POOYA NAJAF, Ph.D. Candidate
E-mail: pnajaf@uncc.edu
University of North Carolina at Charlotte
Department of Civil and Environmental Engineering
Charlotte, NC, USA
SINA FAMILI, M.Sc.
E-mail: sina.famili@modares.ac.ir
Tarbiat Modares University
Department of Civil and Environmental Engineering
Tehran, Iran

Traffic Management
Original Scientific Paper
Accepted: Aug. 26, 2012
Approved: May 23, 2013

APPLICATION OF AN INTELLIGENT FUZZY REGRESSION ALGORITHM IN ROAD FREIGHT TRANSPORTATION MODELLING

ABSTRACT

Road freight transportation between provinces of a country has an important effect on the traffic flow of intercity transportation networks. Therefore, an accurate estimation of the road freight transportation for provinces of a country is so crucial to improve the rural traffic operation in a large-scale management. Accordingly, the focused case study database in this research is the information related to Iran's provinces in the year 2008. Correlation between road freight transportation with variables such as transport cost and distance, population, average household income and Gross Domestic Product (GDP) of each province is calculated. Results clarify that the population is the most effective factor in the prediction of provinces' transported freight. Linear Regression Model (LRM) is calibrated based on the population variable, and afterwards Fuzzy Regression Algorithm (FRA) is generated on the basis of LRM. The proposed FRA is an intelligent modified algorithm with an accurate prediction and fitting ability. This methodology can be significantly useful in macro-level planning problems where decreasing prediction error values is one of the most important concerns for decision makers. In addition, Back-Propagation Neural Network (BPNN) is developed to evaluate the prediction capability of the models and to be compared with FRA. According to the final results, the modified FRA estimates road freight transportation values more accurately than BPNN and LRM. Finally, in order to predict the road freight transportation values, the reliability of the calibrated models is analyzed using the information from the year 2009. The results show higher reliability for the proposed modified FRA.

KEY WORDS

road freight transportation modelling, modified fuzzy regression, artificial neural network, temporal reliability

1. INTRODUCTION

Transportation planning plays an important role in a macro-level management system in every country, since its economic, social, cultural and political effects are quite obvious. Freight transportation is defined as displacement of various types of commodities by different modes of transportation such as road, railway, air, and marine. In an efficient transportation network, all available modes are expected to operate consistently to decrease the traffic congestion on roadways. However, without using roadway networks, connecting all provinces in a country is very expensive and to some extent impossible. Therefore, the accurate estimation of road freight transportation (RFT) between various provinces of a country is specifically remarkable in macro-level planning.

Dependence on environmental characteristics and weather conditions, variable transportation costs based on the transportation distance, and uncertainty resulting from roadway characteristics, are some of the disadvantages of RFT. However, it does also have some advantages such as flexibility (shipping commodities in different sizes and shapes) and availability (using different routes and delivery scenarios). These advantages cause RFT to be implemented as the main mode for both freight and passenger transportation in several developing countries, like Iran. Iran has one of the historically main connecting routes between Asia and Europe. Due to the natural, tourist and pilgrimage attractions of Iran, road transportation is the easiest and most prevalent way of passengers and freight displacement.

Furthermore, a great number of heavy vehicles transport essential freight for users, factories, industries, mines and agriculture. Iran's road transportation fleet, with an annual capacity of more than 600 million tons of freight and 350 million passengers [1], manage more than 80 percent of the whole transportation. Iran's RFT has risen from 226.4 million tons in 1999 to 511.5 million tons in 2008 that shows a total growth of 126 percent and an annual average growth rate of 9.5 percent [2]. In 2008, there were 84 percent of commercial freights in Iran carried along roadways [3].

RFT modelling seems crucial in the future studies regarding prediction and planning. Accurate prediction of future RFT has significant impact on planning to develop transportation facilities. Additionally, macro-level planning techniques such as population control can contribute to the maintenance of the amount of RFT below the capacity of existing road networks. Attracted freight transportation for each province is assumed as the road freight transportation value in this research. This value has also a significant correlation with the produced freight transportation. Correlations between RFT and some basic variables such as average cost and distance of freight transportation, population (POP), area, Number of Cities (NOC), Number of Villages (NOV), average household income, and GDP of the province have been analyzed. The correlations illustrate that RFT is highly dependent on the population of the province. To predict RFT, LRM is calibrated using the POP variable. Subsequently, by applying fuzzy theory, a new modified FRA is generated on the basis of the developed LRM. In addition, BPNN is trained to predict RFT values. Along with the evaluation of models' fitting ability based on the information of the year 2008, their reliability and prediction ability are also investigated for the information in the year 2009.

2. LITERATURE REVIEW

This section concentrates on the application of fuzzy regression and artificial neural networks in freight transportation modelling. Tortum et al. [4] used artificial neural networks and adaptive neuro-fuzzy inference to model the mode choice of intercity freight transport. The complex non-linear relationships between different variables were analyzed efficiently by combining the learning ability of artificial neural networks and the transparent nature of fuzzy logic. Tsung et al. [5] predicted the volume of Taiwan air cargo exports applying a fuzzy regression model. GDP was used as the independent variable in this research. To enhance the validity and reliability of the fuzzy regression model, they tried to adopt the asymmetric triangular fuzzy method.

Celik [6] used three different types of artificial neural networks to model the inter-regional freight transportation of 48 continental states of the USA based on the 1993 U.S. Commodity Flow Survey Data. Their results showed an improvement in comparison with Celik and Guldmann's [7] Box–Cox regression model. Tianwen [8] compared feed forward and back propagation neural networks to predict railway freight transportation. The results showed higher prediction ability for the feed forward neural network. Bo and Min [9] predicted freight transportation using a radial basis neural network function. They also studied effective variables in prediction of the freight transportation through an AHP model.

Min et al. [10] developed the BPNN model to predict the freight transportation. They evaluated several different national economy characteristics such as "GDP, proportion of the second industry, output of coal, output of steel, throughput goods of port, infrastructure investment, and railway market share". Yong and Xiang [11] also applied the BPNN model to predict the railway freight volume. The developed model was able to identify and simulate the non-linear and complex relationships between the railway freight volume and effective independent variables. Furthermore, Ling and Zhuo [12] analyzed several qualitative and quantitative factors and predicted the railway freight volume using the BPNN model.

3. METHODOLOGY

3.1 Fuzzy Regression Algorithm (FRA)

Since this section is briefly extracted from Tsung et al. [5], Zadeh [13] and Tanaka [14] papers can provide more information about fuzzy set theory, fuzzy sets and triangle fuzzy numbers.

Tanaka [14] introduced the fuzzy linear regression considering the vagueness. The main assumption of this algorithm is that the residuals between estimator and observation are caused by uncertain parameters in the model. Therefore, the parameters in an FRA model are fuzzy numbers. Equation 1 shows the initial form of FRA:

$$Y = A_0X_0 + A_1X_1 + \ldots + A_iX_i + \ldots + A_pX_p, \quad (1)$$

where A_i, $i = 0,1,2,\ldots,p$ are triangular fuzzy numbers, and $X_0 = 1$, $X_i > 0$, $i = 0,1,2,\ldots,p$ are variables with crisp values. Assuming fuzziness for $A_i = (c_i, a_i, b_i)$, $i = 0,1,2,\ldots,p$, triangular fuzzy number Y is:

$$Y = \left(\sum_{i=0}^{p} c_i x_i, \sum_{i=0}^{p} a_i x_i, \sum_{i=0}^{p} b_i x_i\right). \quad (2)$$

$F_Y(x)$ is the membership of Y as follows:

$$f_Y(x) = \begin{cases} \dfrac{x - \sum_{i=0}^{p} c_i x_i}{\sum_{i=0}^{p} a_i x_i - \sum_{i=0}^{p} c_i x_i}, & \sum_{i=0}^{p} c_i x_i \le x \le \sum_{i=0}^{p} a_i x_i \\ \dfrac{x - \sum_{i=0}^{p} b_i x_i}{\sum_{i=0}^{p} a_i x_i - \sum_{i=0}^{p} b_i x_i}, & \sum_{i=0}^{p} a_i x_i \le x \le \sum_{i=0}^{p} b_i x_i; \\ 0, & \text{o.w.} \end{cases} \quad (3)$$

$x_{i,j}$, $i = 1,2,\dots,p$; $j = 1,2,\dots,n$ represents the i^{th} independent observation in the j^{th} sample, so Y_j is a triangular fuzzy number, $Y_j = (d_j, e_j, f_j)$, with a membership function $f_{Y_j}(x)$ shown as follows:

$$f_{Y_j}(x) = \begin{cases} \dfrac{x - d_j}{e_j - d_j}, & d_j \le x \le e_j \\ \dfrac{x - f_j}{e_j - f_j}, & e_j \le x \le f_j \\ 0, & \text{o.w.} \end{cases}; \quad (4)$$

h-cut of fuzzy number A is represented by $A^h = \{x \mid f_A(x) \ge h, h \ge 0\}$. Assuming Y_j and $\hat{Y}_j$ are the observation and estimator of the j^{th} sample, the largest value of h_j (fitness evaluation value of j^{th} sample) can provide $Y_j^{hj} \subset \hat{Y}_j^{hj}$. Fitness evaluation value h_j is very important to determine the values of observation and estimator of j^{th} sample. "The more fit value of a sample, the better the level of fit between observation Y_j and estimator $\hat{Y}_j$" [5].

Using Equation 3, the estimator of j^{th} sample's observation, $\hat{Y}_j = (m_j, n_j, o_j)$, is determined as follows:

$$m_j = \sum_{i=0}^{p} c_i x_{ij},\ n_j = \sum_{i=0}^{p} a_i x_{ij},\ o_j = \sum_{i=0}^{p} b_i x_{ij}.$$

If $Y_j^{h_j} \subset \hat{Y}_j^{h_j}$, then h_j will be determined using Equations 5 or 6.

First scenario: $e_j > n_j$, $o_j > f_j$ and $d_j > m_j$.

h_j can be derived by using Equation 3 (*Figure 1*):

$d = (e_j - n_j) + (1 - h_j)(f_j - e_j)$ and $1/(1 - h_j) = (o_j - n_j)/d$,

Therefore

$$h_j = 1 - \frac{e_j - n_j}{(o_j - n_j) - (f_j - e_j)}. \quad (5)$$

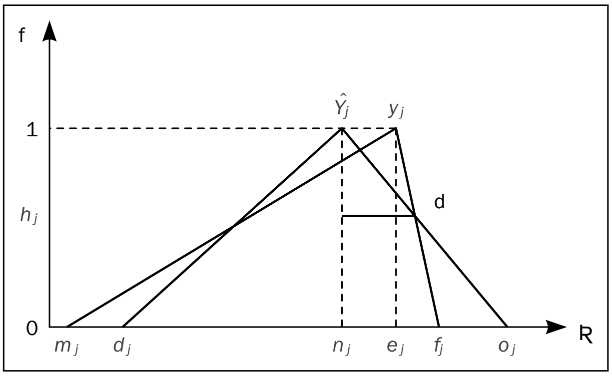

Figure 1 - Observation Y_j and estimation $\hat{Y}_j$ in first scenario [5]

Second Scenario: $m_j < d_j$, $e_j < n_j$ and $o_j > f_j$,

h_j can be derived by using Equation 3 (*Figure 2*):

$d = (n_j - e_j) + (1 - h_j)(e_j - d_j)$ and
$1/(1 - h_j) = (n_j - m_j)/d$,

Therefore

$$h_j = 1 - \frac{n_j - e_j}{(d_j - m_j) - (n_j - e_j)}. \quad (6)$$

To estimate c_i, a_i and b_i, the value of h will be a threshold. All h_j values for observations and estimators should be greater than or equal to h, $h_j \ge h$,

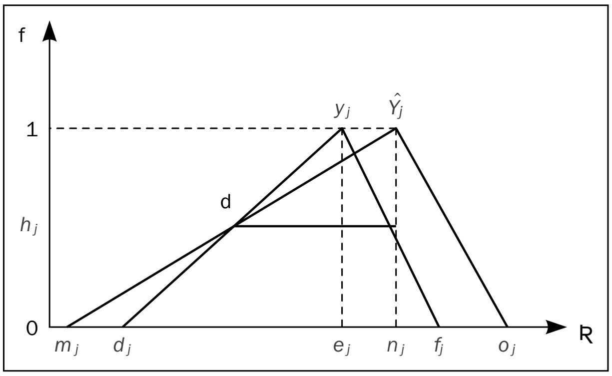

Figure 2 - Observation Y_j and estimation $\hat{Y}_j$ in second scenario [5]

$j = 1,\dots,n$. Therefore, considering Equations 5 and 6 in the first and second scenarios, two limitations are generated as follows:

$$e_j - n_j \le [(o_j - f_j) + (e_j - n_j)](1 - h),\ j = 1,\dots,n \quad (7)$$

$$n_j - e_j \le [(d_j - m_j) + (n_j - e_j)](1 - h),\ j = 1,\dots,n; \quad (8)$$

Assuming $h - cut = 0.5$:

$$e_j - n_j \le [(o_j - f_j) + (e_j - n_j)](1 - h),\ j = 1,\dots,n,\ h = 0.5,\ e_j = f_j,$$

$$n_j - e_j \le [(d_j - m_j) + (n_j - e_j)](1 - h),\ j = 1,\dots,n,\ h = 0.5,\ d_j = e_j,$$

Therefore:

$$\begin{cases} o_j + n_j \ge 2e_j \\ m_j + n_j \le 2e_j \end{cases}; \quad (9)$$

Subject to these two limitations, the fuzzy estimator $\hat{Y}_j$ with a triangular membership function with the smallest spread is considered to maximize the accuracy. Therefore, "the target function of fuzzy parameter $A_i = (c_i, a_i, b_i)$ from summing up all of the triangular membership functions' spread of the sample estimators would be subject to Equations 7 and 8" [5]. Finally, the target function to minimize the total amounts of the spread with n sample estimators is defined as follows:

$$\min J = \sum_{j=1}^{n} ((b_0 - c_0) + (b_1 - c_1)|x_{1j}| + (b_2 - c_2)|x_{2j}| + \dots + (b_p - c_p)|x_{pj}|). \quad (10)$$

3.2 Scenario index and index of optimism

This section is also extracted briefly from Tsung et al. [5]. The $\alpha - cut$ is used to determine the unpredictability nature of different scenarios. For explicit scenarios, definite values and clear information, the assumed value for $\alpha - cut$ should be higher. On the contrary, smaller values of $\alpha - cut$ should be considered in an ambiguous environment. Therefore, $\alpha = 0$ represents the most ambiguous scenario and $\alpha = 1$ represents the clearest one.

$$\hat{Y}_{\lambda}^{\alpha} = \lambda \times U_{\hat{Y}}^{\alpha} + (1 - \lambda) \times L_{\hat{Y}}^{\alpha}. \quad (11)$$

The alpha cut for the triangular fuzzy value $A_i = (c_i, a_i, b_i)$, $i = 1, \ldots, p$, A_i would be

$$[L^{\alpha}_{A_i}, U^{\alpha}_{A_i}] = [(a_i - c_i)\alpha + c_i, -(b_i - a_i)\alpha + b_i].$$

The upper and lower boundaries for the fuzzy regression value

$$\hat{Y} = \left(\sum_{i=0}^{p} c_i x_i, \sum_{i=0}^{p} a_i x_i, \sum_{i=0}^{p} b_i x_i\right)$$

after applying the alpha cut will be determined as follows:

$$[L^{\alpha}_{A_i}, U^{\alpha}_{A_i}] = \left[\sum_{i=0}^{p} x_i((a_i - c_i)\alpha + c_i), \sum_{i=0}^{p} x_i(-(b_i - a_i)\alpha + b_i)\right]. \quad (12)$$

The Index of Optimism λ represents the level of optimism under the same external environment. The index of optimism can be used, after determining the upper and lower boundaries of FRA. The value of $\hat{Y}^{\alpha}_{\lambda}$ will be considered at the upper boundary, if our assumptions are fairly optimistic and confident. On the other hand, the lower boundary of $\hat{Y}^{\alpha}_{\lambda}$ is considered when the assumptions are more pessimistic and less confident.

3.3 Modifying fuzzy regression algorithm

This section is added to the routine fuzzy regression algorithm by authors to obtain higher prediction accuracy. The main concept of this modification is finding a way to determine the index of optimism, λ values, more consistent to the reality. By increasing the accuracy of λ values, the error values will decrease significantly. In this research, a sub-modelling procedure to develop a model to compute λ values is suggested. Certainly, the proposed model must be reliable, statistically significant, solvable with available database, and not time consuming. In this way, the modified FRA will try to decrease its error values intelligently by choosing the best possible values for the index of optimism.

The most important part of this process is to find a range for *U* and *L* values, $[L^{\alpha}, U^{\alpha}]$, which contains all values of dependent variable. By increasing α values, the range will decrease and consequently the final error prediction will decrease. The first reasonable suggestion for α could be 0.5.

If all values of the dependent variable are located in this range $[L^{\alpha}, U^{\alpha}]$, the most accurate (exact) λ value for observations is calculated as follows:

$$\lambda'_j = \frac{RFT_j - L^{\alpha}{}_j}{U^{\alpha}{}_j - L^{\alpha}{}_j}, \; j = 1, 2, \ldots, J, \quad (13)$$

where λ'_j is the modified λ. If the exact value of λ'_j can be estimated without any error, the value of $\hat{Y}^{\alpha}_{\lambda\,j}$ will be equal to RFT_j. In other words, the error value for the estimated $\hat{Y}^{\alpha}_{\lambda\,j}$ will be zero.

The next step is to develop an equation to estimate $\hat{\lambda}$ values. The estimated $\hat{\lambda}$ values will be used as λ in FRA modelling. If a sub-model can be developed to predict the values of $\hat{\lambda}$ very close to the best possible values of λ', the error prediction of FRA will decrease intensely. The proposed sub-modelling procedure is a simple linear regression model using available dataset and existing variables.

3.4 Back-Propagation Neural Network (BPNN)

This section briefly introduces the BPNN model, extracted from [15] and [16]. *Figure 3* shows a simple structure of BPNN including an input layer, a hidden layer, an output layer and connections between them.

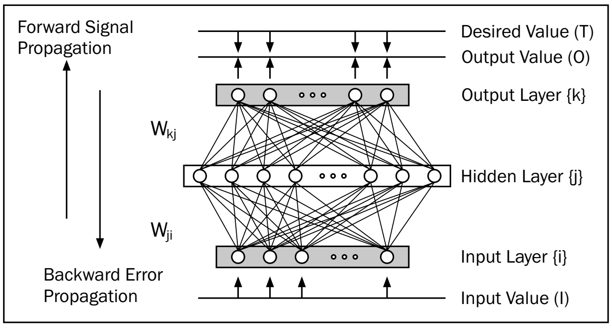

Figure 3 - Structure of BPNN [15]

Back-propagation learning algorithm consist both forward and backward phases in learning process. This procedure is based on an iterative generalized delta rule with a gradient descent of error. The final goal is to minimize the total error between the actual desired values after modification of connection weights [15]. The initial values for connection weights W_{ji} and W_{kj}, and biases θ_j and θ_k must be assumed. In the input layer, the input values net_{pi} are activated on the neurons. Then, training and testing values are prepared. Calculation of the "input values of a hidden layer *j*, net_{pj}, using the output values of an input layer *i*, O_{pi}, connection weight W_{ji}, and biases θ_j between an input layer *i* and a hidden layer *j* is the next step. Finally, the output values of the hidden layer *j*, O_{pj}, are derived from net_{pj}" [15]:

$$net_{pj} = \sum_i W_{ji} O_{pi} + \theta_j, \quad (14)$$

$$O_{pj} = f_j(net_{pj}), \quad (15)$$

Where $f(\,.\,)$ is an activation function. In this study, the sigmoid function is used as an activation function, because it can balance the linear and non-linear behaviours [16]:

$$f_x = \frac{1}{1 + e^{ax}}, \quad (16)$$

where α is the slope parameter of the sigmoid function.

"Input values of an output layer k, net_{pk}, are computed using the output values of a hidden layer j, O_{pi}, connection weight W_{kj}, and biases θ_k between a hidden layer j and an output layer k. Then, the output values of an output layer k, O_{pk}, are derived from net_{pk}" [15]:

$$net_{pk} = \sum_j W_{kj} O_{pj} + \theta_k, \quad (17)$$

$$O_{pk} = f_k(net_{pk}). \quad (18)$$

To modify the connection weights and biases based on the generalized delta rule, the error at output neurons is propagated backward to the hidden layer, and then to input neurons. These steps are from the hidden layer to output layer neurons:

$$\Delta W_{kj} = \eta \delta_k O_{pj} \text{ and } \Delta B_k = \eta \delta_k, \quad (19)$$

where $\delta_k = (T_k - O_{pk}) f'(net_{pj})$ and η = the learning rate; and from input layer to the hidden layer neurons:

$$\Delta W_{ji} = \eta \delta_j net_{pi} \text{ and } \Delta B_j = \eta \delta_j, \quad (20)$$

where $\delta_j = W_{kj} \delta_k f'(net_{pj})$.

Error E between the calculated value O_{pk} and the desired value T_k is defined as:

$$E = \frac{1}{2} \sum_{k=1} (O_{pk} - T_k)^2. \quad (21)$$

This procedure should be repeated until error E goes below the target value.

4. MODELLING

4.1 Step 1: Correlation

The studied dataset [2, 17], from the statistical yearbook of Iran Road Maintenance and Transportation Organization in the year 2008 contains information of all 30 provinces of Iran. The relationship between RFT and other variables such as average cost of freight transportation, average distance of freight transportation, POP, area, NOC, NOV, GDP and average household income of each province is analyzed by computing Pearson Correlation to determine the significance of independent variables. *Table 1* shows the correlation between RFT and independent variables.

Several references have introduced a range (generally ± 0.7 to ± 1) for the correlation coefficient to identify a strong relationship between two variables [18]. According to *Table 1* RFT of each province has a close relationship with its population which is the only significant independent variable with a correlation of more than 0.7. Therefore, the population will be applied as the main independent variable in the modelling process. *Table 2* represents the statistical characteristics of POP and RFT variables. Also, the values of these variables for all provinces are represented in *Table 4*.

4.2 Step 2: LRM

LRM is calibrated by SPSS software [19] to model RFT. Several LRMs have been developed to find the best descriptive linear regression model, considering two main assumptions: 1 - developing the model using significant variables (assuming significance level: 0.01) and 2 - developing the model without any multicollinearity. All insignificant variables were omitted in a step-by-step backward modelling procedure. Finally, the most appropriate statistical characteristics are obtained in the model with POP (as the only independent variable).

In this research, the main goal is not to find the effective factors on RFT prediction. Applying an accurate methodology to develop a macro-level model is the final aim. Indeed, we will just try to develop a more accurate and flexible model to predict large-scale values. Furthermore, it is very difficult to identify several significant variables in an aggregate (not discrete) model such as this research in which the degree of freedom is very low. Therefore, models will be developed using POP as the only significant independent variable.

Table 3 shows the model summary and predicted values of this LRM are presented in *Table 4*. According to the generated LRM, values of RFT are estimated by the following equation:

$$y_{LRM_j} = 0.351 + (2.842 \times POP_j),$$

where y_{LRM} is LRM estimation value for RFT.

Table 1 - Correlation between road freight transportation and studied independent variables

Pearson Correlation	Population (10^6 Person)	Area (10^4 km^2)	Number of Cities	Number of Villages	Average Cost (Rial* per ton-km)	Average Distance (km per ton)	GDP of Province	Mean Household Income (Rial)
Freight Transportation (10^6 ton)	0.941	0.088	0.555	0.313	-0.016	0.014	0.553	0.692

**Rial is the currency in Iran.*

Table 2 - Statistical characteristics of road freight transportation and population variables

Descriptive Statistics							
Variable	Description	Type	N	Mean	Min	Max	Std. Deviation
RFT	Road Freight Transportation (10^6 ton)	Dependent	30	7.027	1.384	41.405	7.509
POP	Population of Province (10^6 Person)	Independent	30	2.349	0.546	13.413	2.485

Table 3 - Linear regression model

LRM Summary							
Constant	Coefficient	t-Statistics	P-Value	R Squared	Adjusted R Squared	Degree of Freedom	F-Statistics
0.351	2.842	14.673	0.000	0.885	0.881	28	215.300

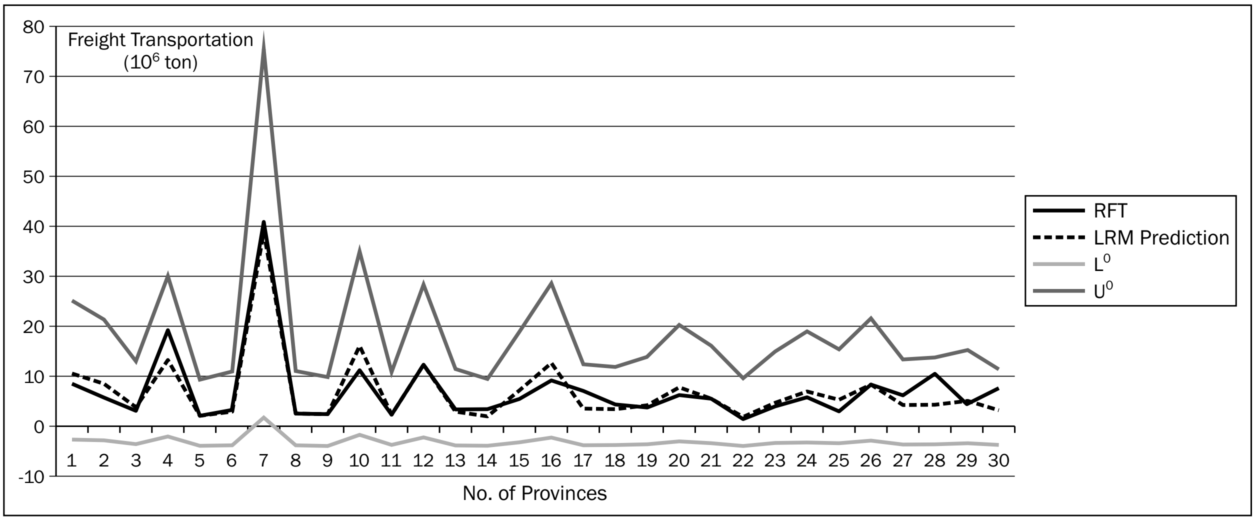

Figure 4 - The estimated boundaries by FRA with α = 0, LRM predictions and RFT real values

4.3 Step 3: Developing FRA

In this step, FRA is generated using the calibrated LRM equation. According to Equations 9 and 10:

$$\min Z = \sum_j \left((b_0 - c_0) + (b_1 - c_1)\left| x_{1j} \right|\right),$$

and

$$\begin{cases} o_j + n_j \geq 2e_j \\ m_j + n_j \leq 2e_j \end{cases};$$

where

$$o_j = \sum_{i=0}^{p} b_i x_{ij} = b_0 + b_1 x_j,$$

$$n_j = \sum_{i=0}^{p} a_i x_{ij} = a_0 + a_1 x_j,$$

$$m_j = \sum_{i}^{p} c_i x_{ij} = c_0 + c_1 x_j$$

and

$$e_j = y_j = RFTD_j.$$

Therefore:

$$\min Z = 30b_0 - 30c_0 + 70.473b_1 - 70.473c_1,$$

$$2b_0 + b_1(POP_1) + c_1(POP_1) \geq 2RFTD_1 \Rightarrow$$

$$\Rightarrow 2b_0 + b_1(3.603) + c_1(3.603) \geq 2(8.524),$$

$$\vdots$$

$$2b_0 + b_1(POP_{30}) + c_1(POP_{30}) \geq 2RFTD_{30} \Rightarrow$$

$$\Rightarrow 2b_0 + b_1(0.991) + c_1(0.991) \geq 2(7.448),$$

$$c_0 + b_0 + 2c_1(POP_1) \leq 2RFTD_1 \Rightarrow$$

$$\Rightarrow c_0 + b_0 + 2c_1(3.603) \leq 2(8.524),$$

$$\vdots$$

$$c_0 + b_0 + 2c_1(POP_{30}) \leq 2RFTD_{30} \Rightarrow$$

$$\Rightarrow c_0 + b_0 + 2c_1(0.991) \leq 2(7.448).$$

After solving this Linear Programming (LP) problem by GAMS software [20], the values of parameters are estimated as follows:

$$a_0 = 6.3577,\ a_1 = 0.4427,\ b_0 = 6.3577,$$
$$b_1 = 5.1788,\ c_0 = -4.1511 \text{ and } c_1 = 0.4427.$$

Thus, $U_{\hat{Y}}^{\alpha}$ and $L_{\hat{Y}}^{\alpha}$ for different values of α can be calculated according to Equation 12. *Figure 4* shows the predicted values of LRM, the real values of RFT variable, $U_{\hat{Y}}^{0}$ and $L_{\hat{Y}}^{0}$. The situation of $\alpha = 0$ is generally selected in the case of perfect uncertainty which causes FRA to predict the most extensive boundaries for $\hat{y}$. In fact, the higher values of α lead to the smaller prediction boundaries and the higher certainties of the predicted values. In this study, 0.5 is supposed for α, and the calculations will be done based on $\alpha = 0.5$. Furthermore, $U_{\hat{Y}}^{0.5}$ and $L_{\hat{Y}}^{0.5}$ values are shown in *Table 4*.

4.4 Step 4: Modifying FRA

Figure 4 and *Table 4* clarify that the values of RFT for all 30 provinces are in the interval $(L^{0.5}, U^{0.5})$. Therefore, λ values for all observations can be calculated as follows:

$$\lambda'_j = \frac{RFT_j - L^{0.5}{}_j}{U^{0.5}{}_j - L^{0.5}{}_j},\ j = 1, 2, \ldots, 30,$$

where λ'_j is the modified λ. The values of λ' are presented in *Table 4*.

The next purpose of this step is to find an equation to estimate $\hat{\lambda}$ values. This research has tried to find a linear regression model to predict the most accurate values for λ by using available information and variables. After generating several linear regression equations between λ' and other independent variables, λ' had a significant linear relationship with POP, NOC and NOV, as follows:

$$\hat{\lambda}_j = 0.2247 + (0.0328 \times POP_j) + (0.0097 \times NOC_j) + \\ +(-0.0033 \times NOV_j),$$

where $\hat{\lambda}$ is an estimation of λ', and POP, NOC and NOV are population, number of cities and number of villages, respectively. The values of these variables are also illustrated in *Table 4*.

The estimated $\hat{\lambda}$ values will be used as λ in FRA modelling. Now, after calculating Equation 11 using $\hat{\lambda}$, $U^{0.5}$ and $L^{0.5}$ values, the final predictions of the intelligent modified FRA are obtained as shown in *Table 5* and *Figure 5*.

4.5 Step 5: Training BPNN

In this step, BPNN is trained by Neurosolution 5 software [21]. Sigmoid function is used as the activation function, and the network is developed with one hidden layer and four neurons in this layer. BPNN reaches the lower value of its mean square error at the 666th epoch, and the learning rate in the training process is assumed 1. The final values of BPNN prediction are displayed in *Table 5* and *Figure 5*.

Table 4 - Provinces information, LRM prediction and FRA parameters

No.	Province	RFT	POP	LRM Prediction	$L_{\hat{Y}}^{0.5}$	$U_{\hat{Y}}^{0.5}$	λ'	NOC	NOV	$\hat{\lambda}$
1	Azarbayejan Sharghi	8.524	3.603	10.591	2.698	16.485	0.423	58	141	0.440
2	Azarbayejan Gharbi	5.734	2.873	8.516	2.375	14.433	0.279	38	113	0.315
3	Ardebil	2.830	1.225	3.832	1.646	9.801	0.145	23	66	0.270
4	Esfahan	19.172	4.559	13.308	3.122	19.172	1.000	96	125	0.893
5	Ilam	2.220	0.546	1.903	1.345	7.892	0.134	21	40	0.314
6	Busherhr	3.383	0.886	2.869	1.496	8.848	0.257	29	43	0.393
7	Tehran	41.405	13.413	38.471	7.041	44.058	0.928	55	80	0.934
8	Chahar. va Bakhtiari	2.545	0.858	2.789	1.483	8.769	0.146	27	39	0.386
9	Khorasan Jonubi	2.359	0.636	2.159	1.385	8.145	0.144	23	48	0.310
10	Khorasan Razavi	10.978	5.593	16.246	3.579	22.078	0.400	69	159	0.553
11	Khorasan Shomali	2.044	0.812	2.659	1.463	8.640	0.081	16	41	0.271
12	Khuzestan	12.253	4.275	12.501	2.996	18.374	0.602	54	127	0.470
13	Zanjan	3.196	0.965	3.094	1.531	9.070	0.221	17	46	0.269
14	Semnan	3.334	0.590	2.028	1.364	8.016	0.296	17	29	0.313
15	Systan va Baluch.	5.322	2.406	7.189	2.168	13.120	0.288	36	102	0.316
16	Fars	8.979	4.337	12.677	3.023	18.548	0.384	78	197	0.473
17	Ghazvin	6.985	1.143	3.599	1.609	9.570	0.675	25	46	0.353
18	Ghom	4.398	1.041	3.310	1.564	9.284	0.367	6	9	0.287
19	Kordestan	3.586	1.439	4.441	1.740	10.402	0.213	23	84	0.218
20	Kerman	6.263	2.652	7.888	2.277	13.812	0.346	59	143	0.412
21	Kermanshah	5.467	1.879	5.691	1.935	11.639	0.364	29	85	0.287
22	Kohgel. va Boyer.	1.384	0.634	2.153	1.384	8.140	0.000	14	41	0.246
23	Golestan	3.879	1.617	4.947	1.819	10.903	0.227	25	53	0.345
24	Gilan	5.621	2.405	7.186	2.168	13.118	0.315	49	109	0.419
25	Lorestan	2.894	1.717	5.231	1.863	11.184	0.111	23	84	0.227
26	Mazandaran	8.048	2.921	8.652	2.396	14.568	0.464	52	115	0.445
27	Markazi	6.103	1.350	4.188	1.701	10.152	0.521	29	62	0.346
28	Hormozgan	10.304	1.404	4.341	1.725	10.304	1.000	26	81	0.256
29	Hamedan	4.167	1.703	5.191	1.857	11.144	0.249	27	72	0.305
30	Yazd	7.448	0.991	3.167	1.542	9.143	0.777	24	51	0.322

Table 5 - Predicted values of LRM, FRA and BPNN

No.	RFT	LRM Prediction	FRA Prediction	BPNN Prediction	No.	RFT	LRM Prediction	FRA Prediction	BPNN Prediction
1	8.524	10.591	8.737	9.078	16	8.979	12.677	10.325	11.121
2	5.734	8.516	6.148	7.283	17	6.985	3.599	4.414	4.107
3	2.830	3.832	3.841	4.224	18	4.398	3.310	3.783	3.967
4	19.172	13.308	17.428	11.780	19	3.586	4.441	3.615	4.544
5	2.220	1.903	3.399	3.350	20	6.263	7.888	7.004	6.792
6	3.383	2.869	4.382	3.762	21	5.467	5.691	4.709	5.272
7	41.405	38.471	41.621	40.904	22	1.384	2.153	3.042	3.452
8	2.545	2.789	4.292	3.726	23	3.879	4.947	4.950	4.827
9	2.359	2.159	3.477	3.454	24	5.621	7.186	6.740	6.273
10	10.978	16.246	13.763	15.068	25	2.894	5.231	3.966	4.992
11	2.044	2.659	3.405	3.668	26	8.048	8.652	7.797	7.393
12	12.253	12.501	10.190	10.940	27	6.103	4.188	4.615	4.408
13	3.196	3.094	3.557	3.865	28	10.304	4.341	3.907	4.490
14	3.334	2.028	3.446	3.400	29	4.167	5.191	4.678	4.969
15	5.322	7.189	5.614	6.275	30	7.448	3.167	3.982	3.899

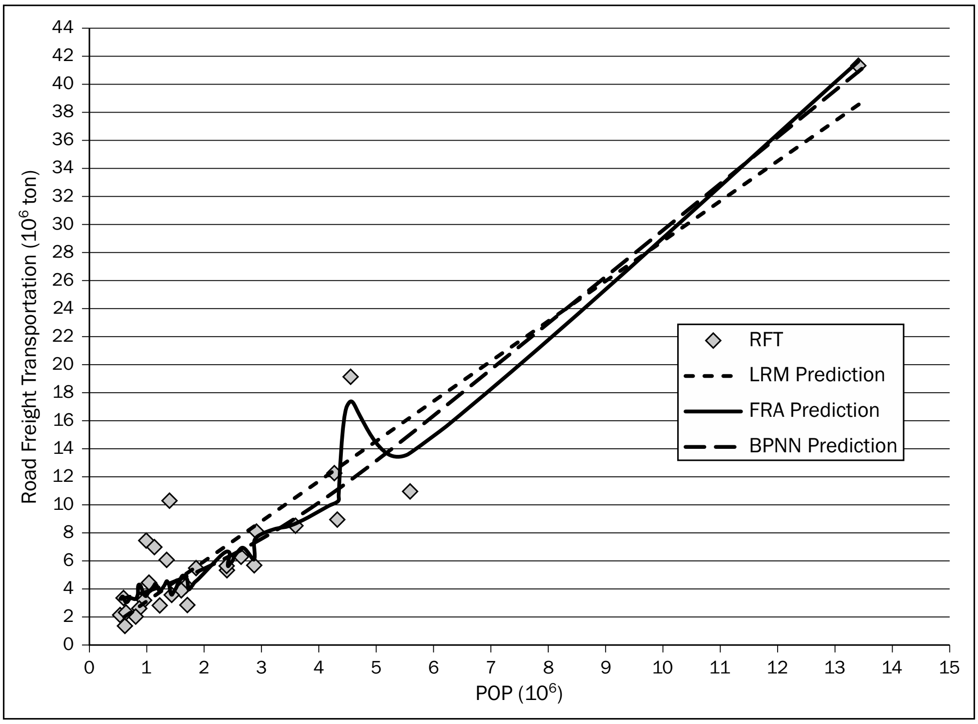

Figure 5 - Fitted values of LRM, FRA and BPNN

5. FITTING ABILITY

As it is clear in *Figure 5*, FRA estimates the desired values with higher flexibility in comparison to BPNN and LRM. BPNN cannot be flexible to predict small noises in RFT values. Indeed, BPNN predicts a smooth curved line while FRA predicts variations well. This is the main superiority of FRA against BPNN which is so effective in large-scale planning and predictions. *Figure 6* shows the predicted values of FRA and BPNN separately, where FRA has higher fitting ability than BPNN in estimation of observations.

In addition, the fitting ability of the generated models is studied through comparing their prediction error values. Errors are computed by the following equations:

$$\text{Mean Squared Error (MSE)} = \frac{\sum_{j=1}^{N}(y_j - \hat{y}_j)^2}{N}, \qquad (22)$$

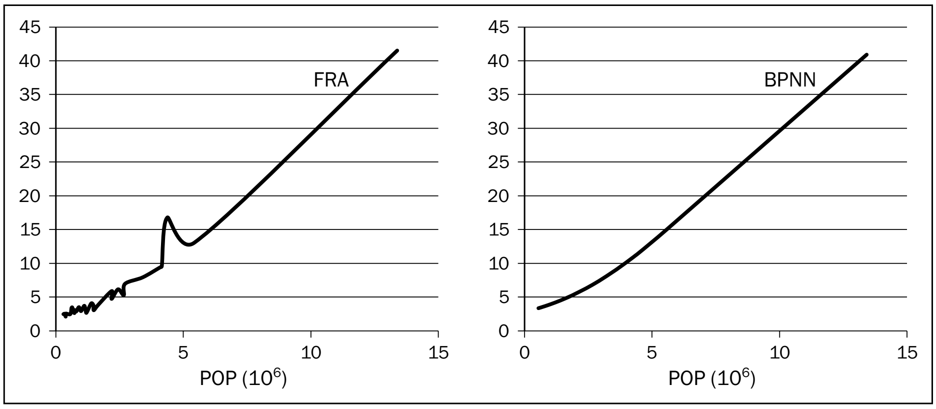

Figure 6 - Comparison of FRA and BPNN's fitting ability

Normalized Mean Squared Error

$$(\text{NMSE}) = \frac{MSE}{\text{Var}(y_j)}, \tag{23}$$

Mean Absolute Error

$$(\text{MAE}) = \frac{\sum_{j=1}^{N} |y_j - \hat{y}_j|}{N}, \tag{24}$$

Minimum Absolute Error

$$(\text{Min AE}) = \min\{|y_j - \hat{y}_j|, j = 1, \ldots, N\}, \tag{25}$$

Maximum Absolute Error

$$(\text{Max AE}) = \max\{|y_j - \hat{y}_j|, j = 1, \ldots, N\}, \tag{26}$$

Mean Absolute Percentage Error

$$(\text{MAPE}) = \frac{1}{N}\sum_{j=1}^{N} \left|\frac{y_j - \hat{y}_j}{y_j}\right|, \tag{27}$$

Root Mean Squared Error

$$(\text{RMSE}) \sqrt{\frac{1}{N}\sum_{j=1}^{N} (y_j - \hat{y}_j)^2}. \tag{28}$$

Table 6 compares models' fitting ability by indicating their fitting error values.

According to *Table 6*, FRA has the most fitting ability since its error values are smaller than those of BPNN and LRM. Also, BPNN has smaller error values than LRM.

6. TEMPORAL RELIABILITY

In this section, the information of the year 2009 [22], presented in *Table 7*, is used to investigate the models' temporal reliability (prediction ability). The main purpose of this part is to study whether the generated models based on the first dataset (2008) can be appropriately applied to predict the new dataset (2009) or not.

Table 7 represents the final estimated values of BPNN, FRA and LRM, too. The linear equation $(0.351 + 0.254 \times POP)$ that was previously generated is applied to calculate the prediction values of LRM. BPNN that had been trained with the first dataset (2008) is tested for prediction of the second information (2009). In fact, BPNN will not be trained with these new observations. Furthermore, in order to evaluate FRA prediction ability for the new dataset, the same constants a_0, a_1, b_0, c_0 and c_1, and the same presented linear equation for estimation of $\hat{\lambda}$ are used.

As a matter of fact, the modelling process can be divided into two parts: 1 - generating models and evaluating their fitting ability using the first dataset (2008), and 2 - evaluating the generated models' prediction ability (temporal reliability) based on the second dataset (2009). All comparisons are performed by calculating the error values. *Figure 7* shows the final prediction ability of the models for the second dataset.

Table 8 represents the models prediction errors based on the information of the year 2009.

The comparison between Tables 6 and 8 indicates that error values of the models have increased slightly. However, it is obvious that models show still appropriate temporal reliability. Moreover, FRA has higher prediction performance than BPNN and LRM. This proves higher accuracy of FRA in both fitting and prediction. Since the road freight transportation models have wide usage in long-term management and macro-level planning, even a slight improvement in RFT prediction will cause more confident policy-making.

*Table 6 - Fitting error values**

	MSE	NMSE	MAE	Min AE	Max AE	MAPE	RMSE
LRM	6.274	0.111	1.858	0.102	5.963	0.297	2.505
FRA	3.227	0.057	1.290	0.029	6.397	0.276	1.796
BPNN	5.354	0.095	1.643	0.066	7.392	0.325	2.314

** These values are computed using the first dataset (for the year 2008) to compare models' fitting ability.*

Table 7 - Second information (for the year 2009) and models predictions

No.	RFT	POP	NOC	NOV	$L_{\hat{Y}}^{0.5}$	$U_{\hat{Y}}^{0.5}$	λ'	LRM Prediction	FRA Prediction	BPNN Prediction
1	9.268	3.691	57	141	2.737	16.732	0.431	10.841	8.772	9.402
2	5.815	3.016	38	113	2.438	14.835	0.318	8.922	6.376	7.707
3	2.696	1.243	23	66	1.654	9.851	0.270	3.884	3.865	4.224
4	19.313	4.8045	98	125	3.230	19.862	0.919	14.005	18.512	12.504
5	2.208	0.566	21	40	1.354	7.949	0.314	1.960	3.427	3.296
6	3.387	0.944	31	43	1.521	9.011	0.414	3.034	4.621	3.788
7	41.790	14.795	55	79	7.653	47.943	0.983	42.398	47.256	41.924
8	2.395	0.893	27	39	1.499	8.868	0.387	2.889	4.348	3.718
9	2.453	0.677	23	49	1.403	8.261	0.308	2.275	3.512	3.434
10	11.231	5.941	69	159	3.733	23.056	0.562	17.235	14.591	15.936
11	1.811	0.839	17	42	1.475	8.716	0.278	2.735	3.487	3.645
12	14.212	4.4715	54	127	3.083	18.926	0.474	13.059	10.597	11.545
13	3.277	0.983	18	46	1.538	9.121	0.279	3.145	3.654	3.842
14	3.270	0.6245	17	29	1.380	8.113	0.314	2.126	3.494	3.368
15	5.761	2.733	36	102	2.313	14.039	0.325	8.118	6.129	7.051
16	9.521	4.529	78	197	3.108	19.088	0.477	13.222	10.725	11.709
17	7.430	1.2125	25	46	1.640	9.766	0.355	3.797	4.521	4.177
18	4.461	1.128	6	9	1.603	9.528	0.290	3.557	3.903	4.051
19	3.502	1.468	23	84	1.753	10.484	0.217	4.523	3.651	4.580
20	6.489	2.947	57	145	2.408	14.641	0.393	8.726	7.221	7.544
21	7.109	1.906	29	85	1.947	11.715	0.287	5.768	4.748	5.347
22	1.491	0.669	16	41	1.399	8.238	0.266	2.252	3.218	3.424
23	4.228	1.687	25	53	1.850	11.099	0.347	5.145	5.059	4.951
24	6.203	2.4535	49	109	2.189	13.254	0.419	7.324	6.827	6.438
25	3.138	1.758	23	84	1.882	11.299	0.227	5.347	4.019	5.077
26	9.015	3.037	52	115	2.448	14.894	0.448	8.982	8.017	7.757
27	6.362	1.392	28	62	1.720	10.270	0.336	4.307	4.596	4.457
28	12.781	1.559	26	71	1.793	10.740	0.293	4.782	4.412	4.732
29	4.291	1.7	27	72	1.856	11.136	0.304	5.182	4.674	4.974
30	7.161	1.066	24	51	1.575	9.354	0.323	3.381	4.091	3.961

*Table 8- Prediction error values**

	MSE	NMSE	MAE	Min AE	Max AE	MAPE	RMSE
LRM	7.136	0.121	1.913	0.033	7.999	0.302	2.671
FRA	5.761	0.098	1.671	0.149	8.369	0.302	2.400
BPNN	6.690	0.113	1.837	0.098	8.049	0.338	2.586

** These values are computed using the second dataset (for the year 2009) to compare models' prediction ability (temporal reliability).*

Table 9 - High flexibility, fitting and prediction ability of the intelligent FRA

Year	2008					2009				
Province	POP	RFT	LRM Prediction	BPNN Prediction	FRA Prediction	POP	RFT	LRM Prediction	BPNN Prediction	FRA Prediction
Esfahan	4.559	19.172	13.308	11.780	17.428	4.804	19.313	14.005	12.504	18.512
Fars	4.337	8.979	12.677	11.121	10.325	4.529	9.521	13.222	11.709	10.725

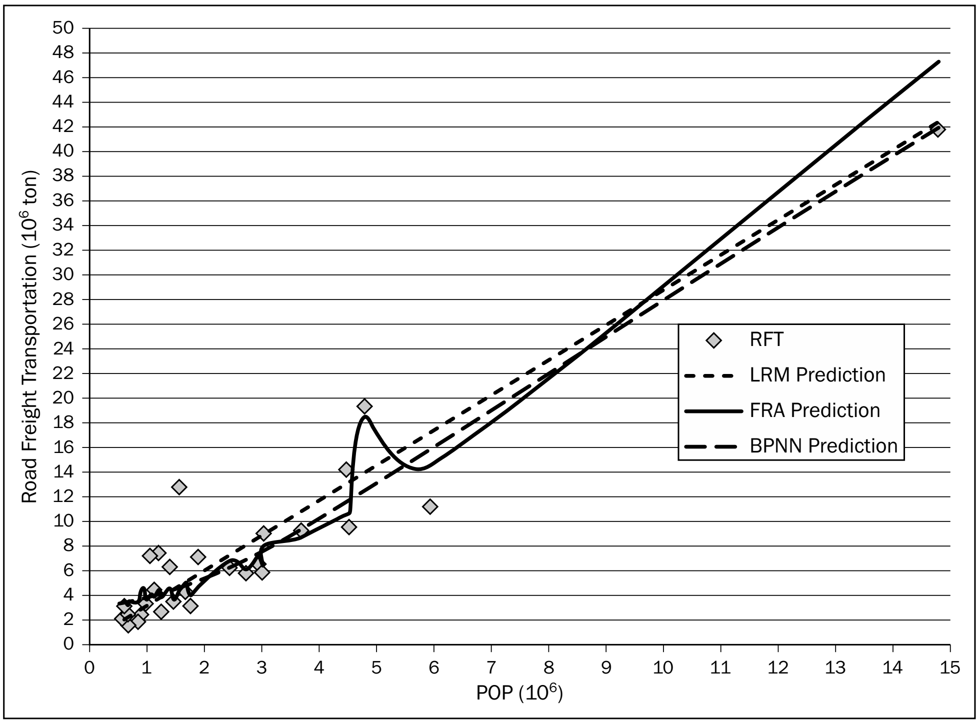

Figure 7 - Predicted values of LRM, FRA and BPNN

Furthermore, *Table 9* shows that the generated FRA model can accurately predict the existing and future data sets. The values in this table are extracted from Tables 4, 5 and 7. For example, Esfahan and Fars provinces have close POP values and different RFT values. Since LRM and BPNN models cannot identify this noise, their predictions for both provinces are almost the same values. However, FRA can predict accurately RFT values of the year 2009 as well as the year 2008. This is the main superiority of the intelligent FRA in comparison with other conventional models.

It is noteworthy to mention that in macro-level and large-scale prediction models, observations' variations from one year to the next year are generally low values. The models should be continuously re-calibrated (updated) for the following years.

7. CONCLUSION

The accurate estimation of RFT between provinces of a country is of great importance in macro-level management and planning. Attracted road freight transportation has been studied as RFT in this research. The first part of the studied dataset, containing information of all 30 Iranian provinces in the year 2008 is used to develop models and evaluate their fitting abilities. To determine the significance of independent variables, the relationship between RFT and population, area, number of cities, number of villages, average cost of freight transportation, average distance of freight transportation, GDP and average household income of each province is analyzed through computing Pearson correlation. The results show that RFT has a close relationship with the POP of the province.

As result, POP is applied as the main independent variable in the modelling process. LRM is calibrated considering RFT and POP as dependent and independent variables, respectively. Afterwards, the intelligent modified FRA is generated based on the LRM. Furthermore, BPNN is trained using the first part of the dataset. The fitting ability of the models is evaluated by computing the error values. Modified FRA estimates RFT values with higher flexibility in comparison with BPNN and LRM, so it has more fitting ability. The proposed modification procedure helps FRA to determine the index of optimism values more realistically.

It should be mentioned that the generated models are studied to clarify whether they have appropriate temporal reliability in prediction of the second part of information (2009) or not. Computations prove that FRA has higher prediction ability and temporal reliability than both BPNN and LRM. Therefore, the proposed intelligent FRA is more effective than LRM and BPNN in both fitting and prediction. Since a slight improvement in RFT prediction will cause more confident policy-making in long-term planning and large-scale management, this intelligent fuzzy regression method is suggested as a powerful tool to analyze and model road freight transportation.

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