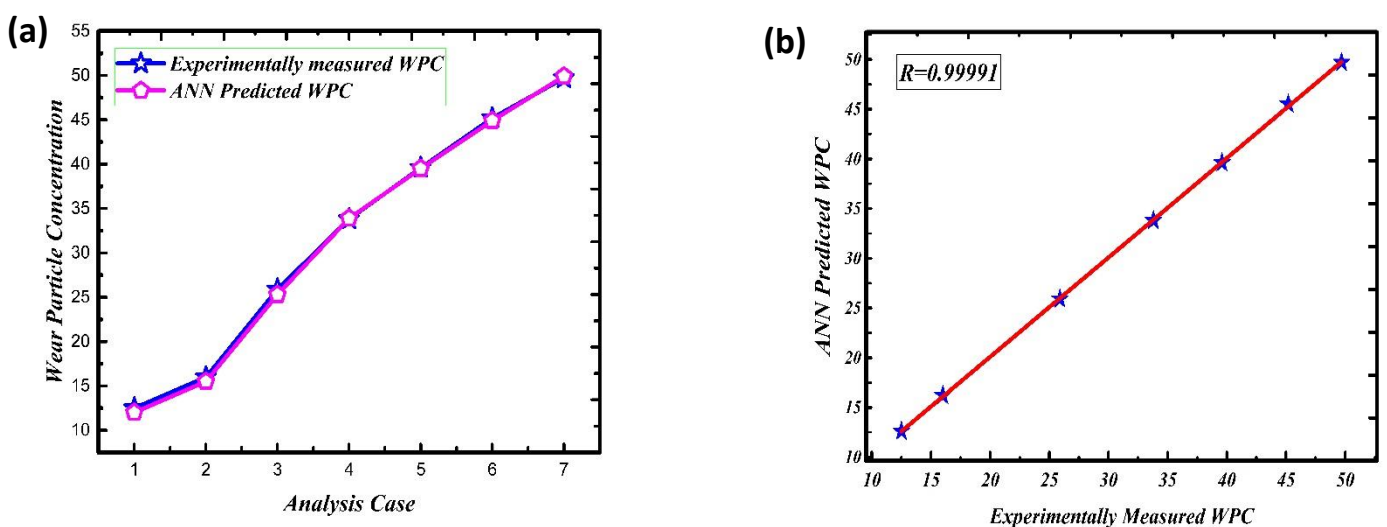


Fig.9. (a) and (b) Analysis of WPC obtained experimentally with predicted WPC from ANN.

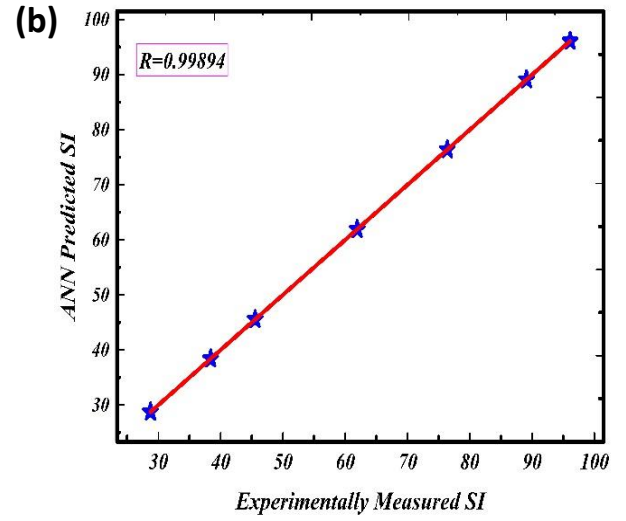
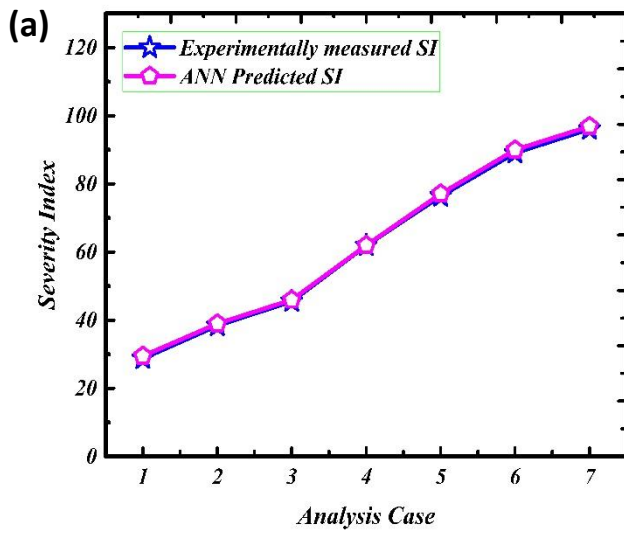


Fig.10. (a) and (b) Analysis of SI obtained experimentally with predicted SI from ANN.

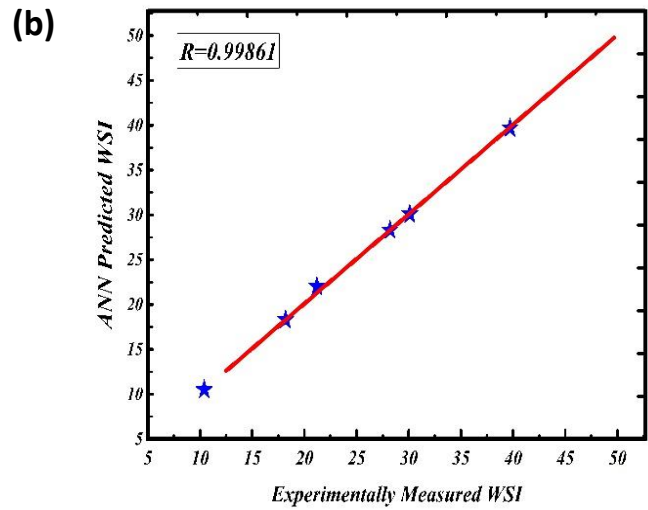
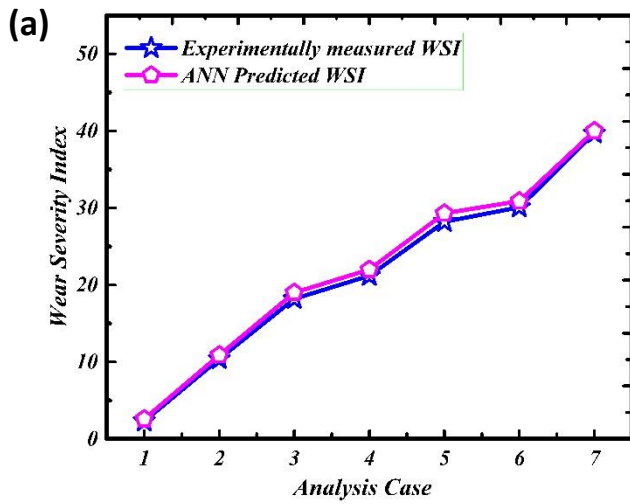


Fig.11. (a) and (b) Analysis of WSI obtained experimentally with predicted WSI from ANN.

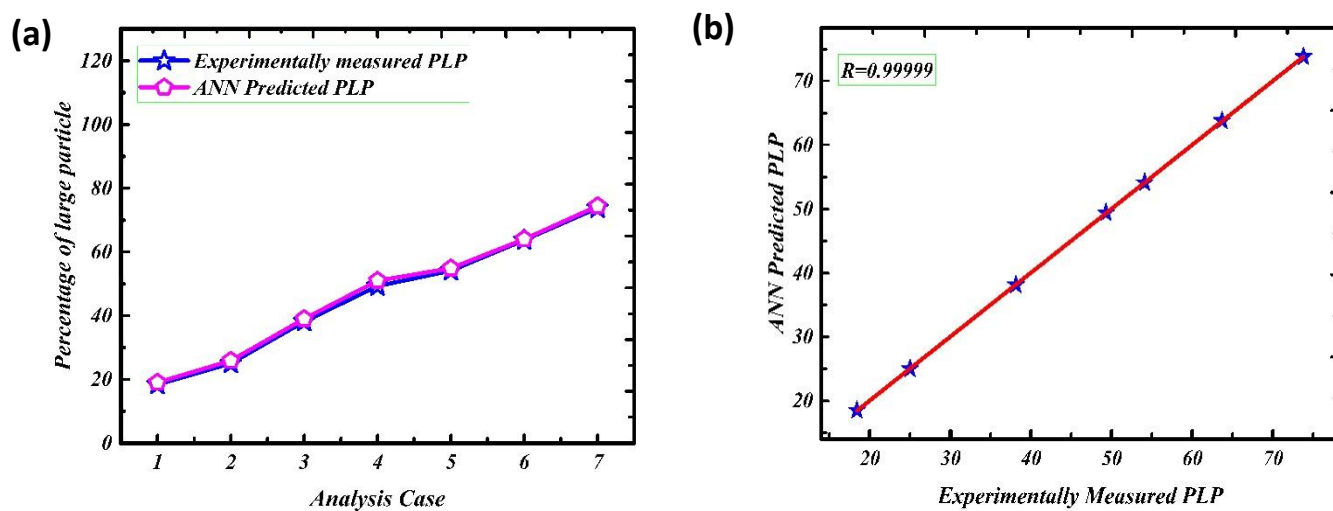


Fig.12. (a) and (b) Analysis of PLP obtained experimentally with predicted PLP from ANN.

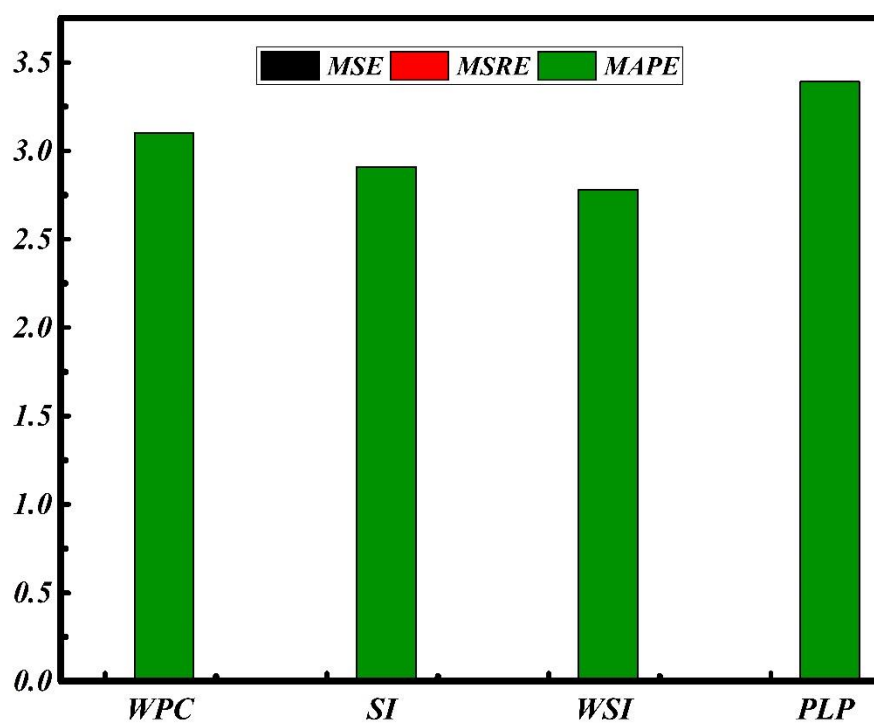


Fig.13. Comparative analysis of Quantitative Parameters for error Measurements

Conclusions

In this paper, the NARX neural network has been demonstrated and applied to simulate the fault diagnosis from engine data. Some significant concluding remarks from the above work are point up below

- The research discusses the impact of integrating a NARX predictive model with the CNG engine diagnostic condition monitoring methodology by conveying early warning signs of fault prediction and mitigating the future problem in advance.
- Topology 3-10-4 was used as the best model optimisation and was considered optimal for the prediction of numerous engine parameters as input data and the use of quantitative parameters as responses. The autocorrelation error function below 95% confidence trust limit expected healthy prediction accuracy outcomes of R, MSE, MAPE values as 0.978678-0.9999877, 0.0000789-0.222324, and 2.96-3.99% respectively. The minimum value of MSE reached optimal topology demonstrates the model efficiency in simulating the actual diagnostic condition of the engine.
- An ANN diagnostic classification for the whole engine unit may be treated for the exceptional capacity of the model to correctly represent the pattern of the calculated data to measure the optimum condition monitoring method.

Declarations

Availability of data and materials

Already data is associate with the submitted manuscript.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Not applicable.

Authors' contributions

SM is responsible for writing the entire paper , conducting the optimisation model and checked the validation results. SP provided advice on the abstract and computational technique. SH reviewed the introduction . SM ,SP and SH were involved in the experiment and the data collection process. All authors read and approved the fnal manuscript.

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Figures

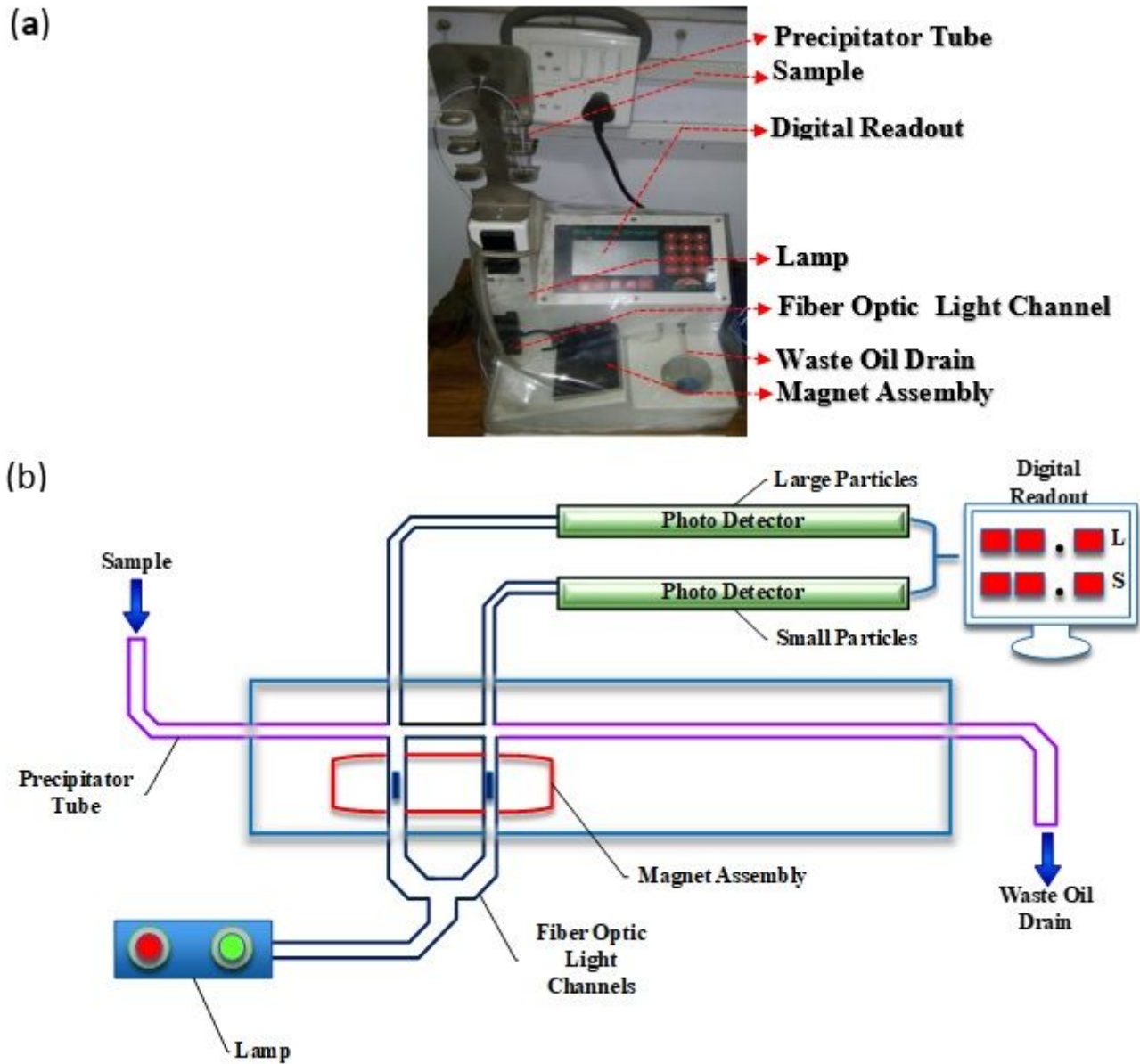


Figure 1

(a) DR-V Ferrograph and (b) Schematic diagram of DR-V Ferrograph.

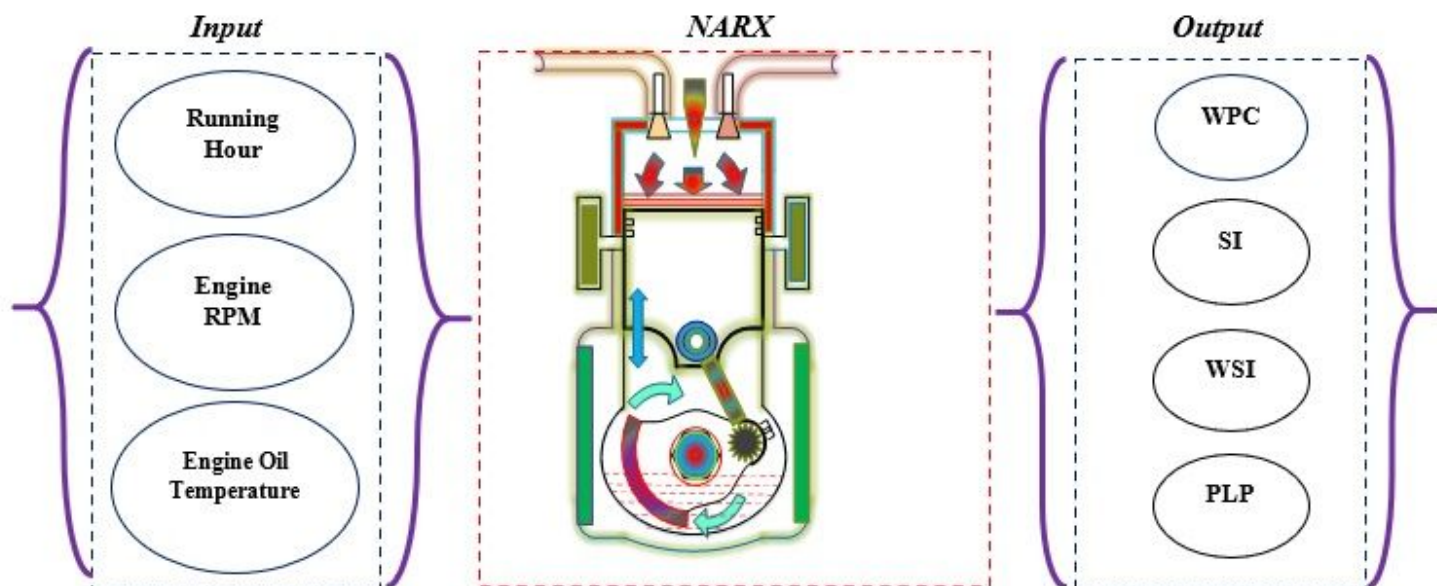


Figure 2

Graphical outline model of NARX.

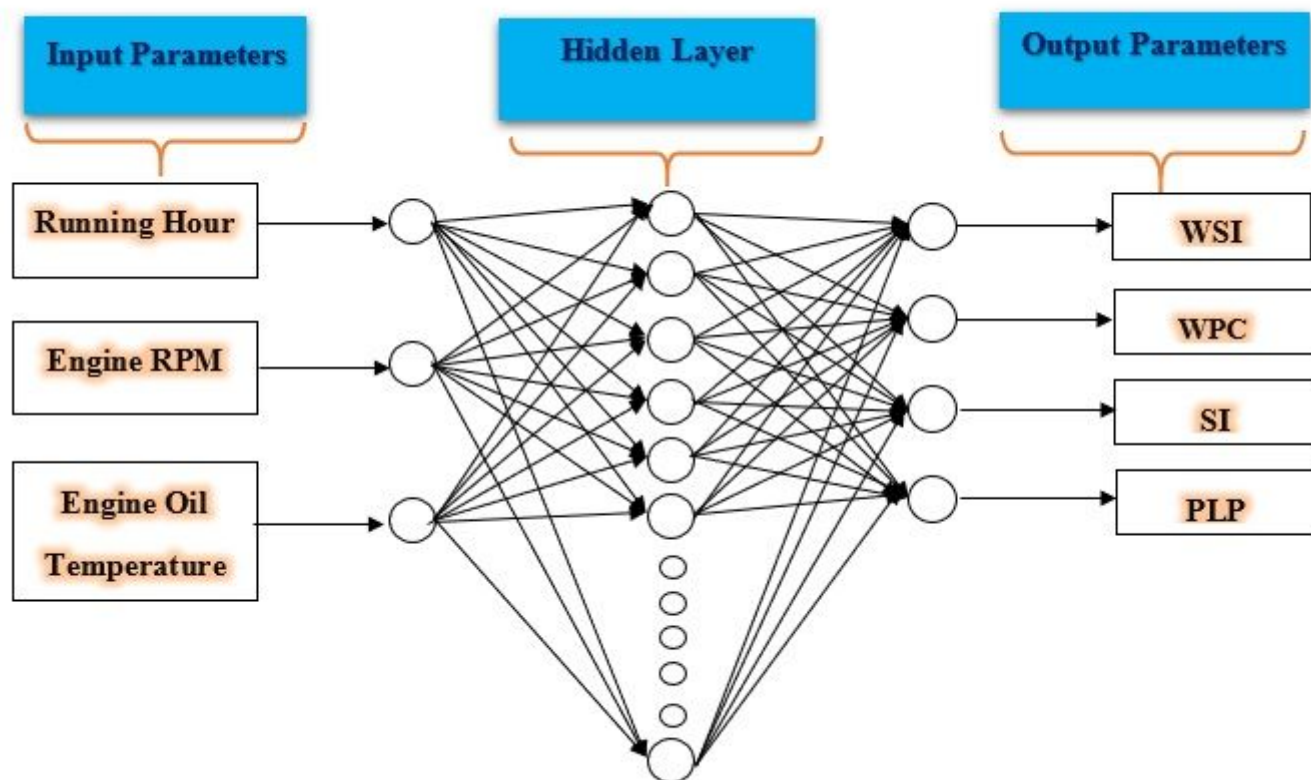


Figure 3

General ANN model configuration.

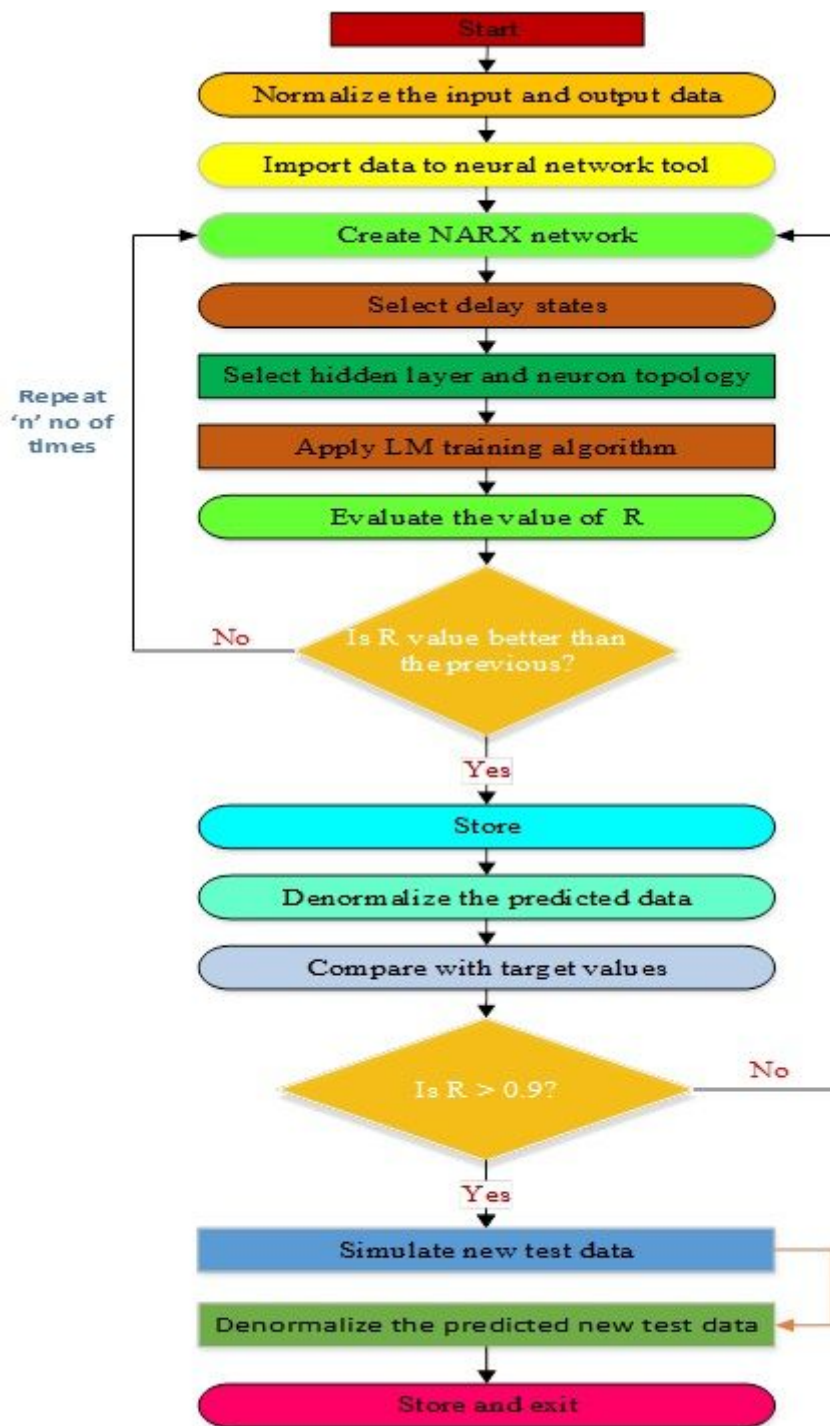


Figure 4

Flowchart of NARX model

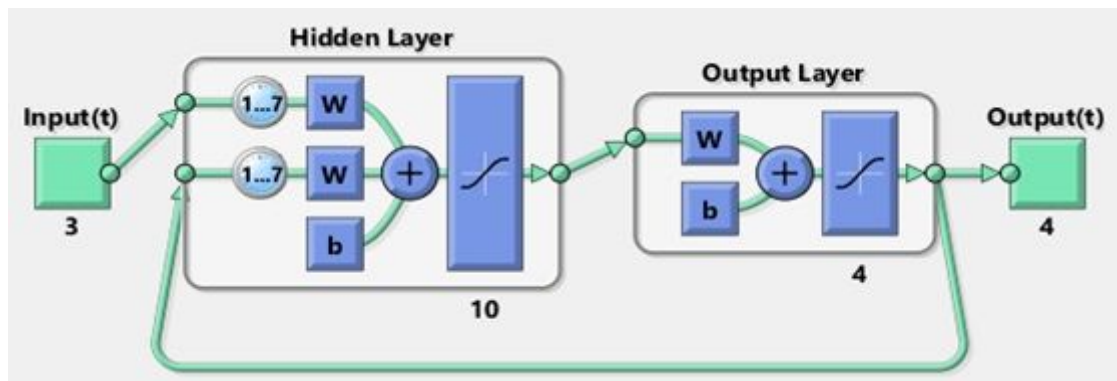


Figure 5

Representation of NARX model.

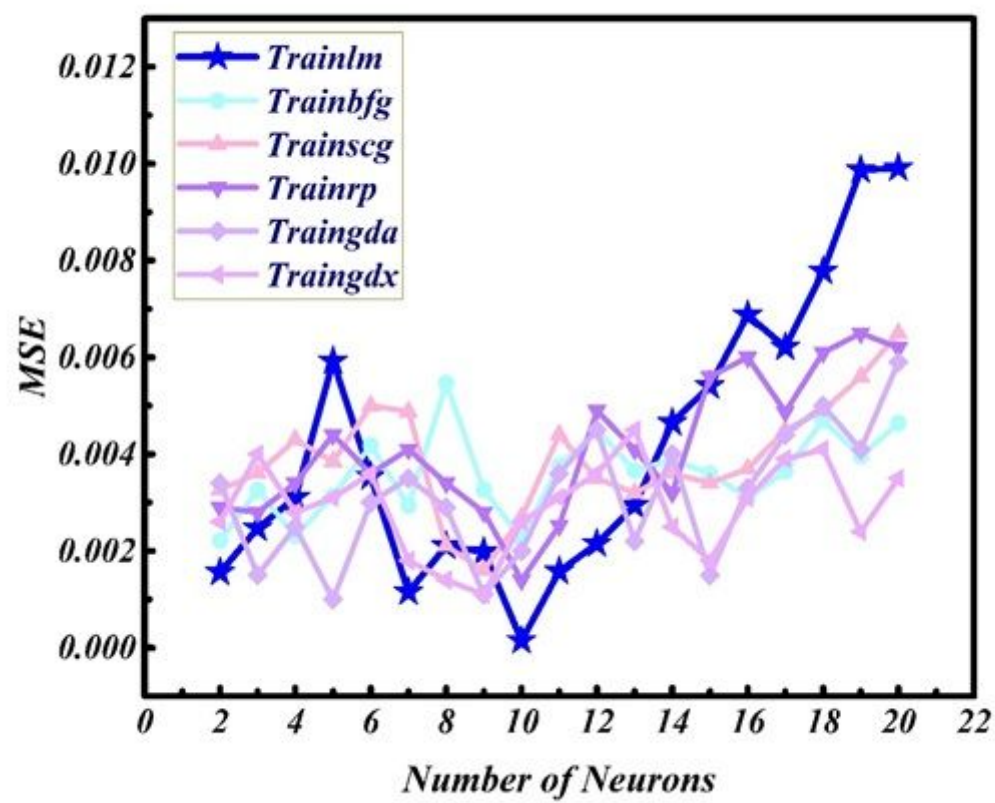


Figure 6

Variation of Number of Neurons with MSE.

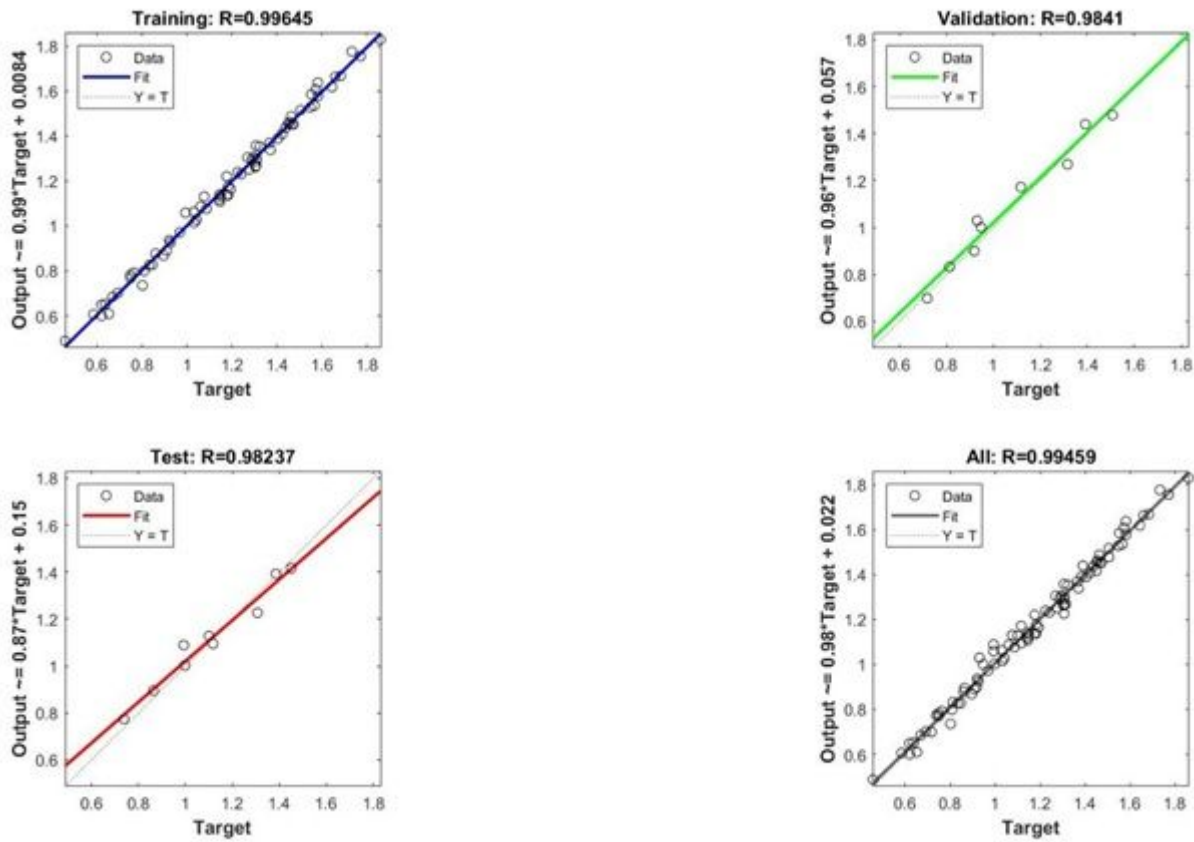


Figure 7

Overall R values for the selected trainlm algorithms.

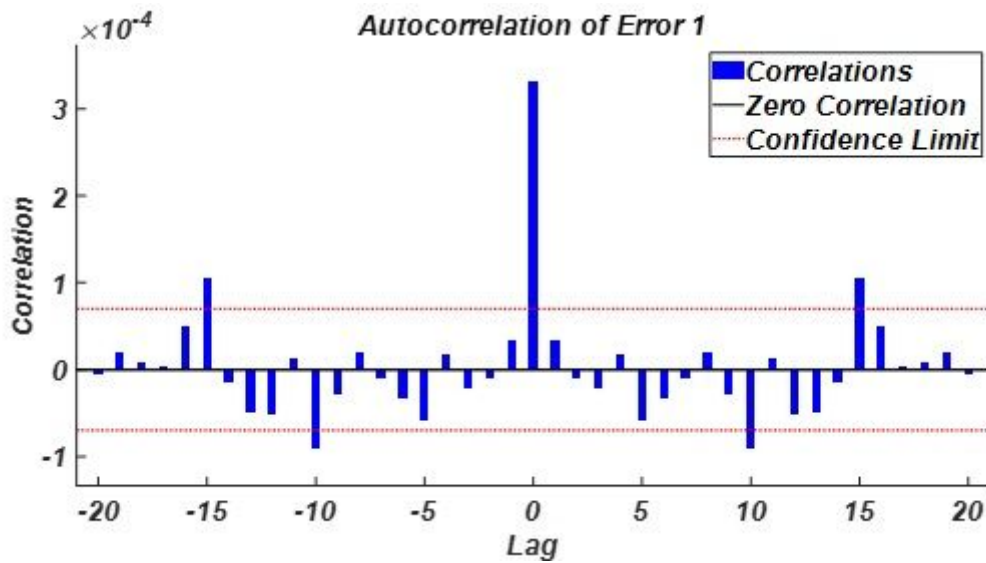


Figure 8

Error autocorrelation function.

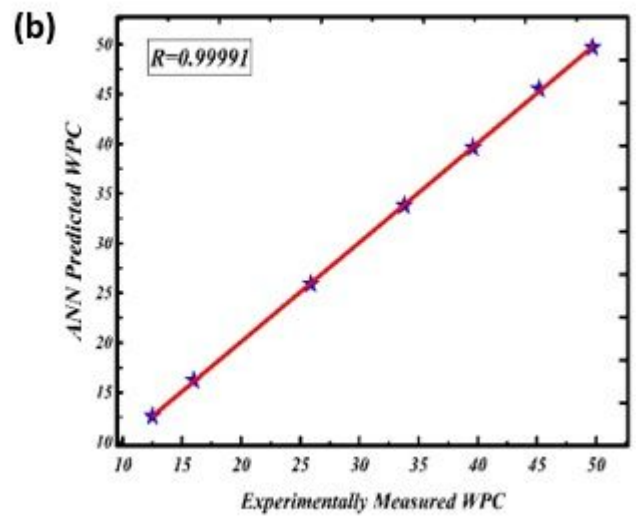
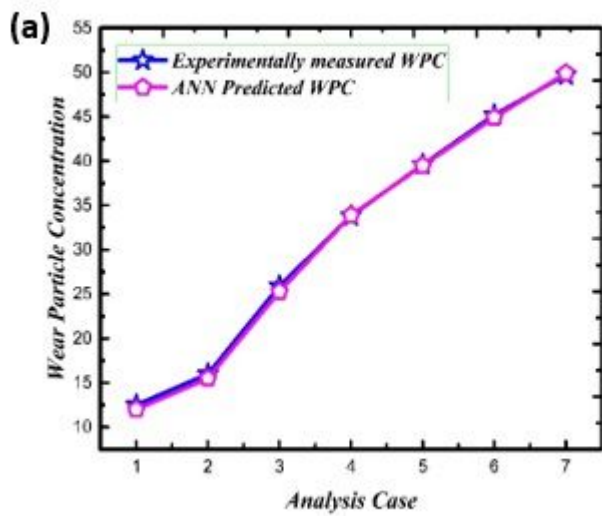


Figure 9

Analysis of WPC obtained experimentally with predicted WPC from ANN.

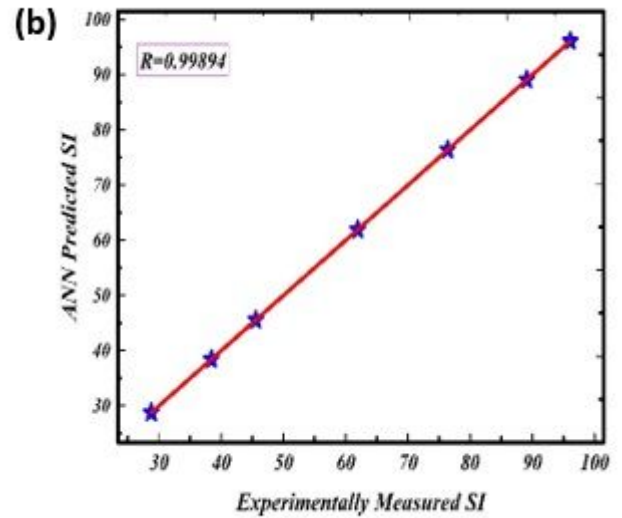
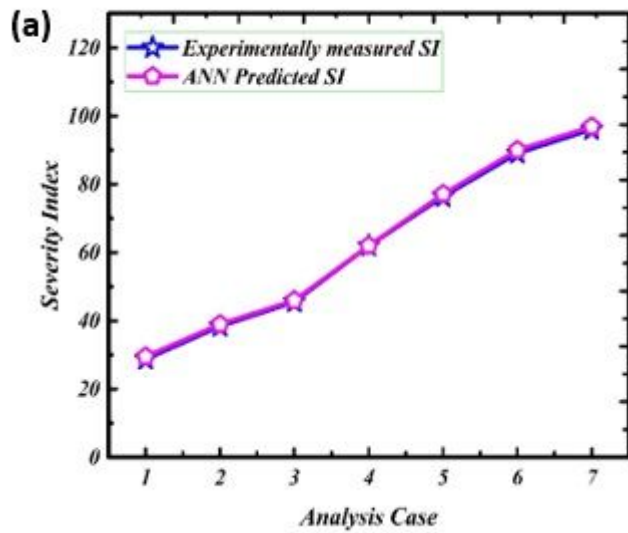


Figure 10

(a) and (b) Analysis of SI obtained experimentally with predicted SI from ANN.

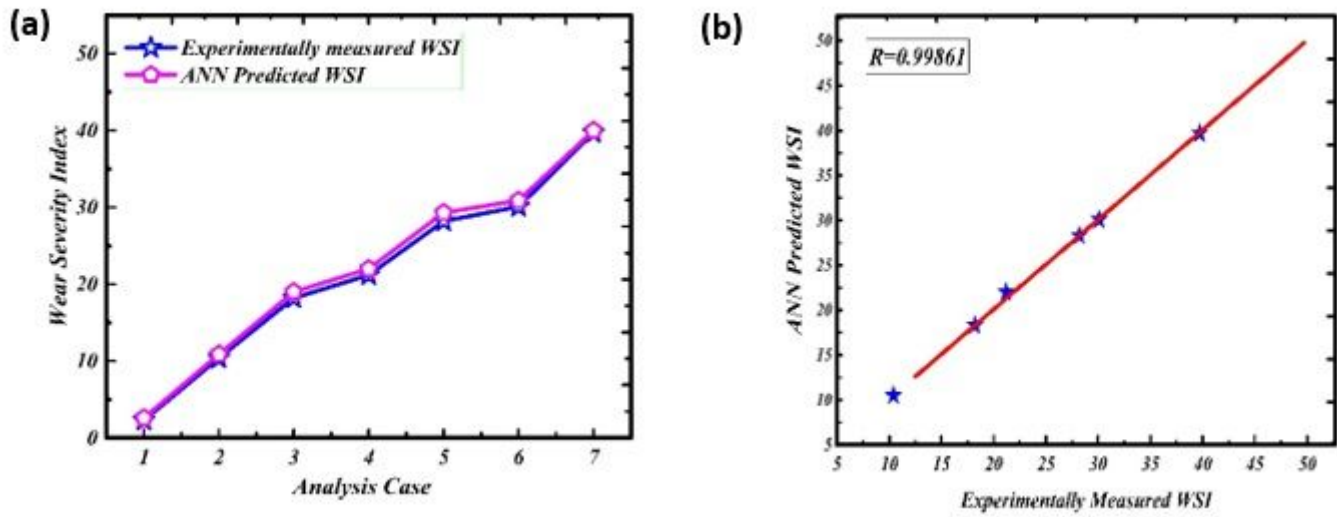


Figure 11

(a) and (b) Analysis of WSI obtained experimentally with predicted WSI from ANN.

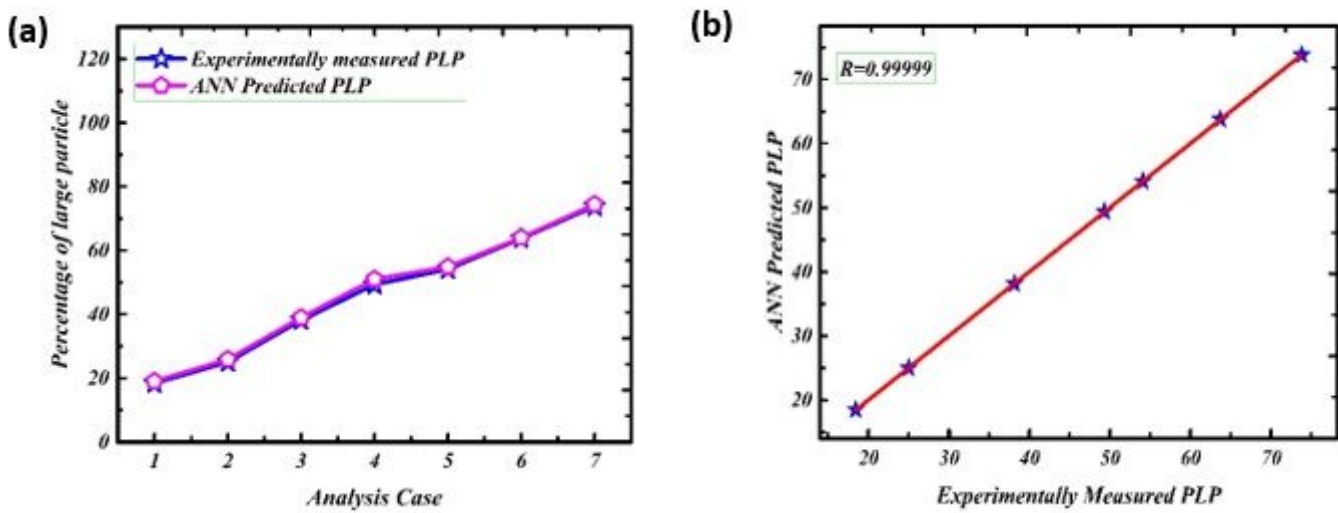


Figure 12

(a) and (b) Analysis of PLP obtained experimentally with predicted PLP from ANN.

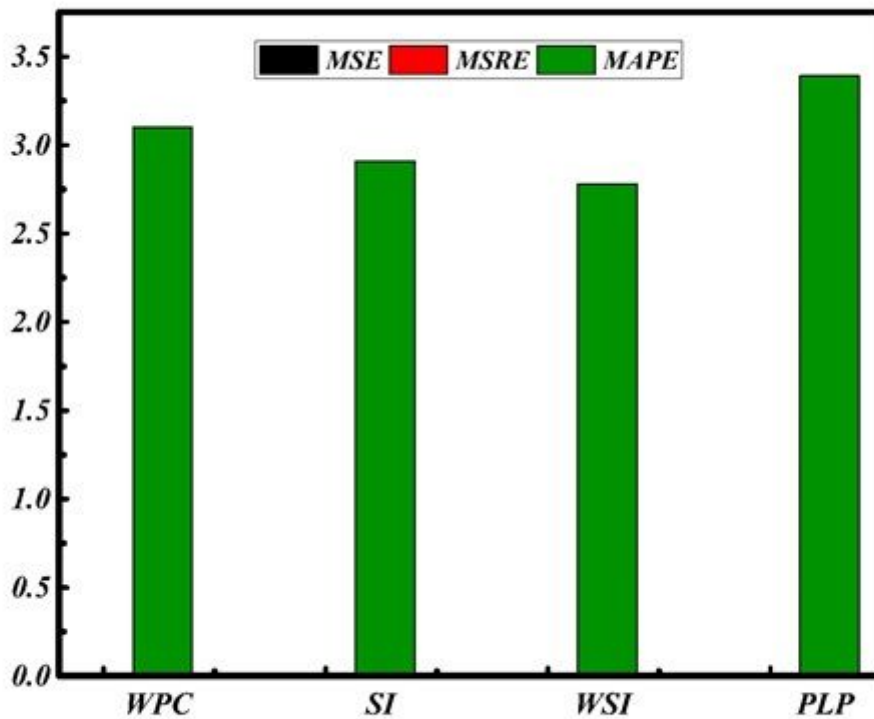


Figure 13

Comparative analysis of Quantitative Parameters for error Measurements.

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