Expert Systems with Applications 39 (2012) 1883–1888

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

# A forecasting system for car fuel consumption using a radial basis function neural network

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ARTICLE INFO

*Keywords:*
Car fuel consumption
Artificial neural network
Radial basis function algorithm

ABSTRACT

A predictive system for car fuel consumption using a radial basis function (RBF) neural network is proposed in this paper. The proposed work consists of three parts: information acquisition, fuel consumption forecasting algorithm and performance evaluation. Although there are many factors affecting the fuel consumption of a car in a practical drive procedure, in the present system the relevant factors for fuel consumption are simply decided as make of car, engine style, weight of car, vehicle type and transmission system type which are used as input information for the neural network training and fuel consumption forecasting procedure. In fuel consumption forecasting, to verify the effect of the proposed RBF neural network predictive system, an artificial neural network with a back-propagation (BP) neural network is compared with an RBF neural network for car fuel consumption prediction. The prediction results demonstrated the proposed system using the neural network is effective and the performance is satisfactory in terms of fuel consumption prediction.



## 1. Introduction

Carbon dioxide ($CO_2$) has significantly increased over recent centuries with atmospheric concentrations rising since human times because of increased fossil fuel emissions. These unprecedented emissions of $CO_2$, in conjunction with other greenhouse gases, have contributed to increased global temperatures in the 20th century and may also be associated with changes in climatic extremes such as increases in the number of extreme warm days. Transport vehicle emissions are known to be the fastest rising and a major source of anthropogenic $CO_2$ emissions (Papagiannaki & Diakoulaki, 2009). The trend of $CO_2$ emission from automobile travel rises every year (Kwon, 2005; Paravantis & Georgakellos, 2007). Thus, and so far, environmental issues demand cars with high fuel efficiency and low emissions. Also the dependency on oil and rising fuel prices trigger the interest of car manufacturers to produce vehicles with low fuel consumption. Oil depletion is inevitable and is rapidly approaching. The trend of fossil fuel use is increasing year by year and is one of the reasons for the fossil fuel crisis (Asche, Gjolberg, & Volker, 2003). In the wake of the 1973 oil crisis and the Kyoto Protocol, many countries require a certain reduction in the combustion of fossil fuels (Holtsmarka & Mæstad, 2002). Carbon emissions will increase in many countries if no new policies are carried out (Viguiera, Babikera, & Reilly, 2003). For the above reasons, humans began to pay attention the problem of $CO_2$ emissions from vehicles.

Many countries instituted fuel economy regulations under different test modes. For example, Japan instituted fuel economy regulations for improving fuel consumption (Clerides & Zachariadis, 2008; Plotkin, 2001). All gasoline-powered vehicles in Japan must conform to the fuel economy regulations or else the vehicle cannot be sold. In Taiwan, the government instituted fuel economy regulations stating all gasoline vehicles in Taiwan must conform to the fuel economy regulations or they cannot be sold. Eventually, the United States of America (USA), instituted fuel economy regulations for gasoline-powered vehicles. If the vehicle does not conform to the fuel economy regulations, the USA government will levy a tax on car manufacturers, also known as the gas-guzzler tax. The corporate average fuel economy calculation (CAFE), CAFE standard for new cars and light trucks sold in the USA was established by the USA energy policy and conservation act of 1975. All car manufacturers must comply with the CAFE standards of 27.5 mpg (1 mpg = 0.425 km/l) for passenger cars and 22.5 mpg for light trucks, equaling the actual fuel-economy standards in effect in 2008. The trend of CAFE standards goes up year-by-year (Bezdek & Wendling, 2005), so the car manufacturer's technological development is also upgrading year-by-year (Sprei, Karlsson, & Holmberg, 2008). Car manufacturers must comply with the CAFE standard or else the USA government will levy a tax of $5.50 per vehicle on the annual output from the car manufacturers for the types not meeting the CAFE standard of 0.1 mpg (Rubin & Leiby, 2000). Various countries have established a large number

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doi:10.1016/j.eswa.2011.07.139

of laws and regulations with the sole purpose of reducing greenhouse gas emissions.

From the consumer's point of view, fuel price is very important. The consumers will care more about cars' fuel consumption when buying new cars. Low fuel consumption vehicles are popular compared with high fuel consumption vehicles. The proposed system aims to provide consumers and car manufacturers with accurate and convenient fuel consumption figures for a new car. Every new car must have an emission test so it does not contravene the statutes and regulations of its country. In Taiwan and Japan, if a new car does not pass the emission test, it will be rejected and not be approved for sale. That new car's manufacturer must redesign it until it passes the emission test. In the USA, if a new model does not pass the emission test, that new car can still be sold but the USA government will levy a heavy tax on it. Therefore, the world's car manufacturers need to know a new car's emission test results and fuel consumption numbers ahead of time. In this way, the world's car manufacturers can forecast the operating costs of their factories.

For the above-mentioned reasons, the fuel consumption of cars has become one of the most important issues in car design. Earlier papers mentioned the BP neural network takes a long training time in a predictive system (Wu, Hsu, & Chen, 2009). The RBF neural network can rapidly converge, is able to automatically determine the number of neurons in the hidden layer, and can avoid complicated and prolix calculations. Thus, the time required for training can be much faster than that of the BP network (Wu, Wang, Chiang, & Bai, 2009). Yu et al. used the RBF neural network in designing a forecasting system and attaining good predictive system performance (Yu, Lai, & Wang, 2008). In the present study, the technique of a predictive system for cars fuel consumption using the RBF neural network will be described. The information and data of car fuel consumption were obtained from an auto energy website in Taiwan. The information was also used to obtain the relationship between the impact factors and the fuel consumption. In the next paragraph, this study will pick some important impact factors for the car fuel consumption system. The prediction of fuel consumption for various cars has been studied by the RBF neural network to increase accuracy and reduce forecasting errors. The RBF network is the most suitable for a complex structure because the adaptive learning capability can approximate the non-linear system. The following sections will describe the modeling of cars' fuel consumption and the principle of the RBF network in the proposed system.

## 2. Characteristic and modeling of car fuel consumption

The prediction of car fuel consumption system has three parts: databank of car fuel consumption, fuel consumption forecasting algorithm and performance analysis. In the data acquisition, the information and data of car fuel consumption is acquired from an auto energy website in Taiwan. This system picks five important impact factors for car fuel consumption including the make of car, engine styles, weight of car, types of vehicle and transmission types, which are used as input patterns in the neural network training and fuel consumption forecasting procedure.

For the above-mentioned five important impact factors for car fuel consumption, each has its own characteristics affect this prediction. For the make of a car, all car manufacturers employ different science and technology in manufacturing their vehicles (i.e., variable vale timing lift, intelligent and fuel stratified injection) (Bezdek & Wendling, 2005). Therefore, the impact factor leads to different fuel consumption. Two researchers have provided useful information in designating that the displacement has more fuel consumption when looking at engine size (Ross & An, 1993). That impact factor is directly proportional to fuel consumption and engine displacement. The weight of cars and transmission types affect the physical characteristics that directly influence fuel consumption (Tolouei & Titheridge, 2009). For the weight of the car, a greater weight indicates higher engine loads. This can affect engine loads for fuel consumption (Saboohi & Farzaneh, 2009). A diagram illustrating a car sitting on a gradient is shown in Fig. 1. The tractive force $F_T$ required at the interface between the tires of the driven wheels and the road is expressed with the equation (Hucho, 1998):

$$F_T = D + R + m\frac{dV}{dt} + mg\sin\alpha \quad (1)$$

where $D$ is the aerodynamic drag, $R$ is the tire rolling resistance, $m$ is the vehicle's mass, $V$ is road speed, $g$ is the acceleration of gravity, and $\alpha$ is the inclination angle of the road. The $m\frac{dV}{dt}$ is termed acceleration resistance and $mg \cdot \sin\alpha$ is climbing resistance. All resistances will reduce the power of the engine production.

The weight of the car, acting vertically downwards, can be determined by two components: $B$ parallel to the slope and $U$ perpendicular to the slope. To prevent the car from rolling downwards, a force equal and opposite to $B$ has to be applied by the driven wheels at their contact with the road surface. If the car is to be impelled up the slope, not only that force but also an additional force must be applied, to neutralize the aerodynamic and rolling resistances as well as force $B$. It follows the gradient resistance $B$ is relying solely on the steepness of the slope and is unaffected by the speed of the car, provided it is constant, either up or down the gradient. Note, however, during acceleration another force acting, in effect, through the center of gravity of the car is introduced.

For the weight of car and vehicle types, the two impact factors having to be overcome are rolling resistance and air resistance (Crouse & Anglin, 1993). The rolling resistance $R$ of a vehicle depends on its mass and a coefficient of rolling resistance, and is expressed by this equation (Hucho, 1998):

$$R = f_r \cdot G \quad (2)$$

where $f_r$ is coefficient of rolling resistance, $G = mg$ is the force that vehicle exerts on the ground, and $m$ is the vehicle's mass. Rolling resistance is attributable to the exhaustion of energy by the continuous impact of the tire on the road. When a loaded wheel and tire is coerced to roll in a given direction, the tire body at the ground interface will be deflected due to a combination of the perpendicular load and the forward rolling effect on the tire body. The perpendicular load tends to flatten the tire's circular profile at ground level, whereas the forward rolling movement of the wheel will compress and spread the leading contact edge and wall in the area of the tread. Simultaneously, the trailing edge will be apt to reduce its

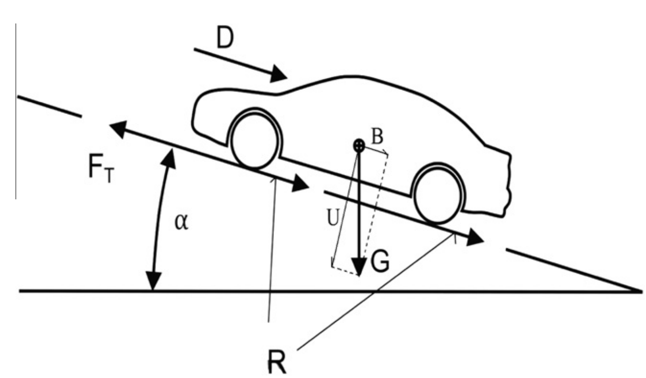


**Fig. 1.** Definitions of vehicle weight $G$, tractive force $F_T$, tire rolling resistance $R$, aerodynamic drag $D$, and road grade $\alpha$.

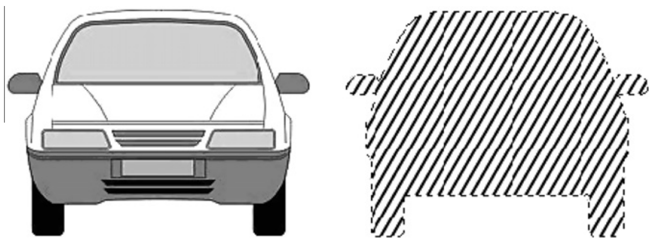

Fig. 2. Frontal area of vehicle.

contact pressure and expand as it is progressively freed from the ground reaction. The consequences of the uninterrupted distortion and recovery of the tire carcass at the ground level means energy is being used in rolling the tire over the ground and it is not all returned as strain energy as the tire returns to its original shape. Note, this has nothing to do with the tractive force being applied to the wheel to propel it forward, which is directly proportional to rolling resistance and the vehicle's mass.

The fuel consumption is also affected by the vehicle's frontal area (Sprei et al., 2008). A diagram representing a vehicle's frontal area is shown in Fig. 2. In front of the vehicles, the shadow is an orthographic projection area frontal area. Aerodynamic drag depends on the size of a vehicle which is characterized by a vehicle's frontal area. The aerodynamic drag $D$ can be expressed as (Hucho, 1998):

$$D = \frac{1}{2}\rho C_d A V^2 \tag{3}$$

where $\rho$ is the air density, $C_d$ is the coefficient of the aerodynamic drag, $A$ is the vehicle's frontal area and the square of the road speed $V$. Air offers a resistance to the passage of bodies through it, as does water or any other fluid. The extent of this resistance directly depends on the shape and frontal area of the body exposed to the fluid it is passing through, and to the square of its velocity. A mathematical formula representing air resistance against the speed of a vehicle is shown in Eq. (3). It can be seen doubling the speed and quadrupling the air drag. The total resistance to the motion of a vehicle is the sum of the above three resistances: the rolling resistance and gradient resistance depend on the weight of the vehicle; the aerodynamic resistance depends on the frontal area and vehicle's velocity. All the resistances directly affect the vehicle's fuel consumption. Therefore, all five impact factors can supply efficacious parameters to train the BP network. The BP network also can accurately forecast the fuel consumption of cars under varied input conditions.

## 3. Design of the predictive system using the neural network

The neural network is created by humans and is known as a man-made neural network. The man-made neural network imitates the biological neural network. The biological neural network is composed of many biological neurons and is shown in Fig. 3. Biological neurons are composed of nucleus, dendrites, axon and synapse. Dendrites receive various forms of external information or the energy to send signals to the nucleus. The nucleus adds various forms of external information or the energy up, and then uses non-linear conversion to generate a new pulse signal. The new pulse signal will be transmitted through the axon to the dendrites to become the next neuron input signal. A synaptic is a neural network memory on behalf of two neurons between the link intensity, known as weights. Thus, scientists imitate the biological neural system to form a man-made neural system. Fig. 4 presents the mathematical model of the man-made neurons. Link a large number of man-made neurons to form an artificial neural network (Hagan, Demuth, & Beale, 1996). In the system database, gasoline engines and home use vehicles are built in the proposed system. The information on fuel consumption is obtained from the FTP-75 (USA) consumption test method on the auto energy website. There are fourteen brands of automobile in this study. There are seven domestic brands and seven imported brands as Hyundai, Mitsubishi, Nissan, Mazda, Toyota, Suzuki, Ford, BMW, Lexus, Mercedes-Benz, Saab, Subaru, Volkswagen, and Volvo marks. The first seven brands are domestic and the remaining seven brands are imported vehicles in the Taiwan market. The auto energy website supplies the engine styles as well as the weight of the car. This provides conformity with the engine styles and weight of car in the predictive system. There are two parameters to use for the types of vehicle: sedan and station wagon; sport utility vehicle (SUV) and multi-purpose vehicle (MPV). The two kinds of parameters are distinguished because of the height of car. For the height of the car, sport utility vehicle (SUV) and multi purpose vehicle (MPV) are higher than sedans and station wagons. Therefore, higher vehicles have a larger frontal area influencing the fuel consumption of cars. The transmission types will consider three transmission types: automatic transmission (AT), continuous variable transmission (CVT) and manual transmission (MT).

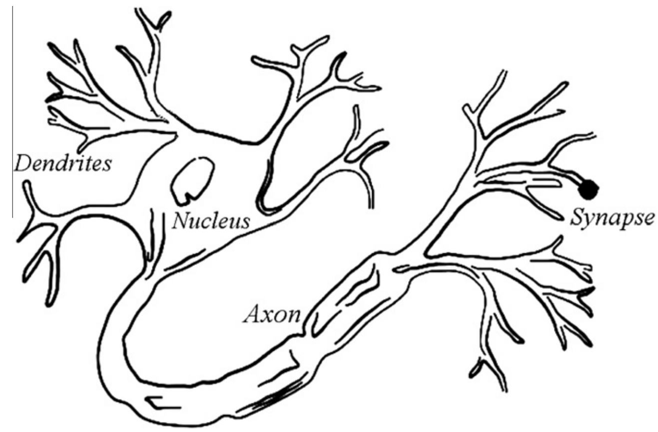


Fig. 3. Schematic of biological neuron.

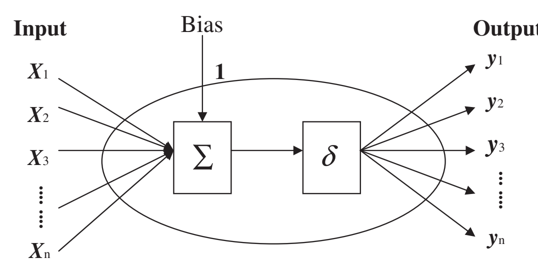


Fig. 4. Mathematic model of neural network neuron.

As well as settling on the above input parameters, the RBF network will settle on certain basic parameters. The hidden layer of the RBF network has several forms of radial basis activation functions. The transfer function of the hidden layer is generally a non-linear Gaussian function. The RBF network can rapidly converge and automatically determine the number of neurons in the hidden layer. The RBF network can avoid complicated and prolix calculations, and the time required for training can be much less than that of the BP network. In the present research model, the prediction of fuel consumption system finally obtained the accuracy percentage (AP), and can be defined as:

$$\mathrm{AP}\ (\%) = 1 - \left|\frac{T - A}{T}\right| \times 100\% \tag{4}$$

where $T$ means the target fuel consumption in the auto energy website and $A$ represents the fuel consumption from the proposed neural network system. The percentage of accuracy can easily represent the work efficiency for the prediction performance of cars' fuel consumption system.

## 4. Principle of the radial basis function network

In recent years, the applications of artificial neural networks have been extended, such as in forecasting (Afantitis et al., 2005; Yu et al., 2008). Broomhead and Lowe were the first to use radial basis functions (RBF) in designing neural networks (Broomhead & Lowe, 1988). Radial functions are a special class of functions. Their typical feature is the response decreases, or increases, monotonically with distance from a center point. It has been shown the RBF neural network can estimate any continuous function mapping with a reasonable level of accuracy.

### 4.1. RBF network design

Constructing the RBF neural network includes three different layers: input layer; hidden layer and output layer. Fig. 5 shows the RBF network design, which is similar to a traditional three-layer back-propagation neural network (BPNN) (Sarkar, Yegnanarayana, & Khemani, 1998). Both the two neural networks are feed-forward neural networks. First, the input signals ($x_i$) composing an input vector is sent to a hidden layer composed of RBF neural units. The second layer is the output layer, and the transfer functions of the neurons are linear units. Connections between the input and hidden layers have unit weights. The hidden layer of the RBF network has several forms of radial basis activation functions. The transfer function of the hidden layer is generally a non-linear Gaussian function which is shown in Fig. 6, and this equation defines it as:

$$a_j = a(\upsilon_j) = \exp\left(-\frac{\upsilon_j^2}{2\sigma_j^2}\right) \tag{5}$$

where $\sigma_j$ is the width of the $j$th neuron, $\upsilon_j$ is ordinarily selected by the Euclidean norm of the distance between the input vector and the neuron center calculated as follows:

$$\upsilon_j(X) = \|X - c_j\| = \sqrt{\sum_{i=1}^{m}(x_i - c_{i,j})}, \quad i = 1, 2, \ldots, m \tag{6}$$

where $X = [x_1, x_2, \ldots, x_m]^T$, $c_j$ is the center of the $j$th RBF unit, that is a vector whose dimension equals the number of inputs to the neuron $j$. The network output $Y$ is shaped by a linearly weighted sum of the number of basis functions in the hidden layer. The values for the output nodes can be defined as:

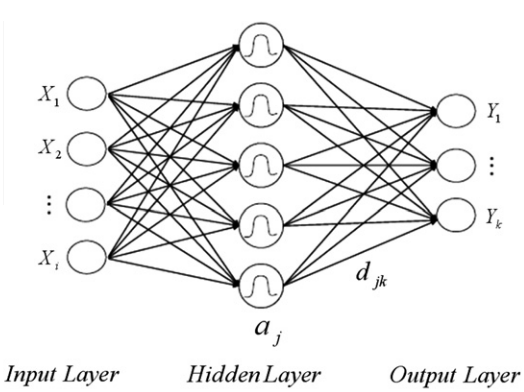


**Fig. 5.** RBF neural network structure.

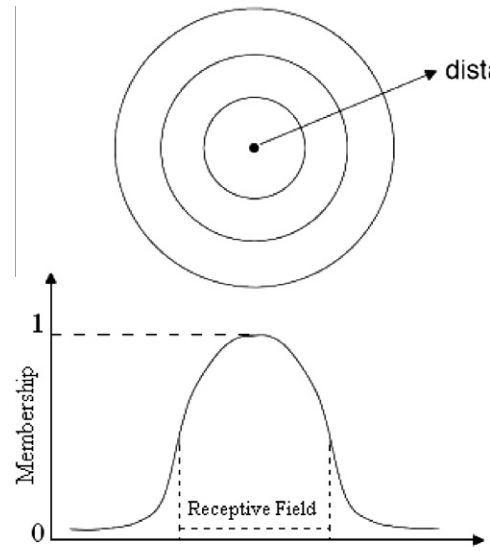


**Fig. 6.** Non-linear Gaussian transfer function.

$$y_k = \sum_{j=1}^{n} d_{jk} a_j \tag{7}$$

where $y_k$ the $k$th component of the $Y$, is the output of the $k$th node in the output layer, $d_{jk}$ is the weight from the $j$th hidden layer neuron to the $k$th output layer neuron, and $a_j$ is the output of the $j$th node in the hidden layer. With the described structure, the hidden layer consists of $j$ hidden nodes, which use nonlinear transformations to the input space. However, the output of the network is a linear combination of the basis functions computed by the hidden layer nodes.

### 4.2. Principles of RBF network training and testing

There are two operating modes named training and testing in the RBF neural network. Training the RBF network involves determining the number of RBF units, the width of RBF units and the output layer weight values. The criterion is to minimize the sum of squared errors ($SSE$) expressed as:

$$SSE = \frac{1}{2}\sum_{i=1}^{N}\sum_{k}\{t_k^i - y_k^i(X^i)\}^2 \tag{8}$$

where $t_k^i$ are the target values of the network output input vector $X^i$, and $N$ is the number of training samples. The number of hidden RBF units is an important factor affecting the predictive properties of the network. The number of hidden units is automatically calculated until the target $SSE$ value in this research is found. The neural network uses many RBF units to estimate the best predictive performance. RBF can rapidly converge and automatically determine the number of neurons in the hidden layer.

In the training procedure, a key point is determining the positions of the node centers of kernel functions in an RBF network, because the outputs of the kernel functions supply essential information to the network's generalization capabilities. There are many methods to find the centers of the RBF units in the hidden layer, and the $k$-means clustering is the most public algorithm. This $k$-means clustering was used in this work and is useful. This algorithm aims to find a set of $k$ cluster centers and minimize $E$. That

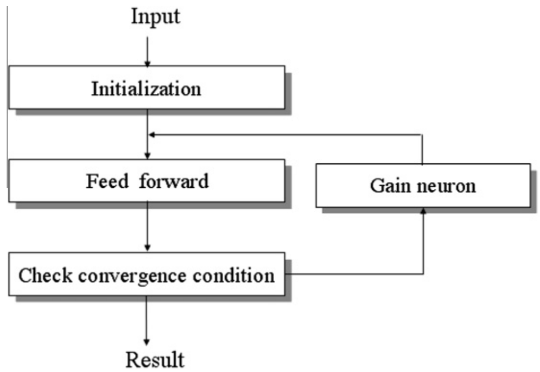


**Fig. 7.** Flow chart of the radial basis function neural network training procedure.

$E$ is the sum of the Euclidean distances between each cluster center $c_j$ and the training points apportioned to the special cluster:

$$E = \sum_{j=1}^{n} \sum_{i=1}^{N} B_{ji} \| c_j - x_i \| \tag{9}$$

where $N$ is the number of training data that will be presented to the network, and $B_{ji}$ is a $n \times N$ membership matrix.

The width of each RBF unit can be determined when the centers of the RBF units have been set up. The width of an RBF unit is selected as the root mean-square distance to the nearest $p$th RBF unit. For the $j$th unit, the width $\sigma_l$ is given by the following equation:

$$\sigma_j = \left( \frac{1}{p} \sum_{h=1}^{p} \| c_j - c_h \|^2 \right)^{\frac{1}{2}} \tag{10}$$

where $p$ is the value of the overlapping parameter for the nearest neighbor. The value $p$ can be determined using the S-fold cross-validation procedure, where $c_1, c_2, \ldots, c_p$ are the nearest node centers to the node $j$. When the center and width have been selected, the supervised learning algorithm is applied to train the weights between the hidden and the output layer nodes. The least mean squares (LMS) algorithm is used to train the output layer weights in the present work.

In summary, the construction of an RBF neural network can be divided into three basic steps.

- Compute the number $n$ of RBF units on the hidden layer.
- Compute the centers and the widths of the hidden layer units.
- Decide on the weights of the output layer.

The flowchart of the network training procedure is shown in Fig. 7. When the above steps are completed, then the RBF neural network is completely determined. On that occasion, the RBF neural network can easily calculate the results and be a useful tool for predicting cars' fuel consumption system.

**Table 1**
Percentage of prediction performance in seven domestic car manufacturers.

| | All data training | | Half data training | | One third data training | |
|---|---|---|---|---|---|---|
| | BP | RBF | BP | RBF | BP | RBF |
| Number of train/number of test | 124/124 | 124/124 | 62/124 | 62/124 | 42/124 | 42/124 |
| City mode (%) | 97.69 | 100 | 95.19 | 94.20 | 94.08 | 93.60 |
| Highway mode (%) | 97.85 | 100 | 95.74 | 94.72 | 94.24 | 94.12 |
| Average mode (%) | 98.14 | 100 | 96.06 | 94.75 | 94.54 | 94.20 |
| Time (s) | 10 | 0.02 | 10 | 0.02 | 10 | 0.02 |

## 5. Performance evaluation of prediction

In this section, the results and system efficiency for predicting cars' fuel consumption are described. Once the database is completed, the database is used for two artificial neural network (ANN) training and testing the prediction of fuel consumption systems. The database findings tested the prediction performance by 124 data (seven domestic car manufacturers) and 217 data (seven domestic and seven imported car manufacturers), respectively. When in the training stage, the database is divided into three parts, one database, half a database and one-third of a database. In the testing stage, database is tested from all. The database was constructed from seven domestic car manufacturers in Table 1, indicating the percentage of accuracy and prediction performance using different database quantities and ANN to predict a car fuel consumption system. Both ANNs for the car consumption system obtained a high quality prediction performance. In Table 1, these results of training and testing from all databases showed the RBF network was better and faster than the BP neural network. For the half database and one-third database training, the prediction performance of the RBF network was slightly worse than the BP neural network. However, the training time of the RBF network was much quicker than the BP neural network. The database constructed from seven domestic and seven imported car manufacturers in Table 2 shows the accuracy percentage and prediction performance using different database quantities and ANN to predict a car fuel consumption system. Both ANN for the car consumption system also achieved high quality prediction performance. In Table 2, the results of training and testing from all databases showed the RBF network was better and faster than the BP neural network. For the half database and one-third database training, the prediction performance of the RBF network and BP neural network was about equal. However, the training time of the RBF network was much quicker than the BP neural network. The predictive performance achieved remarkable success predicting cars' fuel consumption systems. The consumer can accurately and conveniently obtain the fuel consumption of a new car. The consumer will choose a low fuel consumption vehicle to save money on fuel. The car manufacturers can reduce the time spent on vehicle emission tests.

**Table 2**
Percentage of prediction performance in domestic and imported car manufacturers.

| | All data training | | Half data training | | One third data training | |
|---|---|---|---|---|---|---|
| | BP | RBF | BP | RBF | BP | RBF |
| Number of train/number of test | 217/217 | 217/217 | 109/217 | 109/217 | 73/217 | 73/217 |
| City mode (%) | 95.47 | 100 | 93.92 | 92.61 | 92.65 | 92.84 |
| Highway mode (%) | 95.38 | 100 | 94.62 | 93.50 | 92.69 | 92.65 |
| Average mode (%) | 96.07 | 100 | 95.13 | 93.58 | 93.01 | 93.35 |
| Time (s) | 10 | 0.02 | 10 | 0.02 | 10 | 0.02 |

## 6. Conclusions

In the present study, a fuel consumption prediction technique using the RBF for cars network was proposed. The research successfully verifies the effectiveness of the RBF network to forecast the fuel consumption of cars, and the RBF network can prove better forecasting performance than the BP neural network. The network training process can modify the system parameters to increase the credibility of the system output. The percentages of accuracy and prediction performance were used to estimate the forecasting efficiency of the proposed system. Finally, the prediction system for cars' fuel consumption can be used by consumers and car manufacturers to accurately and conveniently obtain the fuel consumption of a new car.

## Acknowledgement

The study was supported by the National Science Council of Taiwan, Republic of China, under Project No. NSC-98-2221-E-018-004.

## References

Afantitis, A., Melagraki, G., Makridima, K., Alexandridis, A., Sarimveis, H., & Iglessi-Markopoulou, O. (2005). Prediction of high weight polymers glass transition temperature using RBF neural networks. *Theochem, 716*, 193–198.
Asche, F., Gjolberg, O., & Volker, T. (2003). Price relationships in the petroleum market: An analysis of crude oil and refined product prices. *Energy Economics, 25*, 289–301.
Bezdek, R. H., & Wendling, R. M. (2005). Potential long-term impacts of changes in US vehicle fuel efficiency standards. *Energy Policy, 33*, 407–419.
Broomhead, D. S., & Lowe, D. (1988). Multi-variable functional interpolation and adaptive networks. *Complex Systems, 2*, 321–355.
Clerides, S., & Zachariadis, T. (2008). The effect of standards and fuel prices on automobile fuel economy: An international analysis. *Energy Economics, 30*, 2657–2672.
Crouse, W. H., & Anglin, D. L. (1993). *Automotive mechanics* (10th ed.). McGraw-Hill.
Hagan, M. T., Demuth, H. B., & Beale, M. H. (1996). *Neural network design*. Boston, MA, USA: PWS Publishing Co.
Holtsmarka, B., & Mæstad, O. (2002). Emission trading under the Kyoto Protocol – effects on fossil fuel markets under alternative regimes. *Energy Policy, 30*, 207–218.
Hucho, W.-H. (1998). *Aerodynamics of road vehicles* (4th ed.). SAE International.
Kwon, T-H. (2005). Decomposition of factors determining the trend of $CO_2$ emissions from car travel in Great Britain (1970–2000). *Ecological Economics, 53*, 261–275.
Papagiannaki, K., & Diakoulaki, D. (2009). Decomposition analysis of $CO_2$ emissions from passenger cars: The cases of Greece and Denmark. *Energy Policy, 37*, 3259–3267.
Paravantis, J. A., & Georgakellos, D. A. (2007). Trends in energy consumption and carbon dioxide emissions of passenger cars and buses. *Technological Forecasting and Social Change, 74*, 682–707.
Plotkin, S. E. (2001). European and Japanese fuel economy initiatives: What they are, their prospects for success, their usefulness as a guide for US action. *Energy Policy, 29*, 1073–1084.
Ross, M., & An, F. (1993). The use of fuel by spark ignition engines. *SAE Paper 930329*.
Rubin, J., & Leiby, P. (2000). An analysis of alternative fuel credit provisions of US automotive fuel economy standards. *Energy Policy, 13*, 589–601.
Saboohi, Y., & Farzaneh, H. (2009). Model for developing an eco-driving strategy of a passenger vehicle based on the least fuel consumption. *Applied Energy, 86*, 1925–1932.
Sarkar, M., Yegnanarayana, B., & Khemani, D. (1998). Backpropagation learning algorithms for classification with fuzzy mean square error. *Pattern Recognition Letters, 19*, 43–51.
Sprei, F., Karlsson, S., & Holmberg, J. (2008). Better performance or lower fuel consumption: Technological development in the Swedish new car fleet 1975–2002. *Transportation Research Part D, 13*, 75–85.
Tolouei, R., & Titheridge, H. (2009). Vehicle mass as a determinant of fuel consumption and secondary safety performance. *Transportation Research Part D, 14*, 385–399.
Viguiera, L. L., Babikera, M. H., & Reilly, J. M. (2003). The costs of the Kyoto Protocol in the European Union. *Energy Policy, 31*, 459–481.
Wu, J. D., Hsu, C. C., & Chen, H. C. (2009). An expert system of price forecasting for used cars using adaptive neuro-fuzzy inference. *Expert Systems with Applications, 36*, 7809–7817.
Wu, J. D., Wang, Y. H., Chiang, P. H., & Bai, M. R. (2009). A study of fault diagnosis in scooter using adaptive order tracking technique and neural network. *Expert Systems with Applications, 36*, 49–56.
Yu, L., Lai, K. K., & Wang, S. (2008). Multistage RBF neural network ensemble learning for exchange rates forecasting. *Neurocomputing, 71*, 3295–3302.