A COMPARISON BETWEEN LEVENBERG-MARQUARDT (LM) INTELLIGENT SYSTEM AND BAYESIAN REGULARIZATION (BR) INTELLIGENT SYSTEM FOR FLOW REGIME CLASSIFICATION

Oleh:

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SARJANA MUDA KEJURUTERAAN (KEJURUTERAAN ELEKTRONIK)

Pusat Pengajian Kejuruteraan
Elektrik dan Elektronik
Universiti Sains Malaysia

May 2006

ABSTRAK

Projek ini dilaksanakan untuk membuat perbandingan di antara Sistem Kecerdikan Buatan Levenberg-Marquardt (LM) dan Sistem Kecerdikan Buatan Bayesian Regularization (BR) dari segi prestasi, tempoh pembelajaran serta output yang dihasilkan oleh kedua-dua sistem kecerdikan buatan ini melalui masalahan pengklasifikasian. Perbandingan ini dibuat adalah untuk membantu di dalam pemilihan algoritma pembelajaran untuk penyelesaian masalah. Masalah pengklasifikasian dihasilkan menggunakan proses Tomografi Kemuatan Elektrik (TKE) yang menyediakan data bagi mengenalpasti rejim-rejim aliran minyak di dalam saluran penghantaran. TKE mengenalpasti kemuatan bendalir yang berbeza dan seterusnya menghasilkan data untuk proses pengklasifikasian ini. Perseptron Berbilang Lapisan (MLP) merupakan bentuk Rangkaian Neural Buatan (RNB) yang biasa digunakan untuk masalah pengklasifikasian dibina dengan menggunakan perisian MATLAB 7®. Perbandingan yang dilaksanakan akan menunjukkan bahawa algoritma pembelajaran LM adalah algoritma yang lebih pantas berbanding algoritma pembelajaran BR manakala algoritma pembelajaran BR mampu membina sebuah sistem kecerdikan buatan yang lebih bagus dari segi prestasi keseluruhan sistem

ABSTRACT

The purpose of this project is to study the performance, leaning time and, output of Levenberg-Marquardt (LM) intelligent system and Bayesian Regularization (BR) intelligent system through a classification problem. These studies will help in choosing the right training algorithm for classification problem involved. These intelligent systems have to classify flow regimes in a closed line with the data are provided by Electrical Capacitance Tomography (ECT). ECT measured the different capacitance value of fluid and produced the data for the classification problem. Multilayed Perceptron (MLP), a type of artificial neural network (ANN) which is widely used in a classification problem is developed using MATLAB 7®. The comparison made showed that LM learning algortihm is a faster training algorithm compared to BR training algorithm meanwhile BR learning algorithm capable of building a superior intelligent system in term of the overall system performance.

ACKNOWLEDGEMENT

Assalamualaikum w.b.t.

I would like to express my gratitude to Allah because of his consent that I have the strength to complete my final project successfully.

Thousand thank you goes to Dr. Junita Mohamad Saleh, as my supervisor, always full of guidance, support and suggestion for the completion of this project.

I also like wish thank you to my friends who always willingly to help me and give me valuable advices when I really need it.

Not to forget to my family who always there for me and always give me their unwavering support in this project. And also to the one who always motivated me throughout this project. Thank you.

Lastly, I would like thank to all parties around me who always lends a hand and made this project successful.

Thank you.

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CHAPTER 1

INTRODUCTION

An introduction will be presented in this chapter describing general overview of classification of flow regime. The objectives of this project and also the thesis guidance also will be discussed in this chapter.

1.1 Classification of flow regime

In the real world, classification process is very important because it can improve process control. In industries such as the oil industry, process control is very important because without it, industries may face with big losses.

In industrial application, capacitance tomographic technique allows more detailed monitoring of the process and gives more complex control of process equipment. It opens up the new possibilities for higher quality products and an increase in the safety of operation (Reinecke and Mewes, 1996).

Electrical Capacitance Tomography or ECT functions by measuring the difference in capacitance value between two electrode sensors. In this project, 12 electrode sensors will be placed around a closed vessel. The capacitance value differs depending in the different permittivity and distribution. This value the will be fed into an artificial neural network and it will classify the flow regime into groups that it has been train to classify.

The usage of Artificial Neural Network (ANN) in classifying flow regime is an attempt to mimic the human brain. The human brain is a powerful tool in solving problems and also flexible to accommodate new information from time to time by a learning process. By attempting to imitate the human brain, we can create a tool that can think outside the learning process and also help to solve problems that are complicated to both human brain and computer. In this project, ANN will classify the flow regime based on the capacitance values as in the learning process.

Both Levenberg-Marquardt (LM) and Bayesian Regularization (BR) are two training algorithms that are widely in used for classification problems. Comparing these algorithms will eliminate the unnecessary complication and unwanted delay when using these intelligent systems for classification problems. By comparing these two algorithms, their pros and cons can be taken into consideration when choosing the training algorithm in the real world.

1.2 Project objectives

The objectives of this project are:

- To make comparison of LM intelligent system and BR intelligent system in the sense of the performance, learning time, and the output of each system.
- Understanding the theory and application of ANN.
- Understanding the concept of ECT.
- Understanding and using MATLAB®.

1.3 Thesis guidance

This thesis comprises of five main chapters which are Introduction, Literature Review, Implementation, Result and Conclusion.

The theory and concept of ANN and ECT will be presented in Chapter 2. Past methodology also will be discussed in this chapter.

Chapter 3 will be discussing about the implementation of the project. In this chapter, a profound explanation of the project will be presented including the flow regime or pattern, ECT and ANN design, and training algorithms.

All the results and the discussion will be included in Chapter 4 while the conclusion of the project is in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

In this chapter, a profound review on tomography and also neural network will be presented. Also discussed in this chapter is past methodology of classification method.

2.1 Tomography

The term tomography originated from the Greek language, *tomos* meaning slice or cross-section and *graphy* meaning picture or image. Therefore, tomography is a method to produce the cross-sectional images. Tomography is first used and still widely use in medicine field. Body scanner has the ability to glimpse inside the human body and produce images of the organs inside the body. The same principle is used when using tomography in industrial field but changes need to be done to the equipment compared those in the medicine field. Tomography is used to detect oil leakage in an underground tank, fluid flow pattern, oil velocity in a vessel and many more.

2.1.1 Electrical Capacitance Tomography (ECT)

ECT is used to image cross-section of industrial processes containing dielectric material. It is suitable for imaging industrial processes in which the components have different permittivity. With the varying permittivity, an image will be constructed according to the data. ECT system consists of (Yang and Peng, 2002):

(a) multi-electrode sensor,

(b) the sensing electrode, and

(c) computer for hardware control and also data processing, including image reconstruction.

A typical ECT system is as shown in Figure 2.1. ECT has several advantages over other tomographic techniques, e.g. low-cost, rapid response, portability, non-invasion, and robustness (Cao and Wang, 2000).

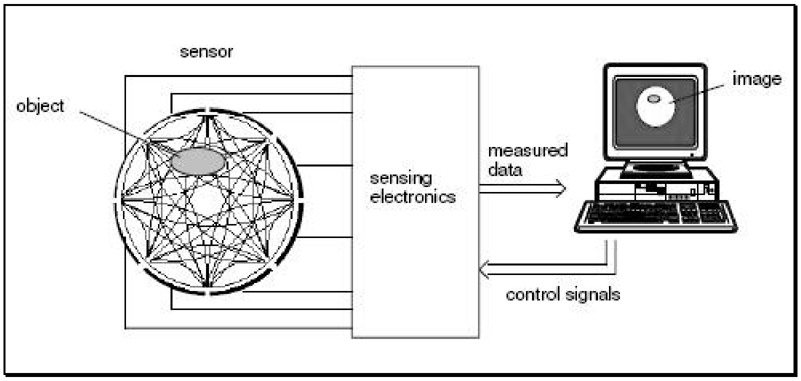

Figure 2.1: ECT System. (Yang and Peng, 2002)

The sensing electrodes are mounted equally around the desired section of a pipe or vessel. The capacitance values between all single-electrode combinations are measured. The sensing electronics provides excitation signals and converts the capacitances into voltage signals, which are conditioned and digitized for data acquisition. The computer controls the system hardware and implements image reconstruction to show the permittivity distribution (Yang and Peng, 2002).

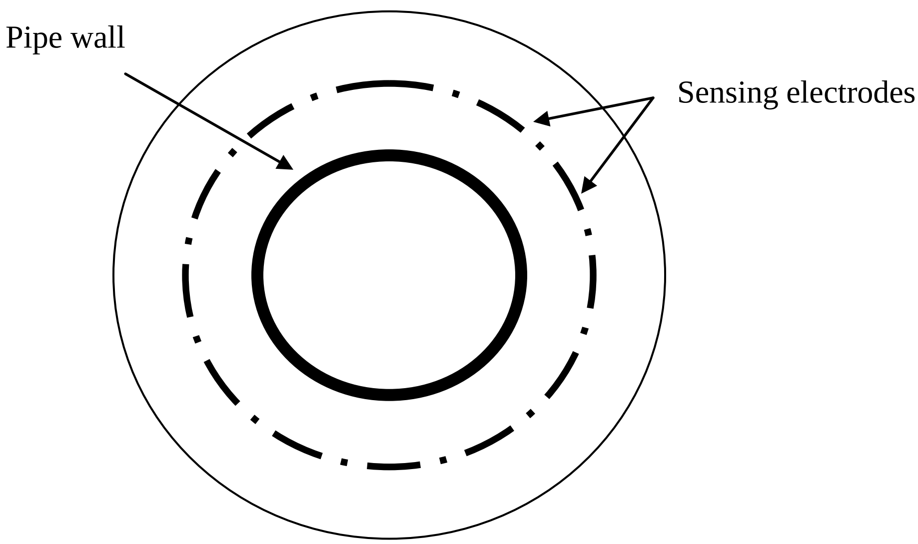

Figure 2.2: Sensing electrodes position.

2.1.2 Capacitance Calculation

Capacitance calculation starts with the first capacitance which is given a positive voltage. The electrode becomes the source electrode while others will be called controller electrode. It will then measure the capacitance between the first electrode and the second electrode. This process will go on until between the first electrode and the twelfth electrode. This process will repeat itself but this time the second electrode will be the source electrode and others will be the controller electrode (Xie et al, 1992).

This process will produce 66 data for 12-electrode ECT system. This is according to the equation (2.1) shown below:

$$D = \frac{n(n-1)}{2} \tag{2.1}$$

where:

D	=	produced data
n	=	number of electrodes

Figure 2.3 showing the cycle of the capacitance calculation and Figure 2.4 showing the electric field line distribution. C12 denotes the process of measuring the capacitive value between sensor 1 and sensor 2 and so on.

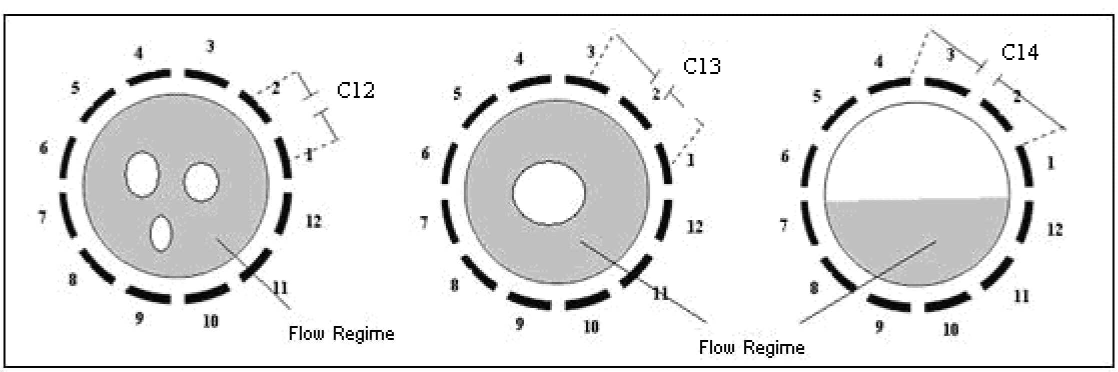

Figure 2.3: The cycle of capacitance calculation

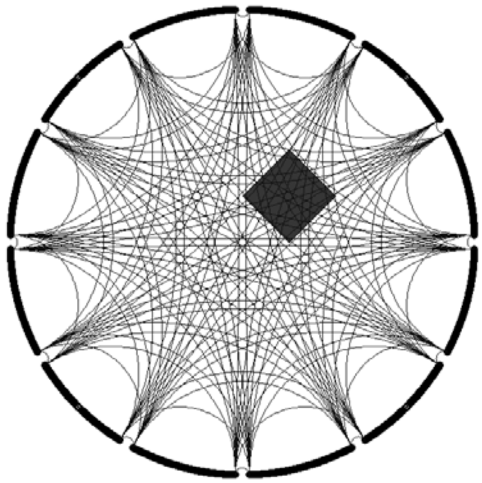

Figure 2.4: Electric field line distribution. (Zhang and Huaxiang, 2005)

2.1.3 Data normalising

The data needs to be normalised because of the varying value. By normalising the data, the data can easily be manipulated into the next step. Equation (2.2) (Byars, 1995) showing the formula to normalising the data:

$$\lambda_{i,j} = \frac{C_{i,j} - C_{i,j(empty)}}{C_{i,j(full)} - C_{i,j(empty)}} \tag{2.2}$$

where:

$\lambda_{i,j}$	=	normalise value
$C_{i,j}$	=	data that need to be normalise
$C_{i,j(empty)}$	=	data for empty flow regime
$C_{i,j(full)}$	=	data for full flow regime

Empty flow regime is the flow regime that contain no oil in the vessel while full flow regime is full off oil in the cross section of the vessel.

2.2 Artificial Neural Network (ANN)

Artificial Neural Network or ANN is a model of the human brain. The human brain is the most sophisticated machine ever known to man. Although, man has been studying the human brain for centuries, the true potential and the understanding of the human brain is far from being unlocked. Therefore, by creating a system that mimicking the human brain, we hope that we can learn more about it.

Artificial neural network is an attempt of designing a system closely resembles biological structure of the human brain. The mechanism of information processing in the biological nervous systems (i.e. the human brain) is the inspiration behind the neural network. Neural network represent an alternative computational paradigm in which the solution to a problem is learned from a set examples (Bishop, 1994)

In the human brain, the amount of neuron is estimated at 100 billion, which are irreplaceable. Each cell is capable of storing and processing the information for any action. The basic biological neuron (Figure 2.5) consists of synapses, the soma, the axon and dendrites. Dendrites act as an input for the neuron meanwhile axon is the output that connects the neuron to another neuron. Synapses are connections between neurons, which are not physically connected but a gap allowing electrical signal to go from neuron to neuron. These electrical signals are then passed across to the soma which performs some operation and sends out its own electrical signal to the axon. The axon then distributes this signal to dendrites and this cycle repeats itself (Matthews, 2000).

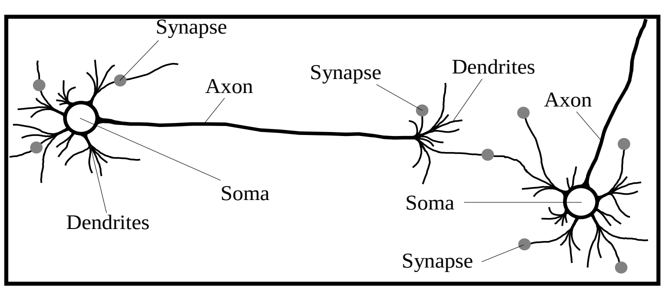

Figure 2.5: Basic biological neuron.

Neural network is capable of learning general solution to a problem from a set of specific examples but the disadvantages is in providing a suitable set of example data for network training (Bishop, 1994)

2.2.1 History of ANN

Artificial Neural Network (ANN) has been around since its introduction by McCulloch and Pitts on 1940's. Table 2.1 showed notable contributions in ANN field in the early years.

Table 2.1: Researchers and their contribution in ANN. (Mashor, 1994)

Researcher	Year	Contribution
W. McCulloch and W. Pitts	1949	Introducing ANN model
D. Hebb	1949	Created *Hebb's Law* for ANN learning
F. Rossenblatt	1958	Created ANN called *Perceptron*
B. Widrow and M. E. Hoff	1960	Created ANN called *Adaline*
J. J. Hopfiled	1982	Created ANN called Hopfield
K. Fukushima	1983	Created ANN called *Neocognitron*
T. Kohonen	1984	Created ANN called *Kohonen*
D. E. Remulhart and J.L. McClelland	1986	Re-introduced and broaden the *back-propagation algorithm.*

2.2.2 ANN structure

Generally, ANN structure is very much the same as the biological neuron. As in the biological neuron, ANN has input, output, weight and processing element (PE) or processing unit called 'neuron'. In ANN, PE is arranged in input layer, hidden layer, and output layer. Each layer connected through a link with weighted values (Mashor, 1994; Mohamad Saleh, 2005). These weighted values determine the strength of input and also have the power of influencing the PE. Figure 2.6 show a general ANN structure.

Neural Network composed of a set processing units or processing elements, called nodes, neurons or units. All processing in a neural network is carried out by these nodes. Neural networks are envisioned to be collections of individual processors, each capable of a few simple computations. These processing units are in layers of (Sriram, 1997; Mohamad Saleh, 2005):

- input units, which receives input from external sources, compute their activation level, compute their output as a function of activation level, and transmit this output to the rest of the network;
- output units, which upon receipt of input from the rest of the network, compute and broadcast their output to external receivers; and
- hidden units, which only receive input from, and broadcast their computed output to, units within the network

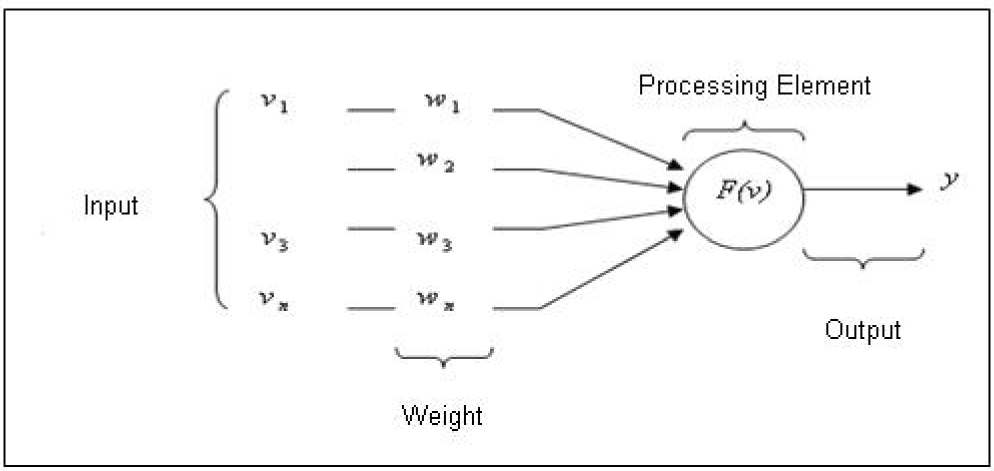

Figure 2.6: General ANN structure.

ANN has the ability to store processed information in the weighted connection and this weighted connection can be altered or updated depending on the type training algorithm used during the learning process. A good performance ANN must take into account three important aspects which are activation function, type of ANN, and weight.

A neuron components are as follow:

(a) Input

Send input data (output from other neuron) to its neuron

(b) Weight

Weight has the ability to stores information and influencing the neural network. Weight can change the strength of information for each input.

(c) Associative function

Combine each input together with its respective weight using Equation (2.3):

$$u_k = \sum_{j=1}^{p} w_{kj} x_j \tag{2.3}$$

where:

u_k	=	sum of input and weight for k neuron
w_{kj}	=	weight for combination of k and j neuron
x_j	=	input for j neuron
p	=	amount of input for j neuron

(d) Activation function

Used in hidden layer and output layer neuron to determine the output. Some of the activation functions used is *hard-limit symmetric hard-limit, linear, tansig* and *logsig*. Refer to Figure 2.7.

(e) Threshold value, θ

Lower the input to the activation function.

(f) Output

Output based upon its transfer function. The output will be determined by Equation (2.4):

$$y_k = \varphi\left(u_k - \theta_k\right) \tag{2.4}$$

where:

y_k	=	k output
u_k	=	sum of input and weight for k neuron
θ_k	=	threshold value

2.2.3 Types of ANN

ANN consists of three groups which are feedforward network, feedback network and layered network. Listed below are the three groups:

(a) Feedforward network

Neurons from one layer feed input to other neurons in another layer in a forward path.

(b) Feedback network

Neurons produce an output and also feed it back into the input neurons.

(c) Layered network

A typical layered network consists of three different layers, input layer, hidden layer, and output layer. Hidden layer can consist more than one layer.

In this project, a feedforward (FF) network is used and the type of layered network used is *Multilayered Perceptron* (MLP).

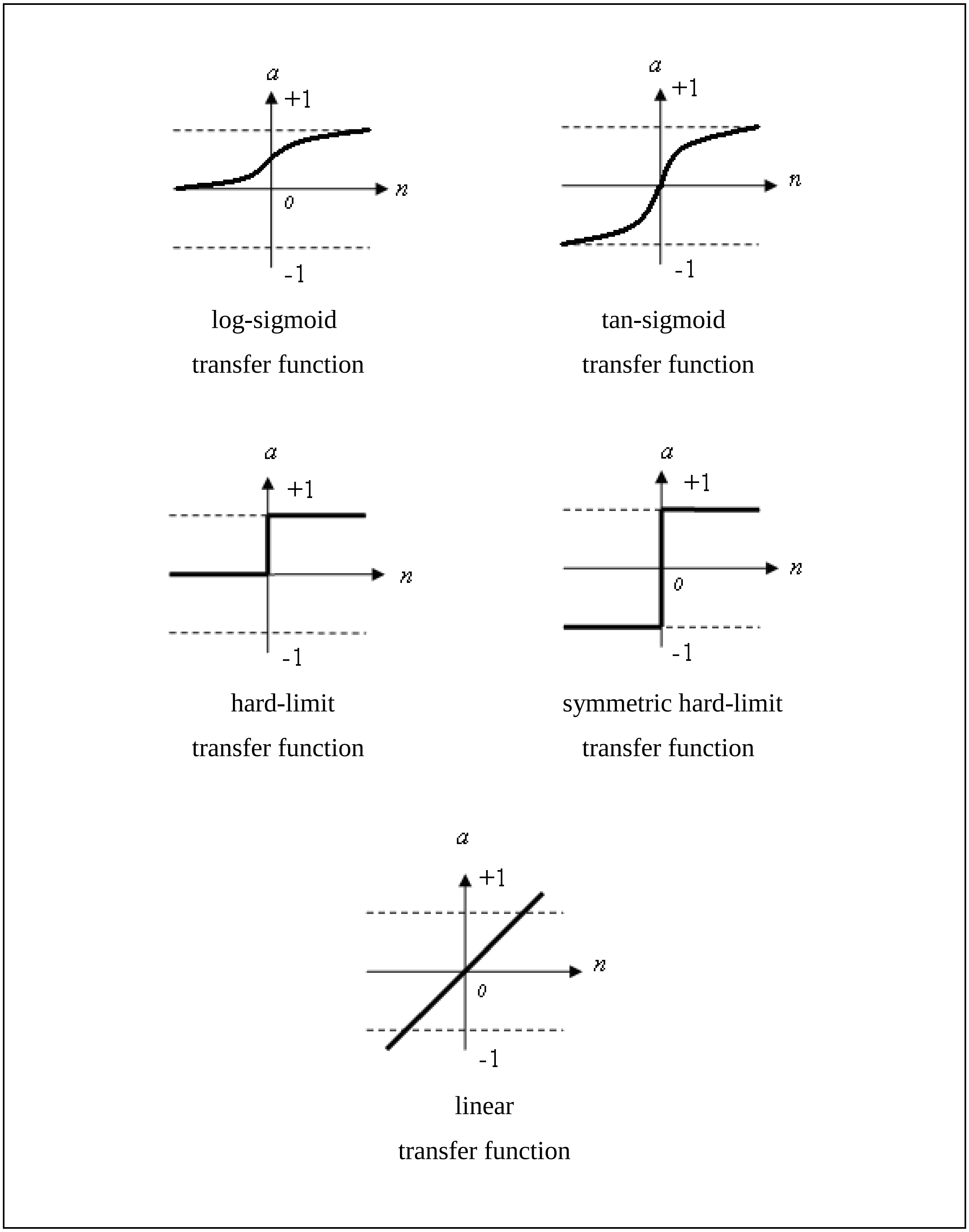

Figure 2.7: Activation function.

2.2.4 Multilayered Perceptron (MLP)

In MLP, neurons from one layer are connected to all neurons in another layer to construct a parallel neural network structure. A simple MLP consists of an input layer, a hidden layer, and an output layer. The hidden layer can consists of more than one layer and the amount of hidden layer depends on the complexity of the problems. A MLP network is shown in Figure 2.8.

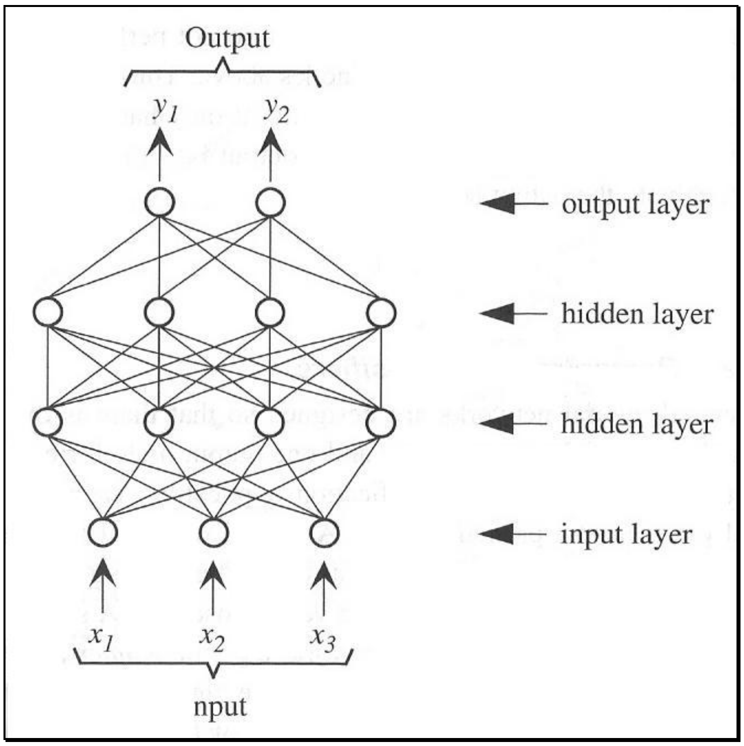

Figure 2.8: A MLP network

Input data will be fed into input layer neurons and then will be sent to each hidden layer neurons. The output of these neurons will be the input to each neuron in the second hidden layer (if applicable). This process will repeat itself according to the existing hidden layer. The output then will be send to neurons in output layer and this output layer will produce the output for the network. Data processing happened in the hidden layer and output layer neurons using the activation function.

Each neuron in the hidden layer and output layer has two associative function and transfer function. Figure 2.9 show a basis of a *i* neuron in the *j* layer. The output from *j* neuron from *k* hidden layer can be shown in Equation (2.5).

$$v_j^k(t) = F\left(\sum_{i=1}^{n_k-1} w_{ij}^k v_i^{k-1}(t) + b_j^k\right) \qquad ; \text{for } 1 \le j \le n_k \qquad (2.5)$$

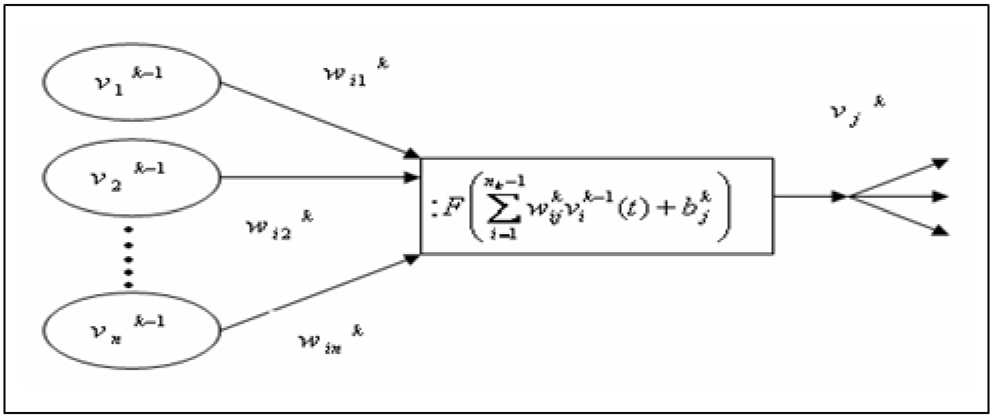

Figure 2.9: Neuron

Output for *i* neuron in the *m* output layer given in Equation (2.6)

$$y_i(t) = \sum_{i=1}^{n_m-1} w_{ij}^m(t) v_i^{m-1}(t) \qquad ; \text{for } 1 \le i \le n_0 \qquad (2.6)$$

where:

n_k	=	amount of neuron in *k* layer
n_0	=	amount of neuron in output layer
w	=	weight
b	=	threshold value
$F(.)$	=	activation function

2.2.4.1 Hidden layer

In designing a MLP, we need to determine the quantity of hidden layer needed. As mentioned before, the amount of hidden layer depends on the complexity of the problems involved. The hidden layer also depends on the input given while the output layer depends on the designer wish. As a rule of thumb, for example, 66 input data needed 66 neurons. If the output needed is only one, therefore only one neuron is needed in the output layer.

In order to determine the right hidden layer in MLP network, learning and training process needs to be executed. Learning or training process done by putting a neuron one at a time until a satisfactory result is produced. Adding hidden layer will produce a different output weight each time and it will influence the performance of the network. Optimum performance will be achieved by doing the learning or training process repeatedly.

2.2.4.2 Activation function

Hidden layer and output layer uses activation function or transfer function to produce the weight and the threshold value. In MLP, the most common activation function used in these two layers is the sigmoid transfer function (refer to Figure 2.7). The sigmoid function is divided into two, which are tan-sigmoid function (tansig) and log-sigmoid function (logsig) (Demuth and Beale, 2000). Tansig function is given in Equation (2.7) meanwhile logsig function given in Equation (2.8). Selection of the activation function also influence in the learning process time (Mohamad Saleh, 2005).

$$f\left(x\right)=\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{2.7}$$

$$f\left(x\right)=\frac{1}{1-e^{-x}} \tag{2.8}$$

where:

x = sum of weighted input for one neuron

2.2.5 Learning

An important aspect of an ANN model is whether it needs guidance in learning or not. Based on the way they learn, all artificial neural networks can be divided into two learning categories - supervised and unsupervised (Hodju and Halme, 1999; Mohamad Saleh, 2005). In solving a classification problem, the choice of learning algorithm to train ANN lies upon the problems itself. The trade-off between time and the output for the intended problem, weight heavily on the type of algorithm. ANN learning process can be categorized into three different groups which are (Hodju and Halme, 1999; Mohamad Saleh 2005):

(a) Supervised Learning

- Use input and output data as a training module.
- Use the target result (mapping) to guide the formation of neural parameters

(b) Unsupervised Learning

- Use only input as a training guide. Data- driven with no target result
- ANN will search the relationship of the input to produce the output.

(c) Graded Learning (Mashor, 1997)

- Use only input as a training guide.
- The performance will be assessed once in a while and the result will be feedback to improve the performance.

2.2.5.1 Learning Algorithm

MLP is a supervised learning neural network. Therefore, in this project, the learning algorithms that needed to train the network is Levenberg-Marquardt (LM) and Bayesian Regularization (BR). Training algorithm plays a major role in shaping an optimal ANN. The suitable algorithm depends on the problem given because it has a connection between learning time and also the performance.

Learning time is determined by a learning cycle or epoch. Learning time also determine the performance of the ANN. If the learning cycle is short, the ANN may not capable enough to solve the problem while if the learning cycle is too long, the training error will be small but it will not be flexible and this condition is called overtraining that will result in overfitting. The term overfitting meaning that the ANN memorize the learning data and it will become a problem when the ANN is presented with data that never been learned before.

In order to have an optimized performance, validation error must be as small as possible without regard of learning error. With small validation error, the weights are in the optimum value and will be used with problem presented to the ANN (Haykin, 1999; Mohamad Saleh, 2005).

2.2.5.2 Levenberg-Marquardt Algorithm

Levenberg-Marquardt algorithm is an example of back propagation algorithm. It is for second-order training without taking into account the Hessian matrix (Demuth and Beale, 2000). Hessian matrix is represented by:

$$H = J^T J \tag{2.9}$$

while its gradient is represented by:

$$g = J^T e \tag{2.10}$$

where

J	=	Jacobian matrix with the first derivative of network error
e	=	network error vector

Levenberg-Marquardt algorithm uses approximation of Hessian matrix in the Newton-like method:

$$x_{k+1} = x_k - \left[J^T J + \mu I \right]^{-1} J^T e \tag{2.11}$$

2.2.5.3 Bayesian Regularization Algorithm

Bayesian regularization algorithm uses a modification of mean of sum squared of the network error to improve its generalization capabilities. Mean of sum squared of network error are:

$$F = E_d = \frac{1}{N} \sum_{i=1}^{N} (e_i)^2 \tag{2.12}$$

where

N	=	number of training data set
e_i	=	error between the network output and the training data output for the *i* training data

To further improve its generalization, the performance function (2.12) is expanded by adding a term consisting of the mean of the sum of squares of the network weights:

$$F = \beta E_d + \alpha E_w \tag{2.13}$$

where

α = $(1-\beta)$

β = performance ratio and

$$E_w = \frac{1}{n}\sum_{j=1}^{n} w_j^2 \quad . \tag{2.14}$$

The weights and biases of the network are random variables according to the Gaussian distributions. Optimal regularization technique requires costly computational of Hessian matrix. By using Gauss-Newton approximation can overcome the costly computational. (Doan and Liong, 2004)

2.2.5.4 Errors in designing ANN

During the training process, these errors are the indicator of the state of the ANN learning process. The errors are (Mohamad Saleh, 2005):

(a) Training error

- This error is connected with the learning process when the training data set were used.
- Error is calculated based on the output produced by ANN and the real output given by the training data set.
- Calculated by Mean Square Error (MSE) given by Equation (2.15)

$$MSE = \frac{1}{Q}\sum_{k=1}^{Q}\left[t(k) - a(k)\right]^2 \tag{2.15}$$

where:

Q = amount of input data

$t(k)$ = the real output data

$a(k)$ = network output data

- Error is exponentially with the learning time but the ANN performance is not necessarily better.

(b) Validation error

- The error exist during training process with MSE is calculated after each cycle or epoch.
- This error is the indicator of learning performance and reliability of ANN during the specific cycle.
- When ANN is optimum, the error is in a minimum value.

(d) Test error

- Exist after an optimum ANN is achieved and the test process is executed using test data set.
- This error is the determination of the real performance of ANN.

2.3 ECT for flow classification

Electronic Capacitance Tomography (ECT) is placed around a vessel in order to calculate the different permittivity because of different fluid level in the vessel. The data collected by the ECT then are reconstructed by a reconstruction algorithm to produce a cross-section of the vessel and the level of the fluid contained at the section. Model-based reconstruction algorithm such as Linear Back Projection (LBP), Iterative LBP reconstruction algorithm, and Algebraic Reconstruction Technique are some of reconstruction algorithm used in image reconstruction. As an example, in the case of LBP, it is simple to use and fast but the produced image is not accurate. But when using Iterative LBP reconstruction algorithm, the image produced by this algorithm is more accurate compared to LBP but the process done by this algorithm is time-consuming. After the image reconstruction, by using interpretation algorithm, then only the system can acknowledge the image and classify it.

By using Artificial Neural Network (ANN), there is no need for image reconstruction. Therefore, we have eliminated a step in the classification process and saves valuable time. It also widely known that ANN is accurate but time-consuming because of the need of training for the neural network. This training is done by using training algorithms such as Levenberg-Marquardt and Bayesian Regularization. With ANN, the data collected by ECT will be interpreted directly by the neural network, bypassing the need of image reconstruction.

CHAPTER 3

<u>IMPLEMENTATION</u>

3.1 Work description

This section will be discussing an overview of work description for this project. Complete work done in this project will be discussed starting in the next section.

i. <u>ECT design</u>

   Parameters for ECT need to be determined in order to design ECT. Reading from ECT will be the data to produce the geometry for the classification problem.

ii. <u>Data preprocessing</u>

   Geometry needs to be generated using the data from ECT simulation. Each geometry data will consists of 66 data for capacitance measurement using 12 sensing electrodes. All data will be saved in a file in order for easier access for normalised and randomised. The data the will be divided into three group.

iii. <u>ANN design</u>

   The ANN type chosen for this project is MLP and the chosen training algorithm is Levenberg-Marquardt and Bayesian Regularization. Selection of activation function and number of hidden layer need to be determined to achieved optimum ANN.

iv. <u>Training, validate and test process.</u>

Data will be fed into the MLP to begin the training process using training data set for both of the training algorithm. Observation on the errors involved in the training process must be made. Validation and test process will commerce after an optimum ANN achieved after the training process.

v. <u>Comparison</u>

Comparison made to the output by MLP trained by Levenberg-Marquardt and Bayesian Regularization.

3.2 Flow regime

For this project, there are six different flow patterns that will be considered for the classification problem. Those patterns are shown in Figure 3.1. Oil is represented by the shaded area while gas is represented by the unshaded area.

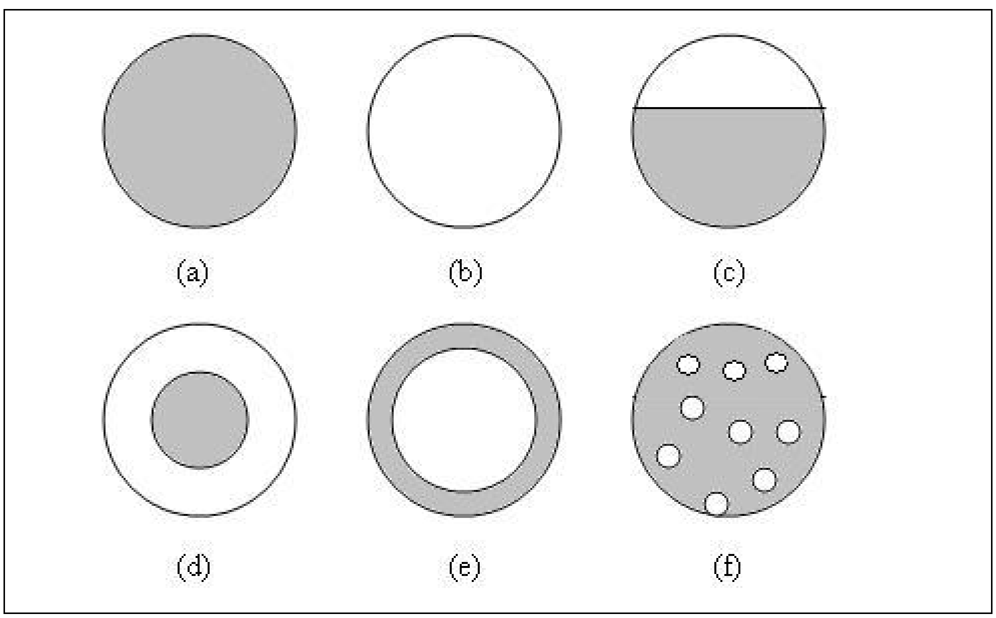

Figure 3.1: Flow patterns- (a) full pipe, (b) empty pipe, (c) strata, (d) core, (e) annulus, and (f) bubble.

3.3 ECT design

In designing ECT, there are parameters that need to be determined before the project implementation. This will ensure that the parameter for all reading is uniform throughout the implementation. Figure 3.2 show all the parameter involve in this project.

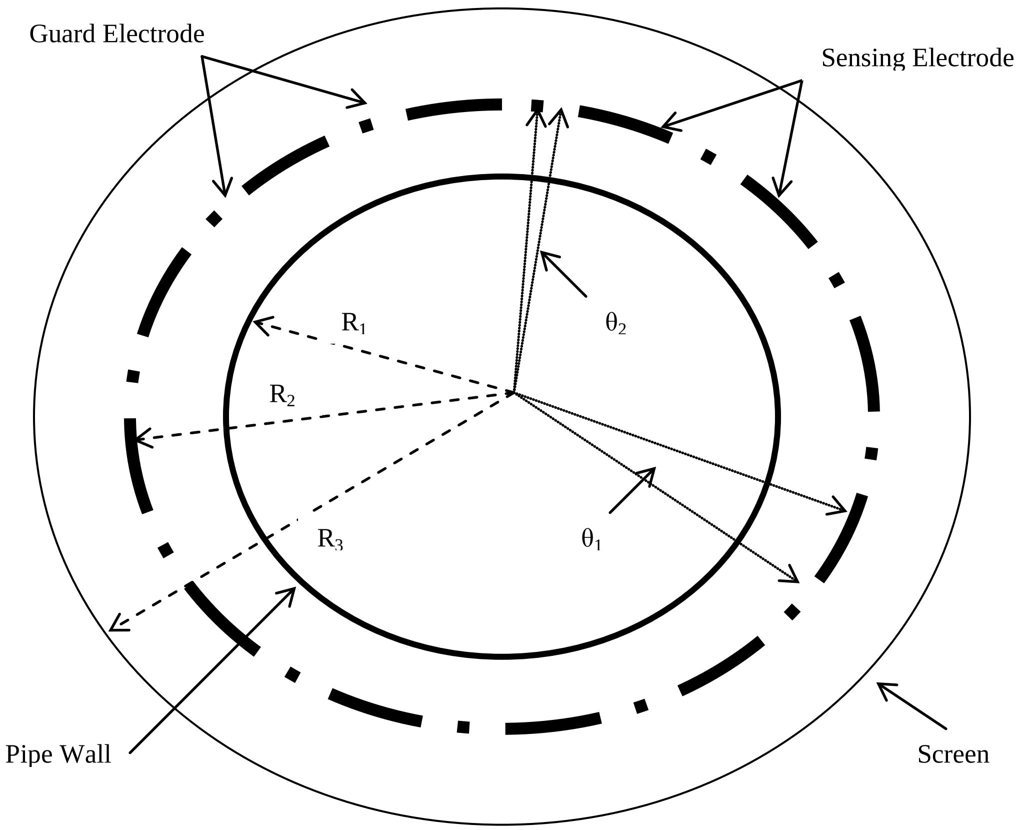

Figure 3.2: Pipe cross-section.

In this project, the parameters explanation and its respective value are listed below:

R_1 = radius of imaging area = 1.0 unit

R_2 = centre to electrode distance = 1.2 unit

R_3 = centre to screen distance = 1.4 unit