

Prediction of Noise Level for Industrial Zone using Bayesian Regularization Neural Network Training Algorithm

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ABSTRACT

Hidden layers are very useful to visualize the performance of neural network design mainly to deal with the complex problems where the accuracy and the time complexity are the main constraints. The process of deciding the number of hidden layers and number of neurons in each hidden layer is one of the prominent tasks in neural network architecture. In this study, we have proposed a method to determine the number of hidden neurons in hidden layer and compare it with the existing methods. Using the proposed method of obtaining the hidden neurons in hidden layer, we then applied Bayesian Regularization neural network training algorithm and obtained the accuracy measures. The study concluded that proposed method is better than the existing conventional methods in predicting the noise levels in Industrial zone of Lucknow, India.

Keywords: Noise Level, Neural Network, Bayesian Regularization.

Mathematics Subject Classification Number: 68T07

Journal of Economic Literature (JEL) Classification Number: C 4, C-45.

1. Introduction

Noise is generally described as unwanted sound that creates annoyance, hampers mental and physical peace and generate unpleasant psychological effects on an individual. Due to rapid urbanization, industrialization and environment degradation, noise level is very much affected. Thus, the prediction of noise levels is of considerable importance in knowing the real condition of problem arises due to disturbances in noise. Noise prediction models are productive for urban planning, environmental management and to create healthy and noise pollution free environment. Therefore, many researchers are always curious for methods that are practically significant in predicting noise levels accurately. It is therefore important to accomplish systems that could be utilized to predict

accurately, noise pollution levels in an urban area. Noise pollution in urban environment is emerging as a threat to quality of life impacting the peace of outside working environment.

Artificial neural networks (ANNs) are the computational techniques and mathematical models that belong to the field of machine learning (Kelleher *et al.*, 2015) and are very popular in modern era for the prediction purposes. The advantages of ANN approach over the conventional methods are that they are fast and reliable for the computation of multi-variable, non-linear and complex computations. Many researchers (Prakash *et al.*, 2015; Wang *et al.*, 2016; Rahman *et al.*, 2020; Singh *et al.*, 2021) have considered fuzzy soft computing techniques, (Bhavyashree *et al.*, 2017; Rana *et al.*, 2019; Baffoe *et al.*, 2019; Dasarathy *et al.*, 2020) considered multiple regression techniques, (Chen *et al.*, 2017; Refonaa *et al.*, 2019) considered genetic algorithm, (Garg *et al.*, 2016; Halliyavar *et al.*, 2020) used ARIMA technique for the predicting purposes. The predictive strength of ANN technique is found to be more superior than other predictive models (Mishra *et al.*, 2020; Alsaawy *et al.*, 2020; Asogwa *et al.*, 2020; Ranpise *et al.*, 2021; Ramakrishna *et al.*, 2021; Zhang *et al.*, 2021; Mishra *et al.*, 2021).

The main aim of the present work is to predict the noise levels in industrial zone of Lucknow by using Bayesian Regularization (BR) neural network training algorithm. The noise level prediction using ANN technique has now gained increased attention in present era and has wide application in many real-life problems. Thus, this study is helpful for policy makers to take wiser steps in noise management in order to maintain low noise exposures, such that human health and well-being are protected.

2. Materials and Methods

2.1 Study Area

The study area considered here is the Talkatora, Industrial zone of Lucknow. Lucknow is situated on the north western bank of Gomti River, is not only the largest but also the capital city of Uttar Pradesh. This city is developing very fast due to rapid increase in urbanization, industrialization & population growth. Figure 1 shows this city with its surroundings.

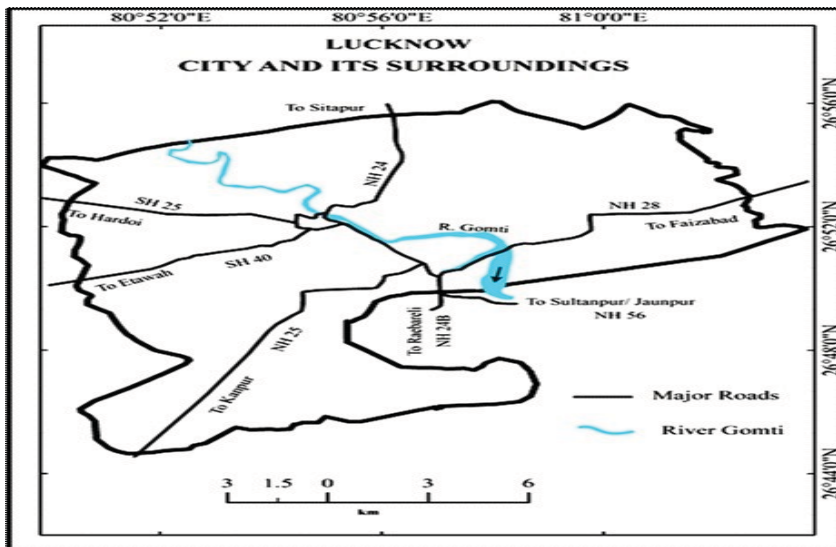


Figure1: Location of Study Area and its Surrounding

In this study, the ambient noise level in industrial zone was monitored with the help of sound level meter placed at a height of 1.2 meter from the ground surface, 15 meters from the centre of the road and 3 metres away from the reflecting surface and the readings are noted down during day time (6 am to 9 pm) and evening time (9 pm to 6 am).

2.2 Data sources

The secondary data of standard noise level as our output variable and seven meteorological parameters i.e., maximum temperature (in °C), minimum temperature (in °C), relative humidity (in % at 07 hrs), relative humidity (in % at 14 hrs), wind speed (in km/hr), rainfall (in mm) and duration of sunshine (hr/day) as our input variables X_i (for $i = 1, 2, \dots, 7$) has been gathered for the period 2011-12 to 2015-16 from the www.indiastat.com, Indian Meteorological Department (IMD), Lucknow and Uttar Pradesh Pollution Control Board, Lucknow. The data analysis has been performed using the MATLAB Software and MS-EXCEL.

2.3 Artificial Neural Networks (ANNs)

Artificial Neural Networks are a special type of machine learning algorithms that are modelled after the human brain. That is, just like how the neurons in our nervous system are able to learn from the past data, similarly, the ANN is able to learn from the data and provide responses in the form of predictions or classifications. An artificial neural network has three main elements: neurons, connection, and training rules (Figure. 2) [Dagli, 1994; Fausett, 1994; Haykin, 1994]. In addition, an ANN is comprised of three layers with interconnected neurons which are input layer, output layer and hidden layer. The hidden layer just receives signals from the input layer and sends signals to the output layer and their number is determined by way of trials.

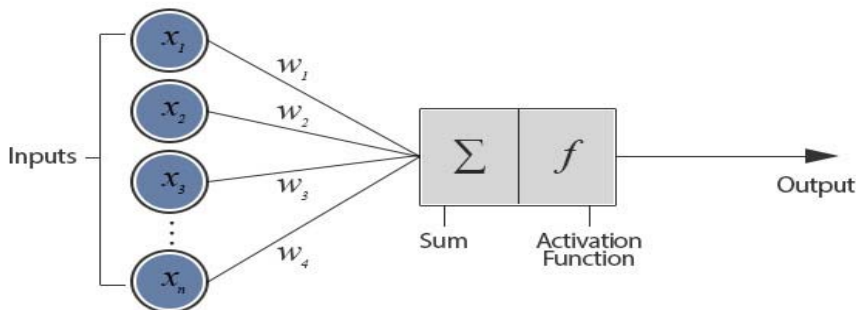


Figure. 2: Architecture of Artificial Neural Network

The traditional model of ANN (Fig. 2), the net input can be computed as follows:

$$y_{in} = x_1 \cdot w_1 + x_2 \cdot w_2 + x_3 \cdot w_3 + \dots + x_m \cdot w_m \quad (1)$$

i.e., net inputs

$$y_{in} = \sum_{i=1}^m x_i \cdot w_i \quad (2)$$

The output can be computed by implementing the activation function over the net input i.e.

$$Y = F(y_{in}) \quad (3)$$

Output = function net input calculated

2.4 Multi-layered perceptron

Multilayer perceptron (MLP) is the unique arrangement of an artificial neural network that has been accounted as one of the most powerful tools for solving the problems which are non-linear in nature. There are three types of layers MLP comprise of i.e., an input layer which plays an important role in transferring the input signals to neurons which are present in the hidden layer, hidden layer which performs the processing of all input signals and output layer which is used to get optimum output signals of the ANN model (Figure. 3).

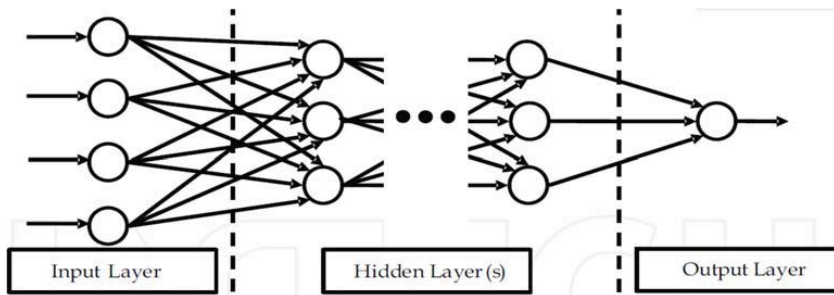


Figure. 3: A Multi-layered preceptor (MLP) network

2.5 Selection of Hidden neurons in Hidden Layer

The most important task in the neural network architecture is to get the reliable number of hidden neurons in the hidden layer which helps in getting the optimum results and solves the complex problems. Hidden layers act as intermediary layer between input and output layer. Hidden layers are not capable to communicate directly with the outer environment but still they play an important role in influencing the final output. Several authors have worked in this direction in the determination of hidden neurons in hidden layer by using different approaches. (Sheela *et al.*, 2013) have considered try and error method, (Karsoliya, 2012) have considered the rule of thumb method, two-phase method and (Berry, 1997) have considered the sequential orthogonal method for determining the number of hidden neurons in hidden layer. (Panchal *et al.*, 2014) have calculated the number of hidden neurons in hidden layer by considering the similarity between input data. Some authors like (Onoda, 2001, Yuan *et al.* 2003; Choi *et al.*, 2006; Jiang *et al.*, 2008; Jinchuan and Xinzhe, 2008; Trenn, 2008; Xu and Chen, 2008; Shibata and Ikeda, 2009; Doukim *et al.*, 2010; Wu and Hong, 2007; Hunter *et al.*, 2012; Peter *et al.*, 2013; Sheela *et al.*, 2013; Wang *et al.*, 2015; Pitambare *et al.*, 2016; Meng *et al.*, 2016; Sundaram *et al.*, 2019) developed their separate algorithm for determining the number of hidden neurons in the hidden layer in forecasting application.'

2.6 Validation for the selected proposed method

We have propounded a technique to deduce the number of hidden neurons in the hidden layer. The propounded method is given below

$$N_h = \frac{(7N_i^2+5)}{(N_i^2-7)}$$

where N_i = number of input parameters.

The validation for the estimation and fixation of number of hidden neurons is initiated based on convergence theorem. The characteristics of the convergence theorem (Dass, 2009) are given below:

1. The limit of the convergent sequence is finite and bounded.
2. The limit of the oscillatory sequence is neither finite and nor bounded.

Consider the sequence,

$$N_h = \frac{(7N_i^2 + 5)}{(N_i^2 - 7)}$$

On applying the convergence theorem, we have the following result

$$\lim_{N_i \rightarrow \infty} \frac{(7N_i^2+5)}{(N_i^2-7)} = \lim_{N_i \rightarrow \infty} \frac{N_i^2(7+\frac{5}{N_i^2})}{N_i^2(1-\frac{7}{N_i^2})} = 7, \text{ finite limit value.}$$

Hence, the above sequence is convergent, where N_i is the number of input parameters involved.

2.7 Prediction of day time and night time noise levels using ANN model

ANN is a massive parallel-distributed information processing system that has certain performance characteristics. All 72 dataset has divided for training, validation and testing. Using GUI in neural network toolbox in MATLAB, different network configuration with different number of hidden neurons is trained and their performance is checked. There are 50 samples used for training, 11 samples for validation and 11 samples for testing. In this study ANN consist of three layers (Figure 4).

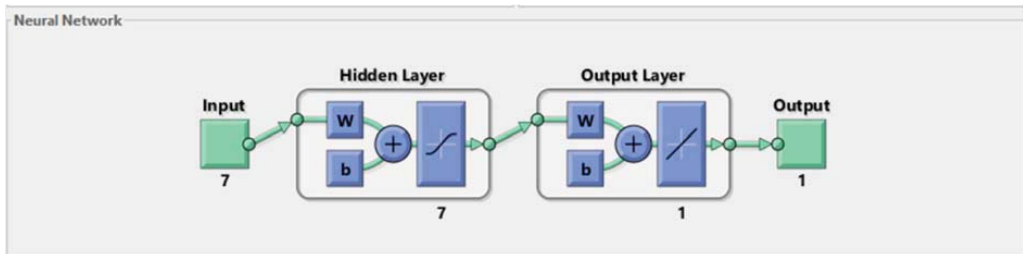


Figure 4: Abbreviated view of ANN model in MATLAB window

where the first layer is input layer (7) which is triggered using the sigmoid activation function whereas the second layer is hidden layer (7) and the third layer is output layer (1) which is triggered using activation function. The network is trained using Bayesian Regularization (BR) algorithm.

2.8 Bayesian Regularization (BR) Algorithm:

This algorithm has been derived from the Thomas Bayes Theorem. This iterative training algorithm minimizes a linear combination of square errors and weights to determines the correct combination to produce the weight parameters of the neural network (Kayri, 2016). It also changes the linear

combination so that the resulting network has good generalization characteristics (Setiaji *et al.*, 2020). It is a probabilistic network, which used posterior inferences. It uses maximum likelihood estimator for the updating of weights. During training process, sample data is processed to the network and weights are modified to achieve a greater approximation of the desired output (Usman *et al.*, 2020). This algorithm is helpful in dealing with the problem of overfitting. Bayesian regularization method took longer training time than other algorithms of neural network and has been used widely to solve many complex problems (Krishnasree *et al.*, 2016).

3.Result and Discussion

A comparison of the proposed method for determining the number of hidden neurons in hidden layer has been done with some existing methods. Consequently, the proposed method is found to be better than the existing methods in terms of accuracy measures i.e., Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R-square (R^2) and Mean Absolute Percentage error (MAPE). Now, these accuracy measures for noise level of day and night time are obtained by various authors in different years has been shown in the table 1 and table 2 respectively.

Table 1: Performance Analysis of various approaches for day time noise level									
S. No.	Different Approaches	Year	Formula used	Hidden neuron	MSE	RMSE	MAE	R^2	MAPE
1.	Tamura <i>et al.</i>	1997	$N_h = N_i - 1$	6	4.4101	2.100	1.4366	0.4201	0.0216
2.	Li <i>et al.</i>	1995	$N_h = \frac{\sqrt{1 + 8N_i} - 1}{2}$	3	5.5888	2.3641	1.3980	0.3929	0.0208
3.	Shibata <i>et al.</i>	2009	$N_h = \sqrt{N_i N_o}$	3	6.6779	2.5842	1.4389	0.3317	0.0211
4.	Sheela <i>et al.</i>	2013	$N_h = \frac{(4N_i^2 + 3)}{(N_i^2 - 8)}$	5	6.8583	2.6188	1.8919	0.3163	0.0287
5.	Gue <i>et al.</i>	2013	$N_h = \sqrt{N_i + N_o + a}$	3	6.4901	2.5475	1.7377	0.2628	0.0261
6.	Peter <i>et al.</i>	2013	$N_h = \frac{6N_i}{(N_i + 1)}$	5	6.6546	2.5796	1.7276	0.3001	0.0259
7.	Wang <i>et al.</i>	2015	$N_h = \frac{\sqrt{(N_i + N_o)}}{2}$	1	6.6603	2.5808	1.6241	0.3193	0.0241
8.	Proposed approach	2022	$N_h = \frac{(6N_i^2 + 5)}{(N_i^2 - 7)}$	7	3.2747	1.8096	1.1545	0.8422	0.0174

Table 2. Performance Analysis of various approaches for night time noise level

S. No.	Different Approaches	Year	Formula used	Hidden neuron	MSE	RMSE	MAE	R ²	MAPE
1.	Tamura <i>et al.</i>	1997	$N_h = N_i - 1$	6	7.4519	2.7298	1.9765	0.4671	0.0338
2.	Li <i>et al.</i>	1995	$N_h = \frac{\sqrt{1 + 8N_i}}{2} - 1$	3	7.7206	2.7785	2.0615	0.5027	0.0353
3.	Shibata <i>et al.</i>	2009	$N_h = \sqrt{N_i N_o}$	3	8.8626	2.9770	2.2392	0.5311	0.0379
4.	Sheela <i>et al.</i>	2013	$N_h = \frac{(4N_i^2 + 3)}{(N_i^2 - 8)}$	5	5.7109	2.3897	1.6341	0.6646	0.0281
5.	Gue <i>et al.</i>	2013	$N_h = \sqrt{N_i + N_o + a}$	3	8.3155	2.8836	2.0163	0.5953	0.0345
6.	Peter <i>et al.</i>	2013	$N_h = \frac{6N_i}{(N_i + 1)}$	5	9.1844	3.0301	1.8724	0.5833	0.0316
7.	Wang <i>et al.</i>	2015	$N_h = \frac{\sqrt{(N_i + N_o)}}{2}$	1	10.3282	3.2137	2.2861	0.3561	0.0389
8.	Proposed approach	2022	$N_h = \frac{(6N_i^2 + 5)}{(N_i^2 - 7)}$	7	2.8384	1.6847	0.9716	0.8200	0.0169

From table 1 and 2, it is clear that the proposed method is better than the existing methods in terms of low values of accuracy measures and high value of R². Hence, the proposed method is found to be more reliable in predicting the noise levels of day and night time respectively.

4. Conclusion

In the present study, we have proposed a method to determine the optimal number of hidden neurons in the hidden layer of a neural network. Further, we obtained the values of accuracy measures and R² by applying MLP-BP algorithm of neural network for predicting the day time and night time noise levels. This technique is found to be superior as the variability between the actual and predicted value for noise level of day and night time is found to be lesser than the considered conventional approaches. Hence, this work is helpful for industrial researchers to maintain the balance between noise level and health condition of human and provides the basis for significance level of each metrological parameter contributing to the prediction of the noise level in industrial zone of Lucknow.

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5. References

- Alsaawy, Y., Alkhodre, A., Benaida, M. and Khan, R. A., 2020, A Comparative study of Multiple regression analysis and Back propagation neural network approaches for predicting financial strengths of Banks: An Indian Perspective. *WSEAS Transactions on Business and Economics*. **17**, 627-637.
- Asogwa, O. C., Eze, N. M., Eze, C. M., Okonkwo, C. I. and Ojide, K. C., 2020, On the Efficiency of Multiple Linear Regression over Artificial Neural Network. *International Journal of Statistics and Application*. **10(1)**, 1-9.
- Berry, M. J. A. & Linoff, G., 1997, *Data Mining Techniques*, New York: John Wiley & Sons.
- Bhavyashree, S., Mishra, M. & Girisha, G. C., 2017, Fuzzy regression and Multiple linear regression models for predicting mulberry leaf yield: A comparative study. *International Journal of Agricultural and Statistical Sciences*. **13(1)**, 149-152.
- Baffoe, P. E. and Duker, A. A., 2019, Evaluation of Two Noise Level Prediction Models: Multiple Linear Regression and a Hybrid Approach. *Urban and Regional Planning*. **4(3)**, 91-99.
- Choi, B., Lee, J. H. & Kim, D. H., 2008, Solving local minima problem with large number of hidden nodes on two-layered feed-forward artificial neural networks. *Neurocomputing*. **71(16-18)**, 3640-3643.
- Chen, L., Jamal, M., Tan, C. and Alabbadi, B., 2017, A Study of Applying Genetic Algorithm to Predict Reservoir Water Quality. *International Journal of Modeling and Optimization*. **7(2)**, 98-104.
- Dagli, C. H., 1994, Artificial neural networks for intelligent manufacturing. *Operating Research Journal*. **6(1)**, 1-26.
- Dass, H. K., 2009, *Advanced Engineering Mathematics*, Sultan Chand and Company Limited. First Edition 1988, reprint 2009.
- Doukim, C. A., Dargham, J. A. & Chekima, A., 2010, Finding the number of hidden neurons for an MLP neural network using coarse to fine search technique. *Proceedings of the 10th International Conference on Information Sciences, Signal Processing and Their Applications (ISSPA'10)*. 606-609.
- Dasarathy, A. K., Selvi, M. T., Suresh, C. and Ponkumarllango, S., 2020, Multiple linear Regression models for Leq estimation in noise emission measurement. *Journal of critical reviews*. **7(04)**, 1255-1262.
- Fausett, L., 1994, *Fundamentals of neural networks. Architectures, algorithms and applications*. Prentice Hall, USA, 461pp.
- Garg, N., Sharma, M. K., Parmar, K. S., Soni, K., Singh, R. K. and Maji, S., 2016, Comparison of ARIMA and ANN approaches in time-series predictions of traffic noise. *Noise Control Engineering Journal*. **64(4)**, 522-531.
- Haykins, S., 1994, *Neural Networks: A Comprehensive Foundation*. Macmillan Publishing. New York.
- Halliyavar, D., Shwetha, M. P., Puneeth, S. and Chikop, S. A., 2020, Production Analysis and Prediction of TOP using ARIMA Model. *International Journal of Engineering Research & Technology*. **9(07)**, 945-949.
- Hunter, D., Yu, H., Pukish III, M. S., Kolbusz, J. & Wilamowski, B. M., 2012, Selection of proper neural network sizes and architectures: a comparative study. *IEEE Transactions on Industrial Informatics*. **8(2)**, 228-240.
- Jiang, N., Zhang, Z., Ma, X. & Wang, J., 2008, The lower bound on the number of hidden neurons in multi-valued multi-threshold neural networks. *Proceedings of the 2nd International Symposium on Intelligent Information Technology Application (IITA '08)*. 103-107.

Jinchuan, K. and Xinzhe, L., 2008, Empirical analysis of optimal hidden neurons in neural network modeling for stock prediction. Proceedings of the Pacific-Asia Workshop on Computational Intelligence and Industrial Application. **2**, 828–832.

Karsoliya, S., 2012, Approximating Number of Hidden layer neurons in Multiple Hidden Layer BPNN Architecture. *International Journal of Engineering Trends and Technology*. **3(6)**, 714-717.

Kelleher, J. D., Mac, N. B. and D'arcy, A., 2015, Fundamentals of machine learning for predictive data analytics: algorithms, worked examples, and case studies. Second Edition. *MIT Press*.

Kayri, M., 2016, Predictive Abilities of Bayesian Regularization and Levenberg–Marquardt Algorithms in Artificial Neural Networks: A Comparative Empirical Study on Social Data. *Mathematical and Computational Applications*. **21(20)**, 1-11.

Krishnasree, K. S. and Rao, M. R. N., 2016, Diagnosis of heart disease using neural networks-comparative study of Bayesian Regularization with multiple regression model. *Journal of Theoretical and Applied Information Technology*. **88(3)**, 638-643.

Meng, A., Ge, J., Yin, H. & Chen, S., 2016, Wind speed forecasting based on wavelet packet decomposition and artificial neural network strained by criss cross optimization algorithm. *Energy Conversion Management*. **48(2)**, 75–88.

Mishra, M. and Thakur, K. R., 2020, Superiority of Artificial neural network model over multiple linear regression model for predicting broccoli yield. *International Journal of Agricultural and Statistical Sciences*. **16(2)**, 757-762.

Mishra, M. and Thakur, K. R., 2021, Performance of Neural Networks for predicting the noise levels in Industrial Zone of Lucknow using different number of hidden neurons. *International Journal of Agricultural and Statistical Sciences*. **17 (Supplement 1)**, 2437-2444.

Onoda, T., 2001, Neural network information criterion for the optimal number of hidden units. IEEE International Conference on Neural Networks, Perth, WA, Australia. **1**, 275-280.

Panchal, F. S. & Panchal, M., 2014, Review on Methods of Selecting Number of Hidden Nodes in Artificial Neural Network. *International Journal of Computer Science and Mobile Computing*. **3(11)**, 455-464.

Prakash, T. N. and Veerappa, B. N., 2015, Interpretation of noise pollution effects of human being using fuzzy logic techniques. *International Journal of Computer Science and Mobile Computing*. **14(4)**, 670-683.

Pitambare, D. P., 2016, Survey on Optimization of Number of Hidden Layers in Neural Networks. *International Journal of Advanced Research in Computer and Communication Engineering*. **5(11)**, 537-540.

Peter, S. E., Kulkarni, S., Raglend, I. J. & Simon, S. P., 2013, Wavelet based spike propagation neural network (WSPNN) for wind power forecasting. *International Review on Modelling and Simulation (IREMOS)*. **6(5)**, 1513–1522.

Rana, S., Elgohari, H. & Islam, F., 2019, Temperature modelling of Rangpur division, Bangladesh: A comparative study between artificial neural network and linear regression models. *International Journal of Agricultural and Statistical Sciences*. **15(1)**, 123-130.

Refonaa, J., Lakshmi, M., SrinivasaRao, R. S. S. and Prasad, P. E., 2019, Rainfall Prediction using Genetic Algorithm. *International Journal of Recent Technology and Engineering*. **8(2S3)**, 597-600.

- Rahman, M. M., Shafiullah, M., Rahman, S. M., Khondaker, A. N., Amao, A. and Zahir, M. H., 2020, Soft Computing Applications in Air Quality Modeling: Past, Present, and Future. *Sustainability*. **12**, 1-33.
- Ramakrishna, V., Saigiri, N., Chakribabu, K., Sultana, S. and Dhanunjay, M., 2021, Modeling and Prediction of Traffic Noise Levels. *IOSR Journal of Engineering*. **11(1)**, 1-13.
- Ranpise, R. B., Tandel, B. N. and Singh, V. A., 2021, Development of traffic noise prediction model for major arterial roads of tier-II city of Surat, India using Artificial neural network, *Noise Mapping*. **8**, 172-184.
- Singh, D., Upadhyay, R., Pannu, H. S. and Leray, D., 2021, Development of an adaptive neuro fuzzy inference system based vehicular traffic noise prediction model. *Journal of Ambient Intelligence and Humanized Computing*. **12**, 2685–2701.
- Shibata, K. & Ikeda, Y., 2009, Effect of number of hidden neurons on learning in large-scale layered neural networks. Proceedings of the ICROS-SICE International Joint Conference 2009 (ICCASSICE'09). 5008–5013.
- Sheela, K. G. & Deepa, S. N., 2013, Review on Methods to Fix Number of Hidden Neurons in Neural networks. *Mathematical Problems in Engineering*. **12**, 1-11.
- Sundaram, K. M. & Karthigai, S., 2019, Determining Hidden Neurons with Variant Experiments in Multilayer Perception using Machine Learning Neural Networks. *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*. **8(9)**, 2725-2729.
- Setiaji, P., Widjanarko, B., Syahidin, Y., Himawan, H., Siregar, N. A., Harmayani, Samboteng, L., Gulo, N. A. and Kartikaningsih, R., 2020, Best model and performance of Bayesian Regularization method for data prediction. *Journal of Physics: Conference Series*. **1933**, 1-9.
- Trenn, S., 2008, Multilayer perceptrons: approximation order and necessary number of hidden units. *IEEE Transactions on Neural Networks*. **19(5)**, 836–844.
- Usman, S. M., Singh, N. P., Dutt, T., Tiwari, R. and Kumar, A., 2020, Comparative study of artificial neural network algorithms performance for prediction of FL305DMY in crossbred cattle. *Journal of Entomology and Zoology Studies*. **8(5)**, 516-520.
- Wang, J. & Hu, J., 2015, A robust combination approach for short-term wind speed forecasting and analysis-combination of the ARIMA (autoregressive integrated moving average), ELM (extreme learning machine), SVM (support vector machine) and LSSVM (least square SVM) forecasts using a GPR (Gaussian process regression) model. *Energy*. **93**, 41-56.
- Wu, Y. K. & Hong, J.S., 2007, A literature review of wind forecasting technology in the world. Proceedings of the IEEE Lausanne Power Tech: 504–509.
- Wang, Y., Chen, Y. and Lian, J., 2016, Fuzzy Prediction for Traffic Flow Based on Delta Test. *Mathematical Problems in Engineering*. 1-13.
- Xu, S. & Chen, L., 2008, A novel approach for determining the optimal number of hidden layer neurons for FNN's and its application in data mining. Proceedings of the 5th International Conference on Information Technology and Applications (ICITA'08): 683–686.
- Yuan, H. C., Xiong, F. L. & Huai, X. Y., 2003, A method for estimating the number of hidden neurons in feed-forward neural networks based on information entropy. *Computers and Electronics in Agriculture*. **40(1–3)**, 57–64.
- Zhang, X., Kuehnelt, H. and Roeck, W. D., 2021, Traffic noise prediction applying multivariate bi-directional recurrent neural network, *Applied Sciences*. **11**, 1-26.