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Thermal Intelligence for Hydro-Generators: Data-Driven Prediction of Stator Winding Temperature Under Real Operating Conditions

Zangpo, Munira Batool * and Imtiaz Madni

Department of Electrical Engineering, Engineering Institute of Technology, Perth, WA 6005, Australia; 1703246@student.eit.edu.au (Z.); imtiaz.madni@eit.edu.au (I.M.)
* Correspondence: munira.batool@eit.edu.au

Abstract

Hydropower remains one of the primary sources of power generation. It can be operated as either a base-load or peak-load plant due to its rapid, easy start-up and stop-down capability. However, power plants, old or new, need to be operated and maintained optimally to meet energy demand and maximise economic returns. While the older plants without digital controls such as the Supervisory Control and Data Acquisition (SCADA) system are unable to leverage the evolving technology including big data and Artificial Intelligence (AI), the newer plants or plants that already have some form of data acquisition system have the advantage of leveraging the newer platforms for efficient operation, monitoring and fault diagnosis. Thus, an Artificial Neural Network (ANN), a machine learning (ML) algorithm, was chosen for this case study to predict the generator's operational stator temperature by selecting six parameters that could potentially affect it. Real data from the 336 MW Chhukha Hydropower Plant (CHP) in Bhutan were used to train the ANN. The prediction of temperature using an ANN in MATLAB® yielded an R^2 (correlation coefficient) of 96.8%, which is impressive but can be further improved through various optimisation and tuning methods with increased data volume and complexity. The performance of ANN prediction was validated against other regression models, and the ANN was found to outperform them. This demonstrated its capability to predict and detect generator temperature faults before failures, thereby enhancing hydropower operation and maintenance (O&M) efficiency. The model's interpretation was also done through Shapley Additive ExPlanations (SHAP).

Keywords: hydropower; machine learning (ML); Artificial Intelligence (AI); operation; maintenance; predictive maintenance (PdM); Artificial Neural Network (ANN)

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1. Introduction

Hydropower remains one of the largest renewable primary energy sources, with a 14.3% share of global power, and dependence on it is expected to grow further despite the effects of melting glaciers and a changing climate due to global warming [1]. With total contribution amounting to 24.6 GW in 2024 alone adding up to a staggering total installed hydropower capacity of 1254 GW worldwide [2], conventional as well as pump-storage type hydropower development continues to rise. A special focus is also put on small hydropower development due to large-scale policies related to electricity [3] as it offers convenience of operation such as peaking in addition to base-load as wind, solar and

other types of renewable energy penetrate the existing mix of power generation requiring means for stabilisation. Despite increasing demand for hydropower, with its minimal operation and maintenance cost of around 2.5% of the total generation [4], there remains the challenge of O&M with strict grid commitment. This compels plant management to keep up with the evolving technological advances to improve O&M efficiency. The older plants, despite having numerous O&M efficiency improvement platforms, have not been able to leverage their use. This is attributable to their old technology or the high cost of upgradation but most of them have some form of digitization through the PLC or SCADA system. For power plants with fully functional SCADA and fault diagnostic systems, even remote control is possible, eliminating human resource intensity or expertise requirements and bringing efficiency from operations and controls to planning, scheduling, and fault diagnosis [5]. While fault diagnosis or prediction of operational parameters is partially possible with existing data acquisition and diagnostic tools, big data technology can be harnessed to enhance hydropower operation performance. However, the availability of big data does not serve its purpose unless it is properly filtered to make it more useful. So, ref. [6] developed research to manage and resolve the issue of large, heterogeneous alarms and monitoring data in SCADA, streamlining data processing and tremendously improving maintenance decision-making. The availability of big data has also been improved through the integration of sensing devices with intelligent data acquisition and fault-diagnostic systems, which has gained particular traction over the last decade [7,8]. Conventional tools, which are physics- and rule-based, can detect thresholds, parameter gradients, and anomalies, but they struggle to monitor, model, and analyse complex, high-dimensional, and non-linear data compounded by other hydrological and electromechanical uncertainties [9]. Different conditioning monitoring variables and fault analysis methods utilised by hydropower have been highlighted by [10]. For some analysis, one or two inputs do not provide adequate insight into the equipment state and thus require the collation of multiple parameters, which conventional methods cannot provide. Further, reference [11] provided various smart yet conventional monitoring and analysis tools, such as Siemens' SIMATIC PCS 7 (Germany), Schneider Electric's EcoStruxure Power Monitoring Expert (France), ABB's 800xA DCS (Switzerland), GE's Proficy Digital Historian Software 2024 (USA), and 4th Generation SCADA. However, from a safety, stability, and performance perspective, a definitive shift towards state-of-the-art tools like ML, whose ability to analyse available data extends beyond numerical or categorical data to include images, sound, and other forms of unstructured data, is imminent. ML's tremendous capabilities can be leveraged from long-term resource assessment to real-time control and monitoring of hydropower equipment, as it can uncover inherent patterns, trends, and relationships that are not possible to discover with conventional modelling.

AI-related studies in hydropower encompasses condition monitoring, prediction, and fault diagnosis, aiding maintenance and ultimately curtailing O&M expenses [12,13]. However, it is evident that ANN- and NN-based models are widely used in comparative and performance studies across different fields, and they stand out as powerful models that can improve performance with increasing dataset complexity [14]. ANN performance is also widely commendable for better generalisation of non-linear and multi-modal data, with excellent scalability from shallow to Deep Neural Network (DNN), unlike other algorithms such as Linear Regression (LR), Decision Tree (DT) and Support Vector Machine (SVM). These models also learn through patterns and historical anomalies, are good at exploration of features which are embedded deep in the data and do excellently in attributable space representation [14,15]. While the ANN outperforms in many ways, especially in terms of non-linearity and high dimensionality, its performance can be further improved by tuning hyperparameters such as the number of hidden layers, nodes, and activation functions.

While the nodes are linked to the capability to update settings, the activation function relates to the transferability of the input features [15]. With increasing depth, the ANN becomes more complex and incurs higher computational costs. In this case, the number of hidden layers has been optimised using the Rectified Linear Unit (ReLU) activation function to handle non-linear input data better.

2. Similar Works

A few studies that encompassed ANN models are proposed by [16] who compared the performance of the ANN with other models such as Random Forest (RF), Adaptive Neuro-Fuzzy Interference System (ANFIS), Auto Encoder Neural Network (AENN), and DT for condition assessment of the Hydro-Generator Unit (HGU) to support maintenance scheduling. However, the prediction performance was below 70%, which is very low given the capabilities of each model. The other reference [12] also shows the use of an ANN with Long Short-Term Memory (LSTM) and an autoencoder for detecting bearing temperatures in the HGU. Reference [17] reported a study of maintenance scheduling using stator winding testing data, where the ANN's performance was found to be impressive. The ANN was also combined with the Analytical Hierarchy Process-Technique for Order Preference by Similar Ideal Solution (AHP-TOPSIS) to determine the Mean Time Between Failure (MTBF) for maintenance scheduling of the HGU [18]. However, re-evaluation is required to learn different periods, such as no-faults, maintenance, and fault study, for optimised scheduling. A prediction study for HGU parameter degradation was done using vibration data using the Radial Basis Function-Empirical Mode Decomposition-Approximate Entropy-Artificial Neural Network (RBF-EMD-APEn-ANN) ensemble by [19] and found to achieve higher accuracy than normal models. A partial discharge (PD)-based HGU fault detection by [20] showed that it classified better, with a 98% recognition rate. A study of the ANN model, along with other models, was also considered by [21] for outer case fault studies related to Induction Motors (IMs). It indicated that real-world data should be used for training and testing, since it had been trained and tested on simulated data. In tandem with other models such as Principal Component Analysis (PCA), Multi-Layer Perceptron (MLP) and RBF, the ANN was also employed by [22] to also diagnose a short-circuit fault in an IM.

The ANN internal activation function is also modified according to the targeted performance requirement, and, as such, a Wavelet NN has been employed by [23], which is activated using a wavelet function, for diagnosing faults related to the hydraulic wear of seals and the oil pressure unit of pistons. It generally improved convergence speed and addressed the initial sensitivity issue, which is normally handled with ReLU/Sigmoid or Tanh in ANNs. Likewise, ref. [24] also used an Ant Colony Optimisation (ACO)-initialised Wavelet NN to detect vibration-related faults in a hydropower generator unit, achieving better convergence speed and generalisation than the Wavelet NN. Another pertinent NN hybrid utilised in studies is the ANFIS, which combines the Neural Network and fuzzy logic reasoning, offering better interpretability and potentially erasing the inherent black-box nature of ANNs. So, the ANFIS has been used to detect stator winding temperature anomalies using voltage and generator current as inputs [25]. It was modelled using MATLAB Simulink, but it lacked actual fault data as simulated data was used. So, the actual implementation would mean modelling with real data, as well as with adequate data, since the data available for the case study was insufficient. A deep learning One-Dimensional CNN (1-D CNN) and a Back Propagation Neural Network (BPNN) were also employed to detect HGU faults using vibration data [26], with the faults detected 2 days ahead of actual fault occurrence. However, improvements in generalisation ability and the unavailability of faulty data were among the issues that required further work. A 1-D CNN with

Long Short-Term Memory (LSTM) has also been utilised to study bearing fault diagnosis/classification of the HGU, achieving a good accuracy of 99% but with a large computational requirement, which can always be a trade-off for deployment purposes [27]. An ANN with LSTM and particle swarm optimisation was employed by [28] to develop a healthy hydropower state model using active power data and net head, ultimately to study unit degradation. A Representational Dissimilarity Matrix-Weighted NN (RDM-WNN) was also employed by [29], which overcame the requirement for domain knowledge in ML models by using healthy, partially healthy, and faulty unit conditions of the HGU. Reference [30] used Ensemble Deep Learning to isolate the PD source and recognise it for decision-making. Reference [31] used a Self-Organising Map (SOM)-based NN after extracting features with the empirical wavelet transform and singular value decomposition to classify gearbox faults from four different vibration signals. The review by [32] highlights the use of the ANN, Convolutional Neural Network (CNN), and deep learning for bearing fault classification and IM fault detection. It provides directions for research on physics-informed NNs, hybrid deep learning, and digital twins with IoT and blockchains. The author of [33] has studied the ANN with Multi-Linear Regression to understand the performance of Kaplan turbines, focusing primarily on erosion due to silt and part-load operation, resulting in an R^2 of around 88.1%, which needed further improvement. A deep learning hybrid network using CNNs, LSTMs, and autoencoders has been presented by [34] to study anomaly detection in hydropower plants using a time-series dataset, which indicated that hybrid learning performed better than singular models in accuracy, reduced false positives, and early fault detection. Temperature prediction for a Nam Ngum 1, Laos hydro-generator was performed using an RNN, a Gated Recurrent Unit (GRU), and LSTM to capture temporal dependencies, and LSTM was found to outperform the other models with an R^2 of 98.6% [35]. However, vibrational parameters and other excitation parameters, including ambient temperature features, have not been considered, limiting feature studies. Using deep learning LSTM [36], the carbon brush temperature trend was analysed, providing a prediction error within 0.4 °C, which is very impressive, indicating the operational state of the generator based on which carbon brush replacement, misalignment of the shaft or excitation system anomalies, if any, can be tackled before the actual problems degrade. Likewise, the author of [37] has used a fuzzy-based Recurrent Neural Network (RNN) for the analysis of time series data and convolutional autoencoders for the detection of any abnormal condition of the generator rotor poles based on temperature monitoring and analysis, but not for stator temperature. Reference [38] used a feed-forward NN with a state transition function to estimate Induction Motor rotor temperature, using measured stator case temperature (computed from stator and rotor currents as well as angular speed) as input to the NN, along with a thermal model. The author of [39] employed incremental deep learning to estimate the rotor temperature in real time for synchronous motors, thereby overcoming dynamic operational challenges, constraints imposed by mechanical structures, and the forgetting problem in incremental learning. Taking the temperature data input from different parts of a PMSM (Permanent Magnet Synchronous Motor) using a Gradient Boosting DT to estimate rotor temperature, this method proved better in accuracy than the traditional methods [40].

From Table 1 below, we can see that the ANN or its associated DNNs have been used only sparingly, especially for predicting generator stator slot temperature or diagnosing related faults, using real hydropower data and features similar to those in the current case study. Even [9], which reviews AI applications for hydropower generation optimisation, states that ANNs are mostly used for generation forecasting, inflow prediction, energy demand prediction, and economic feasibility studies, and less so for PdM and associated learning, which is, nevertheless, picking up. The ANN and Deep Neural Network-

based ML models used specifically for prediction and temperature studies are referenced in [35–40]. Specifically, CNNs, which use layers such as convolution and pooling to extract features and reduce dimensionality, are more effective and applicable for image-based studies. An RNN processes sequential data using a feedback loop to improve memory, but faces the vanishing gradient problem. Due to increased memory usage, the model becomes heavier and risks overfitting on small- and medium-sized datasets, a problem that LSTM addresses. However, LSTM also requires a large training dataset to learn, as it has complex memory cells and gated mechanisms. Since the data collected from the hydropower plant is moderate, collected directly from the sensors, and to avoid overfitting, an ANN is a suitable choice for this particular study. While the ANN is a widely used model, its performance on real hydropower multi-dimensional data has not been tested, as this data has not been modelled before. The model's ability to converge and predict stator winding temperature, using six different linear and non-linear input features as shown in Figure 1, can indicate its usefulness in real-world hydropower systems. Specifically, the Chhukha Hydropower Plant, from which the data was collected, operates in a manner that varies with seasonal hydrological inflow and other operational and maintenance practices. While the normal stator operating temperature is around 90 °C, it reaches 95 °C during peak summer under 10% overload. At other times, it operates at a lower temperature due to part-load or intermittent operation. Stator temperature depends directly on the generator load (MW) and its current, and has a non-linear dependence on unit vibration and cooling water system parameters. Thus, the novelty of this study lies in the following:

Table 1. Comparative table for the review.

Reference	Equipment	ML Models	Type of Data	Performance
[16]	HGU-M schedule	ANN, RF, ANFIS, DT, AENN	Stator winding testing data	70% accuracy
[12]	HGU-anomaly detection through fault classification	ANN, LSTM Autoencoder	Multi-dimensional time series data	70% ANN, >90% RNN (accuracy)
[17]	HGU-failure prediction	GPR	Multi-dimensional real-time monitoring data	2.12% (MAE)
[18]	HGU-M schedule	AHP-TOPSIS	11 years of fault data of the equipment	R^2 = 91.0%, 0.03 (MAPE)
[19]	HGU-degradation prediction	(RBF-EMD-APEn-ANN)	Vibration	1.35% average relative error
[20]	HGU-partial discharge	ANN	PD online data	98% recog. rate
[21]	IM-fault diagnosis review	ANN, SVM, kNN, RF, DT, Bayesian Classifier, DL	Various means	
[22]	IM-stator fault identification	RBF, PCA, MLP, ANN	Simulated data	>98% accuracy
[23]	Piston System: hydraulic seals and OPUs faults	Wavelet NN	Raw oil pressure data	99.5% accuracy
[24]	HGU-vibrational fault detection	ACO initialised Wavelet NN	Vibrations	0.93% diag. error
[25]	HGU-stator winding fault	ANFIS	V&I	
[26]	HGU-fault detection	1-D CNN, BPNN	Vibration	98.7% accuracy
[27]	HGU-bearing fault classification	1-D CNN, LSTM	Bearing signal data set	99% classification rate

Table 1. *Cont.*

Reference	Equipment	ML Models	Type of Data	Performance
[28]	HG-healthy state	ANN with LSTM and particle swarm optimisation	Power and net head of water	5.44% (MAPE), 1.5% (RMSE)
[29]	Healthy, semi-healthy and faulty HGU	RDM-WNN	Multi-dimensional	Between 98 and 98.9% (accuracy)
[30]	HGU PD isolation	Ensembled Deep Learning	PD online data	87–96% accuracy
[31]	Gearbox faults	SOM-NN	Vibration	100% recognition accuracy rate
[32]	Bearing faults classification—IM (review)	ANN, CNN, Deep Learning	Multi-dimensional	91.54–100% accuracy (different faults)
[33]	Kaplan Turbine—erosion	ANN-MLR	Silt and hydraulic data	88.1% accuracy
[34]	HGU fault detection	CNN, LSTM, Autoencoders	Time series data	Deduced in the figure but not provided separately.
[35]	HGU-average generator temperature detection	RNN, Gated Recurrent Unit (GRU) and LSTM	Power, current and cooling water system	R^2 = 98.6
[36]	HGU-carbon brush temperature trend	LSTM	Carbon brush temperature	Error < 0.4 °C
[37]	HGU-rotor temperature fault detection	GRU-RNN, LSTM-RNN, Fuzzy-based RNN, Convolutional Autoencoder	Temperature-based time series and image data	Not specified
[38]	IM-rotor temperature	Feed-Forward NN	Stator and rotor I, angular speed	Deduced in the figure but not provided separately.
[39]	Sync-Motor—rotor temperature prediction	Incremental DL (CNN, RNN, LSTM, DenseNet)	Experimental test bed	CNN (RSME/MAE-24.64/24.63), RNN (RSME/MAE-7.24/2.27), LSTM (RSME/MAE-7.63/7.63), DenseNet (RSME/MAE-37.95/37.92)
[40]	PMSM-rotor temp detection	Gradient Boosting DT	Experimental test bed (Temperature of tooth, winding and yoke)	MAE-0.36/MSE-0.38

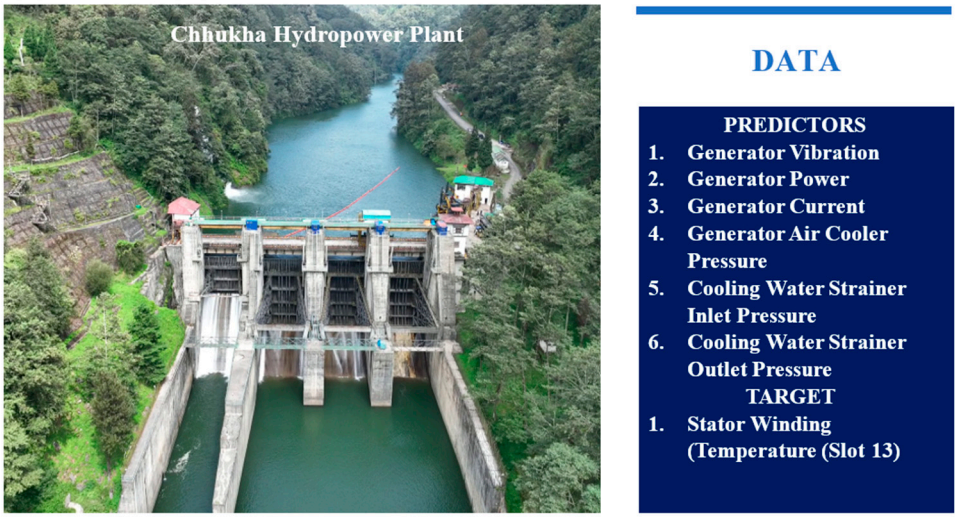


Figure 1. Chhukha Hydropower Dam and parameter selection.

1. This study represents the first mapping of Bhutan's hydropower plant dataset through ML, let alone the application of an ANN for stator temperature detection. This high-head, glacier melt run-off river power plant experiences specific Himalayan geological and climatic conditions and offers specific pattern of hydropower operation as described above in addition to reactive and preventive maintenance practices of the plant.
2. Unlike other modern power plants or the use of a synthetic and test bed dataset, it utilises operational data from the Chhukha Hydropower Plant, Bhutan—an old power plant commissioned in 1986. Its semi-operated SCADA platform offers limited access to operating parameters as monitoring is done mostly for critical parameters only. The novelty therefore lies in the ANN's practical application possibility due to its good generalisation despite fewer features, a unique operational pattern and data inconsistencies inherent to real-world Himalayan hydropower operations. The opportunistic practical implementation in this old power plant can be a scalable ML application blueprint for other newer power plants to follow and reap the ML benefit for Bhutanese power plants.
3. This is the first study to the author's knowledge and according to prior reviews which provides direct prediction of individual temperature rather than an average, as opposed to [35]. Averaging of the target value temperature would undermine the individual variations or spikes either due to load changes, other monitoring parameter changes or impending faults which would be localised in some spots and have minimal effect on other areas. This provides better preparedness and readiness for early detection of faults, moving towards predictive maintenance.

The contribution of this research can be described as follows:

- It predicts the stator winding temperature of a hydro-generator using real multi-dimensional non-linear operation data of a hydropower plant using an Artificial Neural Network ML algorithm. The ANN learns from this complex real-world data to calculate trends and predict, providing operators with early warning of faults and an opportunity to intervene before they occur.
- Conventional sensors, PLC or SCADA, which the majority of hydropower plants are equipped with, provide current states and fault logs but cannot mine data for providing useful information on impending faults or anomalies. Thus, hydropower generator performance can be improved through modelling with an ANN for pre-

diction or anomaly detection, utilising large datasets available in the hydropower plant repository.

- This temperature prediction can act as a reference estimate and can be used to detect faulty sensors, and can thus improve monitoring reliability through redundancy. More importantly, the prediction model can act as a virtual temperature-sensing device to gauge temperature in areas where sensor installations are not feasible due to space limitations and severe electromagnetic environments, thereby reducing sensor installation costs.
- With a reliable prediction model, generator loading can be optimised without overheating and also aid in cooling system control.
- MATLAB® 2022b was used for training and validation of the model for the prediction study, and was compared with other regression models to validate the huge potential of the ANN.

The paper is presented as follows: Section 3 defines hydroelectricity and the plant selection for data collection in the case study. Section 4 outlines the methodology adopted, including data curation and evaluation matrices used for prediction, as well as the ANN model, the main algorithm utilised in the study. Section 5 presents the experimental results obtained alongside other regression models, and Section 6 presents the discussion and conclusions.

3. Hydroelectricity and Selection of Plant for Case Study

The general layout of a hydropower station, showing its broad components, is shown in Figure 1. All hydropower stations have a similar layout, differing only in the tail pools or tail race, depending on the type of turbines used.

In hydroelectric power generation, water stored in a reservoir/dam has its potential energy converted to kinetic energy, which is then converted into mechanical energy as it passes through turbines. Turbines are coupled to a generator, and thus, mechanical energy is converted to electrical energy, which can then be transmitted through high-voltage lines and transmission towers. Mathematically, the hydraulic power generated with respect to water head and water flow rate is provided as [41,42]:

$$\mathbf{Ph} = \boldsymbol{\rho} * \mathbf{g} * \mathbf{H} * \mathbf{Q}, \quad (1)$$

where Ph = hydraulic power generated (Watt), $\boldsymbol{\rho}$ = water density (kg/m^3), g = gravity of acceleration (9.8 m/s^2), H = water net head (m), and Q = rate of water flow (m^3/s).

However, this hydraulic power needs to be converted to electric power, which can be expressed as follows:

$$\mathbf{Pe} = \eta\mathbf{Ph}, \quad (2)$$

where Pe = electrical power (Watt) and η = percent efficiency;

The 'Q' flow rate depends on the cross-sectional area of the conduction tube, which is normally called the head race tunnel/penstock. Its relationship can be expressed as:

$$\mathbf{Q} = \mathbf{A} * \mathbf{v}, \quad (3)$$

where A = cross-sectional area of water conduction system (m^2) and v = water velocity/speed (m/s).

While the electrical power at Equation (2) shows its relationship with the hydraulic power, its actual electrical power generated in terms of the electrical equivalent circuit can be expressed as:

$$\mathbf{Poutput} = \sqrt{\mathbf{3}} * \mathbf{Vt} * \mathbf{Cos\theta} \quad (4)$$

where Poutput = electrical power (Watts), Vt = terminal voltage (Volts), and I_L = line current (amps), and Cosθ = power factor.

Other independent variables, or the selected vibrational feature inputs, are by-products of machine operation, and stator slot temperature has been selected as the dependent variable for performance monitoring and prediction.

For data collection, a 4 × 84 MW CHP in Bhutan [43] was selected, and the input feature parameters and the ANN model's output are also shown in Figure 1. It has 6 multimodal inputs and an output containing data time-stamped at 1 h intervals for a period of one year, totalling 61,320 data points. This paper restricts the study to predicting and detecting irregularities in stator slot temperature; further research would entail anomaly detection and prognosis (Remaining Useful Life (RUL)) to complete the research-to-real-world application cycle.

4. Methodology

4.1. Collection of Data and Preparation

The actual hourly operational data of the 4 × 84 MW (CHP) for Unit-1, i.e., Generated Power, UGB Vibration, Generator Terminal Current, Cooling Water System parameters, and Stator Temperature of Slot 13, were acquired for the whole year of 2022 for training and validation, and 8750 data points from 2023 for testing purposes were prepared for the actual modelling in the MATLAB format. Since CHP is only semi-SCADA controlled, it has a very poor data acquisition system, wherein the data is manually logged in from different field PLC controller systems, as well as, due to varying operational requirements, quite an appreciable amount of data being either found missing or not logged, in addition to the semi-structured data furnished in raw form. While non-deliberate missing data could be identified by running through each hourly data log, there were, however, missing data in batches lasting 3–4 months due to the unit being out of operation, either due to generator rationing or due to weekly, monthly, or annual maintenance. These missing values, especially those where the generator was not operational, were removed, but other missing values, which may have been due to faulty sensing systems, were retained. Thus, these few missing values were appropriately filled in using the k-Nearest Neighbours (kNN) method of estimation with k = 5. This method has the advantage of retaining past and future trends, which ultimately helps maintain data consistency, even though the data is non-linear. Moreover, the imputation of missing electric power data for energy management systems indicated that kNN and SVR performed better than other methods [44]. A data imputation method was compared for missing power consumption measurements by [45] also shows that kNN and Dynamically Clustered kNN perform better than other imputation methods for the various non-linear data. A total of 35,441 data points were considered after removing missing data due to generator non-operation and filling them in with kNN. A total of 325 data counts filled up through kNN constitutes 0.92% of the total data used for modelling. The raw data plot is shown in Figure 2, and Figure 3 shows the plot after removing missing values for which the generator was not running, with only sporadic missing values which are marked in red circles. While this small fraction of missing values is unlikely to materially bias the prediction result, they are also spread amongst vibration and cooling water parameters, further diluting the values. Figure 4 shows the plot of data after filling in missing values.

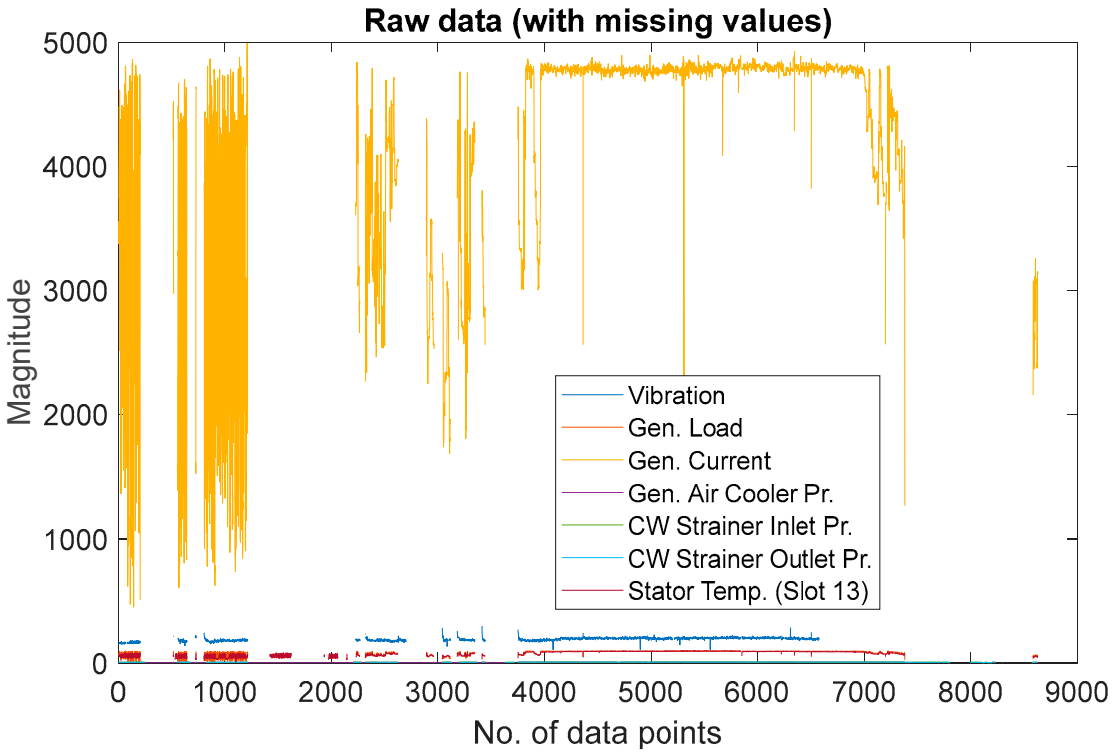


Figure 2. Raw data plot with missing values.

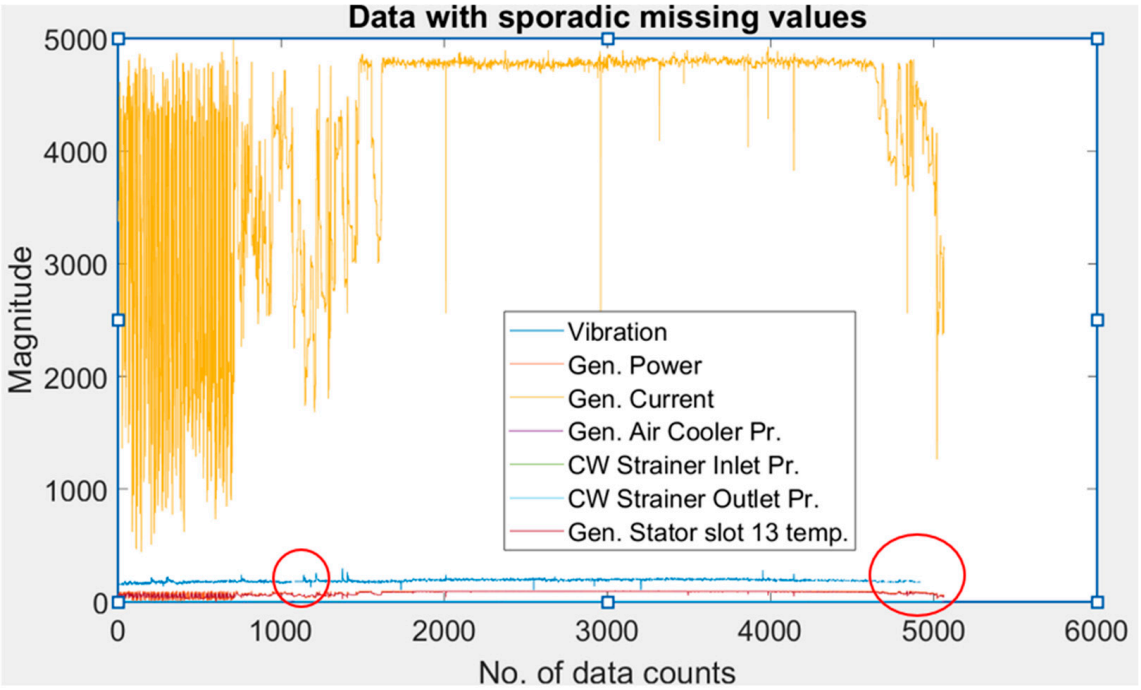


Figure 3. Raw data after removal of missing values.

The raw data after filling the missing values have been subjected to box plots to understand the variances. Figure 5 below shows the box plot of the data after missing values have been filled in.

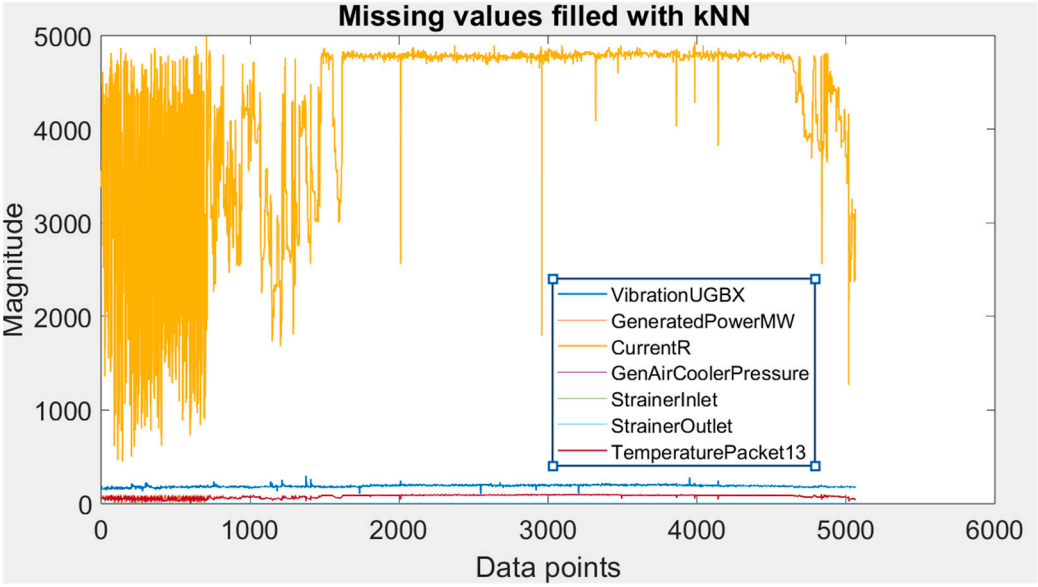


Figure 4. The data after filling the values through kNN with k = 5.

From the box plot above, we can see that the data is skewed, with outliers on both the positive and negative sides. To improve the ANN model, it may be important to remove outliers, which may be due to erroneous readings or faulty sensor data, but it is more important not to mask the actual characteristics of the input and output parameters to obtain the prediction as close as possible. Upon careful study of the data, it is observed that some of the negative outliers (below the interquartile range of 1) are normal, as the unit sometimes needs to operate at low power due to power rationing or fluctuating demand. Likewise, parameters that depend on generator power, such as generator current, vibration, and stator temperature, would follow the same trend, indicating values outside the first-quartile range. Thus, these features should not be mistaken for outliers, and they have been retained without removal.

One of the most important data curation steps involves normalisation. The input and output data plots in Figures 2–4 show that stator slot temperature, generator power, and cooling water parameters (which are lower than the other parameters) are at the bottom and overlap with the other parameters. In contrast, generator current, being the most significant in magnitude, is at the top. For the ANN model to work properly, the data needs to be normalised. Depending on the data type, the Z-score normalisation method was applied, and the normalised data plots are shown in Figure 6.

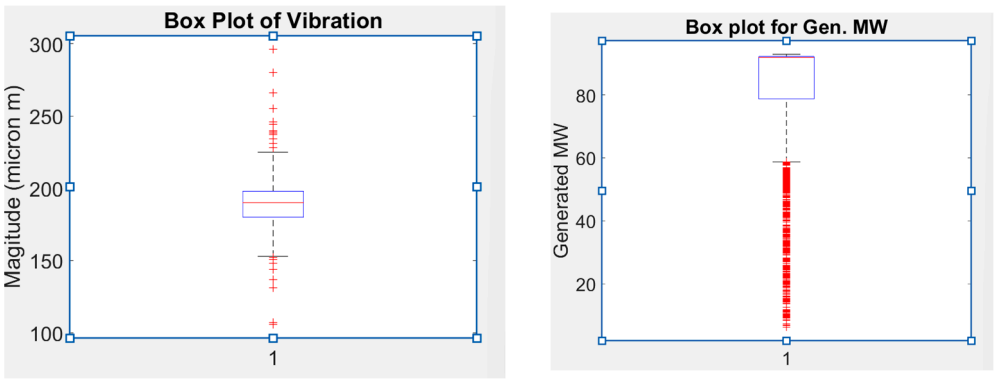


Figure 5. *Cont.*

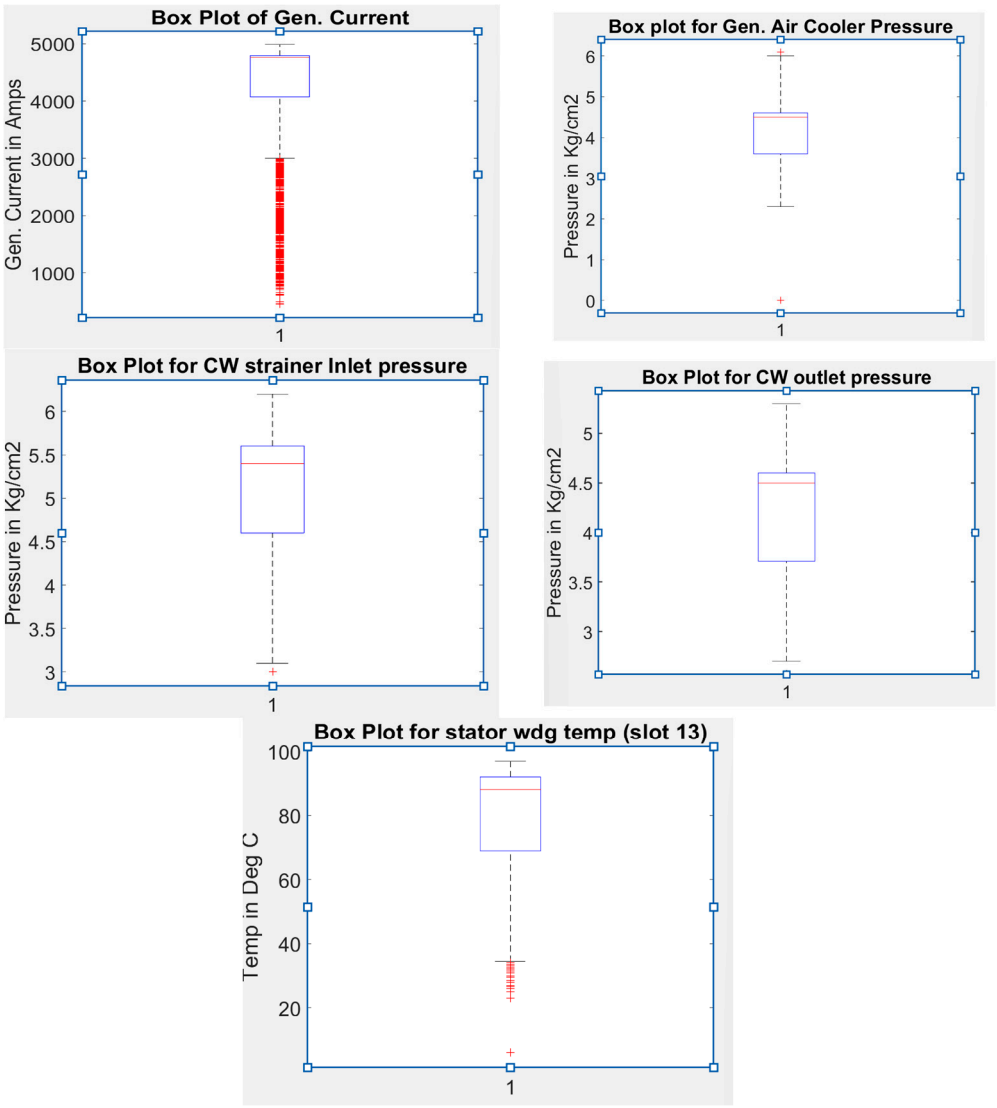


Figure 5. Box plots of inputs and outputs.

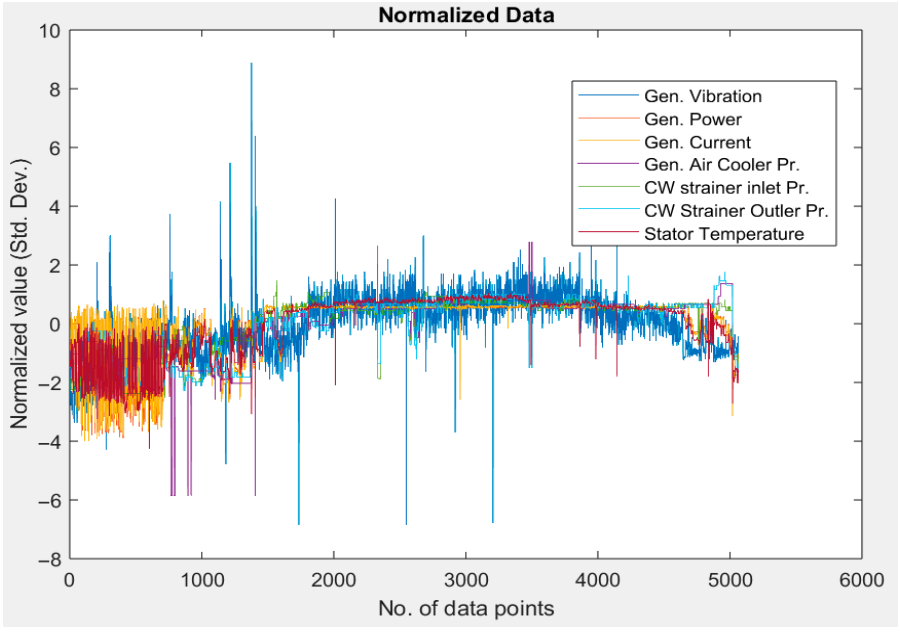


Figure 6. Normalised data plot.

From Figure 6, we can see that while fluctuations in the input/output variables are visible relative to their original measurements, the data is being standardised, with the data mean falling below or above zero standard deviation. It means that the significance of the input features is standardised to leverage the benefit of their effect on the normalised output. Otherwise, if the data is not normalised, the stator current, being highly significant relative to other inputs, would disproportionately affect the output, making the prediction/fault prediction more erroneous.

4.2. Evaluation Matrices

To analyse the machine learning regression model's performance, two metrics, the correlation coefficient (R^2) and Root Mean Squared Error, are used. The following formula represents the correlation coefficient (R) [46]:

$$R = \frac{\sum_i^n (x_i - \bar{x}) - (y_i - \bar{y})}{\sqrt{\sum_i^n (x_i - \bar{x})^2 (y_i - \bar{y})^2}} \quad (5)$$

$x_i - \bar{x}$ is the x_i deviation from the response variable mean, $y_i - \overline{y}$ is the deviation of the target or predictor from its mean, and n is the number of observations. The Mean Squared Error (MSE) is represented by the formula provided below [47]:

$$MSE = \frac{1}{n} \Sigma_1^n (h_i - h_n)^2 \quad (6)$$

h_i is the real output, and hm is the forecasted output for the ith training vector, with n being the number of training vectors. R^2 and RSME can thus be derived from the above formula.

4.3. Artificial Neural Network (ANN)

Similar to the human brain, which can learn, utilise experience and also store information, an ANN can also learn from the set of data that is provided as inputs and outputs [48,49]. The generic representation of an ANN structure is provided in Figure 7:

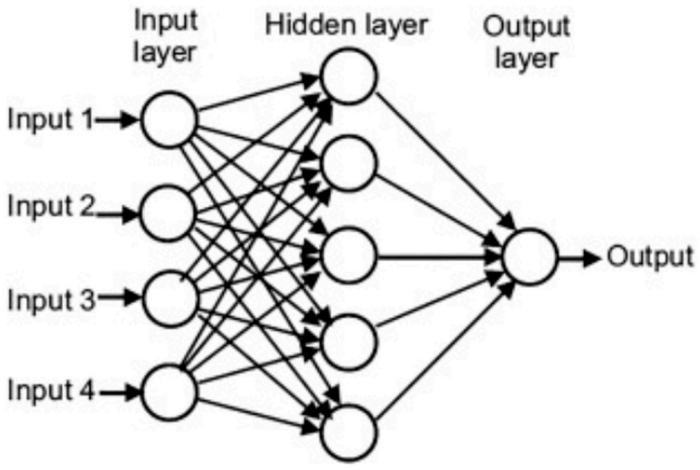


Figure 7. Generic structure of ANN.

Storage occurs in the synaptic weights of neurons. An ANN structure is represented by Figure 8.

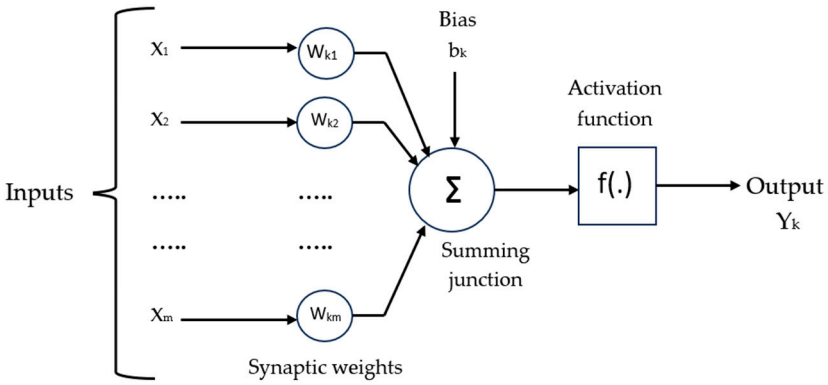


Figure 8. ANN internal structure representation [18].

The ANN is represented by the formula provided below:

$$y_k = f\left(\sum_{i=1}^{n}(w_{k_i}x_i)+bk\right) \quad (7)$$

where Xi = the input value, Wki = the weight connecting input i-k, Bk = the bias of neuron k, f(.) = the activation function, and Yk = the output (activation) of the neuron.

For the development of the robust ANN model, a single layer with 27 nodes feed-forward neural network with the Levenberg–Marquardt learning algorithm was adopted, as shown in Figure 9 below:

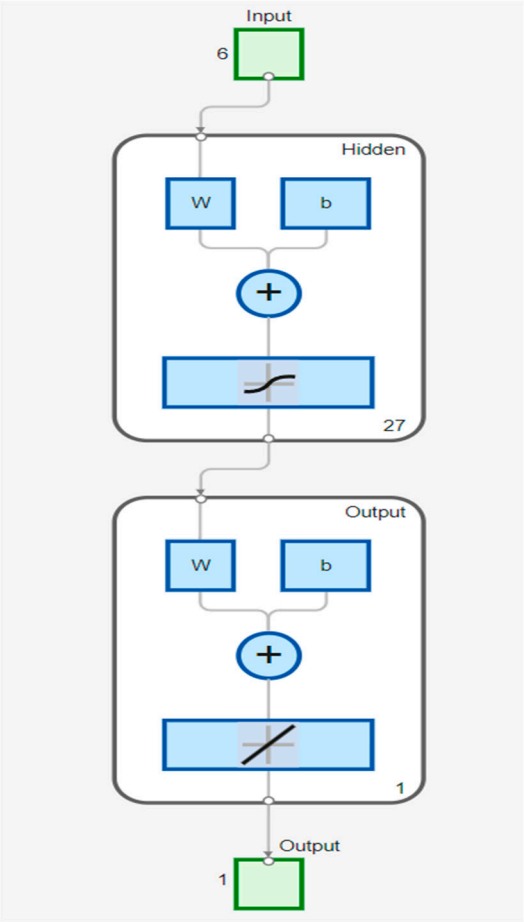


Figure 9. Actual ANN model used for training, validation and testing.

For simplicity, an activation function was not used, but the effect of using an activation function can also be checked by incorporating an appropriate activation function in the ANN block. There are several activation functions, such as the sigmoid and the hyperbolic tangent.

(Tanh), ReLU, LogSig, etc., are possible activation functions, and for this study, ReLU was employed, with the number of hidden layers optimised as shown in Figure 10.

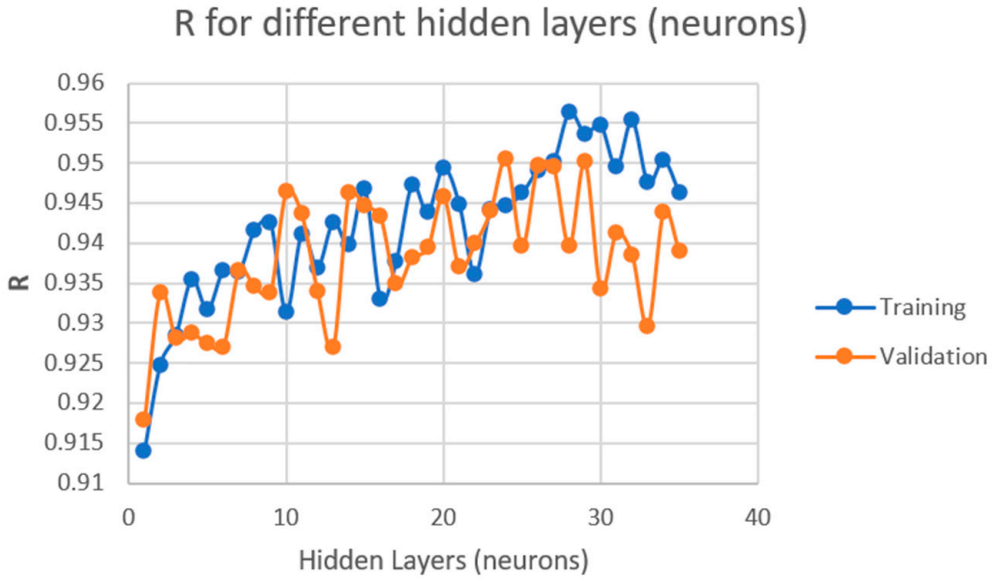


Figure 10. Selection of optimal hidden layer size.

To select the optimal hidden layer (neuron) size for the input block, the ANN model was trained by iterating hidden layer sizes from 1 to 35. As evident from Figure 10, training and validation matched at around R = 0.95 (considered the maximum R). It is also worth noting that training and validation matched at hidden layer 7, but the R is lower than that of hidden layer 27. Thus, 27 was selected as the optimal hidden layer size for the input block. The fluctuating training and validation R values indicate over- and underfitting of the model. If the R of training is greater than that of validation, it indicates overfitting or data issues, which may be due to inadequate training or a simpler model being deployed. Conversely, if the R of training is lower than that of validation, it indicates overfitting. It may generalise well during training but may not perform well on unseen data. This may happen due to the acquisition and inclusion of noisy data in the training set, which requires a simpler model. Thus, selecting the optimal hidden layer is of paramount importance. For the output block, the layer was kept at 1, since the output is a single temperature prediction that a linear network can always represent. So, the ANN application steps, from the start of data acquisition to the final prediction, are shown in Figure 11 below as a flowchart.

For proper training and to assess its performance, 85% of the data was allocated for training, 15% for validation, and a new set of 8750 data points continuing to the year 2023 was used for the testing purpose.

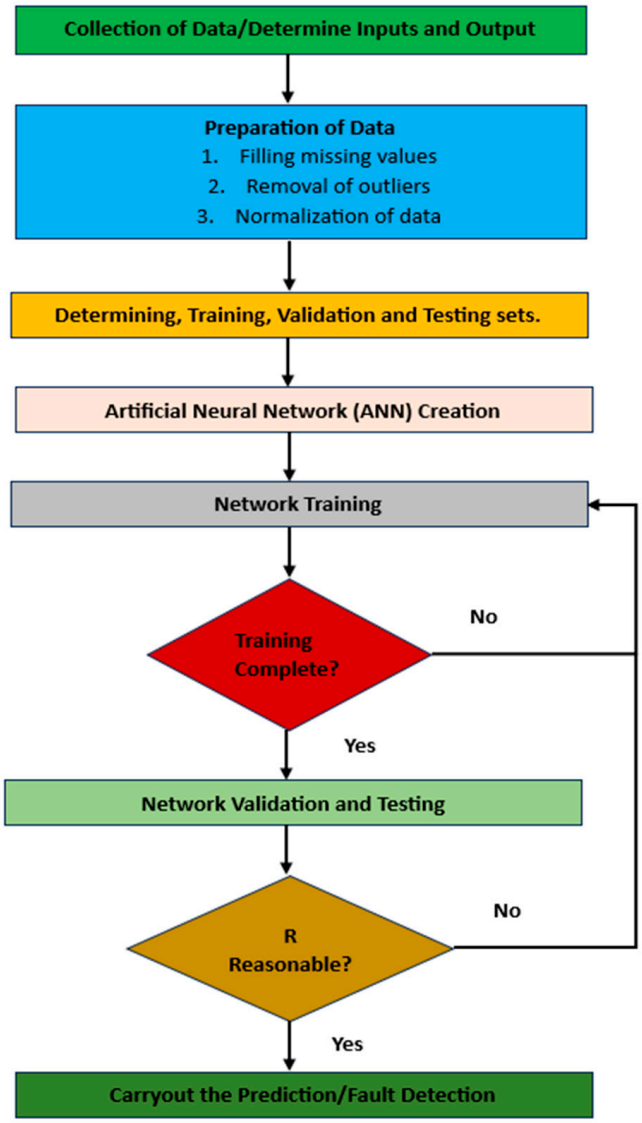


Figure 11. ANN model application process.

5. Results

As the ANN model learned during training, it was iterated multiple times until validation R exceeded training R, thereby improving generalisation. For comparing its performance, the ANN was trained using the Levenberg–Marquardt (L-M) and Bayesian Regularisation (BR) methods. The results (prediction, summary and training epochs obtained from L-M and BR) are provided in Figures 12–16.

From the above results, it can be seen that the R values for L-M are greater than 0.955, whereas those for BR are slightly higher. It can also be seen that, while BR performance (generalisation) is slightly better than L-M, its iterative epochs, which culminated in the least MSE, are 868, which is way higher than the 17 epochs of L-M. Thus, BR takes much more time to train than L-M. While the value of R is not ideal and could be improved, it nonetheless demonstrates the ANN's ability to learn and generalise from the obtained coefficient correlations.

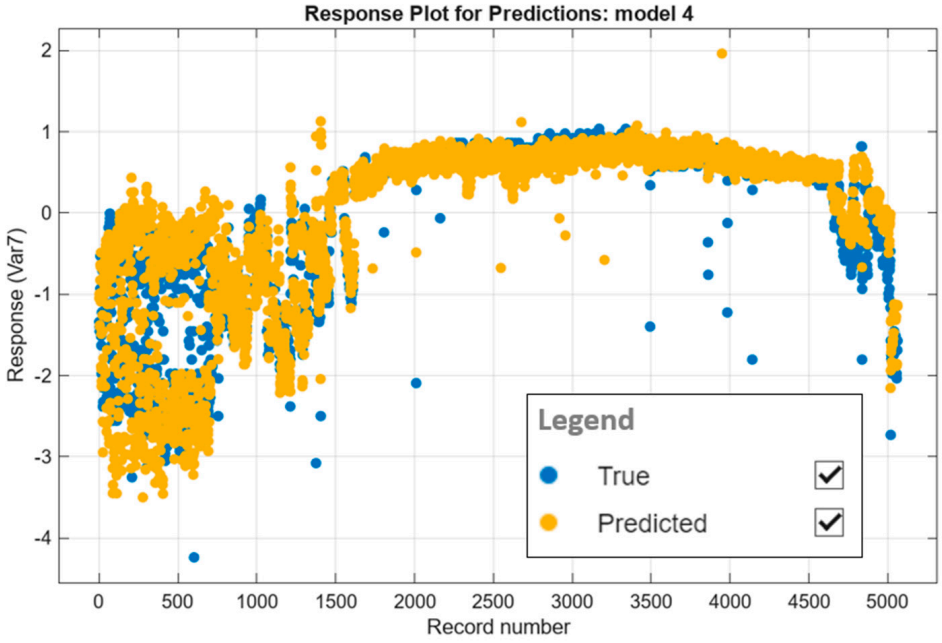


Figure 12. ANN response plot for the prediction.

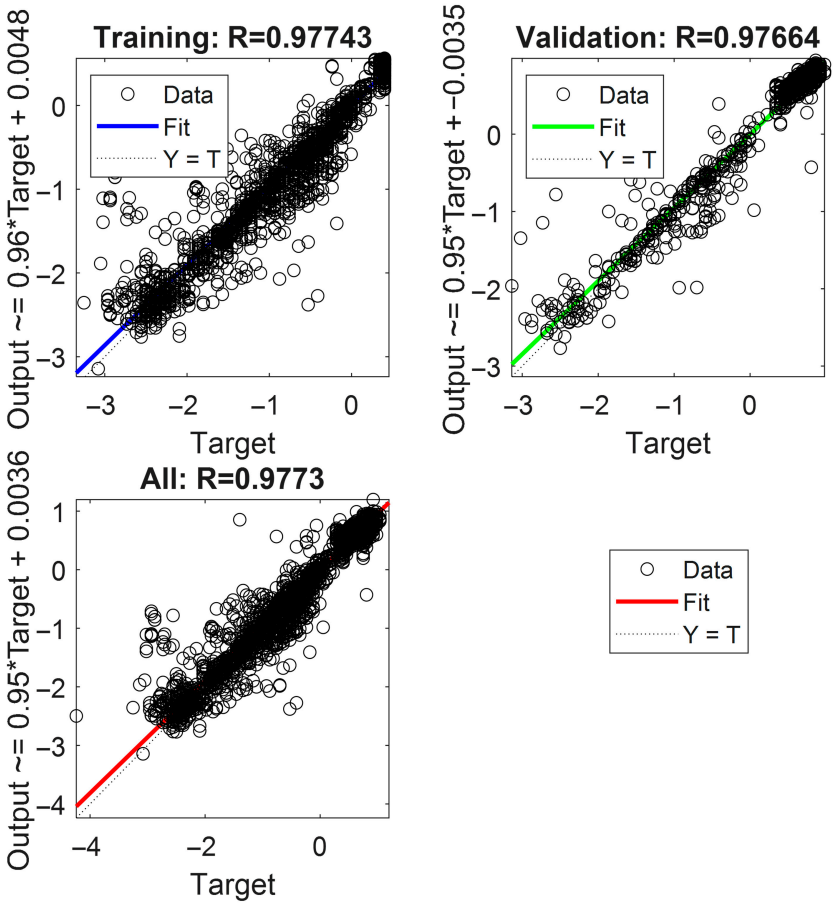


Figure 13. Prediction plots for ANN (L-M): prediction with respect to the ideal line.

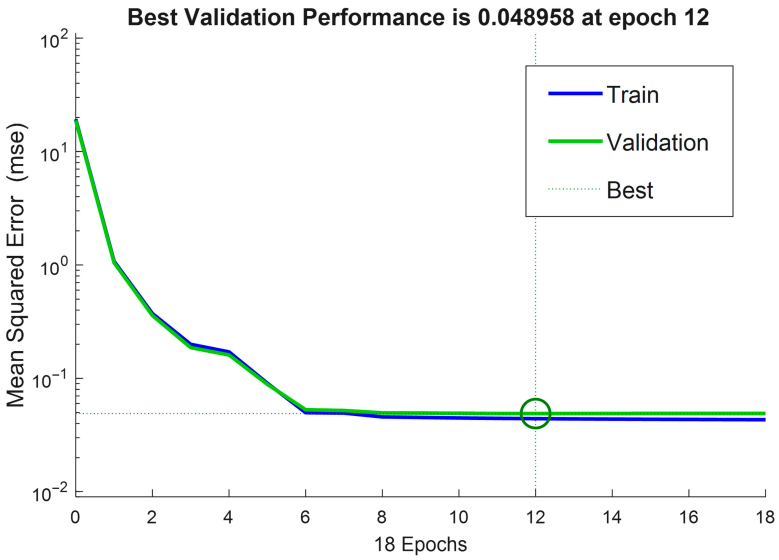


Figure 14. Epoch count for minimum MSE for ANN (L-M).

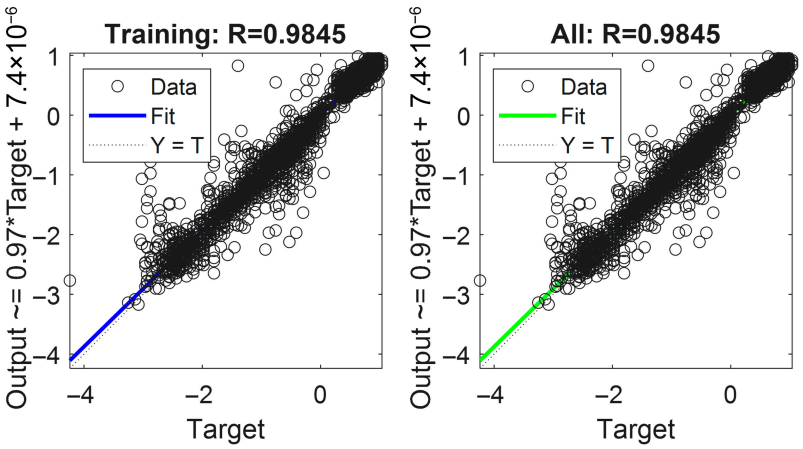


Figure 15. Prediction plots for ANN (BR): prediction with respect to the ideal line.

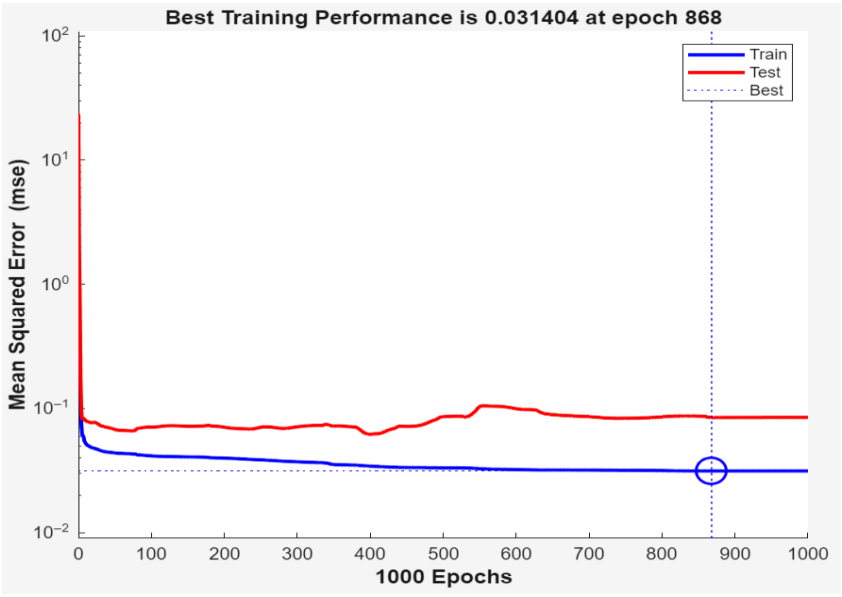


Figure 16. Epoch count for minimum MSE for ANN (BR).

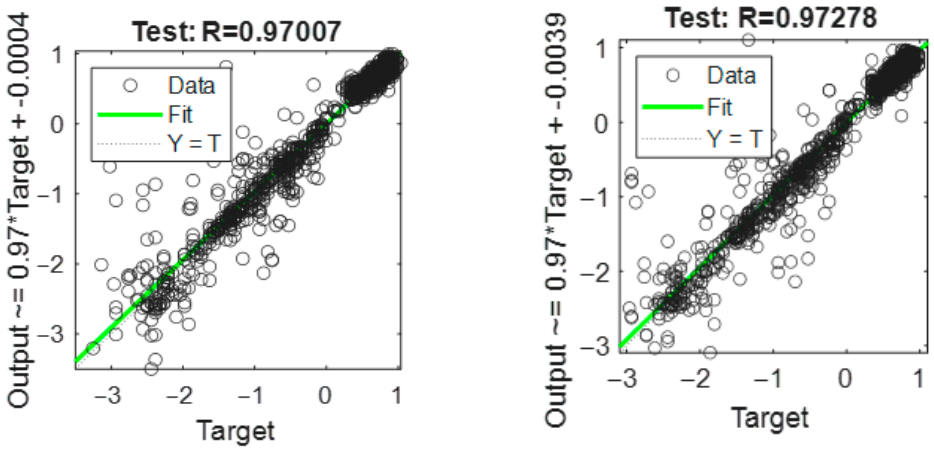
The comparative table showing ANN model performance with Levenberg–Marquardt (L-M) and Bayesian Regularisation (BR) is provided in Table 2, given below:

Table 2. Comparison of ANN training methods.

Levenberg–Marquardt (L-M)		Bayesian Regularisation (BR)	
R^2 (%)	RSME (%)	R^2 (%)	RSME (%)
95.5 [1]/95.4 [2]/94.1 [3]	2.1 [1]/2.3 [2]/2.4 [3]	96.9 [1]/94.6 [3]	1.8 [1]/2.2 [3]

[1] Training, [2] Validation, [3] Testing.

The ANN-trained model was also tested on a new set of 8750 data points for the year 2023 succeeding the year 2022 (training and validation data). Figure 17 shows the testing result with an R of 97.01% and 97.3% for L-M and BR respectively and Figure 18 shows the plot of predicted output vs. actual values, which shows it generalising well, with the trend following closely within the errors of the L-M modelling method.



(**a**) (**b**)

Figure 17. Test prediction plots: (**a**) prediction for L-M, (**b**) prediction plot for BR.

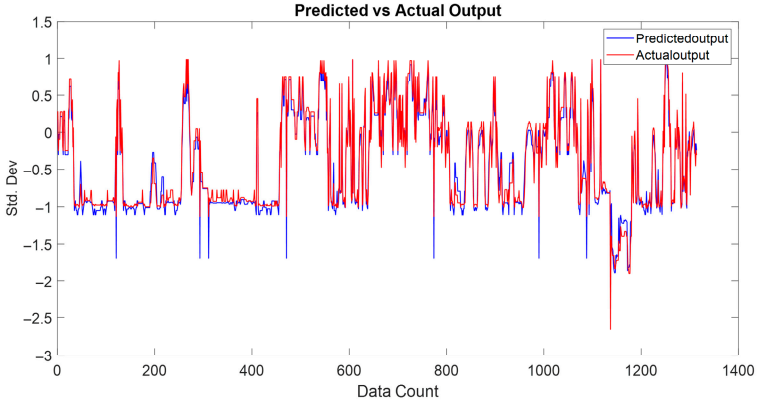
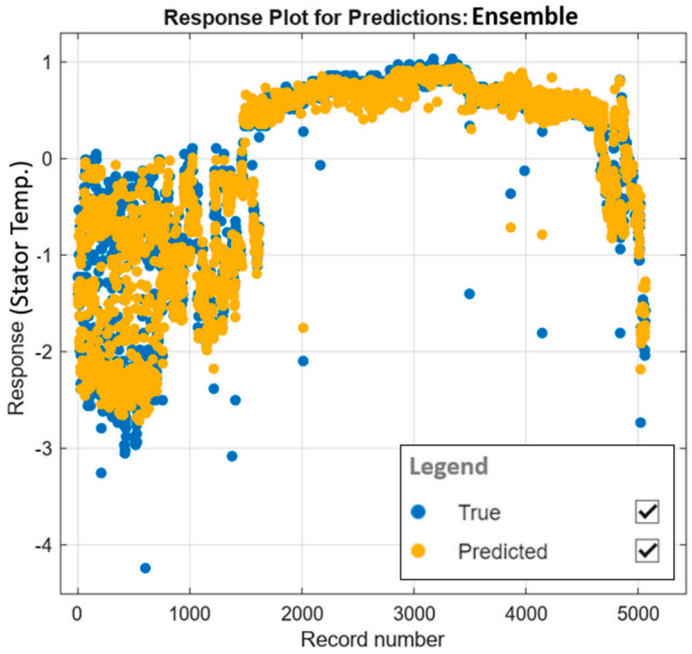
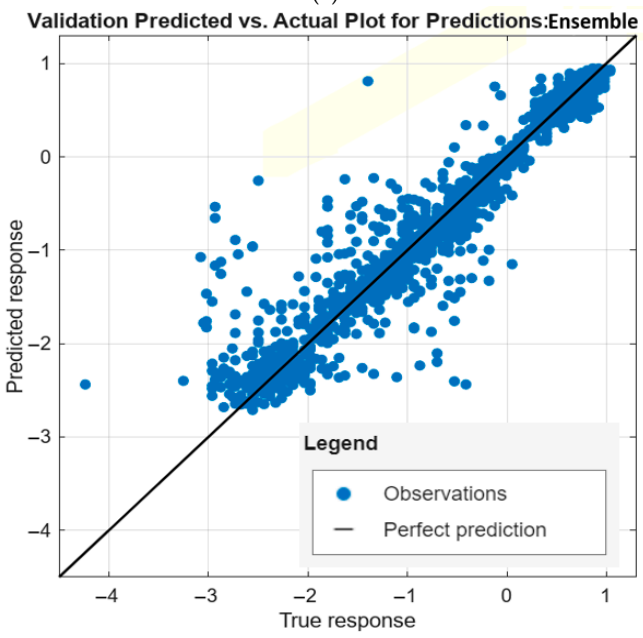


Figure 18. Predicted vs. actual output plot (L-M).

To compare the ANN results with those of other ML regression models, the same curated data was used to train and validate those models. Tree, LR, SVM, Ensemble (Bagged Tree), GPR (Exponential), Kernel (Least Squares Regression) and sample prediction results obtained for Ensemble are provided below in Figure 19.



(**a**)



(**b**)

Figure 19. Prediction plots for Ensemble: (**a**) prediction with respect to true values, (**b**) prediction with respect to ideal line/values.

The generalisation of the prediction within the performance range of Tree can be understood from the figures above, with the difference between the true and predicted colour legends. After training all the regression models, the results obtained have been collated for comparison purposes and are provided in Table 3 below:

Table 3. Comparison of prediction performance amongst different prediction ML models.

ML Algorithms	Performance Matrices		Model Size
	R^2 (%)	RSME (%)	
ANN	95.5 [1]/95.4 [2]/94.1 [3] (L-M) 96.9 [1]/94.6 [3] (BR)	2.1 [1]/2.3 [2]/2.4 [3] (L-M) 1.8 [1]/2.2 [3] (BR)	~200 kB (Light)
Tree	90.3 [2]	2.3 [2]	176 kB (Light)
LR	86.0 [2]	2.5 [2]	19 kB (Light)
SVM	90.3 [2]	2.3 [2]	83 kB (Light)
Ensemble (Bagged Tree)	92.2 [2]	2.0 [2]	3.0 MB (Moderate)
GPR (Exponential)	90.3 [2]	2.4 [2]	248 kB (Light)
Kernel (Least Squares Regression)	79.2 [2]	3.2 [2]	10 kB (Light)

[1] Training, [2] Validation, [3] Testing.

The performance matrix R and the obtained MSE have been converted to R^2 and RMSE by performing the required computations.

To enhance the physical interpretability of prediction made by the ANN, Shapley Additive ExPlanations (SHAP) values were computed to quantify the contribution of each feature to individual predictions. Shapley importance in Figure 20 shows the feature ranking of the features affecting prediction output. It indicates generator power as the most influential feature, contributing more than 40%, followed by cooling water strainer inlet pressure and generator current, with the least influential feature being cooling water strainer outlet pressure. While still persistent, generator air cooler pressure, vibration and cooling water strainer output pressure features contribute less than 10% each to the prediction.

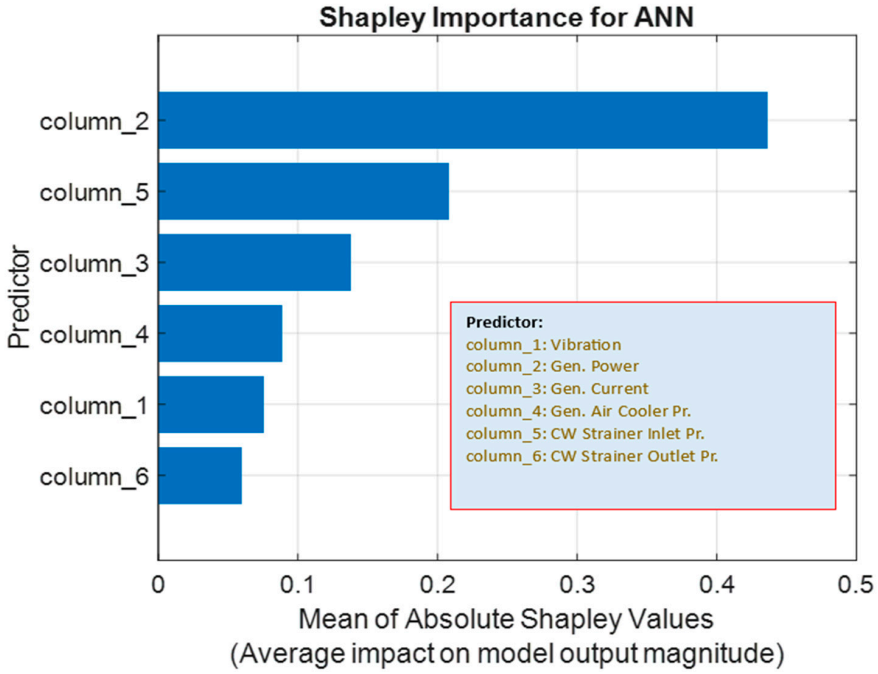


Figure 20. Shapley feature importance.

Figure 21 below shows the positive and negative contributions made by each feature on the prediction output. The most yellowish scatter points depict the most positive influence pushing the model to make higher prediction, whereas dark blue scatter points indicate the most negative influence making the model lower the prediction. It can thus be

inferred that all features selected for this study contribute to the prediction both positively and negatively albeit with varied strengths, indicating the actual influence of features on the generator stator temperature.

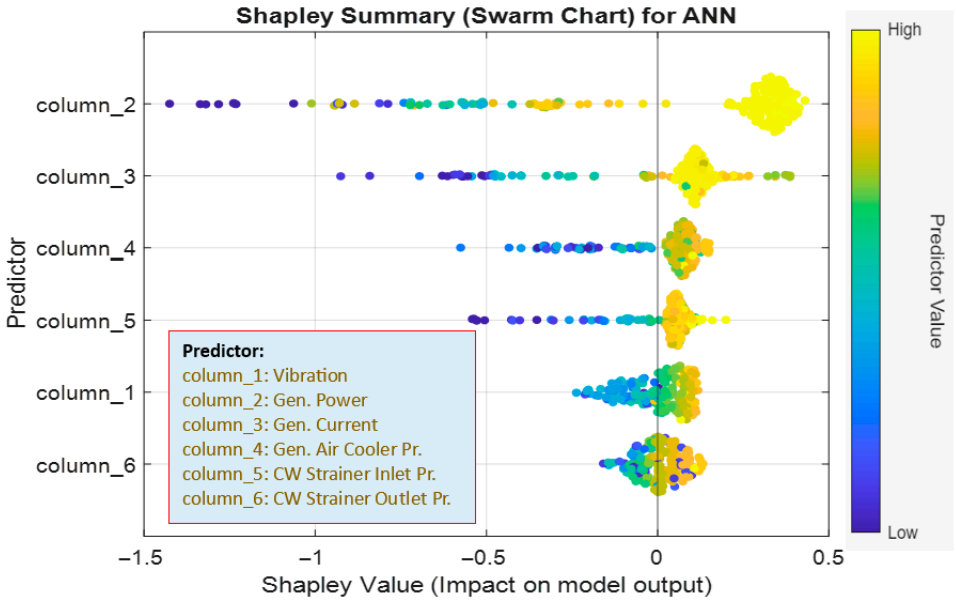


Figure 21. Shapley summary (swarm chart) for ANN interpretability.

Hyperparameter values for the regression models used in the comparative analysis are provided in Table 4 below to ensure clarity and reproducibility.

Table 4. Hyperparameter values of regression models.

Models/Hyperparameters	Values
1. Trees	
Preset	Fine Tree
Minimum leaf	4
Surrogate decision splits	Off
2. Linear Regression	
Preset	Interactions linear
Terms	Interactions
Robust option	Off
3. SVM	
Preset	Medium Gaussian SVM
Kernel function	Gaussian
Kernel scale	2.4
Box constraint	Automatic
Epsilon	Auto
Standardise data	Yes
4. Ensemble	
Preset	Bagged Trees
Minimum leaf size	8
Number of learners	30
Number of predictors to sample	All
5. Kernel	
Preset	SVM Kernel
Learner	SVM
No. of expansion dimension	Auto
Regularisation strength	Auto
Kernel size	Auto
Epsilon	Auto
Iteration limit	1000
Standardise data	Yes

6. Findings and Discussions

Performance predictions of the ANN model and other models are evaluated on actual generator data, for which the generator stator slot 13 temperature was predicted from four relevant features. From the results obtained above, the findings and discussions are as follows:

1. From Figure 18 it can be seen that the ANN model-predicted output and actual value trends matched quite well, with minor differences, even during the spikes within the boundary of the R^2 and RMSE. The difference between predicted and actual values can be computed, and this error can potentially indicate high/low temperature, which in turn can also be a fault in the generator windings, if it has not been caused by other contributing factors such as erroneous data, cooling water system issues, or sensor faults. Thus, this prediction study can also be used for trend analysis as well as for fault detection, and can accordingly be used for alarm or trip settings for generator operation in real time.
2. Comparison of the L-M and BR methods of ANN modelling provided in Table 2 indicated that, while the R^2 and RMSE are slightly better for BR, it took a much longer time to generalise with the increased epochs of 868 compared to the 12 for L-M for the amount of data utilised for the training. For the actual deployment, the amount of data would be much greater than that utilised in the study, thus increasing training/generalisation time. So, the employment of L-M or BR will need to consider careful trade-offs against the utility's performance requirements.
3. The comparative analysis made of the ANN and other ML models provided in Table 3 shows that the ANN has performed better with an R^2 of more than 94.1% and RMSE lower than 2.4%, followed by Ensemble (Bagged Tree) with an R^2 of 92.2% and RMSE of 2.0%, and SVM and Tree with and R^2 of 90.3% and RMSE of 2.3%. Kernel (Least Squares Regression) performed the least well with an R^2 of 79.2% and an RMSE of 3.2%. So, this comparative analysis provides an overview of performance and potential trade-offs to consider for deployment, based on the actual requirements/priorities of the performance matrices.
4. Since the plant under study is not fully operated through the SCADA/PLC system, most of the data are either not available or not usable as they contain less or more unstructured data. While cooling water system parameters such as generator air cooler pressure and cooling water strainer inlet/outlet pressures have been considered for the study, which definitely influence the stator slot temperature, cooling water system temperatures and ambient temperature were not monitored and thus could not be included as input. These temperature effects, along with the reactive power output and excitation system parameters, can be considered in future research. However, the selected feature interaction with the output shows that the minimum effect shown by cooling water strainer outlet pressure is around 7% while the highest interaction provided by generator power is more around 43% indicating good interactions of all the features.
5. The tuning of the hyperparameters and selection of activation functions are important for ANN performance. As is evident, optimisation of the number of neurons and the use of ReLU were employed in the current study. However, it is seen that ReLU had minimal influence on this current data; with more non-linear data input and increasing complexity, the use of the ReLU function may become more prominent. Likewise, other ANN hyperparameters will become more important with more complex data, which is always an area to explore and optimise.
6. Author [49] has developed a generator–rotor virtual temperature sensor model using data logged in the Centralised Management System (CMS), which was then trained

and validated using MLP, RNN-GRU and LSTM. Continuous monitoring of the sensor model developed from that particular CMS provided ±1 °C and ±2 °C prediction errors when the same virtual model was transferred to monitor IM casing temperature, which generally operated in parallel as digital twins. These kinds of models can reduce dependence on complex, physics-based sensing devices required to obtain signals from the field. Thus, more research is required to experiment with such virtual models and digital twins, to test and validate them for robust use in real-world utilities.

7. Considering the performance of an ANN and DNN for various applications, like the one trained and validated for the current case, it can be inferred that, while the value of RMSE and R^2 is quite impressive given the kind of real hydropower operational data available, its improvement can be tested with other ensembles, hybrid models or optimisation tools available. However, as learned through this study, the quantity, types, and completeness of the data made available are seen to be the most important criteria for proper and robust machine learning modelling to provide accurate and correct information for the purpose of prediction, so as to detect the fault before it occurs. So, before implementing ML for such prediction or diagnosis, the power plant's readiness to integrate such tools needs to be properly assessed and prepared for through the implementation of intelligent sensors and diagnostic tools to collect as much important operational and fault data as possible for data mining, interpretation, and prognosis, including RUL studies. Integration or hybridisation of ML tools and intelligent data collection centres with IoT, cybersecurity systems, thermal cameras, and even blockchains, along with other optimisation techniques, can be leveraged to stand out amongst the best ML models for actual deployment in hydropower plants.

7. Conclusions

An Artificial Neural Network was successfully trained, validated, and tested using real hydropower plant operational parameters in MATLAB®. It was found that the ANN learned the non-linear dynamics of the input signals, thereby implicating generator stator temperature as the output. With $R > 0.97$ and an R^2 of 94.1% across training, validation, and testing, it shows strong generalisation and can be deployed to predict trends and faults before actual occurrences. Considering the limited data availability at the Chhukha Hydropower Plant, for which data are not available year-round due to load requirements, inflow fluctuations, maintenance requirements, forced outages, etc., its RSME and R^2 performance is commendable. However, definite and realistic improvement could be achieved if the data had fewer missing values, better structure, and fewer outliers caused by sensor faults or maloperations. With larger, more dimensional data, performance can degrade; however, it can be enhanced through hyperparameter tuning, additional feature selection, and other available hybrid and optimisation tools. To validate the performance of the ANN, comparisons were made with other models such as SVM, Tree, Ensemble, GPR, Kernel, and LR; the ANN performed better, followed by Ensemble. The performance of Ensemble was impressive, with an R^2 of 94.1% and an RMSE of 2.0%. SVM, GPR, and Tree performed equally well, with an R^2 of 90.3% each, while Kernel performed the least well, with an R^2 of only 79.2%. An R^2 of 98.6% was obtained for RNN, GRU and LSTM performance for average stator temperature prediction by [34], an RMSE of 24.64% (CNN), 7.2% (RNN) and 7.6% (LSTM) obtained for synchronous motor rotor temperature prediction by [39] and an RMSE of 0.61% (Gradient Boosting DT) for PMSM rotor temperature detection by [40]. Comparing the specific temperature detection studies done by the above authors, the ANN performance of R^2 and RMSE, obtained up to 96.9% and 1.8%, respectively, for this study is remarkable, given the data diversity and availability. For the model

performance, features interaction explainability with predicted outputs has also been done through SHAP. All features contributed to the prediction both positively andnegatively, although with diverse strengths, indicating the actual influence of features on the generator stator temperature.

Predicting generator stator temperature is just one area of application, considering the huge potential of an ANN in hydropower. With targeted studies, it can be used for plant operation and control, reservoir management, flood forecasting, sedimentation studies, power generation optimisation, fault detection, and predictive maintenance, making hydropower systems smarter, safer, and more efficient. Future research can continue experimenting with other electrical and mechanical parameters that affect stator winding temperature, such as ambient temperature, cooling water temperatures and flows, and excitation parameters, to improve predictability. Hybridisation of the ANN with other optimisation techniques and integration with other intelligent systems, including image processing, IoT, and blockchains, remain attractive and necessary areas of research to improve the model's performance.

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Abbreviations

The following abbreviations are used in this manuscript:

HGU	Hydro-Generator Unit
IM	Induction Motor
PMSM	Permanent Magnet Synchronous Motor
ANN	Artificial Neural Network
LR	Linear Regression
RF	Random Forest
SVM	Support Vector Machine
ANFIS	Adaptive Neuro-Fuzzy Interference System
DT	Decision Tree
AENN	Auto Encoder Neural Network
LSTM	Long-Short Term Memory
CNN	Convolution Neural Network
RNN	Recurrent Neural Network
DNN	Deep Neural Network
GRU	Gated Recurrent Unit
MLP	Multi-Layer Perceptron
kNN	k Nearest Neighbour
MTBF	Mean Time Between Failure
ML	Machine Learning
AI	Artificial Intelligence
O&M	Operation and Maintenance

SCADA	Supervisory Control and Data Acquisition System
PLC	Programmable Logic Controller
R^2	Correlation Coefficient
RMSE	Root Mean Square Error
SHAP	Shapley Additive ExPlanations

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