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Using adaptive network-based fuzzy inference system to forecast automobile sales

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ABSTRACT

Improving the sales forecasting accuracy has become a primary concern for automobile industry. Here, we only focus on new automobile sales in Taiwan. The data set is based on monthly sales, and the data can be divided into three styles of automobile sales. To address our concern, we developed a sales forecasting methodology that considers several variables such as current automobile sales quantity, coincident indicator, leading indicator, wholesale price index and income. First, we use the stepwise regression to select most influential variables as our input variables. Then, we input the influential variables and sales in adaptive network-based fuzzy inference system (ANFIS) to obtain the forecast. Finally, we compare our model with two forecasting models: autoregressive integrated moving average model (ARIMA) and artificial neural network (ANN). Empirical results demonstrate that the application of the ANFIS model outperforms the other two models. In addition, we modified the historical and holdout periods to improve forecasting accuracy while considering the impact from the financial tsunami in 2008.

1. Introduction

Beginning in 1998, automobile sales in Taiwan experienced instable sales. Taiwan Transportation Vehicle Manufacturers Association reported a monthly sales variation rate of 265% for peak period and 0.33% for slack periods (TTVMA, 2009). Overestimating the demand will result in excess inventory, while underestimating will lead to lost sales. The accurate forecasting of future demand is very important when planning activities for enterprise. In production planning in the automobile industry, a very detailed demand forecast of the size and location is required. In either plant designing or budgeting, a precise forecast of the total market will be needed. To supply users (each representing different organizational functions and management echelons) with decision support information, the reliance for family based forecasting is stressed.

Automobile industry plays an important role in modern manufacturing in Taiwan. Taiwan automobile manufacturing consists of three basic process stages: initial, growth, and maturity. Because Taiwan is short of natural resources and enormous market, the automobile industry is different from those in advanced countries. The Taiwan automobile industry started in 1953. The initial stage established many measures, including stipulate protective trade, tariff quotas, and an import quota system that protected the local automobile company from the abroad enterprise. In the automobile industry, advanced technology is of utmost importance in manufacturing cars. Therefore, in the growth stage, Taiwan government encouraged both abroad and local enterprises to establish an associated automobile company. Taiwan enterprises obtained critical technical exchange in this stage. In the final stage, Taiwan government abated and revised the protectionism statutes to establish unfettered market control. Before this stage, form 1953 to 1992, the automobile sales in Taiwan was on the rise. However, a mature automobile market depends on the index of key factors including wholesale price, population, income, and oil price causes the demand in automobile sales instability in this current market. Thus, predicting the trend of demand has become a primary concern for Taiwan manufacturers. In the past, the demand forecasting method of automobile in Taiwan was only based on the quarter sales data, derived from a traditional univariate forecasting model. The forecasting accuracy of the model for all vehicles was not sufficient in terms of the mean absolute percent error (MAPE), seeing as the mean absolute percent error for vehicles at all levels was between 20% and 30%. Such misrepresentations will result in excess inventory cost and lost sales. Clearly, there are ways in which the accuracy of demand forecasting can be improved.

In this study, we proposed a multivariate methodology for automobile demand forecasting in Taiwan. This article is divided into the following sections. The related literature of the research problem and the forecasting study are reviewed in Section 2. In Section 3, we proposed a modified forecast model for automobile demand forecasting in Taiwan. To validate our model, we compare the proposed model with other models. In Section 4, we analyze the results produced by proposed methodology with a real data set

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from the real vehicle sales data in Taiwan. Finally, we conclude the findings along with further research in Section 5.

2. Literature review

Our review of the literature indicates that the demand forecasting of automobile sales studies consist of two types. The first is the introduction of the common forecast models presents the demand forecast. The second is the set of studies that uses techniques to forecast the sales of automobile industry.

2.1. Forecasting

Demand forecasting is only an effective management method if and when it helps managers make company's decision in an uncertain environment. Demand forecasts can be produced by many linear and nonlinear models such as Delphi technique, Naïve, Gompertz, Logit, exponential smoothing, regression analysis, autoregressive integrated moving average (ARIMA), decomposition, Bass diffusion model, etc. However, a forecasting model is usually suitable for particular situation. Rink and Swan (1979) provided a literature review of product life cycle (PLC), which includes the four stages of introduction (birth), growth, maturity, and decline (face-off). Bayus (1998) suggested that enterprises must have a different strategy for each product life stage in a competitive market. Levenhach and Cleary (2006) offered a standard practice for suitable forecasting methods in a PLC (see Fig. 1). According to the sales data in the past 10 years, Taiwan's automobile industry can be classified as a maturity market.

2.2. The techniques to forecast the sales of automobile industry

As with univariate modeling, the purpose of multiple input modeling is to find the model that accounts for the predictable portion of the dependent series. In order to predict automobile sales, researchers around the globe usually consulted economical index or statistics to improve forecasting accuracy. They used the multiple regression models with many variables that included income, traffic policies, maintenance cost, car sales price, and fuel price to forecast automobile demand (Carlson & Umble, 1980; Chin & Smith, 1997; Romilly, Song, & Liu, 1998; Tanner, 1978). Based on different markets, Fowkes and Button (1997) adopted Logit model with population to obtain the forecast. Ralph (1999) applied Gompertz model which integrate the population, income, transport policy, and price impact to count the car sales in the future. The result has shown that variables influence the automobile demand. Abu-Eisheh and Mannering (2002) considered the Pakistan employment, world oil price, GDP, exchange rate, the Pakistan policy, and consumer price index (CPI) to build up a dynamic simultaneous-equation system to get the automobile demand forecast in this country. However, linear methods also contain many limitations. For example, some helpful relations are disregarded by linear method inference and liner models also contain fewer variables.

Besides the linear and statistical analysis models, several nonlinear methods have been used to forecast sales. Artificial neural networks (ANNs) and adaptive network-based fuzzy inference system (ANFIS) are two common nonlinear techniques for sales forecasting in recent years. In the late 1940s, Donald Hebb made the first embryo hypotheses for a mechanism of neural network, Hebbian learning. Although the ANNs were very innovative at that time, their developments were restricted by computer arithmetic ability. To change with each passing day, the computer arithmetic ability is growing fast with Moore's Law. After the 1990s, the use of the computer has originated many other reforms and applications. The purposes of ANNs are for classification, cluster and prediction. ANFIS, first proposed by Jang (1993), combined the benefits of ANNs and fuzzy inference systems. FIS is the use of either prior experiences or knowledge into a set of constraints to obtain the optimal solution. The ANNs structure can capture quite obvious patterns. ANFIS can adapt the parameters of the membership functions quickly and optimize them depending on the input data. Among many FIS models, the Takagi–Sugeno model is the most commonly used fuzzy model (Takagi & Sugeno, 1985). It provides a methodical method to generate fuzzy rules from a set of input–output data pairs. Both of them have a predominant visibility in many forecasting problems as they do not require rigid conditions of the operational model of the problem.

For the long-term time series data, many researchers recently demonstrated the forecasting correctness of these models. A variety of applications have been proposed to predict the amounts of time series data, such as hydrology, stock price, and exchange rate. The result of these papers prove that the forecasting performance of ANFIS superior to ARIMA and ANNs (Atsalakis & Minoudaki, 2007; Banik, Chanchary, Rouf, & Khan, 2007; Firat & Güngör, 2008; Nayak, Sudheer, Rangan, & Ramasastri, 2004)

All of the above models exhibit three points. First, the product stage of PLC and economic variables that are essential fundamentals of the sales forecasting. Second, while automobile sales studies exist in our literature, no study has utilized nonlinear forecasting models and employed a time-series predict approach with monthly time-series observations. Finally, previous studies have shown that the ANFIS is an outstanding forecasting model for long-term time series data. Thus, ANFIS might be suitable to forecast the future automobile sales forecasting in Taiwan.

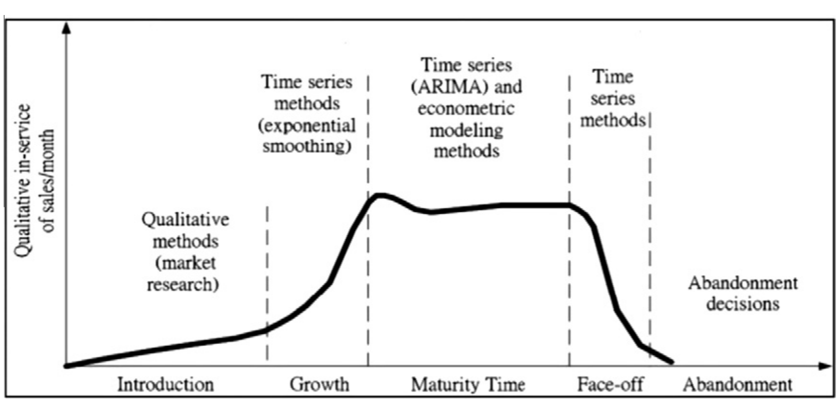

Fig. 1. The PLC curve with its suitable forecasting methods (Levenhach & Cleary, 2006).

3. Estimation model and the variables

3.1. Model setting

This part suggests a sales forecasting method that considers the economic norm effect for future demand in the Taiwan automobile market. The proposed methodology of sales forecasting for Taiwan automobile market consists of two stages. The descriptions of these two stages are as follows:

Stage 1. Selection of predictor variables: Automobile on the market has various forms with different styles. By existing statistical information in Taiwan, three independent car styles can be identified; sedan, small commercial vehicle (under 3.5 tons), and large commercial vehicle (exceed 3.5 tons). Aforesaid vehicles are summed up in one byword "whole vehicle". The stepwise regression is designed to obtain the most parsimonious set of predictors that are most effective in predicting the dependent variable. To determine the useful economic variables, we use the stepwise regression procedure to select the most influential variables as our input variables. We first made use of stepwise regression method, then chose the suitable independent variables, and produced the adjusted determination coefficient table (*R*-square: R^2) and independent variable coefficient table and analysis to see whether the selected independent variables can explain the dependent variable and achieve the regression equation at the same time (Thompson, 1995). In our model, we will use threshold α (0.05) and β (0.1) as the level of significance for our problems. This is accomplished by the repetition of a variable selection. On the iteration, a single variable is entered from the model. For each step, simple regression is performed using the previously included independent variables and one of the excluded variables. Each of these regressions is subjected to a statistically significant test. If the significance value of the variable is smaller than α, then it is added to the model. On the other hand, if the significance value of the variable is higher than β, then it is removed from the model.

Stage 2. Forecasting by ANFIS: The first-order Sugeno fuzzy model has become a common practice on ANFIS implements in the past studies. Thus, we used the same model (see Fig. 2) and the detailed processes of each layer are given as follows:

Layer 1: In this layer, each node is called an input linguistic node and corresponds to one input linguistic variable. The nodes directly transmit input forecasts to the next layer. Each node function can be modeled by fuzzy membership function. The existing functions are triangular, trapezoidal, bell, and Gaussian, respectively. In this paper, we chose the best forecast performance of membership function by comparing it to others.

$$O_{1ji} = u_j(x_i) = \text{membership function format} \quad \forall i = 1,2,\ldots,N;\ j = 1,2,\ldots,M. \tag{1}$$

Layer 2: Each node in this layer calculates the firing strength of a rule via multiplication.

$$O_{2p} = w_p = \Pi_{i=1}^{N} u_{ji}(x_i) \quad \forall ji = 1,2,\ldots,M;\ p = 1,2,\ldots,P. \tag{2}$$

Layer 3: The *i*th node in this layer calculates the ratio of the *i*th rule's firing strength to the sum of all the rules' firing strengths. The result would be the normalized firing strengths. For convenience, the output of this layer will be called the 'normalized firing strengths'.

$$O_{3p} = \bar{w}_p = \frac{w_p}{\sum_{p=1}^{P} w_p}. \tag{3}$$

Layer 4: In this layer, each node *i* in this layer is a square node with a node function. Parameters in this layer will be referred to as consequent parameters by node function.

$$O_{4p} = \bar{w}_p f_p = \bar{w}_p \left(\sum_{i=0}^{N} r_{pi} x_i \right) \quad \text{where} \quad x_0 = 1. \tag{4}$$

Layer 5: The single node in this layer computes the final combining forecast as the summation of all incoming forecasts.

$$O_{5,1} = \sum_{p=1}^{P} \overline{w}_p f_p. \tag{5}$$

All of the ANFIS functions were carried out in the mathematical software package MATLAB (Jang & Gulley, 1995), the most common software package used in developing the ANFIS model.

3.2. Variables

In the past studies, most of them used quarterly or yearly data to establish forecast. The 22 important economic indicators (see Table 1) which refers to previous academic publications and our conjecture employed in this research are collected from National Statistics Taiwan (NST, 2009). The population and unemployment rate are commonly used statistics in economics. The population is a proxy for the size of the potential market, and unemployment rate is portentous for purchasing power. We also considered the exchange rates the N.T. dollar against the US dollar and the Euro dollar. Two additional kinds of indicators (coincident indicators and leading indicators) are considered in this analysis. Both indicators vary simultaneously with the related economic trend, thereby providing information about the current state of the economy. Coincident indicators largely came from the positive cyclical movements in industrial production index, real customs-cleared exports, the sales of manufacturing, the sales index of wholesale, retail, and food services, the employment of non-agricultural, the total power consumption (enterprise), and real machineries and electrical equipments imports. Leading indicators are operative

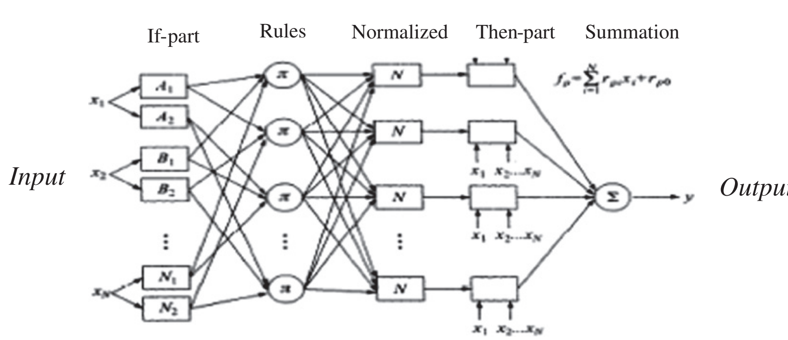

Fig. 2. The concept of ANFIS (Takagi & Sugeno, 1985).

Table 1
Summary of selected economic variables.

Classification	Variables	
Coincident indicators	Industrial production index	CI_1
	Real customs-cleared exports	CI_2
	The sales of manufacturing	CI_3
	The sales index of wholesale, retail, and food services	CI_4
	Real machineries and electrical equipments imports	CI_5
	The employment of non-agricultural	CI_6
	The total power consumption (enterprise)	CI_7
Leading indicators	Average monthly overtime in industry and services	LI_1
	The index of export orders	LI_2
	The superficial measurements of housing starts and building permits	LI_3
	The indexes of producer's inventory	LI_4
	Real monetary aggregates M1B	LI_5
	SEMI book-to-bill ratio	LI_6
	Stock price index	LI_7
Wholesale price indices	The prices of automobile	PI_1
	The oil prices	PI_2
	The prices of automobile components.	PI_3
Independent indices	Population	Po.
	Unemployment rate	Unem.
	The average earnings of employees in industry and services	AverEarn.
Exchange rate	Exchange rates the N.T. dollar against the US dollar	R_1
	Exchange rates the N.T. dollar against the Euro dollar	R_2

reference materials intended to forecast future economic trend. These indicators have historically turned downward before a recession and upward before an expansion. The leading index mainly came from the positive cyclical movements in average monthly overtime in industry and services, the index of export orders, the superficial measurements of housing starts and building permits, the indexes of producer's inventory, real monetary aggregates M1B, SEMI book-to-bill ratio, and stock price index. The wholesale price indices by basic group are related to consumer desire. Among the several components, three important variables are the prices of automobile, the oil prices, and the prices of automobile components. While variables such as population and income serve as a proxy for the magnitude of demand on sales, the number of flights provides a measure of supply. The average income could also reflect the potential market size. Thus, we adopted the average earnings of employees in the automobile industry and services as our reference variable.

4. Empirical results

In this study, the whole automobile market in Taiwan can be divided into three different styles which are sedan, small commercial vehicle, and large commercial vehicle (see Fig. 3). To demonstrate the application of the proposed methodology, we presented the analysis results using the above section. First, stepwise regression was used to obtain the expediency variables in forecasting fitted model for each style. The results were applied to ameliorate forecasting accuracy. Second, we compared the ANFIS model with two forecasting models: ARIMA and ANN for each car style. Here, the ANN model is based on back-propagation network (BPN). Finally, we present the forecasting results using the ANFIS model for revised periods, especially the impact from the 2008 financial crisis.

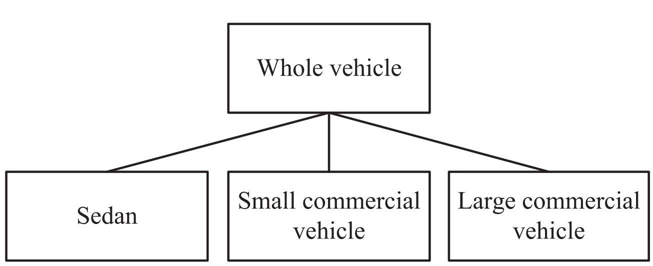

Fig. 3. The framework of the automobile market in Taiwan.

4.1. Analysis of the stepwise regression

According to the data from Taiwan automobile market and National Statistics Taiwan, we use the stepwise regression procedure to select most influential variables as our input variables. In this stage, the sales of each automobile style are dependent variables and the variables introduced in Section 3 are independent variables. All models have been checked by the residual analysis. From Tables 2 and 3, we find that both sales of whole vehicle and sedan are affected mainly by the average earnings of employees in industry and services, the oil prices, and the superficial measurements of housing starts and building permits.

Two types of commercial vehicles using the stepwise regression are summarized in Tables 4 and 5. The influence variables of small commercial vehicle are the average earnings of employees in industry and services, the indexes of producer's inventory, average monthly overtime in industry and services, the oil prices, and the superficial measurements of housing starts and building permits. The industrial production index is only effectual variable for large commercial vehicle. To enhance the next solution procedure, the input data not only includes the mentioned above selected parameters of the stepwise regression but also monthly sales data for each automobile style.

4.2. The results of forecast

The monthly sales data from 2002/8 to 2009/1 are obtained from Taiwan Transportation Vehicle Manufacturers Association. The last 18 months are used as the holdout periods to test the forecasting accuracy of the period ahead. We compare the ANFIS model with the other two forecasting models (ARIMA and ANN).

Table 2
The stepwise regression statistical table of whole vehicle.

Selected model (predictors)		Unstandardized coefficients		Standardized coefficients	t	Sig.	R	R^2	Adjusted-R^2	SE of estimate
		β	SE	β						
1	AverEarn.	0.732	0.03	0.955	24.668	0.000	0.955	0.912	0.910	9779
2	AverEarn.	0.496	0.084	0.646	5.889	0.000	0.961	0.923	0.921	9185
	LI_3	4.204	1.411	0.327	2.979	0.004				
3	AverEarn.	0.598	0.076	0.780	7.867	0.000	0.972	0.944	0.941	7928
	LI_3	8.889	1.592	0.691	5.582	0.000				
	PI_2	−219.868	48.134	−0.513	−4.568	0.000				

Table 3
The stepwise regression statistical table of sedan.

Selected model (predictors)		Unstandardized coefficients		Standardized coefficients	t	Sig.	R	R^2	Adjusted-R^2	SE of estimate
		β	SE	β						
1	AverEarn.	0.521	0.021	0.954	24.508	0.000	0.954	0.911	0.909	6997
2	AverEarn.	0.329	0.059	0.603	5.583	0.000	0.962	0.926	0.923	6429
	LI_3	3.405	0.988	0.372	3.447	0.001				
3	AverEarn.	0.391	0.056	0.718	7.053	0.000	0.970	0.941	0.938	5787
	LI_3	6.264	1.162	0.685	5.389	0.000				
	PI_2	−134.178	35.136	−0.440	−3.819	0.000				

Table 4
The stepwise regression statistical table of small commercial vehicle.

Selected model (predictors)		Unstandardized coefficients		Standardized coefficients	t	Sig.	R	R^2	Adjusted-R^2	SE of estimate
		β	SE	β						
1	AverEarn.	0.203	0.009	0.944	21.972	0.000	0.944	0.891	0.889	3037
2	AverEarn.	0.264	0.024	1.230	11.032	0.000	0.951	0.904	0.900	2880
	PI_2	−36.876	13.377	−0.307	−2.757	0.008				
3	AverEarn.	0.203	0.023	0.947	8.937	0.000	0.967	0.936	0.933	2371
	PI_2	−86.478	14.392	−0.721	−6.009	0.000				
	LI_3	2.548	0.476	0.708	5.351	0.000				
4	AverEarn.	0.160	0.028	0.748	5.668	0.000	0.970	0.942	0.938	2280
	PI_2	−89.428	13.897	−0.745	−6.435	0.000				
	LI_3	1.801	0.556	0.501	3.242	0.002				
	LI_1	419.147	176.664	0.431	2.373	0.021				
5	AverEarn.	0.193	0.029	0.899	6.571	0.000	0.974	0.949	0.944	2160
	PI_2	−43.784	21.338	−0.365	−2.052	0.045				
	LI_3	1.360	0.551	0.378	2.468	0.017				
	LI_1	1793.823	532.690	1.845	3.367	0.001				
	LI_4	−171.892	63.235	−1.808	−2.718	0.009				

Table 5
The stepwise regression statistical table of heavy commercial vehicle.

Selected model (predictors)		Unstandardized coefficients		Standardized coefficients	t	Sig.	R	R^2	Adjusted-R^2	SE of estimate
		β	SE	β						
1	CI_1	4.255	0.206	0.937	20.684	0.000	0.937	0.879	0.877	149.3

In the ANFIS model, we investigated four fuzzy functions (triangular, trapezoidal, bell, and Gaussian) and reported the best function for the comparison study. Four common indices such as Akaike information criterion (AIC), mean square error (MSE), mean average percentage error (MAPE), and the coefficient of determination (R^2) were used as performance measures. These reflect the goodness of model fit adjusted for the number of estimated parameters. The forecasting results using three methods are summarized in Table 6. The best fuzzy function of the ANFIS model for all sales data is triangular.

We found that the best-fitted model for whole vehicle was the ANFIS model. The AIC values for the three different models in the historical periods are 1001.36, 785.94, and 583.66, respectively. The MSE values for the three models in the historical periods are 17,315,474, 427,472, and 14,682, respectively. The R-square values for the three models are 84.65%, 99.62%, and 99.99%, respectively. The MAPE values for the three models in the historical periods are 11.65%, 1.55%, and 0.33%, respectively. Similarly, we found that the best-fit model for all styles was the ANFIS model. The diagnostic checks of all models can validate the assumptions.

Table 6
The comparison results of different models for all styles.

Styles	Models	Historical periods				Holdout periods
		R^2	MSE (%)	R^2	MSE (%)	R^2 (%)
Whole vehicle	ARIMA	1001.36	84.65	173,15,474	11.65	45.97
	ANN	785.94	99.62	427,472	1.55	11.38
	ANFIS	583.66	99.99	14,682	0.33	27.09
Sedan	ARIMA	941.62	81.8	105,20,198	12.92	44.71
	ANN	750.01	99.58	234,862	1.75	10.45
	ANFIS	558.93	99.98	9722	0.36	26.84
Small commercial vehicle	ARIMA	872.49	82.15	20,16,509	15.06	49.10
	ANN	696.84	99.19	90,588	2.96	11.29
	ANFIS	449.89	99.99	1478	0.44	38.1
Large commercial vehicle	ARIMA	534.35	70.88	6765	18.54	39.27
	ANN	306.56	99.34	155	3.21	4.25
	ANFIS	14.65	99.99	1.19	0.22	0.79

Table 7
The summary results of individual style.

Style	Best fitted model	AIC	R^2 (%)	MSE	Historical periods MAPE (%)	Holdout periods MAPE (%)
Sedan	ANFIS (triangular)	711.55	99.99	9292.66	0.52	0.76
Small commercial vehicle	ANFIS (triangular)	710.74	99.94	8730.31	1.10	18.53
Large commercial vehicle	ANFIS (triangular)	14.01	99.99	1.14	0.27	0.25

Table 8
The comparison results of whole vehicle.

Style	AIC	R^2 (%)	MSE	Historical periods MAPE (%)	Holdout periods MAPE (%)
Whole vehicle	712.10	99.99	9359.14	0.38	0.91
Whole vehicle (combining individual vehicle forecasts)	732.14	99.99	13125.73	0.36	3.59

4.3. The forecasting results of revised periods

As above results show, the best fitting model in the three given forecasting models was the ANFIS model. In general, the best fitting performance in historical periods accompanies the best fitting performance in the holdout periods. However, the MAPE of holdout periods was not exactly analog. In fact, the third quarter of 2008 actual sales in holdout periods was the lowest in over the years. To illustrate the contradictory results, we make a supposition. The subprime mortgage crisis brought grave dislocation to the economy and the speedy change in the coefficients of the primary variables that pertain to the consumer expenditure and the economical composition in the entirely environment: GDP, average income, unemployment rate, SEMI book-to-bill ratio, stock price index, etc. We surmise that these events varied our degree of accuracy. To verify forecasting accuracy and considering these adverse effects from the financial crisis, we modified the historical and holdout periods. The holdout periods changed from the last 18 months to the last 4 months to test the forecasting accuracy of the period ahead. Based on the description of input data in Section 4.1 and of the best fitting model in Section 4.2, the results are shown in Table 7.

According to the data from modified periods, we found that the AIC values for the three style vehicles in the historical periods are 711.55, 710.74, and 14.01, respectively. All R-square values for the ANFIS model are greater than 99%. The MSE values for ANFIS in the historical periods are 9292.66, 8730.31, and 1.14, respectively. The MAPE values for the ANFIS model in the historical periods are smaller than 2%. Each style MAPE of holdout periods has obvious improvement. The diagnostic checks for all fitted models can still validate the assumptions. The whole vehicle results compare with the sum of the forecasts of individual vehicle (see Table 8). Thus it can be seen that the direct forecasts outperforms the combining forecasts for the whole market.

5. Conclusions

This study has made three important contributions. First, we have empirically shown that some economic variables are good predictors of Taiwan's automobile sales. Our results indicate that several variables can be explained significantly in the forecasting model. The results also show that stepwise regression may do a better job of explaining future automobile market than traditional methods. Second, we have shown that the ANFIS model, if used in conjunction with the stepwise regression, may become the best effective forecast tool than traditional methods. We have empirically tested the model's capability to predict automobile sales in Taiwan and showed that it can give reasonably provide accurate predictions of each style of automobile sales. Third, the ultimate results can provide valuable insights for manufacturers in understanding the relationship of individual and whole market. This finding may give interesting implications to manufacturers and researchers with respect to the dynamic relationship between single style and whole market. This information may assist policy makers in regulating the markets by utilizing consumer in regulating and affecting the price observed in different regional markets.

Further research issue can be extended to combine the different heuristic inferential method. Second, our model does not account for the unobserved heterogeneous variables such as policy, promotion, etc. Although in theory we can use either the fixed-effect or the random-effect method to capture the heterogeneity, neither would work for this study. If proper methods of controlling individual heterogeneity are developed in the future, researchers may re-estimate our models and examine the robustness of the empirical results reported in this paper.

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