Electrical Capacitance Tomography for Gas Column Radius Determination

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Abstract

The paper discusses a preliminary work on determining the radii of bubble columns in gas-oil flow process based on a set of simulated electrical capacitance tomography (ECT) data. A pipe is modeled and a model of an ECT sensor system is mounted around the periphery of the pipe to acquire ECT measurements for various values of bubble column radii. The measurement set and their corresponding radii values are used as the input and output, respectively, to a Multi-Layer Perceptron (MLP) neural network in a training process. The trained MLP has been shown to be able to estimate the radii values of bubble columns based on unseen ECT measurement.

Keywords: Industrial application, tomography, process interpretation, neural network

1. Introduction

Process interpretation is important in many industries. In oil transportation for example, process interpretation is vital for improving the control of oil transportation and design of oil transportation equipment. One of the flow-regimes that occur during liquid flow is annular, where a column of gas or air is formed in the middle of a pipe or vessel whilst the other material is pushed towards the periphery of the process equipment (see figure 1). The gas column size determination is crucial in order to obtain other important information about the flow, such as void fraction and mass flow rate of a flowing component. It is often difficult to determine the exact size of a gas column because it is located in the center of a process equipment, where the sensitivity of a sensing system is very low. Hence, not many research has focused on this matter.

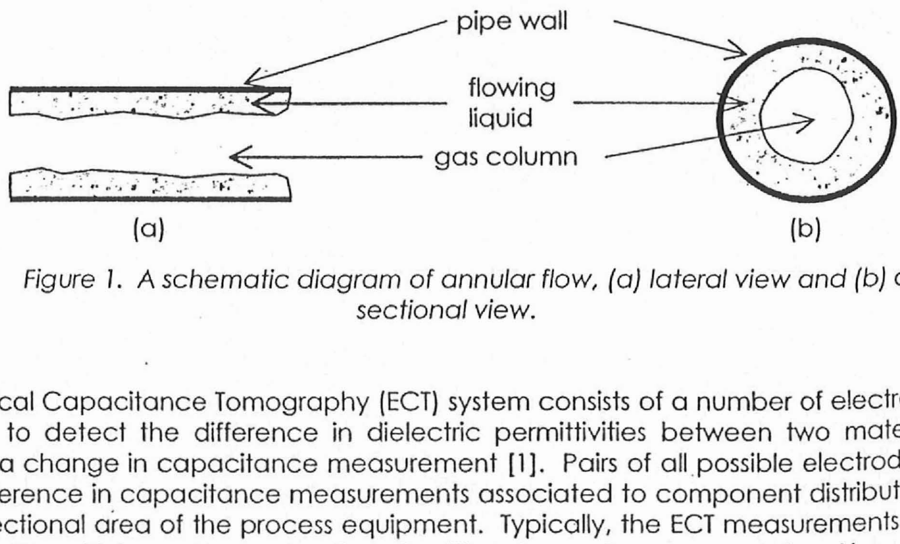

Figure 1. A schematic diagram of annular flow, (a) lateral view and (b) cross-sectional view.

An Electrical Capacitance Tomography (ECT) system consists of a number of electrodes that are able to detect the difference in dielectric permittivities between two materials and produce a change in capacitance measurement [1]. Pairs of all possible electrodes give a set of difference in capacitance measurements associated to component distribution within a cross-sectional area of the process equipment. Typically, the ECT measurements are used in conjunction with image reconstruction algorithms to produce cross-sectional images of the sensed area. From the images, various process parameters such as gas column size can be obtained. Nevertheless, the simple Linear Back Projection imaging method normally produce distorted reconstructed images, while the iterative imaging techniques are too slow for real-time processes [2]. Due to these drawbacks, gas column radii estimated via such reconstruction techniques may not be accurate.

To overcome the problem, Artificial Neural Network (ANN) imaging approach has been employed [3]. This techniquqe has been able to produce accurate reconstructed images even around the centre part of a sensing area. Thus, the use of this approach should be able to give accurate gas column radius estimations. However, in many cases, estimation of key process parameters is of more interest than the estimation of images. Hence, this research effort is channeled toward a direct method (i.e. that do not include image reconstruction) of estimating gas column size from ECT measurements. By incorporating the neural network methodology, this direct method should be more efficient and cost effective than the conventional imaging techniques.

2. ECT Model and Data

Theoretically, the ECT system parameters such as the number of electrodes, electrode size and pipe wall thickness, affect the sensitivity of the system measurement. However, this preliminary work focuses more on the estimation of bubble column radii using artificial neural network approach.

For this preliminary investigation, the ECT model used is as schematically shown in figure 2. The ECT sensor has 12 electrodes equally spaced around the pipe. Each electrode extends to 22° of angular angle. The ratio between the ECT sensor and pipe radii is 1.2, and the ratio between the sensor screen and pipe radii is 1.4. The sensor is mounted around the periphery of the pipeline at a point of interest. The pipeline material is perspex and the flowing material is gas and crude oil.

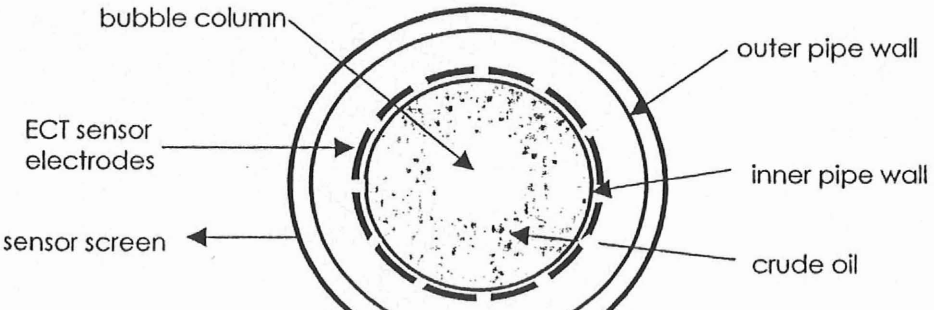

Figure 2. A schematic diagram of the ECT model attached to the periphery of a pipe.

A total of 91 sets of ECT measurements corresponding to various radii values of gas column have been gathered using the designed ECT sensor. The simulation is done using an ECT simulator based on a two-dimensional finite-element method [4]. Each set of the ECT data consists of 66 difference in capacitance measurements between all possible combinations of pairs of electrodes for a 12-electrode ECT system. The measurements are then normalized using [5],

$$N_{ij} = \frac{C_{ij}^{meas} - C_{ij}^{gas}}{C_{ij}^{oil} - C_{ij}^{gas}} \quad (1)$$

where N_{ij} is the normalized capacitance measurement between electrodes *i* and *j*, C_{ij}^{meas} is the measured capacitance between electrodes *i* and *j*, C_{ij}^{gas} is the measured capacitance between electrodes *i* and *j* when the cross-section is fully filled with gas and C_{ij}^{oil} is the measured capacitance between electrodes *i* and *j* when the cross-section is fully filled with oil.

Out of the total dataset generated, 70% of the dataset is used to train a Multi-Layer Perceptron (MLP) neural network for the gas column radius determination.. The remaining 30% of the data was used to validate and test the trained system. The MLPs have been trained using the Levenberg-Marquardt training algorithm. Through the training processes, an optimum MLP (i.e. one with an optimum number of processing elements) that produces the least error when tested with the test dataset has been developed. This is done through a "network-growing" method of determining the optimum number of processing elements in the hidden layer of the MLP.

The test errors have been calculated using the mean of absolute error (MAE) based on the following equation,

$$\%MAE = \frac{1}{k}\sum_{i=1}^{k} | A_i - E_i | \times 100\% \tag{2}$$

where *k* is the total number of datasets, A_i is the actual oil height value for the *i-th* dataset and E_i is the MLP-estimated oil height value for the *i-th* data. The results are then analyzed.

3. Results and Discussion

Table 1 shows the result of the "network-growing" method applied to investigate the optimum number of processing elements needed in the hidden layer of the MLP. The corresponding plot of the results is shown in figure 3. The plot also shows the standard deviation error bars for each of the MAE values. It can be seen from the plot that the MAE values decrease from about 0.57% to about 0.26% when the number of processing elements increases from 1 to 7. They then start to increase when the MLP has 8 to 11 processing elements in its hidden layer. When 12 processing elements are used, the MAE value drops a little and then starts to increase again. After this point, any decrease in the MAE value may not be lower than that of 7 processing elements.

On the whole, the results showed that the system was able to estimate gas column radius to about 0.26% of mean absolute error with a standard deviation of about ±0.09%. This is produced by an MLP that has 7 processing elements in its hidden layer. The results may be better if the ECT sensor had been designed specifically for this purpose.

Table 1. MAE of produced by the MLP estimator at estimating bubble column radii of gas-oil flows using the "network-growing" approach.

No. of processing elements	Test set MAE (%)	Standard deviation (%)
1	0.5680	± 0.1094
2	0.4700	± 0.1623
3	0.4621	± 0.1699
4	0.3676	± 0.0434

5	0.3016	± 0.0649
6	0.2833	± 0.0627
7	**0.2619**	**± 0.0911**
8	0.2676	± 0.0510
9	0.3101	± 0.0278
10	0.2871	± 0.0537
11	0.3695	± 0.0704
12	0.2999	± 0.0588
13	0.3128	± 0.1060
14	0.3138	± 0.0579
15	0.3286	± 0.0783

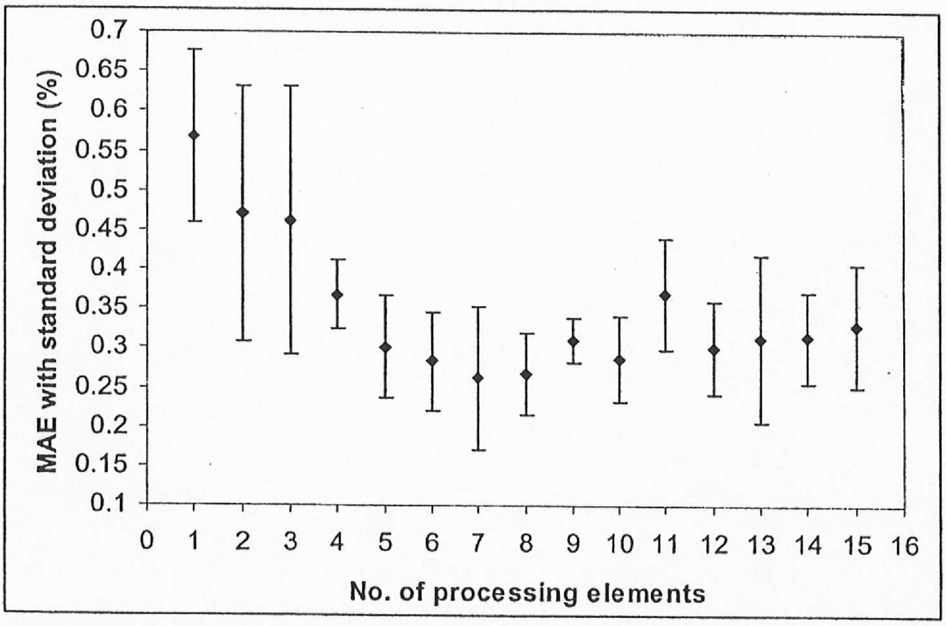

Figure 3. MAE values produced by the MLP at estimating the bubble column radii for gas-oil flows.

4. Conclusion

The work on bubble column radius determination has been described. The preliminary results clearly demonstrate that it is feasible to obtain direct gas column radius estimation from ECT measurements using artificial neural network approach. As discussed, the sensitivity of the ECT sensor gets lower towards the center of the sensing area. Hence, proper investigation on the design of the ECT sensor may help increase the sensitivity of the sensor system. This work is in progress and could result in better accuracies of bubble column radii estimations by the neural estimator.

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