PREDICTION OF EMISSIONS FROM BIODIESEL FUELED TRANSIT BUSES USING ARTIFICIAL NEURAL NETWORKS

Abhisek Mudgal[1], Kasthurirangan Gopalakrishnan [2], Shauna Hallmark[3]
[1,2,3]Iowa State University, Department of Civil, Construction and Environmental Engineering, Ames, IA 50011, USA

Received 13 May 2011; accepted 22 June 2011

Abstract: The growing demand of freight transportation and passenger cars has led to air pollution, green house gas emissions (especially CO_2) and fuel supply concerns. Research has been carried out on biodiesel which is shown to generate lower emissions. However, the amount of emissions generated is not well understood which entails more vigorous data collection and development of emissions models. A comprehensive data collection plan was developed and emissions (NO_x, HC, CO, CO_2 and PM_{10}) from biodiesel fueled transit buses were collected using a portable emissions measurement system (PEMS). Linear models were developed and tested for each emission. However, the models could not capture the emissions spikes well resulting in very low R^2 values. Artificial neural networks (ANNs) based models were then employed on this data because of their ability to handle nonlinearity and not requiring assumptions on the input data as needed by statistical models. Sensitivity analysis was performed on the input parameters, number of hidden layers, learning rate and learning algorithm to arrive at an optimum ANN architecture. The optimal architecture for this study was found to be two hidden layers with 50 hidden nodes for each of NOx, HC, CO, and PM and one hidden layer for CO_2. The emissions were predicted using best-performance ANN models for each emission. Scatter-plots of observed versus predicted values showed R^2 of 0.96, 0.94, 0.82, 0.98 and 0.78 for NOx, HC, CO, CO_2 and PM emissions, respectively. Histogram on prediction error showed low frequency for large errors.

Key words: artificial neural network (ANN), back-propagation, biodiesel, vehicular emissions.

1. Introduction

Road transportation is a major contributor to air pollution both on local and global scale. In general, oxides of Nitrogen (NO_x), Hydrocarbons (HC), Carbon monoxide (CO), Carbon dioxide (CO_2) and Particulate Matter (PM) emissions are crucial. This is because NO_x and HC contribute to formation of ozone and consequently smog, CO forms carboxyhemoglobin (inhibits the oxygen carrying capacity of blood). PM gives rise to respiratory problem such as bronchitis while CO_2 is responsible for global warming and climate change. Engines burning vegetable oil after trans-esterification with alcohols are considered to provide better performance by some measures than diesel (Anthony, 2007). The technical process used in the formation of biodiesel is as illustrated in Fig. 1.

[2] Corresponding author: rangan@iastate.edu

Biodiesel has been proved to be biodegradable, non-toxic (in small quantity), non-hazardous fuel with high cetane number (measure of the ignition quality of fuel oil), high lubricity and high flash point (combustible, not flammable). Research has shown that it decreases HC, CO, CO_2 and PM, but increases NO_x emissions (EPA, 2002). Biodiesel increases fuel lubricity, even when used in very small quantities, as demonstrated through a variety of bench scale test methods (NBB, 2000). However, certain compounds in biodiesel can form crystals in the fuel at low temperature and this can cause undesirable effects like plugging of fuel filters so that fuel cannot travel to the engine. Biodiesel also has low oxidation stability. These advantages support biodiesel as a promising sustainable transportation fuel.

In the present work, emissions (NO_x, HC, CO, CO_2 and PM) from biodiesel run transit buses (Ames Transit Agency) were measured using PEMS to generate a database to be used for modeling the emissions. Modeling serves as a low cost measure of estimating the emissions. A good model would reduce the necessity for elaborate measurement procedures which is expensive and time consuming. In this case, deterministic models are difficult to develop owing to the complexity of emissions formation mechanism. Therefore, a non-linear modeling approach (ANN) was adopted for modeling and prediction.

In recent years, ANNs are increasingly being used to solve engineering problems that deal with highly nonlinear functional approximations (Gopalakrishnan et al. 2010). Predictive models on emissions with various vehicle, engine and fuel parameters (properties) have been successfully developed. Canakci et al. (2006) investigated the applicability of ANNs to evaluate the performance and exhaust emission values of diesel engines fueled with biodiesel from different feedstock and regular diesel. The input layer consisted of fuel properties such as average molecular weight (W, kg/ kmol), net heat of combustion (NH, kJ/kg), specific gravity (SG), kinematic viscosity (KV, mm^2/s), C/H ratio (R) and cetane number (CN). Brake specific fuel-consumption (BSFC, g/kWh), exhaust manifold temperature (Texh), smoke number (SN), and emissions (O_2, CO, CO_2, HC and NO_x) constituted the output layer. Results showed R^2 values of 0.99 and the mean % errors of less than 4.2 for the training data, while the R^2 values of 0.99 and the mean % errors smaller than 5.5 for the test data. Hashemi et al. (2007) trained chassis dynamometer data from a heavy-duty diesel vehicle to predict NO_x, HC, CO, CO_2 and PM. Axle speed, torque, their derivatives in different time steps, and two novel variables that defined speed variability over 150 seconds were inputs to the ANN. Off-cycle operation (leading to high NOx emissions) was still difficult to model. Results showed an average accuracy of 0.97 for CO_2, 0.89 for NOx, 0.70 for CO, and 0.48 for HC over the course of various standard driving tests conditions. Ghobadian et al. (2009) developed an ANN model using speed and biodiesel blends and two other inputs and predicted brake power, torque, specific fuel consumption and exhaust emissions of the engine. The number of hidden layers varied from one to two. The activation function for the hidden layer was selected to be *logsig* while linear function was assigned to the output layer. Results showed R^2 values of 0.9487, 0.999, 0.929 and 0.999 for the engine torque, SFC, CO and HC emissions, respectively. Clark et al. (2001) used engine speed and torque to predict NO_x and CO_2 from vehicles in conjunction with a powertrain simulator for conventional and hybrid electric vehicles. Krinjnsen et al. (2000) successfully used ANN to model NOx emissions. Yuanwang et al. (2002) implemented ANN on cetane number to predict the exhaust emissions from an engine. Fuel composition parameters along with engine torque and speed were used by De Lucas et al. (2001) to predict PM with NNs.

Although, various other researchers have trained an ANN on diesel engine data alone; not many have used ANNs on (on-road) real-time emissions data which is necessary for evaluating the impact of real-time driving conditions/modes. Also, they have not considered important engine parameters such as rpm, temperature and manifold absolute pressure which play a vital role in engine kinetics. In the present research, real time emissions from transit bus powered by various blends of biodiesel were measured and used in emissions models.

2. Experimental Design and Data Collection

The three most common methods for measuring vehicular emissions are – dynamometer system, on-road remote sensing (Fig. 2), and portable emission measurement system (PEMS, Fig. 3). Dynamometer testing is a standard laboratory emissions testing cycle defined by the United State Department of Environmental Protection Agency (USEPA). It provides simulated road

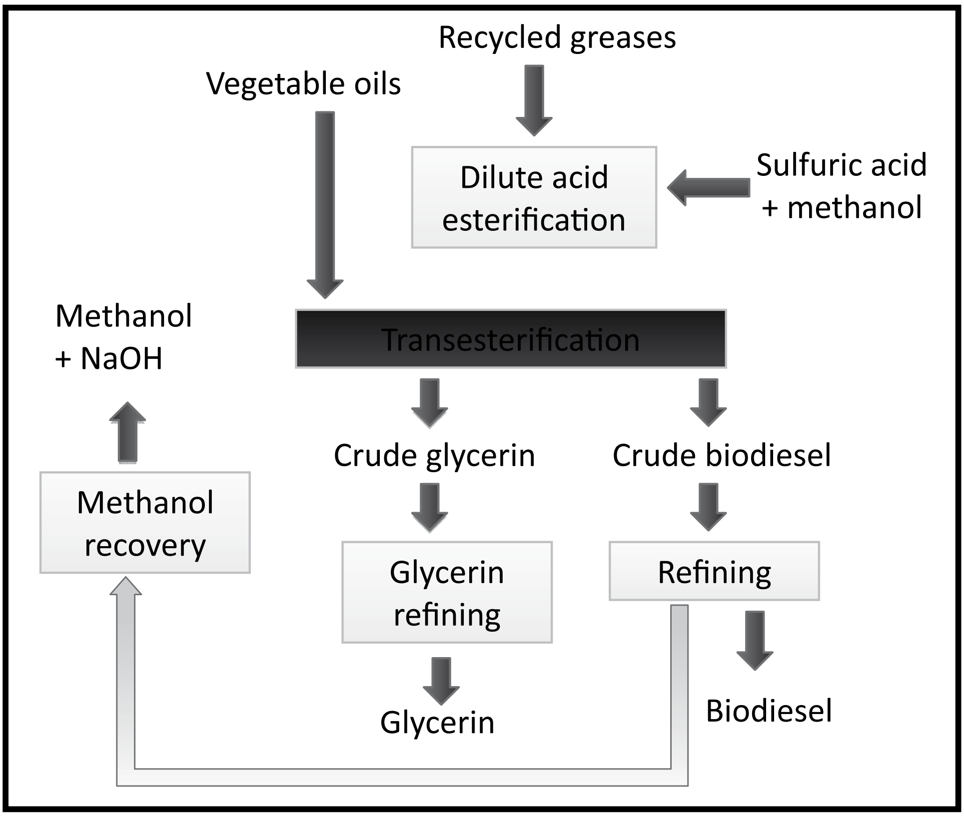

Fig. 1.
Block Diagram of Biodiesel Production

loading of either the engine or full power-train inside the laboratory. Although it allows repeatability and controlled environment, it fails to represent actual driving conditions and operation. Therefore, impact of transportation policies cannot be assessed by using this method.

In a remote sensing system, IR beam of light is projected perpendicular to the road. The beam is obstructed by the emissions cloud coming out of the tail pipe and is then sensed by the sensor. Based on intensity of the transmitted beam, the amount of emissions in the exhaust would be estimated by the equipment. This method helps in measuring the exhaust emissions of a vehicle as it passes by on the road. Since the system has to be set up at a single point on a roadway, it only measures one point in time and does not account for vehicle speed and acceleration, air conditioning use or other vehicle parameters. It is also difficult to use this method for measuring emissions on multiple lanes with significant traffic flow, such as on primary arterials or freeways.

Frey et al. (2002) pointed out that development of reliable new-generation emissions models would require data from both real-world and laboratory measurements. PEMS provide the advantages of portability with ability to perform micro-scale study. Emissions study as a function of road grade and environmental condition and driver variability (Ahn et al., 2002; Frey, 1997) can be effectively done using PEMS. Research pertaining to investigation of the effect of signal timing on vehicle emissions (Unal et al., 2003), quantification of vehicle emissions hotspots (Unal et al., 2004), analysis of High Occupancy Vehicle (HOV) lanes (Rilett et al., 2004) and measurement of off-highway construction equipment emissions (Vojtisek-Lom and Wilson, 2003) have been successfully carried out using PEMS (OEM2100™). In addition, the portability of PEMS allows quick instrumentation and ability to do the test at any place such as a hilly region.

Our study comprised of collecting emissions and engine data from transit buses fueled with three blends of biodiesel – B0 (regular diesel), B10 (10 % biodiesel in regular diesel) and B20 (20 % biodiesel in regular diesel). The objective was to develop predictive models for emissions based on fuel-blend and many other parameters in on-road emissions. Transit buses were fueled with biodiesel from April 2008 through July 2008 in Ames, Iowa. At a frequency of 1 Hz, emissions (NO_x, HC, CO, CO_2 and PM), speed, intake air temperature (T), engine rpm, and manifold absolute pressure (MAP) at the air intake were recorded. In addition, the passengers in the bus between consecutive bus stops were also counted to account for dynamic load of the vehicle. Frey et al. (2001) found that in general 2.5-15 % of the on-road emissions data would be invalid. This pertains to equipment failure, wrongly placed sample and reference lines and improper calibration. After removing erroneous data, 15000 rows were randomly selected each for training and testing emissions models in this study. Vehicle specific power (VSP), derived from vehicle dynamics (Jiménez-Palacios, 1999; Frey, 2007) was used as another independent variable, Eq. (1):

$$VSP = v.(a + 0.092) + 0.00021 \cdot v^3 \quad (1)$$

Where, 'v' is the vehicle speed in m\s while 'a' is the acceleration in m/s^2. Road grade was assumed to be zero.

3. Analysis Methods

Emissions studies generally extend across various engines, fuels and road characteristics. It is expensive and time consuming to measure the emissions from all the different types of engine-fuel combinations. Appropriate models have the potential to provide reasonable estimates of emissions without going through extraneous arrangements. For this study, traditional statistical models were inappropriate and therefore non-traditional computational intelligence techniques were used. Table 1 summarizes the descriptive statistics and normality test results for the measured emissions data.

Linear models were developed for each of the emissions, but the models could not capture the spikes in the data. These spikes are important for they are generated during high or sudden acceleration events.). However, the models could not capture the emissions spikes well resulting in very low R^2 values (maximum of 0.47). This may be due to the Therefore, ANN models were explored for each emissions variable. In general, ANN has been shown to provide fast, accurate and reliable predictions, especially where statistical and mathematical methods fail. There is also a significant simplicity in using ANN due to its power to deal with multivariate and complicated problems without requiring any conditions (such as independency) on the inputs.

ANNs are parallel connectionist structures constructed to simulate the working network of neurons in human brain. They attempt to achieve superior performance via dense interconnection of non-linear computational elements operating in parallel and arranged in a pattern reminiscent of a biological neural network. The perceptrons or processing elements and interconnections are the two primary elements which make up a neural network (Haykin, 1999).

An artificial neuron receives information (signal) from other neurons, processes it, and then relays the filtered signal to the other neurons (Tsoukalas and Uhrig, 1997). The receiving end of the neuron has incoming signals X_1, X_2,... X_n. Each of them is assigned a weight, which is given based on experience and which may change during the training process. The summation of all the weighted signal amounts yields the combined input quantity I_k. The combined input quantity I_k is then sent to a pre-selected transfer function (sometimes called an activation function) T, and a filtered output Y_k is generated in the outgoing end of the artificial neuron k through the mapping of the transfer function. The process can be written in the form of the following equations, Eq. (2), Eq. (3):

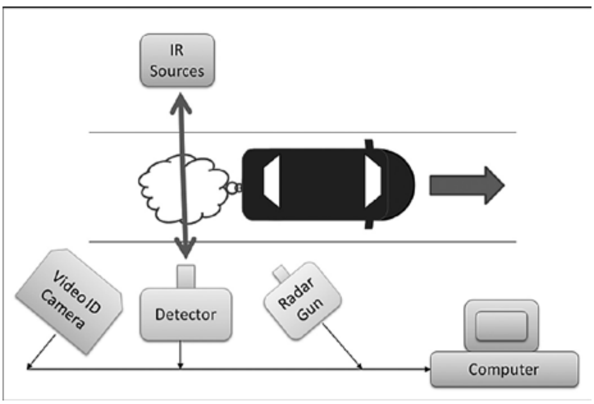

Fig. 2.
Typical Layout of a Remote Sensing Device

$$I_K = \sum_{i=1}^{n} w_k \, x_i \tag{2}$$

$$Y_K = T(I) \tag{3}$$

There are several types of transfer functions that can be used, including sigmoid, threshold, and Gaussian functions. The transfer function most often used is the sigmoid function because of its differentiability. The sigmoid function can be represented by the following equation, Eq. (4), Eq. (5):

$$logsig\ (I) = \frac{1}{(1+\exp(-I))} \tag{4}$$

$$T(I) = \frac{1}{1+\exp(-\varphi I)} \tag{5}$$

where j = positive scaling constant, which controls the steepness between the two asymptotic values 0 and 1 (Tsoukalas and Uhrig, 1997). The *Backpropagation* (BP) learning algorithm is the most commonly used ANN training algorithm in which the network learns the relationship between stipulated input-output data pairs in a supervised manner. In the BP learning algorithm, the error energy used for monitoring the progress toward convergence is the generalized value of all errors that is calculated by the least-squares formulation and represented by a Mean Squared Error (MSE) as follows (Haykin, 1999), Eq. (6):

$$MSE = \frac{1}{MP} \sum_{1}^{P} \sum_{k=1}^{M} (d_k - y_k)^2 \tag{6}$$

where y_k and d_k are actual and desired outputs, respectively, M is the number of neurons in the output layer and P represents the total number of training patterns. Other performance measures such as the Root Mean Squared Error (RMSE), Average Absolute Error (AAE), etc. are also used.

3.1 ANN Architecture

The development and testing of the ANN models were performed in MATLAB

Fig. 3.
The PEMS (OEM2100TM Montana System)

(7.6.0.324 R2008a). Neural networks learning algorithm error minimization process was achieved through a gradient descent rule while the accuracy of the models was examined using Mean square error (MSE) and R^2. ANN architectures were evaluated and trained using the collected data. The activation function for the hidden layer was selected to be *logsig* and a linear combiner model was used for the output layer.

A three-layer ANN architecture (1 input layer and 2 hidden layers) was chosen for NO_x, HC, CO and PM (Fig. 5) while a two-layer (1 input layer and 1 hidden layer) network was sufficient for CO_2 predications (Fig. 6). The ability to 'learn' the mapping between inputs and outputs is one of the main advantages that make the ANNs so attractive. Efficient learning algorithms have been developed and proposed to determine the weights of the network, according to the data of the computational task to be performed. The learning ability of the ANNs makes them suitable for unknown and non-linear problem structures such as pattern recognition, medical diagnosis, and time series prediction.

Considerable research has been carried out to accelerate the convergence of ANN learning algorithms which can be broadly classified into two categories: (1) development of ad-hoc heuristic techniques which include such ideas as varying the learning rate, using momentum and rescaling variables; (2) development of standard numerical optimization techniques. The three types of numerical optimization techniques commonly used for ANN training include the conjugate gradient algorithms, quasi-Newton algorithms, and the Levenberg-Marquardt (LM) algorithm (Hagan and Menhaj, 1994). Although numerous training algorithms appear in recent neural network literature, it is difficult to know which algorithm works best, in terms of convergence speed and accuracy, for a given problem. A number of factors, including the complexity of the problem, the number of datasets used in training, the number of weights and biases in the network, the error goal, and whether the ANN is used for function approximation or classification, etc., seem to have influence (Coskun and Yildrim, 2003).

In this study, several ANN learning algorithms were considered including *trainsgf*, *trainda*, *trainfgc*, *traindm* and *trainlm* (see Table 2 for brief descriptions of these algorithms). Out of these, *trainlm* (Levenberg-Marquardt BP algorithm) proved to be the best choice for the given problem. The LM BP training algorithm uses the supervised training technique where the network weights and biases are initialized randomly at the start of the training phase. It is a second-order numerical optimization technique that combines the advantages of Gauss–Newton and steepest descent algorithms. While this method has better convergence properties than the conventional BP method, it requires

Table 1
Descriptive Statistics of the Emissions (SD = standard deviation)

Emissions	NO_x (g/s)	HC (g/s)	CO (g/s)	CO_2 (g/s)	PM (mg/s)
Mean	0.0318	0.0017	0.0014	2.6848	0.0664
Median	0.023	0.001	0.00086	1.298	0.02
Maximum	0.248	0.019	0.0312	29.347	1.83

$O(N^2)$ storage and calculations of order $O(N^2)$ where N is the total number of weights in an Multi-Layered Perceptron (MLP) BP. The LM training algorithm is considered to be very efficient when there are few hundred weights. This efficiency overrides the computational recourse required for each iteration. This is especially true when high precision is required (Haykin, 1999).

Sensitivity analysis was carried out with learning rate and momentum constant to arrive at the optimal parameter settings for maximizing network prediction performance. Based on the results of sensitivity analysis, two or three hidden layers (Figs. 4 and 5) with 50 neurons each were chosen according to the emissions.

3.2. ANN Inputs and Outputs

The eight input nodes of the ANN architecture consisted of % biodiesel (0, 10 or 20), speed, acceleration, rpm, VSP, passenger count, T and MAP. Table 3 describes the inputs in detail. The desired outputs from the ANN were the five emissions (NO_x, HC, CO, CO_2 and PM). Separate ANN models were developed for each of the outputs using the same architecture. The ANN emissions prediction models were trained using 70 % of the emissions data, while 15 % of the data were utilized for validation, and the rest 15 % for testing. Validation is an important aspect of model development as it controls over-fitting of the data.

4. Results and Discussions

The predicted emissions were compared with those measured by the PEMS. Figs. 6, 8, 10, 12 and 14 shows the time plot of predicted and measured emissions. For the purpose of clarity, only 500 points are shown in each figure. Error histograms (Figs. 7, 9, 11, 13, 15) were drawn to evaluate the errors. Table 4 summarizes the ANN structure, parameters and prediction accuracy. The accuracy increased when the number of nodes in hidden layer was increased from 20 to 50. A greater number of nodes are needed depending on the complexity of the model. This may corroborate high complexity of emissions formation. Different emissions are correlated with each other and therefore HC, NO_x and CO_2 were used as additional inputs to predict PM, but no significant improvement in prediction was observed. Error histograms depict that frequency of large errors for individual predictions were low for all pollutants except CO which showed moderately high error in predictions.

5. Summary and Conclusions

Biodiesel, a renewable energy source has various advantages such as lower emissions and higher lubricity. A low cost method to evaluate these fuels is to have predictive emissions models. The data analysis and the complexity of the combustion process indicated superiority (or usefulness) of using ANN. Any suitable model needs good quality data which was obtained from PEMS, an instrument for on-road emissions measurement. It was found in the study that based on vehicle data (speed, acceleration) and engine parameters (T, MAP), emissions from higher biodiesel blends can be appropriately predicted by ANN models. The predicted emissions were compared with the actual collected data. The results obtained showed reasonable accuracy. It should be noted that this is an initial study with limited scope specifically targeted towards the emissions from biodiesel. However, the results highlight the potential for extending this concept for developing generic ANN-based models which

Table 2
Ann Learning Algorithms Considered in This Study

Learning algorithm	Description
trainsgf	Conjugate gradient backpropagation with Fletcher-Reeves updates
traingda	Gradient descent with adaptive learning rate backpropagation
traincgf	Conjugate gradient backpropagation with Fletcher-Reeves updates
traingdm	Gradient descent with momentum backpropagation
trainlm	Levenberg-Marquardt backpropagation

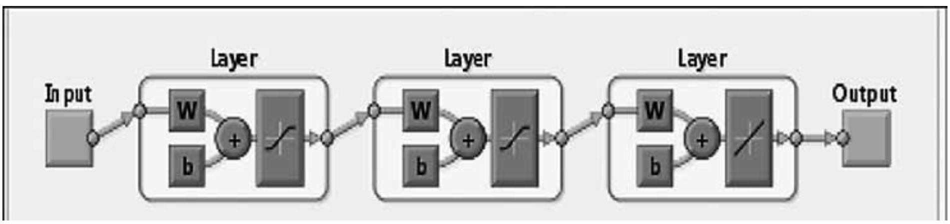

Fig. 4.
The ANN Architecture Used in This Study for Predicting NO_x, HC, CO and PM

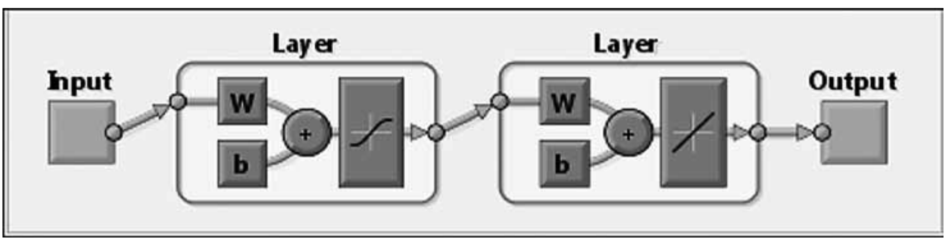

Fig. 5.
The ANN Architecture Used in This Study for Predicting CO_2

Table 3
Description of the ANN Inputs

Variables	Description
% biodiesel, BX	This represents the % of biodiesel in the fuel mixture. BX means X % biodiesel and (100-X) % regular diesel. Percentage of biodiesel has a significant effect on emissions (EPA, 2002; Frey et al., 2005)
Speed	The speed (mph) of the bus
Acceleration	The acceleration (mph/s) of the bus every second. In general, emissions are found to have the following trend (Em = Emissions): Emissions (idling) < Emissions (deceleration) < Emissions (cruise) < Emissions (acceleration) (Rouphail et al., 2001)
rpm	Engine speed (revolution per second)
VSP	Vehicle specific power (Watt/kg) represents the power demand of the vehicle. It is evaluated using Eq. (1).
Passenger count	This represents the number of passengers in the bus. This imparts weight to the whole moving system which is responsible for higher power demand.(Frey et al., 2007)
Intake air temperature, T	This is the temperature of the air entering the engine chamber. Temperature has influence on emissions. (Vijayan et al., 2008)
Manifold Absolute pressure, MAP	This is the pressure in the incoming air. This controls the emissions reactions and has significant effect on emissions. (Frey et al., 2008)

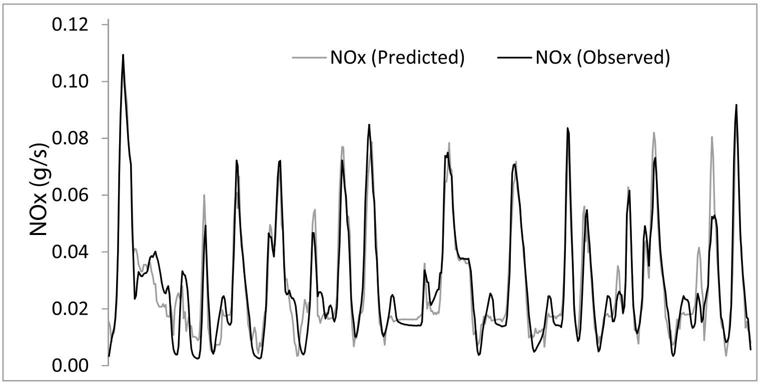

Fig. 6.
ANN Prediction Results for NO_x

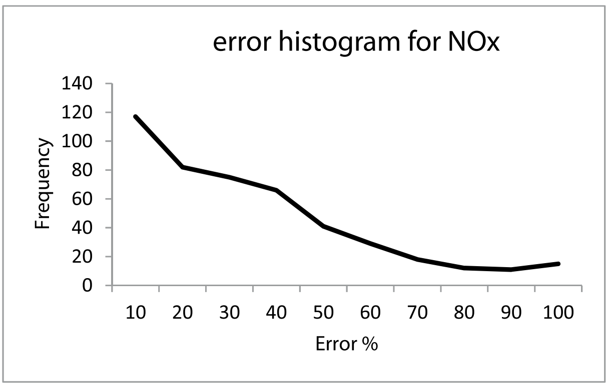

Fig. 7.
Prediction Error Histogram for NO_x (g/s)

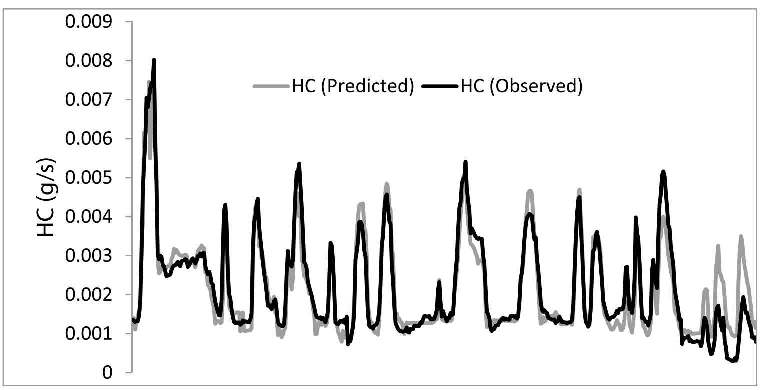

Fig. 8.
ANN Prediction Results for HC

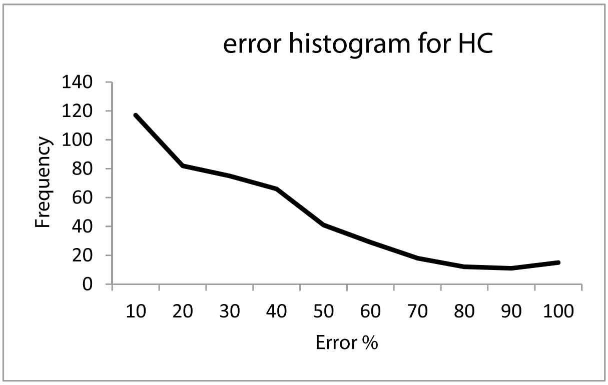

Fig. 9.
Prediction Error Histogram for HC (g/s)

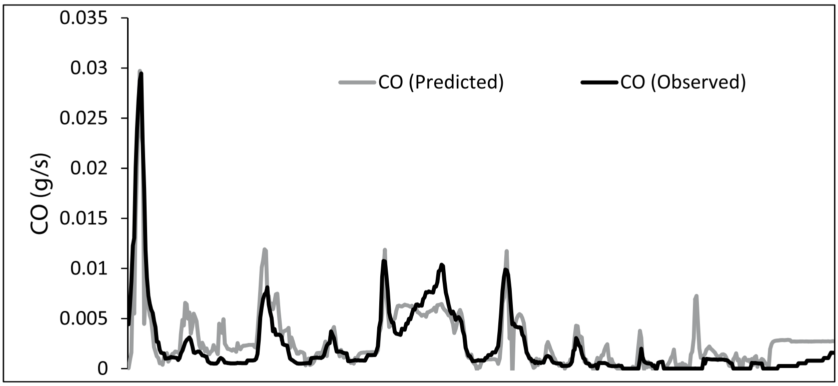

Fig. 10.
ANN Prediction Results for CO

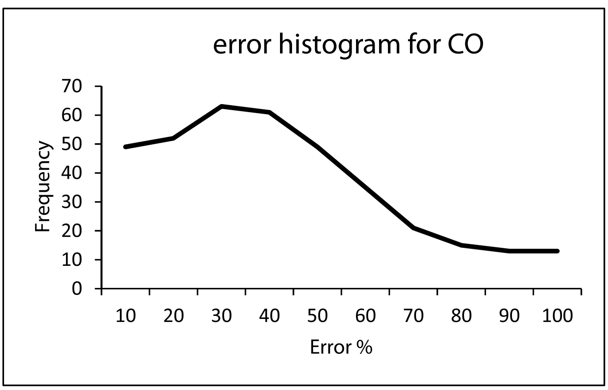

Fig. 11.
Prediction Error Histogram for CO (g/s)

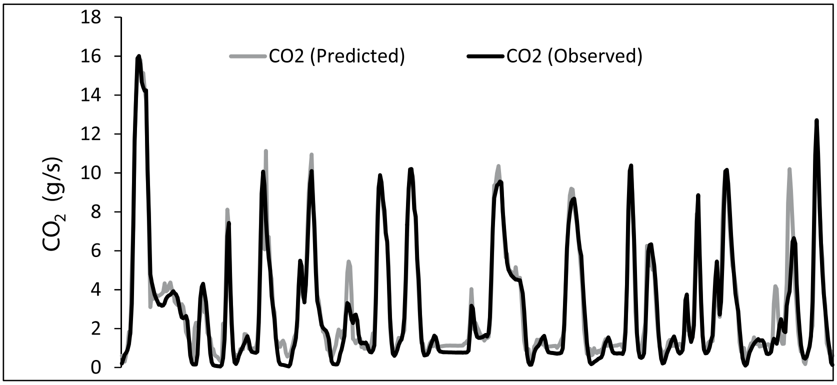

Fig. 12.
ANN Prediction Results for CO_2

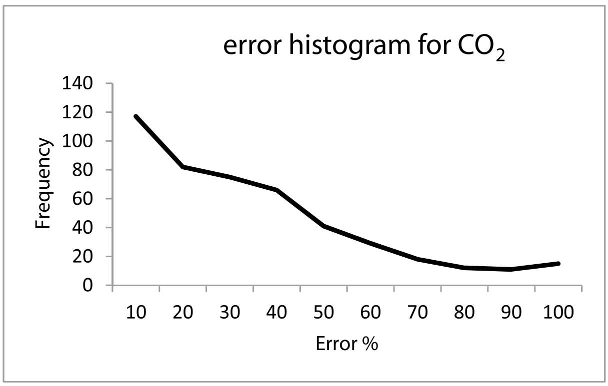

Fig. 13.
Prediction Error Histogram for CO_2 (g/s)

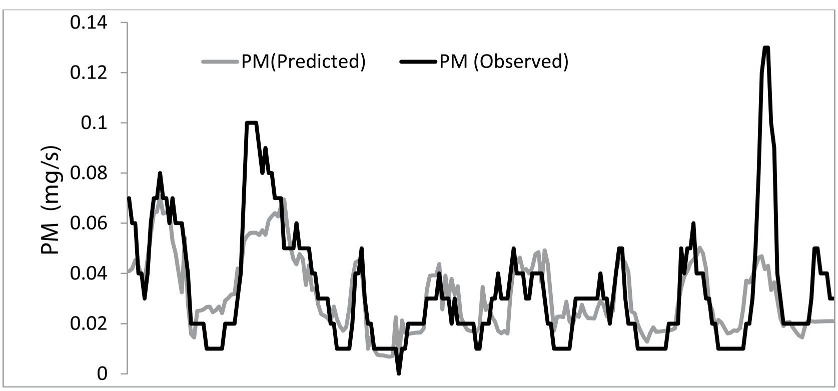

Fig. 14.
ANN Prediction Results for PM

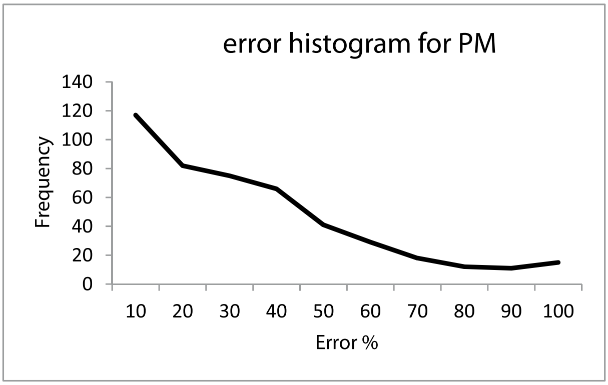

Fig. 15.
Prediction Error Histogram for PM (mg/s)

Table 4
Summary of Best-Performance ANN Prediction Models

Emission Variable	No. of Input nodes	Number of Hidden neurons	Number of Hidden layers	R^2	MSE
NO_x	8	50	2	0.960	$7.34 \cdot 10^{-5}$
HC	8	50	2	0.940	$3.85 \cdot 10^{-7}$
CO	8	50	2	0.825	$1.43 \cdot 10^{-6}$
CO_2	8	50	1	0.983	0.942
PM	8	50	2	0.784	$1.41 \cdot 10^{-4}$

would be useful in the analysis of routine real-time data. This could be accomplished by training the ANN models developed in this study over a broad range of input values with controls on driver and environmental conditions.

ANN prediction models for NO_x, HC and CO_2 showed reasonable accuracy while CO models could be further improved.ANN-based PM prediction models were not within reasonable accuracy and need further investigation. Lack of accuracy may be attributed to error in the equipment (due to vibration and excess heat generatd inside the unit because of prolonged use), insufficient understanding of emission formation and high variability in data. We recommend experiments using other computational intelligence tools such as Support Vector Regression (SVR) and Adaptive Neuro-Fuzzy Inference System (ANFIS) should be carried out in the future.

The study contributes to the fact that two layers 50 hidden neurons and one (CO_2) or two (NO_x, HC, CO and PM) hidden layers are appropriate for training emissions with different blends of biodiesel. The study also encompasses passenger load into the model. Increase in weight makes the engine work harder and in turn burn more fuel resulting in higher emissions. One of the limitations of this study is that data were collected during April –July and therefore, the results may be biased due to climatic conditions.

Acknowledgement

The authors would like to acknowledge CenSARA (Blueskyways Collaborative) and Iowa Department of Natural Resources (IDNR), the sponsors of the project. Special thanks are due to CyRide, the transit agency and Clean Air Technologies International, Inc. the provider of PEMS.

References

Ahn, K.; Rakha, H.; Trani, A.; Van Aerde, M. 2002. Estimating vehicle fuel consumption and emissions based on instantaneous speed and acceleration levels, *ASCE Journal of Transportation Engineering* 128(2): 182-190.

Antony, R. 2008. *Biodiesel Performance, Costs, and use*. Available from internet: <http://www.eia.doe.gov/oiaf/analysispaper/biodiesel>.

Canakci, M.; Erdil, A.; Arcaklioglu, E. 2006. Performance and exhaust emissions of a biodiesel engine, *Applied Energy* 83(6): 594-605.

Clark, N.; Conley, J.; Jarrett, R.; Nennelli, A.; Toth-Nagy, C. 2001. Emissions modeling of heavy-duty conventional and hybrid electric vehicles. *SAE paper 2001-01-3675*.

Coskun, N.; Yildrim, T. 2003. The effects of training algorithms in MLP network on image classification. In *Proceedings of the International Joint Conference on Neural Networks*, 1223-1226.

De Lucas, A.; Duran, A.; Carmona, M.; Lapuerta, M. 2001. Modeling diesel particulate emissions with neural networks, *Fuel* 80(4): 539–548.

EPA. 2002. *A Comprehensive Analysis of Biodiesel Impacts on Exhaust Emissions*. US: Environmental Protection Agency.

Frey, H. 1997. Variability and Uncertainty in Highway Vehicle Emission Factors. In *Proceedings of the Conference Emission Inventory: Planning for the Future*, 208-219.

Frey, H.; Kim, K. 2005. Operational Evaluation of Emissions and Fuel Use of B20 Versus Diesel Fueled Dump Trucks. Federal Highway Administration FHWA/NC/2005-07. Center for Transportation and the Environment, North Carolina State University, Raleigh, NC.

Frey, H.; Rouphail, N.; Unal, A.; Colyar, J. 2001. *Emissions Reduction Through Better Traffic Management: An Empirical Evaluation Based Upon On-Road Measurements*. NC: North Carolina State University.

Frey, H.; Rouphail, N.; Zhai, H. 2008. Link-Based Emission Factors for Heavy-Duty Diesel Trucks Based on Real-World Data. *Submitted to Transportation Research Board 2008 87th Annual Meeting.*

Frey, H.; Rouphail, N.; Zhai, H.; Farias, T.; Goncalves, G. 2007. Comparing real-world fuel consumption for diesel- and hydrogen-fueled transit buses and implication for emissions, *Transportation Research Part D: Transport and Environment* 12(4): 281-291.

Frey, H.; Unal, A.; Chen, J. 2002. *Recommended Strategy for On-Board Emission Data Analysis and Collection for the New Generation Model*. Raleigh, NC: North Carolina State University.

Gopalakrishnan, K.; Ceylan, H.; Attoh-Okine, N. 2010. *Intelligent and Soft Computing in Infrastructure Systems Engineering: Recent Advances*. Studies in Computational Intelligence (SCI) Series, Vol. 259, Springer-Verlag, Inc., Berlin.

Hagan, T.; Menhaj, M. 1994. Training feedforward networks with the Marquardt algorithm, *IEEE Transactions on Neural Networks* 5(6): 989-993.

Hashemi, N.; Clark, N. 2007. Artificial neural network as a predictive tool for emissions from heavy-duty diesel vehicles in Southern California, *International Journal of Engine Research* 8(4): 321-336.

Haykin, S. 1999. *Neural networks: A comprehensive foundation*. NJ, USA: Prentice-Hall, Inc. 823 p.

Jiménez-Palacios, J. 1999. *Understanding and Quantifying Motor Vehicle Emissions with Vehicle*. Cambridge: Massachusetts Institute of Technology.

Krijnsen, H.; Van Kooten, W.; Calis, H.; Verbeek, R.; Vanden Bleek, C. 2000. Evaluation of an artificial neural network for NO prediction from a transient diesel engine as a base for ANN would be well suited to inventory prediction from transient diesel engine as base for NO_x control, *Canadian Journal of Chemical Engineering* 78(2): 408–417.

NBB (National Biodiesel Board). 2000. *Accessed 4/28, 2008*. Available from internet: <http://www.biodieselgear.com/documentation/NBB_Biodiesel_brochure.pdf>.

Rilett, L.; Zietsman, J.; Kim, S.; Tydlacka, J. 2004. *Portable Emissions Measurement Systems: Lessons Learned*. Washington DC: TRB.

Rouphail, N.; Frey, H.; Colyar, J.; Unal, A. 2001. Vehicle Emissions and Traffic Measures: Exploratory Analysis of Field Observations at Signalized Arterials. In *Proceedings of the 80th Annual Meeting of the Transportation Research Board Conference.*

Tsoukalas, L.; Uhrig, R. 1997. *Fuzzy and neural approaches in engineering*. New York: Wiley. 600 p.

Unal, A.; Frey, H.; Rouphail, N. 2004. Quantification of highway vehicle emissions hot spots based upon on-board measurements, *Journal of the Air & Waste Management Association* 54(2): 130-40.

Unal, A.; Rouphail, N.; Frey, H. 2003. *Effect of arterial signalization and level of service on measured vehicle emissions*. Washington DC:Transportation Research Record 1842, In: National Academy of Sciences. 47–56.

Vijayan, A.; Kumar, A.; Abraham, M. 2008. Experimental analysis of vehicle operation parameters affecting emission behavior of public transport buses operating on alternative diesel fuels, In *Proceedings of the 87th Transportation Research Board Annual Meeting Conference*.

Vojtisek-Lom, M.; Wilson, P.; 2003. *Real-World, in-use Exhaust Emissions from Front-End Loaders Equipped with Continuously Regenerating Diesel Particulate Filters (DPF) at the World Trade Center Site*. Clean Air Technologies Project Report to MJ Bradley and Associates.

Yuanwang, D.; Meilin, Z.; Dong, X.; Xiaobei, C. 2002. An analysis for effect of cetane number on exhaust different from the existing tests cycles, *Fuel* 81(15): 1963–1970.

PROCENA EMISIJE IZDUVNIH GASOVA GRADSKIH AUTOBUSA SA POGONOM NA BIODIZEL UPOTREBOM VEŠTAČKIH NEURONSKIH MREŽA

Abhisek Mudgal, Kasthurirangan Gopalakrishnan, Shauna Hallmark

Sažetak: Porast potražnje za transportom tereta i automobliskim prevozom doveo je do povećanja zagađenja vazduha, emisije gasova staklne bašte (posebno CO_2) i problema vezanih za snabdevanje gorivom. Prikazano istraživanje je bazirano na upotrebi biodizela koji kako je pokazano stvara manje emisije štetnih gasova. U radu je razvijen sistem za prikupljanje podataka primenom prenosnog sistema merenja emisija na osnovu koga su prikupljeni podaci o emisijama (NO_x, HC, CO, CO_2 i PM_{10}) gradskih autobusa sa pogonom na biodizel. Svaka od razmatranih emisija razvijena je i testirana na bazi linearnih modela koji su usled varijacija u emisijama doveli do niskih vrednosti R^2. Iz tog razloga, na dobijene podatke primenjene su veštačke neuronske mreže zbog prednosti nad statističkim modelima u pogledu tretiranja nelinearnosti i određenih pretpostavki u vezi ulaznih podataka. Optimalna struktura veštačke neuronske mreže dobijena je na osnovu analize osetljivosti ulaznih parametara, broja skrivenih slojeva, brzine učenja i algoritma učenja. Detaljnom analizom je ustanovljeno da optimalnu strukturu čini 50 skrivenih čvorova, dva skrivena sloja za NO_x, HC, CO i PM i jedan skriveni sloj za CO_2. Procena emisija je izvršena primenom najadekvatnijeg modela veštačkih neuronskih mreža za svaku emisiju pojedinačno. Na dijagramima je izvršeno poređenje dobijenih u odnosu na procenjene vrednosti, pri čemu su za R^2 dobijene vrednosti od 0.96, 0.94, 0.82, 0.98 i 0.78 za emisije NO_x, HC, CO, CO_2 i PM, respektivno.

Ključne reči: veštačke neuronske mreže, back-propagation, biodizel, emisije izduvnih gasova, vozila.