ISSN 2229-5518

Artificial Neural Network Model for Predicting Wet Scrubber Performance

Bashir Ahmed Danzomo, Momoh-Jimoh E. Salami, Md Raisuddin Khan

Abstract - Increased public awareness posed for global climate change has led to greater concern over the impact of environmental changes due to constant emissions of air pollutants from industrial production. Wet scrubbers have important advantages when compared to other air pollution control devices. They can collect particulates like flammable and explosive dusts, foundry dusts, cement dusts, large volume of gaseous pollutants, acid mists and furnace fumes. In this study, a three layer feed forward neural network has been used to predict the performance of wet scrubber system for air pollution control. The theoretical performance, η_{perf} of the system was calculated using 206 scenarios for 8 data sets for the operating variables with nonlinear and complex characteristics. The performance fitness of the neural network (MSE = 0.00000107 and R-value = 0.9979) describes the effectiveness of the ANN model in predicting the performance of the scrubber system and the model follows the pattern of the theoretical data describing the scrubber performance at a higher efficiency range.

Index Terms: artificial neural network, modeling, wet scrubber, performance

1. INTRODUCTION

Wet scrubber device mimics natural processes where contaminant gases or dust laden air is cleaned by rain, snow or fog. It can collect flammable and explosive dusts safely, absorb gaseous pollutants, and mists and it has been successfully used for medical waste incineration and other industrial applications. The first industrial scrubbers attempted to duplicate this natural cleaning with dusty air ascending through a rain of liquid droplets in a large, vertical tube and subsequent developments reduced the space requirements for scrubbers, (Liu and Liptak, [1]).

During wet scrubbing process shown in Figure 1, water droplets are introduced at the top of an empty chamber through atomizing nozzles and fall freely at their terminal settling velocities counter-currently through the rising gas stream containing particles from industrial production. The particles are then separated from the gas stream and collected in a pool at the bottom of the chamber.

The cleaned gases exiting the scrubber passes through a mist pad which removes water droplets from the gas

- *Corresponding Author: Bashir Ahmed Danzomo, B. Engr. (Mech. Engr.), M. Engr. (Energy Engr.), currently pursuing a PhD degree program in Mechatronics Engineering in International Islamic University (IIUM), 53100, Gombak, Malaysia. E-mail: bdzomo@yaoo.co.uk*
- *Co-Author 1: Momoh-Jimoh E. Salami is a Professor in the Department of Mechatronics Engineering, IIUM.*
- *Co-Author 2: Md Raisuddin Khan is an Associate Professor in the Department of Mechatronics Engineering, IIUM.*

Several attempts have been made to investigate the performance of wet scrubber system (Makkinejad [2], Kim et al [3], Rahimi *et. al* [4], Bingtao [5], Garba [6] and Bozorgi *et. al* [7]). In most of the studies, analytical solutions were provided for the performance of the system while others are more complex and require numerical solution and iterations with a computer.

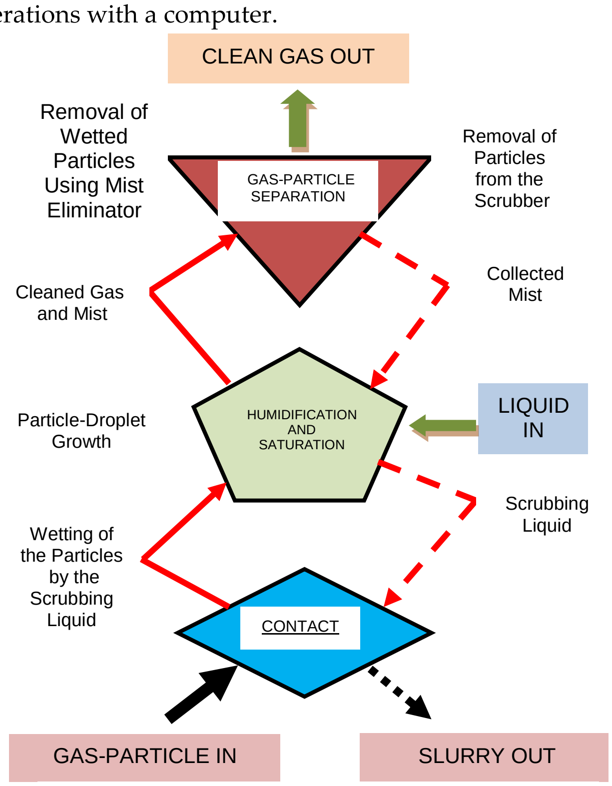

Figure 1: Schematic Diagram of Wet Scrubbing Process

Nevertheless, the operating variables of wet scrubber system; gas velocity, temperature profile, particle diameter, terminal settling velocity of liquid droplets, liquid droplet's diameter, liquid to gas ratio and particle density plays a significant role in the gas-particle separation process. They represent a non-linear and multivariable condition for the determination of the dynamic behavior of the scrubber system. But, Artificial Neural Networks (ANN) imitates learning process of the human brain which can process problems involving non-linear and complex data especially when the underlying data relationships are not known, imprecise, random or noisy.

The network comprised of different types of layers such as the input-layer, one or more hidden layers and an output layer (Figure 2). ANN Modeling technique is a valuable tool for understanding the dynamic behavior of a system and it provides a significant potential for solving operational problems. The approach can be used for testing control strategies at a reasonable cost and the results obtained can be evaluated for different operating data before concepts are translated into full scale plant.

ANN system is not labor intensive, it possessed self learning and tuning capabilities and it is ideally suited for modeling environmental air pollution problems such as in air quality prediction in Barai *et. al* [8], modeling of industrial air pollution in Boger [9], modeling of air pollutants dispersion over an urban area in Peace [10], optimization of predictor for air pollution in Raihane *et al,* [11], prediction of indoor air quality in Mirhan [12], prediction of $N0_X$ level in Bukovsky and Kolovratnik [13], prediction of air pollution levels in Berastegi *et al* [14], prediction of ambient air quality in Mahanija, *et al*. [15] and prediction of tropospheric ozone concentration levels in Abdul-Wahab and Al-Alawi [16].

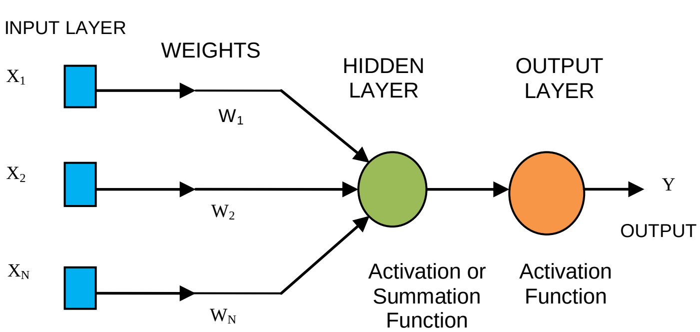

Figure 2: Architecture of a Typical ANN Model

It has also been used for vehicular pollution modeling in Sharma *et al* [17], control of air-fuel ratio for automotive fuel injection system in Cesare [18], Management and Control of Air Pollution Minimization and Mitigation Processes in Christine and Guo [19] and characterization of atmospheric PM_{10} and $PM_{2.5}$ concentrations in Karaca [20].

Aiming at the periodicity and randomness features of the operating variables in wet scrubber system, a stochastic data which includes values in the form of probability distribution should be considered so as to capture the complex and nonlinear characteristics of the problems and obtain an appropriate treatment of the uncertainties. This predicts what conditions might be likely under different characteristics of these variables. Method of using this approach has been reported in environmental pollution problems and produces efficient results depending on the actual values that the random variables take in each realization as presented in Qin [21], Omar and Rosario [22], Gosavi [23], Zhiyong and Hiroshi [24], and Phaedon and Andre [25].

The combination of stochastic and neural network techniques in a system will improve the prediction accuracy and produces a hybrid system that is cost effective (Luciana *et al.* [26]). The approach has been applied to a broader range of problems with stochastic behavior such as in the study involving a stochastic modeling based on static feed-forward neural network approach and linear-nonlinear regression analysis techniques for the prediction of single droplet collection efficiency in spray tower scrubber conducted by Yetilmezsoy and Saral in [27].

In the study, 205 different artificial scenarios were considered for the neural network approach. The scenarios were used to form five input variables selected from the operating conditions of the scrubber system. However, the combined effect of all the operating conditions of the scrubber system such as the liquid to gas ratio (δ) and the terminal settling velocity of the scrubbing liquid droplets (U_{td}) was not considered which seems to be the limitations of their study.

The main objective of this study is to develop a suitable Artificial neural network (ANN) model for predicting wet scrubber performance by considering feed-forward back propagation learning algorithms using 206 data set scenarios generated from stochastic method and computational analysis and evaluate the model using the performance fitness of neural network (MSE and R-value).

ISSN 2229-5518

2. THEORETICAL ANALYSIS

The US Environmental Protection Agency, EPA and National Association of Clean air Agency, NACAA in [28] indicated that, mathematical models provide a means for generating datasets for estimating scrubber performance when empirical data and pilot scale data is not available. In this regard, mathematical models with respect to the operating variables of the scrubber system design specifications (Z, D, d_{supply}, d_{spray}) and the system performance characteristics (Q_L, Q_G, C_f, C_D, Re, η_{sep}, U_g, μ_g, ρ_g, d_P, d_D, ρ_P, U_{td}) has been used to generate datasets that predicts the dynamic behavior of the system by considering the performance efficiency, η_{perf} obtained from mass balance across a differential section of the scrubber system shown in Figure 3.

The mass of particle that enters the system must by *law of conservation of mass* either leave the system or accumulate within the system defined by the mass balance:

Mass in - Mass out - Mass collected = Accumulation (1)

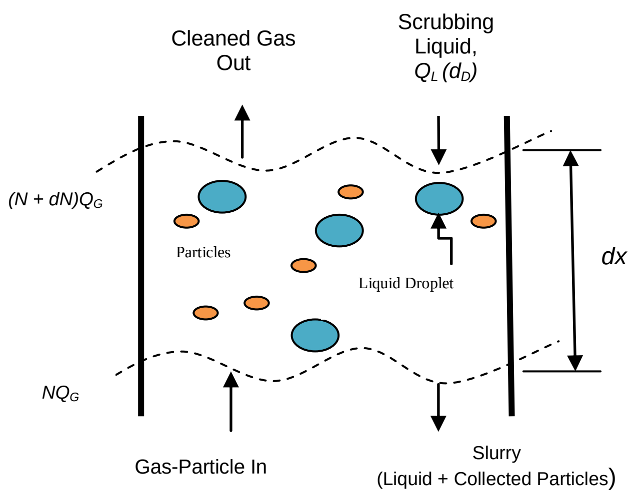

Figure 3: Mass Balance across the Scrubber Cross-section

From the Figure,

$$NQ_G - (N + dN)Q_G - M_C = 0 \quad (2)$$

But, the total amount of particle collected is given as the product of mass of particles collected by one droplet, during the contact time and the total number of drops entering the cross-section per unit time, Δt. This implies that:

$$\int_{N_0}^{N_Z} \frac{dN}{N} = -\left[\frac{3}{2}\,\eta_{sep}\left(\frac{U_r}{U_r - U_g}\right)\frac{Q_L}{d_D}\right]\frac{1}{Q_G}\int_0^z dx \quad (3)$$

Integrating and making further substitutions, the performance efficiency is given by (4)

$$\eta_{perf} = 1 - \frac{N_z}{N_0} = 1 - \exp\left\{-\frac{3}{2}\,\zeta\,\frac{U_r}{U_r - U_g}\,\delta\,\frac{z}{d_D}\right\}$$

(4)

From (4), the dependent variable, η_{perf} is the performance characteristics for predicting the dynamic behavior of the scrubber system. ζ is the separation efficiency for single liquid droplet (as function of ψ, ρ_P, d_D, d_P, μ_g, U_r, U_g, U_f, T), δ is the liquid to gas ratio, (Q_L, Q_G) and Ur is the relative velocity of ga and liquid (U_{td}, U_g, U_f, Re, C_D). These variables played vital role in the scrubber operations. They posed complexity and uncertainties in the system as such; they tend to represent a non-linear and multivariable condition.

To obtain datasets for the performance efficiency (η_{perf}), computational analysis was carried out for the data scenarios given in the large range of the operating variables using the mathematical models described as follows:

2.1 The separation efficiency, ζ

This depends upon three mechanisms, impaction, interception and diffusion. Costa *et al* in [29] indicated that, Impaction mechanism is the dominant separation mechanism for separating particles that are ≥ 0.5μm. The separation efficiency due to impaction is given by (5);

$$\zeta = \left(\frac{\psi}{\psi + b}\right)^a \qquad a = 2,\ b = 0.35, \quad (5)$$

2.2 The impaction number, ψ

Considering (5), impaction number is the determining factor for particle separation due to impaction mechanism. Generally, it is anticipated that the larger the value of the impaction number, the higher the separation efficiency [6].

$$\psi = \frac{C_f\,\rho_p\,(U_{td} + U_g)\,d_p^2}{18\,\mu_g\,d_D} \quad (6)$$

2.3 The Cunningham Correction Factor, C_f

To allow for slip, the Cunningham correction factor, C_f is introduced into the impaction number.

$$C_f = 1 + Kn\left[1.257 + (0.4)\,\exp\left(\frac{-1.1}{Kn}\right)\right] \quad (7)$$

$$Kn = Knudsen\ number = \frac{2\lambda}{d_P} \quad (8)$$

$$\lambda = mean\ \ free\ \ path\ of\ \ gas$$

$$= \frac{0.0234 + 0.0001464\,(T+273)}{0.499\left(\dfrac{P\,M_g}{R_1\,(T+273)}\right)\sqrt{\dfrac{8R_2\,(T+273)}{\pi\,M_g}}} \quad (9)$$

P is the atmospheric pressure (1atm), M_g is the molecular weight of the gas assumed to be air (29 g), T is the gas temperature (^{0}C), R_1 and R_2 are the universal gas constants (0.08206 m^3 atm/mol K and 8.31448 J/mol K).

2.4 The Gas Viscosity, μ_g

Depending on the temperature values, the gas viscosity μ_g can be calculated using equation described by Yetilmezsoy and Saral in [27].

$$\mu_g = 0.0234 + 0.0001464\left(T+273\right) \quad (10)$$

$$\rho_g = \frac{PM_g}{R_1\,(T+273)} \quad (12)$$

$$C_D = \frac{24}{\mathrm{Re}_D}\,f \quad (13)$$

$$f \begin{Bmatrix} 1+0.0916\,\mathrm{Re}_D \quad for\ \ 0.1 \le \mathrm{Re}_D \le 5 \\ 1+0.1588\,\mathrm{Re}_D \quad for\ \ 5 \le \mathrm{Re}_D \le 1000 \\ 1+\dfrac{3}{\sqrt{\mathrm{Re}_D}}+0.34 \quad for\ \ \mathrm{Re}_D \le 10^5 \end{Bmatrix} \quad (14)$$

$$\mathrm{Re}_D = \frac{\rho_g\,(U_{td} - U_g)\,d_D}{\mu_g} \quad (15)$$

TABLE 1: STATISTICAL PROPERTIES OF THE STOCHASTIC DATA SETS

VARIABLES	UNIT	STATISTICAL PROPERTIES				
		Stochastic Scenarios	Maximum Value	Minimum Value	Range	Step
Droplet's Diameter, d_D Particle	μm	206	2000	40	1960	9.5610
Diameter, d_p	μm	206	10	0.5	9.5	0.0463
Particle Density, ρ_p Temperature	kg/m^3	206	3000	1000	2000	9.7561
Profile, T	^0C	206	200	25	175	0.8537
Gas Velocity, U_g,	m/s	206	1.5	0.025	1.475	0.0072
Liquid to Gas Ratio, δ	l/m^3	206	2500	5	2495	12.1707

2.5 The Terminal Settling Velocity of Liquid Droplets, U_{td}

A condition where the droplet is falling in still air, then its terminal velocity, U_{td} given in (22) is the velocity at which the drag force, F_d is just balanced by the gravitational force, F_g on the droplet.

$$U_{td} = \sqrt{\frac{4}{3}\;\frac{g\,d_D\,(\rho_D - \rho_g)}{C_D\;\rho_g}} \quad (11)$$

The variables ρ_D and ρ_g are liquid droplets and gas densities. C_D is the drag coefficient as a function of the Reynolds number, Re_D of the water droplets given by the equation;

3. MATERIALS AND METHOD

Scope of possible future outcomes of a stochastic data is observable by considering scenarios for the given independent variables. Using the stochastic approach in this study, 206 scenarios for the operating variables has been considered and their statistical properties are shown in Table 1. The advantage of this approach is that it can create a map of uncertainty that can capture the range of possibilities and explore the future dynamics of the scrubber system.

For the ANN modeling in this study, 8 input variables (X1-X8) shown in Table 2 and one output variable (Y) has been considered. These data sets include 6 operating parameters (X1, X2, X3, X4, X5 and X6) generated using stochastic scenario approach while the variable X7 is computed as a function of X4 using (10).

TABLE 2: DATA SETS OF INPUT VARIABLESCONSIDERED IN THE ANN

INPUT VARIABLES		UNITS	SCENARIOS
X1	→ Particle Diameter, d_P	µm	206
X2	→ Particle Density, ρ_P	kg/m³	206
X3	→ Droplet's Diameter, d_D	µm	206
X4	→ Temperature, T	⁰C	206
X5	→ Gas Velocity, U_g	m/s	206
X6	→ Liquid to Gas Ratio, δ	l/m³	206
X7	→ Dynamic Viscosity of Gas, μ_g	kg/ms	206
X8	→ Terminal Settling Velocity, U_{td}	m/s	206

In most studies, the terminal settling velocity of the scrubbing liquid droplet (X8) is computed by iterations using (11). But, using this approach may not be enough as the drag coefficient chosen may be wrong.

contains 34 data sets of size domains; 100µm ≤ d_D ≤ 5800µm. In this study, the size domain for the experimental data was divided into 25 data for training and 9 data for validation and this was used to develop a curve fit model (Figure 4) for the prediction of the terminal settling velocity of the stochastic liquid droplets.

The curve fit model was developed having the best goodness of fit statistics; mean square error, MSE is 1.0680e-005, the sum of squares of the regression is 0.00542 and the correlation coefficient, R-square is 1. Using the curve fit model, the terminal settling velocities for the stochastic droplet sizes were estimated.

.

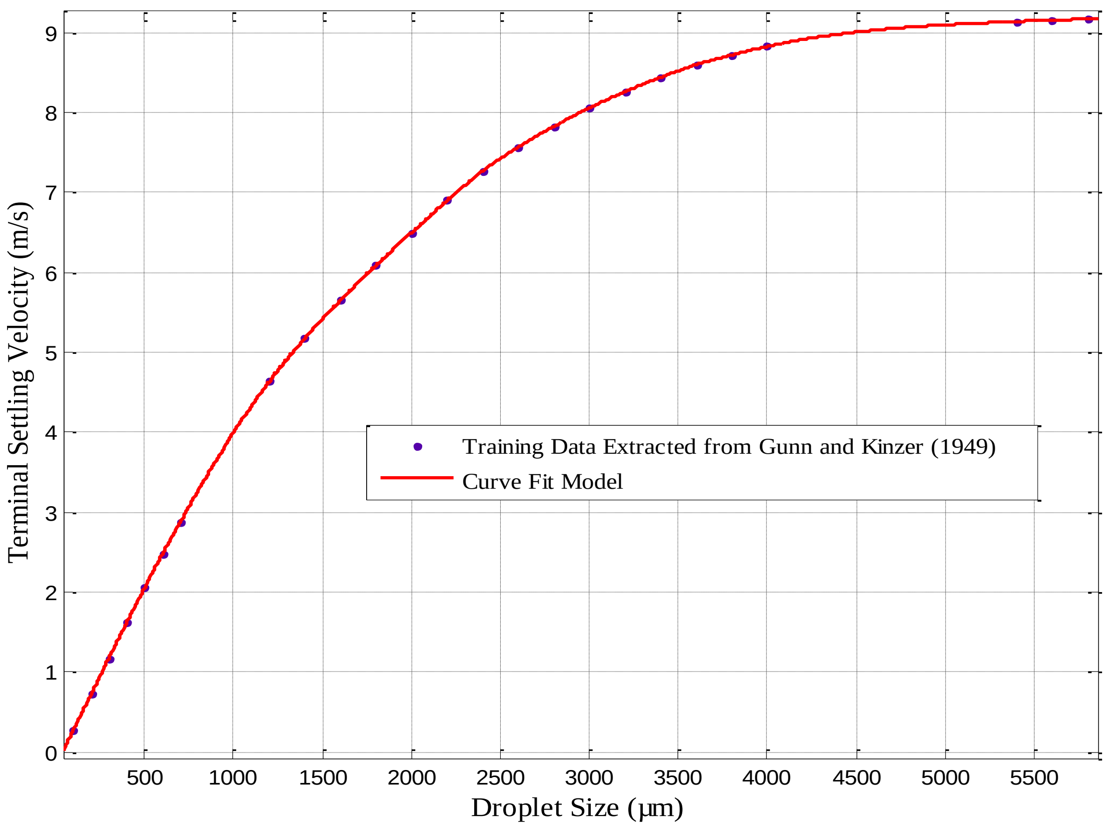

Figure 4: Experimental Data and Curve Fit Model for the Terminal Velocities

The most used and most reliable experimental measurements of X8 in the raindrop size ranges are those of Gunn and Kinzer in [30]. The experimental measurement

Considering the residuals from the fitted model (Figure 5), it appears that the residuals randomly scattered around zero (systematically negative) indicating that the model describes the experimental data well.

ISSN 2229-5518

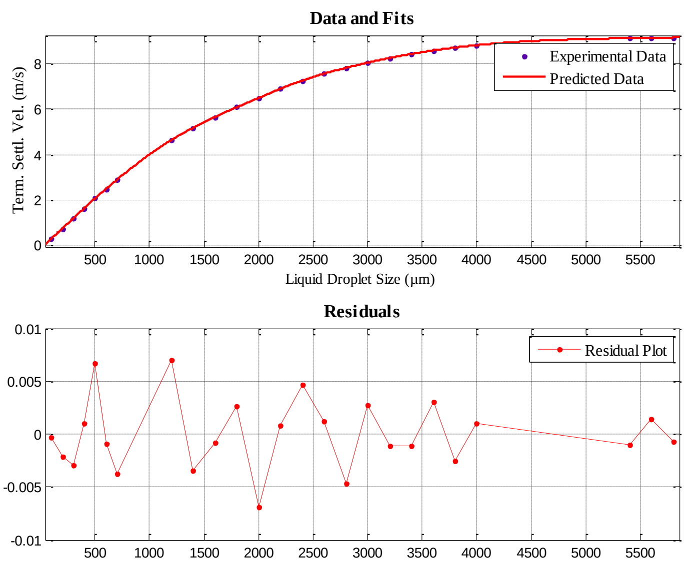

Figure 5: Residuals of the Fitted Model

However, a three layer neural network model shown in Figure 6 (comprising of one input, one hidden, and one output layers), twenty five hidden neuron numbers and 50 epochs number were considered in this study.

The network used back propagation algorithm with sigmoid transfer function (*tansig*) at the hidden layer and linear transfer function (*purelin*) at the output layer based on the input vector (8×206) of 8 operating variables and the target vector (1×206) obtained from the computational analysis.

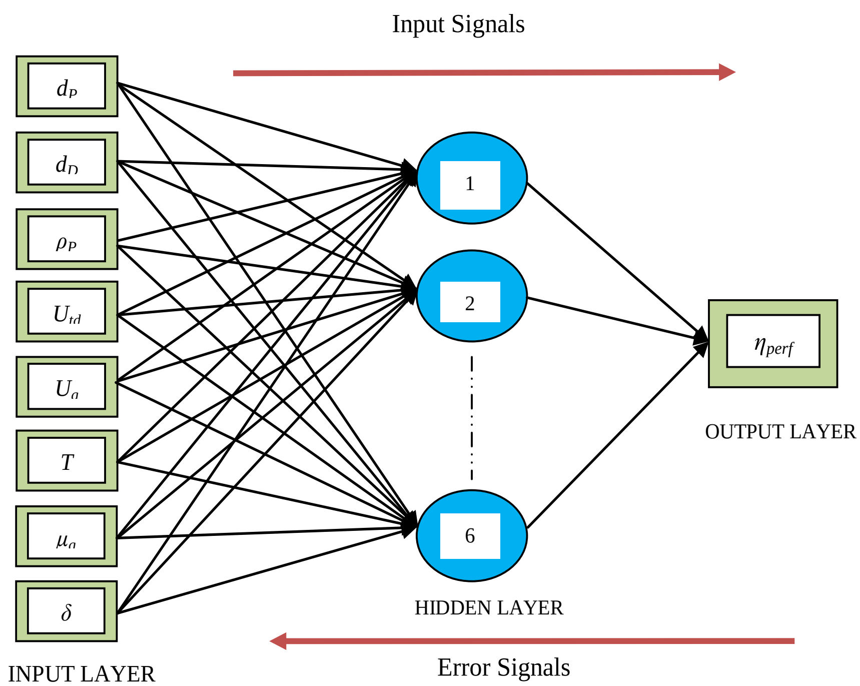

Figure 6: Neural Network Architecture for Predicting the Scrubber Performance

There are a number of different parameters that must be decided upon when developing a neural network model. Among these parameters are the number of layers, the hidden neuron numbers and the epoch's number (number of training iterations).

Also, in order to obtain the best algorithm for the training, eight (8) most used back propagation training algorithms (Table 3) have been considered.

TABLE 3: BACKPROPAGATION (BP) ALGORITHMS CONSIDERED IN THE STUDY

S/N	BACKPROPAGATION ALGORITHM	ACRONYM
1.	Resilient BP(R_{prop})	RP
2.	Fletcher-Reeves Conjugate Gradient BP	CGF
3.	Polak-Ribiere Conjugate Gradient BP	CGP
4.	Powell-Beale Conjugate Gradient BP	CGB
5.	Levenberg-Marquardt BP	LM
6.	Scaled Conjugate Gradient BP	SCG
7.	BFGS Quasi-Newton BP	BFG
8.	One-Step Secant BP	OSS

First step for the ANN modeling is loading the input and output data into the MATLAB® workspace and this is followed by dividing the data into 136 inputs (*p*) and output (*t*) data sets for training and 70 input (*a*) and output (*s*) data sets for testing as presented in Table 4.

TABLE 4: INPUT-OUTPUT DATA SETS FOR THE ANN

UN-NORMALIZED PARAMETERS	NORMALIZED PARAMETERS	NUMBER OF DATA SETS
Training Input, p	pn	136
Training Output, t	tn	136
Testing Input, a	an	70
Testing Output, s	sn	70

To make the Neural Network more efficient, the input and output data sets were normalized to gain zero mean and unity standard deviation. The principal component analysis (PCA) was then used to eliminate less than 2% of of the variation in the data sets.

4. RESULTS AND DISCUSSION

One of the important factors in using the ANN for predicting the performance of the scrubber system requires setting the appropriate parameters as the accuracy of the network is largely dependent on the selection of these parameters. This includes setting up the number of hidden neuron numbers and fastest back propagation training algorithm. The correlation coefficients which include the R-value and the mean squared error (MSE) are useful indicators of the neural network's performance evaluation.

In the present study, optimization procedure for obtaining the best performance of the scrubber system was carried out between the mean squared error (MSE) with the hidden neuron number and the training algorithms and several values were obtained as shown in Table 5. Considering the MSE goal of 0 values, the lowest value was obtained to be 0.00000107 and this corresponds to the optimum hidden neural numbers of 6 as indicated in Figure 7.

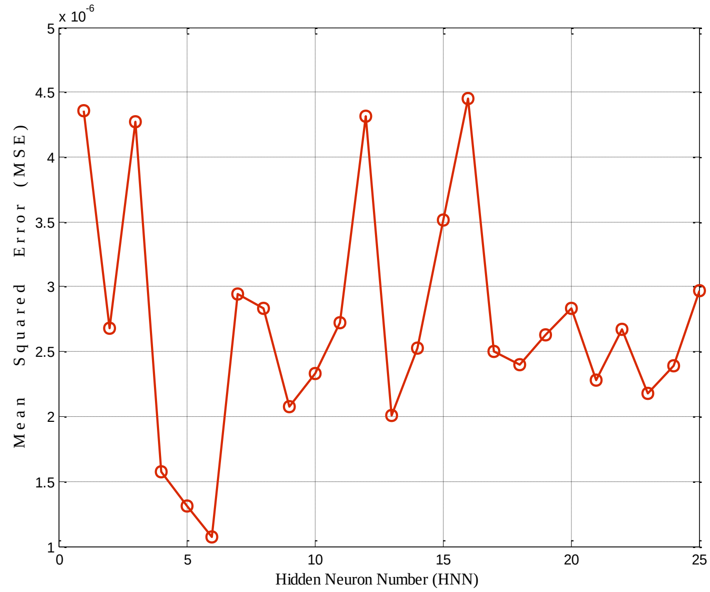

Figure 7: Comparison of Neuron Number and MSE

This is followed by evaluations of the three layer network to obtain the fastest training algorithm to be selected from the eight back propagation algorithms. As shown in Table 5, the Powell-Beale Conjugate Gradient Back propagation (CGB) was determined to be the best training algorithm with the least MSE (0.00000107). Comparison between these algorithms and the MSE is shown in Figure 8.

The neural network output and the corresponding targets are in the post processing regression analysis (*postreg*) which returned different values of correlation coefficient (R-value).

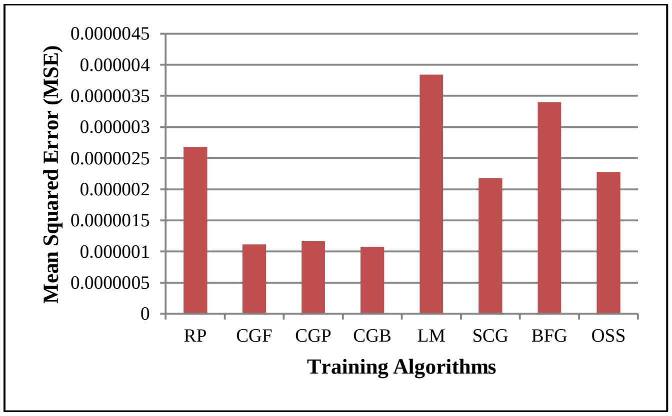

Figure 8: Comparison of MSE and Back propagation Training Algorithms

TABLE 5: .CORRELATION VALUES FOR THE BACKPROPAGATION ALGORITHMS CONSIDERED

S/NO.	BACKPROPAGATION ALGORITHM	ACRONYM	R-VALUE	MSE
1.	Resilient Backpropagation (R_{prop})	RP	0.86042	0.00000268
2.	Fletcher-Reeves Conjugate Gradient Backpropagation	CGF	0.96338	0.00000112
3.	Polak-Ribiere Conjugate Gradient Backpropagation	CGP	0.96059	0.00000117
4.	Powell-Beale Conjugate Gradient Backpropagation	CGB	0.99793	0.00000107
5.	Levenberg-Marquardt Backpropagation	LM	0.77066	0.00000384
6.	Scaled Conjugate Gradient Backpropagation	SCG	0.96313	0.00000218
7.	BFGS Quasi-Newton Backpropagation	BFG	0.79707	0.00000340
8.	One-Step Secant Backpropagation	OSS	0.88619	0.00000228

From R-values described in Table 5, the highest value having the best fit was evaluated to be 0.99793 and this corresponds to the optimum hidden neuron number (6), the lowest MSE and the fastest training algorithm CGB. Considering Table 5 and plots of the Comparisons in Figure 7 and 8, it can be seen that the performance fitness of the neural network (MSE and R-value) describes the effectiveness of the ANN model in predicting the performance of the scrubber system and the ANN model follows the pattern of the theoretical data describing the scrubber performance at a higher efficiency range. It is well known that the perfect correlation between the outputs and the targets is described by the best fit that is closer to 1.

5. CONCLUSION

The present study described the use of Artificial Neural Network (ANN) modeling approach for predicting the performance of wet scrubber system for air pollution control. The results obtained are quite encouraging and suggests the usefulness of ANN based modeling method in accurate prediction of the scrubber system with nonlinear operating characteristics as an alternative to the analytical approach which appears to be more complex and requires numerical solutions. The study concludes that, the ANN model output follows the trend of the theoretical output of the scrubber performance at a higher level and all the prediction proved to be satisfactory with the correlation value of about 0.9979 and mean squared error of 0.00000107.

REFERENCES

[1] D. H. F. Liu, and B. G. Liptak, "*Environmental Engineers' Handbook*" Second Edition, CRC Press, 1997, (www.crcpress.com).

[2] N. Makkinejad, "Temperature Profile in Counter current/concurrent Spray Towers" *International Journal of Heat and Mass Transfer*, Vol. 44, pp. 429-442, 2001.

[3] H. T. Kim, C. H. Jung, S. N. Oh, and K. W. Lee, "Particle Removal Efficiency of Gravitational Wet Scrubber Considering Diffusion, Interception and Impaction" *Journal of Environmental Engineering Science*, Volume 188 Number 2, 2011.

[4] A. Rahimi, M. Taheri and J. Fathikaljahi, "Mathematical Modeling of Heat and Mass Transfer in Hot Gas Spray Systems" *Journal of Chemical Engineering Communications*, Vol. 189, pp. 959-973, 2002.

[5] Z. Bingtao, "Modeling of Particle Separation in Bends of Rectangular Cross section" *American Journal of applied Sciences*, Vol. 2 No. 1 pp. 394-396, 2005

[6] M. N. Garba, "Gas Particle Separation Using Wet Scrubber Method" *M.Eng Thesis Submitted To The Department of Mechanical Engineering, Bayero University Kano, Nigeria,* In partial Fulfillment For the Award of Master Degree in Energy Engineering, 2005.

[7] Y. Bozorgi, P. Keshvarz, M. Taheri, and J. Fathikaljahi, "Simulation of a Spray Scrubber Performance with Eulerian/Lagrangian Approch in the Aerosol Removing Process" *Journal of Hazardous Material B137*, pp. 509-517, 2006, (www.elsevier.com/locate.jhazmat).

[8] S. V., Barai, A. K. Dikshit, and S. Sameer, "Neural Network Models for Air Quality Prediction: AComparative Study", *Indian Institute of Technology and TCE Consulting Engineering Ltd, India*, 2012.

[9] Z. Boger, "Artificial Neural Network Modeling to Reduce Industrial Air Pollution" *Optimal Neural Systems Ltd, Israel and Optimal Neural Informatics, USA*, 2012.

[10] H. V. Peace, "Neural Networks used as Control Technique for Dispersion Modeling over an Urban Area" *Dalton Research Institute, Manchester Metropolitan University, UK.*, 2012.

[11] M., Raihane, A. A. Talab and B. Cherroun, "Opitimization of Neural Predictor for Air Pollution" *Proceedings of the World Congress on Engineering*, Vol. II, WCE 2012, London, UK., 2012.

[12] K., Mirhan, K. Yong-Su, S. Su-Whan, and Y. Chang-Kyo, "Data-Driven Prediction Model of Indoor Air Quality by the Pre-Processed Recurrent Neural Network" *ICROS-SICE International Joint Conference and Fukuoka International Congress Center, Japan*. (2009)

[13] I. Bukovsky, and M. Kolovratnik, "A Neural Network Model for Predicting NOx at the Melnik 1 Coal-Powder Power Plant" *ACTA Polytechnica,* Vol. 52, No. 3, 2012.

[14] G I. Berastegi, J. Saenzz, A. Ezcurra, A. Elias and Barona, A. "Using Neural Network for Short-Term Prediction of Air pollution Levels" *ACTEA Conference (IEEE Indexed)*, Zouk Mosbeh, Lebanon, 2009.

[15] M. K. Mahanijah, J. Rozita and L. A. S. Ruhizan "Prediction of Ambient Air Quality Based on Neural Network Techique" *4th Students Conference on Research Development (ScoRed)*, Selangor, Malaysia, 2006.

[16] S .A. Abdul-Wahab, and S. M. Al-Alawi, "Assessment and Prediction of Tropospheric Ozone Concentration Levela using Artificial Neural Network", *Environmental Modeling and Software Journal*, Vol. 17, No. 3, pp. 219-228, 2005.

[17] N. Sharma, K. K. Chaudhry and C. V. R. Chalapati, "Vehicular Pollution Modelling using Artificial Neural Network Techniques", *Journal of Scienctific and Industrial Research,* Vol. 64, pp. 637-647, 2005.

[18] A. Cesare, R. Cosimo, de and P. Vincenzo, "A Neural Network Based Control Solution for Automotive Fuel Injection Systems" *Journal of IEEE Transactions on Systems, Man and Cybernetics-Part C: Application and Reviews,* Vol. 33, No.2, 2012.

[19] W. C. Christine, and H. H. Guo, "Artificial Intelligence for Management and Control of Pollution Minimization and Mitigation Processes", *Engineering Application of Artificial Intelligence Journal,* Volume 16, pp. 75-90, 2003.

[20] F. Karaca, O. Alagha and F. Erturk, "Characterization of Atmospheric PM_{10} and $PM_{2.5}$ Concentrations at Non-Impacted suburban Site of Istanbul, Turkey" *Cemosphere Journal,* Vol. 59, No. 8, pp. 1183-90, 2005.

[21] X. S. Qin, "Management Of Environmental Pollution Control Problems Under Stochastic Uncertainty" *Management of Innovation and Technology (ICMIT), IEEE International Conference,* School of Civil and Environmental Engineering, Nan yang Technology University, Singapore,pp.366-371 (2012)

[22] C. Omar, and R. Rosario, "A Stochastic Model for the Environmental Transnational Pollution Control Problem" *DOI: Environmetrics* Volume 22, Issue 4, pp. 541-552, 2011.

[23] A. Gosavi, "Stochastic Models for Analysis and Control of Air Pollution in a Manufacturing System" *Pollution Control in a Manufacturing System Technical Report* SOPTL-05-01 Missouri University of Science and Technology, 2005.

[24] H. Zhiyong and M. Hiroshi "Water Pollution Models based on Stochastic Differential Equations" *Department of Earth and Environmental Sciences, Graduate School of Environmental Studies, Nagoya University*, 2004, http://webdoc.sub.gwdg.de/ebook/serien/e/nagoya-pp/2004-2.pdf

[25] C. K. Phaedon and H G. J. Andre "Stochastic modeling of atmospheric pollution: a spatial time-series framework. Part II: application to monitoring monthly sulfate deposition over Europe" *Journal of Atmospheric Environment,* Volume 35 pp. 2339-2348. (2001)

[26] C. D. C. Luciana, M. B. R. Marley and G. L. L. Vellasco, "A Stochastic Model Based on Neural Networks" *Proceedings of International Conference on Neural Networks (IEEE Indexed),* San Jose, California, USA., 2011.

[27] K. Yetilmezzsoy, and A. Saral, "Stochastic Modeling Approaches Based on Neural Network and Linear-Nonlinear Regression Techniques for the Determination of Single Droplet Collection Efficiency of Counter Current Spray Towers" *Journal of Environmental Model Assessment* (Springer Science Indexed) Vol. 12, pp. 13-26, 2007.

[28] US Environmental Protection Agency, EPA and National Association of Clean Air Agencies, NACAA (EPA, 2012 Module 8) "Control of Particulate Matter Emissions" *APTI 413 Lesson 8 Student Manual*, pp. 39-40 [www.epa.gov/apti/Materials/APTI413student/413StudentManual/SM_ch8.pdf]

[29] M. A. M. Costa, P. R. Henrique, J. A. S. Goncalves and J. R. Coury, "Droplet Size in a Rectangular Venturi Scrubber" *Brazilian Journal of Chemical Engineering*, Volume 21, No. 2, pp. 335-343, 2004.

[30] R. Gunn and G. D. Kinzer, "Terminal Velocity of Fall for Water Droplets in Stagnant Air" *US Weather Bureau, Washington DC*, USA., 1949.

.