USE OF SELF-ORGANIZING NEURAL NETWORKS TO IDENTIFY TWO-PHASE AIR-WATER FLOW REGIMES IN A HORIZONTAL PIPE

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Abstract: One of the main problems associating the transport and manipulation of multiphase flow is the existence of flow regimes, which have a strong influence on important parameters of operation. An example of this occurs in gas-liquid chemical reactors in which maximum coefficients of reaction can be attained by keeping a dispersed-bubbly flow regime and thus maximizing the total interfacial area. Thus, the ability to identify flow regimes automatically is very important, specially to maintain multiphase systems operating properly. This work consists in the development and implementation of a self-organizing map (neural network) adapted to the problem of identification of regimes of two-phase air-water flow in a horizontal pipe. The readings of capacitance, variation of pressure in the piping and fluctuating pressure were taken as the starting point, to be stored as associative patterns in the neural network. Next, the training phase of the neural network consisted of identifying appropriate values for its synaptic coefficients during a representative set of tests. A competitive layer of 10 neurons was chosen, allowing for more regimes than those usually required. The neural network was able to find independently just the six regimes already known, even having 10 neurons in the grid. This demonstrated the ability of the self-organizing map to identify flow regimes in previously unknown situations. Tests were made to verify the performance of the neural network, using experimental data collected in the pilot pipe-line of the Center for Thermal Engineering and Fluids of the University of São Paulo School of Engineering at São Carlos.

***Keywords*:** neural networks, self-organizing maps, two-phase flow, flow regimes, diagnosis.

1. Introduction

The existence of characteristic dynamic patterns or regimes is, without any doubt, one of the most important factors in the engineering of multiphase flows. This justifies the large number of technical and scientific studies in the field, some of which focus on specific technological aspects such as models of pressure drop in given situations and regimes and others on wider aspects, for example the construction of objective and universal criteria for the identification of multiphase flow regimes.

In 1970, researchers in the petrol industry began to identify certain basic physical mechanisms that could be used to distinguish flow and gas bubble velocity regimes in liquid columns. Around this time, Taitel & Dukler (1976) published a model which predicted flow regime transitions on the basis of the physical relations between the following variables, predicted to occur at these transitions: superficial velocity of gas and liquid, physical properties of the fluids and geometry of the pipes. The transition mechanisms are based on physical concepts adapted to laboratory observations of two-phase flow (Brill, 1992). Among the many different variables that may be used to diagnose flow regimes, the void fraction is, certainly, one of the most important. Several methods of measuring this variable have been developed in the last 40 years. A wide range of principles have been applied in order to quantify, or just to reveal the presence of, one of the two phases in the mixture. Some of the measuring techniques require sophisticated equipment such as X-ray absorption spectrometers, while others involve simpler items such as resistance sensors (Moreira, 1989).

It is well-established that, in two-phase flow, an abrupt change in the pressure-drop is frequently associated with a change of flow regime (Wambsganss *et al.,*1994). Lin & Hanraty (1987) used the measurement of pressure to detect the intermittent flow regime. Osman & Aggour (2002) introduced a neural network model to predict the pressure-drop in horizontal multiphase flow. The model was developed and tested on field data and a wide range of variables. Sekoguchi *et al.* (1987) applied a statistical method and the mean void fraction to identify flow patterns. Regarding non-classical techniques of signal analysis, Gional *et al.* (1994) and Seleghim & Hervieu (1998) used, respectively, fractal techniques and joint time-frequency analysis, in the characterization of transitions between horizontal two-phase flow regimes. In this field, the use of neural network techniques to analyze signals from two-phase flows shows great potential (Monji & Matsui, 1998) and much research has been published in which this approach is adopted. Crivelaro *et al.* (2002) used a neural network to process signals emitted by a direct imaging probe in order to diagnose the corresponding flow regime. Smith *et al.* (2001) utilized self-organizing maps to compare flow regime classifications based on traditional analysis. Statistical values of impedance signals were used as inputs for a neural network, which grouped the results within a number of predetermined categories. Mi *et al.* (1998) employed a supervised neural network and an unsupervised neural network (self-organizing map) to identify flow patterns, the input signal being a non-intrusive impedance measurement. Cai *et al.* (1994) demonstrated a technique to classify the patterns of air-water two-phase flow by applying a self-organizing neural network. The principle of the technique lay in the characterization and classification of the turbulent pressure signal in relation to flow regimes. More recent research has been based on the use of neural nets in association with genetic algorithms and fuzzy logic; a detailed discussion of these techniques may be found in Annunziato & Pizzuti (1999) and Tarca *et al.* (2002).

The aim of the research described here was to identify flow regimes by developing and implementing a self-organizing neural network which would act as the logic unit of a sensor device capable of diagnosing the patterns in real time during tests. Specifically, it was hoped that the various patterns of air-water two-phase flow in horizontal pipes would be recognized by the network. It should be stressed that this question is of great relevance for the efficient operation of equipment and installations involving multiphase fluid transport and represents one of the great challenges nowadays in the petrochemical and thermonuclear industries, among others.

2. Self-organizing artificial neural networks

The self-organizing system considered here belongs to a special class of artificial neural networks (ANN) known as feature maps. It can be described in formal terms as a monotonic, nonlinear, ordered mapping of n-dimensional input data on to the elements of a vector space of few dimensions. From the point of view of the information in the data and how it is visualized, the self-organizing nature of the mapping implies that the statistical and nonlinear metric relations among the n-dimensional input data are converted into simple geometric relations between variables located at the nodes of a 2-D net (Kohonen, 2001). In other words, to the extent that a self-organizing map projects the information contained in the primary data space on to a 2-D network, without altering significantly the topological relations, it may be regarded as a tool capable of creating abstractions. These two attributes - visualization and abstraction of data - are of great importance in complex information-analysis applications, such as the problem of identifying multiphase flow regimes and others involving the use of artificial intelligence (Seleghim Júnior, 2002).

These networks are characterized by competitive learning, a process in which the output "neurons", or nodes of the map, compete among themselves to become activated while a data-pattern is presented to the inputs. Eventually, just one output neuron , or one in each local group, becomes the "winner" of the competition and remains active.

The basic idea underlying these self-organizing maps (SOM) was first introduced and described in terms of computer models of biological neural nets by C. von der Malsburg and Stephen Grossberg (see Hagan *et al.,*1996), to explain how topological maps form in the brain. Using a neural net with a highly simplified model of processing in the neuron, von der Malsburg demonstrated how topographical maps can be obtained by local learning. This model involved two basic assumptions: (1) an activated node will send activating signals to its near neighbors by internode connections, and (2) the "weights" of these "synaptic" connections (signal strengths) will change as a result of a learning rule.

In the SOM, the neurons are connected in a grid that may be 1-D or 2-D. Maps with higher dimensions are possible, but rarely used. A 2-D grid of neurons often used with discrete maps is sketched in Figure 1. Each neuron in this grid is fully connected to all those in the input layer.

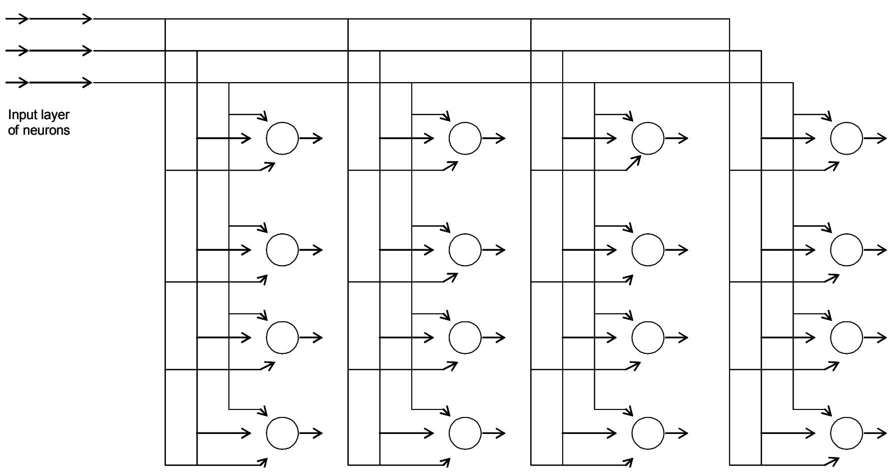

Figure 1. 2-D grid of neurons

A topographical map is formed in the SOM from the input patterns, in which the spatial locations (coordinates) of the neurons in the grid reflect intrinsic statistical features within the input patters - hence the name self-organizing maps (Haykin, 1996).

Each input pattern presented to the network is equivalent to a certain region of input space. The position and nature of that region usually vary from one input pattern to the next. All the neurons in the SOM should be exposed to a sufficiently large number of different patterns to ensure that the self-organizing process has the chance tof evolve correctly and develop a complete feature map.

The layer of nodes in a SOM are arranged initially in physical positions, in conformity with the topology adopted for the map: they can be connected in a rectangular or hexagonal 2-D grid, or even in a random multidimensional net. The topological distances between a pair of nodes is calculated from their positions by applying one of several distance functions; in this study, the physical Euclidean distance is used.

The basic architecture of this competitive network is shown in Figure 2. The box ||ndist|| receives the input data vector **p** and the input weight matrix $\mathbf{W}_{1,1}$ (representing weights of all the synaptic connections from the R inputs to S^1 neurons in layer C). The box measures the distance between **p** and each weight vector (equivalent to a row in $\mathbf{W}_{1,1}$) and outputs a vector of S^1 elements that represent the minus values of each distance. Each input n to the competitive layer C then subtracts the Euclidean distance (between its input weight vector $\mathbf{W}_1$ and the data vector **p**) from a fixed bias b, so that the smaller the distance, the higher the input n^1. Clearly, if all zero biases are used, the highest possible input to any neuron is zero, which occurs when **p** is identical to the corresponding weight vector.

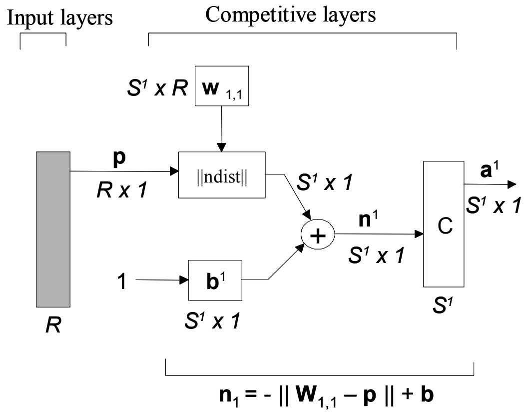

Figure 2. Architecture of a competitive neural network.

The activation function of the neurons in a competitive layer is such that only the winning neuron, associated with the most positive input element n^1, is activated and produces an output signal of 1, all other neurons returning the output 0. In the case of zero bias values, the neurons whose input (i.e. the negative distance between its weight vector and **p**) is least negative wins the competition and has an output 1 (HAGAN *et al.,* 1996).

The SOM is generated by the following algorithm. First, all the synaptic weights (elements of **W**) are initialized. This may be done by using a random-number generator to produce small initial values, so that no *a priori* order is imposed on the SOM. Three essential processes are then involved in the emergence of the self-organized map, which are now summarized:

1. **Competition.** As each input pattern is presented, the neurons in the network calculate their respective values of a discriminant (matching) function, which will become the basis of interneuron competition. The neuron with the highest value of this function is the winner.

2. **Cooperation.** The winning neuron determines the center of a topological neighborhood of activated neurons, as if all neurons near the winner were excited by its output signal. Thus, within the competitive layer, neighboring neurons exhibit cooperation.

3 **Adaptation of synaptic weights.** This mechanism enables the excited neurons to increase their individual values of the discriminant function, with respect to the current input pattern, by making suitable adjustments to their synaptic weights. These adjustments augment the response of the winning neuron (and neighborhood) to subsequent presentations of similar input patterns, so that this neuron may become a decoder (identifier) for a class of inputs. Note that redundancy in the input data set is essential for learning to occur in the SOM (Haykin, 1996).

3. Experimental set-up

Several experimental runs were performed in this study. The measurements were carried out on the pilot oil pipeline at the Núcleo de Engenharia Térmica de Fluidos (Thermal Engineering and Fluids Research Center - NET&F) of the

Escola de Engenharia de São Carlos da Universidade de São Paulo (University of São Paulo School of Engineering at São Carlos - EESC/USP), which is designed for gas-liquid two-phase flow transient tests.

The three-phase pilot pipeline sketched in Figure 3 works with gas-liquid-liquid mixtures and has straight test sections of length 12m and internal diameter 45, 30 and 24 mm, mounted on a hinged platform that can be inclined up to 10^0 from the horizontal. A system of tanks installed downstream from the test section is responsible for the primary separation of air from liquid and, subsequently, the separation of oil from water. Centrifugal pumps equipped with 7.5 kW frequency inverters recirculate the liquid phases, controlling the flows with the help of orifice plates mounted in the respective injection lines. A 50 kW screw-compressor supplies the flow of air, which is controlled by electropneumatic servo-valves equipped with flow-sensors. The analytical instruments include rapid-response pressure-sensors to measure total and differential pressure-drops, a capacitance sensor to estimate the phase fraction and an acoustic sensor to produce echograms of the flow. A microcomputer with an analog-to-digital converter is used to acquire the signals from the measuring devices (both operational and analytical), as well as from control devices (servo-valves and frequency inverters).

In this study, tests were performed on air-water two-phase flow. The pipeline test section used was a 12 m straight pipe of internal diameter 30 mm.

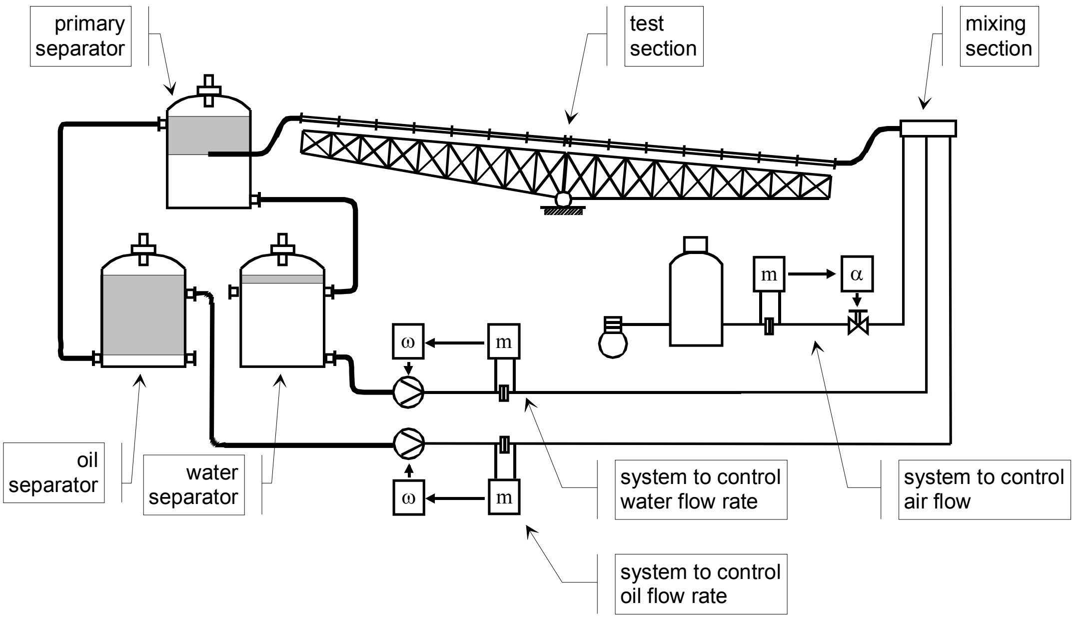

Figure 3. Sketch of the pilot three-phase pipeline at NET&F.

4. Results

For each of the main types of horizontal two-phase flow pattern, series of tests of long duration were carried out in the experimental circuit described above. The signals used in the analysis corresponded to measurements of electrical capacitance, pressure-drop in the along pipe and local pressure gradient, collected respectively by a capacitative probe and pressure meters. For each test, the signals were sampled at the rate of 30 Hz until the storage memory was used up (2^{14} samples). Each test lasted for 546 seconds. The classes of test are defined in Table 1.

Table 1. Classification of regimes tested.

Label	Test	Q_1(kg/s)	Q_2 (kg/s)
1	Smooth stratified	0.0800	0.0014
2	Wavy stratified	0,0840	0,0075
3	Rough stratified	0,1060	0,0190
4	Intermittent	0,6910	0,0020
5	Bubbles	7,05	0,0120
6	Annular	0,3500	0,0400

Steady state tests were done in a sufficient number of different pairs of air and water flow-rates to reproduce, as well as possible, the whole range of variation of every flow regime.

The data from the flow-regimes listed in Table 1 were arranged in matrices of 16,384 rows by 3 columns, 16,384 being the number of samples while the columns contained, respectively, the measurements of capacitance, pressure-drop in the pipe and fluctuating pressure.

On the basis of preliminary studies, the architecture of the SOM was defined as a layer of 3 inputs and a grid with 10 neurons. The number of neurons was chosen to enable the network to learn complex tasks by the progressive extraction of significant features from the input patterns (Haykin, 1994). This number is not fixed theoretically and may be chosen equal to the number of classes that the SOM is expected to identify or a larger number. In this case, the network was supposed to identify 6 different flow regimes, but had 10 neurons. In this way, it was possible to discover whether the SOM would autonomously identify 6 regimes and no more, despite possessing a larger number of potential class decoders. After training with the data set, the network did indeed identify 6 different classes of data, which coincided with the flow regimes.

The topology of the competitive layer used here was hexagonal, this being preferred for the purpose of unbiased visualization (Kohonen, 2001). The distance calculated between the nodes was Euclidean, which is the commonest distance function found in SOM applications. During the first phase of learning, the ordering of weights, the number of epochs was 1000 and the learning-rate fixed at 0.9; in the second phase, used for fine adjustment of the map, there were also 1000 epochs, but the learning-rate dropped to 0.01. In general, published studies recommend that the second phase be much larger than the first, but in the present study the two periods had the same number of epochs and the SOM achieved good results.

To train the SOM, data matrices of 300 rows by 3 columns were chosen, small enough for each training run to reach a successful conclusion in a reasonable time, yet not so small that features from the recorded sets of signals would be lost. 10 of these matrices were used for each regime during training. By the end of this training, the SOM had encoded the six distinct flow regimes on six separate neurons (numbered 1, 2, 4, 7, 8, and 10), as shown in Table 2.

Table 2. Neurons identifying the flow regimes in the trained neural net.

Flow regime	Identifying Neuron
Annular	1
Rough stratified	2
Intermittent	4
Smooth stratified	7
Wavy stratified	8
Bubbles	10

To test generalization, characteristic signals for each of the flow regimes were presented to the SOM, in order to verify whether the expected code (neuron index) was output by the ANN. Several simulations of flow-regime tests were performed, using test data not utilized during training. The figures below display classifications produced in these tests.

Figure 5 shows results from simulated data not used during training. 10 sets of data from each flow regime were presented to the ANN, without mixing; i.e. examples 1 to 10 contained data representing the annular regime, 11 to 20 the bubble regime, 21 to 30 intermittent, 31 to 40 smooth stratified, 41 to 50 rough stratified and 51 to 60 wavy stratified. Each asterisk represents one example (i.e. one 300 x 3 matrix) one of the flow regimes. In Figure 5, it can be seen that the ANN identified correctly all the regimes, in accordance with the code developed in the training.

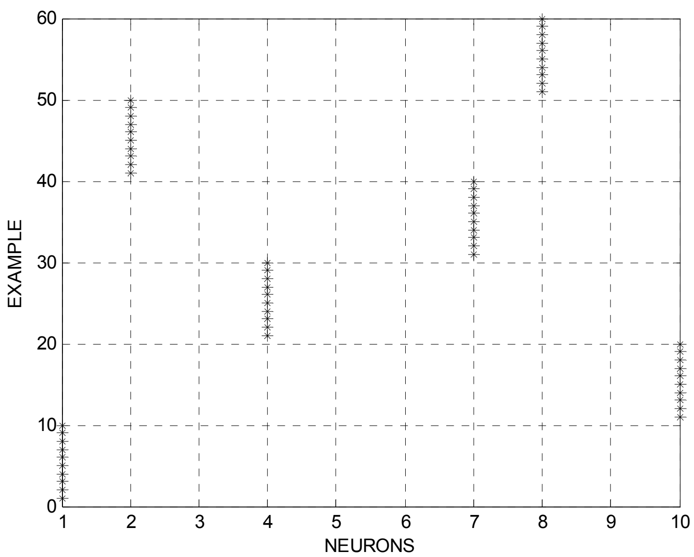

Figure 5. Neural net identification graph for data not used in training.

A second simulation was carried out with new data. In this case, each set of 10 examples presented consisted of two subsets of 5 examples of independently-chosen regimes. Thus, the examples were mixed in the consecutive groups. Only the sample data for the bubble flow regime were presented as a set of 10 examples. Table 3 shows the order in which the examples were presented, together with the number of examples of each regime and the neuron that encoded that regime in the trained SOM.

Table 3. Simulation data.

Regime	Number of Examples	Identifying neuron
Annular	1 to 5	1
Wavy stratified	6 to 10	8
Bubbles	1 to 10	10
Intermittent	1 to 5	4
Smooth stratified	6 to 10	7
Rough stratified	1 to 5	2
Intermittent	6 to 10	4
Smooth stratified	1 to 5	7
Rough stratified	6 to 10	2
Wavy stratified	1 to 5	8
Annular	6 to 10	1

The graph in Figure 6 shows the identifications made by the neural net. As in the first simulation, the SOM successfully identified the flow regimes in each example.

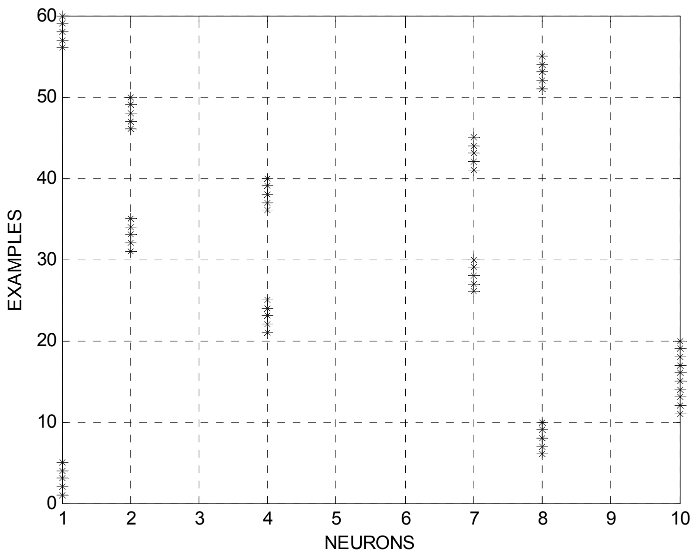

Figure 6. Neural net identification graph for data not used for training, presented in groups of 5 examples for each flow regime.

On the basis of these simulations with data not used in the SOM training, it may be concluded that this ANN is a powerful tool for the identification of two-phase flow regimes.

5. Conclusions

The employment of a self-organizing artificial network in the identification of two-phase flow regimes in a horizontal pipe has been demonstrated in this study. Data were collected from a pilot pipeline, designed to allow measurement of capacitance, fluctuating pressure and pressure drop, and were then used to train this ANN. To verify the ability of the network to generalize, fresh data obtained from the sane experimental circuit were presented to it, i.e. data not used during its training.

To validate the proposed methodology, tests of identification were used. Signals characteristic of each of the flow regimes were presented to the ANN, which responded by outputting class codes (indices of the activated neurons). The identification index for the flow regimes achieved by the network was 100%.

These results are extremely promising and strongly justify further research in this direction. Firstly, the self-organizing neural network proved capable of identifying, completely autonomously, all the main flow-regimes that occurred in the horizontal test-section in the pilot pipeline at NET&F (São Carlos, Brazil). Secondly, the detection-rate with untrained data was 100%. The study of the optimization of the parameters and hidden variables of the training of the network showed that its performance depended critically on the time of presentation of the training data matrices. Under the right conditions, a self-organizing map is seen to be a very powerful and flexible tool, both for the analysis of experimental data in research and for direct application in the in-line monitoring of industrial processes.

6. References

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