Modelling and Energy Optimization of a Thermal Power Plant Using a Multi-Layer Perception Regression Method

VASILIOS XEZONAKIS[1], EFSTRATIOS L. NTANTIS[2]
[1]University of East London, Docklands Campus, London, UK
[2]Amity University Dubai, Academic City, Dubai, UAE

Abstract: - This research paper studies a thermal power plant model with an Artificial Neural Network that contributes to the accuracy improvement of actual measurement data. Neural Networks process the paradigm of algebraic expressions, and their training occurs via a Feed-Forward Back Propagation algorithm implemented in a *MATLAB* environment. The applied training case in a thermal power plant in Paracha includes three different algorithms, the Levenberg-Marquadt, the Scaled Conjugate Gradient, and the Bayesian Regularization, considering less number of samples to achieve more reliable results. The outcome highlights Bayesian Regularization Networks' superiority in accuracy and performance compared to Levenberg-Marquadt and the Scaled Conjugate Gradient. The regression analysis estimates the relationship between input-independent and output-dependent variables, forecasts the energetic data, and highlights the benefits of the Bayesian Regularization method in the energy sector.

Key-Words: - Thermal Plant, Neural Networks, Bayesian Regularization, Regression Analysis

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1 Introduction

In recent years, the construction of thermal plants has experienced a decrease in terms of capital costs, installation time, and the availability of fuel resources. Despite these factors, the currently operational power stations still account for approximately 65% of global energy production, [1]. Recently, the electricity generation from thermal power plants presents some concerns, such as the low-efficiency value and significant thermal energy losses. Optimising thermal power performance is adopted to overcome these issues by introducing novel modelling techniques such as Fuzzy Logic, Neural Networks, Artificial Neural Networks (ANNs), Simulated Neural Networks (SNNs), and regression analysis, [2].

Neural Networks are widely recognised as one of the leading methods for advancements in thermal power. They can effectively address and model the nonlinear interactions among thermodynamic input and output parameters. As a result, they can accurately predict the output power generation and thermal power plant efficiency across different operating conditions, [3]. Neural Networks was initially introduced in 1944 by Walter McCullough and Walter Pitts, researchers from the University of Chicago. They later joined the Massachusetts Institute of Technology in 1952 to explore the modelling of human-brain interactions using limited computing capabilities. However, with the advancement of computing power over time, Neural Networks have become capable of effectively handling more complex and high-dimensional datasets, [4].

The research paper aims to apply Neural Networks to predict thermal power production in a thermal power plant. The study optimises thermal power performance by introducing novel training cases like the Levenberg-Marquadt (LM), the Scaled Conjugate Gradient (SCG), and the Bayesian Regularization (BR).

The benefits of the paper lie in its potential to improve the efficiency, cost-effectiveness, simulation simplicity, and environmental impact of power plants by employing advanced Neural Network models for thermal power production forecasting. The findings and insights presented in this paper can be valuable to academia and industry professionals in the energy sector.

2 Literature Review

Researchers across various real-world engineering applications, including the solar sector, have widely adopted Neural Networks. For instance, [5], highlighted its usage in this domain. Additionally, other researchers have utilised Neural Networks to forecast the impact of solar power on islands, [6]. The forecasting of the energy produced via the Neural Networks toolbox using *MATLAB R2017b* over the various databases from solar power plants has also been highlighted, [7].

Researchers in the thermal power plants sector proposed models for many input and output datasets over long periods with encouraging results. The modelling of the power output in a Combined Cycle Power Plant (CCPP) has also been predicted with accurate results, considering the steam turbine's relative humidity, atmospheric pressure, ambient temperature, and exhaust vacuum as input parameters, [8]. Various Machine Learning (ML) methods are compared using the regression analysis technique to predict the power output at full working conditions of a base load-operated CCPP, [9]. The highlighted aspect was the demonstration of the validity and reliability of ANNs in assessing the impact of ambient temperature on power generation and fuel consumption in a straightforward gas turbine power plant, [10].

An ANNs-based modelling analysis in various engineering applications, including simple power cycles, gives encouraging results, [11]. An interesting adoption of Neural Networks in the modelling, monitoring, and performance analysis of a combined heat and power plant is studied, [12]. The implementation of Neural Networks in a Combined Heat and Power (CHP) model applied to micro gas turbines with optimum results has also been achieved, [13]. A control methodology of a CCPP plant using a linearisation model technique was highlighted, [14]. The modelling and optimisation of a thermal power plant's Nitrogen Oxide (NOx) emissions have been accomplished by implementing a Neural Network, which accurately predicts these emissions, [15]. The adoption of a Back-Propagation (BP) Neural Network model to control the drum level of a thermal power plant is achieved successfully, [16]. In [17], the author conducted a study on the modelling and optimisation of a Combined Gas And Steam (COGAS) power plant. The study involved implementing a Multi-Layer Perception (MLP) model, which resulted in an efficiency above 60%. Additionally, a novel configuration was explored as part of the study.

The performance of an industrial gas turbine can be accurately modelled using ANNs by considering the relative humidity, ambient pressure, and ambient temperature as input parameters. This modelling process requires 10.000 to achieve satisfactory results, [18]. Furthermore, using Neural Networks to model the hourly demonstrates significant improvements in the two-fold approach and Mean Square Error (MSE). Moreover, the application of ANNs in modelling the electrical output power of a COGAS power plant demonstrates significant improvements in the two-fold approach and MSE, with enhancements of 3.176 and 0.99675, respectively, [19]. Moreover, the implementation of Neural Networks in predicting the failure rates of power equipment in a power plant, which directly affects its performance, has been accomplished, [20]. Using Neural Networks to model an industrial oil-fired boiler plant system has also produced promising outcomes, [21].

The compressor's map has been successfully predicted by employing Neural Networks, improving efficiency by reducing measured data noise and enhancing data quality, [22], [23]. Comparing the efficiency of ANNs and Autoregressive Moving Average Exogenous (ARMAX) time series models in a steel thermal plant, where various input variables were considered, it was determined that ANNs involved its implementation in a Combined Cooling, Heating and Power (CCHP) plant to accurately predict the exergy efficiency, overall exergy destruction rate, and performance prognosis of a tri-generation power plant, yielding precise results, [24]. The successful utilisation of Neural Networks in controlling the combustion process of a western Balkan power plant has led to improved overall performance and precise results, [25]. Additionally, in the *MATLAB R2017b* environment, ANNs have been employed to optimise the economic generation and planning of the integrated Nigerian power network, which comprises seventeen stations, [26], [27]. This optimisation process aims to minimise operational costs and includes an economic generation model proposal.

A study of load forecasting in power plants using Neural Networks occurred, with encouraging outcomes. Furthermore, a hybrid model that combines ANNs with a fuzzy logic exergy-controlling model for a CHP system has been examined to predict its performance accurately, demonstrating favourable outcomes, [28]. Additionally, a comparative analysis between the MLP and Radial Basis Functions (RBF) was carried out to identify fault analysis in gas turbines, concluding that RBF outperforms Neural Networks MLP, [29]. The adoption of Neural Networks for reducing indirect thermal losses in a thermal power plant with encouraging results has been studied, [30]. A depiction of another technique is presented, which utilised the ANNs method to predict the performance of coal-based thermal power plants. The process was validated through successful and reliable experiments, ensuring minimal errors and producing robust results, [31]. An alternative approach is suggested for simulating thermodynamic systems in power plants, utilising ML and soft computing techniques, [32], [33]. This approach has shown promising and precise output power results. The methodology of the Neural Networks to be followed is discussed below.

3 Methodology

This research study entails the design of a Neural Networks model, which follows a set of steps outlined in the flow chart presented in Figure 1. Subsequent sections will elaborate on each stage in detail.

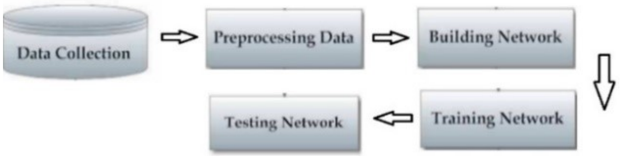

Fig. 1: Flowchart of building a Neural Network

3.1 Data Collection

Thermal power plants rely on specific inputs and outputs to function effectively. Among the primary input variables crucial for their operation are the fuel flow, water flow, and base load, among others. In the context of this paper, the system's output parameter of interest is the superheater temperature. Notably, these selected input and output parameters are well-suited and comprehensive for the efficient operation of the thermal power plant under investigation.

The data was collected from Paricha Thermal Power Station Jhasi with 210 MW plant capacity for the present analysis. Table 1 shows the actual data of the 210 MW plant, [34].

3.2 Pre-Processing Data

The subsequent stage involves pre-processing, the collected data to prepare it for feeding into the Neural Network model. During this phase, the numerical data is carefully organised and formatted based on the information presented in Table 1, [32]. This comprehensive breakdown of the data includes the relevant input and output parameters obtained from a sample population of 45 measurements. It encompasses various parameters such as the Fuel Feed Mass Rate (FFMR) in kg/hr, the Feed Water Flow Rate (FWFR) in kg/hr, the Base Load (BL) in kW/hr, and the Superheater Temperature (SH) in Kelvin. The population set presented in Table 1 is divided into training and testing portions to facilitate effective training and testing of the Neural Network. The division is implemented using the Neural Network Toolbox available in *MATLAB R2017b*, which automatically handles the partitioning process. However, it is worth noting that due to the predictive limitations of the *MATLAB* software, a reduced number of 20 samples (*see* Table 2) from the dataset is thoughtfully selected to ensure a reasonable best-fitting of the actual data.

Table 1. Data from the thermal power plant

Sample	FFMR (Input) (kg/hr)	FWFR (Input) (kg/hr)	BL (Input) (kW/hr)	SH Temperature (Output) (K)
1	149.06	591.99	195.81	520.11
2	149.21	615.96	199.17	517.15
3	150.41	595.69	197.29	524.08
….	……..	……..	……..	……..
43	154.54	576.41	189.2	513.59
44	153.59	567.62	183.71	519.22
45	154.98	577.25	184.59	524.33

Table 2. Sample of actual data

Sample	FFMR (Input) (kg/hr)	FWFR (Input) (kg/hr)	BL (Input) (kW/hr)	SH Temperature (Output) (K)
1	149.06	591.99	195.81	520.11
2	149.21	615.96	199.17	517.15
3	150.41	595.69	197.29	524.08
….	……..	……..	……..	……..
18	156.79	600.2	193.93	517.2
19	156.56	592.5	193.3	518.03
20	156.78	591.33	194.55	526.53

3.3 Building Network

The design process involves various stages, such as the architecture of the Neural Networks, the number of neurons, layers, training functions, and the learning algorithms. The Neural Networks toolbox for the respective test case is implemented in this case study, building the network automatically with *MATLAB R2017b* software's Graphical User Interface (GUI) capabilities.

3.4 Training Network

The ANN model is supplied with the pre-processed input and target data in the training stage. The model automatically adjusts its weight biases during learning to align the output data with the target values. The choice of the learning algorithm, such as back-propagation, conjugate gradient, or Bayesian regularisation, significantly influences the speed and accuracy of the training process. To ensure the efficiency and generalisation of the model, an appropriate training algorithm is carefully selected, and parameters are through iterative refinement. This iterative training approach allows observing the model's performance, convergence, and prediction accuracy.

3.5 Testing Network

The network database's testing process and performance evaluation focus on metrics such as the Root Mean Square Error (RMSE) and the Mean Bias Error (MBE). The RMSE is utilised to express the accuracy of short-term forecasted data. At the same time, the MBE provides insights into the model's performance by indicating the average deviation between predicted and actual data. The network's performance is validated if the results meet the desired criteria. However, the network will retrain and retest if the results are unsatisfactory.

4 Results

The Neural Network Toolbox in *MATLAB R2017b* GUI capabilities of the Input/Output fitting tool uses three different available training algorithms such as the Scaled Conjugate Gradient (SCG), the Levenberg Marquardt (LM), and the Bayesian Regularization (BR) is applied and analyzed in the following subsections. The theoretical background analysis of these training algorithms is omitted.

4.1 Training Process with LM Algorithm

The training employs the LM algorithm to address the software's limitations and obtain reliable outcomes after unsuccessful attempts with different neuron configurations, a network design with 150 neurons is utilised. Figure 2 illustrates the structured network for the test case. The validation of the best performance occurs in the first iteration after three epochs, as plotted in Figure 3. Additionally, Table 3 depicts the sample values for training, testing, and validation of the MSE and the Regression coefficient (R). The network's performance in the MSE and the R. The network's performance in the MSE and R is 1.84e^-2 and 9.985e^-1, respectively.

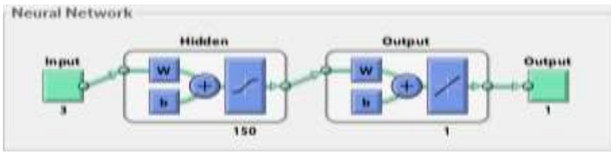

Fig. 2: Structured Neural Network for the test case

Table 3. MSE and R values for trained, validated, and tested samples

Results	Samples	MSE	R
Training:	14	1.83851e-2	9.98477e-1
Validation:	3	82.22035e-0	-8.15702e-1
Testing:	3	146.93110e-0	-9.52407e-1

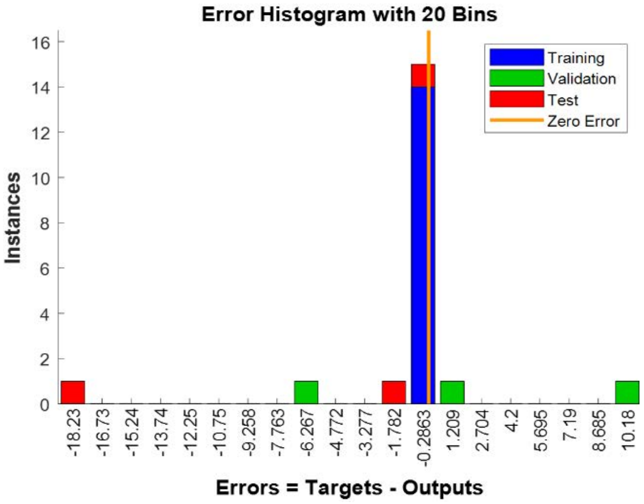

Fig. 3: Error Histogram for Regression Analysis

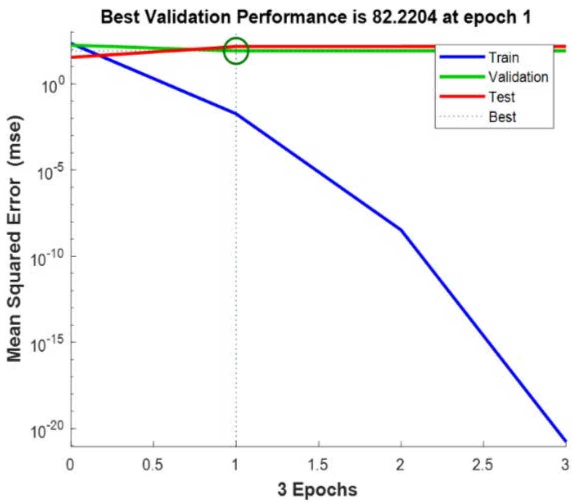

Fig. 4: Best validation performance of the LM network for 150 neurons

Figure 3 depicts the error distribution graph and the regression analysis results of the trained network, highlighting the occurrences of errors (i.e., disparities between the target and the output). This analysis includes cases where the error is zero and instances where differences exist between the output and the desired target. Generally, the targets exhibit varying degrees of deviation from the expected values, ranging from minor discrepancies to more substantial disparities. Figure 4 depicts the best validation performance of the LM network with the assigned value of the MSE of 82.204e^-2 in the 1st out of 3 iterations. Furthermore, novel computational attributes are depicted, whilst testing and validation performance metrics coincide.

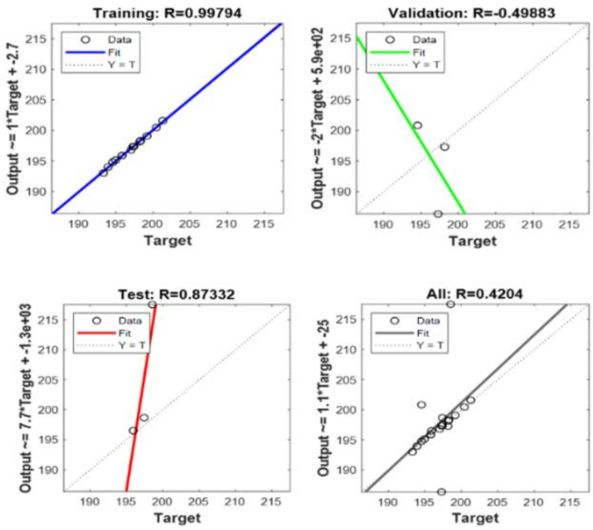

Fig. 5: Regression Analysis for the training data

Figure 5 displays the alignment between the output and the target data, specifically focusing on the regression values, demonstrating how well the training samples align with the validated and tested examples. When regression values approach 1, it indicates a strong match between the output and the target. However, the validation and testing samples exhibit lower regression values, suggesting the network's poor performance.

4.2 Training Process with BR Algorithm

Due to software limitations, the training process employed the BR Algorithm to obtain reliable results with different numbers of neurons. After unsuccessful attempts with various neuron numbers, a network design involving 150 neurons was chosen. Figure 6 illustrates that the best performance for this network architecture was validated during the 959th iteration out of one thousand iterations (epochs). The network achieved its highest performance regarding MSE, with a value of 2.645e^-10. Table 4 presents the corresponding sampling values for the MSE and the regression coefficient (R) across the training, testing, and validation sets. Figure 7 illustrates the error histogram and the regression analysis of the trained network, identifying the instances that the error occurs, including the zero margins and the differences between the output and the target. In most instances, the targets present a very small to a higher divergence between the output and the target values.

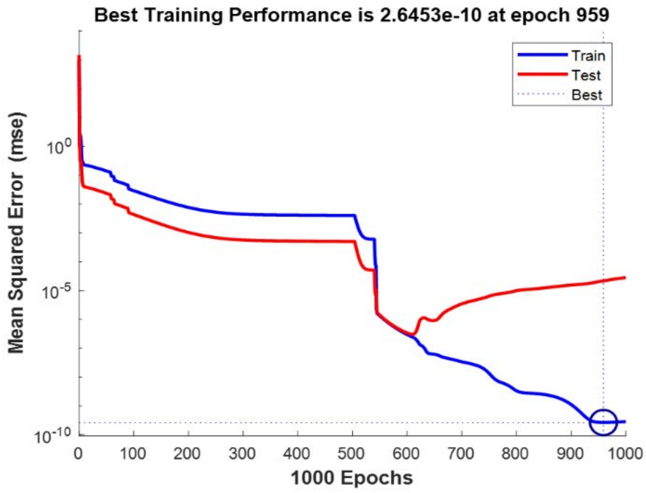

Fig. 6: Best training performance of the BR network for 150 neurons

Table 4. MSE and R values for the trained, validated, and tested samples

Results	Samples	MSE	R
Training:	14	1.13986e-0	8.54341e-1
Validation:	3	3.33664e-0	3.94591e-1
Testing:	3	18.06370e-0	8.90240e-1

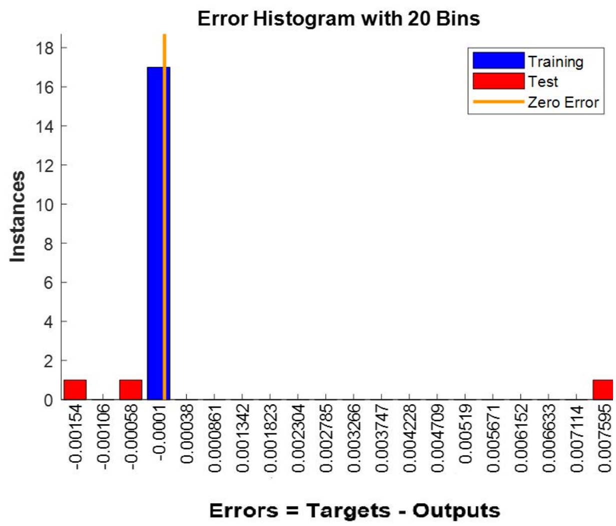

Fig. 7: Error Histogram for Training data

In Figure 8, the alignment between the output and target data is visually represented, showcasing how closely they match each other. The regression value of 1, indicates a perfect fit, implying that the network's output accurately captures the desired target values. By comparing the training samples with the validated and tested samples, it becomes evident that this network performs exceptionally well. The network's ability to generalise beyond the training set is demonstrated through the high consistency between the predicted outputs and the actual target values in the validation and testing phases. This level of agreement reaffirms the network's effectiveness and reinforces its reliable performance in real-world scenarios.

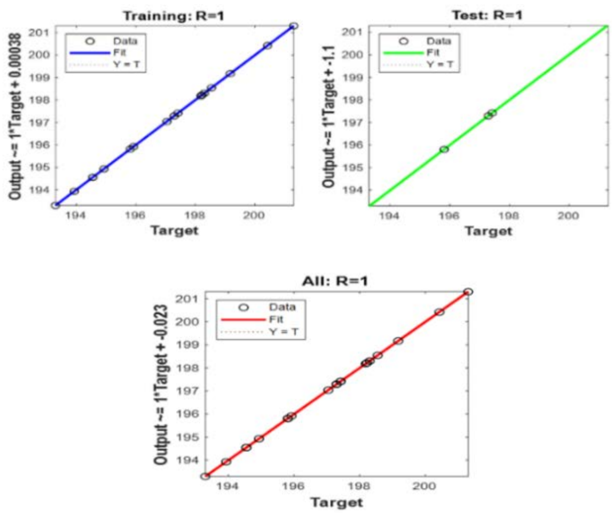

Fig. 8: Regression Analysis for the training data

4.3 Training Process with SCG Algorithm

After unsuccessful attempts, different numbers of neurons were employed in this process. Its optimal performance was validated during the 9th iteration out of 15 iterations. The information is illustrated in Figure 9, showcasing the same structured network as in the previous two cases. The MSE of the network demonstrates exceptional performance, measuring at 1.14e^-10.

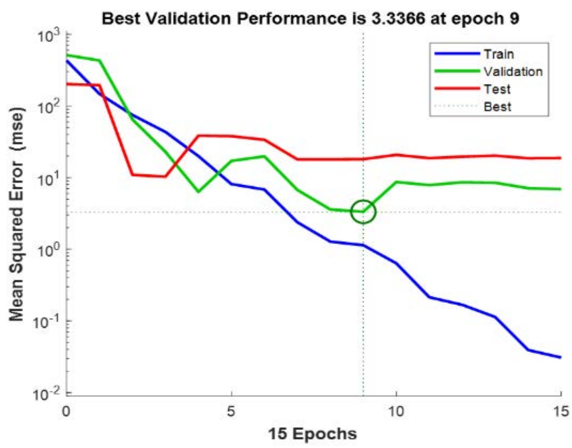

Fig. 9: Best validation performance of the SCG network for 150 neurons

Table 5 provides a comprehensive overview of the MSE and regression values for the sampling set, i.e. training, testing, and validation.

Table 5. MSE and R values for the trained, validated, and tested samples

Results	Samples	MSE	R
Training:	14	1.13986e-0	8.54341e-1
Validation:	3	3.33664e-0	3.94591e-1
Testing:	3	18.06370e-0	8.90240e-1

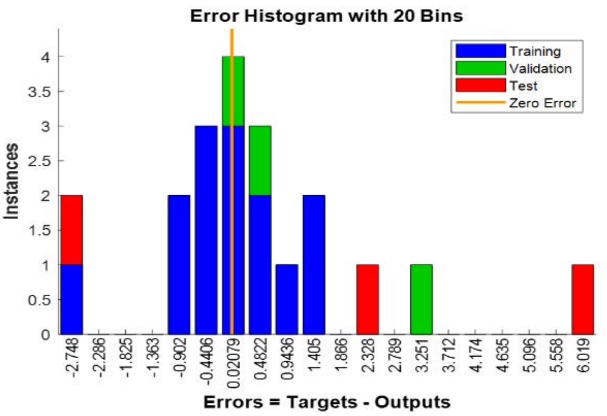

Fig. 10: Error histogram for the training data

Figure 10 illustrates the trained network's error histogram and regression analysis, highlighting the errors (error = target – output) and identifying instances of zero margins and disparities between the output and the target. In most cases, the targets exhibit varying degrees of deviation from the outputs, ranging from small to more significant discrepancies.

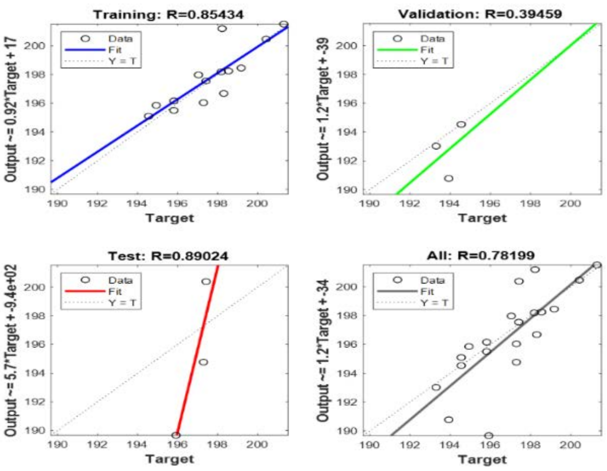

Fig. 11: Regression Analysis for the training data

Figure 11 showcases a satisfactory alignment between the output and the target data, with R ranging from 0.78 to 0.89. Comparing the training data to the validated and tested data, it is evident that the network demonstrates a good fit. The regression values for the validation and testing samples are below 1 and close to 0.8, indicating a moderate level of performance by this network.

4.4 Process between Training Algorithms

Table 6 (Appendix) compares the three training techniques used in the current test case. Comparing the performance of the training methods, namely SCG, LM, and BR, the following observations are made regarding different parameters.

Training Iterations: One noticeable difference between the training algorithms is the number of iterations required for convergence. The SCG algorithm demonstrates relatively fast convergence, reaching an acceptable level of performance in just 15 iterations. On the other hand, the BR algorithm exhibits significantly longer training iterations, with approximately 1000 iterations needed for convergence. The LM algorithm falls between the two, requiring only 3 iterations to achieve satisfactory results. This observation indicates that the choice of training algorithm can affect computational efficiency and resource requirements during the training process.

Mean Square Error (MSE): Evaluating MSE across the training, testing, and validation sets provides essential insights into the model's accuracy. The BR algorithm stands out with the lowest MSE value, indicating its ability to minimise prediction errors effectively. The SCG algorithm records a higher MSE value, while the LM algorithm falls within an average range. The lower MSE associated with the BR algorithm underscores its superior performance in capturing the relationships between input parameters and superheater temperature, leading to more accurate predictions.

Regression Values: The regression values (R) measure how well the predicted outputs align with the target values. The BR algorithm exhibits excellent regression values close to 1, indicating high precision in its predictions. However, The SCG algorithm shows lower regression values, suggesting relatively poorer performance in predicting superheater temperature accurately. The LM algorithm falls in between, with regression values classified as very good, further affirming its effectiveness.

Performance Parameter: The performance parameter, which incorporates various metrics such as MSE and regression values, assesses the training algorithm's effectiveness. The SCG algorithm achieves an acceptable performance parameter, suggesting it can still yield reasonably accurate predictions. The LM algorithm records an improved performance parameter, indicating enhanced performance over the SCG algorithm. Notably, the BR algorithm outperforms both, showcasing its ability to achieve superior accuracy and reliability in short-term thermal power production prediction.

Error Histogram: The error histogram illustrates the distribution of errors between predicted and target values. The SCG algorithm exhibits a histogram that indicates relatively poorer predictions, while the BR algorithm displays fewer errors, highlighting its ability to make more accurate predictions. The LM algorithm shows an error histogram with intermediate characteristics indicating moderate performance.

The comparative analysis of the three training algorithms demonstrates that the LM and BR algorithm is more promising and effective for thermal power production prediction than the SCG method. Especially for the BR algorithm, its exceptional accuracy, low MSE, high regression values, and minimal prediction errors position it as the preferred algorithm for this specific predictive modelling task.

5 Discussion

Despite the promising outcomes, this study acknowledges limitations that should be considered when interpreting the findings. Firstly, the dataset used for training and testing the Neural Network was collected from a single thermal power plant with a capacity of 210 MW. This limited dataset may only partially capture other power plants' diverse operational conditions and characteristics, potentially impacting the model's generalizability. Secondly, while the selected input and output parameters were deemed appropriate for the current thermal power plant, other plants with different configurations may require additional or alternative variables for more accurate predictions. Thus, future research should explore the inclusion of additional relevant parameters to enhance the model's performance across different power plant types.

Specific improvements can be considered to overcome the limitations mentioned earlier and further enhance the model's predictive capabilities. This study opens up several exciting avenues for future research in thermal power plant optimization using Neural Networks. One potential direction is the development of hybrid models that combine Neural Networks with other Machine Learning algorithms, such as Fuzzy Logic or Genetic Algorithms, to leverage the strengths of each approach and overcome individual limitations. Moreover, investigating the applicability of more recent and sophisticated Neural Network architectures, such as Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks, could lead to improved performance in capturing temporal and spatial dependencies in the data. Furthermore, conducting a comparative analysis between the Neural Network-based model and other state-of-the-art prediction techniques, such as physics-based modelling or deep learning methods, would provide valuable insights into the strengths and weaknesses of each approach. Lastly, applying the developed model in real-world thermal power plant settings and integrating it into existing power plant management systems would validate its practical effectiveness and potential for industry adoption.

6 Conclusions

This paper presents an innovative approach that offers a methodology for predicting short-term thermal power production in Pariccha, eliminating the necessity for complex mathematical modelling and extensive calculations. Instead, it harnesses the power of the *MATLAB R2017b* Neural Network toolbox to achieve accurate predictions. The study compares different methods and algorithms by evaluating error rates and regression values. The findings reveal that the LM and BR algorithms outperform the SCG methods in terms of performance. The superiority of the BR training functions is particularly noteworthy, demonstrating exceptional capabilities in producing reliable predictions. The results of this research emphasise the potential and effectiveness of utilising neural networks and the specific algorithms mentioned, such as the LM method and BR, for forecasting thermal power production in the short term. These findings pave the way for more streamlined and efficient prediction models to assist decision-making processes and optimise thermal power generation.

NOMENCLATURE

ANN	Artificial Neural Network
ARMAX	Autoregressive Moving Average Exogenous
BL	Base Load
BR	Bayesian Regularization
CCHP	Combined Cooling, Heating and Power
CCPP	Combined Cycle Power Plant
CHP	Combined Heat and Power
CNN	Convolutional Neural Network
COGAS	Combined Gas And Steam
FWFR	Feed Water Flow Rate

FFMS	Fuel Feed Mass Rate
GUI	Graphical User Interface
LM	Levenberg-Marquardt
LSTM	Long Short-Term Memory
MBE	Mean Bias Error
ML	Machine Learning
MLP	Multi-Layer Perceptron
MSE	Mean Square Error
R	Regression Coefficient
RBF	Radial Basis Functions
RMSE	Root Mean Square Error
SCG	Scaled Conjugate Gradient
SH	Superheater Temperature
SNN	Simulated Neural Network

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APPENDIX

Table 6. Comparison between training functions

	SCG	**LM**	**BR**
Training (iterations)	15	3	1000
Mean Square Error	Higher	Acceptable	Lower
Regression Values	Low	Very good	Excellent
Performance Parameter	Acceptable	Low	Very Low
Error Histogram	Bad	Acceptable	Good

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Vasilios Xezonakis carried out the simulations and post-processing of the results, implemented the Neural Network in Toolbox in MATLAB, and wrote the initial manuscript.

Efstratios Ntantis has organised and proofread the manuscript.

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