ARTIFICIAL NEURAL NETWORK (ANN) – AN ALTERNATIVE NUMERICAL MODELING TECHNIQUE TO EVALUATE COMPLIANCE TO PERFORMANCE BASED STANDARDS

Saravanan Muthiah and Bohdan T. Kulakowski

Pennsylvania Transportation Institute, The Pennsylvania State University
University Park, PA 16802, USA

Abstract

Performance Based Standards (PBS) aim to provide a viable means of reducing the existing gap between intended vehicle design and actual vehicle performance. Under PBS, numerical modeling is being offered as an option since actual field tests required can be cumbersome and expensive. Historically, modeling methods have relied on using dynamics software packages to predict vehicle behavior. This paper looks at the use of Artificial Neural Network (ANN) as an alternative to traditional computer modeling.

The structure and methodology of an ANN is based on the functioning of human brain. ANN consists of many interconnected but “artificial” neurons which weight, sum and threshold incoming signals to produce an output. ANN offers some distinct advantages such as (1) elimination of the need to make any pre-assumptions on the form of the functional relationship between inputs and outputs, (2) ability to serve as a universal function approximator, and (3) ease of implementation and robustness to data noise.

In this study, ANN is used to predict transit bus fuel efficiency on three commonly used driving cycles – Central Business District (CBD), Arterial (ART) and Commuter (COM) – in the United States. The data used in the study are from the Bus Testing Program at The Pennsylvania Transportation Institute and includes information on over 100 new diesel bus models dating from 1990 to 2004. The inputs to the neural network are bus design parameters that are easy to obtain. From an initial set of bus design parameters, a much smaller subset is chosen based on an input selection methodology that uses correlation. Further reduction in the number of inputs is accomplished by the ANN using input pruning. Results show that ANN offers promise as an alternative modeling tool.

The authors would like to note that fuel efficiency is not amongst the performance measures presently under consideration for implementation of PBS. However, as the modeling methodology (incorporating an ANN) presented in this paper is very general in nature, it seems reasonable to expect that one should be able to successfully use it with other performance measures as well.

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1. INTRODUCTION

Heavy vehicles form an integral part of a modern economy. However, as with any technological means, their use is not devoid of any negative impact. Historically, prescriptive or Design Based Standards (DBS), that place limits on size and weight, have been employed to minimize this negative impact. The reasons for the same are ease of regulation, lack of complete understanding of the relationship between vehicle performance and design parameters, difficulty in performance evaluation and non-uniformity in conditions of vehicle use. In the last two decades, it has been widely recognized that this approach leads to a situation wherein there are wide discrepancies between the actual road performance of the vehicle and its intended design.

The concept of alternatively employing Performance Based Standards (PBS) was given an impetus by the 1986 report of the Road Transport Association of Canada (RTAC). The benefits of employing PBS approach to the regulation of heavy vehicles include better matching between the capabilities of the vehicle and road systems, stimulation of technological/design advances, consistency in assessment of application techniques and specific use vehicles, and improvements in road safety, traffic operations and infrastructure management (Edgar et al., 2002). Effective PBS can only be framed if we have a good knowledge of the complex relationships that exist between vehicle design parameters controlled by regulations and the actual performance of a heavy vehicle. Despite a great deal of advancement in this area, there is still a need to have a mathematical representation of the relationships.

At present, it is expected that PBS regulations will offer both field tests and numerical modeling as options to measure compliance. Since tests can be expensive and time consuming to conduct, validated numerical models offer an exciting alternative. Traditional modeling methods involve usage of commercial software packages to predict vehicle behavior. In this paper, the use of Artificial Neural Network (ANN) as a viable modeling alternative is investigated. ANN is used to study the relationship between the design parameters of a heavy vehicle (transit bus) and a sample performance feature, namely fuel efficiency on Central Business District (CBD), Arterial (ART) and Commuter (COM) cycles. The authors would like to note that fuel efficiency is not amongst the performance measures presently under consideration for implementation of PBS. However, it was chosen in this study for two reasons:

a) Fuel efficiency stands out as one of the most researched performance measures in literature in the last few decades. Hence enough background information on the effect of various vehicle design inputs is already available. This makes it relatively straight forward to evaluate the performance of ANN as a new modeling tool by comparing its results with what is already known.

b) Fuel efficiency is known to be influenced by a lot of input parameters in a complex manner. Hence if a modeling tool is able to predict fuel efficiency and bring forth its relationships with various inputs satisfactorily, it can reasonably be expected to perform well with other performance measures as well.

2. FUNCTIONING OF AN ARTIFICIAL NEURAL NETWORK

The motivation for artificial neural network (ANN) is the complex but efficient functioning of the human brain and its ability to learn from examples. Human brain consists of a large number (10^{11}) of highly interconnected elements called neurons. It is astonishing to note that even though biological neurons are very slow (10^{-3} s) when compared to electrical circuits (10^{-9} s), the brain is still able to perform many tasks much faster than a computer due to its massive parallel structure! Each biological neuron has 3 principal components: cell body, axon and dendrites as shown in Figure 1 (Hagan et al., 2002). The point of contact between an axon of one neuron and the dendrite of another neuron is called synapse. The arrangement of neurons and the strength of synapses determine the functioning of a biological neural network.

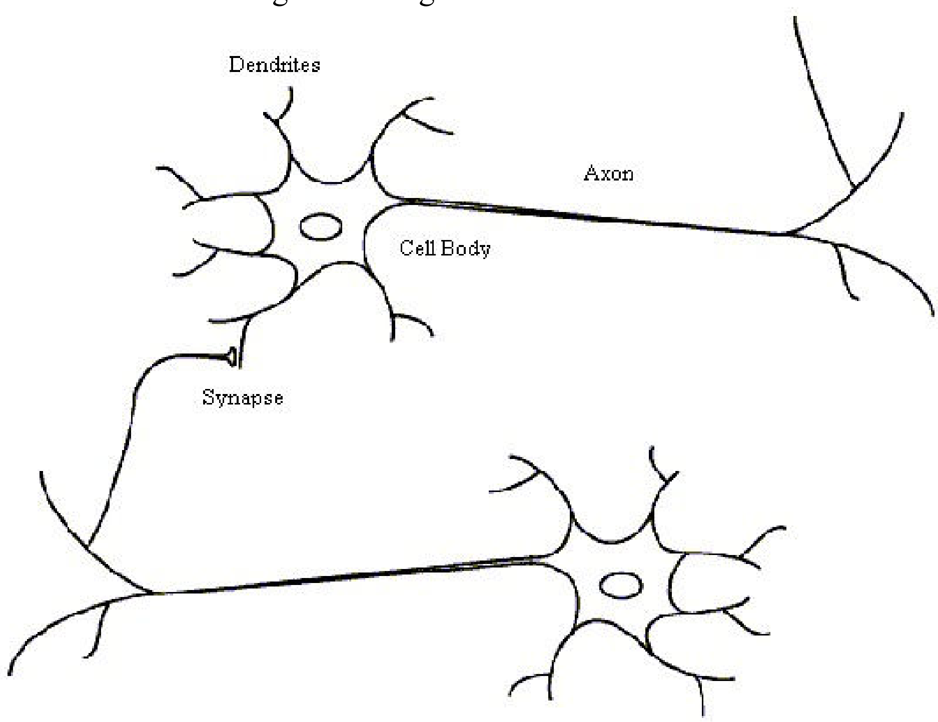

Figure 1. Schematic drawing of biological neurons.

ANN is not as complex as a biological neural network in structure but still bears two close similarities, namely (a) building blocks of both networks are simple computational devices and (b) both are highly interconnected structures with the strength of the interconnections determining how a network functions. The "artificial" neurons of an ANN weight, sum and threshold incoming signals to produce a net input. This is further modified by a transfer function to get the neuron output. An ANN can have many layers of neurons. Information is stored within the strengths of the interconnections or weights and the thresholds/biases. Knowledge is acquired through a learning process (training algorithm) that modifies the synaptic weights of the network in an orderly fashion to attain a desired objective. During learning, the network is presented pairs of input/output data and an attempt is made to search for a global minimum on the performance function (usually mean square error) surface over the space of the network parameters or weight values. Once trained, the ANN can then be used to predict outputs from unseen inputs. Figure 2 depicts the basic structure of a feed forward back-propagation network which is the most commonly used form of ANN (Hagan et al., 2002). The name is derived from the fact that the input propagates forward while the errors (difference between target outputs and ANN outputs) propagate backwards from the output layer to the input layer.

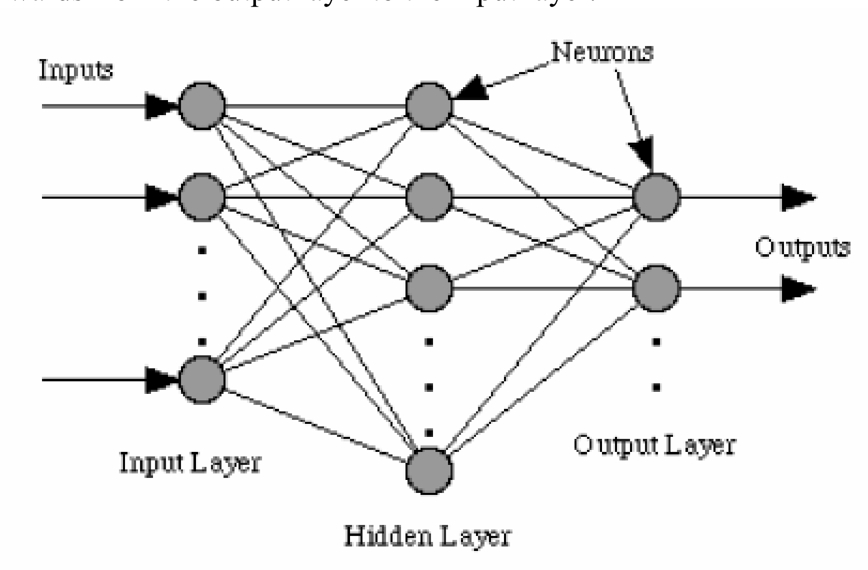

Figure 2. General structure of a feed-forward ANN.

The advantages of ANN particularly relevant to modeling complex nonlinear relationships are:

1) A feed-forward ANN can serve as a universal function approximator.
2) No assumptions need to be made on the form of the model/relationship.
3) ANN is robust to noise and easy to implement.
4) ANN can be parallelized where rapid computation is critical.

These advantages have enabled the ANN to be successfully employed by researchers over the past 20 years in solving a wide variety of engineering problems.

3. DATA COLLECTION AND PRE-PROCESSING

Since 1989, the Bus Testing Program at The Pennsylvania Transportation Institute (PTI) has been testing buses for fuel efficiency on Central Business District (CBD), Arterial (ART) and Commuter (COM) cycles. The speed versus time traces for these cycles are shown in Figures 3 to 5 (DieselNet, 2005).

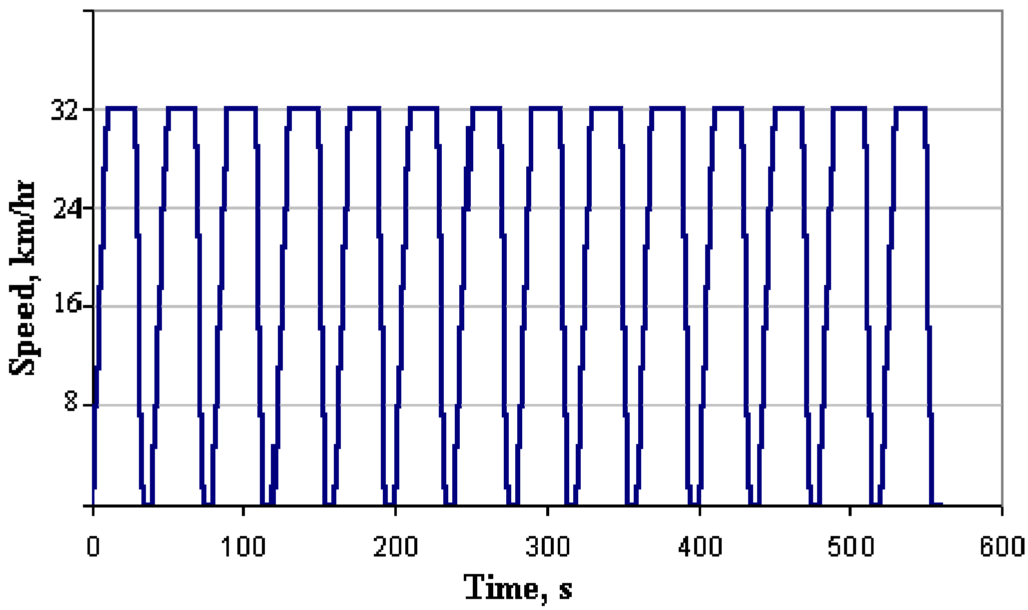

Figure 3. Central Business District cycle.

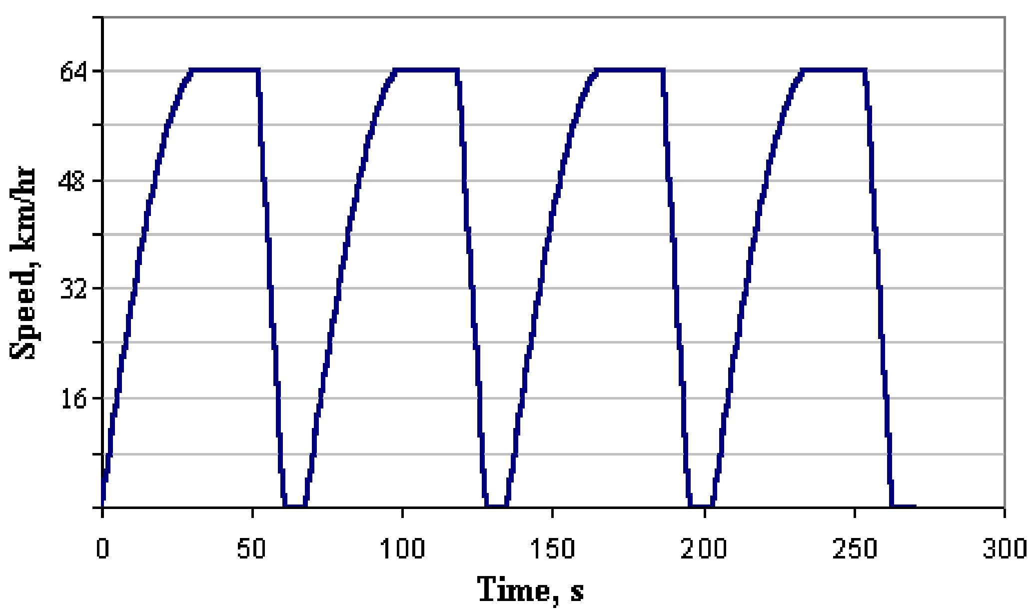

Figure 4. Arterial cycle.

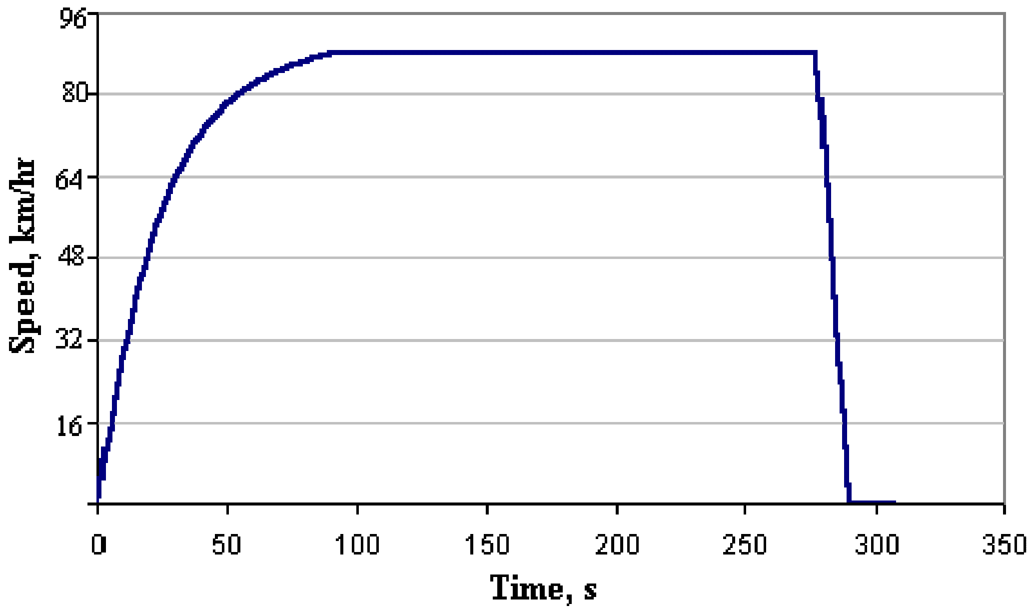

Figure 5. Commuter cycle.

It should be noted that, at PTI, the Commuter cycle is done at a maximum speed of 64 km/hr due to track limitations.

In this study, fuel efficiency data for a total of 111 diesel-powered two-axle transit buses from year 1990 to 2004 have been used for analysis. Data were obtained for a total of 21 inputs variables and 3 outputs. These are listed in Tables 1 and 2. The input variable 'Weight to Power Ratio' is a calculated ratio of 'Seated Load Weight-Total' and 'Engine Power'. All data were normalized before use in the ANN simulation model. Normalization of inputs, i.e. centering by subtracting the mean value and dividing by standard deviation is a standard procedure used in neural networks to avoid an ill-conditioned error surface arising out of a vast difference in magnitude between inputs.

The first step in any function mapping process is the proper selection of inputs. This is required in an attempt to decrease the computation effort, increase model accuracy and make the final model less complex. In this study, a two-stage input selection method was used. In the first stage, the correlation matrix was used to select those inputs that are least correlated with other inputs. The second stage is a part of the ANN model itself. The primary idea behind using correlation was to select those inputs whose behaviors could not be predicted by inclusion of other inputs. A cutoff value magnitude of 0.7 was chosen for the correlation coefficient since a value of 0.7 would mean that less than 50 % of the variation in one variable can be explained by the other. Using this method, the number of inputs was reduced from 21 to 9. The nine inputs (design parameters of a diesel transit bus) that were selected include width, height, wheelbase, rear overhang, ground clearance, total seated loaded weight (SLW), axle ratio, engine power and engine displacement. The main drawback of this approach of using correlation coefficients for selection of inputs is that the correlation coefficient works best only if the relationship between two variables is linear.

Table 1. List of input variables.

Sr. No.	Input	Min.	Max.	Mean	Std. Dev.
1	Length (m)	6.17	12.54	9.99	1.75
2	Width (m)	2.16	2.69	2.49	0.08
3	Height (m)	2.56	3.50	3.05	0.17
4	Wheel Base (m)	3.10	7.59	5.42	1.22
5	Front Overhang (m)	0.69	3.04	1.68	0.69
6	Rear Overhang (m)	0.762	5.54	2.86	0.52
7	Ground Clearance (m)	0.08	0.34	0.22	0.05
8	Curb Weight - Front (kN)	14.02	46.06	30.44	8.65
9	Curb Weight - Rear (kN)	19.58	89.89	53.46	20.88
10	Curb Weight - Total (kN)	34.26	128.87	83.90	27.79
11	Seated Load Weight - Front (kN)	14.15	57.32	35.64	11.60
12	Seated Load Weight - Rear (kN)	24.59	109.96	68.94	22.57
13	Seated Load Weight - Total (kN)	41.16	158.24	104.54	32.66
14	Gross Vehicle Weight - Front (kN)	14.02	64.97	39.73	14.69
15	Gross Vehicle Weight - Rear (kN)	24.59	123.84	75.76	25.62
16	Gross Vehicle Weight - Total (kN)	41.61	192.95	115.54	39.44
17	Axle Ratio	2.9	6.6	4.4	0.7
18	Engine Power (kW)	123.09	223.8	166	25.11
19	Engine Displacement (cm^3)	4250.8	10831.8	7211.5	1362.65
20	Wheel Diameter (m)	0.41	0.57	0.53	0.06
21	Weight to Power Ratio (kN/kW)	0.26	0.92	0.63	0.15

Table 2. List of output variables.

Sr. No.	Output	Min.	Max.	Mean	Std. Dev.
1	Fuel Efficiency – CBD, km/l	1.14	3.66	2.04	0.56
2	Fuel Efficiency – ART, km/l	1.32	4.24	2.25	0.58
3	Fuel Efficiency – COM, km/l	2.01	7.06	4.00	1.04

4. ANN SIMULATION MODEL

Feed-forward neural network with a single hidden layer can approximate any given continuous function on any compact set with arbitrary precision provided there are sufficient units in the hidden layer (Setiono et al., 2001). In this paper, a two layer (i.e. one hidden layer and one output layer) feed-forward backpropagation network was developed using Neural Network (NN) Toolbox available in MATLAB. Hyperbolic tangent sigmoid (tansig) activation function was used for the hidden layer while the output layer had just one neuron with linear activation function. ANN was trained using 'Trainscg' function that is based on scaled conjugate gradient algorithm. The selection was based on the fact that conjugate gradient algorithms perform well over a wide variety of problems, particularly for networks with a large number of weights (Mathworks, 2005).

One of the problems that can occur during neural network training is over-fitting. It refers to a case where the error on the training set is driven to a very small value, but when new data is presented to the network the error is large. The problem of over-fitting can be mitigated to a great extent by employing the following methods:

a) Using a network that is just large enough to provide an adequate fit
b) Regularization
c) Early stopping of the training process

In this study, all three methods were employed simultaneously. The inputs and the output were first divided randomly into 3 subsets: the training set (89 buses ~ 80%), the cross-validation set (11 buses ~ 10%) and the test set (11 buses ~10%). The error on the validation set was then monitored during the training process. The validation error normally decreases during the initial phase of training, as does the training set error. However, when the network begins to over fit the data, the error on the validation set typically begins to rise. Training was stopped when the validation error increased for a pre-specified number of iterations.

For regularization, the performance function given by Setiono et al. was used (Setiono et al., 2002). Using the training data set, a network with H hidden units was trained, so as to minimize the performance function $E(\mathbf{w},\mathbf{v})$, which is the sum of squared errors, SSE, augmented with a penalty term $\phi(\mathbf{w},\mathbf{v})$

$$E(\mathbf{w},\mathbf{v}) = SSE + \phi(\boldsymbol{w},\boldsymbol{v}) \qquad \textbf{(1)}$$

$$\phi(\mathrm{w},\mathrm{v}) = \varepsilon_1\left(\sum_{i=1}^{H}\sum_{j=1}^{N}\frac{\beta w_{ij}^2}{1+\beta w_{ij}^2} + \sum_{i=1}^{H}\frac{\beta v_i^2}{1+\beta v_i^2}\right) + \left(\sum_{i=1}^{H}\sum_{j=1}^{N} w_{ij}^2 + \sum_{i=1}^{H} v_i^2\right) \qquad \textbf{(2)}$$

where ε_1, ε_2, β are positive penalty parameters, w_{ij} is the weight of the connection from input unit *j* to hidden unit *i* and v_i is the weight of the connection from the hidden unit *i* to the output unit. As per Setiono et al., the penalty term $\phi(\mathbf{w},\mathbf{v})$ when minimized, pushes the weight values toward the origin of the weight space, and in practice results in many final weights taking values near or at zero. This enables removal of such network connections from the network without sacrificing network accuracy.

The network was initially trained with a high number of neurons in the hidden layer. Once the network was trained, its hidden neurons and inputs were inspected as candidates for possible elimination by a network pruning algorithm. This network pruning algorithm is based on N2PFA (Neural Network Pruning for Function Approximation) algorithm proposed by Setiono et al. N2PFA removes redundant and irrelevant units by computing the mean absolute error of the network's prediction.

5. RESULTS AND DISCUSSION

A neural network with 5 hidden neurons and the 9 inputs selected by the correlation method was first trained with Trainscg training algorithm. The trained network was then pruned. Simulation was repeated at least 10 times to enhance the chances of ANN finding the global optimum. Finally, the pruned network with the least mean square error on the test set of 11 buses was selected as the optimal solution. Table 3 shows the results of the 10 simulation runs done for fuel efficiency on the CBD cycle. In the table, MSE refers to mean square error and HLN refers to the number of neurons in the hidden layer. 'X' is used to indicate the inputs that were pruned by N2PFA algorithm.

Table 3. Simulation results for fuel efficiency on CBD cycle.

No.	MSE $(km/l)^2$	HLN	Width	Height	Wheel Base	Rear Over.	Ground Clear.	SLW Total	Axle Ratio	Power	Engine Disp.
1	0.078	2									
2	0.051	4									
3	0.055	2	X		X	X	X		X	X	X
4	0.053	4					X				
5	0.073	4			X		X				X
6	0.037	2	X				X				X
7	0.063	4	X		X	X	X		X	X	X
8	0.062	4	X		X	X	X		X	X	X
9	0.059	3		X	X	X	X				
10	0.051	2	X		X		X		X		

Table 3 clearly brings out the capabilities of neural network as a viable means of modeling vehicle behavior. It should be noted that the inputs that are consistently pruned such as ground clearance, wheel base, vehicle width, engine displacement and rear overhang are expected to have marginal effects on fuel efficiency on CBD. ANN did not reject seated load weight in any of the simulation runs. This corroborates well with previous studies on fuel efficiency of buses (Kulakowski et al., 2004). As per Zub, nearly 43 % of the energy is spent on overcoming the effect of vehicle weight (inertia) in a CBD cycle (Zub, 1984).

The characteristics of the optimal ANN solutions for the 3 driving cycles obtained after pruning the trained networks are given in Table 4. ART and COM are cycles with very few stops. Hence pruning of variables such as axle ratio and wheelbase appears reasonable.

Table 4. Characteristics of pruned neural network.

	Properties of Pruned Network			
Fuel Efficiency	Hidden Neurons	Inputs	Pruned Input Variables	Mean Square Error $(km/l)^2$
CBD	2	6	Width Ground Clearance Engine Displacement	0.037
ART	2	7	Rear Overhang Axle Ratio	0.055
COM	3	8	Wheelbase	0.030

Figures 6 to 8 show the comparison plots between the actual fuel efficiency and the fuel efficiency predicted by the ANN for the eleven buses in the test set. It is clear from the plots that ANN is able to predict fuel efficiencies with a good level of accuracy.

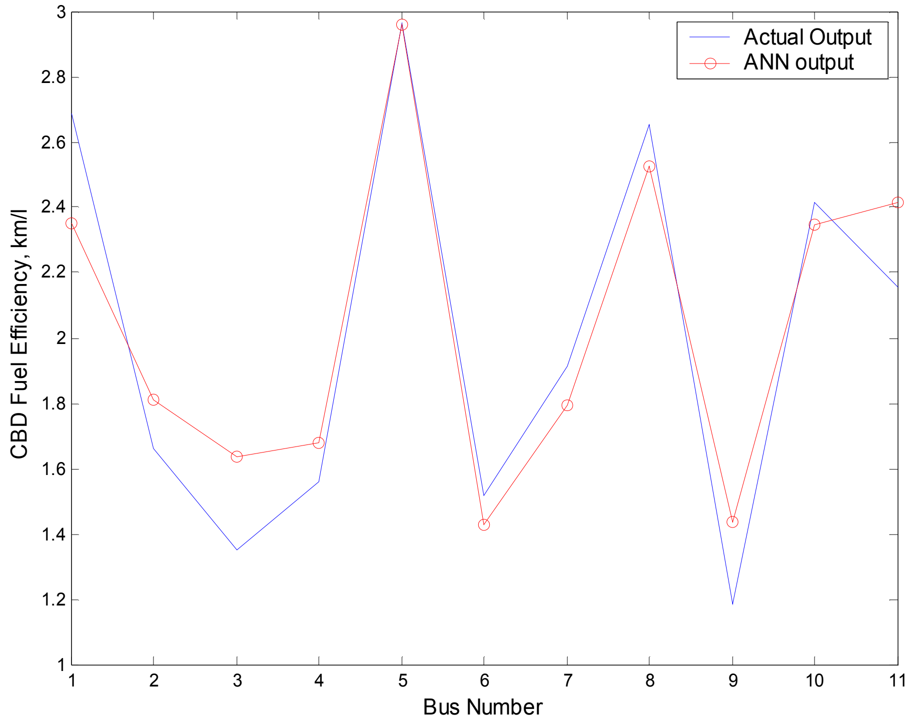

Figure 6. Comparison plot for CBD fuel efficiency on test set.

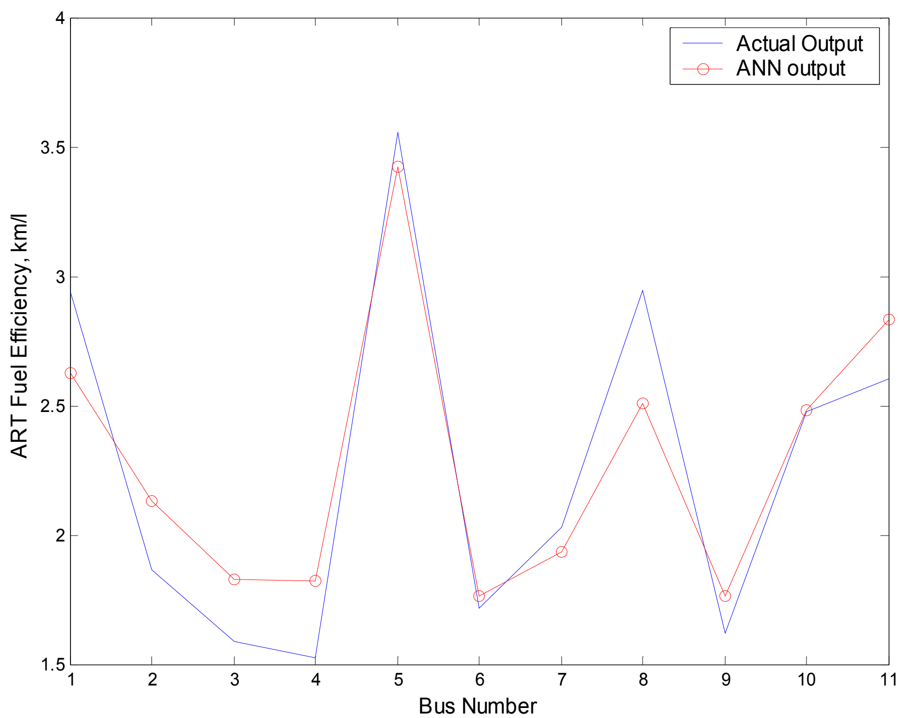

Figure 7. Comparison plot for ART fuel efficiency on test set.

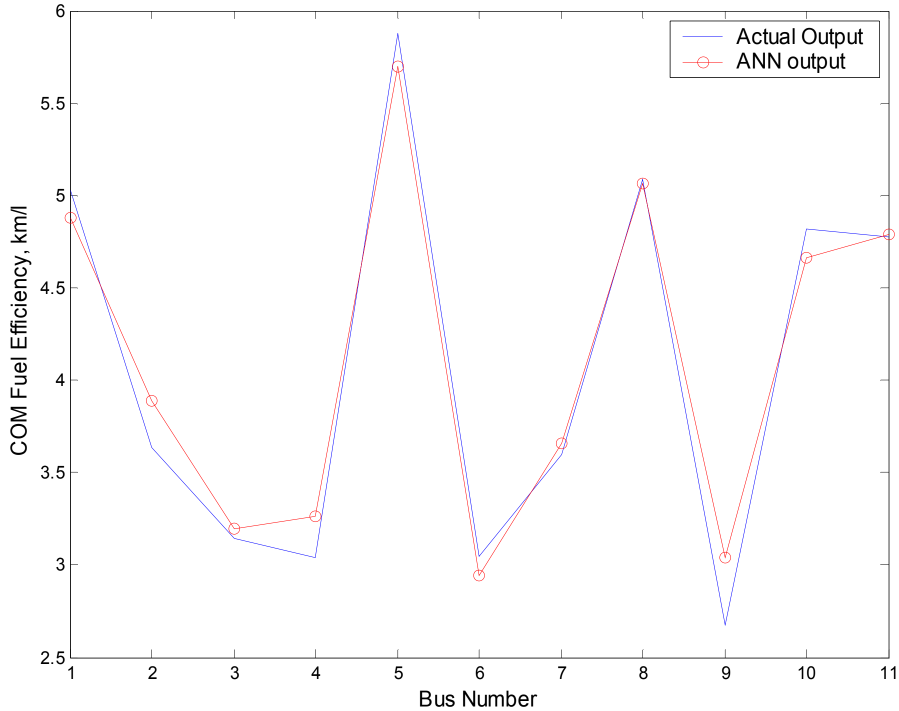

Figure 8. Comparison plot for COM fuel efficiency on test set.

6. CONCLUSIONS

Implementation of performance based standards (PBS) calls for an in-depth understanding of the relationships between the design parameters of a heavy vehicle and its performance. In this study, the mathematical relationships between a reduced number of design parameters of a diesel transit bus and the fuel efficiencies on three driving cycles were investigated by use of neural networks. After initial training, the ANN was pruned to get a smaller network configuration that gives desired accuracy. Sample results indicate that use of neural networks as means for modeling vehicle behavior holds promise.

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