J. Basic. Appl. Sci. Res., 3(7)484-491, 2013
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ISSN 2090-4304
Journal of Basic and Applied Scientific Research
www.textroad.com

Machinery Cost Prediction Based on a New Neural Network Method

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ABSTRACT

Artificial neural networks are mathematical models that have been inspired by the human nervous system and brain. In this study, the purpose is establishing a method to predict the cost of tractor repair and maintenance more accurately. In this paper, the multi-layer neural network with Feed Forward Backpropagation training algorithm (FFBP) has been used to predict repair and maintenance costs of tractor. In addition, 60 real data from two-wheel drive tractors existing in Razavi agro-industry in Iran have been used to train and test the network. The appropriate parameters for network training have been selected through error test on data. In this study, the performance of Backpropagate Declining Learning Rate Factor algorithm (BDLRF) has been compared with Feed-Forward Backpropagation algorithm (FFBP), with error criteria (MAPE, MSE, and RMSE) and the result shows that training Feed Forward Backpropagation algorithm (FFBP) surpasses the (BDLRF) algorithm in predicting tractor repair and maintenance costs by using separate networks rather than a single network.
KEYWORDS: Artificial neural network, FFB Palgorithm, BDLRF algorithm, Multilayer Perceptron, Tractor, Repair and maintenance cost

1. INTRODUCTION

These days, the climate changes in agricultural areas have resulted in serious damages to farmers. One of the factors which results in the reduction of these damages and also increasing farmers' profits is predicting and then reducing the repair and maintenance costs of agricultural machines. Since tractor is one of the most vital agricultural machines, prediction of its costs is vital. Moreover, tractor is one of the most determinant devices in performing agricultural processes in time [1]. Economic decision making for achieving the highest profit is one of the most prominent factors in the administrators' success [2]. Having the knowledge of costs plays an important role in making appropriate decisions about the management of machines [3, 4]. Repair and maintenance costs are deeply dependent on location, time, and management policy. Therefore, accurate prediction of such costs is very difficult [5]. Prediction means: what is going to happen in the future [6]. When the costs of tractor are increasing; or in other words, the tractor is time worn, the manager should think of replacing it with a new tractor. As a result, using accurate prediction tools seems inevitable [7]. In Previous studies, regression and neural network techniques were used to predict the costs of maintenance and repair of the tractor. Rotez proposed a model to estimate the costs of maintenance and repair [4]. Fuls proposed a model to which he managed to add new parameters like the effect of management policies and the proficiency of the person, estimating the repairs and maintenance costs[8]. Regression Analysis is a variable that can determine the relationship between the dependent variable and one or more independent variables [9]. Up to the present time, all presented mathematical models have been based on sampling of Rotez's regression model. In most cases, for analyzing non-linear data, we use linear regression which will not be valid if it isn't applied accurately [10]. These are obvious defects of this technique. The other tool and technique which can be a replacement for regression model is the neural network. Neural network is used in numerous applications such as a tool of decision making. This usage refers to the fact that neural network tries to model the capacity of human's brain[11].Artificial neural networks are simplified models of central nervous system and similar to the brain, transfer the rules hidden behind the data to the network structure by processing and analyzing experimental data. An artificial neural network is combined of neurons which make up the basis of neural networks functions [12].Therefore, without relying on assumptions such as initial form of function, potential distribution, and number of variables, the neural network could determine the final model by learning the initial data [13]. Without assuming any prior information about the relationships between the studied parameters, the neural network is able to determine a relationship between a group of inputs and outputs in order to predict the corresponding output of a desirable input [14, 15].

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Morris [16] has done a research on the repair and maintenance costs of a number of tractors in England. The calculated costs are based on the type of the tractor and the total annual working hours which are modified as a percentage of the initial purchase cost. Ashtianni-Erghi et al. [17] in their research have used a power regression model to predict the repair and maintenance costs of the tractor based on cumulative usage hours for 27 active tractors in Dasht-e-Naz agricultural company in Mazandaran. Ajabshichi et al. [18] in their research, have used polynomial regression model in order to predict the repair and maintenance of costs of the tractor based on cumulative usage hours for 47 active tractors in Astan-e-Ghods Razavi farms of Khorasan, Iran. Ranjbar et al. [19] have used two different structures of neural networks to predict the repair and maintenance costs of the tractor, and the results show that a network, which predicts the cost criteria simultaneously, will a better performance. Rohani et al. [20] have used a neural network and its comparison with the regression model in order to predict the repair and maintenance costs of two-wheel-drive tractors. Based on the outcome results neural networks have a better performance as compared to the regression model. Mohammadi et al. [21] in their researches have used the condition monitoring in order to predict the repair and maintenance costs in Iran. The research has used mathematical models like regression to predict the repair and maintenance costs of the tractor. Rohani et al. [11] in their study have used two types of training algorithms to train the neural network to predict the repair and maintenance costs. The results show that the BDLRF algorithm has fewer errors in comparison with BB algorithm.

In this study, a neural network along with of Feed-Forward training algorithm is used in order to predict the repair and maintenance costs of the tractor. The main difference of this study from the other similar studies is that in the current study two separate and similar neural networks, whose duty is to predict one index individually, are used in order to predict the indexes of repair and maintenance costs. Moreover, as compared to former studies, done by linear regression, this study has far less error.

The scientific contribution of this paper is: 1) The BDLRF and FFBP performances were compared. 2) Maintenance and repair costs prediction through FFBP algorithm has a better performance. 3) Two separate neural networks were used to predict each parameter. 4) Separate network training resulted in decreasing error criterion.

Section 2 concentrates on collecting, standardizing, and processing the data. Section 3 describes the multilayer perceptron networks and its training algorithms. Section 4 illustrates the results of training and testing of the neural network to predict the repair and maintenance costs. Finally, section 5 is the obtained result of the research which is done.

2. MATERIALS AND METHODS

2.1. Collecting information

Monthly repair costs and maintenance data of 60 two-wheel drive tractors, between the years of 1986 and 2003, is used in this study. The data consists of monthly repair costs (cost of spare parts and wages), monthly maintenance costs (fuel, oil, oil filter and fuel filter), date of purchase, date of manufacturing and tractor model. This data was assembled by Astan Ghods Razavi Corporation in Iran and because of the lack of access to laboratory information; it must be assumed asvalid and accurate. In order to create the neural network, first, information must be divided into two phases: learning and testing. The method of this dividing plays an important role in the evaluation of ANN. The learning set is used for estimating the model parameters and the test set is used for studying the modelfeasibility of generalization [11]. In this study, the learning and testing sets consist of 130 and 86 samples. If the model performance does not yield desirable results, the learning set could be reformed [22].

2.2. Data standardization

The scope of this study is to obtain a tool to predict the repair and maintenance costs of tractors. Prediction of repair and maintenance costs and then reducing them plays a prominent role in the farming industry. These costs are different among different models of tractors. The Inflation effect is a concerning factor when making a conscious business decision about cash flows [11]. The total inflation rate is reflecting the tendency of changes of costs in all goods and also reflecting services in economy. Before calculating the cumulative cost, the effect of inflation on prices must be calculated and adjusted. Because of different repair and maintenance costs, and also different purchasing prices of tractors, and the natural differences between different tractors because of their uses in various agricultural fields, these costs are standardized using the following formula [5].

$$CCI_t = \frac{\sum_0^t C_t}{dd_0} \times 1000 \quad (1)$$

Where CCI_t indicates the cumulative cost at time (t), C_t is the repair and maintenance cost at time (t), and dd_0 is the initial price of the tractor. In the lifetime of a tractor, this function always has an ascending or fixed trend [20].Tractor age is an input in this network. Age has three definitions: calendar age, age based on number of manufactured units and CHU (Cumulative hours of usage). Between these definitions, CHU is the most favorable description of the tractor's age [5]. CHU is the number of hours in which the tractor has worked.After standardization of the costs by using cumulative cost indicator, the cumulative repair cost (CCI_{repair}) and cumulative oil cost (CCI_{oil}) indicators were calculated and used as the outputs of the neural network.

2.3. Data processing

Based on the data investigated in this study, CHU was calculated based on 100 hours and was chosen as the input variable of the neural network. After determination of input and outputs of the neural network, the data should be normalized in the range of [0 1] before carrying out each ANN learning process. The goal of this normalization is that all learning data has a uniform statistical distribution. Linear normalization has been used for data conversion in this study.

$$X_n = \frac{X}{X_{\max}} \quad (2)$$

In this formula X, X_n, and X_{max} represent initial data, normalized inputs or outputs, and the maximum of initial data respectively.

3. Multilayer Perceptron Neural Network

Perceptron neural networks are categorized as feed forward neural networks. These neural networks are constructed based on a computation unit called perceptron. A perceptron takes a vector of inputs of actual values and computes a linear combination of these inputs. The aim of the Perceptron neural network's training and learning is to determine parameters including weights and biases whose correct training leads to creation of a proper model with less error in order to be predicted. Multilayer Perceptron Neural Network (MLP) has a major significance in case of application among Artificial Neural Networks (ANNs). MLP has one input layer, one output layer, and one hidden layer in its structure. Fig. 1 shows a multilayer perceptron neural network in which the input layer consists of as many neurons as input variables of network. In this paper, the only input of the network is the CHU. The hidden layer consists of different neurons, which are obtained by trial and error method for minimizing the error (MSE, MAPE, and RMSE). The output layer consists of parameters that should be predicted based on input variables. The number of neurons in the output layer is equivalent to the number of parameters in the same layer. By selecting separate parameters for performing calibration (simultaneous with the learning process in the neural network), greater certainty about the absence of pre-learning could be achieved [23, 24]. In this paper a Multilayer Perceptron (MLP) with Feed-Forward Back propagation algorithm (FFBP), as well as Tansig transfer function and TRAINLM learning technique were used, and the LEARNGDM technique was used to minimize the error cost functions. In order to train the MLP, two algorithms (BDLRF and FFBP) were compared. The software codes for these algorithms were constructed in MATLAB. Fig. 2. Is the flow chart to train the neural network in order to predict the repair and maintenance costs of the tractor.

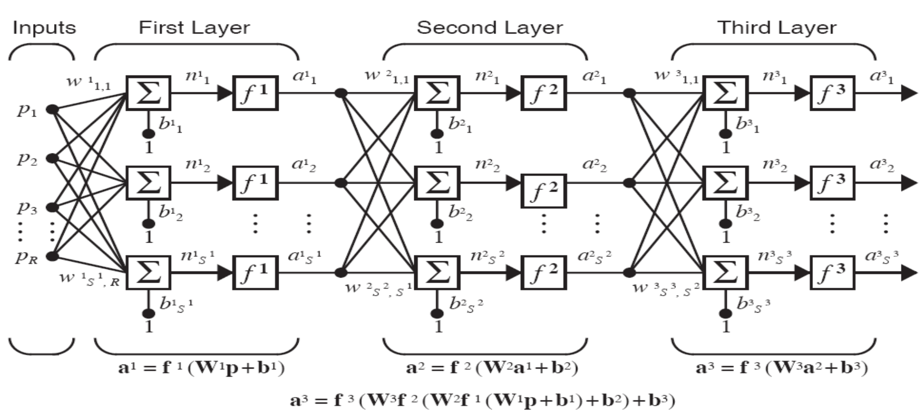


Fig. 1. Multi-layer Perceptron Neural Network

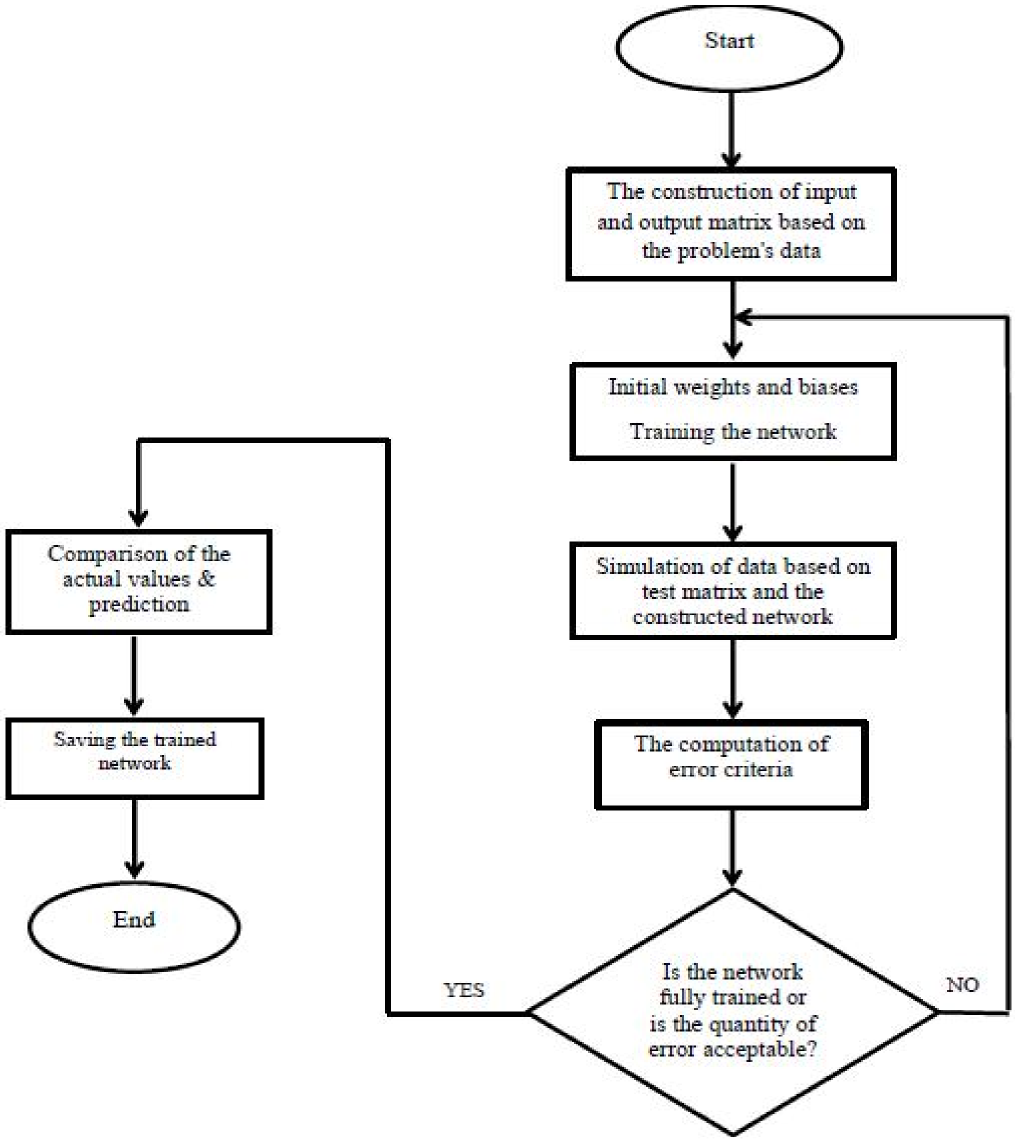


Fig. 2. Flow chart of training neural network.

3.1. Backpropagate Declining Learning Rate Factor algorithm (BDLRF)

This algorithm is a revised version of the original Backpropagating algorithm [25]. This learning algorithm starts with a constant high learning rate and momentum factor, and before the network becomes unstable or its convergence rate becomes slow, during P repeat (3<P<5), the learning rate and momentum factor reduce uniformly with an arithmetic progression until they reach x percent of their initial values. These parameters are reduced with the following formula:

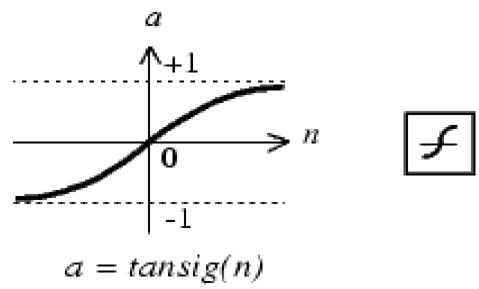
$$m = \frac{(O - k_1)}{P} \qquad (3)$$

$$k_n = h_0 + k\ h_0 \frac{x-1}{m} \qquad (4)$$

Where m is total number of arithmetic progression, k_1 is starting point of BDLRF, k_n is the learning rate at the k^{th} member of the progression and $h_0$is the initial value of the learning rate, respectively.

3.2. Feed-Forward Backpropagation algorithm (FFBP)

The static structure of this algorithm (independent of time) is useful in engineering problems and scientific calculations [26]. Neurons, the elements of signal processor, are connected by synapse connections between feed forward layers. Input and output may be related to using non-linear mapping functions. The goal of using this algorithm in MLP is to minimize the error criteria (MSE, RMSE and MAPE). In order to calculate the output of a layer from its absolute input value, a tangent sigmoid transfer function (Tansig) is used in this algorithm. This function is illustrated in fig. 3. It is alsodesigned in algorithm (FFBP) of training function (TRAINLM), the adjustment of learning function (LEARNGDM) and evaluation and error (MSE).



tansig(n) = 2/(1+exp(-2n))-1

Fig. 3. Tan-Sigmoid Transfer Function

3.3. TRAINLM training function

TRAINLM is a neural network training function that performs weight and bios updating based on Levenberg-Marquardt optimization method. In this paper, after performing the trial and error process, the best training function was found to be TRAINLM method, which gave the least error. Like Quasi-Newtonian methods, the TRAINLM training function is designed to estimate the second order very quickly without the need of Hessian Matrix calculation [27].

3.4. Neural network evaluation criteria

In order to evaluate neural network application for predicting repair and maintenance costs indicators, the following criterions are used: Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Percentile Error (MAPE). The formulae used for comparison between predicted and actual values are as follows:

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n}\sum_{i=1}^{m}\left(x_{ji} - y_{ji}\right)^2}{nm}} \qquad (5)$$

$$MAPE = \frac{1}{nm}\sum_{j=1}^{n}\sum_{i=1}^{m}\left|\frac{x_{ji} - y_{ji}}{x_{ji}}\right| \times 100 \qquad (6)$$

$$MSE = \frac{\sum_{j=1}^{n}\sum_{i=1}^{m}\left(x_{ij} - y_{ij}\right)^2}{nm} \qquad (7)$$

where x_{ij} is the i^{th} component of the actual output of the j^{th}model, y_{ij} is the i^{th} component of the estimated output by neural network of the j^{th}model and n and m are the number of patterns and output variables, respectively [11].

4. RESULTS AND DISCUSSIONS

Because of the high costs of maintenance and repairing as well as the need of their decrease, we want to find a method for predicting the exact amount of costs so that managers can make an accurate decision. In this study, two separate neural networks to predict the cumulative cost of oil (CCI_{oil}) and cumulative maintenance cost index (CCI_{repair}) are used. Prediction of these costs separately will decrease the error criterion noticeably. One of the most important factors that decreases the error criterion in these problems is training and testing the network separately because when a network is trained separately, the speed of training is high and assimilation of answers is better. Table 1 shows the number of neurons in each network algorithm in FFBP.

Table 1. Values variation of a three – layer FFBP-MLP.

Number of neurons in hidden layer												
Parameters Crinterion		5	6	7	8	9	10	11	12	13	14	15
CCI_{oil}	MAPE(%)	0.261	0.269	0.268	0.145	0.262	0.295	0.26	0.184	**0.108**	0.237	0.195
	RMSE	0.002	0.002	0.003	0.003	0.003	0.003	0.003	0.009	**0.002**	0.002	0.003
	MSE	0.005	0.005	0.008	0.009	0.012	0.01	0.007	0.011	**0.003**	0.004	0.01
CCI_{repair}	MAPE(%)	0.404	0.339	**0.137**	0.211	0.383	0.231	0.229	0.242	0.153	0.245	0.327
	RMSE	0.005	0.003	**0.002**	0.004	0.004	0.002	0.003	0.003	0.003	0.003	0.004
	MSE	0.024	0.012	**0.004**	0.013	0.014	0.006	0.008	0.008	0.007	0.009	0.013

MSE=mse*10^{-3}

Table 2. Values of BDLRF algorithm and FFBP algorithm in prediction of tractor repair and maintenance costs indices.

Parameters of cost	**Training algorithm**	**MAPE (%)**	**RMSE**	**MSE**
CCI_{oil}	BDLRF	1.68	0.0415	0.0015
	FFBP	**0.1083**	**0.00172**	**0.0000025**
CCI_{repair}	BDLRF	2.74	0.3674	0.0019
	FFBP	**0.1371**	**0.1349**	**0.0000037**

Figures4 to 7 show the comparison between the predicted and actual data in different graphs. In this paper, MSE, RMSE, and MAPE are used to compare the training algorithm FFBP with training algorithm BDLRF standard error of. According to Table (2) it is indicated that the training algorithm FFBP outperforms in comparison with the training algorithm BDLRF.

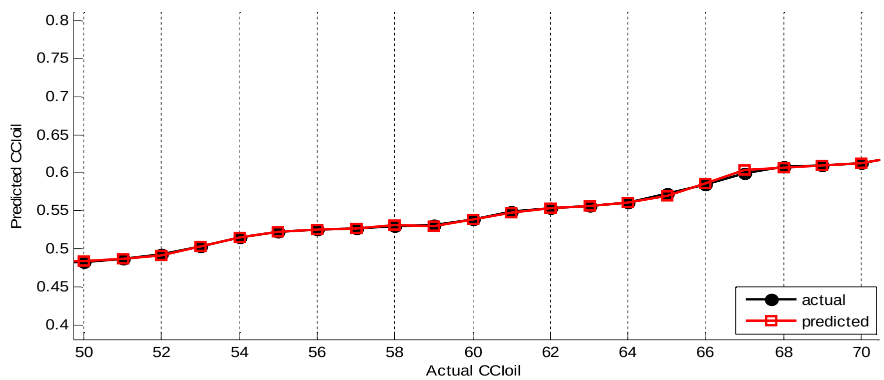


Fig. 4. Comparison of actual and predicted values for training data (CCI_{oil})

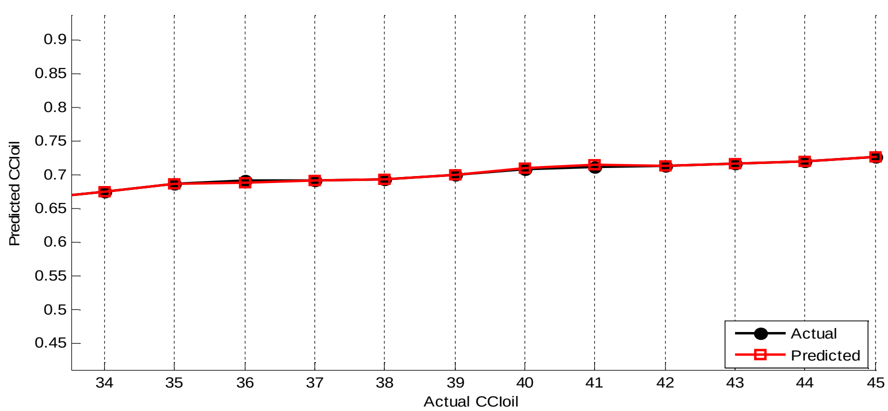


Fig. 5. Comparison of actual and predicted values for testing data (CCI_{oil})

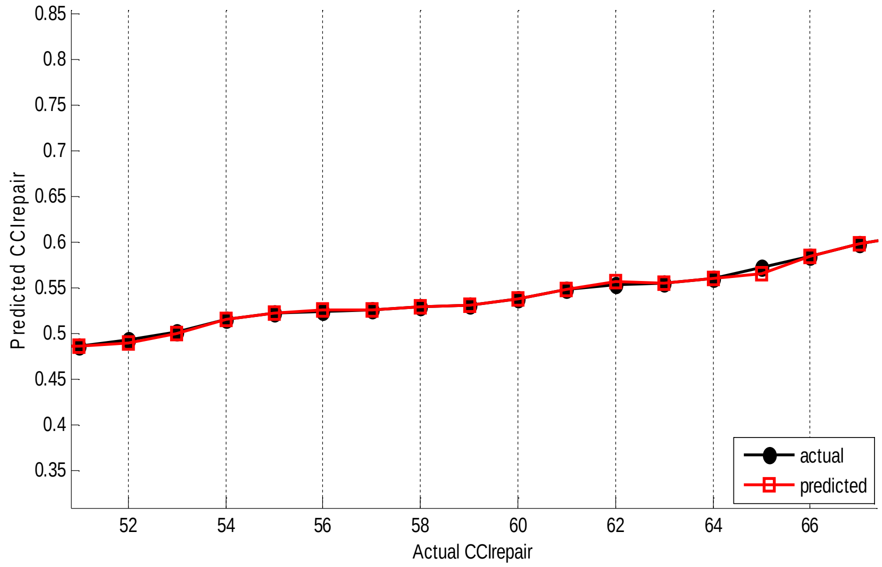


Fig.6. Comparison of actual and predicted values for training data (CCI_{repair})

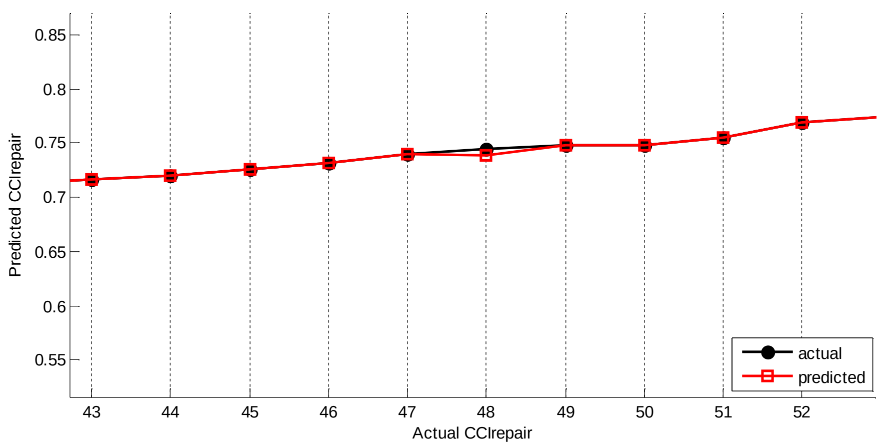


Fig.7. Comparison of actual and predicted values for testing data (CCI_{repair})

5. Conclusion

The goal of this study was to predict repair and maintenance costs of tractors in order to minimize error criterion. In order to illustrate the applicability of the proposed method, actual monthly tractor repair and maintenance data from Astan Ghods Razavi Corporation between the years of 1986 and 2003 were collected. After collecting data, by building the MLP neural network and studying behavior of the error criteria, it was found that the FFBP learning algorithm is more favorable in most experiments than the BDLRF learning algorithm. Because predicting repair and maintenance costs is of so much value, the goal of future studies is to make the predicted values become closer to actual values by changing the learning process and offering new ideas.

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