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An expert system of price forecasting for used cars using adaptive neuro-fuzzy inference

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ABSTRACT

An expert system for used cars price forecasting using adaptive neuro-fuzzy inference system (ANFIS) is presented in this paper. The proposed system consists of three parts: data acquisition system, price forecasting algorithm and performance analysis. The effective factors in the present system for price forecasting are simply assumed as the mark of the car, manufacturing year and engine style. Further, the equipment of the car is considered to raise the performance of price forecasting. In price forecasting, to verify the effect of the proposed ANFIS, a conventional artificial neural network (ANN) with back-propagation (BP) network is compared with proposed ANFIS for price forecast because of its adaptive learning capability. The ANFIS includes both fuzzy logic qualitative approximation and the adaptive neural network capability. The experimental result pointed out that the proposed expert system using ANFIS has more possibilities in used car price forecasting.

1. Introduction

The quantity of used cars has been gradually increasing with frequent car replacements in recent years. The price of used cars is an important aspect of the trading market. Accurate and effective price forecasting has become more and more important as trading information for consumers when buying a used car. In other commodity markets such as the stock market, agriculture commodity markets and supermarkets, price forecasting has always been the focus of studies because of its importance (Baba & Kozaki, 1992; Snyder, Sweat, Richardson, & Pattie, 1992; Wang, 2002). Simply speaking, a used car is also a commodity, the price of which can be forecast in the same way. However, a used car has different characteristics from other commodities because it is a used commodity. The sale price will be affected by the rate of depreciation, mark of car, manufacturing year, engine style, etc. Therefore, a consumer finds it difficult to accurately obtain the purchasing price of a used car. An excessively simplistic price forecasting method using a forecast of the commodity price will unsurprisingly be inaccurate. In recent years, many intelligent forecasting techniques have been developed, such as fuzzy system (Al-Kandaria, Solimanb, & El-Hawaryc, 2004; Chen, Cheng, & Teoh, 2007; Chen & Wang, 1999; Lee & Chen, 2001; Pai, 2006), artificial neural network (Catalão, Mariano, Mendes, & Ferreira, 2007; Law, 2000; Malik & Nasereddin, 2006; Srinivasan, 1998; Yalcinoz & Eminoglu, 2005; Yao, Li, & Tan, 2000), and adaptive neuro-fuzzy inference system (Singh, Sinha, & Singh, 2007; Zaheeruddin & Garima, 2006).

In the above-mentioned methods, the ANN and ANFIS proved to be simple and powerful tools for forecasting a practical system. For example, Gareta and others (Gareta, Romeo, & Gil, 2006) used an artificial neural network to forecast short-term hourly electricity pool prices. The ANN can obtain the structure of a complex system by repeated network training procedure and it does not need to describe its property using mathematical equations. Finally, the methodology pointed out that the ANN can improve power plant generation capacity management and lead to more profitable operation of pools. In 1993, Jang (Jang, 1993) proposed an ANFIS algorithm consisting of a combination of a fuzzy logic approximation and an ANN adaptive capability. The ANFIS model used the adaptive learning algorithm to train the fuzzy logic system approximating the expectation outputs. In 2008, Ying and Pan (Ying & Pan, 2008) proposed a forecasting technique using ANFIS model for forecasting the regional electricity loads in Taiwan. Based on the mean absolute percentage errors and statistical results, the ANFIS model verified that it had better forecasting performance than other models, such as the regression model, artificial neural network (ANN) model, support vector machines with genetic algorithms (SVMG) model, recurrent support vector machines with genetic algorithms (RSVMG) model and hybrid ellipsoidal fuzzy systems for the time series forecasting (HEFST) model. These research results pointed out that ANN and ANFIS can accurately and powerfully forecast some unknown parameters, such as price, load, and human work efficiency. The forecasting results were more satisfactory than those from traditional estimation methods.

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In this study, a new technique for price forecasting of used cars using BP network and ANFIS model will be described. The information and data of used cars were obtained from a used car website in Taiwan (Ocar, 2008). The information also was used to obtain the relationship between the impact factors and the price. The price forecasting of various used cars has been studied by the BP network and ANFIS model to increase accuracy and reduce forecasting error. The BP network and ANFIS model are the most suitable for complex structures because the adaptive learning capability can approximate the nonlinear system. The following sections will describe the principle and experimental work of the BP network and ANFIS model in the proposed system.

2. Principle of artificial neural network technique and adaptive neuro-fuzzy inference system

2.1. Structure of BP

The basic elements of an artificial neural network are denoted as neurons or the so-called processing elements. The mathematical model of a neuron is presented in Fig. 1. A multilayer BP artificial network is shown in Fig. 2. In the figures, x_1, x_2, ..., x_i are the input elements, w_1, w_2, ..., w_n are the synaptic weights, Σ is the summation parameter, φ is the activation function and y_1, y_2, ..., y_i are the output elements. The summation parameter will sum the elements of the input vectors and synaptic weights. The activation function will reflect the result y_i of output elements. The three layers of the multilayer network include input layer, hidden layer and output layer. There are many neurons in each layer and every neuron is connected by synaptic weights. In the BP network system; there is only a single input and output layer, but there can be one or more layers in the hidden layer. The operation procedure of artificial neural network can be divided into two sections: learning procedure and recalling procedure. The learning procedure includes both the establishment of the initial conditions and network training work. The initial conditions determine the initial values of each weight and bias. The most common weight and bias initialization function are random, which generates random values between -1 and 1. The network training work will adjust each weight and bias to approach the expectation output. The network training work can obtain the relationship between the input and the output to form the unknown problem. The training process can make the network output approximate the expectation output by the learning algorithm.

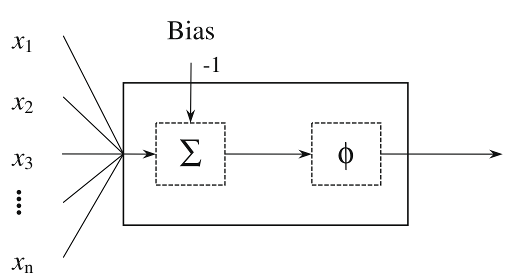

Fig. 1. Mathematical model of a neuron.

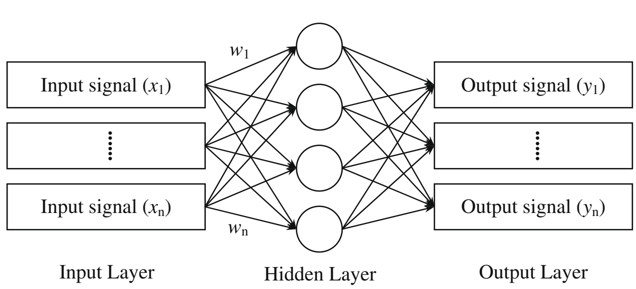

Fig. 2. BP network structure.

The learning algorithm of the BP network contains two stages: feed-forward and back-propagation. In the feed-forward stage, the weights will be fixed and each neuron calculates the output values. The algorithm of the feed-forward stage will be represented by the following equation:

$$v_j(n) = \sum_{j=1}^{p} w_{ij}(n) \cdot y_i(n) \tag{1}$$

where w_{ij} is the jth weight value of the ith layer, y_i is the output value of the ith layer, p is the number of the neurons, v_j is the net internal activity level of jth neuron and index n labels the iteration number. Finally, the network will produce an actual output by activation function φ; here uses a hyperbolic tangent sigmoid transfer function. Fig. 3 presents the rough sketch of the BP network hyperbolic tangent sigmoid transfer function. The output result can be expressed as

$$y_j(n) = \varphi(v_j(n)) = \frac{2}{(1 + e^{(-2\times v_j)}) - 1} \tag{2}$$

Finally, the BP network calculates the actual output, and the network will count the error value E between the expectation and the actual output. The error value E can be defined as

$$E = \frac{1}{2}\sum_j (T_j - y_j)^2 \tag{3}$$

where E is the error value, T_j is the expectation output value, y_j is the actual output value. The actual output value y_j will approach the expectation output value when the error value is smaller. The weight values of BP network will be repeated to modify until the output conforms to the expectation output. Next is the back-propagation stage. In this stage, every weight value of neurons will be modified by

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n), \tag{4}$$

where w_{ij} is the weight value, Δw_{ij} is the correction value, and index n labels the iteration number in the learning process. The correction value can be obtained by

$$\Delta w_{ij} = -\eta \cdot \frac{\partial E}{\partial w_{ij}} \tag{5}$$

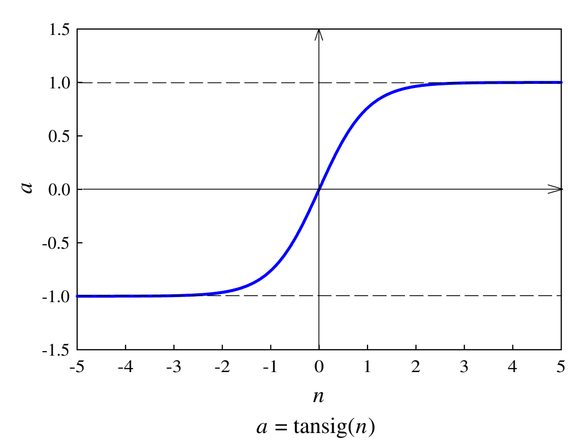

Fig. 3. Rough sketch of BP network hyperbolic tangent sigmoid transfer function.

where Δw_{ij} is the network correction value, η is the learning rate. Eq. (5) can be written as

$$\Delta w_{ij} = -\eta \cdot \frac{\partial E}{\partial w_{ij}} = -\eta \cdot \left(\frac{\partial E}{\partial y_j} \cdot \frac{\partial y_j}{\partial w_{ij}} \right) = -\eta \cdot (T_j - y_j) \cdot (-x_i)$$
$$= \eta \cdot \delta_i \cdot x_i \tag{6}$$

where δ_i is the local gradient function. Substitution of Eq. (6) into Eq. (4) gives

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n) = w_{ij}(n) + \eta \cdot \delta_i(n) \cdot x_i \tag{7}$$

The BP network will check the output values to see if the results conform to the convergence conditions after the network training process. Otherwise, the weights value will be repeated to modulate until it conforms to the convergence conditions. The flowchart of the network training procedure is shown in Fig. 4. The BP network has been verified to be a simple and useful tool for the price forecasting system.

2.2. Structure of ANFIS

In 1993, Jang proposed an ANFIS algorithm based on Sugeno fuzzy inference model (SFIM) (Jang, 1993). The ANFIS model can construct an input–output mapping based on both the fuzzy if–then rules and the stipulated input–output data pairs. The if–then rules of SFIM are often applied for obtaining the inference of an imprecise model. A conclusion can be reached in the indefinite system, which is better than human experience. These if–then rules based on stipulated input–output training data pairs by suitable membership functions are then produced. The ANFIS model employs the neural network training procedure to adjust the membership function and the associated parameter that approaches the desired data sets. For simplicity, suppose that the ANFIS under consideration has two inputs x and y, and one output f. For a first-order SFIM, a typical rule set with two fuzzy if–then rules can be expressed as

$$\begin{aligned} &\text{Rules 1}: \text{If } (x \text{ is } A_1) \text{ and } (y \text{ is } B_1) \text{ then } (f_1 = \alpha_1 x + \beta_1 y + \gamma_1) \\ &\text{Rules 2}: \text{If } (x \text{ is } A_2) \text{ and } (y \text{ is } B_2) \text{ then } (f_2 = \alpha_2 x + \beta_2 y + \gamma_2) \end{aligned} \tag{8}$$

where x and y are the inputs, A_1, A_2, B_1 and B_2 are the fuzzy sets determined during the network training procedure, f_1 and f_2 are outputs, $\alpha_1, \alpha_2, \beta_1, \beta_2, \gamma_1$ and γ_2 are linear parameters, which are also determined during the network training procedure. The two rules

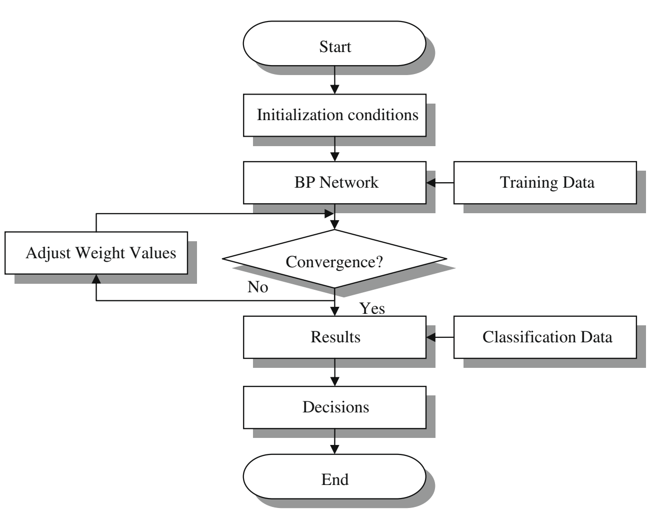

Fig. 4. Flowchart representation of BP learning algorithm.

will be determined to construct the ANFIS framework as shown in Fig. 5. The ANFIS framework has five layers, and a concise introduction of the system is as follows:

In the first layer, these nodes represent input nodes, and are also termed as adaptive nodes. Each node of this layer generates a membership grade, which corresponds to using the membership

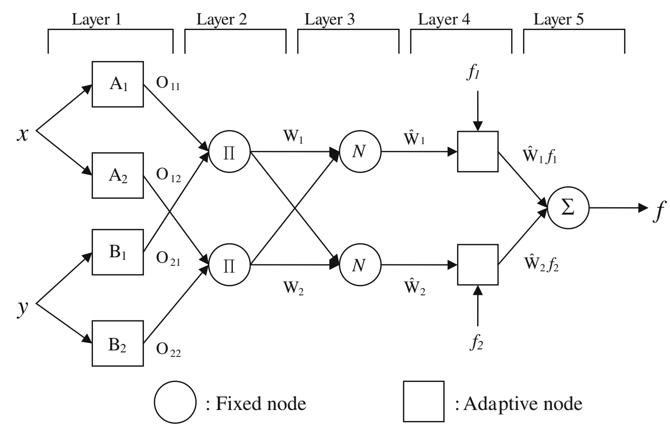

Fig. 5. ANFIS structure.

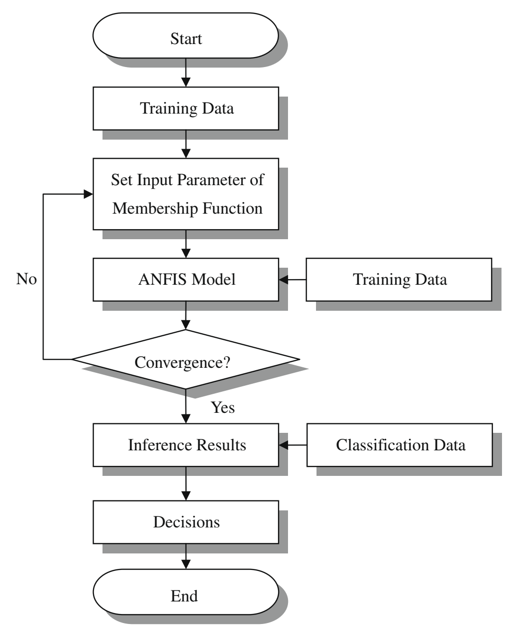

Fig. 6. Flowchart representation of ANFIS hybrid learning algorithm.

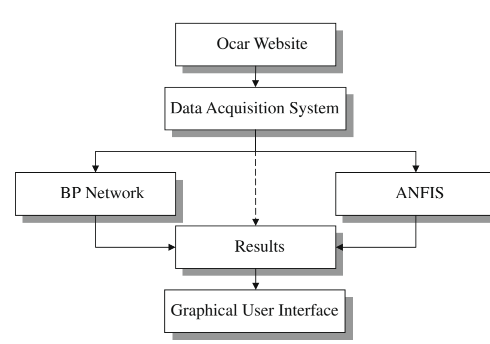

Fig. 7. Flowchart representation of used cars price forecasting system.

Table 1
Using different inputs to forecast the price of various used cars for BP network.

Inputs	Marks	Absolute percentage error (%)							
		⩽5	6–10	11–15	16–20	21–25	26–30	31–35	36–40
3	Ford	29	11	3	4	1	0	0	0
	Mitsubishi	40	5	3	0	0	0	0	0
	Nissan	37	2	5	3	0	1	0	0
	Toyota	42	5	1	0	0	0	0	0
4	Ford	31	12	4	1	0	0	0	0
	Mitsubishi	43	5	0	0	0	0	0	0
	Nissan	41	7	0	0	0	0	0	0
	Toyota	43	3	2	0	0	0	0	0

Table 2
Using different inputs to forecast the price of various used cars for ANFIS model.

Inputs	Mark	Absolute percentage error (%)							
		⩽5	6–10	11–15	16–20	21–25	26–30	31–35	36–40
3	Ford	22	11	5	6	3	1	0	0
	Mitsubishi	27	9	9	0	3	0	0	0
	Nissan	27	15	0	3	3	0	0	0
	Toyota	38	10	0	0	0	0	0	0
4	Ford	36	6	5	0	1	0	0	0
	Mitsubishi	40	5	3	0	0	0	0	0
	Nissan	41	6	1	0	0	0	0	0
	Toyota	47	0	1	0	0	0	0	0

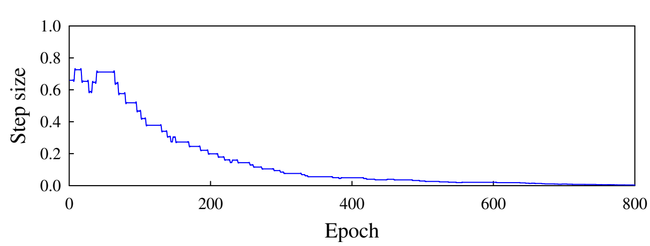

Fig. 8. Adaptation parameter step curve of ANFIS training procedure for used cars price forecasting.

function to obtain the grade of the linguistic label. The membership function of the first layer can be given by

$$O_{1i} = \mu_{A_i}(x), \quad i = 1,2$$
$$O_{2i} = \mu_{B_i}(y), \quad i = 1,2 \tag{9}$$

where x and y are the crisp inputs, O_{1i} and O_{2i} are the linguistic labels characterized by appropriate membership functions μ_{A_i} and μ_{B_i},, respectively, and i represents the i nodes. Generally, the Gaussian and the bell-shaped memberships possess the characteristic of smoothness and succinctness, and are extensively applied to fuzzy set. The bell-shaped membership is very suitable for a nonlinear system, and is better than Gaussian membership. Therefore, the bell-shaped membership will be used in the study, and theμ_{A_i} and μ_{B_i} can be given by

$$\mu_{A_i}(x) = \frac{1}{1 + \left|\frac{x-c_i}{a_i}\right|^{2bi}} \qquad \mu_{B_i}(y) = \frac{1}{1 + \left|\frac{y-c_i}{a_i}\right|^{2bi}} \tag{10}$$

where a_i, b_i and c_i are the parameter set of the membership function in the premise part of if–then rules. These parameter values can change the shape of the membership function. These parameters are termed the premise part parameters or the so-called nonlinear parameters.

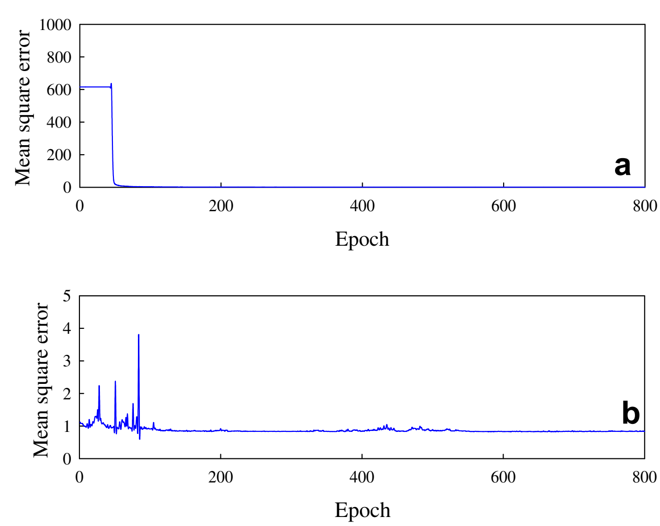

Fig. 9. Network error convergence curve for used cars price forecasting:(a) BP network and (b) ANFIS model.

In the second layer, these nodes are fixed nodes. They are labeled as Π, which apply the AND operation to obtain the output results of firing strength. Firing strength means the weight degree of if–then rules in the premise part. The weight degrees w_i of this layer are products of the corresponding degrees from the first layer, and can be expressed as:

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) = O_{1i} \times O_{2i} \quad i = 1,2 \tag{11}$$

In the third layer, these nodes are also fixed nodes. They are labeled as N, indicating that they play a normalization role to normalize the firing strengths from the previous layer. The outputs of this layer can be represented as

$$\hat{w}_i = \frac{w_i}{\sum_i w_i} \quad i = 1,2 \tag{12}$$

In the fourth layer, these nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first-order polynomial. The polynomial is a first-order SFIM, the parameters of which are denoted as linear parameters or the so-called consequent parameters. Thus, the outputs of this layer can be given by

$$\hat{w}_i f_i = \hat{w}_i(p_i x + q_i y + r_i) \quad i = 1,2 \tag{13}$$

where $\hat{w}_i$ is the normalized firing strength from the previous layer, p_i, q_i and r_i are linear parameters of the first-order SFIM.

In the fifth layer, there is only one single fixed node, which is labeled as Σ. The node performs the summation of all the incoming nodes, which represents the defuzzification procedure. Therefore, the single output of the ANFIS model can be given by

$$f = \sum_i \hat{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad i = 1,2 \tag{14}$$

The ANFIS structure consists of a combination of three fixed layers and two adaptive layers. The adaptive layers are the first and the fourth layer, respectively. In the first layer, there are three modifiable parameters (a_i, b_i and c_i) related to the input membership function. In the fourth layer, there are also three modifiable parameters (p_i, q_i and r_i), pertaining to the first-order polynomial of SFIM. These adaptive parameters can obtain a desirable value by learning algorithm. The learning algorithm will introduce the principle in the following statement.

In this study, the learning algorithm of ANFIS is based on the hybrid learning algorithm. The algorithm consists of a combination of the LSEA and the SDA. The task of the learning algorithm modifies all the modifiable parameters of the adaptive layers. These modifiable parameters are modified to make the ANFIS output approach of the expectation output. Fig. 6 shows the flowchart of the ANFIS hybrid learning algorithm. The membership functions are fixed when these parameters (a_i, b_i and c_i) are obtained from the training data sets. Eq. (12) can be written as

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{15}$$

Substitution of Eq. (10) into Eq. (13) gives

$$f = \hat{w} f_1 + \hat{w}_2 f_2 \tag{16}$$

Substitution of the first-order SFIM into Eq. (14) yields

$$f = \hat{w}1 + (p_1 x + q_1 y + r_1) + \hat{w}2(p_2 x + q_2 y + r_2) \tag{17}$$

After rearrangement, the output can be expressed as

$$f = (\hat{w}_1 x_1)p_1 + (\hat{w}_1 x_2)q_1 + \hat{w}_1 r_1 + (\hat{w}_2 x_1)p_2 + (\hat{w}_2 x_2)q_2 + \hat{w}_2 r_2 \tag{18}$$

which is a first-order linear combination of the modifiable consequent parameters S_1:{p_1, q_1, r_1, p_2, q_2 and r_2}. Here, the premise

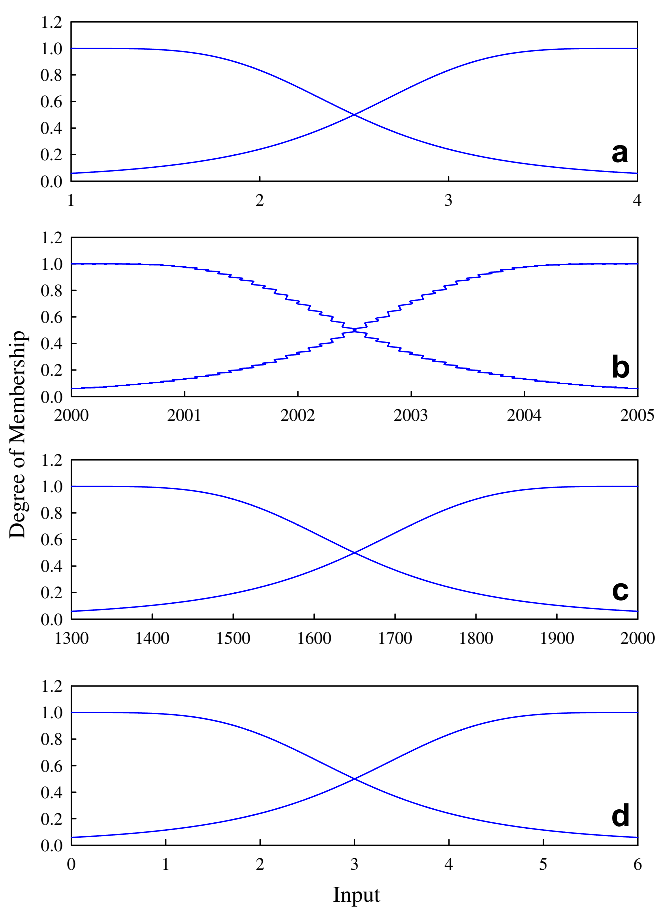

Fig. 10. Initial generalized bell-shaped membership function of ANFIS model for used cars price forecasting: (a) input 1 (Mark of car), (b) input 2 (Manufacturing year), (c) input 3 (Engine style) and (d) input 4 (Equipment index).

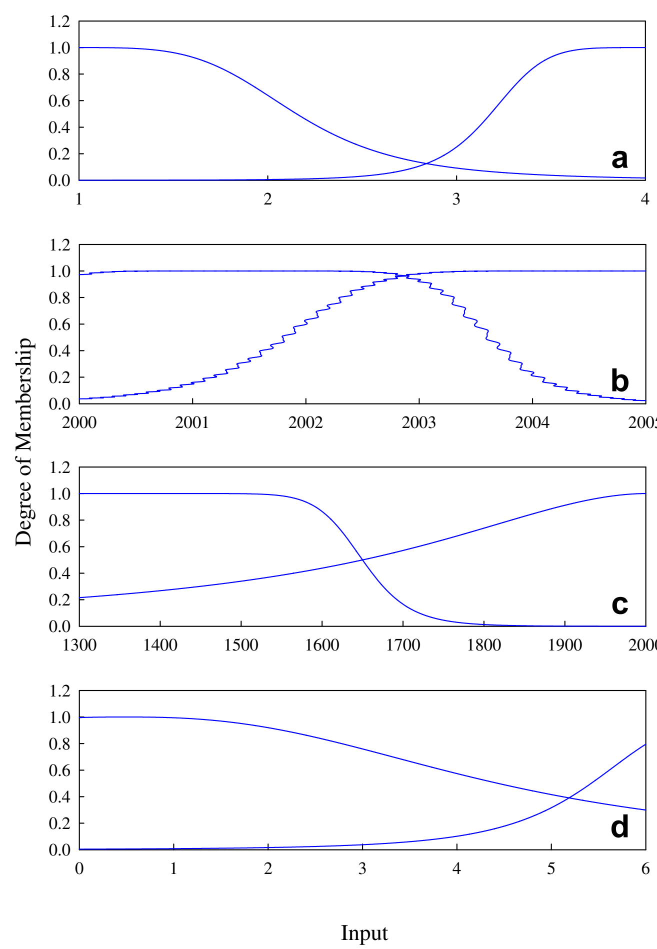

Fig. 11. Final generalized bell-shaped membership function of ANFIS model for used cars price forecasting: (a) input 1 (Mark of car), (b) input 2 (Manufacturing year), (c) input 3 (Engine style) and (d) input 4 (Equipment index).

parameters are expressed as S_2:{a_1, b_1, c_1, a_2, b_2 and c_2}. The LSEA can be used to modify the S_1 parameters with the forward pass training method. The training method optimizes the S_1 parameters with the S_2 parameters fixed. The estimation method of the optimum modulation can be defined by

$$E = \frac{1}{2}(y_d - f)^2 \tag{19}$$

where y_d is ANFIS output, f is expectation output, and E is the output of the mean square error value. When E reaches the convergence condition it will produce the inference results. Otherwise, the S_1 parameters will be fixed, and the S_2 parameters can be modified with SDA. The SDA is a backward pass training method, which adjusts the optimum S_2 parameters. These optimum S_2 parameters are modified corresponding to the fuzzy sets in the input domain. After the new parameters of premise part are obtained, the output of ANFIS is calculated again by employing the S_1 parameters found by the forward pass training method. The hybrid learning algorithm causes the E error value corresponding to the convergence condition. The ANFIS will generate results of the optimum inference. The inference result has proven that this hybrid learning algorithm is highly efficient for training the ANFIS.

3. Experimental design of the price forecasting system

The price forecasting system consists of three parts: data acquisition system, price forecasting algorithm and performance analysis. In the data acquisition system, the information and data of used cars are acquired from a used car website in Taiwan. The impact factors for used cars price include the mark of car, manufacturing year and engine style. These are used as input pattern in the network training and price forecasting procedure. The impact factors can provide good parameters to train the BP network and ANFIS model. Therefore, the BP network and ANFIS model can accurately forecast the price of used cars under various input conditions. The flowchart representation of used cars price forecasting is shown as Fig. 7. In the experimental design, four marks such as Ford, Mitsubishi, Nissan, and Toyota are selected as the mark of the car. The manufacturing years include 2000, 2001, 2002, 2003, 2004, and 2005. The engine styles are 1300, 1600, 1800 and 2000 cc. After the data acquisition, the database was established by eight data for each year, which are used to train and test the BP network and ANFIS model, respectively. Nevertheless, the number of input selections will be considered before the network training and price forecasting procedure. The structure of the BP network and ANFIS model will become complicated by using too many input conditions, but it is difficult to accurately forecast the difference in price forecasting between the same input conditions when using too few input conditions. Because the region and market factors will easily affect the price variation of used cars, and it is also difficult to gain the information. Therefore, the equipment of the car will be used to increase the accuracy of price forecasting in the proposed system.

The equipment of the car will be considered as three estimation parameters, anti-lock braking system (ABS), traction control system (TCS) and supplement restraint system (SRS). The equipment index is proposed to point out the difference between the equipment of the car and price and reduce the complexity of the input conditions. The equipment index is based on the price influence to define the grading demarcation. In this study, the ABS, TCS, and SRS are defined as one star, two stars, and three stars, respectively. Therefore, the lowest and highest equipment index is zero

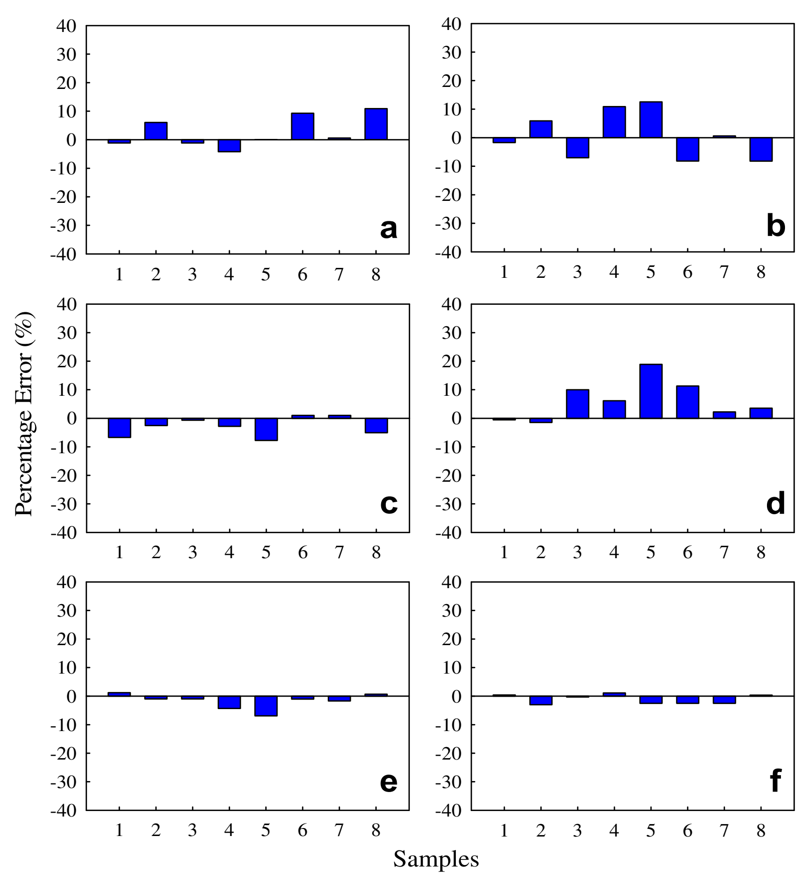

Fig. 12. Percentage error of BP network for Ford mark price forecasting at different manufacturing years: (a) 2000, (b) 2001, (c) 2002, (d) 2003, (e) 2004 and (f) 2005.

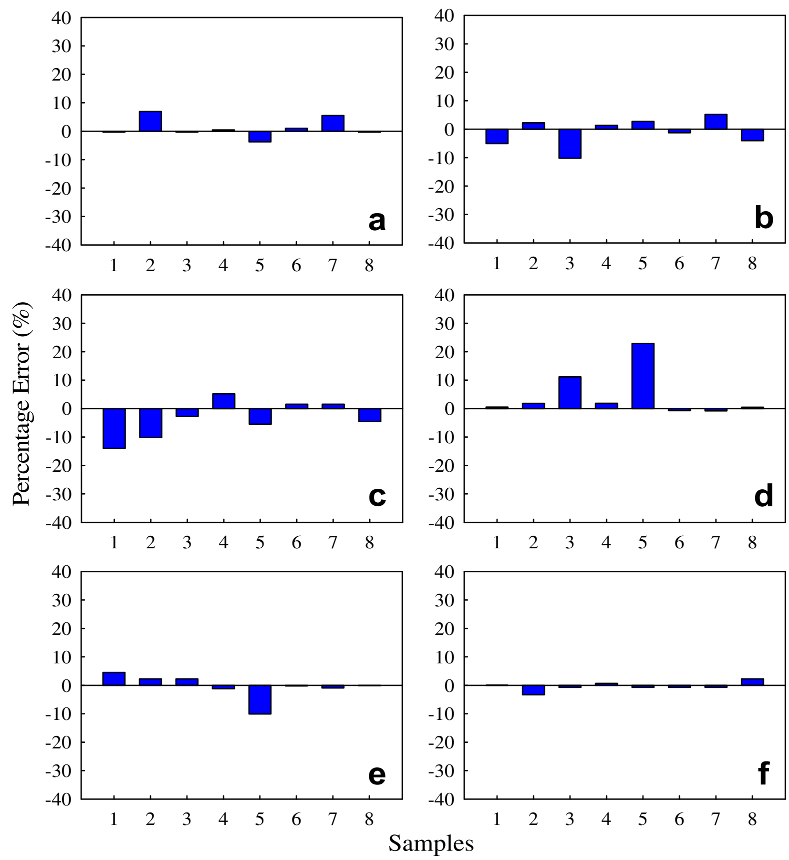

Fig. 13. Percentage error of ANFIS model for Ford mark price forecasting at different manufacturing years: (a) 2000, (b) 2001, (c) 2002, (d) 2003, (e) 2004 and (f) 2005.

Table 3
Using four inputs to test the performance of used cars price forecasting for BP network.

Tests	Marks	Absolute percentage error (%)							
		⩽5	6–10	11–15	16–20	21–25	26–30	31–35	36–40
1	Ford	34	11	3	0	0	0	0	0
	Mitsubishi	43	5	0	0	0	0	0	0
	Nissan	45	2	1	0	0	0	0	0
	Toyota	43	4	1	0	0	0	0	0
2	Ford	28	16	4	0	0	0	0	0
	Mitsubishi	39	9	0	0	0	0	0	0
	Nissan	43	5	0	0	0	0	0	0
	Toyota	36	10	2	0	0	0	0	0
3	Ford	32	9	5	1	1	0	0	0
	Mitsubishi	43	4	1	0	0	0	0	0
	Nissan	35	12	1	0	0	0	0	0
	Toyota	34	12	2	0	0	0	0	0
4	Ford	3	5	6	2	3	4	4	5
	Mitsubishi	10	8	2	2	1	3	1	4
	Nissan	6	0	3	9	5	1	2	5
	Toyota	5	5	10	7	2	0	8	4

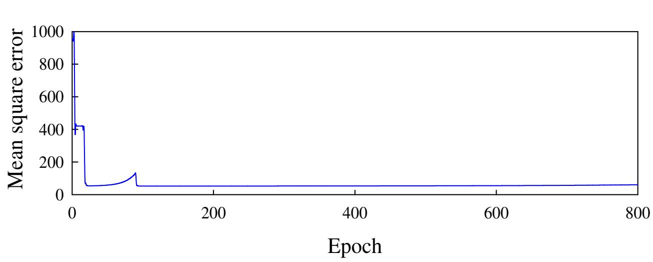

Fig. 14. Network error without convergence curve of BP training procedure for used cars price forecasting.

star and six stars, respectively. As well as the input selection, the BP network and ANFIS model will establish some basic parameters. When the BP network uses too many neurons the hidden layer will overly complicate the BP network and increase the training time. Simultaneously, determining the number of input membership function is also an important initial condition in the ANFIS training process. Too many input membership functions will increase the inference rules and training time. The increasing number of inference rules can be expectably obtained by

$$\text{Inference rules} = M^n \tag{20}$$

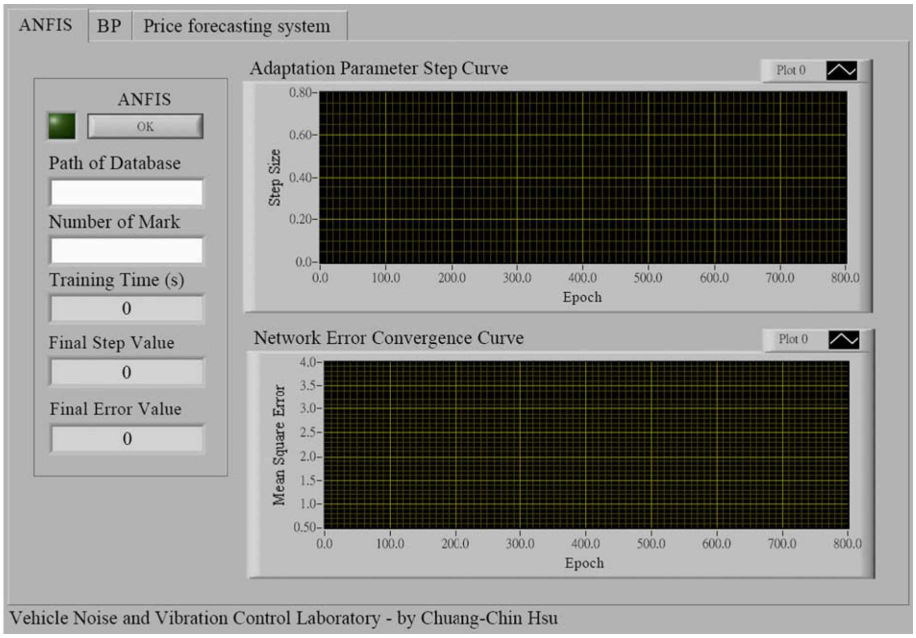

Fig. 15. Graphical user interface of used cars price forecasting system.

where M represents the number of each input using membership function and n represents the number of input. Besides, the initial conditions of BP network and ANFIS model are also considered to converge at expectation targets. In the BP network, the number of neurons and hidden layer, learning rate, and training epoch are chosen to be 250, single layer, 0.55 and 800 training epochs, respectively. In this study, the membership function type, initial step size and training epoch of ANFIS that are selected are two bell-shaped memberships, 0.66 and 800 training epochs where the inference results will generate 2^4 inference rules. The price forecasting system finally obtained the percentage error (PE), and can be defined as

$$\mathrm{PE}(\%) = \frac{F_{\mathrm{price}} - A_{\mathrm{price}}}{A_{\mathrm{price}}} \times 100\% \tag{21}$$

where F_{price} represents the forecasting price and A_{price} represents the actual price. To clearly obtain the forecasting performance, the absolute percentage error (APE) will be defined as

$$\mathrm{APE}(\%) = \left|\frac{F_{\mathrm{price}} - A_{\mathrm{price}}}{A_{\mathrm{price}}}\right| \times 100\% \tag{22}$$

Therefore, the APE can easily represent the work efficiency for the price forecasting system.

4. Results and discussions

This section describes the results of the proposed price forecasting system in the used car market. The database is used to train and test the price forecasting system when the database is complete. The input selection tested the forecasting performance by three inputs (mark of car, manufacturing year and engine style) and four inputs (mark of car, manufacturing year, engine style and equipment index), respectively. Table 1 and Table 2 point out the APE and forecasting performance using different input conditions and forecasting system to forecast the price of used cars. These results using three input conditions show that the BP network was better than the ANFIS model because the BP network uses many neurons. These neurons can effectively learn the relationship between the inputs and the outputs in the complex system. Nevertheless, the number of neurons for the ANFIS model was fixed when the training procedure begun. Simultaneously, the performance of using four input conditions was more satisfactory than using three input conditions in the proposed system. Therefore, using four input conditions can serve as a useful parameter in used car price forecasting. The step variation of the ANFIS adaptation parameter is shown in Fig. 8. The strategy of step size modulation is introduced in the following statement. The step size increases when the error undergoes four consecutive decreases. Contrarily, the step size is decreased when the error measure undergoes two consecutive combinations of an increase followed by a decrease. At the end of 800 training epochs, the convergence curve of the mean square error for the training process of the BP network and ANFIS is shown in Fig. 9a and Fig. 9b. From the curve it was found that the final convergence values are 0.83477 and 0.6531. Fig. 10 and Fig. 11 show the initial and final membership functions of each input in the ANFIS model, respectively.

The difference in price between the practical price and the proposed price forecasting system for the Ford mark is summarized in Fig. 12 and Fig. 13. Further, the variation influence of weight and bias initialization function for forecasting performance will be examined with four forecasts in the BP network. Table 3 shows the APE and forecasting performance for four price forecasts in the proposed BP network. The results pointed out that the price forecasting differs in each training procedure. For the fourth forecast, the quantity of price forecasting was insufficient for a total of 48 data for each mark of car because the APE exceeded 40% inaccuracy. Fig. 14 points out that there is no convergence condition for the BP network in the fourth forecasting result. These results pointed out that the price forecasting with the weight and bias of random initialization values will increase or decrease the forecasting accuracy. Nevertheless, the ANFIS model will not need to consider this question because the ANFIS only needs to calculate the membership function of each input from the training data. The results of price forecasting will not be changed with each network training procedure in the proposed ANFIS model. One can see that the forecasting performance of the ANFIS model is used to forecast the price of used cars more accurately than the BP network. Finally, the graphical user interface (GUI) shown in Fig. 15 was designed to reduce of complexity of the operation procedure. These experimental results showed that the ANFIS model is a good tool for price forecasting in used car markets.

5. Conclusions

This paper introduced a new price forecasting technique for used cars using the BP network and ANFIS model. The equipment index can effectively reduce the number of network inputs and the complex structure of BP network and ANFIS model. The research successfully verifies the effectiveness of the BP network and ANFIS model to forecast the price of used cars. The ANFIS mode can provide better forecasting performance than the BP network. The presented ANFIS model combined the neural network adaptive capability and the fuzzy logic qualitative approximation. The network training process can adjust the system parameters to increase the credibility of the system output. The APE was used to estimate the forecasting efficiency in the proposed system. Finally, the consumer can accurately and conveniently obtain the purchasing price of used cars by GUI, and the experiential results pointed out that the proposed system can provide an accurate and convenient price forecasting technique.

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