Forecasting the emission parameters and performance of 750 KVA Diesel Generator using Artificial Neural Network

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***Abstract*— Growing demand for electricity made several states in India under energy crisis. Diesel Generators (DGs) are adapted almost in all kinds of industries to meet the power requirement and to compensate the power shortage. At the same instant, significant amount of greenhouse gases is also be released into the atmosphere and gets polluted. Hence it is important to assess the level of emission of DGs and to ensure the effective and smoother operation. Keeping this in view, in this paper, an Artificial Neural Network (ANN) model is proposed for the prediction of emission of DGs. This study considers 750 KVA, three phase DG and required data are collected through number of experiments considering various parameters such as load, speed, torque as inputs and CO_2, CO/CO_2 and gross efficiency (η_g) as outputs. The developed model showed satisfactory results in terms of error percentage, prediction accuracy and seems to be an effective tool to predict the emissions from the DG.**

Keywords* — *Forecasting; Diesel generator; Emission; Artificial Neural Network.

I. INTRODUCTION

Diesel generator is one of the essential components in all industrial sectors for the remediation of power crisis. However prediction of its emission becomes one of the most important things in this present scenario. Artificial Neural Network (ANN) models are more accurate [2] and efficient in handling the nonlinear relationship of data [3],[1]. The ANNs approach has been useful to predict the performance of various thermal and energy system [4]. Neural networks have been applied to different engine investigation such as modeling of engine performance and prediction of exhaust emissions [5],[6]. A standard back propagation algorithm was used in that model it was observed that the ANN model is capable of predicting the engine performance and exhaust emissions [7]. The predictive ability of ANN results from training on experimental data and then validation by independent data. An ANN has the ability to re-learn to improve its performance if new data are available [8]. In addition it is possible to remove or add input output variables in the ANN if it is needed [1]. ANNs for modeling the operation of internal combustion engines is a more recent progress. This approach was used to predict the performance and exhaust emissions of diesel engines [9],[10]. In the current work, the effect of using CPO(crude palm oil) - OD(Ordinary Diesel) blend as a fuel in the CI for performance study using ANN [11].

The main objectives of this study were to investigate the emission of CO_2, CO from 750 KVA diesel generators and then, predicting them by developing ANN model using back propagation algorithm. All required data were collected through number of experiments considering various parameters such as load, speed, torque as inputs and CO_2, CO/CO_2 and gross efficiency (η_g) as outputs. The model shows the less number of errors with respect to the experimental data.

II. METHODOLOGY PROPOSED

The experimental data of a 750 KVA diesel generator was taken and with the help of few data a graph was plotted. Using the software called ‘DigitizeIt’ we predicted the two hundred sets of data corresponding to the real time value. These data’s are helpful to train the artificial neural network in a proper way and also with less error. In this study we estimate the emission parameter of a DG and took one hundred and fifty sets of data from two hundred, these data are given into the neural network for training purpose and fifty sets of data taken for testing purpose. Increasing the number of data for training purpose may reduce the error percentage. Standard back propagation algorithm is designed for three inputs and three outputs with hidden layers. Hidden layer are nothing but the neurons, these neurons are responsible for the change in training error. The inputs were load, speed, torque and the outputs were CO_2, CO/CO_2 and gross efficiency (η_g). We took the minimum error that obtained at 3-10-3. In ANN the input and output are normalized in 0 and 1. The ANN predicted data are merely match with the experimental data. ANN itself shows the prediction accuracy and the epochs value. Epochs are nothing but the iteration taken by the ANN to predict or match the given experimental data with its own generated data.

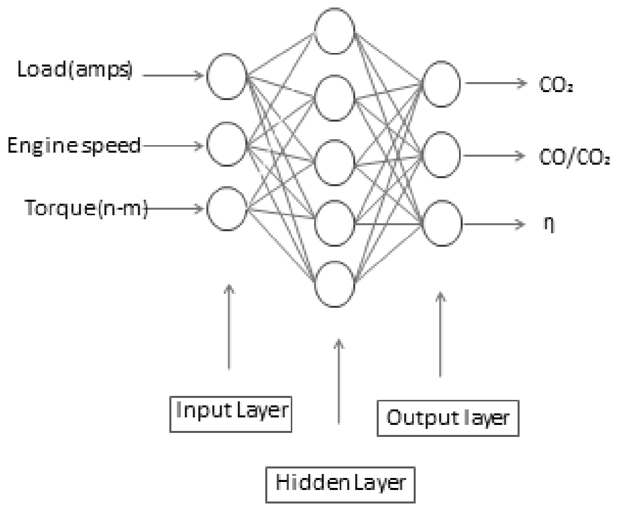


Fig.1. Artificial Neural Network structure

A. Artificial Neural Network

The Artificial neural networks are mathematical inventions inspired by observations made in the study of biological systems, thought loosely based on the actual biology. An artificial neural network can be described as mapping and input space to an output space. This concept is analogous to that of a mathematical function. The principles involved have resulted in man-made inventions that bear little resemblance to the biological systems that spawned the creative process. The neural network consists of following elements such as input, output, weights, activation and summation functions. The summation function used for this study is given in equation (1).

Out i= f(net i) = f $\sum_{j=1}^{n}$ w_{ij} out j + bi (1)

Where, Out i – output of the i^{th} neuron in the layer under consideration; Out j – output of the j^{th} neuron in the preceding layer, w_{ij} are the connection weights between the i^{th} neuron and the j^{th} inputs and bi is a constant called bias.

The weight matrices used in this study is

$$W_{ij}(k+1)=W_{ij} + \Delta W \qquad (2)$$

Where, W_{ij} – weight from hidden unit I to output unit j at time k*;*

ΔW_{ij} – weight adjustment.

The synaptic weighting and aggregation operations performed by the synapses and soma respectively provide a ‘similarity measure, between the input vector I and the synaptic weights [V] and [W] (accumulation knowledge base). When a new input pattern that is significantly different from the previously learned pattern is presented to the neural network, the similarity between this input and the existing knowledge base is small. As a neural network learns this new pattern by changing the strengths of the synaptic weight. The distance between the new information and accumulated knowledge decreases.

Most of the neural network structure undergo ‘learning procedure’ during which synaptic weights W and V are adjust. Algorithm for determining the connection strength to ensure learning is called ‘Learning rules’. The objective of planning rules depends up on the applications. In classification and functional approximation problems, each cycle of presentation of all case is usually referred (learning epochs) however, there has been no generalization as to how a neural network can be trained [12].

B. Input And Output Parameters

The DG input and output parameters are discussed below.

Load:	This load is taken for an electrical system. Whereas it is measured in Kilo Volt Ampere.
Speed:	Engine rpm is measured as the speed.
Torque:	The opposing force which is responsible for the fluctuation of the engine.
CO:	Carbon Monoxide reading indicated in ppm or mg/m^3.
CO/CO_2 Ratio:	The CO/CO_2 ratio, is the ratio of measured CO divided by calculated CO_2. It gives an indication of the following :- • How good a gas sample the instrument is reading. • How clean the boiler is running.
Gross Efficiency %:	= 100 - {dry flue gas losses + wet losses} = 100 – {[20.9 x K1g x (Tnet) / K2 x (20.9 - O_2 m)] + [K3 x (1 + 0.001 x Tnett)]}

III. RESULT AND DISCUSSION

A. Experimentation vs. ANN model

The comparison between the experimental and the artificial neural network result shows the high accuracy. Prediction using ANN gives a new approach to investigate the check the emission result using this software. MATLAB has been chosen as the platform to precede the following ANN study. The comparison graphs of CO_2, CO/CO_2, η_g with ANN results are shown in the Fig 2, 3, 4. The change in the hidden layers depends upon the error occur during the training of ANN. The neurons act as a role in training the network. The ANN network iteration time and weighted method are shown in the Fig 5, 6. The testing mean standard error is 4.0722e-4 and the training mean standard error is 1.2859e-4. For different standard back propagation values and hidden neurons the table is plotted in Table 1 and discuss about the training error and its testing error of 750 KVA DG. The time taken for the prediction the value from the trained data is much lesser than the experimental. Time taking for this process takes few seconds and as a time concern its depend upon the processor speed. For different network structure the time and training value differs. Predicted accuracy percentage is calculated with respect to the experimental and the ANN values. The accuracy of the data are 97-99.99% for CO_2, CO/CO_2 accuracy is 83-100% and the gross efficiency (η_g) is in between the 97-99.50% approximately. In Fig 6 shows that the mean square error that occur during the trial run of the ANN. The Fig.5 shows the epoch of 295 iteration that performed during the run of ANN using back propagation algorithm.

B. *The experimental data is verified by the ANN predicted data*

The following graphs shows the comparison between the experimented data vs. the ANN predicted data for the gross efficiency, CO_2 and CO/CO_2.

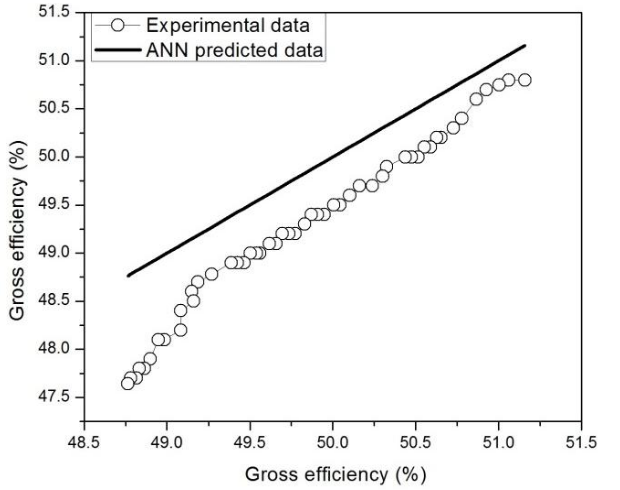


Fig. 2. Evaluation of experimental data and ANN predicted data for gross efficiency

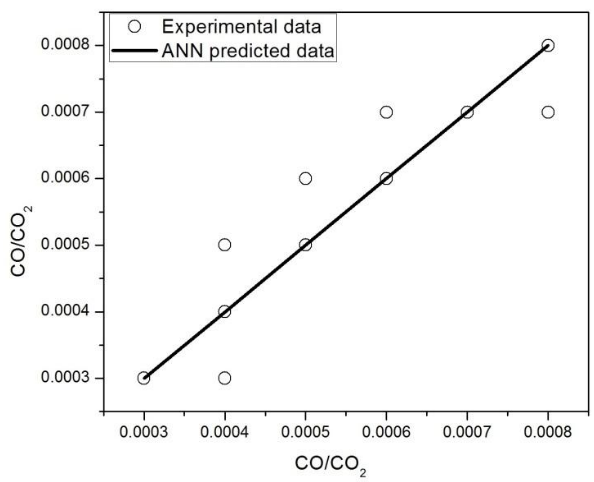
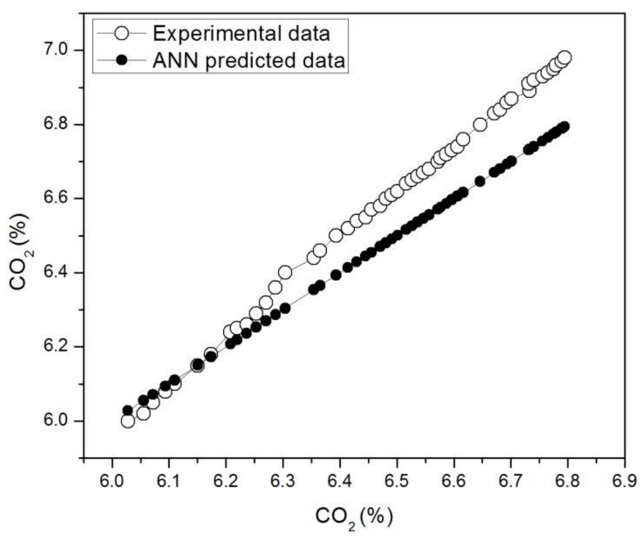


Fig.3. Evaluation of experimental data and ANN predicted data for CO/CO_2

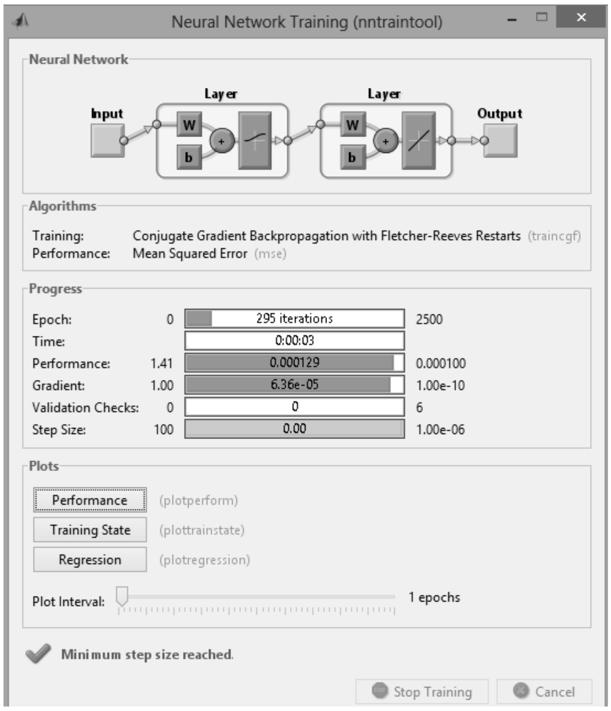


ratio

Fig.4. Evaluation of experimental data and ANN predicted data for CO_2

Fig.5. Neural Network training

C. *Performance of ANN*



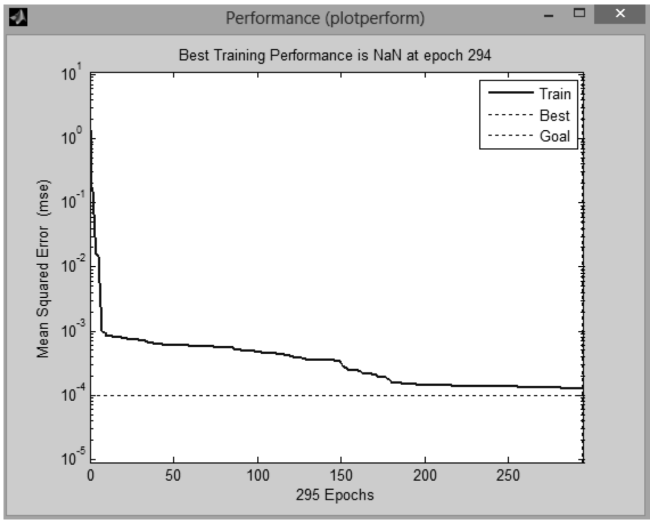


Fig.6. Training regression plot

The mean square error of this ANN is plotted above inn Fig.6. The performance and the error percentage are discussed in the following table. The hidden layers are the responsible for the change in error percentages. In this study the prediction of emission and performance are more accurate to the real time experiment. The time taken for prediction makes the ANN as the best tool. Epochs value for this ANN model has taken 295 iterations for 150 sets of training data. The iteration taken was shown in the Fig.5.

TABLE.I Training and testing performance data

Learning algorithm	Network structure	750 KVA		
		Testing MSE	*Training MSE*	*Training time (sec)*
Standard Back propagation	3-1-3	0.0032	$6.1216e^{-4}$	3.0781
	3-2-3	0.0036	$1.8000e^{-4}$	8.9531
	3-3-3	0.0029	$1.1966e^{-4}$	8.5156
	3-4-3	0.0044	$9.9998e^{-5}$	7.5000
	3-5-3	0.0014	$1.2393e^{-4}$	9.7656
	3-6-3	0.0018	$1.2561e^{-4}$	7.7500
	3-7-3	0.0016	$7.0021e^{-4}$	1.3750
	3-8-3	0.0037	$7.8222e^{-4}$	1.1719
	3-9-3	0.0011	$1.0594e^{-4}$	9.1406
	3-10-3	$4.0722e^{-4}$	$1.2859e^{-4}$	7.2813

IV. CONCLUSION

The prediction of emission parameters of 750 KVA, three phase diesel generator was obtained using artificial neural network. The developed ANN shows the exact match with the experimental data and the ANN simulated data. This shows that the ANN is one of the powerful tools for predicting the exhaust emissions from DG. It produces the minimum error during the estimation. In this study, the suitable neuron is identified as 10 and the error that occurs during training was $4.0722e^{-4}$. This study reveals the ANN is most useful and accurate in training the network especially for DGs. Its prediction accuracy with less number of errors keeps the ANN output data better than the existing techniques. The existing techniques are experimental study and mathematical analysis or modeling for estimation of emission in DGs. The mathematical modeling shows the same number of error for increase in number of data. Whereas in ANN increase in data decrease the error percentage.

APPENDIX

TABLE.II Prediction accuracy values for CO_2, CO/CO_2 ***ratio*** *and Gross efficiency (η)*

CO_2			CO/CO_2			Gross efficiency (η)		
Experimental value	*ANN predicted value*	*Predicted accuracy (%)*	*Experimental value*	*ANN predicted value*	*Predicted accuracy (%)*	*Experimental value*	*ANN predicted value*	*Predicted accuracy (%)*
6	6.0278	99.54	0.0008	0.0008	100	50.8	51.1592	99.23
6.05	6.0719	99.64	0.0007	0.0007	100	50.6	50.8665	99.48
6.15	6.1505	99.99	0.0006	0.0007	85.71	50.1	50.5893	99.03
6.24	6.2078	99.48	0.0006	0.0006	100	49.9	50.3259	99.15
6.32	6.2702	99.21	0.0006	0.0005	83.33	49.5	50.0445	98.91
6.44	6.3543	98.67	0.0005	0.0005	100	49.3	49.8314	98.93
6.57	6.4551	98.25	0.0004	0.0005	99.99	49.1	49.6186	98.95
6.71	6.5766	98.01	0.0004	0.0004	100	48.9	49.4255	98.94
6.87	6.7009	97.54	0.0004	0.0004	100	48.5	49.1606	98.66
6.98	6.7943	97.34	0.0003	0.0003	100	47.64	48.7649	97.69

ANN – Artificial Neural Network

DG – Diesel Generator

KVA – Killo Volt Ampere

CO – Carbon Monoxide

CO_2 – Carbon-di-Oxide

η_g – Gross Efficiency

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REFERENCES

[1] B. Ghobadian, H. Rahimi, A.M. Nikbakht, G Najafi, and T. F. Yusaf, “Diesel engine performance and exhaust emission analysis using waste cooking biodiesel fuel with an artificial neural network,” *Renewable energy*, pp. 976-982, 2009.

[2] K. Cheenkachorn, “Predicting properties of biodiesels using statistical models and artificial neural networks,” *Asian J energy environ*, vol. 7, pp. 299-306, 2006.

[3] S. A. Kalogirousa, “Application of artificial neural networks for energy systems,” *Appl energy* , vol. 67, pp. 17-35, 2000.

[4] M. Murat Caner, E. Gadik, A. Kecebas, “Investigation on thermal performance calculation of two type solar air collector using artificial neural network”, *Expert syst Appl*, vol. 38(3), pp. 1668-1674, 2011.

[5] F. V. Tinaut, A. Melgar, B. Gimenesz, M. Reyes, “Prediction of performance and emission of an engine fuelled with natural gas/hydrogen blends”, *Int J Hydrog Energy*, vol. 36, pp. 947-56, 2011.

[6] W. K. Yap, T. Ho, B. Karri, “Exhaust emissions control and engine parameters optimization using artificial neural network virtual sensors for a hydrogen powered vehicle”, *Int J Hydrog Energy*, vol. 37, pp. 8704-15, 2012.

[7] G. Najafi, B. Ghobadian, T. Tavakoli, D. R. Buttsworth, T. F. Yusaf, M. Faizollahnejad, “Performance and exhaust emissions of gasoline engine with ethanol blended gasoline fuels using artificial neural network”, *Appl Energy*, vol. 86, pp. 630-9, 2009.

[8] J. Hertz, A. Krogh, R. G. Palmer, “Introduction to theory of neural computation”, Addison-Wesley publishing company, Redwood city, NJ 1991.

[9] M. Canakci, A. Erdil, E. Arcaklioglu, “performance and exhaust emmissions of a bio diesel engine”, *Applied energy*, vol. 83, pp. 594-605, 2006.

[10] E. Arcaklioglu, I. Celikten, “A diesel engine performance and emmissions”, *Applied energy*, vol. 80, pp. 11-22, 2005.

[11] S. Rajasekaran, and G. A. Vijayalakshmi Pai, “Neural Networks, Fuzzy Logic and Genetic algorithm synthesis and application”.

[12] T.F. Yusaf, B.F. Yousif, M.M. Elawad, “Crude palm oil fuel for diesel engine: Experimental and ANN stimulation approach”, *Energy* vol. 36, pp. 4871-4878, 2011.