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Experimental design of supervisory control functions based on multilayer perceptrons

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Abstract

This article presents the results of research concerning possibilities of applying multilayer perceptron type of neural network for fault diagnosis, state estimation, and prediction in the gas pipeline transmission network. The influence of several factors on accuracy of the multilayer perceptron was considered. The emphasis was put on the multilayer perceptrons' function as a state estimator. The choice of the most informative features, the amount and sampling period of training data sets, as well as different configurations of multilayer perceptrons were analyzed.

Keywords: Cross Validation, Multilayer Perceptron, Neural Networks, Supervisory Control

1. INTRODUCTION

The growth of industrial production causes an increase in energy consumption. It is reflected in a more severe operation of large energy production and distribution systems such as, for example, the natural gas pipeline network and the electric power systems. The staff of the dispatching centers is faced with increasingly high demands concerning the reliability and security in providing the required energy. For that reason, intensive research is being conducted to find new, faster, and more accurate computer methods for implementation of high-level supervisory control functions, such as fault diagnosis or monitoring. Traditional algorithmic approaches use methods of filtering and estimation (Isermann, 1984; Saif, 1998). Expert systems are also one of the approaches, but an extensive heuristic knowledge base is required for their operation (Kramer & Finch, 1988). However, in cases when the information about the system state is incomplete or a mathematical model of the processes is ill defined, methods of machine learning are much more suitable (Gupta & Rao, 1994). The artificial neural networks (ANNs) represent the learning technique that is capable of acquiring and storing new "process knowledge" on the basis of representative training samples regarding system behavior in different operating conditions. ANNs are widely used in the areas of identification, control (Narendra, 1996), signal processing (Feldkamp & Puskorius, 1998), resource scheduling (Kartam & Tongthong, 1997), and project control (Al-Tabtabai et al., 1997). Recently, this approach was frequently applied in developing high-level supervisory control functions (Lee et al., 1996; Edwards et al., 1999).

This article presents the results of the research conducted to apply the multilayer perceptron (MLP) type of artificial neural network in designing a set of advanced functions of the supervisory control system: functions for estimation and prediction of selected process variables, as well as the fault diagnosis function. The accuracy of supervisory functions depends upon external influences originating from input variables, and upon internal characteristics of the MLP used. The external influence on the MLP's performance was extensively investigated by means of training sets reduction (with regard to the number of samples and features that describe each input sample). The impact of the internal characteristics of MLP was tested by using changes of the number of hidden neurons and a type of neuron's activation function. The performance evaluation of MLP-based supervisory control functions is mostly done with the aid of the 10-fold cross validation experimental procedure (Peterson et al., 1995; Leisch et al., 1998). Final assessment of statistical significance of the influences is made with the use of Fisher's test. After a great number of different MLP training and testing runs, the following three factors were cho-

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sen as the most significant: the choice of the features, the number of inputs, and the sampling period.

The next section of the article describes the structure of the system with supervisory control functions designed by using MLPs. The third section gives the general overview of the procedure for analyzing the influence of the factors on the accuracy of MLP performance. The forth section gives the detailed experimental results of the performance analysis of the MLP-based supervisory control functions.

2. DEVELOPMENT OF A SUPERVISORY CONTROL SYSTEM BY USING MLPs

A gas pipeline network is a large-scale and spatially distributed system with a great number of sensors. But even such a large number of measurements is not sufficient to cover the complex nonlinear dynamics of this system's behavior (Osiadacz, 1987). That is why it is very important to have, within computer-based control of that system, a supervisory function capable of indicating undesired or unpermitted states and taking appropriate actions to maintain the process and to avoid damages or accidents.

The major part of the Yugoslav natural gas transmission and distribution network is located in the province of Vojvodina, the northern part of Yugoslavia. The central supervising station of the Supervisory Control And Data Acquisition (SCADA) system is realized by reliable industrial personal computer stations interconnected via a local area network. The key features of this SCADA system are open architecture, hot stand-by, an effective human–machine interface subsystem, and an information link to the enterprise information system. To achieve better supervision and control over the gas-transport process, basic SCADA functions are augmented with advanced supervisory functions. Figure 1 shows the proposed structure of the supervisory control system based on MLPs. The following functions can be distinguished:

- *State estimation:* estimation of the pressure and flow changes in time in the network's nodes.
- *Short-term forecasting:* prediction of the gas consumption for time intervals from 15 minutes to a few hours. It is possible to make the consumption prediction for the particular consumers—network's sink node, predetermined group of the consumers, or the complete pipeline network.
- *Fault diagnosis:* detection and diagnosis of faulty sensors, and early detection and classification of gas leaks in the pipeline network.

The requirements, imposed with the advanced supervisory functions, have necessitated fulfillment of a number of conditions related to the corresponding program modules and internal database. Major characteristics of these supervisory functions are listed:

1. A connection with the SCADA database is established, with the aim of extraction and filtration of the required values of the process variables.
2. An internal database of supervisory control functions is created. It contains parameters of individual function modules (input–output quantities, time interval, sampling time, etc.). In addition, it contains param-

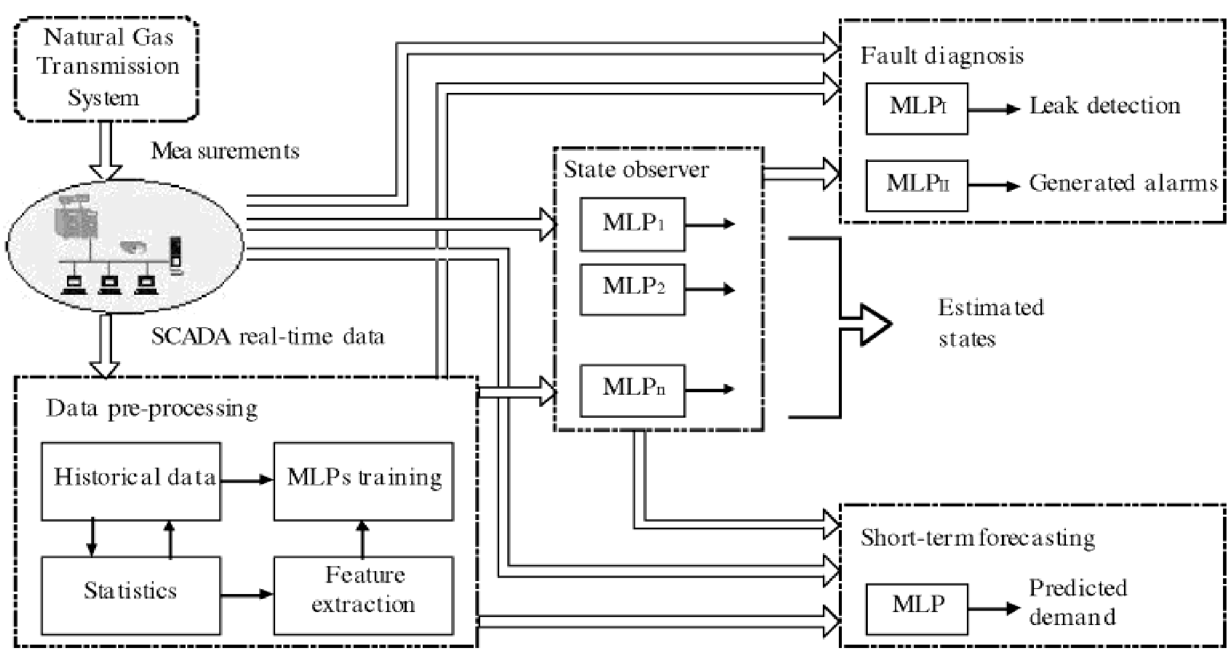

Fig. 1. The schematic representation of the proposed supervisory control system.

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eters of corresponding MLP models (training parameters and model configuration).

3. Procedures for on-line execution of MLP models for the purposes of estimation or prediction of a process variable are embedded.
4. Procedures for training— creation of MLP models are integrated into the system.
5. A module for continuous monitoring of selected estimates of process variables is developed and constitutes a part of the supervisory control functions. These variables are subsequently compared to the corresponding measured values obtained through the SCADA system. This module serves the purpose of fault detection in various parts of the gas pipeline network.

Considering the aforementioned supervisory control functions based on MLPs, different sets of input variables can be chosen. When the MLP performs the state estimator function, the input variables can be the key measured variables or their deviations from reference values (Isermann, 1998). The input variables for an MLP that performs the function of short-term demand prediction are, in most cases, a series of values of previous consumption. The indicators of the week days and/or weather conditions can also be very important (Peng et al., 1992). In case of a diagnostic MLP, the main task is to produce the knowledge concerning the relationships between the symptoms obtained either by measurements or by state estimation, and the unknown faults (causes) (Isermann, 1998).

The design preparation phase of supervisory control functions (see Fig. 1) is very important. It takes several steps. The first step is to systematize the data, measured at the gas pipeline network. The systematization is done on the basis of the operator's knowledge and statistical analysis. The next step consists of choosing states/features that correspond the best to the output function of the given MLP. The training data set, which is indispensable for the training of an adequate MLP, is formed in that way (Carpenter & Hoffman, 1997). The error back-propagation method is used for this purpose (Haykin, 1994).

The samples, which should serve for MLP training and testing, are obtained from the SCADA system. The measured data correspond to the normal state, when there is no leakage or other faulty state. Each sample is described by a set of selected features which support best the function that MLP is trained for. The MLPs performing the function of the state estimator were used to present the experimental design of MLP for supervisory control system. The state estimator for the whole pipeline network consists of numerous MLPs. Each of them has several measured inputs, while the output is a single estimated state variable (see Fig. 1).

As an illustration, Figure 2 depicts comparative chart of estimated and measured pressure in one node of the gas pipeline network. MLP-based pressure estimation functions have shown high accuracy with a relative error that is approximately 1%.

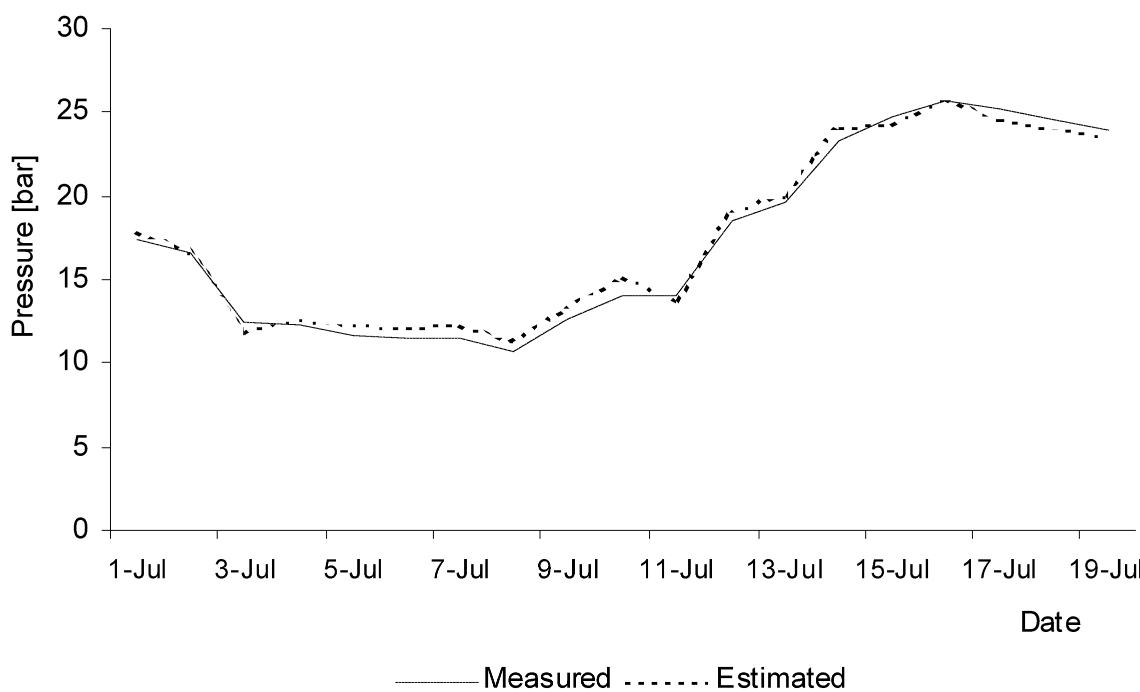

Fig. 2. Actual and estimated pressure changes in Becej.

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3. EXPERIMENTAL DESIGN OF THE MLP NEURAL NETWORK

In the multilayer perceptron type of a neural network with one hidden and one output layer, the mapping of the input sample $\mathbf{x}$ into the output $\mathbf{y}$ is given by the expression

$$\mathbf{y} = \Gamma_O[\mathbf{W}_O \cdot \Gamma_{\boldsymbol{H}}[\mathbf{W_H} \cdot \mathbf{x}]], \tag{1}$$

where $\mathbf{W_H}$ and $\mathbf{W_O}$ are matrices of synaptic weights on hidden and output layers, respectively; and $\Gamma_H[\cdot]$ and $\Gamma_O[\cdot]$ are generally nonlinear diagonal matrix operators containing the activation function of neurons. The accuracy of this neural network can be achieved during network training by adjusting elements of synaptic weights matrices $\mathbf{W}_H$ and $\mathbf{W}_O$. The successful input–output mapping, that is, the accuracy of the neural network, depends on external influences, originating from input vector samples, and on internal characteristics of the neural network. External influences can be assessed by the amount of data, its representativeness, completeness, informativeness, and so on. The internal group of influences consists of factors such as the number of hidden layers and the number of neurons in them, the type of neuron's activation function, neurons connections, the process of learning, and so on. The impact of those factors on the neural network output can be expressed by functional dependence $\mathbf{y} = f(x_1, x_2, \ldots x_i \ldots . x_m)$, where x_i is ith influencing factor and m is the total number of factors.

To assess the influence of external and internal factors on the neural network accuracy, a three-phase experiment is created. The first phase consists of the preparation of initial data, the selection of the state features, and the reduction of the training sample set. If we suppose a fully connected MLP with one hidden layer trained by the back-propagation method, two internal factors are considered: the number of neurons in the hidden layer and the type of activation function. To obtain a training set with the most informative samples and features, it is appropriate to examine the impact of input data informativeness on the accuracy of the neural network. The quality of the information contained in the samples is assessed through two different (external) factors: features selection and data quantity.

In the second phase, many-fold cross validation is used to analyze the learning and generalization abilities of the artificial neural network. With n-fold cross validation and an initial data set of size N, n test trials are carried out. Each trial employs $N - N/n$ samples as the training set and the remaining N/n samples as the test set. In this experiment 10-fold cross validation is used, which means that the initial data set η is partitioned into 10 equal sets $\eta_1, \eta_2, \ldots, \eta_{10}$. During the kth trial, the set $\eta - \eta_k$ is used for training and η_k is left for testing. The error measure used in this experiment is the mean square output error, defined for the kth set as

$$E_{av}^{tr} = \frac{1}{N - N/n} \cdot \sum_{i \epsilon \eta - \eta_k} |d_i - y_i|, \quad k = 1, \ldots, 10, \text{ for training stage;}$$

$$E_{av}^{ts} = \frac{1}{N/n} \cdot \sum_{i \epsilon \eta_k} |d_i - y_i|, \quad k = 1, \ldots, 10, \text{ for testing stage;} \tag{2}$$

where d_i and y_i are the desired and the calculated neural network outputs, respectively. Finally, in the third phase of experiment, the variance is analyzed.

4. DESCRIPTION OF THE EXPERIMENT AND ANALYSIS OF THE RESULTS

To evaluate the impact of external (data contents and quantity) and internal (the structure of the neural network, the choice of activating functions, the training method) factors on the neural network's accuracy, the three-step experiment was conducted. The first step takes data preparation, making the choice of features, and forming the training set. The second step consists of the 10-fold cross validation, which was performed to analyze the neural network's capabilities. The last step consists of dispersion analysis, which serves to define the statistical importance of the factors, with the use of Fisher's test (Lochner & Matar, 1990).

During the first step of the experiment, the statistical method for defining the correlation between separate features was used to establish the existence and the strength of the relation between variables. In that way, the less important features were eliminated. Six out of 15 considered features were selected (those with the greatest correlation coefficient). They are shown in Table 1.

Taking into account the correlation coefficients, two convenient sets of input variables were formed out of those six features. One set contained the pressures, and the other contained pressures and flow, as shown in Table 2.

During the second step of the experiment, the impact of the length of the considered time interval (data quantity) was investigated. The data for the whole year 1998 were considered, with the total of 34,560 samples (the samples were taken every 15 minutes). The MLPs with one hidden layer were trained, and they were given data for 15, 30, and

Table 1. *Correlation between pressure in node Becej (P_{BCJ}) with selected variables*

State Variables	Correlation Coefficients
P_{BCJ} $(k-1)$	0.9885
P_{GSP}	0.9803
P_{HRG}	0.9432
Q_{HRG}	−0.6520
Q_{BCJ}	−0.5333
Q_{BCJ} $(k-1)$	−0.5200

P: pressure, Q: flow, $(k-1)$: previous time instance.

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Table 2. *Input–output selected variable sets*

Selected Features—Set 1	Selected Features—Set 2
Input: P_{HRG}	Input: P_{HRG}
Input: P_{GSP}	Input: P_{GSP}
Input: P_{BCJ} $(k-1)$	Input: Q_{BCJ}
Output: P_{BCJ}	Output: P_{BCJ}

60 days. While evaluating MLP performance, not only were the training or testing errors taken into account, but also the neural networks' training period. The 30-day period gave the best relation between the training period and the trained neural network's error, and the analysis was continued with those data.

Concerning the neural network's internal characteristics, logistic sigmoidal was chosen as the activation function for neurons in the hidden layer, while the pure linear activation function was selected for the output layer. The number of hidden neurons was changed in function of the variation of number of inputs in expression $2N+1$, were N is the variable number of inputs (Lippmann, 1987). The impact of the number of inputs variation on the MLP's accuracy was investigated by reducing the number of inputs from three to two (by excluding the pressure in node Horgos-P_{HRG}).

The experiment was designed and its results were analyzed by using the 10-fold cross validation with Taguchi's method (Lochner & Matar, 1990; Peterson et al., 1995). With this methodological approach it is possible to determine which of the considered factors have the most effect on given neural network errors. The use of Taguchi's method in the second step of the experiment can be briefly described in following way. As has already stated, the output of the neural network is now a function of three variables, whose values can be controlled (i.e., $\mathbf{y} = f(x_1, x_2, x_3)$). The controlled variables x_1, x_2, and x_3 are called factors. The main goal is to find the level of influence of the change of each factor on the neural network diagnostic accuracy. This is done by varying each factor independently of the others, or by varying two or three factors simultaneously in an orderly way, with recording of influences of factors' changes on the neural network output. During this experiment, the considered factors were varied between two values each: factor x_1—selection of features (pressures only, or pressures and flow); x_2—number of inputs (2 or 3); x_3—data sampling period (5 hours or 60 minutes). There were eight trials, each using the combination of two given values, as shown in Tables 3 and 4.

The results of each trial were recorded, repeated for each samples set prepared in the 10-fold cross validation manner. The average value of 10 experiments is written in the Value column. This value is copied along the row of this trial, into cells without an asterisk sign. For example, in trial number 4, the value of x_1 is Set 1 (pressures only), x_2 is equal to two inputs, and x_3 has a value of 60 minutes. Final totals and averages are taken in each column (cells without an asterisk). The last row in the table, Effect, gives the numerical value of the average effect that the changes of the value of each factor have on the neural network error. The values in the Effect row represent the differences between average errors found for the two values in each column.

The results in the Effect row in Tables 3 and 4 indicate that the sampling period has the strongest impact on training error averaged over 80 runs of the 10-fold cross validation. The second factor, number of inputs, has less influence. Further evaluation of the results in the effect row ranks the first factor, selection of features, as a factor with the smallest influence, because its value is much lower then the values of the other two factors. The columns labeled as X_1X_2,

Table 3. *The effects of the three experimental factors on average training error for node Becej*

		X_1		X_2		X_3		X_1X_2		X_1X_3		X_2X_3		$X_1X_2X_3$	
Tr	Value	Set 1	Set 2	3-7-1	2-5-1	5 h	60 min.								
1	0.2250	0.2250	*	0.2250	*	0.2250	*	*	0.2250	*	0.2250	*	0.2250	0.2250	*
2	0.0910	0.0910	*	0.0910	*	*	0.0910	*	0.0910	0.0910	*	0.0910	*	*	0.0910
3	0.5033	0.5033	*	*	0.5033	0.5033	*	0.5033	*	*	0.5033	0.5033	*	*	0.5033
4	0.0961	0.0961	*	*	0.0961	*	0.0961	0.0961	*	0.0961	*	*	0.0961	0.0961	*
5	0.3247	*	0.3247	0.3247	*	0.3247	*	0.3247	*	0.3247	*	*	0.3247	*	0.3247
6	0.0621	*	0.0621	0.0621	*	*	0.0621	0.0621	*	*	0.0621	0.0621	*	0.0621	*
7	0.4924	*	0.4924	*	0.4924	0.4924	*	*	0.4924	0.4924	*	0.4924	*	0.4924	*
8	0.0878	*	0.0878	*	0.0878	*	0.0878	*	0.0878	*	0.0878	*	0.0878	*	0.0878
T	1.8824	0.9154	0.9670	0.7028	1.1796	1.5454	0.3370	0.9862	0.8962	1.0042	0.8782	1.1488			
A	0.2353	0.2289	0.2418	0.1757	0.2949	0.3864	0.0843	0.2466	0.2241	0.2511	0.2196	0.2872			
E		−0.0129		−0.1192		0.3021		0.0225		0.0315		0.1038		−0.0328	

Tr: Trial, A: Average, T: Total, E: Effect.

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Table 4. *The effects of the three experimental factors on average testing error for node Becej*

		X_1		X_2		X_3		X_1X_2		X_1X_3		X_2X_3		$X_1X_2X_3$	
Tr	Value	Set 1	Set 2	3-7-1	2-5-1	5 h	60 min.								
1	0.2742	0.2742	*	0.2742	*	0.2742	*	*	0.2742	*	0.2742	*	0.2742	0.2742	*
2	0.1107	0.1107	*	0.1107	*	*	0.1107	*	0.1107	0.1107	*	0.1107	*	*	0.1107
3	0.5863	0.5863	*	*	0.5863	0.5863	*	0.5863	*	*	0.5863	0.5863	*	*	0.5863
4	0.1028	0.1028	*	*	0.1028	*	0.1028	0.1028	*	0.1028	*	*	0.1028	0.1028	*
5	0.3795	*	0.3795	0.3795	*	0.3795	*	0.3795	*	0.3795	*	*	0.3795	*	0.3795
6	0.0656	*	0.0656	0.0656	*	*	0.0656	0.0656	*	*	0.0656	0.0656	*	0.0656	*
7	0.5256	*	0.5256	*	0.5256	0.5256	*	*	0.5256	0.5256	*	0.5256	*	0.5256	*
8	0.1017	*	0.1017	*	0.1017	*	0.1017	*	0.1017	*	0.1017	*	0.1017	*	0.1017
T	2.1464	1.0740	1.0724	0.8300	1.3164	1.7656	0.3808	1.1342	1.0122	1.1186	1.0278	1.2882	0.8582	0.9682	1.1782
A	0.2683	0.2685	0.2681	0.2075	0.3291	0.4414	0.0952	0.2836	0.2531	0.2797	0.2570	0.3221	0.2146	0.2421	0.2946
E		0.0004		−0.1216		0.3462		0.0305		0.0227		0.1075		−0.0525	

Tr: Trial, A: Average, T: Total, E: Effect.

X_2X_3, and so forth are used for measuring interaction effects. The results show that any combination of the factors interacts in a detrimental way, because absolute values of their effect row are lower then corresponding values for x_1, x_2, and x_3 factors. Similar results are obtained during cross validation of the neural network's test error (see Table 4). So, the same conclusion can be made for both the training and testing stages of neural network output.

The last phase of the experiment consists of the analysis of variance by technique known as factorial experiment 2^3, where the label 2^3 means the experiment with three factors with two values each. Analysis of variance conducted in this way determines statistical significance of the factors by using Fisher's test. After the generation of eight orthogonal contrasts (Lochner & Matar, 1990), and the calculation of the corresponding sums of mean square errors and degrees of freedom are accomplished, Table 5 is created. The criterion v_0, which represents calculated measure of significance of each factor, should be compared with the values from Fisher's distribution tables for the same degree of freedom and for 95% and 99% levels of significance. The results show that the third factor, the sampling period, has the greatest significance. According to the results of the Fisher's test, it has attained the 99% statistical significance in both the training and the testing stages. The second factor, the number of inputs, has attained 95% significance, but only in the training stage, while it is slightly less significant in the testing stage. The first factor, features selection, is not statistically significant. This can be explained by the fact that there is a very slight difference between two training sets—just one of their inputs is different, and they are both formed from features with strong correlation coefficients. Those results coincide with the results obtained by using the Taguchi analysis.

Table 5. *Results of the analysis of variance for node Becej*

Factors	Training v_0	Test v_0	$V = 95\%$	$V = 99\%$
X_1	0.0560	0.0000	3.98	7.01
X_2	4.7881	2.1899	3.98	7.01
X_1X_2	0.1710	0.1379		
X_3	30.7853	17.7477	3.98	7.01
X_1X_3	0.3343	0.0761		
X_2X_3	3.6342	1.7115		
$X_1X_2X_3$	0.3630	0.4077		

5. CONCLUSION

This article presents the results of the research carried out to design the reliable knowledge base for the state estimators of natural gas transmission pipeline networks, by using the artificial neural networks. The existence of the reliable state estimators is tremendously important in designing a successful supervisory control system. The procedure of the proposed system design contains input data preparation and neural network training stages. During data preparation, the input data and feature samples are carefully selected. The MLP neural network is trained by using error back-propagation method. The accuracy of the neural network was investigated from two basic points of view: (1) influence of the amount of training data and the choice of the most important features; and (2) influence of the configuration characteristics of neural networks. Experiments have shown that among the factors considered, the sampling period and the number of inputs might be the most effective in decreasing the error of the neural network-based supervisory functions.

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