Neural Computation for Flow Regime Classification Based on Electrical Capacitance Tomography

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ABSTRACT

Recognition of gas-liquid flow regimes in pipelines is important in an industrial control process such as for oil production. In oil production, gas-liquid flows are normally concealed in a pipe the actual type of flows cannot be easily determined. Also, obtaining measurements corresponding to the flow distribution becomes almost impossible. The emergence of the Electrical Capacitance Tomography (ECT) sensing technique has made it possible to acquire measurements corresponding to flow distributions in a pipe. Generally, there are many types of gas-oil flow regimes that can be formed in a pipe. Among them are annular, bubble, stratified, core and homogenous. Thus far, images of material distribution for determining the type of flow regime is determined using appropriate reconstruction algorithms based on the ECT measurements obtained. However, in cases where the images have been inaccurately reconstructed, the classification results become incorrect. Due to this problem, this project has worked on using an Artificial Neural Network (ANN) system to classify the flow regimes, without going through the image reconstruction process. Two learning algorithms, the Levenberg-Marquardt (LM) and Quasi-Newton (QN) have been used to train Multi-Layer Perceptron (MLP) neural networks for comparison. The results demonstrate the feasibility of using MLP for gas-oil flow-regime classification.

Keywords: Neural Network, Levenberg-Marquardt, Quasi-Newton, Electrical Capacitance Tomography.

1.0 INTRODUCTION

Flow regime classification in gas-oil flows is important in oil production. In gas-oil flow, many types of flow patterns, called flow-regime, could interchangeably form along a pipeline. Among the common ones for horizontal pipeline are annular, bubble, stratified, core and homogenous. All these flow regimes are classified based on their characteristics. Thus far, the process of classifying the flow regimes has been through image reconstruction based on a set of measurements. One of the suitable techniques that can be used to obtain such measurements is the Electrical Capacitance Tomography (ECT) (Beck and Williams, 1996). Thus far, the image reconstruction methods based on the ECT measurements are prone to producing inaccurate images, leading to misclassification of the flow regimes or are computation-intensive due to the iterative methods.

However, because the end result is the type of flow regime, most of the time, the image reconstruction process is not important. Thus, this project investigates the feasibility of using artificial neural network (ANN) system to directly obtain the type of flow regime (from the set of ECT measurements) without going through the image reconstruction process. This is a classification problem which eliminates the problem of long reconstruction time.

1.1 Electrical Capacitance Tomography

ECT is a technique used to obtain sets of measurements corresponding to cross sectional distribution of materials. An ECT system consists of primary electrode sensors, acquisition data system and computer system. Figure 1 below shows a schematic diagram of an ECT system. Pairs of all combinations of electrode sensors, which are sensitive to the dielectric distribution of materials, give a set of difference in capacitance measurements. Different material distributions give different sets of ECT measurements. These sets of measurements become the input to the ANN system.

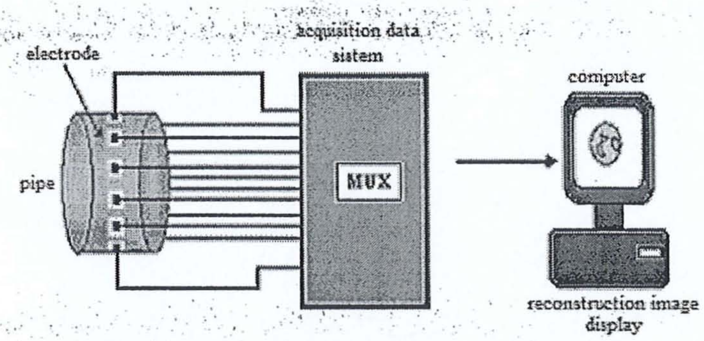

Figure 1: The components of an ECT system.

1.2 Artificial Neural Network

An ANN, or simply referred to as a neural network, is an information processing system. Its existence was inspired by the functions of a human brain. In other words, ANN uses the concept similar to biological neural network, i.e. human brain. It is able to learn and become "intelligent".

Artificial neural network contains a number of simple processing units. Each of them had a link to other processing units and the links have weight values associated to them, representing the strength levels of the interactions. Figure 3 shows a schematic diagram of the components of a basic artificial neuron, or processing unit.

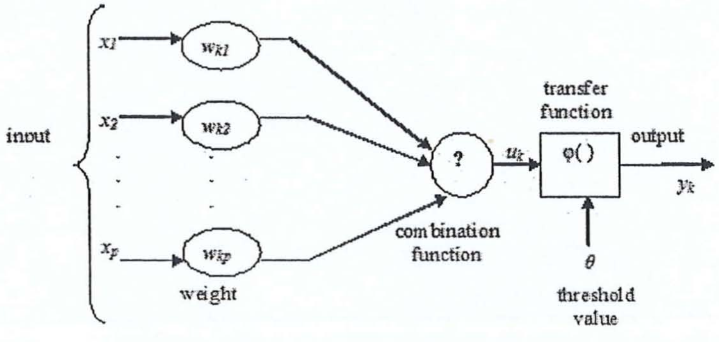

Figure 3: Basic artificial neuron components

When structured in a certain way, the processing units (PU) and links form a specific type of neural network, capable of solving various problems. One commonly used neural network is the feed forward architecture. A variant of the feed forward architecture is the Multi-Layer Perceptron (MLP) (Haykin, 1999). MLPs have been used extensively to solve problems related to recognition, classification, process control, prediction and estimation.

A MLP contains three main layers--the input layer, hidden layer and output layer. The architectural structure is shown in Figure 4. Each layer contains several PUs. The number of PUs in the input layer depends on the number of input values and the number of PUs in the output layer is determined by the number of output values for the problem. Meanwhile, the number of PUs in the hidden layer is determined via the learning process. The optimum number of hidden PUs will produce an optimum MLP for the task (Bishop, 1994). The weights in the MLP alter the intensity of the information at the hidden and output layers. The transfer functions, normally sigmoidal functions, applied at these layers map the resulting weighted input values onto the appropriate output.

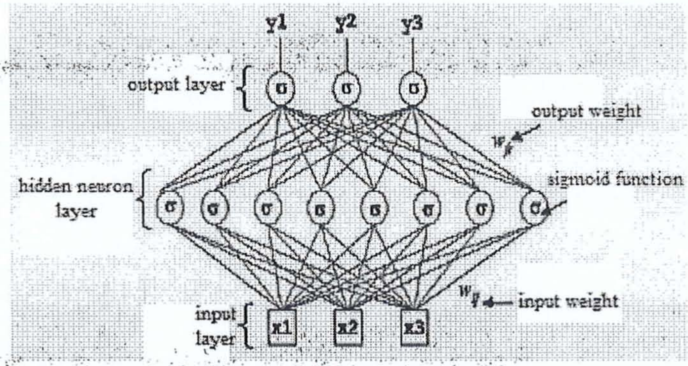

Figure 4: MLP neural network

2.0 METHODOLOGY

Figure 5 show the schematic diagram of the ECT sensor system used in the investigation. For this project, the ECT system used has 12 electrodes, the primary electrode angular angle, θ_1 is 22° and the guard electrode, θ_1 is 2.5°. R_1, R_2 and R_3 are the radius of the pipe's inner pipe wall (i.e. sensing area), the radius from the centre to the electrode, and the radius of the outer pipe wall, respectively. The ratio of R_1:R_2:R_3 is 1:1.2:1.4.

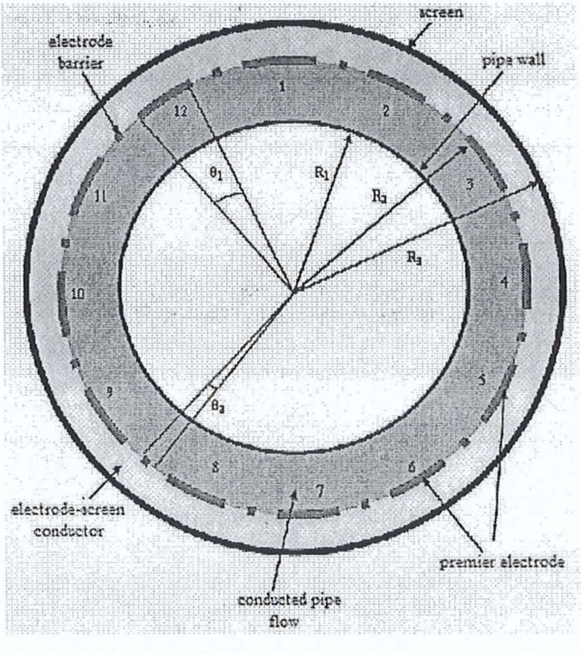

Figure 5: Schematic diagram of a 12-electrode ECT system used.

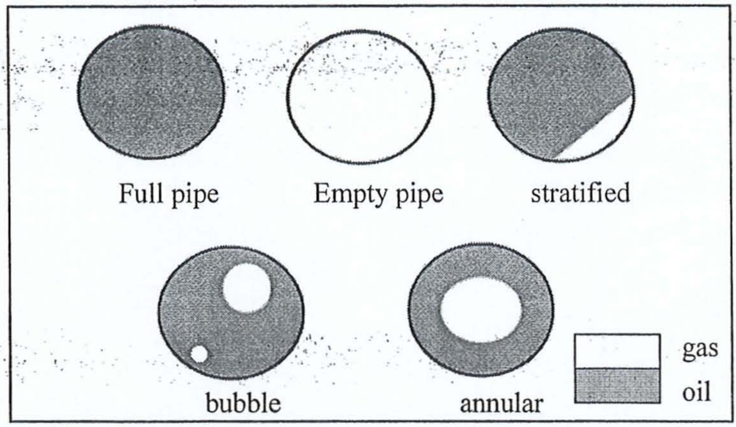

Figure 6: Flow-regimes to be classified.

This project focus on the classification of 5 different flow-regimes—annular, stratified, bubble, empty pipe and full pipe (i.e. pipe cross-section filled with oil). Figure 6 shows a schematic diagram of the flows.

In this investigation, MLP neural network is chosen as the classification system due to its credibility in solving various ECT problems (Hoyle and Nooralahiyan, 1997; Mohamad-Saleh and Hoyle, 2002; Nooralahiyan *et al,* 1994) used The development of the MLP classification system starts with the generation of ECT data for various flow patterns, which will be used to train the system. This is done by using the ECT simulator, which accepts various geometrical patterns of the flow regimes to be classified. Based on the ECT system design parameters and a flow pattern, the simulator calculates a set of capacitance measurements. Each set of the ECT data consists of 66 values, corresponding to the difference in the capacitance values between all possible pairs of 12 electrodes. This number is obtained using equation (Xie *et al*, 1992)

$$M = \frac{n(n-1)}{2} \tag{1}$$

where M is the total number of capacitance values and n is the number of electrodes in the ECT system.

Then, these values are normalized so that they fall into a specific range. The normalization equation is given by (Xie *et al*, 1992)

$$\lambda_{i,j} = \frac{C_{i,j} - C_{i,j(empty)}}{C_{i,j(full)} - C_{i,j(empty)}} \tag{2}$$

where $\lambda_{i,j}$ is the normalized capacitance value, $C_{i,j}$ is the ECT value to be normalized, $C_{i,j(empty)}$ is the capacitance value corresponding to a pipe full with gas, and $C_{i,j(full)}$ is the capacitance value corresponding to a pipe full with oil, for electrode pairs i and j. Figure 7 shows the flow chart on the generation of ECT data for a flow pattern.

Once the ECT data have been generated, they are randomly divided into 3 sets, i.e. training, validation and test. These sets are used to train, validate and test the MLPs to classify the flow-regimes. The numbers of training, validation and test samples are 987, 123 and 123, respectively. The MLP has 66 input PUs (corresponding to 66 ECT values) and 5 output PUs (corresponding to 5 flow-regimes). The output values are binary, depending on the type of flow-regime, as in Table 1.

Two different kinds of training algorithms, the Levenberg-Marquardt (LM) and the Quasi-Newton (QN) have been used to train two different sets of MLPs. The training simulation is done using the MATLAB Neural Network Toolbox (Demuth and Beale, 2000). Figure 8 depicts the flow chart for the training procedure. A training process stops once the validation error fluctuates or fails to decrease any further.

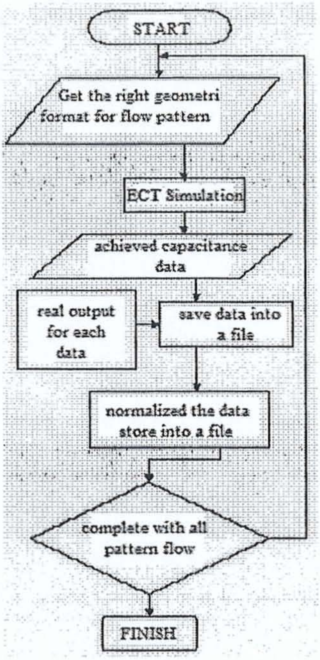

Figure 7: Flow chart for ECT data generation.

Table 1: The target outputs for various flow-regimes

Flow-regime	Target Output
Empty pipe	0 0 0 0 1
Bubble	0 0 0 1 0
Stratified	0 0 1 0 0
Annular	0 1 0 0 0
Pipe full of oil	1 0 0 0 0

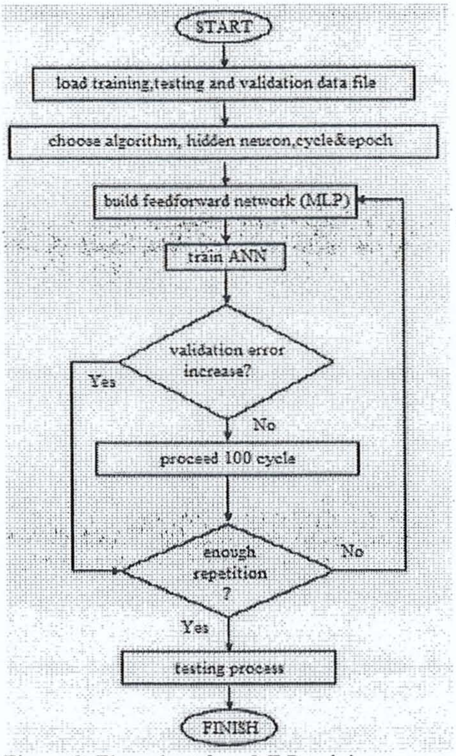

Figure 8: Flow chart for a MLP training process.

3.0 RESULTS AND DISCUSSION

Figures 9 and 10 show the results for the classification accuracy versus the number of hidden PUs for the test data using LM and QN algorithms, respectively. Referring to Figure 9, a MLP structure with 11 PUs gives an accuracy of 97.83% for the LM algorithm. Figure 10 shows that the accuracy for a MLP trained with the QN algorithm (MLP_{QN}) is 99.00%. This corresponds to a MLP with 15 hidden PUs. Although MLP_{QN} gives higher classification accuracy than the MLP_{LM}, it needs more PUs to execute. This means that it requires more computation power and memory space. Nevertheless, when accuracy is of the main concern, the basic necessities become less important.

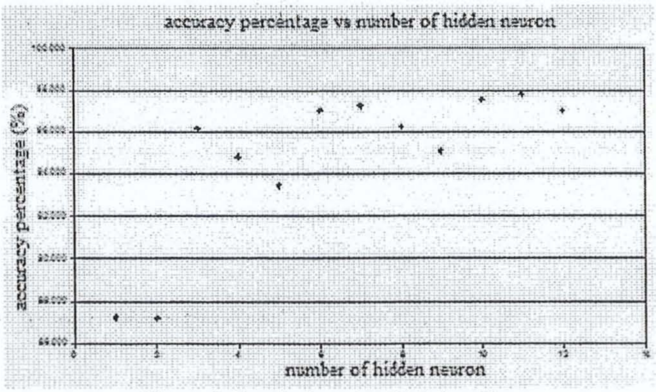

Figure 9: Result for using LM algorithm

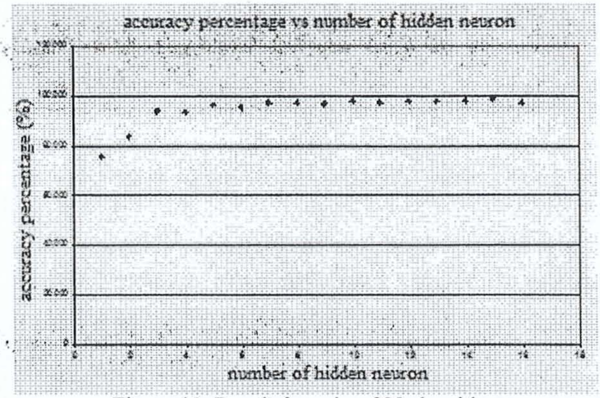

Figure 10: Result for using QN algorithm

4.0 CONCLUSIONS AND SUGGESTIONS

Overall, the investigation has accomplished its aim in developing a gas-oil flow-regime classification system using a MLP. This demonstrates the feasibility of using MLP for the task. From the accuracy values of the two MLPs, it can be concluded that the MLP trained with the QN algorithm has a better gas-oil flow-regime classification ability compared to the MLP trained with the LM algorithm. Although the MLP

For future investigations, to get the optimum result, the repetitions for each number of hidden neurons need to be done more than 15 times. This will help to produce a better MLP classification system in terms of the accuracy of flow-regime classification. It will also reduce the standard deviation values. Another suggestion to improve the accuracy of the system is to investigate other more up-to-date algorithms, such as the Bayesian Regularization, which may produce better MLPs for the task.

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