Artificial Neural Network Modeling Studies to Predict the Amount of Carried Weight by Iran Khodro Transportation System

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Abstract: This paper investigates the use of three artificial neural network (ANNs) algorithms, namely, incremental back propagation algorithm (IBP), genetic algorithm (GA) and Levenberg–Marquardt algorithm (LM) for predicting Carried weight, with an automobile industry namely, Iran Khodro Company (IKCO) used as the study case. These algorithms belong to three classes: gradient descent backpropagation algorithm, genetic algorithm and Levenberg-Marquardt algorithm. The above algorithms were compared according to their prediction ability, prediction accuracy, as well as degree of generalization. The network structure was trained with the algorithms by using some numerical measures as the training set. Those algorithms were then compared according to their performances in training and prediction accuracy in testing based on root mean square error (RMSE) and correlation coefficient (R^2). The results indicate that incremental back propagation performs better than the other algorithms in training and has higher prediction accuracy during the learning period.
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Keywords: Artificial neural network; incremental back propagation algorithm; Levenberg-Marquardt algorithm; Genetic algorithm; prediction

1. Introduction

A company can properly allocate resources for machinery, transport system, labor, and for proper organization if it is aware of the quantity of the items demand. Demand rates can be assessed by using various methods, the most important of which are load-count analysis, weight-volume analysis, and material balance analysis (Smith 2012). Although these methods are the central strategies for estimating demand rate figures, they have some deficiencies. For instance, load-count analysis specifies the collection rate but not the rate of demand. Material balance analysis may produce many errors with a large production rate source. Utilizing new methods and advanced techniques, such as a dynamic and non-linear system, can be useful for computing production and demand rates. Such methods include certain models, classic statistical methods, and many new techniques such as artificial neural networks (ANNs) (Chaudhry et al. 2013; Efendigil & Önüt 2011; Paliwal & Kumar 2009).

The previous studies have focused on the utilization of ANNs in demand and product development in transportation and supply chain literature (Chan et al. 2011; Che 2010). Computational intelligence approaches have already been utilized in different supply chain forecasting and optimization tasks. ANNs in particular are new approach for the optimization and modeling of transportation costs, resource allotment, modeling and simulation (Jafarzadeh et al. 2012; Minis 2010). A computational intelligence method for univariate supply chain request forecasting was previously explored by Liang and Huang (2006), who suggested a solution that applies a genetic algorithm to forecast demands in a multi-echelon supply chain. Their outcomes revealed that in particular presumptions, the suggested approach might universally optimize the general expense of the supply chain.

Gutierrez et al. (2008) used neural systems as univariate models for forecasting lumpy request. These neural systems were observed to perform much better than traditional approaches for various performance measures. The feasibility of using more developed computational intelligence methods as univariate models was also examined by Carbonneau et al. (2008). They used neural systems, recurrent neural systems, and support vector tools to forecast deformed request at the end of a supply chain (bullwhip impact). Then, they compared these approaches with more traditional ones, with naive forecasting, mode, moving average, and linear regression in two datasets (one gained from a simulated supply chain and another from real Canadian Foundries orders). The outcomes showed that recurrent neural systems and support vector tools presented the best function; however, their forecasting authenticity was not statistically remarkably better than that of the regression model by Zhong et al. (2002). Our earlier studies investigated the forecasting capabilities for the spare part production of Iran Khodro Company (IKCO) by using a backpropagation-based ANN with 10 hidden layers (Jafarzadeh et al. 2012).

In this research, an ANN was trained and tested to model the weekly carried weight of IKCO transportation system. Data given by IKCO were based on the observation of the number of trucks, van, lorry, labor and fuel consumption, and the response was amount of carried weight. Monitoring data from 2004 to 2009 were provided and among 312 data points (weeks), the data randomly categorized into testing and training data sets to which close to 44 weeks (1/6) of data were taken as testing data and roughly 268 weeks (5/6) of data as training data. Meanwhile the predicting performance of the three algorithms was compared. Few studies focused on how the predictive ability of the resultant transportation model can be influenced by the training and testing algorithm. MuratandCeylan (2006) evaluated backpropagation for transport energy demand modeling. Bilegan et al. (2008) forecasted freight demand at intermodal terminals by using neural networks and an integrated framework was compared with several learning algorithms such as standard incremental backpropagation (IBP) and genetic algorithm with momentum. More recently, Efendigil and Önüt (2012)developed a decision support system that can forecast demand by using artificial neural techniques, such as the gradient descent, the conjugate gradient, the quasi-Newton, and the Levenberg–Marquardt (LM) methods. In this study, three training algorithms are evaluated: incremental backpropagation (IBP), genetic algorithm (GA) and Levenberg–Marquardt (LM). The predicting and simulating results of this study show that artificial neural network and its training algorithms are feasible and effective on prediction of transportation system demand in the large scale system such as Iran Khodro automobile company (IKCO).

2. Methodology

In this study, a multi-layer perceptron (MLP) based on feed-forward ANN was applied for modeling and predicting the carried weight (unit is ton) for transportation system of Iran Khodro company (IKCO). The network is composed of an input layer, hidden layer and an output layer. The independent variables for the network were season, weeks, number of van, lorry, truck, labor and fuel consumption, and the dependent variable was carried weight. This study used the hyperbolic tangent function as input layer and the linear function as output layer. Trigonometric functions, which are also called circular functions, are considered analogous to hyperbolic functions. The hyperbolic tangent function, which is one of the hyperbolic transcendental functions, can be defined using the following cosh and sinh relationship:

$$\tan(z) = \frac{\sinh(z)}{\cosh(z)}$$

The hyperbolic tangent (tanh) can be derived from two fundamental hyperbolic functions, namely, the hyperbolic sine (sinh) and the hyperbolic cosine (cosh). Similar to other trigonometric functions, the hyperbolic tangent is also periodic. However, the hyperbolic tangent function has periodicity of πi radians instead of 2π, which is the general periodicity of other trigonometric functions. A significant property of the hyperbolic tangent is that tanh (0) is equal to 0. Several properties of the hyperbolic tangent can be obtained as follows:

$$\tan(z) = \tan(z + \pi i)\ \tan(\infty) = 1$$

$$\tan(-z) = -\tanh(z)$$

$$tanh^2(z) + sech^2(z) = 1$$

Inverse hyperbolic functions are denoted as area hyperbolic sine (arsinh) functions and are sometimes expressed as “asinh” or as the misnomer “arcsinh”. In this study, the neural network is trained and tested using the Neural Power software. The following elements constitute the artificial neural model (Mandic 2009):

- Set of synapses: A set of synapses is characterized by the weight or by the strength of each synapse included in the set. In particular, a signal x_j, which is located at the input of synapse j that is connected to neuron k, is multiplied by the synaptic weight w_{kj} unlike brain synapses; artificial neurons have synaptic weights that can be either positive or negative.
- Adder: An adder is needed to sum the input signals, which is then weighted by the corresponding neural synapses.
- Activation or transfer function: An activation function restricts the amplitude of the neural output.

In addition, the proposed artificial neural model may incorporate an externally applied bias (b_k). The value of bias that ranges from being negative to positive may disturb the amount of net input of the activation function (Partovi&Anandarajan 2002). The neuron k can be mathematically described by the following equations:

$$w = \sum_{m} wx$$

$$u_k = \sum_{j=1} w_{kj} x_j$$

Where x_1, …, x_m are the input signals, w_{k1}, …, w_{km} are the synaptic weights of neuron k, and f(net) is the activation function that defines the neural output considerably affecting the network behavior.

$$net = u_k + b_k$$

$$y_k = f(net)$$

The threshold value and f (net) are the activation functions. Three types of activation functions are commonly used in ANNs:

- Piecewise linear activation function

$$f(v) = \begin{cases} 1, & v \geq 1/2 \\ v & -1 < v < 1 \\ 0, v \leq 1/2 \end{cases}$$

- Threshold activation function

$$f(v) = \begin{cases} 1, v \geq 0 \\ 0, x < 0 \end{cases}$$

- Sigmoid activation function

$$f(v) = \frac{1}{1 + \exp\,(-av)}$$

The generalized delta rule undergoes two relevant phase transitions. During the first phase, input x is forward-propagated through the ANN. Afterward, the output values y_0^p of each unit output are computed and then compared with the desired value do. The error signal δ_0^p is computed for each unit output. During the second phase, a backward passed through the network is conducted, and the error signal is passed to each unit in the network. Appropriate weight changes are then calculated. To reduce error on the training data, the weights are adjusted by using the sigmoid activation function (Li&Park 2009). The steps for weight adjustment are given as follows:

- The weight of a connection is adjusted by amount proportional to the product of an error signal δ, on the unit k receiving the input and the output of the unit j sending this signal along the connection:

$$\Delta_p w_{jk} = \gamma \delta_k^p y_j^p$$

- The error signal can be expressed as follows when the unit is an output unit:

$$\delta_0^p = \left(d_0^p - y_0^p\right) F'\left(s_0^p\right)$$

By denoting F as the activation function, we can define the sigmoid function as

$$y^p = F(s^p) = \frac{1}{1 + e^{-s^p}}$$

For the above case, the derivative is given by

$$F'(s^p) = \frac{\partial}{\partial s^p} \frac{1}{1 + e^{-s^p}} = \frac{1}{(1 + e^{-s^p})^2} \left(-e^{-s^p}\right)$$

$$= \frac{1}{(1 + e^{-s^p})} \frac{e^{-s^p}}{(1 + e^{-s^p})}$$

$$= y^p(1 - y^p)$$

Thus, we can express the error signal of an output unit as

$$\delta_h^p = (d_0^p - y_0^p) y_0^p (1 - y_0^p)$$

- To determine the error signal of a hidden unit, we need to identify the error signals of the units to which the hidden unit is directly connected. In addition, we need to determine the weights of the corresponding connections. The sigmoid activation function can be expressed as follow:

$$\delta_h^p = F'\left(s_h^p\right) \sum_{o=1}^{No} \delta_h^p w h_0 = y_h^p \left(1 - y_h^p\right) \sum_{o=1}^{No} \delta_h^p w h_0$$

The proposed method divides data into three parts: the first part of the data is related to network training; the second part is utilized to stop calculations upon increment of integrity error; the third part is concerned with network integrity. Two statistical indexes, namely, the root mean square error (RMSE) and the correlation coefficient (R^2), are used to examine ANN model performance (Moghaddam et al. 2010). These statistical indexes were obtained from the statistical calculations of the observed model output predictions. Decision on the optimum topology and algorithm was based on the minimum error of testing. All topologies were evaluated based on the root mean square error (RMSE) and coefficient of determination (R^2) as a measure of the predictive ability as follows:

$$\text{RMSE} = \left(\frac{1}{n} \sum_{i=1}^{n} (y_i - y_{di})^2\right)^{\frac{1}{2}}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - y_{di})^2}{\sum_{i=1}^{n} (y_{di} - y_i)^2}$$

Where 'n' is the number of points, 'y_i' is the predicted value and 'y_{di}' is the actual value. The ANN modelling was done using Neural Power, professional version 2.5 (CPC-X Software, Regsoft Inc.). Several algorithms can be used for ANN training. Especifically, this paper used the following algorithms for ANN training:

Gradient descent backpropagation algorithm is one of the most popular learning algorithms. It works by determining the output error, calculating the gradient of this error, and adjusting the ANN weights (and biases) in the descending gradient direction (Rumelhart et al. 1986). This algorithm includes different versions such as Standard or Incremental backpropagation (IBP), and the network weights are updated after presenting each pattern from the training data set rather than once per iteration (Medsker&Jain 2010).

Genetic algorithm is a combinatorial optimization technique, which searches for an optimal value of a complex objective function by simulation of the biological evolutionary process based, as in genetics, on crossover and mutation. An optimal value can be searched, in parallel, with a multi-point search procedure. In addition, GA can use ANN models as their guiding function. GA has been successfully used in a wide variety of problem domains (Alhamdy et al. 2013; Gueguim Kana et al. 2012).

Levenberg-Marquardt backpropagation algorithm (LM) is an approximation to the Newton's method (Hagan et al. 1996). This is well suited to the training of the neural network (Piotrowski & Napiorkowski 2011). The algorithm uses the second-order derivatives of the mean squared error between the desired output and the actual output so that better convergence behaviour can be obtained (Mukherjee & Routroy 2012).

3. Results and Discussion

The prices of components and the raw materials for the automobile industry increase from time to time. To maintain and enhance competitive advantage, automobile prices need to be stabilized and even decreased (Mather et al. 2007). Decreasing the price of the components and raw materials is impossible. Therefore, focusing on overhead costs is necessary, and the most important of these are logistic costs, especially transportation (Govindan et al. 2010). Increasing oil prices is another major issue, as such increases significantly affect production and transportation costs. Thus, companies and producers pay considerable attention to optimizing fuel use and the transportation system. To increase the competitive advantage in the automobile market, Iran Khodro automobile company (IKCO) needs to decrease extra costs through effective planning and cost management (Abedini&Péridy 2009). Seasonal carried weight fluctuation in IKCO (2004–2009) is shown in Figure 1. Planning is based on knowledge and prediction. Artificial Neural Network (ANN) will be applied to predict the exact amount of the carried weight by Iran Khodro (IKCO) transportation system.

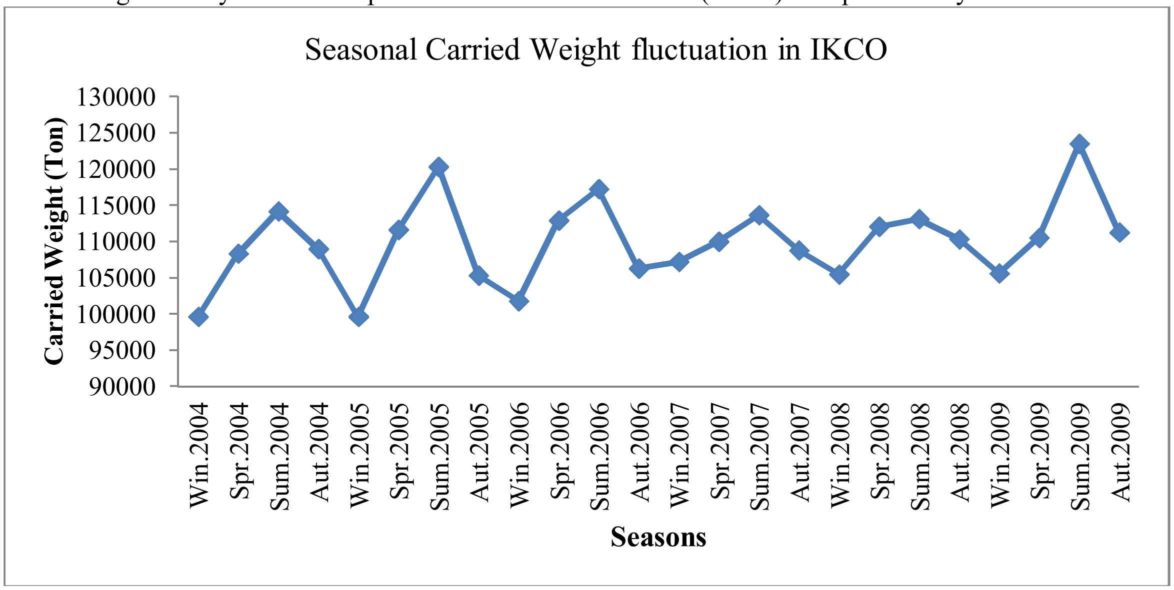


Figure 1. Seasonal Carried Weight fluctuation in IKCO (2004–2009)

3.1. Data Analysis

Estimating and forecasting the production rate depends on factors such as market demand, seasons, economic conditions, existing laws, and local cultural conditions (Tsai et al. 2010). However, these factors do not yield an accurate measurement, and they cannot be used in a precise standard analysis. In this study, the transportation system of Iran Khodro Company was considered as the study case and the secondary data was used as an approach to study the system. The five factors including amounts of van, lorry, truck, labour and fuel consumption were introduced as direct impacts affecting the cost of the transportation system by Iran Khodro and the amount of carried weight was collected as the response of the system. The data were from winter 2004 to autumn 2009.

To evaluate the association between variables, pearson correlation coefficient was applied. Prior to data analysis all data were subjected to normality test using one sample Kolmogorove-Smirnove test. All data analysis was done using SPSS 17.0 (Table 1). This relationship is significant at 0.1 significance level (Table 2).

The results of correlation and the standard strength of the correlation coefficient (Table 2) indicate that all factors have a positive, strong, and significant relationship with carried weight.

Table 1. Correlations between factors and carried weight

	weight	van	lorry	truck	fuel
van	.974**	1			
lorry	.958**	.964**	1		
truck	.971**	.992**	.968**	1	
fuel	.936**	.953**	.974**	.965**	1
labor	.976**	.994**	.986**	.994**	.972**

**. Correlation is significant at the 0.01 level (2-tailed).

Table 2. Standard strength of relationship data

r	Strength of Relationship
< .2	Negligible Relationship
.2 - .4	Low relationship
.4 - .7	Moderate relationship
.7 - .9	High relationship
> .9	Very high relationship

Source: Pallant (2010)

Table 3. One-Sample Kolmogorov-Smirnov Test for normality of research variables

	Van	Lorry	Truck	Fuel	Labour	Weight
N	312	312	312	312	312	312
Mean	521.37	432.45	271.69	57225.69	4902.1	8453.69
Std. Deviation	31.11	26.07	16.00	3675.26	290.15	506.86
Kolmogorov-Smirnov(Z)	0.85	1.18	1.19	0.89	0.79	0.98
Asymp. Sig. (2-tailed)	0.47	0.12	0.12	0.40	0.56	0.29
Minimum	459	383	239	48921	4348	7501
Maximum	604	501	316	66808	5683	9811

The one sample Kolmogorov-Smirnov test, more commonly known as the K-S test, takes the observed cumulative distribution of scores and compares them to the theoretical cumulative distribution of a normally distributed population. Table 3 is produced which details the normality of IKCO transportation system variables.

The first part of the One-Sample Kolmogrove-Smirnov test output table shows N (number of weeks), Minimum, Maximum, Mean and Standard Deviation. To check the normal distribution of the data, Asymp. Sig. (2-tailed) values should be >0.05 to indicate that the observed distribution corresponds to the theoretical distribution. The data is not significantly different to a normal distribution at the $p<0.05$ level of significance (Neave 2013). From the table it can be seen that the variables have Asymp. Sig. (2-tailed) values >0.05, therefore all the variables can be assumed to normally distributed.

3.2. Modeling and Prediction of Carried Weight Using Artificial Neural Network

Different feedforward ANN structures, which contain three layers (input, hidden, and output layers) and comprise hidden layers with varying numbers of neurons, were investigated to identify the optimum ANN structure for carried weight estimation (Yang et al. 2012).

Various learning algorithms were implemented in the Neural Power software, and their performances and properties were studied in this section. As previously mentioned, this study used IBP, GA, and LM as training and testing functions to predict the carried weight during a certain number of weeks, the number of seasons and the number of van, Lorry, truck, labor force and fuel consumption were included among the seven input parameters for the feedforward ANN. They were also used as the tangent hyperbolic function in this model. Suitable models for RMSE and R^2 were selected for the study.

The network structure includes seven inputs, one hidden layer, and one output. To estimate the number of neurons in the hidden layer needed to obtain the best prediction, hidden layers with one to five neurons were examined. Evaluation results of ANN with different numbers of neurons in the hidden layer are shown in Tables 4 and 5. To assess the validity, 1/6 of input data were selected as the testing dataset, and the rest of the data were applied as the training dataset.

Table 4 RMSE comparisons with different neurons in hidden layers applied in training and testing datasets

Network structure		Algorithm							
		IBP			GA			L-M	
		Training	Testing		Training	Testing		Training	Testing
7-1-1		105.28	100.74		106.81	102.28		105.07	100.16
7-2-1		96.93	94.18		100.17	95.93		96.24	99.10
7-3-1		89.58	92.89		103.88	98.90		87.54	86.57
7-4-1		89.50	97.03		101.27	101.06		79.84	89.24
7-5-1		76.93	88.44		104.54	98.73		98.64	115.60
7-6-1		77.94	95.05		104.74	100.34		87.83	114.04
7-7-1		82.89	90.44		100.70	101.79		97.61	116.96

Table 5 Correlation coefficient (R^2) comparisons with different neurons in hidden layers applied in training and testing datasets

Network structure		Algorithm							
		IBP			GA			L-M	
		Training	Testing		Training	Testing		Training	Testing
7-1-1		96.64	97.34		95.57	96.22		97.80	97.17
7-2-1		97.30	96.80		96.05	96.66		98.16	98.22
7-3-1		97.84	97.88		95.76	96.47		98.48	98.66
7-4-1		97.85	97.61		95.77	96.31		98.74	98.55
7-5-1		98.83	98.60		95.70	96.47		98.16	97.99
7-6-1		98.11	97.74		95.69	96.36		96.97	95.31
7-7-1		97.30	97.05		96.01	96.27		96.25	95.06

3.3 Selecting the Best Neural Networks Model

The selected models for various algorithms are summarized and presented in Table 6. The network with the minimum RMSE and maximum R^2, is considered as the best neural network model (Wang et al. 2008; Izadifar and Jahromi. 2007; Basri et al. 2007). As shown in Table 6, an Incremental back Propagation (IBP) has a better performance relative to genetic algorithm and Levenberg–Marquardt algorithms, because in the IBP algorithm (7-5-1 topology) had minimum RMSE and maximum R^2 in both training and testing sets.

According to a summation of errors (RMSE) for each network, the errors increased after increasing the number of neurons in the hidden layers (Widrow et al. 2013). However, all tested ANN structures exhibited high accuracy. According to the results, the ANN structure based on IBP with five neurons in hidden layers (7-5-1) was the optimal structure that can minimize calculations (Figure 2, 3).

Furthermore, IBP has the highest R^2 in test and train among all models (98.60, 98.83). It should be noted, for evaluation of the robustness of a modeling technique, R^2 should be computed and $R^2 > 0.9$ can be regarded as a good overall fit (Bourquin et al. 1997; Ghaffari et al. 2006).

Figures 4 and 5 display the scatter plot of the ANN predicted weight versus the actual weight with best model of mentioned algorithms for the test and train sets. As shown in the Figures, the linear correlation plots drawn between the predicted and actual values demonstrated good values of $R^2 = 0.9860$ for testing set and $R^2 = 0.9883$ for the training set using Incremental backpropagation (IBP) algorithm.

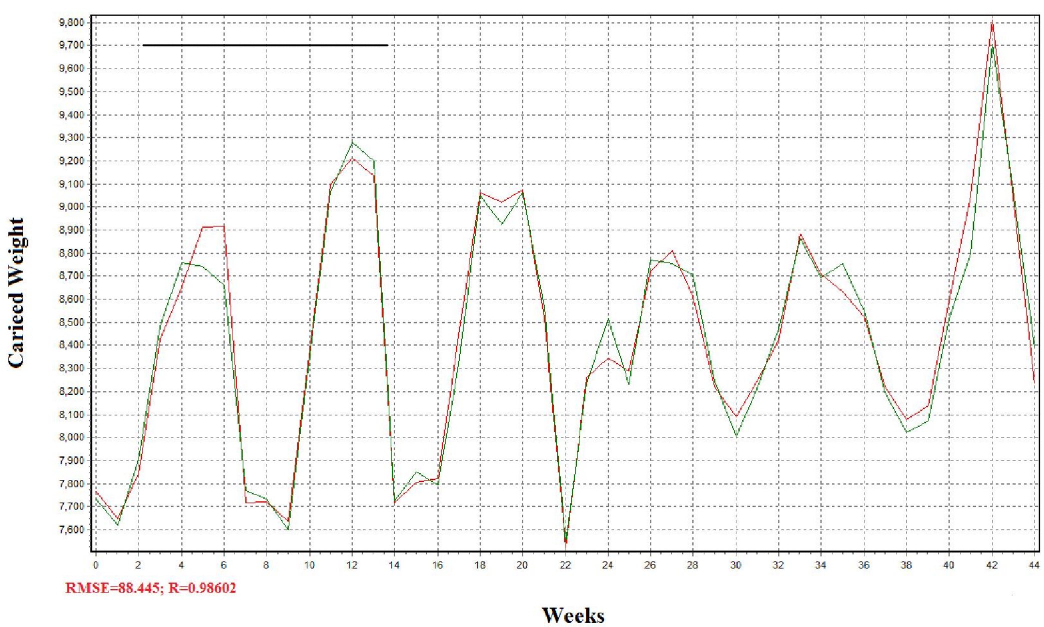


Figure 2. The graph depicting the prediction error (RMSE) of actual weight versus predicted weight in the testing data set for best model (5 neurons) of IBP algorithm.

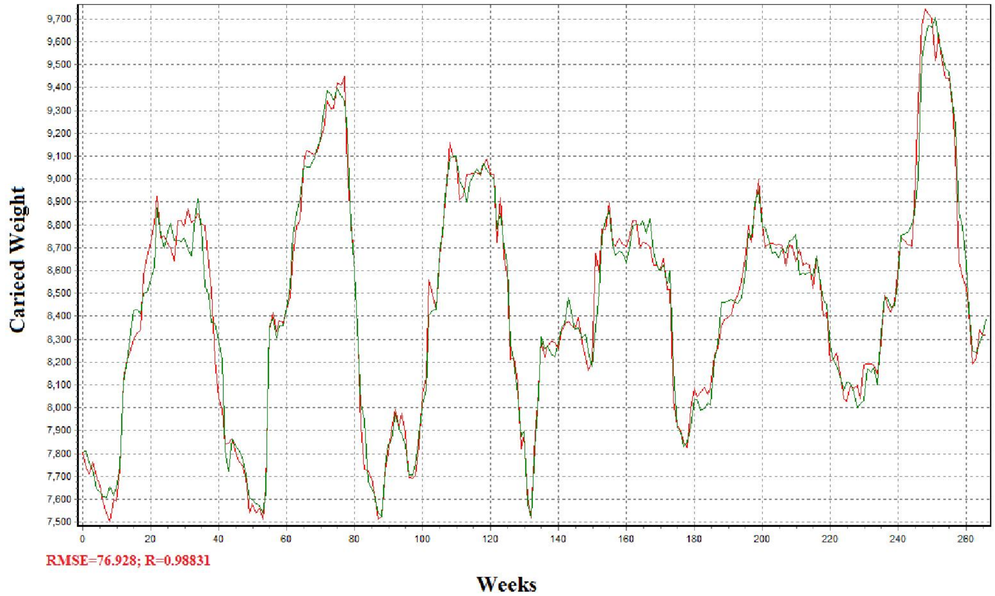
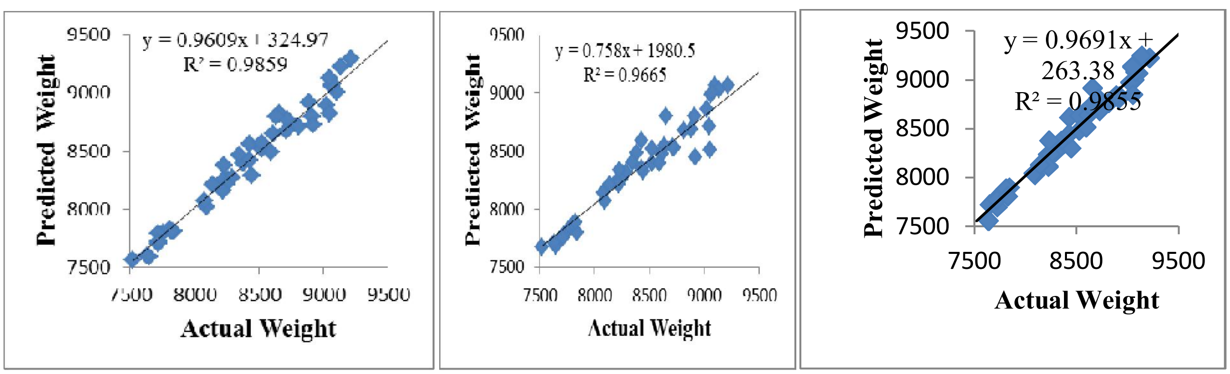
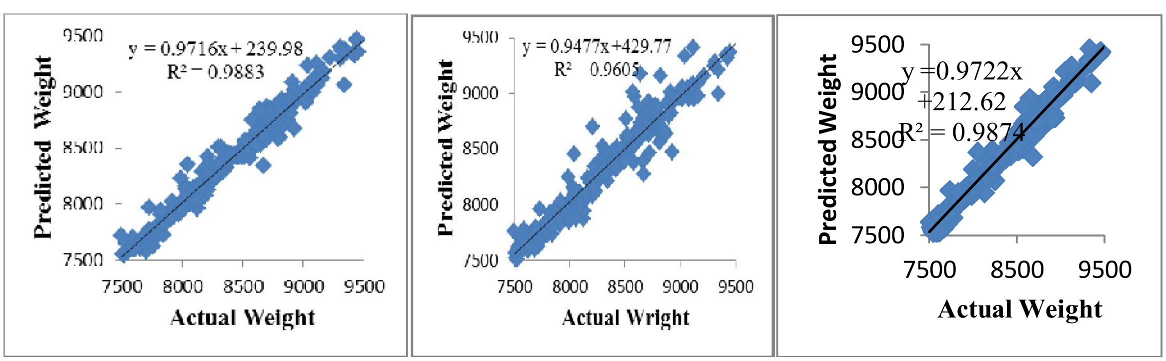


Figure 3. The graph depicting the prediction error (RMSE) of actual weight versus predicted weight in the training data set for best model (5 neurons) of IBP algorithm.



(a) (b) (c)

Figure 4. The scatter plots of ANN predicted weight versus actual weight from (a) Increment backpropagation (IBP), (b) Genetic algorithm (GA) and (c) Levenberg- Marquardt (LM) algorithm for testing data set



(a) (b) (c)

Figure 5. The scatter plots of ANN predicted weight versus actual weight from (a) Increment backpropagation (IBP), (b) Genetic algorithm (GA) and (c) Levenberg- Marquardt (LM) algorithm for training data set

Table 6 Statistical measures and performances of three learning algorithms with the best structure

Algorithm	The best architecture	Training set		Testing set	
		RMSE	R^2	RMSE	R^2
Incremental back Propagation (IBP)	7-5-1	76.93	98.83	88.44	98.60
Genetic Algorithm (GA)	7-2-1	100.17	96.05	95.93	96.66
Levenberg-Marquardt (LM)	7-4-1	79.84	98.74	89.24	98.55

Generally, the results which indicate the performance and prediction accuracy of Increment backpropagation algorithm were better than those of Genetic algorithm and Levenberg-Marquardt algorithms.

4. Conclusion

This study indicated that predicting carried weight is possible by using characteristic of artificial neural network (ANN) that reflect the accurate of nonlinear behavior of transportation system demand. The main properties of ANN modeling techniques were introduced in this study. These modeling techniques are based on computational networks that have designs and functions resembling the biological neural cells of the brain. In this study, to predict carried weight of IKCO transportation system during a certain number of weeks, the number of seasons and number of van, lorry, truck, labour and fuel consumption were applied as the seven input parameters for the feedforward ANN. The training of the network was based on three different methods, namely, incremental back propagation algorithm (IBP), genetic algorithm (GA) and Levenberg–Marquardt algorithm (LM). The precision and the predictive ability of each training algorithm was measured; the predictive abilities of the algorithms were identified in the order of IBP>LM>GA. In summary, IBP is the optimum training algorithm for modeling and predicting carried weight and for comparing the performance of trained ANN algorithms. In the current research, RMSE estimated by training and testing sets for each algorithm. Results show that IBP has the lowest average RMSE, which indicates that the performance indices of this algorithm were better than those of GA and LM. To model and predict of carried weight, the correlation coefficient (R^2) of the testing dataset was computed. The results indicate that the prediction accuracy of IBP was better than that of GA and LM. Finally, the results of this study indicate that to improve stability of supply and demand in the transportation system, the appropriate selection of training algorithm is essential for successful data modeling by ANN.

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