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Leak Diagnosis in Pilot Plant Using Soft Computing Technique.

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ABSTRACT

Leakage in industrial plants results in heavy monitory losses,alteration in model parameters and also affects the product quality. Hence there is a demand for an efficient leak detection system. In this work a method for detection of leak in a nonlinear system using neural networkback propagation algorithm is demonstrated.An artificial leakage was introduced in a spherical tank process during various flow ratesin the range of 3 to 5 lpm, using water and sodium chloride asa tracer.The experimental data was collected for the nonlinear system with online conductivity as monitoring parameter for all possible plant conditions such as with and without leakage .Leak analysis was performed and detected using statistical parameters such as mean, variance, standard deviation and correlation coefficient between the faulty and normal data predicted using neural network. The effect of leak on model parameter was studied and the percentages of leak losses were predicted.

Keywords: Spherical tank, neural network, Sodium chloride, Model, Leakage, correlation coefficient

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INTRODUCTION

Recent time's industrial processes are becoming progressively more and more unmanned and dependent on components, so that the way to improve the processes confidence is by promoting reliability and robustness of these process components. Modeling can be performed by using fundamental laws that govern the process. These models require deep knowledge of the process behavior. For the majority of applications, artificial neural networks perform fairly well, fact that makes them extensively used in generic applications .They are largely used for solving prediction and classifications problems and have also been more and more used to deal with defects detection problems in industrial processes Tinos et al [1] have developed artificial neural networks based residue detection for robots. A neural network of the multilayer perceptron type was utilized for reproducing the dynamic behavior of the manipulator robot. Residues vector was obtained by comparing network outputs with measured variables, some defects were introduced into the robot aiming at generating a defective database. Patan [2] have developed a neural model procedure for defects detection and isolation at the Lublin Sugar factory's evaporation plant. Bueno [3] has developed a defects detection system in a nuclear reactor using neural networks. Almeida has [4] worked out a methodology based on the Markov hidden model for detecting atypical situations in chemical recovery boilers. Moreno et al [5] have used conductivity to control water quality. Billmann [6] has designed a liquid flow sensor for detection of leak in pipes. Hiroki has developed a unit for water leak detection in fusion reactors. Bausch et al [7] have also studied leak in pipelines. Madhavsarma et.al [8] has studied effect of leak on model parameters using microcontroller for a nonlinear spherical process. Sergio Henrique et al [9]. have proposed a system for the detection of incipient faults in industrial processes, based on the application of artificial neural networks and on the concept of residues generation Xiao et.al [10] has developed a neural network-based instrument surveillance and calibration verification system (ISCV) for a chemical processing system. The faults in the sensors were detected by an auto associative neural network structure. Basila et.al [11] has developed a supervisory expert system that uses object based knowledge representation to represent heuristic and model-based knowledge. Leung et al [12] have presented a probabilisticmodel-based expert system for fault diagnosis. Rengaswamy et al [13] have discussed a conceptual framework for monitoring, diagnosis and control of plants. They use a back propagation-based neural network to identify primitives in noisy sensor data and an expert system to make decisions on the normal or abnormal behavior of the plant and to propose actions.Angeli et al [14] have developed an on-line intelligent process monitoring and diagnosis system where acquired data from an actual electro-hydraulic system are recorded, analyzed and presented in a suitable format to obtain the information needed for the control and detection of possible faults in proportional valves. Kordon et al [15] have proposed an expert system for process supervision of a crude unit using model-based reasoning to analyze the static behavior of the unit. Harris et al [16] have reported an expert system that diagnoses the underlying cause of poor behavior in control loops. This work quantitatively analyses the effect of leak on model parameters and also predicts the percentage of leak losses using neural network back propagation algorithm.

Data collection methods

Figure 1. Photograph showing the experimental setup forleak measurement

Figure 1 shows the experimental setup for leak measurement in this work water and tracer sodium chloride solution was metered by Rota meter and fed to the spherical tank at various flow rates. The exit solution conductivity was measured using online Honeywell conductivity sensor. The sensor was interfaced with Pentium IV PC using 16 channel data acquisition card. Figure 2 shows the response curve for a step change in tracer for input flow rate of 3 LPM.Tracer was injected as a step from 0 to 0.5 lpm. The outlet conductivity was recorded. A leak of different magnitude was introduced in the pipeline by manipulating valve for pure water. The exit conductivity with leak was also measured. The variation of conductivity with and without leak for various flow rates of water are given in Figures 3 to 5. Varying quantity of leak as a fraction of main flow rate is introduced after initial stabilization by manipulating valve. Table 1 records the leak induced and the corresponding error in final value of conductivity. Table 2 gives the model parameters with and without leak and the percentage deviation. The process gain (K_P) and time constant (τ_p) are affected up to 1 to 93 percent due to leak as seen from Table 2.

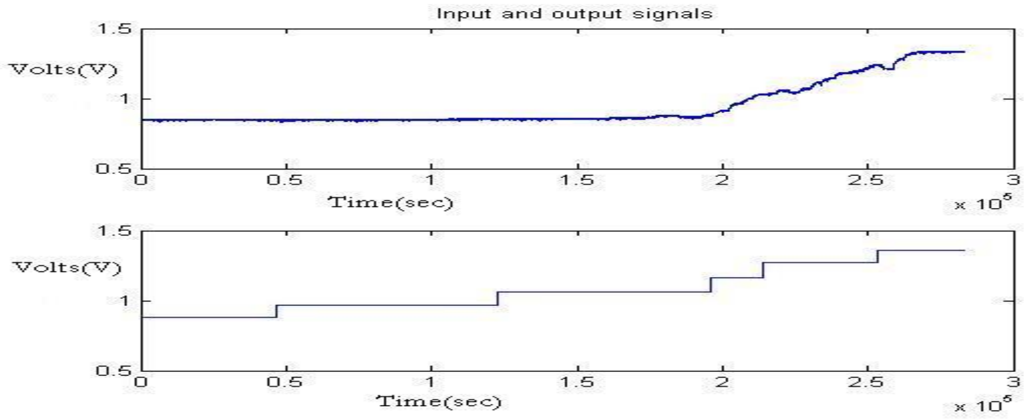

Figure 2: Open loop response for 3 lit/min water flow rate.

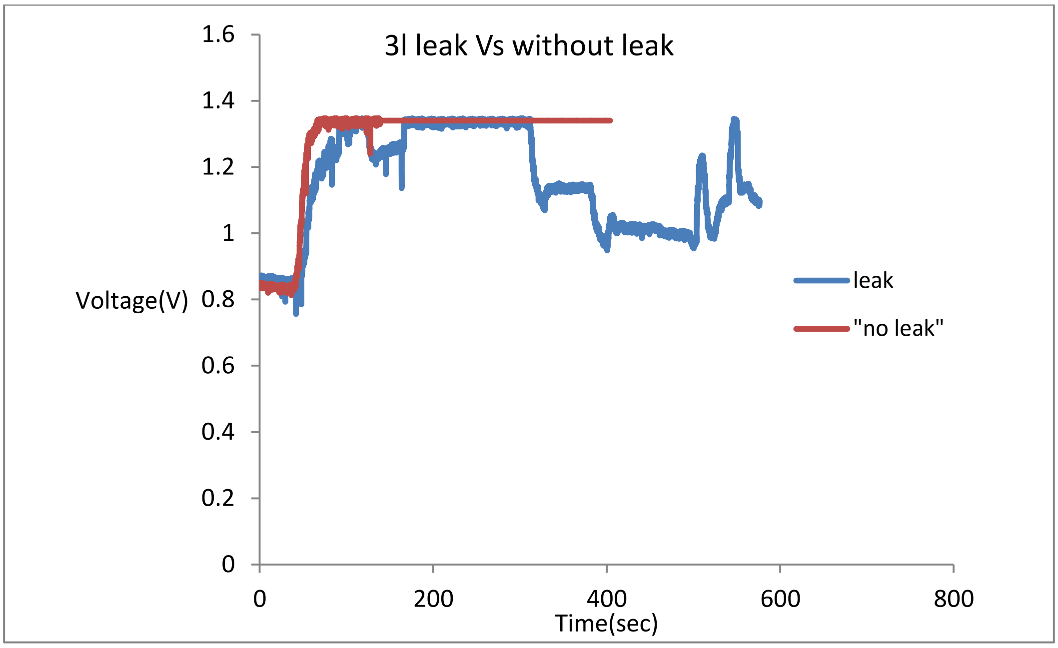

Figure 3: Response for inlet leak at 3lpm flow rate

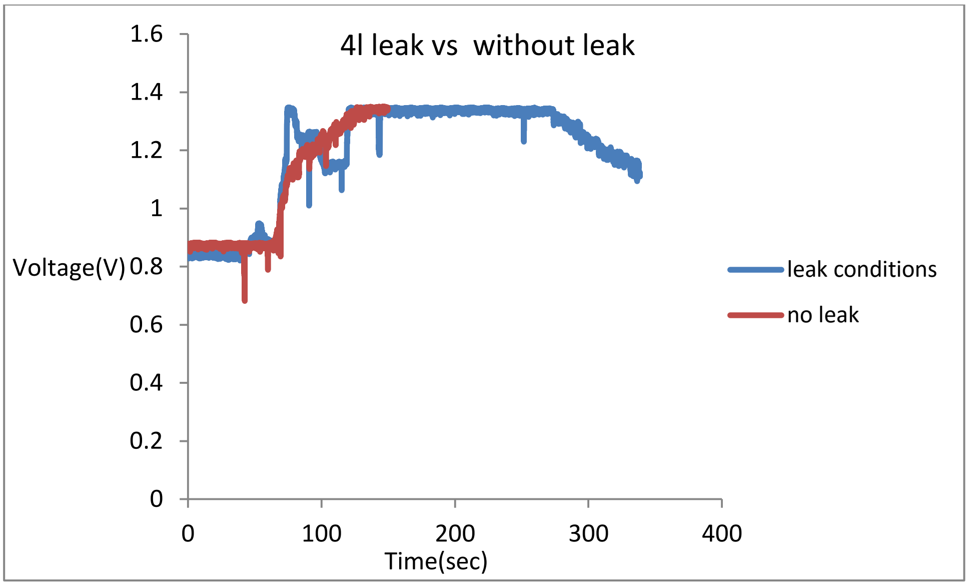

Figure 4: Response for inlet leak at 4 lpm flow rate

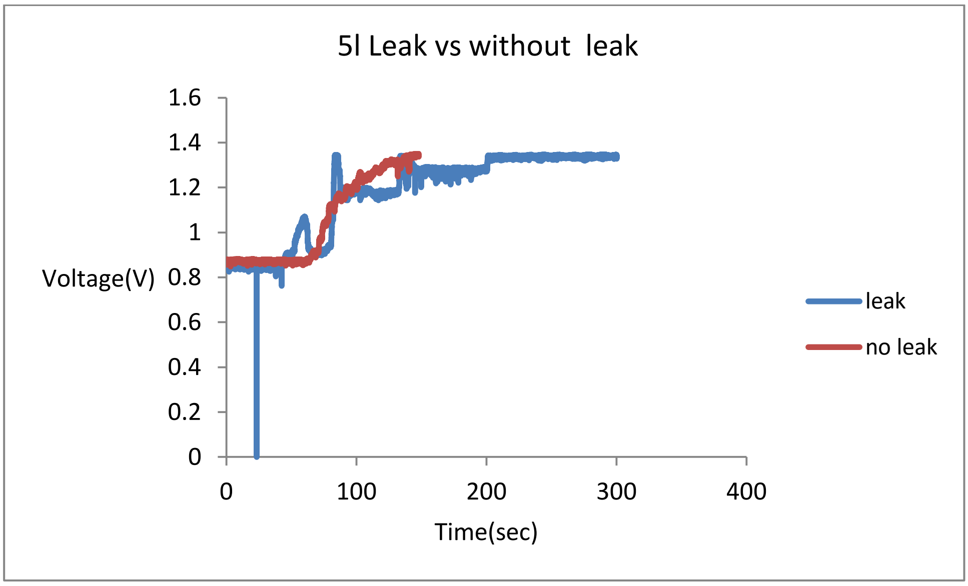

Figure 5: Response for inlet leak at 5 lpm flow rate

Table 1: Variation of model parameters in a spherical tank assembly

S.No	Flow rate (l/min)	Conductivity without Leak(V) (at 100 sec)	Conductivity With leak(V) (at 100 sec)	Error/Deviation in Conductivity
1.	3	1.0	0.87	0.13
2.	4	1.35	1.01	0.34
3.	5.	1.1	0.9	0.2

Table 2: Shows the percentage deviation of model parameters with &without leak condition

S.No	Flow rate	Without leak		Water inlet leak		Percentage Deviation at Leak condition (%)	
	(lit/min)	Kp	Time constant(sec)	Kp	Time constant(sec)	Kp(%)	Time constant(sec)
1.	3	1.119	9564	1.149	143891	3	93
2.	4	1.072	4732	1.167	94621	8	95
3.	5	1.096	4113	1.102	38105	1	89

Back propagation algorithm

The back propagation algorithm for training a network is an extension of the standard back propagation algorithm. It may be derived by unfolding the temporal operation of the network in to a layered feed forward network, the topology of which grows by one layer at every time step. To be specific, let A denote a recurrent network required to learn a temporal task, starting from k all the way up to time k-N. Let A* denote the feed forward network that results from unfolding the temporal operation of the recurrent network A. The unfolded network A* is related to the original network as follows: For each time the interval (k, k-N), the network A* has a layer containing n neurons contained in the network A. In every layer of the network A* there is a copy of each neuron in the network A. For each time step, the synaptic connection from neuron i in the layer l to neurons j in layer l+1 of the network A* is a copy of the connection from neuron i to neuron j in the network A. Neural networks employed for function approximation are generally feed forward type networks, with one or more hidden layers between the inputs and outputs. Each layer consists of some computing units known nodes. The output of the first layer nodes then becomes the input to the second layer, and soon. The outputs of the network are, therefore, the outputs of the nodes lying in the final layer. Usually, all the nodes in a layer are fully connected to the nodes in adjacent layers, but there is no connection between nodes with in a layer. network is operated in two distinct phases called training and recall during training, a set of data is repeatedly presented to the neural networks , which processes each data vector according to the architecture and adjusts its weights , and in some cases also adjusts some processing element parameters , according to the training rule .The purpose of the training rule is to adopt the network weight so that the network processes the batch of training data to achieve some specified result, which is usually the minimization of some objective function of the training data.

Methods for Leak Prediction

A three layered feed forward neural network model trained using Levenberg-Marquett (LM) Back propagationalgorithm with 2 neurons in input layer 20 neurons in hidden layer and two output neurons as shown in figure 6 was used to predict the leakage losses in the pipe line . The back propagation algorithm updates the network weights and bias values to decrease the square sum of the difference (SSE) between the desired output (td) and an output values computed by the net (yd) using gradient decent method which is given in the following equation 1

$$SSE = 1/2\ N \sum (td - yd)\ 2 \qquad (1)$$

where N represents the number of experimental data points used for the training. The steps involved in Back propagation algorithm is as follows: 1.The training data is presented to the input layer of the network. 2. The actual and desired output iscompared.3. The error in each neuron is calculated. 4. The output for each neuron is obtained.5. The weights are updated to minimize the error. The neural model network process consists of three operational steps: prediction, correction and control move determination. The real time experimental data recorded with and without leak condition was used to train the network. In this work the conductivity recorded for various flow rates was the output and input variable respectively. A sampling time of 10 seconds was used for the simulation. A total of 3000 data were taken continuously and it was saved in file. By training the input output data the NN model of the non-linear process was obtained. [17, 18] The back propagation algorithm was used for training the recurrent network. For the network training and validation, the LM back propagation algorithm being known for fast convergence was used. The convergence criterion was selected as 10-3, and this was achieved in 175 epochs. The general methodology for leak prediction flow chart is shown in figure 7and the back propagation algorithm flow chart is shown in figure 7 a. The neural network output is shown in the Figure8a,b,c for normal operating conditions of the system without any leakage. From the Figure 9a,b.c it was observed that neural network was able to track the sudden nonlinear variations present at the input data and track the leakage in the system. Figure10 shows neural network was able to predict the tracer leak conditions of the nonlinear system using Levenberg-Marquett (LM) back propagation algorithm.

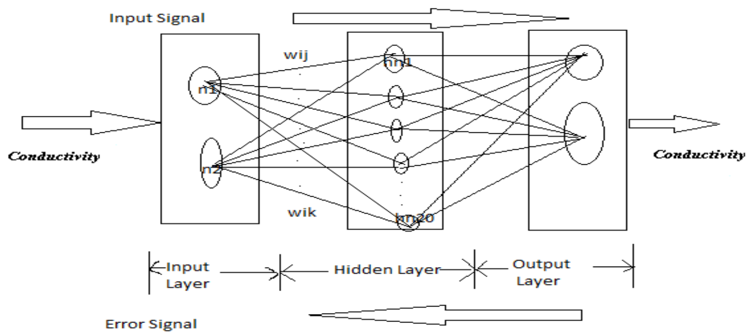

Figure 6: Multilayer Feed Forward Neural Network using Back Propagation

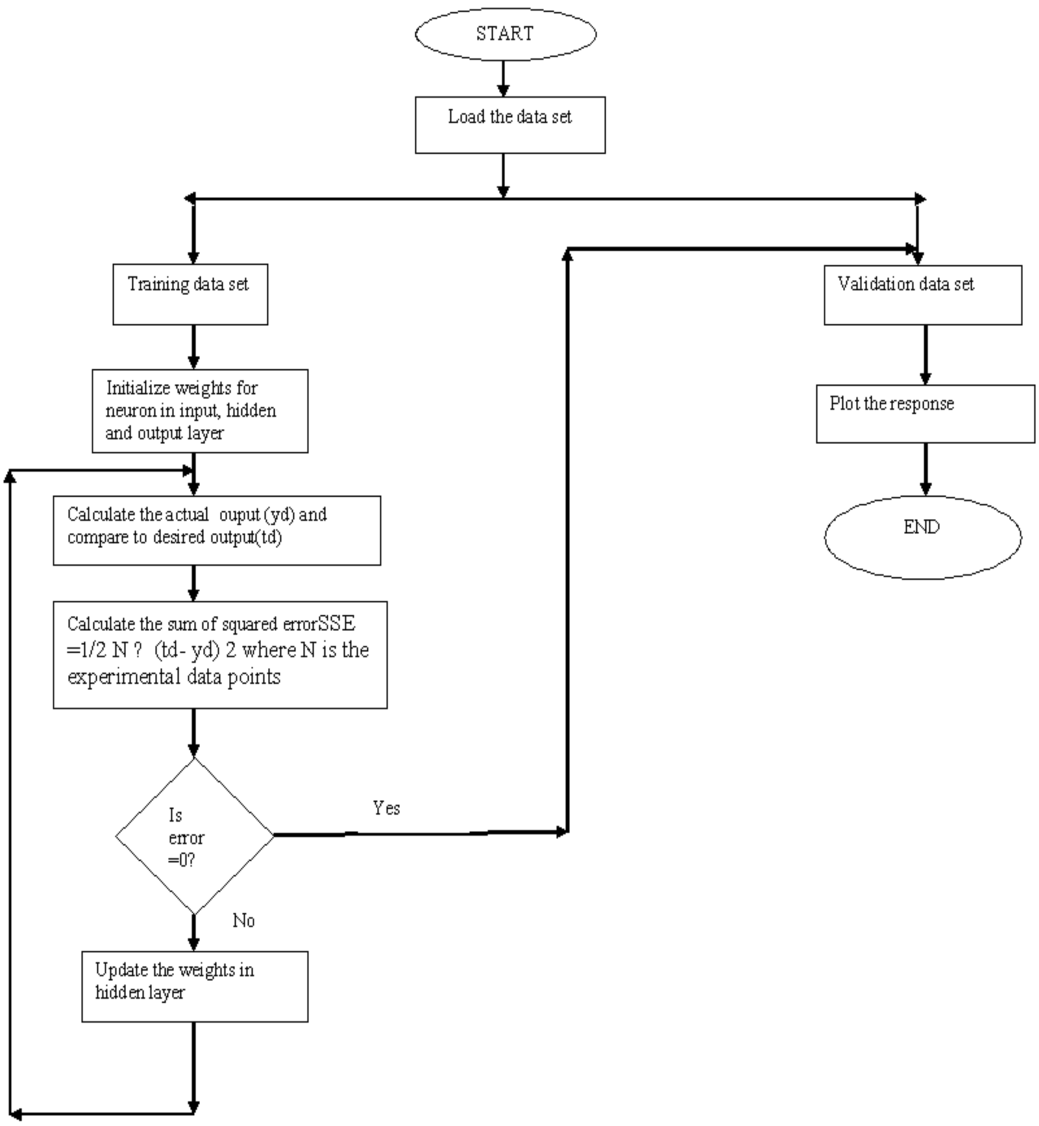

Figure 7: General Methodology for Leak Prediction

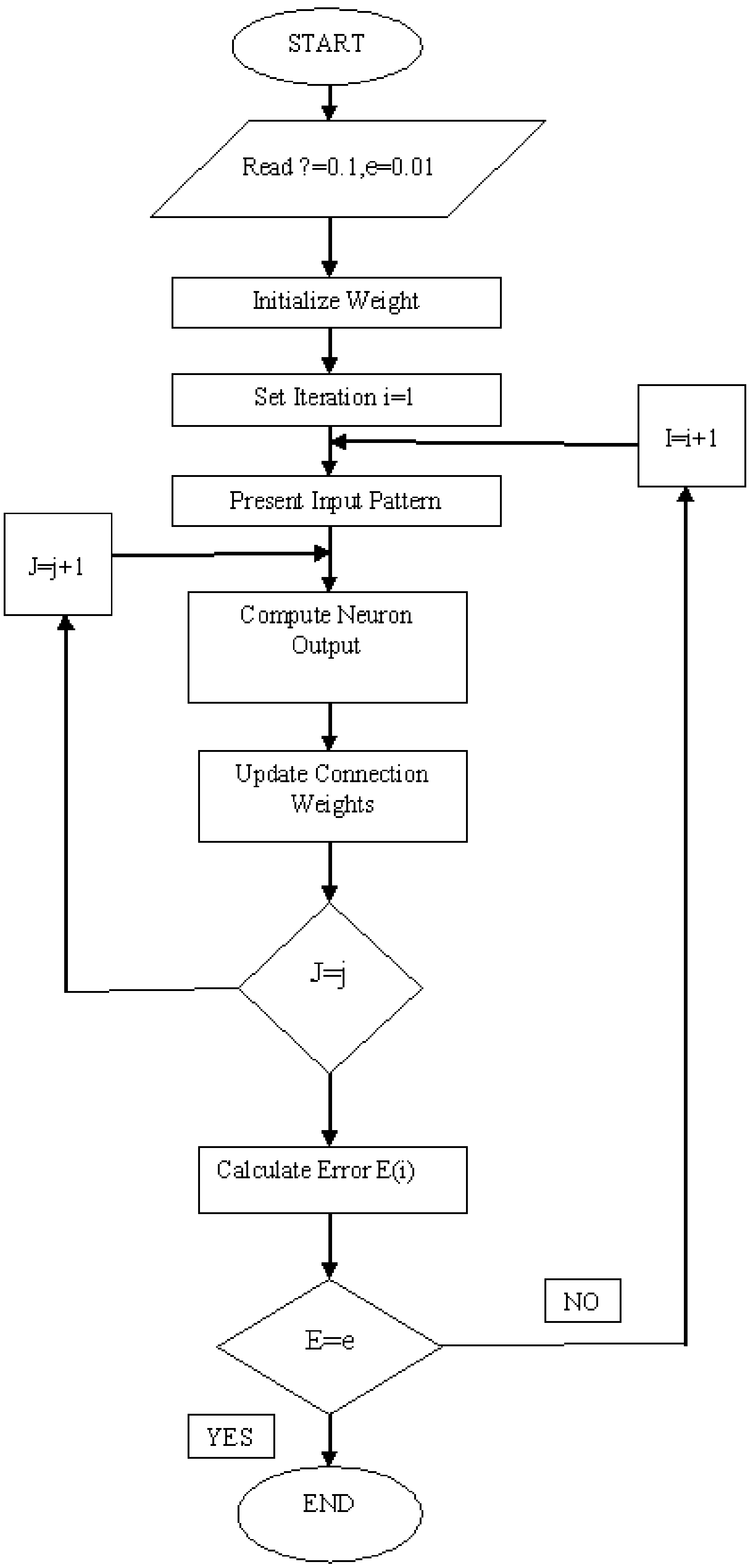

Figure 7a . Flowchart for Back Propagation Algorithm

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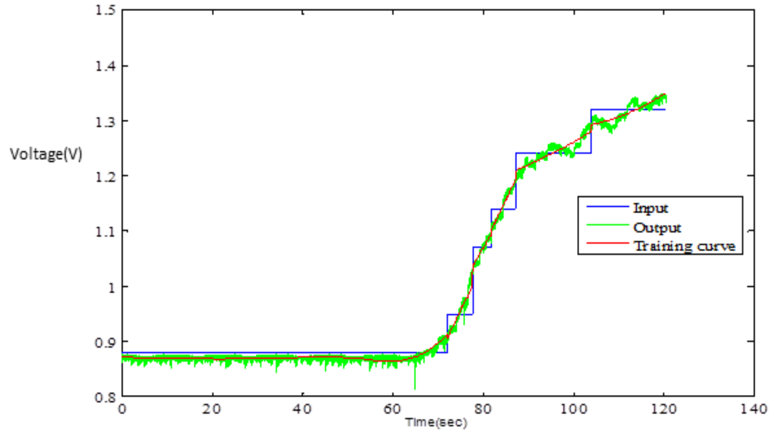
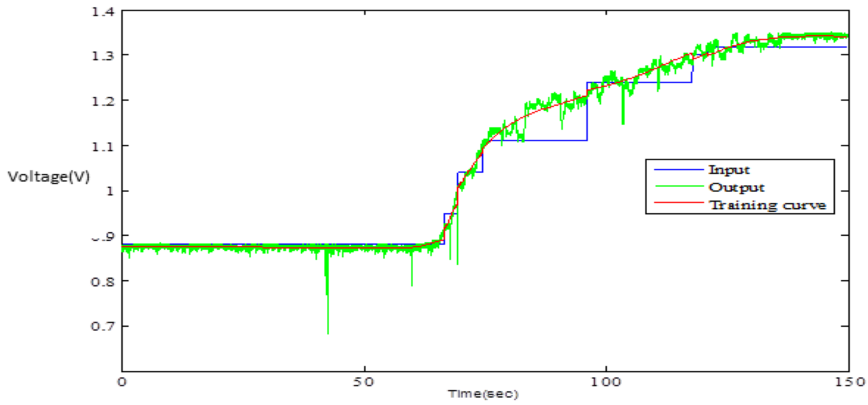
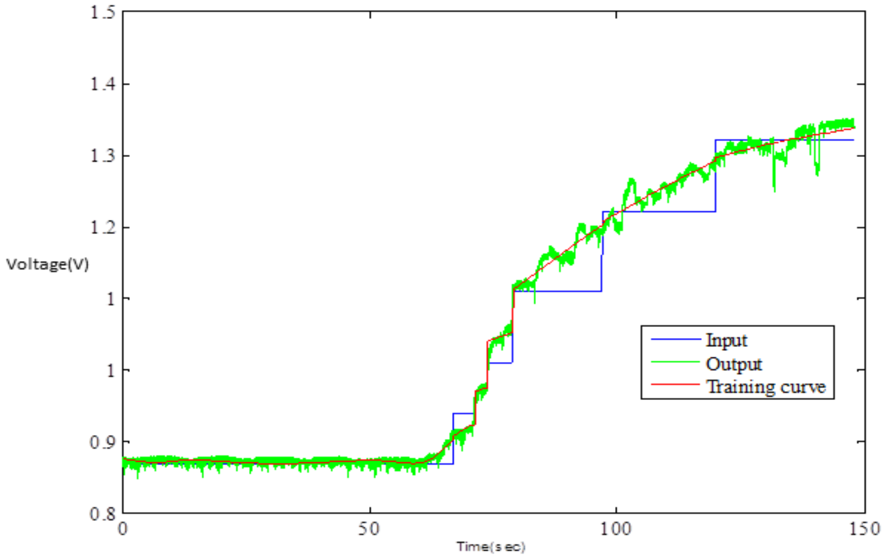


a) 3 lit/min flow rate



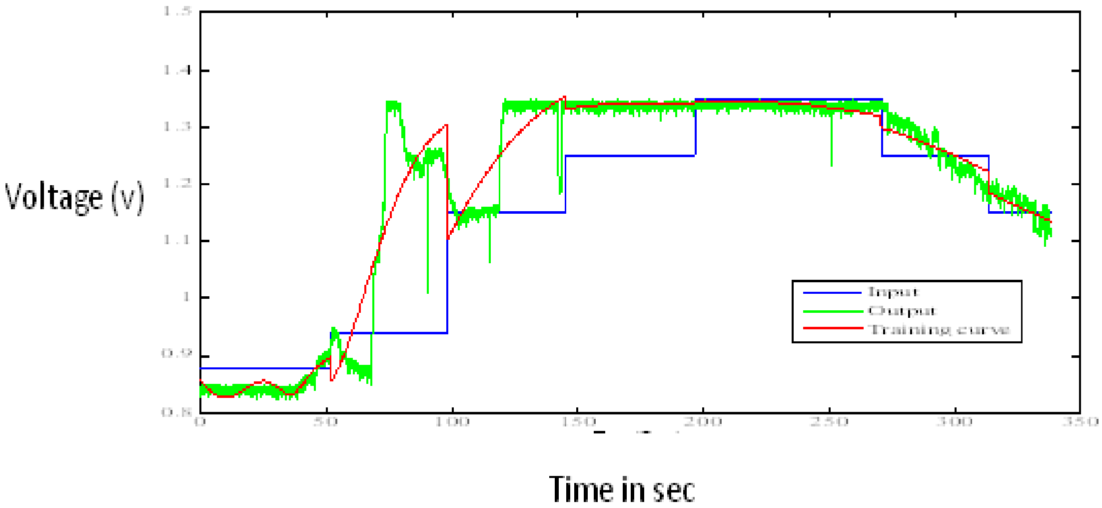
b)4 lit/min flow rate



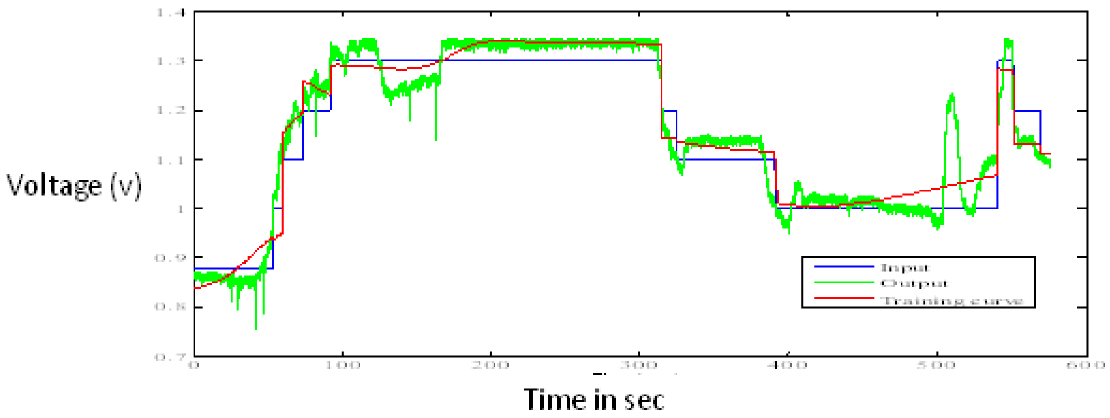
c) 5 lit/min flow rate

Figure 8 (a)(b) (c) .Neural networkpredicted output for the normal operation of the plant for flow rate range 3lpm, 4lpm and 5 lpm without any leak conditions.

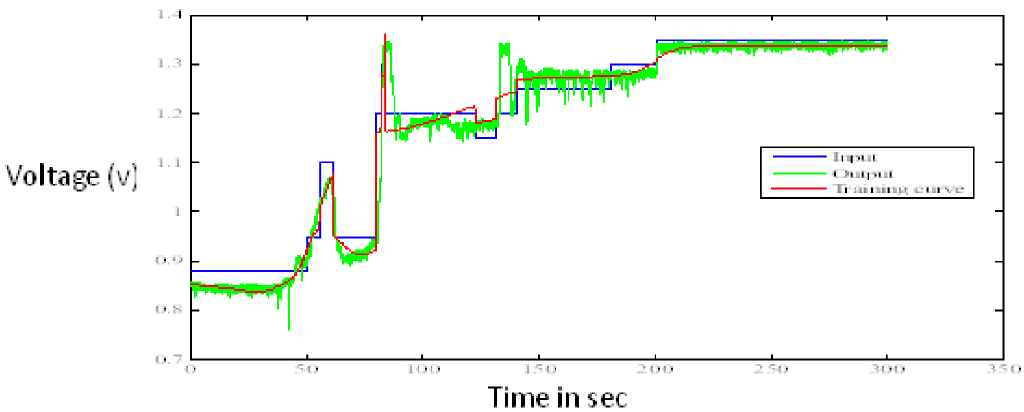
ISSN: 0975-8585



a) 3 lit/min flow rate



b) 4 lit/min flow rate



c) 5 lit/min flow rate

Figure 9(a)(,b)(,c).Neural network predicted outputfor with leak operation of the plant for flow rate range 3lpm, 4lpm and 5 lpm.

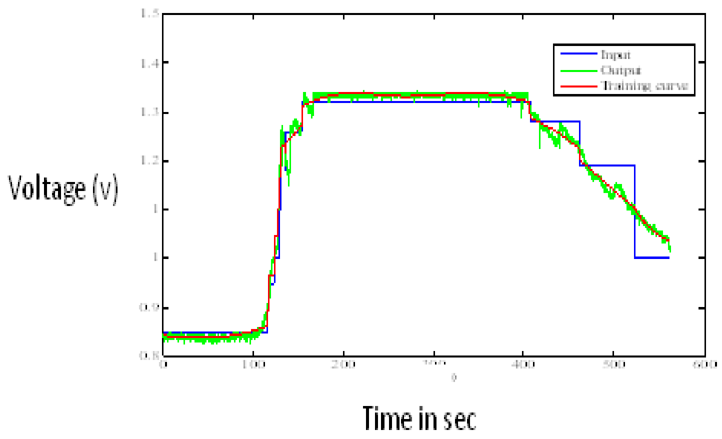


Figure 10. Tracer leak response of neural network

RESULT AND DISCUSSIONS

The neural network is trained for the various process conditions. The training curve predicts the system's response based on the input and output data presented to the network. The training curves appear to converge with the actual experimental response and it is observed that the conductivity of the mixture increases when there is a leak in the water pipeline. The comparison of the training curve with the experimental results using statistical methods detects the leak in plant.The mean, standard deviation and variance of the normal and faulty data are determined and are tabulated in Table3 and Table4. From table 3 large deviations from the normal data is an indication of the presence of fault in the system. The correlation measures the strength and direction of the linear relationship between two quantitative variables. In probability theory and statistics, the variance of a random variable or distribution is the expected, or mean, value of the square of the deviation of that variable from its expected value or mean. Thus the variance is a measure of the amount of variation within the values of that variable, taking account of all possible values and their probabilities or weightings. The standard deviation and the expected deviation can both be used as an indicator of the "spread" of a distribution. The standard deviation is more amenable to algebraic manipulation, and, together with variance and its generalization covariance is used frequently in theoretical statistics. From the table 5 the conductivity of the water and tracer mixture is taken in the normal conditions. The correlation coefficient for two data sample is determined. Then a leak in the tracer and water inlet supply is introduced and the response of the system is recorded. The values of the conductivity of the faulty and normal data are compared. Calculating the correlation coefficient for two variables can give an indication of the strength of the relationship between them .The correlation coefficient measures the degree to which two variable moves together. The correlation coefficient ranges from -1.0to +1.0, with a value of 0 indicating no correlation and 1.0 indication high positive correlation The correlation coefficient is determined between the normal and faulty data. It helps in determining the extent of deviation in the parameters from the normal readings. The statistical method of fault diagnosis is one of the most widely used methods for the fault diagnosis in many process industries. The process parameters are continuously monitored and the alarm signals are provided by the limit checkers whenever any parameter exceeds the upper permissible limit.

Table 3: Comparison of mean values

S.No	Flow rate (l/min)	Without Leak(V)	With inlet leak(V)
1.	3	1.0183	1.1571
2.	4	1.019	1.1982
3.	5	1.0196	1.1767

Table 4 Comparison of standard deviation and variance for various system conditions

Flow rate	Without leak		Inlet leak		Sensor fault		Offset fault	
(l/min)	s.d	variance	s.d	variance	s.d	variance	s.d	variance
3	0.228	0.052	0.157	0.025	0.299	0.0892	0.3625	0.1314
4	0.196	0.039	0.184	0.034	0.287	0.0821	0.2482	0.0616
5	0.19	0.036	0.185	0.034	0.243	0.0588	0.2611	0.0681

Table 5 Comparison of correlation coefficients for Leak &without leak conditions.

Slno	Flow rate lit/min	Without leak	With leak
1	3	1	0.7967
2	4	1	0.9012
3	5	1	0.9123

Table 6: Effect of leak on final value of conductivity

S. No	Main flow rate lit/min	Leak flow rate lit/min	Percentage leak ((Main flow-leak flow) / Main flow)) x 100	Final Conductivity Value millimho/cm		Percentage error in Leak size
				Without Leak	With Leak	
1	3	1	66.66%	700	830	15
2	4	1	75%	560	620	16
3	5	1	80%	490	590	17

CONCLUSION

The system's response to normal operating condition and inlet leak in water and tracer were trained and predicted using neural network. Based upon the statistical analysis, it can be inferred that the mean value of conductivity increases when there is a leak in the inlet water supply. From table 5given it is inferred that a correlation coefficient close to unity indicates normal operating condition of the plant. The deviation of the correlation coefficient is a measure of fault in the system. The percentage of leak and leak size for various flow rates are studied. From the Table 6it is observed that due to leak in the process, model parameters are affected and also conductivity level varies from 15 percent to 17 percent. This shows that leak adversely affects model analysis and effective care should be taken. Thus neural network based leak diagnosis method is found to be the most efficient and reliable method for early detection of leak.

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