International Journal on Advanced Science Engineering Information Technology

Vol.10 (2020) No. 6
ISSN: 2088-5334

An Integrated Model for Forecasting Indian Automobile

Kayalvizhi Subramanian[a,1], Mohammad Othman[a,2], Rajalingam Sokkalingam[a,3], Gunasekar Thangarasu[b], S. Kayalvizhi[c]

[a] *Faculty of Fundamental Science, University Technology PETRONAS , Perak, Malaysia*
E-mail: [1]kayalvizhi_16005735@utp.edu.my; [2]mahmod.othman@utp.edu.my; [3]raja.sokkalingam@utp.edu.my

[b]*Department of Professional, Industry Driven Education (PRIDE), Mahsa University, Malaysia*
E-mail: gunasekar97@gmail.com

[c]*Faculty of Built Environment, Linton University College, Malaysia*
E-mail: skayalvizhi2012@gmail.com

***Abstract*— The automobile industry is one of India's main economic sectors. In recent decades India has attracted many global players in the automobile industry. The industry has significantly benefited from an increase in the paying capacity of the consumers. This has contributed to increased competition in the market. Given that the automobile industry is a very complex process, a tool to predict the future of automotive demand from the modeling point of view is needed because of its high level of complexity and uncertainty. This study aims to introduce a novel integrated model with a combination of Adaptive Multiplicative Triple Exponential Smoothing Holt-Winters (AHW) method and Backpropagation Neural Networks (BPNNs) to improve the likelihood of predicting automobile sales accurately. This study is subject to continue validating a model in real-world automobile selling data against existing methods. This model also incorporates the linear and non-linear characteristics of AHW and BPNN, respectively to form a synergistic model. The proposed model has the higher capability to provide reasonable accuracy in forecasting future sales in terms of average prediction accuracy of 0.974637 than the existing methods namely BPNN 0.9483 and ANN 0.9275. For training and testing purposes, validation is done using the Indian automobile sales data. Finally, the regression fit shows that during the test stage in the car sales data for the period 2016-2017 and 2017-2018, the proposed integrated model is better than the conventional method.**

***Keywords*— adaptive multiplicative exponential smoothing; AHW; backpropagation neural networks; automobile sales industry.**

I. INTRODUCTION

Planning is regarded as a vital procedure in Indian automobile sales activity. Since the market is increasing each year, the demand and sales of automobile vehicles are increasing. Accurate forecasting of automobile sales plays a major role in the market. The accuracy of prediction directly affects the manufacturers in deciding the demands of the current market pattern, identifying the competition and development strategies of manufactured products. The accurate forecasting permits the manufacturers to increase their market performance, plan new policies, and gain profit [1]-[2]. Various factors affect the sales of automobiles, and that has an intrinsic correlation between them. In the last few years, forecasting automobile sales uses conventional time series forecasting methods like moving average, ARIMA, exponential smoothing and multivariate regressions, etc. to study the market and sales patterns. The forecasting accuracy using the conventional models for various automobile vehicles are not sufficient w.r.t mean absolute percent error (MAPE). Since the value of MAPE lies between 20-30% [3]. Hence, the researchers evoked some novel forecasting sales model using a machine or artificial learning model to improve sales and reduce inventory costs. However, the prediction of sales data using machine learning models acquires a lesser accuracy rate than the combination of machine learning with a statistical method.

This study's main objectives are to propose integrating an Adaptive multiplicative triple exponential smoothing Holt-Winters (AHW) method and Backpropagation Neural Networks (BPNNs) to increase the probability of predicting automobile sales accurately further to validate a model against existing methods in terms of real-world automobile sales data. The machine learning models are trained based on recent automotive sales data and time series forecast performance. The section-II includes the material and method, section-III result analysis and discussion, and section-4 conclusion. This paper is structured accordingly.

II. MATERIAL AND METHOD

This section discusses various reviews on common forecast models that use either machine learning or artificial intelligence models to increase the forecasting accuracy of automobile industry sales. Apart from statistical [1-3] and linear models for forecasting sales, several nonlinear methods exist, which are discussed below.

The study showed that management would ambitiously increase its production. Kin Keung et al. [4] compared their Indian motorcycle industry's Holt-Winters and SARIMA models' production capacity. The findings of the analysis indicate that both models function very well. The Holt-Winter model, however, appears to be a more accurate and precise than others. Several factors affect demand from automobile, especially in relation to the study of the automotive industry. According to the marketing theory, population trend is one of the most significant factors influencing automotive production, which enlightens us about production sizes [5- 6].

The most popular techniques in the forecasting of sales have recently come from the Artificial Neural Networks (ANNs) [7-8] and Adaptive Network-based Fuzzy Inference System (ANFIS). In the middle of the 19th century, the Hebbian learning and neural network evoked the sales forecasting. Later with improvements in the computer revolution, the ANN is extended to cluster problem, classification, and prediction tasks. It is then combined with FIS and them with ANFIS [9] to work on forecasting problems. Since, it does not require any firm conditions of the problem. The use of heuristic methods increased the effectiveness in predicting the forecasting ability. In [10], the ANFIS model is used for predicting the model and Genetic Algorithm is used to tune the results of ANFIS. The neural network is further improved using the BP neural network, where the network is optimized using Genetic Algorithm in forecasting the automobile sales data [11].

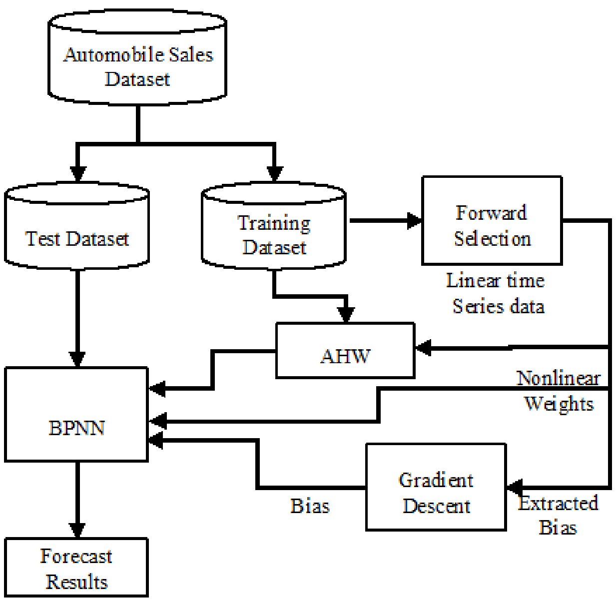

Fig. 1 An Integrated model for Automobile Forecasting (AHW-BPNNs)

The automobile sales forecast is improved with Support Vector Machine in German automobile market [12]. In addition, the Decision Tree model is used to research the automobile sales with German and US-American market as study [13]. However, we found no new studies on machine learning are reported to analyse the Indian automobile sales data. Also, the improvements in ANN are made by combining it with time series methods like ARIMA, however, the focus on the present study is the use of machine learning or artificial intelligence methods. Hence, the studies on other time series models are not considered.

The integrated model uses an Adaptive Multiplicative Triple Exponential Smoothing Holt-Winters (AHW) method and Backpropagation Neural Networks (BPNNs). Hence, the researchers evoked some novel forecasting sales model using a machine or artificial learning model to improve the sales and reduce inventory costs. The prediction of sales data using machine learning model improves the accuracy rate than the conventional statistical methods. Fig-1 shows the integrated model of automobile forecasting (AHW-BPNNs).

A. Holt-Winter Method

The Adaptive Multiplicative Triple Exponential Smoothing Holt-Winters method corrects the rate, weight with learning rate to be α ($0 \geq \alpha \geq 1$). The algorithm appears to become unstable when the learning rate is high and vice versa. The Holt-Winters method uses simple exponential smoothing to predict the three fundamental values of the time series component, namely, level (mean value), trend and season [14]. The following are the equation of the three values for each iteration $t = 1, 2, \ldots$, which are given below:
The level is calculated as:

$$L_t = \frac{\alpha Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{1}$$

The trend is calculated as:

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{2}$$

The seasonality is calculated as:

$$S_t = \frac{\gamma Y_t}{L_t} + (1-\gamma)S_{t-s} \tag{3}$$

The forecast is calculated as:

$$F_{t+m} = (L_t + b_t m)S_{t-s+m}, m = 1,2,\ldots,M \tag{4}$$

Where
s is considered to be the seasonality time,
Y_t is regarded as the current time-series value,
L_t is regarded as the yearly average series level,
b_t is regarded as the trend,
S_t is considered the component of the season and
F_{t+m} is regarded as the prediction for m=1,…, M, and
M is called the horizon of the prediction.

The unrealistic predictions are avoided using linear -trend forecasting, which is defined as follows.

$$F_{t+m} = (L_t + b_t\sqrt{m})S_{t-m} \tag{5}$$

The above equations will help to forecast the sales in the future. A sub-linear trend approach is obtained using the square root of m and this leads to the more conservative trend exploration of data. This forecast value sets the weights for Gradient Descent in BPNN and the bias is same as used in Gradient Descent.

B. Back Propagation Neural Network

Back propagation is known to reduce the gradient by three different stages, including forward propagation, step propagation step and weight change and bias stage. There are three distinct network activity layers, which include the layer of input, the secret layer and the layer of output [15]. The process of BPNN is explained as follows:

Step 1. Initialize weights of BPNN at random

Step 2. Estimate the output using current weights of the network

Step 3. Estimate the error values in the output, hidden layers.

Step 4. Modify the network relation

Step 5. Repeat Step 2 to hit the desired state.

In the output layer, the error is calculated as below:

$$E(i) = O(i)\big(1 - O(i)\big)\big(T(i) - O(i)\big) \tag{6}$$

Where

$O(i)$ is regarded as the output of a node i, and

$T(i)$ is regarded as the output value of trained data node.

In the hidden layer, the error is calculated as below:

$$E(i) = O(i)\big(1 - O(i)\big)\textstyle\sum_j E(j)W(ij) \tag{7}$$

Where

$O(i)$ is known to be the output hidden node i,

$E(j)$ is known to be the node j and error value

$W(ij)$ the tow notes (neurons) are weighted between them.

After estimating the error in each neuron, network weights are modified using the following equation,

$$W(ji) = W(ij) + l \cdot E(j) \cdot O(i) \tag{8}$$

Where

l is regarded as the amount of the learning rate 0 to 1.

The description for BPNN is as follows: (1) initialization of input, initialization of bias, epoch, learning rate, error, target, initial weight and bias. 2. Estimate the value of inputs (z,n) on the hidden layer using the following expression:

$$Z_{in}(j) = b_1(j) + \textstyle\sum_{i=1}^{n} x(1)v(ij) \tag{9}$$

where

b_1 is considered as the input bias parameter, and

y is regarded as the weight.

The output is computed using the sigmoid activation function, which are given below:

$$Z_j = f\big(Z_{in}(j)\big) = \frac{1}{1+Z_{in}(j)} \tag{10}$$

The output signal from the hidden layer is calculated to obtain the output from the output layer using the following expression.

$$y_{in}(j) = b_2(k) + \textstyle\sum_{i=1}^{n} x(i)v(jk) \tag{11}$$

The output Mean Square error is thus estimated using the following expression.

$$MSE = \frac{\sum E^2}{n} \tag{12}$$

In the output unit, the MSE formula is used to correct the values of biases and weights δ. The return signal (δ_{in}) is estimated from the output layer given by the following expression [16].

$$\delta_{in}(j) = \textstyle\sum_{k=1}^{p} \delta(k)w(jk) \tag{13}$$

Estimate the δ_1 in hidden layer unit to optimize the weight value and bias values:

$$\delta(j) = \delta_{in}(j)f^1\big(z_{in}(j)\big) \tag{14}$$

Calculate the optimal weights with Δv and then estimate the bias with Δb, through following expression,

$$\Delta v(ij) = \alpha\big(\delta(j)x(j)\big)\ \Delta b_1(j) = \alpha\delta(j) \tag{15}$$

The bias and weights are fixed at all layers and hence the final output layer is estimated as follows:

$$W(jk) = W(jk) + \Delta W(jk) \tag{16}$$

Finally, the hidden layer is estimated as,

$$v(ij) = v(ij) + \Delta v(ij) \tag{17}$$

C. Forecasting BPNN-AHW model

BPNN, trained using historical automotive sales data to capture the non-linear character of a certain period, is used in the proposed study for time-series forecasting. The AHW connection weights and BPNN node variables are adjusted iteratively to reduce predicative errors. For forecasting using time series data, a mathematical expression can be employed to represent the relationship of input (y_{t-1}, y_{t-2}, …, y_{t-p}) to outputs (y_t) in BPNN. $y_t = a_0 + \sum_{j=1}^{q} a_j f\big(w_{0j} + \sum_{i=1}^{p} w_{ij} y_{t-1}\big) + e_t$(i = 0, 1, 2, …, p) (j = 0, 1, 2, …, q), where a_j is regarded as the bias on j^{th} unit, and w_{ij} is regarded as the connection weights between BPNN hidden layers, $f(\bullet)$ is regarded as the transfer function of the BPNN hidden layer,

p is regarded as the total number of input nodes and q is regarded as the total number of hidden nodes.

The BPNN model typically measures the past observation of nonlinear functional mapping (y_{t-1}, y_{t-2}, …, y_{t-p}) in order to estimate future sales value (y_t), i.e., $y_t = \varphi(y_{t-1}, y_{t-2}, \ldots, y_{t-p}, w) + e_t$ where w is regarded as the parametric vectors and

φ is vector the function formed by the connection weights and network structure. The BPNN has the ability of offering flexible nonlinear mapping between past and future observations. It has the ability to capture the time series non-linear characteristics. However, linear problems cannot be mapped with BPNN model as it may lead to mixed result. Hence the proposed method uses Adaptive Multiplicative

Triple Exponential Smoothing Holt-Winters and it relationship with BPNN is considered to be complementary.

III. Results and Discussion

The proposed approach requires a variety of steps to build the validation approach to check the system proposed against past car sales results. In the first step, the input (sales data of various automobile types) and output data are selected. In the second step, the input and output data in normalized. In the third step, the normalized data is trained using BPNN learning. In the fourth step, the goodness of regression fit of the proposed model is tested and finally, the predicted output is compared with actual output. Input data are collected to identify various factors such as gross turnover, installed capacity, market structure, output patterns, domestic sales trends and export trends. The data is trained using improved BPNN technique. The collected dataset with various factors are divided into training set (70% of collected data) and testing set (30% of testing set).

A. Data Description

The total production data of different vehicles, namely passenger vehicles, commercial vehicles, three wheelers and two wheelers in the Indian Automobile industry between 2004 and 2018 is given in Table 1. The data on total sales amount in Indian Automobile industry between 2004 and 2018 is given in Table 2. Similarly, the data of total exports in the Indian Automobile industry between 2004 and 2018 are given in Table 3

TABLE I
TOTAL PRODUCTION OF VEHICLES IN INDIAN AUTOMOBILE INDUSTRY BETWEEN 2004-2018

Periods	Passenger Vehicles	Commercial Vehicles	Two Wheelers
2004-2005	1,209,876	353,703	06,529,829
2005-2006	1,309,300	391,083	07,608,697
2006-2007	1,545,223	519,982	08,466,666
2007-2008	1,777,583	549,006	08,026,681
2008-2009	1,838,697	417,126	08,418,626
2009-2010	2,357,411	567,556	00512,903
2010-2011	2,982,772	760,735	13,349,349
2011-2012	3,123,528	911,574	15,453,619
2012-2013	3,233,561	831,744	15,721,180
2013-2014	3,072,651	698,864	16,879,891
2014-2015	32,21,419	6,98,298	1,84,89,311
2015-2016	34,65,045	7,86,692	1,88,30,227
2016-2017	38,01,670	8,10,253	1,99,33,739
2017-2018	40,10,373	8,94,551	2,31,47,057

TABLE II
TOTAL VEHICLE SALES IN INDIAN AUTOMOBILE INDUSTRY BETWEEN 2004-2018

Periods	Passenger Vehicles	Commercial Vehicles	Two Wheelers
2004-2005	1,061,572	318,430	6,209,765
2005-2006	1,143,076	351,041	7,052,391
2006-2007	1,379,979	467,765	7,872,334
2007-2008	1,549,882	490,494	7,249,278
2008-2009	1,551,880	384,122	7,437,670
2009-2010	1,951,333	532,721	9,370,951
2010-2011	2,501,542	684,905	11,768,910
2011-2012	2,618,072	809,532	13,435,769
2012-2013	26,65,015	7,93,211	1,37,97,185
2013-2014	25,03,509	6,32,851	1,48,06,778
2014-2015	26,01,236	6,14,948	1,59,75,561
2015-2016	27,89,208	6,85,704	1,64,55,851
2016-2017	30,47,582	7,14,082	1,75,89,738
2017-2018	32,87,965	8,56,453	2,01,92,672

TABLE III
TOTAL VEHICLE EXPORTS IN INDIAN AUTOMOBILE INDUSTRY BETWEEN 2004-2018

Periods	Passenger Vehicles	Commercial Vehicles	Two Wheelers
2004-05	166,402	29,940	366,407
2005-06	175,572	40,600	513,169
2006-07	198,452	49,537	619,644
2007-08	218,401	58,994	819,713
2008-09	335,739	42,673	1,004,174
2009-10	446,145	45,009	1,140,058
2010-11	444,326	74,043	1,531,619
2011-12	507,318	92,663	1,947,198
2012-13	5,59,414	80,027	19,56,378
2013-14	5,96,142	77,050	20,84,000
2014-15	6,21,341	86,939	24,57,466
2015-16	6,53,053	1,03,124	24,82,876
2016-17	7,58,727	1,08,271	23,40,277
2017-18	7,47,287	96,867	28,15,016

The study considers collects the data of 20 automobile company (N = 20), namely Bajaj Auto Ltd., Eicher Motors Ltd., Hero Motocorp Ltd., L M L Ltd., Mahindra Two Wheelers Ltd., T V S Motor Co. Ltd., Ashok Leyland Ltd., Daimler India Comm Vehicles Pvt. Ltd., Defence Land Systems India Ltd., Force Motors Ltd., S M L Isuzu Ltd., Tata Motors Ltd., Fiat India Automobiles Pvt. Ltd., Honda Cars India Ltd., Hyundai Motor India Ltd., Mahindra Reva Electric Vehicles Ltd., Mahindra Vehicle Mfrs., Maruti Suzuki India Ltd., Toyota Kirloskar Motor Pvt. Ltd. and Volkswagen India Pvt. Ltd. The table-4 refers to sales performance between the years 2004 and 2018 for passenger, commercial and two wheeled vehicles. The data are collected from these 20 firms based on its availability between these years. The proposed model's inputs are considered from Table 4 that includes labour cost, capital cost, material cost, energy cost, and gross sales.

TABLE IV
DESCRIPTIVE STATISTICS OF INPUT VARIABLE

Passenger Vehicle (N = 8)				
Statistics	**Mean**	**SD**	**Minimum**	**Maximum**
Gross sales	109,224.80	119,709.60	224,083.71	476,233.70
Labor cost	003,022.18	002,993.58	000,075.56	014,591.20
Capital Cost	014,228.12	012,325.32	000,039.96	054,957.82
Material Cost	057,519.20	060,002.03	000,118.13	202,942.90
Energy Cost	000,007.20	001,032.90	000,003.56	004,171.40
Commercial Vehicle (N = 6)				
Statistics	**Mean**	**SD**	**Minimum**	**Maximum**
Gross sales	084,205.24	134,774.70	0,030.11	482,077.90
Labour cost	005,526.60	000,076.17	0,029.46	023,498.96
Capital cost	016,410.19	023,208.44	0,129.34	070,108.45
Material cost	038,943.39	060,739.28	0,029.13	225,008.66
Energy cost	000,560.22	000,960.47	0,003.46	003,373.48
Two Wheeler Vehicle (N = 6)				
Statistics	**Mean**	**SD**	**Minimum**	**Maximum**

Gross sales	073,557.80	079,429.72	1,159.85	226,265.30
Labour cost	003,677.23	003,489.52	0,194.40	012,289.90
Capital cost	004,796.28	004,916.82	2,162.53	016,881.59
Material cost	038,049.09	041,260.57	0,589.26	116,318.10
Energy cost	000,323.15	000,274.41	0,027.21	000,753.90

B. Obtained Results Comparison with Other Methods

The fig-2 represents the predicted annual forecasting results, assessment using factors related to automobile sales in past years. The evaluation is considered between 2005 and 2018, and the results are evaluated between the proposed BPNN and conventional BPNN and ANN. The result shows a marginal difference between the existing systems and proposed systems on the predicted results. The proposed method achieves higher prediction accuracy than the existing methods. The use of AHW in BPNN improves the prediction probability of BPNN more than conventional BPNN. This shows that the calculation of weights using AHW model improves well the prediction of instances. Finally, we present the predicted results between the proposed and existing methods in terms of actual values. The first five financial years (2011-12, 2012-13, 2013-14, 2014-15 and 2015-16) are chosen for both training and testing the proposed model and another two years (2016-17 and 2017-18) are chosen only for testing purpose. The results between the actual data and predicted data show that the proposed method is more accurate in prediction than the existing methods (BPNN and ANN).

TABLE V
PREDICTED RESULTS USING INTEGRATED MODEL AND EXISTING METHODS

Year	Training/Testing data	Actual	Predicted Results		
			BPNN-AHW	BPNN	ANN
2011-12	Training and Testing	19410552	18900248	18254234	17932244
2012-13		19851230	19420104	18773480	18519074
2013-14		20700330	19965548	19648751	19116341
2014-15		22357491	21919459	21249294	20911856
2015-16		23169816	22637765	22057069	21660256
2016-17	Testing	24558677	24049327	23506421	22688288
2017-18		27996260	27082742	26423822	25721284

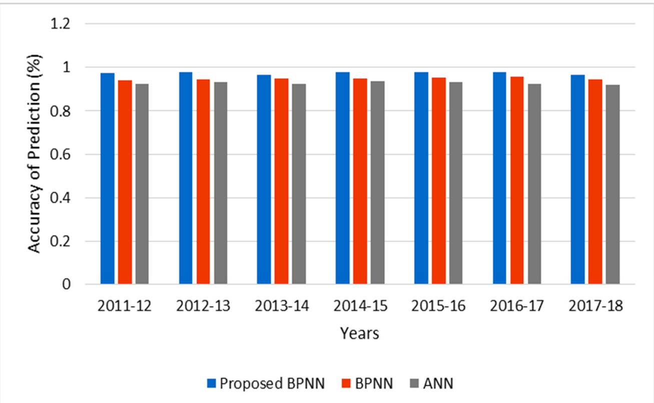

Fig. 2 Accuracy of prediction using proposed method and conventional method of BPNN

The proposed method is tested in terms of mean squared error during training and testing of data instances i.e. automobile sales data. The results of MSE is given in Fig-3. It is seen that best validation performance is acquired at 700th iteration, where the MSE is 0.094837.

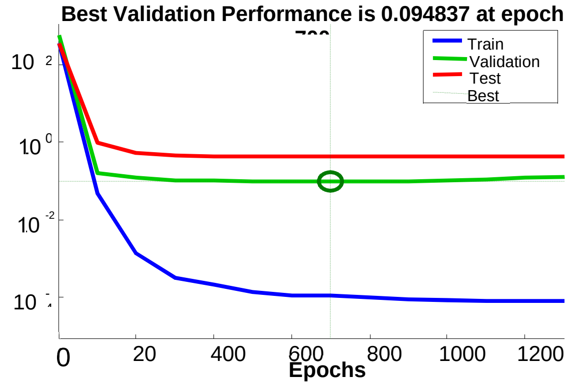

Fig. 3 Results of MSE using Proposed BPNN-AHW

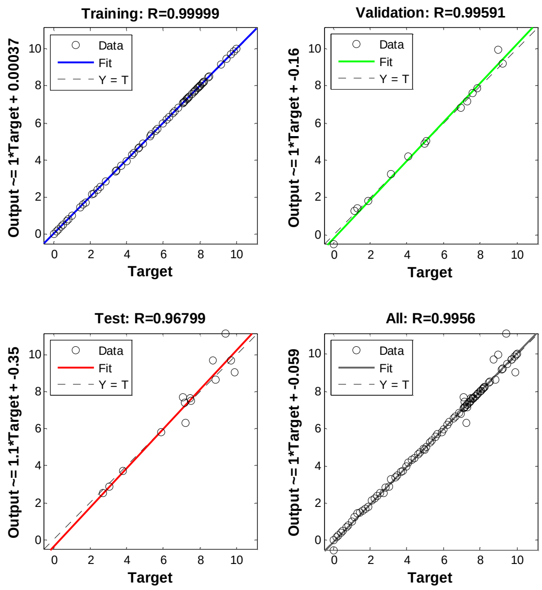

Fig. 4 Mean Squared Error after several iterations using proposed model

The results of training show that MSE acquires reduced MSE than at testing period. The results between proposed validation performance and existing BPNN validation performance show that the proposed method attains reduced MSE than the existing method. The best validation of MSE is reported at 300th iteration i.e. 48,631.The fig 4 and 5 shows the regression fit between the training, testing and validation. The result demonstrates that the match between training and selling data testing is higher than the existing BPNN method in the proposed method. It illustrates that the new approach makes the automotive sales data more efficient than the current method.

The result shows that the proposed BPNN has reduced RMSE and non-changeable R^2 outputs, showing that it is possible to forecast automotive sales data relative to other approaches effectively. The result has outperformed existing BPNN in both training and testing stages. The evaluated result i.e. test data shows that the tuning of results using

AHW that improves the results than the existing BPNN. The R^2 does not provide any improvement in its results. The proposed method's advantage is that the model can update itself at certain time intervals as newer data enters the system. Finally, it can be concluded that the proposed method can be used for improving the prediction of annual automobile sales in India.

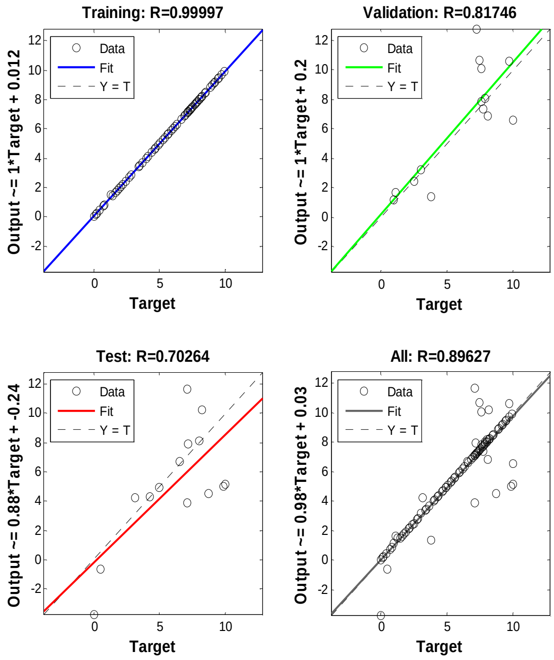

Fig. 5 Results of Regression Plot using existing method

IV. Conclusion

This paper proposes a novel integrated model using the combination of AHW with BPNNs to forecast the sales in automobile industry based on the collected data from manufacturing companies in India. The results indicate that the proposed model serves a better job in improving future automobile industry sales than the conventional methods. The proposed model has the higher capability of providing reasonable accuracy in forecasting future sales in terms of average prediction accuracy (0.974637) than the existing methods namely BPNN (0.9483) and ANN (0.9275). Further, the MSE of the proposed method during training and testing is lesser than the existing BPNN. Finally, the regression fit shows that the proposed integrated model is accurate during the testing phase in predicting the automobile sales data for the year 2016-2017 and 2017-2018 than the conventional system. Further, even if the market is fluctuating the AHW sets the pattern or weights required to increase the forecasting ability of BPNN, as it tunes the results of BPNN.

References

[1] Junjie Gao, Yanan Xie, Xiaomin Cui, Han Yu, and Feng Gu, "Chinese automobile sales forecasting using economic indicators and typical domestic brand automobile sales data: A method based on econometric model", Advances in Mechanical Engineering, 2018, Vol. 10, No.2, pp.1-11.

[2] Amirmahmood Vahabi, Shahrooz Seyyedi Hosseininia, Mahmood Alborzi, "A Sales Forecasting Model in Automotive Industry using Adaptive Neuro-Fuzzy Inference System (Anfis) and Genetic Algorithm (GA)", International Journal of Advanced Computer Science and Applications, 2016, Vol.7, No.11, pp.24-30.

[3] Syed Shahabuddin, "Forecasting automobile sales", Management Research News, 2016, Vol. 32, No. 7, pp. 670-682.

[4] Kin Keung Lai, Lean Yu, Shouyang Wang, and Wei Huang," Hybridizing exponential smoothing and neural network for financial time series predication", International Conference on Computational Science. Springer, Berlin, Heidelberg, 2016, pp. 493-500.

[5] Al-Mubayyed, Osama. M, Abu-Nasser, Bassem.S, Abu-Naser and Samy. S, "Predicting Overall Car Performance Using Artificial Neural Network", *International Journal of Academic and Applied Research*, 2019, Vol.3, No.1, pp. 1-5.

[6] Wang. D, Cao.W, Li. J and Ye. J and Deep. S. D, "Supply-Demand Prediction for Online Car-Hailing Services Using Deep Neural Networks", *IEEE 33rd International Conference on Data Engineering(ICDE)*, San Diego, CA, 2017, pp. 243-254.

[7] Stratis. K, Jino M and Michael. E, "Instantaneous Vehicle Fuel Consumption Estimation using Smartphones and Recurrent Neural Networks", *Expert Systems with Applications*, 2019, Vol. 120, No. 15, pp. 436-447.

[8] Zhiguo. Y and Devenathan. S, "Examining Multi-Category Cross Purchase Models with Increasing Dataset Scale – An Artificial Neural Network Approach", *Expert Systems with Applications*, 2019, Vol. 120, No. 15, pp. 310-318.

[9] Susmita S. M and Megha J. V, "Mining Online Reviews and Tweets for Predicting Sales Performance and Success of Movies". *International Conference on Intelligent Computing and Control Systems*, Madurai, 2017, pp. 334-339.

[10] Yong. Z, Miner. Z, Nana. G and Yunjian. J, "Forecasting Electric Vehicles Sales with Univariate and Multivariate Time Series Models: The Case of China", *PLoS ONE*, 2017, Vol. 12, No. 5, pp. 1-15.

[11] Junjie. G, Yanan. X and Feng. G, "A Hybrid Optimization Approach to Forecast Automobile Sales of China", *Advances in Mechanical Engineering*, 2017, Vol. 15, No. 7, pp. 909-925.

[12] Mahmoud. A, Essam. M. S and Karim. A., "Egyptian Case Study-Sales Forecasting Model for Automotive Section", *International Conference on Smart Applications, Communications and Networking*, Sharm EI Sheik, Egypt 2019, pp. 1-6.

[13] Pradipta Kumar Sahoo, and Badri Narayan Rath, "Productivity growth, efficiency change and source of inefficiency: evidence from the Indian automobile industry", International Journal of Automotive Technology and Management, 2018, Vol.18, No. 1, pp. 59-74.

[14] Mahendran, S., Senthilkumar, A., & Jeyapaul, R., "Analysis of lean manufacturing in an automobile industry-a case study", International Journal of Enterprise Network Management, 2018, Vol. 9, No. 2, pp. 129-142.

[15] Bharadwaj A., "Evolution of the Global Automobile Industry", Environmental Regulations and Innovation in Advanced Automobile Technologies, Springer, Briefs in Economics book series, 2018, pp. 1-9.

[16] Jain, M., Abidi, N., & Bandyopadhayay, A., "E-procurement espousal and assessment framework: A case-based study of Indian automobile companies", International Journal of Technology Management & Sustainable Development, 2018, Vol. 17, No. 1, pp. 87-109.