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OPTIMIZATION OF TRANSPORTATION SYSTEM BASED ON COMBINED MODEL USING ARTIFICIAL NEURAL NETWORKS AND RESPONSE SURFACE METHODOLOGY

Saeid Jafarzadeh-Ghoushchi
Department of Industrial Engineering, Urmia University of Technology, Urmia, Iran

Abstract **The aim of this work is to optimize factors involving in a transportation system by using combined technique of Response Surface Methodology (RSM) and Artificial Neural Network (ANN) .The main idea of RSM is to use a set of designed experiments to obtain an optimal response. In this article ANN was used as a means to improve the estimation in the RSM for optimization of transportation system with using secondary data's. The carry weight by this system was considered as a dependent variable and five independent variables, namely number of Van, Lorry, Truck, Labors and Fuel consumption. Using the ANN, the optimal configuration of the ANN model was found to be 7-4-1 and carry weights of each combination factors was predicted by this model. Predicted DV values from ANN were applied for RSM. The experiment was carried out based on 2-level, 5-variable Central Composite Design (CCD) in RSM and achieved optimal combination factors based on minimum cost. This approach leads to reducing the system cost. Furthermore, it is proposed to use simulated with ANN to consider high capability of carry weight prediction based on IV factors.**

***Index Terms*— Transportation system, Optimization, Combined model, Response Surface Methodology (RSM), Artificial Neural Network (ANN), Central Composite Design (CCD),**

I. INTRODUCTION

Optimizing the elements of a production system is the best strategy for reducing production cost and increasing economic output and optimizing transportation systems has a lot of effects on reducing transportation systems costs and increasing system effectiveness. On the other hand in order to have effective transportation system, there is a need for precise prediction on the amount of productions in order to plan and optimize transportation system. Many techniques and algorithms have been used in different sciences for predicting and optimizing that among them ANN and RSM can be mentioned. Extensive usage area, easiness, and ability in finding nearer and useful answer are the reasons for the successfulness of these methods (MoghaddamandKhajeh, 2011).

A new type of design for experiments and approach for optimization engineering is emerging, termed as; response surface methodology (RSM). The experimental strategy is planned through statistical techniques in this approach, which allows the decisions to be made on the basis of data analysis methods and conclusive strategies. A combination of mathematical and statistical techniques that are used collectively for modeling and analysis of issues were termed under the notion of RSM by Montgomery (2008), which according to him, allowed utilization of several variables to influence a targeted response with the main objective of optimizing this response. An initial research done by BoxandWilson (1951) is originally considered as the foundation of RSM, which have revolutionized the manner in which industrial experiments are perceived by engineers, scientists and statisticians (Myers et al. 2009). In most RSM problems, the form of the relationship between independent variables and the response is unknown, and hence is approximated (Kishore et al., 2012).

In recent years, considerable research has been carried out to issues regarding supply chain management that are classified into four main areas. Many researchers focus on the inventory management (Caggiano et al., 2009; GumusandGuneri, 2009; Haidari et al., 2013; JammerneggandReiner, 2007; LiuandChen, 2012). Others emphasize the role of production planning and scheduling in the Supply chain (Kazemi et al., 2009; Rostamian Delavar et al., 2010; Vimmerstedt et al., 2012; Q. ZengandYang, 2009). Kwon et al., (2007), To et al. (2009) and Y. Zeng et al., (2012) study how to develop the collaboration among the members in the chain. Erbao and Mingyong (2009), Tan et al.,(2007) and Robu et al., (2011) study the transportation and logistics management effect in supply chains, while Chan and Zhang (2011) emphasize the impact of Transportation Management on supply chain performance.

Although the literature on SCM abounds but nowadays, it is clearly seen that mathematical statistics and mathematical programming techniques has been widely applicable for different purposes in SCM and logistic systems. Dellino et al.,(2010) applied Taguchi and RSM to Robust optimization in simulation. Usability of RSM for modeling and optimization has been investigated by Baş and Boyaci (2007). RSM have been used by S.J. Shukla et al., (2010) along with a simulation, Taguchi and Psychoclonal algorithm to optimization of supply chain network. Abbasi and Mahlooji,(2012) used Artificial Neural Network (ANN) and simulated annealing to improving RSM. A combined model of RSM and numerical method applied by Kemper et al., (2006) to optimize continuous time Markov chain models. Kleijnen et al.,(2004) applied a combined model of statistics and mathematical programming methods to overcome problems of Response surface methodology's steepest ascent and step size revisited.

Today, due to the limitations of the resources, if a firm is able to plan and create a supply chain that fulfills the unlimited demands of consumers, it will gain a greater market share. To achieve this aim and fulfill market demands in a profitable manner, efficient resource allocation plays an important role. Therefore, firms should be aware that in relation to what and which aspects of supply chain they have an appropriate performance and where they have a poor performance, so that they can decide to focus on what activities to increase the value added items. Moreover, effective supply chain management needs a simultaneous recovery in the customer service area and efficient internal activities of the chain members. In the automotive industry and some similar industries, on the one hand, the spare parts and raw materials cost is growing generally and on the other hand there exists a need for stabilizing the automobile prices and even reducing it to maintain and improve its position in the world market. So these firms have no choice but to reduce cost prices. Therefore, due to the impossibility of decreasing materials and spare parts costs, it seems necessary to focus on overhead costs and logistics costs in general and transportation costs in particular. In this study, "Iran Khodro" transportation system was selected and reviewed.

Today, firms like "Iran Khodro" have various reasons to improve their transportation system. These reasons include decreasing production and warehousing costs, increasing competitiveness and availability to consumer markets in a rapid manner (Jafarzadeh et al., 2012b). In this study, two methods of RSM and ANN were used to optimize and modeling of transportation system and in relation to defined objectives were carried out in three stages. In the first stage, the best and most precise ANN model to predict and model the carried weight by "Iran Khodro" transportation system was selected. So, weekly data of six years, from winter 2004 to autumn 2009, was put in seven independent variables (Van, Lorry, Truck, Fuel, Labor, Week and Season) and a dependant variable (carried weight) through three algorithms (LM, BP and QP) and based on the largest amount of R^2 and smallest amount of RMSE, the best model, namely QPH4, was selected for predicting and modeling. In the second stage, transportation system data through RSM in CCD order and in two levels suggested fifty compound models from transportation system factors. These compounds were arranged in lowest price order. In fact, the amount of predicted weight for carriage was not considered by this compound. In the third stage, to optimize this model and select the best compound of transportation system factors, according to the lowest cost and the most carried weight, all these fifty compounds were applied to ANN model to predict the carried weight of these compounds precisely for the summer of 2013. Finally, by 2FI model of RSM, the best compound of transportation system with the lowest cost and the most carried weight was selected and results shows a remarkable improvement in "Iran Khodro" transportation system with the help of models and methods applied in this study.

A. MATERIALS AND METHODS

1.1 Response Surface Methodology

A new type of design for experiments and approach for optimization engineering is emerging, termed as; response surface methodology (RSM). The experimental strategy is planned through statistical techniques in this approach, which allows the decisions to be made on the basis of data analysis methods and conclusive strategies. A combination of mathematical and statistical techniques that are used collectively for modeling and analysis of issues were termed under the notion of RSM by Montgomery (2008), which according to him, allowed utilization of several variables to influence a targeted response with the main objective of optimizing this response. An initial research done by Box and Wilson (1951) is originally considered as the foundation of RSM, which have revolutionized the manner in which industrial experiments are perceived by engineers, scientists and statisticians (Myers et al., 2009).

There are three phases of design in the RSM that are conducted in a sequence. A screening experiment is done at first, which is designed to locate the important factors and reduce the number of design variables. The entire process is made more applicable and efficient by this preliminary step. The steepest ascent method is used in the second phase to optimize the process. This is performed on the first-order response surface models. The important control variables are primarily adjusted to optimize the response. The third phase of the process is initiated once the response is optimized. In this phase, the optimum conditions of the process are determined. Curvature is introduced in the response functions by using the second order response surface model that will lead to accurate approximations. The two level factorial and fractional factorial designs are the most popular and widely used experimental designs for process optimization and improvements. Other designs such as, spherical designs or cuboidal designs are also used. these experimental designs have been explained in detail by Montgomery (2008), Borror et al. (2002), and BoxandDraper (1987).

1.2 Artificial Neural Networks

Artificial neural network (ANN) is a simple model of the structure of a biological network and it is a computational system which attempts to simulate the neurological processing ability of the human brain. Artificial neural networks (ANNs) are promising method for experimental modeling, optimization and control of biological processes because of their ability to measure nonlinear relationships in complex processes. Biological processes are very complex in terms of their behavior by considering the time. It is a well-known fact both genetic and environmental factors affect on biological processes and function. These two factors have a very high degree of variability which is reasons for non-linear in nature of biological process (Tang et al., 2013).

A network can be trained based on different data and "learn" to predict other data. The main advantage compared to statistical methods, such as linear regression, is that ANN can evaluate non-linear data and there is no need to specify the form of the model in advance. Another advantage is that ANN does not have the same requirements on the dataset as regression. ANN also has a tolerance to noise and an ability to generalize. One disadvantage is that the results can be hard to interpret (Adielsson, 2005).

The neurons are the main constituents of the biological neural network. Signals or stimuli from other neurons are received by other cells through the synapse connection, as shown in the Figure 1 the dendrites receive the stimuli and then transmit it to the cell body. Another stimulus is generated by the neurons in case of an intense stimulus, which is transmitted through the synapse along the axon to the next neuron.

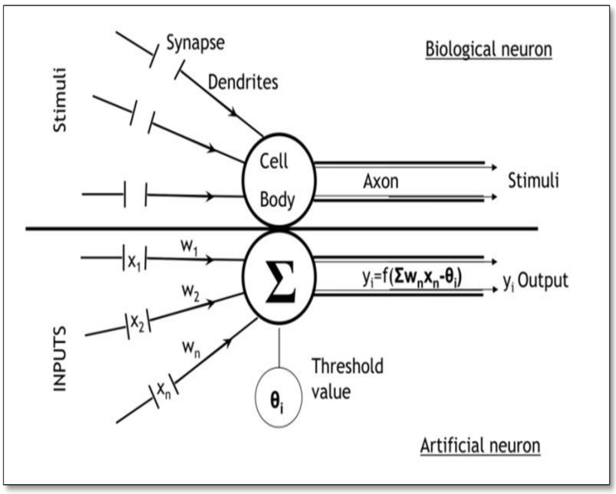

Figure 1 Basic comparison between a biological neuron and an artificial neuron.

Individual processing elements called nodes are interlinked to create a structure called the ANN structure. The adjacent nodes provide inputs that are received by each node and then processed to produce an output signal that is transmitted to the next node. The 'weights' will determine the strength of connection between two units. The input information (X1) is either weighed positively or negatively, while calculating the output (Gallego et al., 2011).

Layers are created by arranging these nodes. A single layer perception (SLP) network, which also includes a single layer of output nodes and inputs, will suffice for the simplest form of ANN. These are directly fed to the outputs through a series of weights, but a three-layered network is the most common structure used, as shown in the Figure 2, an input layer, a hidden layer or an interactive layer and an output layer form the three layered network. This is a multilayered perception (MLP), as it is divided into three layers. An input is produced to the next layer by each layer. The most commonly and widely used models in many applications are the multi-layered perceptions or feed forward neural networks (FF network).

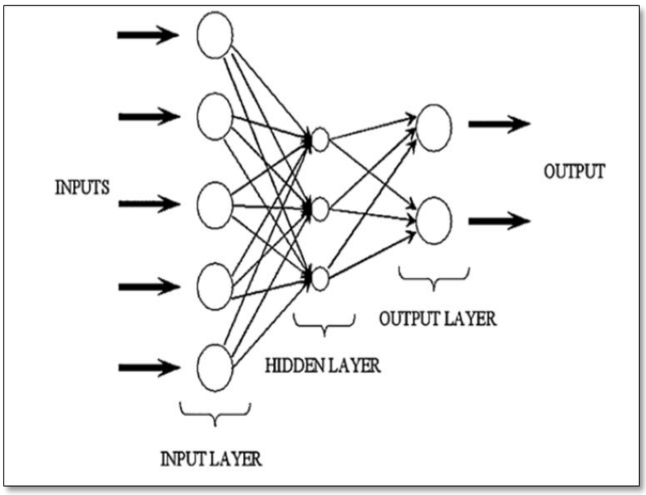

Figure 2 Three layered feed-forward network.

An internal threshold value must also be denoted through the computational method for the stimulation of an output action. The result at each node is a product of the input value (Xn) and their associative weights (Wn). The threshold value (θ) will be used to adjust it. The non-linear weighted sum is used to determine the output as the argument in a function "f" termed as a transfer function or an activation function (equation 1).

$$y_i = f(\sum W_n - X_n - \theta_i) \tag{1}$$

B. METHODOLOGY

1.3 Experimental design

In this study, the effect of five independent variables, X1(4 ton van), X2 (7 ton lorry) and X3 (10 ton truck) and X4 (Fuel) and X5 (Labor) on response variables (Y1, production weight in the seasonal which was predicted by ANN) and (Y2, transportation cost which was calculated by standard unit costs) was evaluated by using response surface methodology. A Central Composite Design (CCD) was applied (1) investigation the main effect of parameters, (2) create models between the variables and (3) determine the effect of these variables to the optimization of the number and kind of trucks, number of labors and fuel cost is done in the study area Iran Khodro (IKCO) an automobile company. Therefore, 50 experiments (Run) were designed based on the second-order CCD with five independent variables. Experiments were randomized in arrangement to minimize the effects of unexplained variability in the actual responses due to extraneous factors. Appendix A shows the agreement of experiments based on the standard orders. Finally our purpose is predicting the amount of Iran Khodro's production weight in summer of 2013 and cost optimization of transportation system. Thus, after predicting the production amount in summer of 2013 by ANN, in the next phase through using the obtained results from prediction as well as seasonally collected data from winter of 2004 to autumn 2009 optimization of Iran Khodro's transportation is done through using multiple regression analysis and Response Surface 2FI Methodology (RS2FIM) model.

3.2 Response surface methodology

A 2-level-5-factor Central Composite Design (CCD) was used in this study. The fractional factorial design consisted of F=2q =25 =32 factor point and 10 axial points (2 axial point for each factor) and with considering α=2.37841 (Standard CCD rotatable value for 5 facto $\alpha = \sqrt[4]{F} = \sqrt[4]{32} = 2.37841$ and 8 center points, totally 50 design produced. In this study, the Response Surface Methodology (RSM) was employed model the five transportation factors, namely, A(Van), B(lorry), C(truck), D(fuel), E(Labor) and also predicted weight with ANN model (QP with 4 hidden layers) and cost of each CCD combination. Design of RSM models in this study was based on minimum cost and maximum weight.

The optimization values were obtained from the model fitting technique, using the software design expert version 6.0.6. Linear, 2FI (two factorial), quadratic and cubic models were fitted to the experimental data so as to obtain the regression equation (second-order polynomial).

$$Y = \beta_0 + \sum_{j=1}^{q} \beta_j x_j + \sum_{j=1}^{q} \beta_{jj} x_j^2 + \sum_{i<k}\sum \beta_{ij} x_i x_j + \varepsilon.$$

Where β_0 is constant; β_j is the liner coefficient; β_{jj} is the squared coefficient and β_{ij} is the cross product coefficient and X_i and X_j are the coded of independent variables; and q is the number of factors.

3.3 Artificial Neural Network Modeling

The computational program of ANN is the medium to conduct the simulation of modeling as well as the ANN prediction (Jafarzadeh et al., 2012a). However, it is desired to develop the whole program of ANN training without using the existing ANN toolbox. With this, the internal parameters and structure can be decided and configured as required in the planned simulation. In this research, the whole program of feed-forward single hidden layer neural network training and simulation with three different algorithms (Bach Back Propagation , Quick propagation and Levenberg-Marquardt algorithms) methods was developed using Neural-Power® software package (version 2.5). From the program, the training sequences for ANN is defined and developed which includes training, testing. Upon the developing of the ANN program, all the important training parameters which are to be predicted were identified in order to ease the optimization process later.

3.4 Determining of Best Neural Network for Prediction

Determining of best topology for ANN part of the most important steps in developing the ANN model. For the number of hidden neurons, its variation would not only change the ANN structure, but the performance of the network. The hidden neuron was varied from 1 to 5 neurons. Addition of noise to the input data (training, testing and validation data) is an interest of study in this case as it provides insight on how ANN could handle the noisy data but maintains its nature of robustness. The simulation results can be finalized and summarized in tables and graphical forms for better understanding and discussion. The ANN performance can be examined based on the statistical judgment on root mean squared error (RMSE), coefficient of determination (R^2) and number of epochs. Determination of every single step in ANN training is important to ensure the ANN is properly trained and fully assessed before it is claimed to be ready for actual modeling (McQuistenandPeek, 2009). The overall training sequences encompasses three major phases, namely training, testing and validation phase which are to be executed sequentially.

In training phase, the ANN is trained and optimized using an algorithm. The best set of weights and biases will be sent to testing phase which acts as cross-validation to assess the network parameters calculated in training phase using new data. Validation phase is introduced after testing phase. There is no parameters adjustment in validation phase but the calculation of error. This serves as final cross-validation step to determine the network performance when using another new set of data. In overall, the designed training sequences cover the features of (1) continual error reduction for effective training and (2) cross-validation for avoidance of over fitting problem.

C. 4. Results and discussion

4.1 selecting the best neural networks model

In this research , to predict the production weight in the number of week ,number of season and number of van, lorry, truck, fuel and labor were applied as 7-input to ANN with feed forward structure. Training of the network was based on the three different Algorithms and also this was used as tangent hyperbolic function as input and linear function as output layer in this model.

Network structure includes 7 inputs, 1 hidden layer, and 1 output. In order to estimate the number of neurons in hidden layer for the best prediction, hidden layers with neurons from 1 to 5 were examined and also 1/6 of input data were selected as testing data set and the rest of data were applied as training data set. Evaluation results of ANN for each algorithm with different number of neurons in hidden layer explain as in following. Two statistical indexes, namely, the root mean square error (RMSE) and the correlation coefficient (R^2), are used to examine ANN model performance. These statistical indexes were obtained from the statistical calculations of the observed model output predictions. Several algorithms can be used for ANN training. Specifically, this study used the Batch Back Propagation (BBP), Quick Propagation (QP) and Levenberg-Marquardt (LM) algorithms for ANN. The Table 1 presents the results for the various algorithms.

Table 1 Statistical measures and performances of three learning algorithms with structurs

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Algorithm	Network structure	Training set		Testing set	
		RMSE	R^2	RMSE	R^2
Batch Back Propagation (BBP)	7-1-1	127.30	96.77	186.12	95.04
	7-2-1	119.48	97.16	188.22	95.56
	7-3-1	108.26	97.68	202.97	95.22
	7-4-1	107.87	97.71	326.06	89.86
	7-5-1	98.83	98.08	223.01	90.86
QuickProp (QP)	7-1-1	105.23	97.80	100.59	98.16
	7-2-1	97.70	98.10	94.93	98.37
	7-3-1	84.96	98.57	91.80	98.48
	7-4-1	64.81	99.17	78.20	98.91
	7-5-1	70.94	99	72.67	99.06
Lvenberg-Marquardt Algorithm (LM)	7-1-1	105.07	97.80	100.16	97.17
	7-2-1	96.24	98.16	99.10	98.22
	7-3-1	87.54	98.48	86.57	98.66
	7-4-1	79.84	98.74	89.24	98.55
	7-5-1	98.64	98.16	115.60	97.99

The best neural network was the one that had the minimum RMSE and maximum R^2. By investigating and comparing amount of RMSE and R^2 in both sets of train and test in this algorithm, which are shown Table 1, QP has the lowest RMSE (78.20, 64.81) in both test and train set and this shows that QP in HL4 has the best fitting. Furthermore, QP has the highest R2 in test and train among all models (99.17, 98.98). Therefore, 7.4.1 model in QP is selected as the best model for modeling and prediction.

The model trained with QP algorithm could be suggested as the most efficient model to be used for this problem. Hence this model was applied for further application in this study. The ANN architecture for the best model is shown in Figure 3.

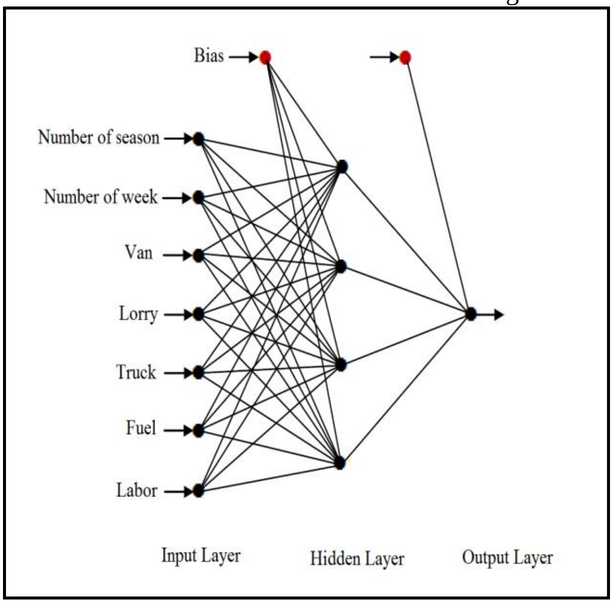

Figure 3 The ANN architecture for the best model with a multilayer feedforward perception (MLP) network consisting of seven inputs, one hidden layer with four neurons and one output

4.3 Response Surface Methodology

In this study, the Response Surface Methodology (RSM) was employed model the five transportation factors, namely, A(Van), B(lorry), C(truck), D(fuel), E(Labor) and also predicted weight with ANN model (QP with 4 hidden layers) and cost of each CCD combination. Design of RSM models in this study was based on minimum cost and maximum weight.

The software design expert version 6.0.6 was used to obtain the optimization values from the model fitting technique and 2FI model was observed to be the highest order model with significant terms, according to this study. The regression method was also used to fit the 2FI model to the experimental data and identify the relevant model terms .The response function which was used to predict production weight for carry with transportation system in the coded variables is as follows:

WEIGHT = -1.98302E+005
+52.25519 * VAN
+20.01229 * LORI
-0.15543 * TRUCK
+0.11663 * FUEL
-0.32375 * LABOR
-2.31521E-003 * VAN * LORI
-3.61168E-003 * VAN * TRUCK
-2.88140E-005 * VAN * FUEL
+1.71297E-006 * VAN * LABOR
+1.63106E-003 * LORI * TRUCK
-4.28442E-006 * LORI * FUEL
-1.58489E-005 * LORI * LABOR
+2.17539E-005 * TRUCK * FUEL
+7.40918E-005 * TRUCK * LABOR
+0.000000 * FUEL * LABOR

When a model is selected, an analysis of variance (ANOVA) is therefore calculated to assess how well the model will represent the data (YadavandSrivastava, 2009). The values of the coefficients and the analysis of variance (ANOVA) are presented in Table 3. The coefficients of the model were evaluated for significance with the Fisher's F-test. The ANOVA indicates that the model is highly significant as the F model value (13.904) is very high compared to the tabulated F14, 15 value (3.56) at P=0.01. In general, the calculated F-value should be several times greater than the tabulated value for the model to be considered or taken as good (Hamzaoui et al., 2008).

Table 4 Analysis of variance (ANOVA) and regression coefficients of the 2FI model equation

ns: not significant

Source	Sum of Squares	DOF	Mean Square	F - Value	Prob > F
Model	3313320430	15	220888028.7	13.9037352***	< 0.0001
A-VAN	958305906.9	1	958305906.9	60.3202973***	< 0.0001
B-LORI	990326604.1	1	990326604.1	62.3358311***	< 0.0001
C-TRUCK	443967261.8	1	443967261.8	27.9453951***	< 0.0001
D-FUEL	43169080.06	1	43169080.06	2.71726567 ns	0.1085
E-LABEOR	36433929.7	1	36433929.7	2.29332352 ns	0.1392
AB	132468289.2	1	132468289.2	8.33817942**	0.0067
AC	154506709.2	1	154506709.2	9.7253816**	0.0037
AD	438286558.3	1	438286558.3	27.5878248***	< 0.0001
AE	8410.072278	1	8410.072278	0.00052937 ns	0.9818
BC	20802588.4	1	20802588.4	1.30941311 ns	0.2605
BD	6397079.978	1	6397079.978	0.40266241 ns	0.5300
BE	475275.9382	1	475275.9382	0.02991611 ns	0.8637
CD	79043842.15	1	79043842.15	4.97539254*	0.0324
CE	4978345.577	1	4978345.577	0.31336057 ns	0.5793
DE	4150548.676	1	4150548.676	0.26125513 ns	0.6126
Lack of Fit	5.4E+8 ns				

R-Squared = 0.8598 Adjusted R^2 = 0.7980

Predicted R^2 = 0.6837 Standard Deviation = 3985.84

Coefficient of variation (CV) = 3.48

*: significant at 5%, **: significant at 1%, ***: significant at 0.1%

The coefficient of determination (R^2) of the model was 0.8598, indicating that 85.98% of the variability in the response could be explained by the model. When R^2 approaches unity, the better empirical model fits the actual data. A regression model with an R^2-value higher than 0.8 is normally considered as the model with a high correlation. Therefore, the present R^2-value reflects a good fit between the actual and predicted values that shown in following figure 5.

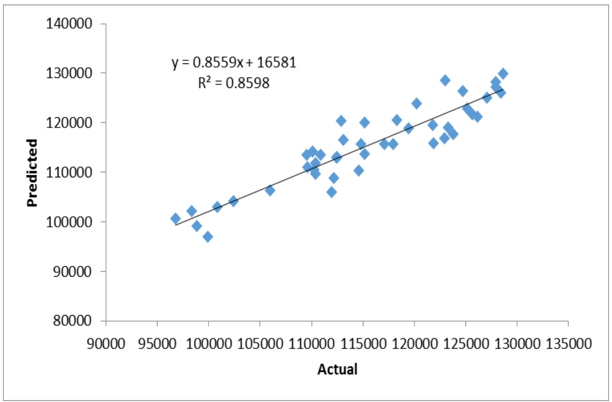

Figure 5 Linear correlation between predicted and actual value

Finally suggested combination by Response Surface Methodology (RSM) for optimisation of IKCO transportation system is as follows: 7930 van, 5379 lorry, 2990 truck, 55900 labor with 624742 fuel consumption. Also based on this combination IKCO productions weight reached from 111254.8 ton in Autumn of 2009 to 123090.9 ton in Summer of 2013. Considering this, amount of production increased 9.61 percent. On the other hand, by using RSM, (2FI) model transportation cost decreased from 1906703.6 $ in Autumn of 2009 to 1684767 $ in summer of 2013. It means that costs decreased 11.64 percent as well (Table 5).

factors	Autumn 2009	Sum 2013(predicted)*	Unit cost US $	Sum cost Aut 2009	Sum cost Sum 2013
Weight ton	111254.8	123090.9	---------	--------	--------
Van 4 ton	6880	7930	30	206400	237900
Lorry 7 ton	5766	5437	50	288300	271850
Truck10ton	3736	2992	85	317560	254320
Fuel liter	770209	624742	0.4	308083.6	249896.8
Labor	65530	55900	12	786360	670800
	Total cost			$1906703.6	$1684767

5. CONCLUSION

With regard to the great number of studies which have been conducted about optimization, experimental techniques have proved high accuracy in this field. In the recent studies, RSM as an experimental technique was considered and offered by many researchers. However, in the present study and some similar studies, it is impossible to carry out the experimental technique individually because it takes great time and cost. For instance, we cannot convince “Iran Khodro” firm to increase or decrease the number of workers or trucks for a month to examine the process and responses of the system. So, in the present study, according to defined factors and levels, RSM suggested optimized compounds based on the lowest costs. Moreover, the responses of these compounds as the carried weight of each compound were predicted and modeled through ANN and then the best compound with regard to the most appropriate response was selected.

In fact, in this study, RSM as an experimental technique, with no application in transportation system optimization and even the supply chain, with the help of ANN was applied . Therefore, a combination of ANN as an accurate tool in prediction and modeling and RSM as a strong and practical model in optimization were applied in this study for the first time.

The methods applied and the results obtained in this study can lead to the increased knowledge and importance of the application of invented and novel methods to optimize different systems in a supply chain toward a continuous improved process. Moreover, this method can be applied as an effective decision-making tool to optimize and manage a system by managers and industry owners and also Since there exists a direct correlation between the transportation system in a supply chain and the inventory and warehousing system, so it is recommended to include the inventory and warehousing factors as influential factors in the optimization of costs in future studies.

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