OIL HEIGHT DETERMINATION FROM CAPACITANCE TOMOGRAPHY MEASUREMENTS USING NEURAL NETWORK

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ABSTRACT

This paper presents a "direct" method to gas-oil interface level determination using an artificial neural network approach based on Electrical Capacitance Tomography (ECT) measurements. "Direct" here means that the gas-oil interface levels are obtained directly from the ECT measurements without recourse to image reconstruction. The preliminary work models a separation tank that is filled with gas and oil. An ECT system, attached around the tank is used to obtain ECT measurements. Sets of ECT measurements together with their corresponding oil heights are fed into a Multi-Layer Perceptron (MLP) neural network system for training processes. After being trained, the MLP is tested by giving it sets of independent ECT measurements. The results show that "direct" gas-oil interface level measurement from ECT data is feasible with the use of a neural network system.

Keywords: Neural Network, Process Tomography, Multi-Layer Perceptron, Process Measurement.

INTRODUCTION

In order to operate gas-liquid processes efficiently, it is often necessary to measure the interface levels between the two components. Typical industrial processes that require such measurements are food manufacturing, separation of gas-liquid and control of liquid levels in chemical plants. Since capacitance change can indicate liquid levels [1], various capacitance-sensing techniques such as using capacitance transducers have been used for the purpose. Capacitance transducer techniques however, have shown to be impractical because the transducers, which are in direct contact with the liquid, have to be taken out for cleaning [2]. Also, the interface level estimates are inaccurate because their locations are specified to be between two electrodes, which could be of a distance apart [3]. Another technique, Electrical Capacitance Tomography (ECT), is a non-invasive technique since the capacitance sensors need not be in contact with the material [4]. Typically, ECT techniques rely upon reconstructed images of a sensing volume for quantification of any parameter of interest. A commonly used reconstruction algorithm for ECT is the Linear Back Projection (LBP) [5], whose reconstructed images are used for process interpretation. The ECT technique had been used to obtain gas-oil interface levels based on reconstructed images [6]. The imaging method however, has shown to give inaccurate estimates of gas-oil interface level due to distorted reconstructed images caused by the soft-field problem. To overcome the problem of distorted images, researchers have turned to iterative reconstruction algorithms. Iterative algorithms such as the MOdel-based Reconstruction (MOR) algorithm have shown to be able to produce more accurate reconstructed images than the LBP algorithm [7] and hence, more accurate gas-oil interface level measurements have been obtained [8]. However, iterative algorithms are time-consuming. Thus, they are impractical when real-time interface level determination is required. Although the problem of reconstruction speed is improving with time and increased computer speed, the use of these algorithms will not be preferable until a satisfactory reconstruction speed is achieved.

Besides the LBP and the iterative reconstruction algorithms, the Artificial Neural Network (ANN) approach has also been used to produce rather accurate reconstructed images [9]. Although being successful, the image-based ANN approach has not been adopted for the estimation of interface-level.

Despite the attempts to improve the image reconstruction algorithms, some researchers have started to realize that image reconstruction should not be the main focus of research. What is important in an industry is the end-product, and it does not necessarily need to be produced based on reconstructed images. For this reason, this paper aims to directly determine gas-oil interface levels from a set of ECT measurements, without recourse to image reconstruction. The estimation is carried out by a ANN model that is trained for the purpose. This should eliminate the problem of inaccurate interface-level measurements due to distorted reconstructed images. Also, it should overcome the problem of time consuming due to the image reconstruction process.

APPROACH AND METHODS

The gas-oil interface level is determined by estimating the fraction of oil height to the total tank height as measured from the base of the tank. For example, if the tank is half-filled with oil as illustrated in Fig. 1, then the oil height, h, is 0.5, meaning that the gas-oil interface level is half-way from the base of the tank.

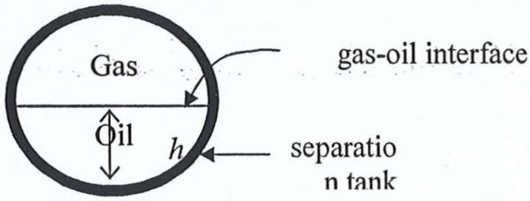

Fig. 1 – Schematic diagram of a separation tank cross-section showing the oil height, h, which is equivalent to the gas-oil interface level.

In this work, the estimation of gas-oil interface level is done by a neural network system that is trained with a set of ECT measurements and their corresponding gas-oil interface level values. On the whole, the research work involves designing an ECT system model, from which the ECT data will be acquired. Then, an appropriate ANN model and training algorithm are used to develop an optimal oil height estimation system. The following sub-sections discuss the approach in more detail.

ECT System and Data

Fig. 2 shows a cross-sectional diagram of a separation tank with an ECT sensor attached to its periphery. The ECT sensor system used in this research consists of 12 electrodes (assigned the numbers 1 to 12 in Fig. 2). R1 is the inner tank wall radius, R2 is the sensor radius, R3 is the sensor screen, θ is the subtended angle of the sensor's primary electrode and β is the subtended angle of the gap between two primary electrodes. The dimensions of R1, R2, R3, θ and β are 1 unit, 1.2 unit, 1.4 unit, 22° and 8°, respectively. Within each 8° gap is the guard electrode having subtended angle of 2.5°.

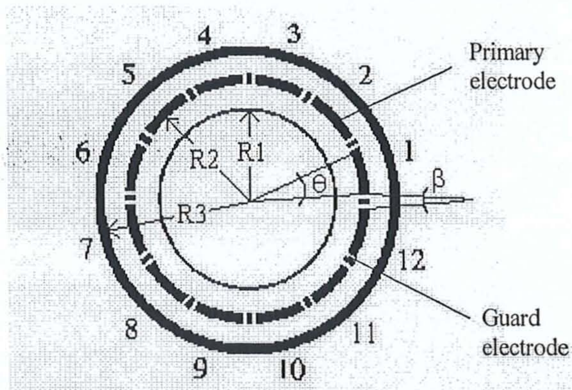

Fig. 2- Cross-sectional diagram of the ECT sensor model used in this research.

Using a 12-electrode ECT system, it is possible to acquire 66 ECT measurements for each flow pattern. This is based on the difference in capacitance measurements between all possible combinations of electrode pairs. The equation used to determine the possible number of ECT measurements that can be obtained is [10],

$$m = \frac{n(n-1)}{2} \quad (1)$$

where m is the total number of ECT measurements acquired and n is the number of electrode used in the sensor system. For this research, 612 gas-oil stratified and 2 homogeneous (gas and oil) flow patterns have been generated using an ECT simulator [11], which is based on a two-dimensional finite element method. The 612 stratified flow patterns correspond to flows having different gas-oil interface levels. The ECT data corresponding to the gas-oil homogeneous flows have been used to normalize all the ECT data gathered based on the equation below [10],

$$N_{ij} = \frac{C_{ij}^{meas} - C_{ij}^{gas}}{C_{ij}^{oil} - C_{ij}^{gas}} \quad (2)$$

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. Data normalization is necessary so that each ECT measurement is constraint within 0 and 1. This would facilitate ANN training.

ANN Estimation System Development

The ANN model selected to solve the problem is a Multi-Layer Perceptron (MLP) neural network. The selection is based on the fact that an ECT system is a non-linear system and thus, a non-linear solution is needed. A MLP is a well-known universal ANN model, capable of dealing with non-linear curve fitting [12]. Hence, MLP should be a suitable choice of ANN model for this problem. Basically, a MLP consists of an input, a hidden and an output layers. Each of these layers consists of simple processing elements (PEs). All PEs are connected to all other PEs in the other layers via links that have weighting values. The numbers of PEs needed in the input and output layers are normally determined by the problem itself. In this work, the number of input PEs is 66 corresponding to 66 capacitance measurements per flow pattern. The number of output PEs is 1 corresponding to the oil height (i.e. interface level) value.

The process of developing a MLP estimation system involves training, validating and testing. The datasets are divided into 80% for ANN training, 10% for ANN validation and 10% for testing the developed ANN system. The training algorithm selected to train the MLP is the Levenberg-Marquardt since it has been shown to be effective for training ANN involving a moderate number of training patterns [13]. Training is done in order to produce an optimal system that has an optimum number of PEs in its hidden layer, and is able to learn the mapping between the input and output data. An optimum MLP can be determined using the network-growing method where by initially, using only one hidden PE in the MLP structure for training. During a training process, input signals are fed into a MLP via its input PEs, which pass the signals to the hidden PEs via the input weight links. The hidden PEs performs some computations and passes the results to the output PEs via the output weight links. The outputs PEs then performs further computations and present the final results. The test errors are calculated using the mean absolute error (MAE) given by,

$$\%MAE = \frac{1}{k}\sum_{i=1}^{k} | A_i - E_i | \text{ x } 100\% \qquad (3)$$

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.

After the use of 1 hidden PE in the MLP structure, more hidden PEs is added to the MLP and the new system is trained again. The processes of adding additional hidden PEs to the structure and repeating the training procedure are repeated until there is no further decrement in the MLP's test error as more hidden PEs are used. At this stage, the training and validating process is stopped and the optimal MLP structure is determined based on the test errors.

RESULTS AND DISCUSSION

The results of the research work are shown in the form of a table, and not graph because the values of the MAE are best reflected this way. The MAE values obtained from using different numbers of hidden PEs are shown in Table 1. It can be seen that the error is the largest when only 1 hidden PE was used. This shows that an MLP with only 1 hidden PE does not produce a system that is sufficiently powerful to solve the problem. The MAE then reduced from 1.004% with 1 hidden PE to 0.517% with 3 hidden PEs. The MAE reduces further to 0.422% when 7 hidden PEs are used. This is the lowest MAE so far. After this point, the MAEs start to increase again as more hidden PEs is used. This demonstrates the effect of over-fitting caused by too many hidden PEs, making the MLP inflexible at estimating oil heights based on the ECT measurements that it has not seen before.

Based on the results tabulated in Table 1, logically, the global minimum value may be located between 5 and 11 hidden PEs. Hence, further ANN training, validating and testing processes have been carried out for 6, 8 and 10 hidden PEs. The results are as shown in Table 2. The MAE values obtain for 6, 8 and 10 hidden PEs are higher than that of 7 hidden PEs. This clearly shows that the optimum MLP system is one that has 7 hidden PEs in its structure. The results also demonstrate that the developed MLP system has been able to estimate gas-oil interface level to a MAE of about 0.422% out of 62 sets of unseen ECT data. This is a small error considering the fact that the MLP has been trained with a rather small number of training cases.

Table 1 – MAE (%) for a range of hidden PEs.

Number of hidden PEs	MAE (%)
1	1.004
3	0.517
5	0.619
7	0.422
9	0.562
11	0.591
13	0.661
15	0.813

Table 2 – MAE (%) for 6, 8 and 10 hidden PEs.

Number of hidden PEs	MAE (%)
6	0.526
8	0.496

10	0.527

CONCLUSION

This paper discusses a "direct" method for determining gas-oil interface level in a separation tank using a MLP neural network estimation model based on ECT measurements. The work has been shown to be quite successful since the MLP estimation system is able to give oil heights almost instantaneously with a mean absolute error of about 0.4%. The error could be reduced if more training patterns were used for MLP training. Although it would be time-consuming to train an MLP with a larger number of training patterns, once the MLP has been developed, it is able to give almost instantaneous oil height estimates.

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