

**Cranfield University**

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**Investigation on the use of  
Raw Time Series and Artificial Neural Networks  
for Flow Pattern Identification in Pipelines**

**School of Engineering**

Ph.D. Thesis



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Supervisor: Prof. C. P. Thompson

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”...Frankly I did not consider that this would be a piece of research. The scientist does not usually think of the writing of books or preparing of lectures as research. Writing seems to him to be a rather tiresome labour that he must do after the fun of laboratory research and discovery is over. I therefore sat down to use the time available more in hope of making a summary than a discovery. But when I began to do this I came to realize the extent to which having to describe the results of one’s thoughts to others is a part of the process of discovery itself...”

Written by Prof. J. Z. Young in 1951, in his Reith Lectures for the B.B.C, titled ”Doubt and Certainty in Science: a biologist’s reflections on the brain”.

# Abstract

A new methodology was developed for flow regime identification in pipes. The method utilizes the pattern recognition abilities of Artificial Neural Networks and the unprocessed time series of a system-monitoring-signal.

The methodology was tested with synthetic data from a conceptual system, liquid level indicating Capacitance signals from a Horizontal flow system and with a pressure difference signal from a S-shape riser.

The results showed that the signals that were generated for the conceptual system had all their patterns identified correctly with no errors what so ever. The patterns for the Horizontal flow system were also classified very well with a few errors recorded due to original misclassifications of the data. The misclassifications were mainly due to subjectivity and due to signals that belonged to transition regions, hence a single label for them was not adequate. Finally the results for the S-shape riser showed also good agreement with the visual observations and the few errors that were identified were again due to original misclassifications but also to the lack of long enough time series for some flow cases and the availability of less flow cases for some flow regimes than others.

In general the methodology proved to be successful and there were a number of advantages identified for this neural network methodology in comparison to other ones and especially the feature extraction methods. These advantages were: Faster identification of changes to the condition of the system, inexpensive suitable for a variety of pipeline geometries and more powerful on the flow regime identification, even for transitional cases.

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# Nomenclature

$a$	signal amplitude
$A$	sine wave amplitude
ANN	Artificial neural network
ANNs	Artificial neural networks
B	Bubble flow regime
$c$	wave velocity
$C$	coefficient used in the Taitel and Dukler flow regime transition model for calculating the friction factors for the gas and liquid phases
CoS	Coefficient of Skewness
$C_2$	coefficient used in the Taitel and Dukler flow regime transition model and it is dependent on the size of disturbance on a liquid surface by a wave
$e$	2.718
$f$	frequency
$h$	hidden units index
$H$	number of hidden units
$i$	input units index
$I$	number of input units
$m$	exponent coefficient used in the Taitel and Dukler flow regime transition model for calculating the gas friction factor
$n$	exponent coefficient used in the Taitel and Dukler flow regime transition model for calculating the liquid friction factor
$N$	number of training patterns
$o$	output units index
O	Oscillation flow regime. Also number of output units in a neural network
pattern file	the file that contains the training or testing or any patterns to be used with the neural networks software
P	pressure (bara)
$R_D$	radiation transmitted through full, with process material of density, $\rho$ , pipe
$R_o$	radiation received by a detector for an empty pipe
S	Slug flow regime

SD	Standard Deviation
SS	Stratified Smooth flow regime
SS1	Severe Slugging 1 flow regime
StS	Stratified Smooth flow regime
SW	Stratified Wavy flow regime
$t$	time. Also average thickness of material in pipe, approximately the pipe internal diameter, in the radiation transmission equation
T(BS)	Transitional flow regime between Bubble and Slug
T(BSW)	Transitional flow regime between Bubble, Slug and Stratified Wavy
test patterns	the data that are passed to a neural network at the testing stage of the training process
training patterns	the data that are passed to a neural network during the training process
T(SSW)	Transitional flow regime between Stratified Smooth and Stratified Wavy
T(SW)	Transitional flow regime between Slug and Stratified Wavy
$u$	velocity in the x direction
$U_{gs}$	gas superficial velocity (m/s)
$U_{ls}$	liquid superficial velocity (m/s)
$w$	weights in a neural network
$W$	number of weights in a neural network
$x$	input to a neural network
$y$	output of a neural network

## Subscripts

G	gas
L	liquid

**Greek Characters**

$\theta$	exponent in <i>Logistic Sigmoidal</i> function which determines the gradient of the curve
$\mu$	absorbtion coefficient of material in pipe at 0.66 Mev
$\rho$	density of material in pipe
$\omega$	angular frequency

# Chapter 1

## Introduction

The problem that is considered in this research work falls in the domain of multiphase flows in pipes. By multiphase flows it is meant, flows of fluids that are formed by components of more than one phase. For example these components could be of a solid, liquid or gas phase. This thesis is concerned only with gas-liquid two-phase flows.

The issue with such fluids is to determine for a given condition and pipe configuration, what will be the flow pattern, which is also called the flow regime. Major influences on the flow regime in a pipe are the following:

- the number of phases in the fluid
- the density of each of the phases; for example is it air, water, oil etc. or any combination of them.
- the configuration of the pipe; for example is it a horizontal pipe, vertical, inclined or any combinations of these.
- the superficial velocity of each of the phases.

Example drawings of the main flow regimes in horizontal gas-liquid flow, are shown in Figure 1.1.

There is a large number of publications in the literature about how important the identification of flow regimes in multiphase flows is [14]. The three main issues are:

1. Certain flow patterns are more production efficient than others, hence more desirable, (e.g. the bubbly flow regime).
2. Certain flow patterns can be dangerous and need to be avoided, (e.g. the Severe Slugging [24], [35] family of flows).

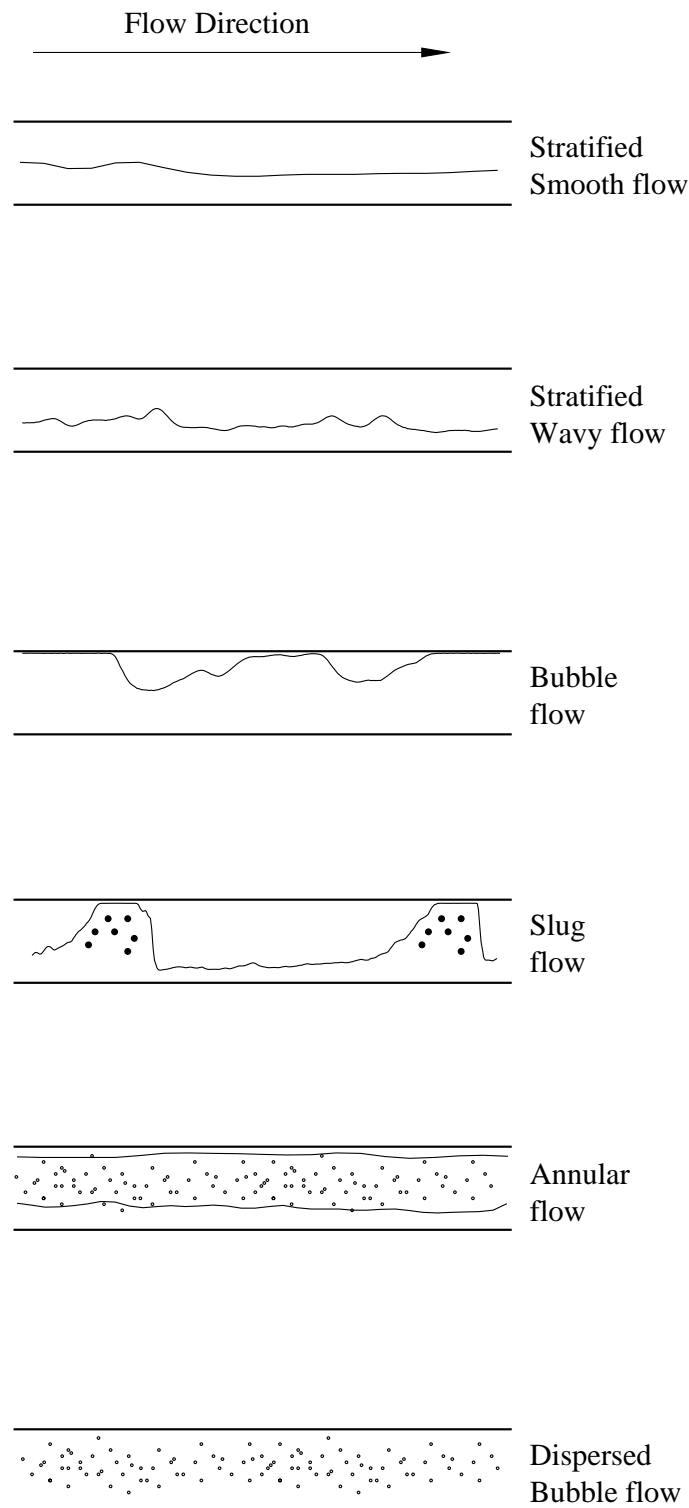


Figure 1.1: Examples of horizontal flow regimes.

3. When designing processing facilities for such multiphase fluids it is important to consider the flow regime before hand as the relationships for quantities like pressure drop, can be different depending on the flow regime. It has been demonstrated that more accurate results can be obtained by giving attention to specific flow patterns ([13]).

Artificial Neural Networks (ANNs) provide an alternative for either modelling phenomena which are too difficult to model from fundamental principles, or reduce the computational time for predicting expected behaviour. Ashforth-Frost *et al.* [1] and Tzes and Borowiec [38] give an overview on the type of applications ANNs have been employed for, in the area of fluid mechanics.

In this thesis a new methodology on the use of Artificial Neural Networks for the identification of flow regimes in pipes is being presented and tested on horizontal flows and S-shaped riser data. The main characteristic of this methodology is the format in which, data from a multiphase flow in a pipe, are presented to the neural network. This format is the unprocessed, raw nature of the data (RD), presented in groups of consecutive data points. Such a way of using data with a neural network has been used before, mainly for prediction purposes [7], [10], [40], [39], but it has not been used for classification purposes like the identification of flow regimes, where it can introduce a number of advantages. The use of features extracted (FE) from the time series, reduces the dimensionality of the data, as one or two values describe the whole signal. This is an advantage when it comes to training the neural network, as the later does not have to be too large and the training process becomes much faster. But it is also a disadvantage as a lot of other information present in the signal is being hidden from the neural network. In addition any major changes in the signal due to, for example changes in the flow regime in a multiphase flow, become unnoticed for a significant period of time, due to the relatively long time series sections [8] that are required for statistical parameters like the mean and standard deviation to be calculated accurately.

The work presented in this thesis, shows that the RD methodology can be used to identify flow regimes in a wide range of pipe configurations. Furthermore during the research it was identified that the methodology has the potential to detect changes in the flow regime as soon as they occur in the pipe, a single network would be adequate, less data would be sufficient during training (compared to the FE methods) and finally a specific highly specialised instrument is not a requirement for monitoring the system.

## 1.1 Objectives

The objectives for this research work were to utilise the capabilities offered by Artificial Neural Networks to achieve flow regime identification in a variety of pipeline geometries with simple and less expensive instrumentation. The main concern with this work is to manage the above in a way so that such a flow regime classifier can be used in real time on systems where multiphase flows occur and the flow pattern is of significant concern.

For this a new methodology had to be developed which would have to consider:

1. how the information obtained from the monitoring system should be used when presented to the classifier. The feature extraction method would not cope with an on-line application due to the reasons that were mentioned above.
2. the neural network architecture that will need to be used to accommodate the above change.
3. monitoring sensors, which can be easily installed on most if not any system but would still provide adequate information for the classification to be achieved.

Finally as this work was carried out towards the fulfilment of the requirements for the degree of Doctor of Philosophy, all the above had to be completed in a time duration limited by these requirements.

## 1.2 Organisation of Thesis

In the rest of the document the research work that is the subject this thesis was organized into the following Chapters. Chapter 2 presents the results of the literature review. The effort for this part of the work was concentrated on collecting techniques which were used in the past for flow regime identification, identify their disadvantages and determine how these could be improved with the new methodology. Emphasis was given on the techniques which utilize the ANN technology as they showed to be the most prominent of all. A general conclusion from this work was that ANNs, being a relatively new technology, are also very new in the area of multiphase flows with not a lot of work being published in the literature. In Chapter 3 a description is given of the new methodology and its advantages and disadvantages are identified and presented. Chapter 4 gives an account of the experimental systems that were considered for the new methodology to be tested on.



The systems are described, together with the instrumentation that was used for data collection and finally the data are presented and analyzed appropriately to be used with the new flow regime identification methodology. Chapter 5 deals with the practical aspects of applying the new methodology and presents the results for the tests that were carried out on all the systems. A detailed description is given on the process of training the neural network for the classification model to be developed and matters that arisen on the data processing that was required for this to be achieved. In Chapter 6 a discussion is carried out on the results that were obtained for each of the systems and on more general matters which are related to the nature of the new classification methodology. Finally Chapter 7 brings the work to its conclusion by highlighting the most important details of the and suggesting a number of areas of research that would be of interest and beneficial to be seen carried out in the future.



# Chapter 2

## Flow Regime Identification: Literature Review

Flow regime identification is important in real world applications where multiphase flows occur. Such an application is the design of transportation systems and processing facilities for the extraction of hydrocarbons from the earth. In these systems the hydrocarbon production rates are affected by the flow regime with which the fluid flows in the pipe, hence the knowledge of the flow regime is necessary for their optimal operation. Furthermore some specific flow regimes can cause damages hence they need to be avoided. Another reason why the identification of flow regimes, which are also known as flow patterns, is important for the more accurate calculation of parameters such as Pressure Drop and Liquid Volume Fraction when designing processing facilities for hydrocarbons.

Some recommended techniques for flow pattern identification fall into three categories:

1. Analytical methods.
2. Visualization methods, including photographic methods, X-radiography and multibeam gamma densitometry.
3. Methods depending on the measurement of fluctuating quantities and the statistical characterization of those in terms of flow patterns.

In the following sections a brief description of the above methods is given. The involvement of the ANNs come under the third of the above categories. A measurement of a fluctuating quantity is taken, this measurement is then processed and instead of a person making a decision on the flow regime, or some other Artificial Intelligence code, the processed signal is used to train

a neural network in deciding which flow regime the signal was taken from. One of the reasons for the involvement of the ANN is to remove as much subjectivity as possible when deciding on the flow regime, as raw signals or even statistical quantities do not always give clear cut indications. An ANN can give more objective flow regime identifications by being trained with clear cut patterns and being used to determine the flow regimes close to boundary regions where the flows are usually more complex. This is a potential offered by the new methodology presented in this thesis and will be discussed in chapter 6.

## 2.1 Computational Methods

Analytical methods are very useful in understanding the mechanics behind natural phenomena and could never be discarded as unnecessary. In the case of determining the flow regime regions for multiphase flows in a variety of pipelines, currently these are separated by thin lined boundaries and in the process of their positioning, a number of assumptions and approximation which add to inaccuracies in the determination of the position and shape of these boundaries, are incorporated. Never the less they are reliable and trusted, as the source of the errors are well known. At the moment they are capable of identifying the main regions of the flow regimes for a variety of pipe configurations ([31], [2], [26]), for different pipe diameters and fluid densities and viscosities. Further improvements need to be made on the more accurate determination of the boundary regions.

Some examples of approximations and assumptions that are used with analytical methods can be found in the Taitel and Dukler 1976 paper [31] where a model for predicting flow regime transitions in horizontal and near horizontal gas-liquid flows is presented. The following examples are given with reference to this paper:

- decision for what values to use for the  $C_L$ ,  $C_G$ ,  $m$  and  $n$  coefficients which are used for the calculation of the gas and liquid friction factors.
- the estimation of the coefficient  $C_2$  is speculated. This coefficient is used for determining the transition criterion of the boundary separating the Stratified region from the Intermittent and Annular regions, and has a significant effect on the calculation.
- The transition between Intermittent and Annular flow is a gradual one unlike the Stratified to Intermittent flows where the transition suggests a sharp well-defined change. So a thin line transition boundary is not appropriate.

- the precise location of the transition curve between the Stratified Smooth and Stratified Wavy regions was not considered important, so it was approximated by using  $u_L = c$  and  $u_G \gg c$ .

## 2.2 Visualization methods

Visualization methods can be separated into two groups:

- the Direct visual observation and Photographic methods and
- the methods depending on the spacial distribution of radiation absorption.

Gad Hetsroni in his *Handbook of multiphase systems* [13] gives a brief description of these and their problems in application.

The first of the above groups require the pipe to incorporate windows or transparent sections, from which the flow can be observed directly or indirectly with the use of mirrors and lenses. Observations can be carried out axially (view inside the pipe) or from the side of the pipe. The need for illuminating the flow is often necessary, especially with photographic methods. For high pressure flows special windows can be constructed (for example of sapphire or calcium fluoride) for visual observations.

Problems in application for this group of visualization methods is that direct visual observations are only applicable to low-speed flows, they are both affected by complex interfacial structures which obscure the view. Such methods only work where suitable visual access can be facilitated and there is a strong element of subjectivity in the determination of flow patterns. Also with the photographic methods there is the element of difficulty in analyzing and interpreting the enormous amount of information that is produced.

The second group of the above methods includes X-radiography and multibeam densitometry. The main principle behind them is to allow an X-ray through the medium for visualization and then determine the amount of the ray that was absorbed in the medium. They can obtain good space and time resolution and can be used with non transparent pipes.

Problems in application for this group is the usual problem of handling radiation. Also they require as thin walls as possible to reduce the absorption of X-rays and increase the time resolution. This introduces a conflict on deciding how thick the walls can be when high pressure operation is required.

## 2.3 Statistical analysis of fluctuating quantities

There are two quantities commonly monitored for the determination of flow regimes:

1. local pressure fluctuations
2. void fraction fluctuations.

Three early examples of research that encouraged this direction of work are those carried out by Jones and Zuber [16], Matsui [19] and Tutu [37].

The time series signals that are collected are statistically analyzed to infer information which can aid in the desired task. Typical statistical calculations that are carried out are:

- mean value of the signal
- Standard Deviation (SD)
- Coefficient of Skewness (CoS)
- power spectral density of pressure signals
- probability distribution of a void fraction signal.

These methods are much more suitable for online applications as there are no requirements for special pipeline materials where instrumentation will be installed. This removes any limitations of operating conditions that the previous methods had. Still they require long time series (see Figure 6.16) in order for accurate calculations to be carried out and they do not always give objective indications for the flow regime in the pipe. For this reason in a lot of research work in the recent years the employment of Artificial Neural Networks (ANNs) was undertaken. ANNs can be trained for many different flow cases and taught to distinguish between them even if there are small differences which would not be picked up by the naked eye. This latest addition seems to give a solution for the subjectivity and misclassification problem mentioned above. The long time series necessary for the calculations of the *mean*, *SD*, *CoS* *e.t.c.* still poses the problem that important information in the time series would be hidden for significant periods of time. For this reason in the work presented in this thesis a new methodology was developed where the measured signals are presented, to the ANN for classification, in their raw time series nature.

## 2.4 Artificial Neural Networks

The involvement of ANNs in the identification of flow regimes in pipes comes under the third category mentioned at the beginning of this chapter (see page 7). One or more quantities which represent the characteristic condition of a system are measured and statistically transformed. The resulting statistical values are fed to an ANN for the flow pattern to be identified.

**General Background** Artificial Neural Networks (ANNs) are a relatively new technology. Although they begun their existence in 1943 when McCulloch and Pitts [20] suggested the simple artificial neuron (see Figure A.2), they only took off in 1986 when Rumelhart, McClelland [15], suggested the Multi-Layer Perceptron and together with Williams the Backpropagation or General Delta learning rule. At this point it was proven that they can solve complicated linear and non-linear problems, which made them widely applicable. Hence 1986 can be considered the birth of the ANN, which is a network of artificial neurons.

These networks usually contain three types of layers (see Appendix A):

1. an input layer
2. a hidden layer and
3. an output layer

There can be more than one hidden layers but usually there is only one input and one output layer. Still there are architectures where there are more than one input and output layers, such as the Time Delay Neural Networks.

Information is usually travelling from the inputs towards the outputs through the hidden layer, with the exception of the Recurrent Networks where there are feedbacks and information travels backwards between the layers or even from a neuron to itself (self-feedback).

### 2.4.1 In Application

The signal of a fluctuating quantity is monitored from the flow, then this is processed and identification of the flow regime is made. The fluctuating quantity usually is either pressure difference across or along the pipe, or void fraction at a cross section of the pipe. The problem usually exists where the processed signal does not always give clear cut indications of which flow regime it belongs to. This is true for both the pressure and void fraction signals. For this reason ANNs are employed at the identification stage by

using the processed signal as its inputs. The reason for their involvement is to improve the classification of less distinctive signals.

As with the statistical analysis methods mentioned in Section 2.3 a number of statistical features are extracted (FE) from the signal. These features are consequently used as inputs to the neural network. Such parameters that have commonly been used are:

- mean
- standard deviation
- skewness

There are a number of research works in the literature where this method has been used on the task of flow regime identification and has been the standard. Bishop and James [3] used the effective path lengths of oil and water from six gamma ray beams to estimate the phase fractions for air oil and water in the fluid. The data they used were synthetically generated for examples of flows with no fluctuations in their phase fractions, i.e. annular, Stratified and Homogeneous but not Slug or Bubble or even Wavy.

Mi *et al.* [21], [22], [23], Smith *et al.* [29] and Tsoukalas *et al.* [36] used data obtained from an 8-electrode impedance void meter to identify a number of flow regimes. Between them, vertical and horizontal flows, plus a number of pipe diameters were considered and some of the parameters that they used to train their neural networks were, *mean* and *SD* among others, determined from the void meter signals.

Hervieu [11] used data from a 16-electrode impedance sensor which monitored features evolving both in time and space. From the measured signals of the sensor, he extracted weighted versions of *mean* and *SD* values for space and frequency components in the measurements. The inputs to the neural network were the average space and frequency components together with the ratio of the standard deviation values between the space and frequency components. This was an attempt to improve the automatic diagnostic capabilities of an earlier work by Hervieu and Seleglim Jr [12] where they used the Gabor transform to carry out unstationarity time-frequency analysis on signals obtained from a multi-electrode impedance sensor. Although the work of the above authors showed some good results; apart from the feature extraction process involved in their methodologies, the choice of their flow monitoring instrument, at least for industrial applications, introduces some limitations. First of all the type of information that is collected by the multi-electrode probe can not be obtained by any other type of instrument due to its plethora of signals it generates simultaneously. So there is no alternative. The instrument itself is not the least expensive and it is difficult



to install as it requires for its electrodes to be electrically insulated from the rest of the pipe. Also as Wu *et al.* [42] have identified, the measurements of an impedance sensor are easily affected by temperature variations, shape and structure of the electrodes and the variation of the dielectric coefficient of the liquid resulting from fluid impurities.

Cai *et al.* [4] used absolute pressure signals from horizontal flows and extracted some amplitude and some frequency-domain features. The amplitude domain ones were *SD*, *Coefficient of Skewness* and *Coefficient of Kurtosis*.

Wu *et al.* [42] used a piezo-resistance differential pressure transducer to monitor a horizontal flow, and fractal theory to extract nine fractal correlation dimensions. They obtained good results but only considered stratified, intermittent and annular flows.

Probably the best flow regime identification results were given by Osman [25], where he considered stratified smooth, stratified wavy, slug and annular flows in a horizontal pipe. His method though, as is also the case for the work carried out by Ternyik *et al.* [34], has one major drawback, which is the use of mean values for the gas and liquid superficial velocities, among others, as inputs to a neural network. Such information for an on-line application is very difficult to obtain, if at all with reasonable accuracy.

There is only one piece of work where a methodology similar to the one presented here was used. This is the work done by Selegheim Jr *et al.* [28]. They used a 16-electrode electrical impedance measuring probe, which has the limitations mentioned above. Their method utilises a separate neural network (MLPs) for each flow regime they wanted to identify, plus a SOM (Self Organising Map) at the end to resolve any multiple classifications obtained from the original MLPs for the same flow regime. Finally they do not separate the Bubble and Slug flows but consider them as a single flow regime the Intermittent flow. They only tested the methodology on horizontal flows, not on an S-shape riser and are using a range of time delays (number of neural network inputs) for each of the flow regimes they considered.



# Chapter 3

## Flow Regime Identification: New Methodology

So far applications of Artificial Neural Networks (ANNs), especially for classification purposes and when working with time series data, would require the extraction of features from one or more time series. These features then would be used as inputs to the neural network.

The process can be computationally intensive and the accurate calculation of the features require the use of long time series, which eventually hide important information from the signal. Such changes could be on flow regimes.

For example one way of extracting features from a time series is by performing an amplitude domain analysis as was done by Mi *et al.* in 1998 ([21]) and 2001 ([22]), Smith *et al.* ([29]), Tsoukalas *et al.* ([36]) and Cai *et al.* ([4]). This can be achieved by calculating the following statistical moments of the Probability Density Function (PDF) [8]:

- mean: average value of the distribution
- standard deviation: measure of the distribution about the mean
- skewness: characterises the asymmetry about the mean.

But the accurate calculation of the mean for a time series is strongly dependent on the length of the time series that will be used, and the mean is part of the calculations in the other parameters as well. The longer the series the more accurate the calculations. Because this accuracy depends on the shape of the series, it is very difficult to determine the minimum amount of data that would be enough, as different time series will require different lengths. The longer these lengths the easier it would be for important variations in

the signal to be hidden for a significant length of time. Inevitably this will reduce the classification ability of the ANN and in turn its response time.

There are applications like control systems, where response time is particularly important. In such cases the above process of feature extraction does not favour very well as they require long with respect to time, time series data, plus significant preprocessing of the data before they can be used.

The new methodology that is proposed here reduces these two factors significantly and provides the grounds for a faster on-line classifier.

### 3.1 The Faster Responding Classifier

This new classification methodology when applied to the flow regime identification in pipelines, is formed of the following parts:

- a time series from an instrument that gives an indication of the liquid level in a pipe.
- a Multilayer Perceptron artificial neural network in a Time Lagged architecture, trained with a supervised learning algorithm, to identify flow regimes that could be present in a system.

Instead of the feature extraction process that was mentioned above the methodology that was used for this work skips this process completely and uses the measured time series, as it is, in its raw form.

For example consider the time series shown in Figure 3.1. Starting from the very first data point of the series the data is split into sections with respect to the time variable. The size of these sections is dependent on the processing window (delay window) that will be chosen. If the window for example is of size  $p$  data points and there are  $n$  number of data points in the series, the resulting sections will be  $[1,p]$ ,  $[2,(p+1)]$ ,  $[3,(p+2)]$ , ...,  $[(n-p),n]$ .

The series is presented to the neural network in the form of such sections (delay windows). Then the neural network is trained to identify the flow regime the currently presented time series section belongs to. This network is of the supervised type, a Multilayer Perceptron (MLP). The number of its inputs is equal to the size of the delay window and the number of its outputs is equal to the number of flow regimes that it is required to identify.

So an important issue for this methodology is deciding on the delay window that should be used. This is not as straight forward as it will be shown in the following chapters where applications of the methodology will be described. From the ANN's point of view it is very important that enough part of the cycle from the time series is present with each input pattern.

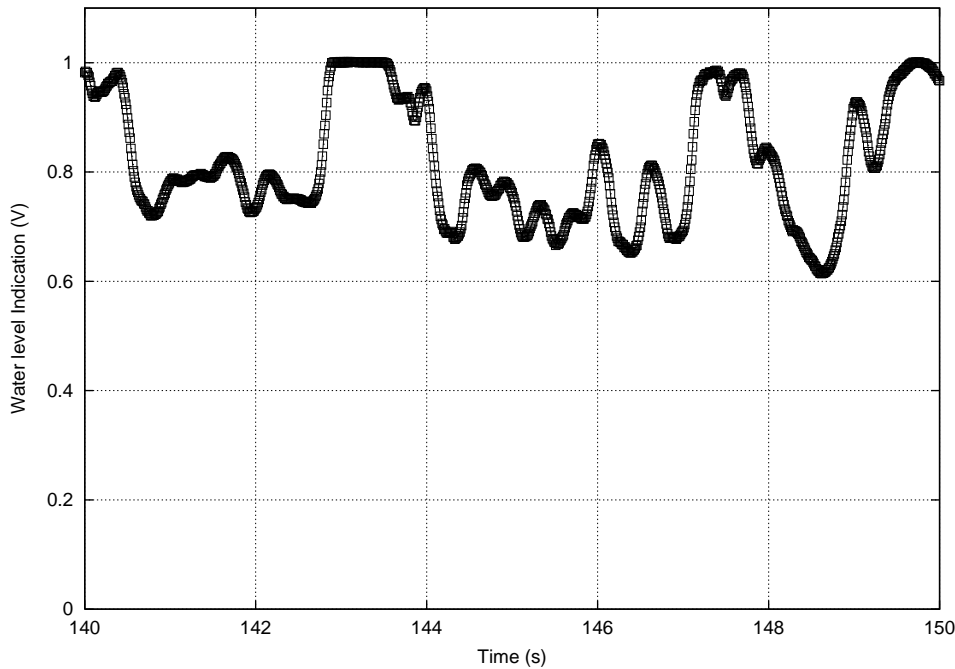


Figure 3.1: An example of a time series.

This makes it certain that the network will learn to distinguish between the different time series. But a cycle is not always present or at least not easily identified in order for the delay length decision to be made. Hence a few tests have to be carried out in order to establish a suitable delay window.

For the systems that the methodology was applied on, it was experimentally found that a delay window of 200 inputs (20 s) of data for the Horizontal Pipeline and 100 inputs (100 s) of data for the S-shape riser, were sufficient for the task of multiphase flow regime classification.

## 3.2 Advantages and Disadvantages

The main application of this new methodology is for the on-line monitoring of dynamic systems. Although it has been tested on multiphase flows in pipelines specifically, it may not be limited to these systems only.

**Advantages** Considering that the on-line monitoring, is the area of application for the new methodology described above, its main advantage is that: *all the information that is collected from the system is also simultaneously present in the ANN inputs for consideration.*

This gives the monitoring system that it will be used with, the potential to identify important changes much faster than the existing neural network methodologies. Thus making it more suitable for online, real time applications.

Furthermore the raw time series nature of the input data allows for the possibility to train the neural network on clear cut, away from transition regions, flow regime cases. This is because the inputs incorporate the distinctive pattern of each flow regime and this same patterns are also there in the signals collected from transitional cases but mixed together. Still not simultaneously mixed, like in the fashion of one pattern on top of the other, but one following the other. This characteristic of the methodology also gives it a more global nature that could make a model trained with data from one system, suitable for another system with the same family of characteristics. For example if the original "*training*" system was an S-shape riser, then the resulting model could be suitable of all S-shape risers. Finally the notion that a model can be built from only clear cut cases, makes the training process much faster as less data will be required to train the network.

As it will be shown in the results and discussion chapters of this thesis (chapters 5 and 6), the new methodology described above identifies the flow regime correctly for cases all around the flow regime map and gives indications of where the boundaries of a transition region lie.

It is logical to deduce from the last statement that apart from using the methodology to identify flow regimes on line it can also be used to generate more realistic flow regime maps, where the transition regions will be portrayed as regions and not as thin lined boundaries.

**Disadvantages** The main disadvantages of the new methodology that was described above are those associated with the nature of the neural network technology, the training process.

This process requires the identification of the characteristic condition(s) of the given system, the ability to reliably measure their physical quantities and finally carry out the necessary experiments to collect enough data from all the required system states.

Assuming that the characteristic conditions are known and can be measured reliably, the data collection process may not be always possible or may be very costly. In such cases the use of simulated data can provide the means for building the model.

### 3.3 Model creation procedure

With this new methodology, where the data is used in its time series (raw) form, one is presented with the issue of how should the data be split into the training, testing and validation groups that are required during the classification model development.

There is an issue here because the input data to the neural network have to be different between the three stages. With current methods of feature extraction and flow regime identification, this meant that the data for each stage had to be derived from different flow cases, ie data points on the flow regime map. This is because only one or two numbers (the features that were chosen) were used to represent each flow case. However the new methodology presented here uses hundred of different inputs from each flow case signal. Hence, is it still necessary to use different flow cases for each of the stages in the model development or would parts of the same ones be enough?

In this work the flow cases that were available were split into *Training* and *Model Validation* cases. Each time series from the training cases was split into two parts: the training and the testing part. In this way it was made sure that there were not any two input sets which contained the same data point from a time series.

#### 3.3.1 Data Preprocessing During Model Development

The following steps were carried out during the model development process:

1. choosing the training and validation data flow cases
2. choosing the time delay with which each flow case data signal will be presented to the neural network. In other words deciding on the number of inputs for the neural network that will be trained.
3. splitting the training data signals into training and testing
4. normalizing the final data files.

#### Choosing the training and validation data flow cases

The general guide that was followed on the choices for the training and validation data was the following.

The training flow cases should be chosen to be the ones which have the highest degree of confidence on their flow regime class that they have been allocated with. They should also spread to all corners and mid areas of the

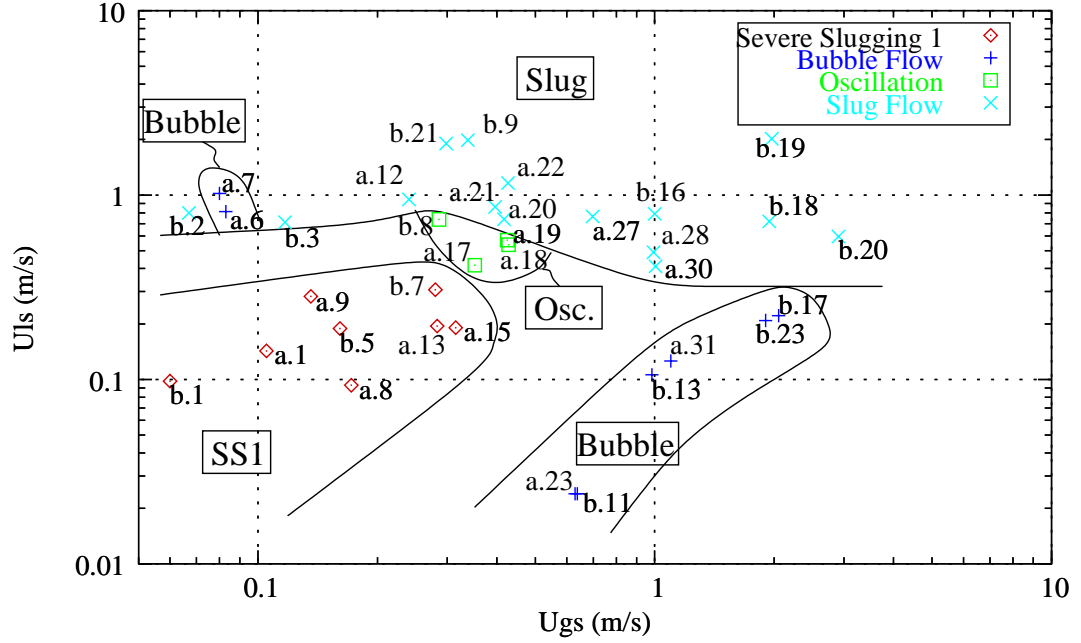


Figure 3.2: The training *a* and testing *b* cases plotted on a flow regime diagram for the S-shape riser.

flow regime regions. More weight should be given to the confidence of their classification as incorrectly classified data will lead to incorrectly trained network.

The validation cases can be the rest of the data in the total data set. It should be made sure that in this data set, there are examples from each flow regime the network is trained to identify.

According to the above the flow cases for the two data sets that were chosen are shown in Figure 3.2. In this figure the training cases are labelled with *a* and the test cases are labelled with *b*.

Although the training cases that are shown in Figure 3.2 do not cover all the corners of the slug regime, so do not comply partially with the second part of the above guide, the main reason why the shown training cases were chosen is that these are the cases whose flow regime class has the most confidence.

### Choosing the Time Delay window

The time delay window was chosen after a rough observation of the training time series. It was decided that the time delay window should be large enough to contain the largest identifiable cycle found in the training time series. But because the longest cycles are the ones found in the Severe Slugging 1 (SS1)



flow cases and these are very long comparing to the cycles found in the other flow regimes, it was decided that a window half of the longest cycle would be sufficient. This was also decided upon because the SS1 time series are also very distinctive even with half the cycle present.

As the longest training data cycle was 230 s, the delay of 100 seconds was chosen.

### Splitting the signals into training and testing parts

It is important that the same amount of data is used from all the flow cases data in the training data set. This is to ensure that equal amount of training is done to the network for each flow case. Although extra training may be needed for a specific type of data, this is because some flow cases may have too complex shapes, or the network seems to perform worse on them, during the first attempts to train a network it is important that there is a uniform training for all the cases. Hence to achieve this and because not all the signals are of the same length, the shortest signal (*base* signal) is found and its length is used to establish the amount of data that will be used from all the signals in the data set. Then each signal is split into training and testing parts, by using a 3:1 ratio respectively, determined from the *base* signal. For any signals that are longer than the *base* signal, after the training part is separated, all the remaining signal was used for testing.

There is also the issue of deciding which parts of the signal should be used for training and which for testing. The aim is to make sure that the two sets of the signal do not share any of the signal's data points. One way to ensure this, is by randomly allocating the delayed blocks of the time series between the training and the testing sets. This would certainly prove to be ideal as it would ensure that the network will be tested with examples from every part of the signal. However this does require a significantly large data sets for the reason that a single *delay* sized data block chosen to be used for training will make  $(2 \times \text{delay} - 1)$  number of data blocks unsuitable to be used for testing. This is because any block which has its origin within the first one will share some of its data points with it and there are  $(\text{delay} - 1)$  data points which can be used as origins for other *delayed* data blocks. For example if the delay is 100 data points, as it was used for some of our experiments, and following the 3-to-1 ratio between training and test data blocks there can be only one set of training/test blocks (300 training and 100 test) from every 600 (300 training + next 100 obsolete + 100 test + next 100 obsolete) data points. If the signal was sampled at 1 Hz this would mean that there could only be one training/test set from every 600 seconds or 10 minutes of data points.

Therefore the random selection of the test data has not been chosen to

be used here especially when some of the data files contain less than 600 s of recording. For this reason the signal is split into blocks whose size is at least the size of the delay window. Then using the 3:1 ratio mentioned above the first part of the signal is used for training and the rest of the signal for testing.

Another issue here is that there should be at least 400 s of recording in any of the data files to be used. The 400 s would give 100 data sets for training and 100 data sets for testing, which is the minimum number of data sets for training and testing that can be obtained. This does not follow the 3:1 ratio mentioned previously but still gives data sets large enough to work with.

In general the data from the different flow regime cases were processed following the concept shown in Figure 3.3.

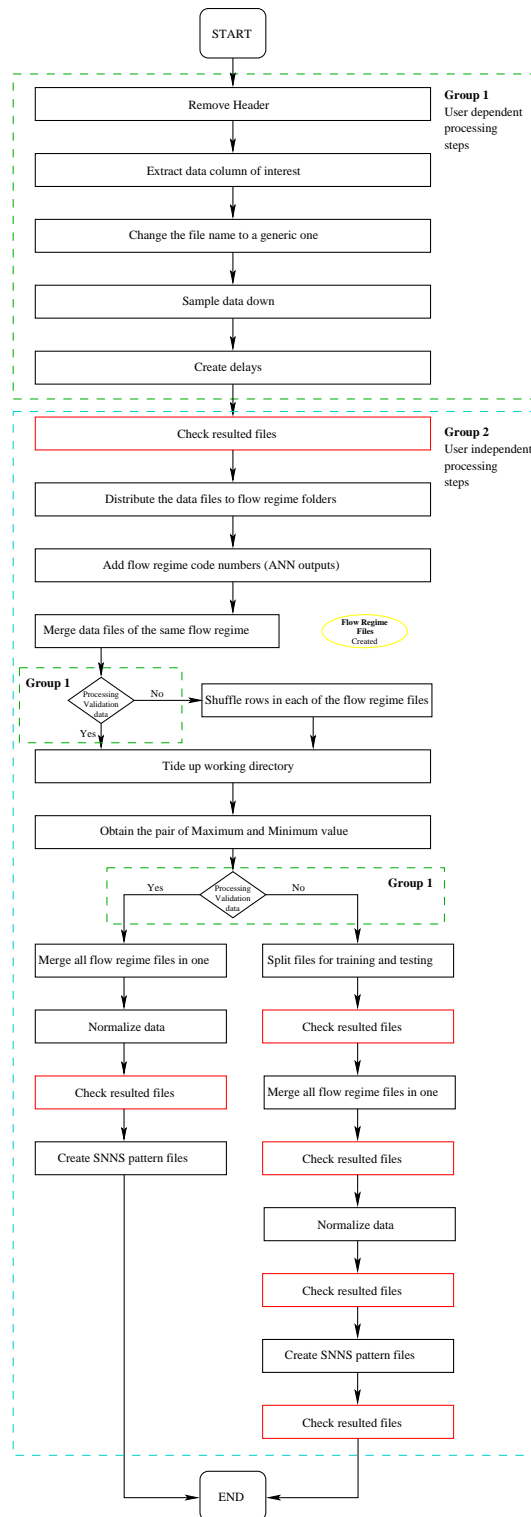


Figure 3.3: Chart of all the processing steps carried out on the data files for each system where a flow regime identification model was attempted to be build.



# Chapter 4

## Multiphase Flow Data Collection Experiments

Three different types of data sets were collected experimentally or synthesized in order for the new methodology to be developed, and in turn to be also tested.

Originally a set of synthetic time series of four well defined classes, was generated, so that the behaviour of the artificial neural networks with respect to inputs of time series data could be investigated. After some important conclusions were made and a methodology was formed, a set of two experimental data sets was obtained in order for the newly developed methodology to be tested with. One of these sets was data from a horizontal multiphase flow system and the second was from a S-shape riser system.

This chapter gives a description of the three sets of data that were obtained, together with the experimental facilities that were used in the process. Also an account on the data analysis that was carried out for each of the data sets is given. Hence the chapter has been organized into three sections, one for each data set, with a number of relevant sub sections.

### 4.1 Synthetic Data

This section describes the first system that the new methodology was applied on. This is a conceptual system which could be thought of as a more general hypothetical dynamic system. The data used here were synthetically generated from combinations of sine waves. The specifications which were followed in order to decide on the type of signals that should be generated were based on observation on pressure signals collected from real multiphase flows in pipes. These signals, among them, had variations in shape, frequency

and magnitude of amplitude. Hence according to these observations, the following equations were used to generate four signals which, among them, incorporated the above three variations. The number of signals types that were going to be generated was chosen arbitrarily. Samples of the actual signals are shown in Figure 4.1

$$a = A \sin(\omega t) \quad \text{Signal No.1}$$

$$a = A \sin(\omega t) + \frac{A}{2} \sin\left(\frac{\omega}{2}t\right) \quad \text{Signal No.2}$$

$$a = A \sin(\omega t) - \frac{A}{4} \sin\left(\frac{\omega}{4}t\right) \quad \text{Signal No.3}$$

$$a = A \sin((t^2) + \sin((\omega t)^2)) \quad \text{Signal No.4}$$

where

- $a$  = signal amplitude
- $A$  = sine wave amplitude, was set equal to 4 for all the Signals except Signal 4, for which it was set equal to 1
- $\omega$  = angular frequency  $\omega = 2\pi f$
- $f$  = frequency, was set equal to 1
- $t$  = time in seconds, it was incremented every 0.25 s (sampling frequency  $f_s$ )

Because the above signals were formed from combinations of sine waves and sine waves from their nature are periodic, this does not reflect the nature of signals obtained from real systems. Such signals are infested with non periodicities and noise. Hence in order to test the methodology with a more realistic conceptual system the data that were generated with the above equations were transformed to “noisy” versions by altering the parameter  $A$  once every two periods ( $T$ ) with  $T = 1\frac{1}{f}$ . The alteration value was allowed to randomly vary within the  $[-0.5, 0.5]$  interval. This random variation of the amplitude  $A$  parameter, altered the amplitude  $a$  of the original signals by  $\pm 10\%$  on average for signals 1, 2 and 3 and  $\pm 50\%$  for signal 4. All the alteration values that were added to the constant parameter  $A$  in the above equations is shown in Figure 4.2.

Another reason for creating this “noisy” version of the signals was to vary each cycle, of the original periodic signals, from the rest. This way a better test would be performed on the abilities of a neural network to learn to identify a signal. This is because each signal will be sectioned into a *training* and a *test* part and the two of them will not contain any subsections which could be common to both parts. The resulted “noisy” signals, are shown in

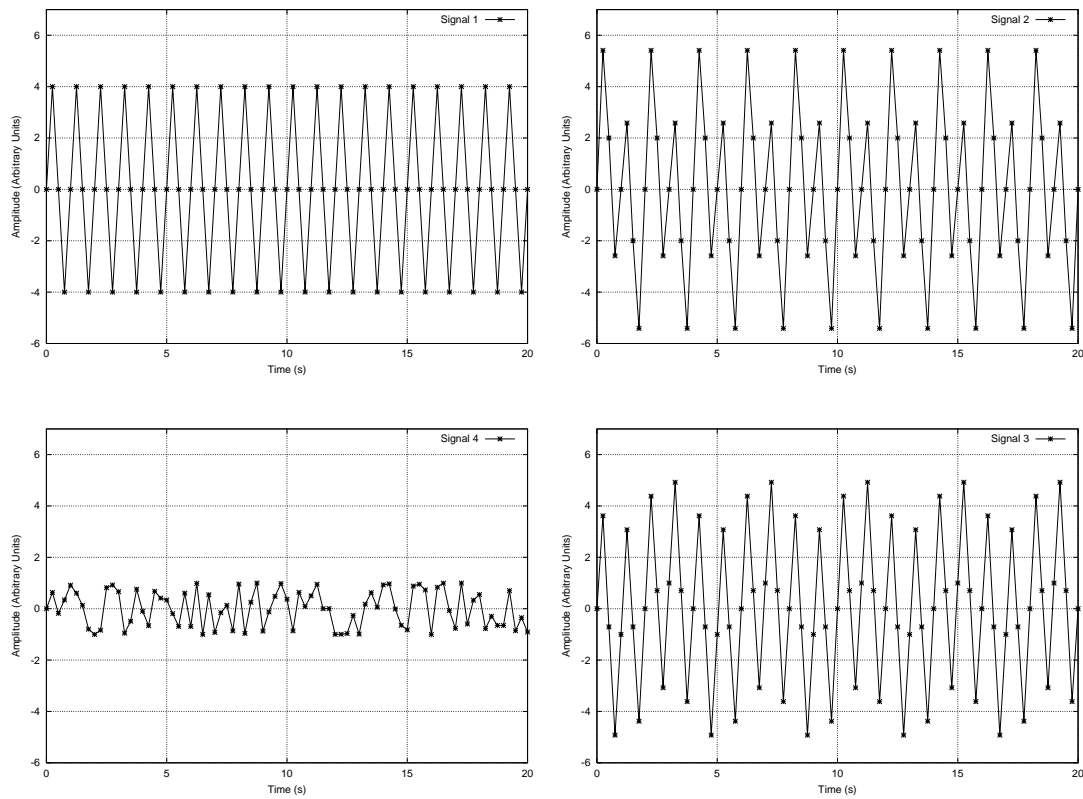


Figure 4.1: Time series examples for the above equations, in the same order, clockwise from top left.

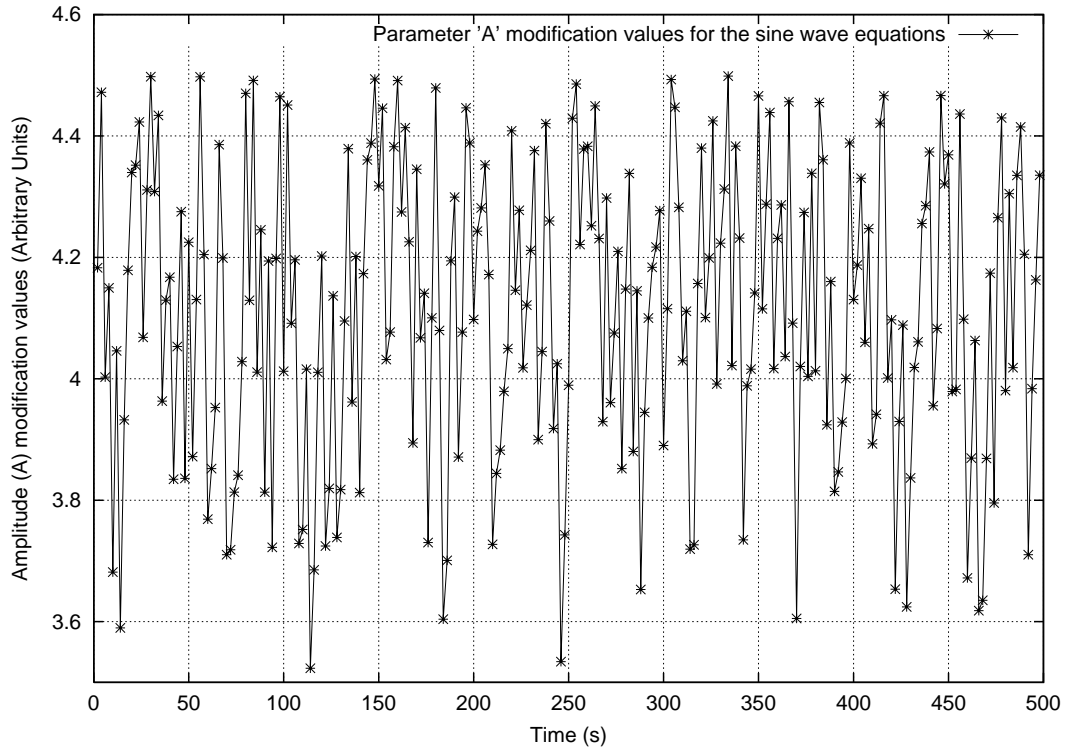


Figure 4.2: All the random amplitude modification values that were used on top of  $A = 4$  for Signals 1, 2 and 3, and  $A = 1$  for Signal 4.

Figure 4.3, all plotted one after the other. For comparison their “clean” from “noise” versions are also plotted in the same fashion and also the same order.

The motivation behind these experiments was:

- to develop and test the methodology against data of well known classes where there was no issue of subjectivity.
- for familiarization purposes both with the
  - ANN theory and software applications that go along with it and
  - working with time series.

### 4.1.1 Data Analysis

Since this set of data was generated synthetically, the classes that each of the signals belonged to was predetermined. Hence there was no need to analyze the data in order to find out how they are clustered with respect to each other. This was all ready known.



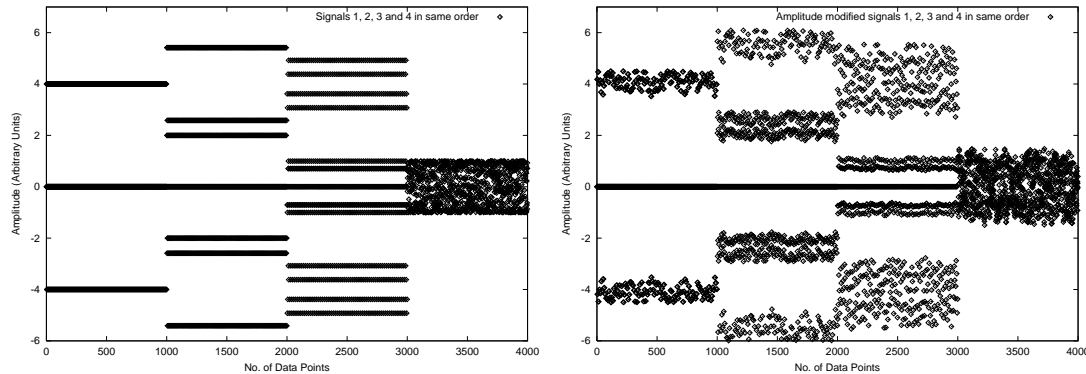


Figure 4.3: The resulted “clean” and “noisy” versions of the above time series (same order, signals 1, 2, 3, 4).

## 4.2 Horizontal Multiphase System

These multiphase flow experiments were required in order to collect two-phase flow data, from a horizontal pipe, for as many flow regimes as possible, given the existing experimental facilities.

### 4.2.1 Three Phase Test Facilities

A simplified description of the 3-phase test facilities that were used, together with the test section employed to collect the data, are shown in Figure 4.4.

The main components of the test facilities that were of most importance for the experiments are the following:

- Air compressor
- Water pump
- Air-Liquid mixer
- Data acquisition system
- Test rig

These are briefly described in the following paragraphs and a description of the test rig is given in Section 4.2.2.

Oil and water are pumped from their reservoirs, through their metering points and into the mixing stage. At the same time air is compressed into a buffer vessel of  $2.57 \text{ m}^3$  to about 10 bar in order to obtain a constant, stabilized flow. The compressed air then expands through its metering point,

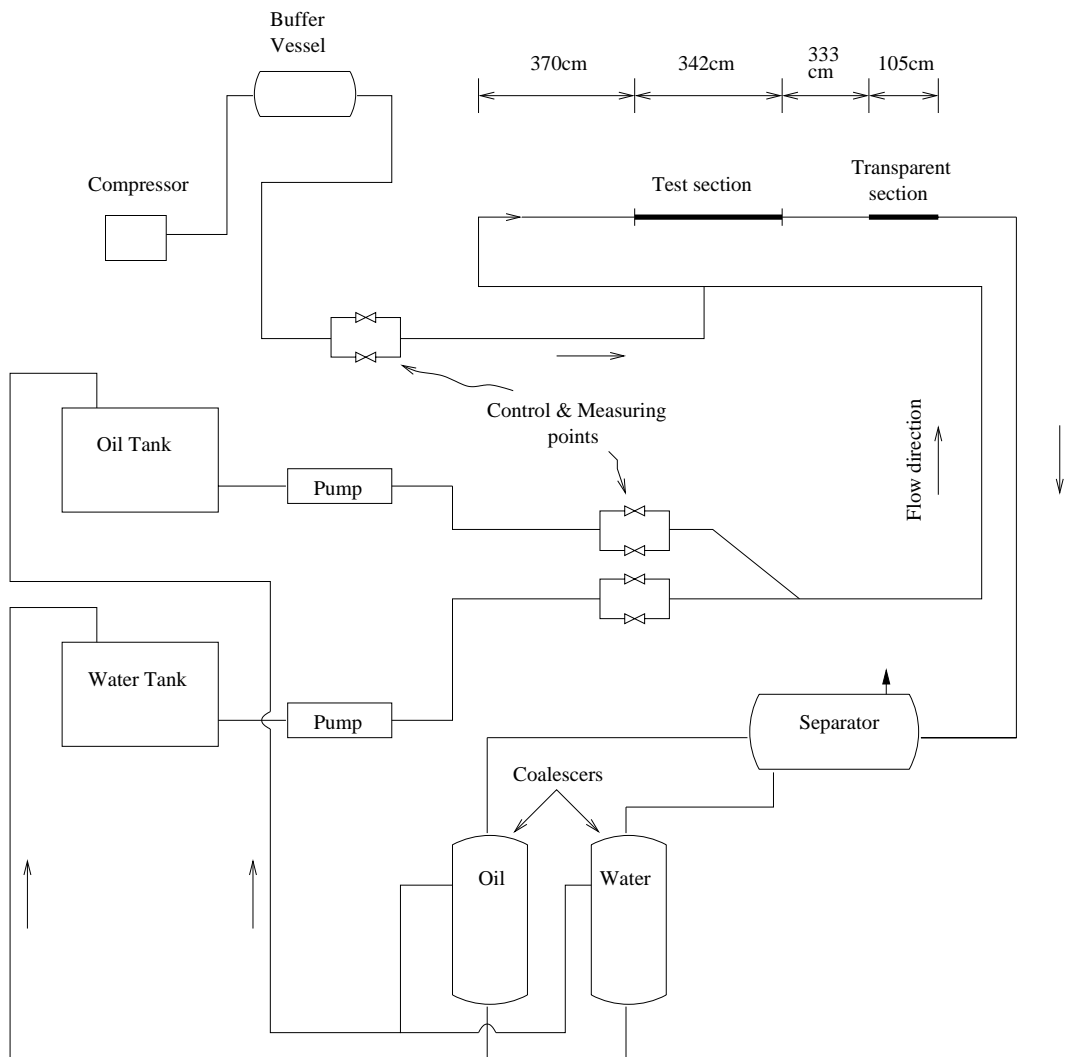


Figure 4.4: Diagram of the multiphase flow facilities incorporating the horizontal test section.

before which, its flow rate is controlled by a needle valve. The liquid and the gas are then mixed together before entering the horizontal part of the test rig and into the test section. From the liquid–air mixing point up to the separator inlet, all pipes were of 4 inch diameter, unless otherwise stated. The horizontal section before the test section was 370 cm long (36 diameters). The test section was 342 cm long and at a distance of 333 cm from its end there was a transparent section, 105 cm long and with 113 mm diameter. The test section was formed of pipes with 102 mm diameter and the rest of the pipeline, apart from some pipe sections on the facilities which were made of steel, connecting the test section to the 3-phase facilities was made of plastic pipes of 100 mm diameter. After the transparent section there was an extra 572 cm of horizontal pipe before the fluid went down a significant length of a gradually lowered pipeline and finally reach a riser of 167 cm height in order to enter into the separator. At this point a primary separation of the phases was carried out, with the air escaping into the atmosphere and the oil and water directed into the respective coalescers for further more fine separation. Finally from the coalescers the two fluids were flushed back into their reservoirs and repeated their cycle.

**The Air Compressor** The compressor supplying the air was an Atlas Copco reciprocating type with a maximum supply capacity of 600  $m^3$ /hr Free Air Delivery (FAD) at 18 bar.

**The Water Pump** The pumps supplying the water and oil were of a Worthington Simpson, positive displacement type. They have maximum capacity of 35  $m^3$ /hr and discharge pressure of 6 bar. Their output flow rate was controlled crudely by using a by-pass line back to the pump inlet, in order to re-circulate any excess fluid.

**The Air-Liquid Mixer** The air-liquid mixing was achieved by inserting a 20 mm diameter pipe, from a T-junction into the main facilities pipe, with an outlet parallel to the direction of the flow (see Figure 4.5).

**The Data Acquisition System** The Data Acquisition (DAQ) system used an Analogue to Digital (A/D) converter card which was installed in a 800 MHz PCI computer. The card was of a PCI-MIO-16E-4 type with a speed of 250 kS/s (250 kHz) in single channel operation. The resolution available was 12 bit which gave 2.4 mV resolution on 10 V full scale. The maximum sampling rate that was allowed by the DAQ software was 1 kHz.

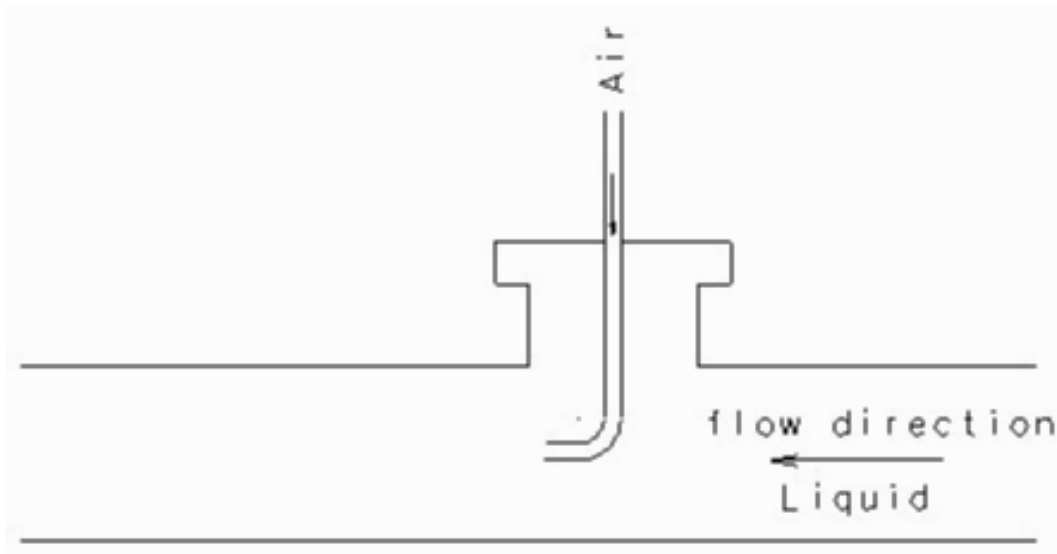


Figure 4.5: Diagram of the Air-Liquid Mixer.

### 4.2.2 The Test Rig

A detailed diagram of the test rig is shown in Figure 4.6 including the horizontal inlet and outlet sections. The instrumentation attached to the rig and their actual order was (see picture in Figure 4.7):

1. Gamma ray density gauge
2. Capacitance measurement system 1
3. Conductance transmitter 1
4. Capacitance measurement system 2
5. Conductance transmitter 2
6. Absolute pressure transducer
7. Differential pressure transducer 1
8. Differential pressure transducer 2
9. Temperature transducer

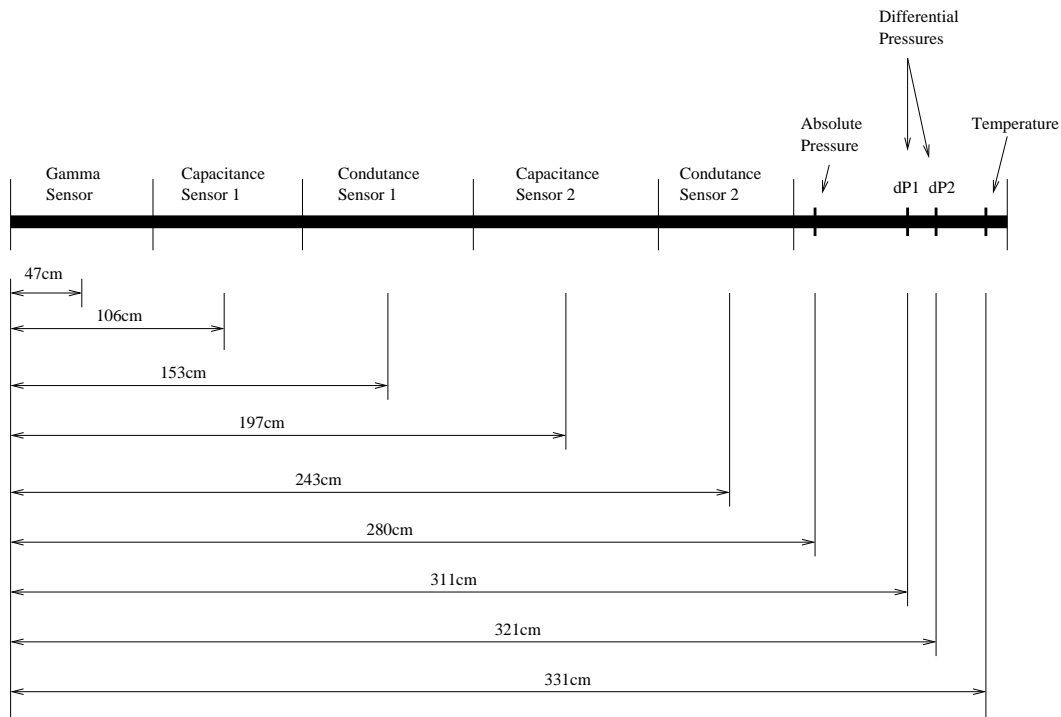


Figure 4.6: Diagram of the test rig that was used for the experiments.

### Gamma Ray Density Gauge

The gamma ray density gauge, by Ronan Engineering Limited, comprises a shielded source holder containing a radioactive Cesium (Cs-137) source, a detector unit and a signal processing box. The source had a strength of 185 MBq.

The source holder and the detector are mounted directly opposite each other across a stainless steel pipe. During operation a beam of gamma radiation is directed from the source holder, through the complete cross sectional area of the pipe and the process material inside it, onto the surface of the detector. Some amount of radiation is absorbed by the material through which it passes and some is transmitted to the surface of the detector. The absorbed radiation is directly related to the density (or mass) of the material it went through while the transmitted radiation is inversely related to that density (or mass).

The electronics in the signal processing box scan the transmitted radiation every 125 ms (8 Hz) and calculate an average of the signal for every 100 ms. This characteristic of the instrument makes it unsuitable for certain flow conditions (e.g. slug flow and bubbly flow). Hence for such flows it is more



Figure 4.7: Picture of the horizontal test rig. The Gamma densitometer is on the far side.

appropriate to use the raw data from the densitometer before the processing, which gives the radiation transmitted through the processing material onto the detector in the form of counts or pulses, which are sampled every 1 ms (1 kHz). These counts can be converted to density values afterwards by using the following equation

$$R_D = R_o e^{-\mu \rho t}$$

### Capacitance Measurement System

This measuring system was supplied by Siemens Milltronics Process Instruments B.V. and combines a flow sensor assembly, model MFT300, and a flow transmitter, model MFT200. It provides a fast signal response of up to every 1 ms (1 kHz). It responds both for water and oil, although its response for the later is much lower in signal output.

### Conductance Transmitter

The conductance transmitter, model MGT9500, was supplied by Siemens Milltronics Process Instruments B.V. It is only suitable for products with high conductivity, e.g. water but not oil. It lets a very small current to flow through the product between a pair of ring electrodes. It has a fast response time of up to 1 kHz.

### Absolute Pressure Transducer

The absolute pressure transducer, model PMP 4010, was supplied by Druck and it was of a silicon diaphragm type. It had a range of 20 bar and an output voltage of 0 to 5 V D.C. It incorporated corrections for thermal induced errors and Non-Linearity and Hysteresis of +/- 0.08 % maximum.

### Differential Pressure Transducer

The differential pressure transducers, model PMP 4110, were supplied by Druck and were of the silicon diaphragm type. They had a range of 0.7 bar and output voltage of 0 to 5 V D.C. They incorporated corrections for thermal induced errors and Non-Linearity and Hysteresis of +/- 0.08 % maximum.

They were mounted across the top and bottom of the stainless steel pipe and measured the differential pressure between the mountings.

Test set	No. of test points	Superficial Velocity range (m/s)		
		Air	Water	Oil
Air-Water	38	0.01 - 5.03	0.005 - 0.85	NA
Oil-Water	8	NA	0.02 - 0.97	0.14 - 0.28
Air-Oil-Water	27	0.03 - 2.97	0.03 - 1.01	0.03 - 0.29

Table 4.1: Table showing the test matrix together with the velocity ranges used for each of the phases.

### Temperature Transducer

The temperature transducer, supplied by CT Services, was a T-type thermocouple. It had a range of -200 to 400 °C. Its signal response was of the order of 1 Hz.

### 4.2.3 Experiments

There were 2-phase (Air-Water and Oil-Water) and 3-phase (Air-Oil-Water) experiments carried out using the three phase test facilities and test rig described at the beginning of Section 4.2.1. The rig operating pressure was kept between 2 and 3 bar.

The procedure for the experiments, involved:

- setting the flow rates for each of the phases involved
- allowing a 5 minutes period for the flow to settle down
- recording data for the next 5 minutes at least. For some flow regimes with long or unrecognizable cycles (e.g. flow regimes close to transitional boundaries or slug flows) the recording time was longer. Sometimes up to 20 minutes long.

The five minutes settling time was decided experimentally.

The test matrix, which shows the number of test points that were obtained and the flow rate ranges for each of the phases, for all the three above mentioned experiments is shown in Table 4.1. The limited number of Oil-Water tests was due to the shortage of oil. Hence tests with higher oil flow rates could not be carried out.

A more detailed description of each of the test cases is given in the following, specific to each case sections. In this thesis only the Air-Water two-phase flows are being presented since they were the only data that was utilized to apply the new methodology on.



A flow regime map that was drawn for the specific test rig and was used as a guide to create a test matrix for each set of experiments is shown in Figure 4.8. This flow regime map was created with the *Barnea*<sup>1</sup> unified model for predicting flow pattern transitions [2].

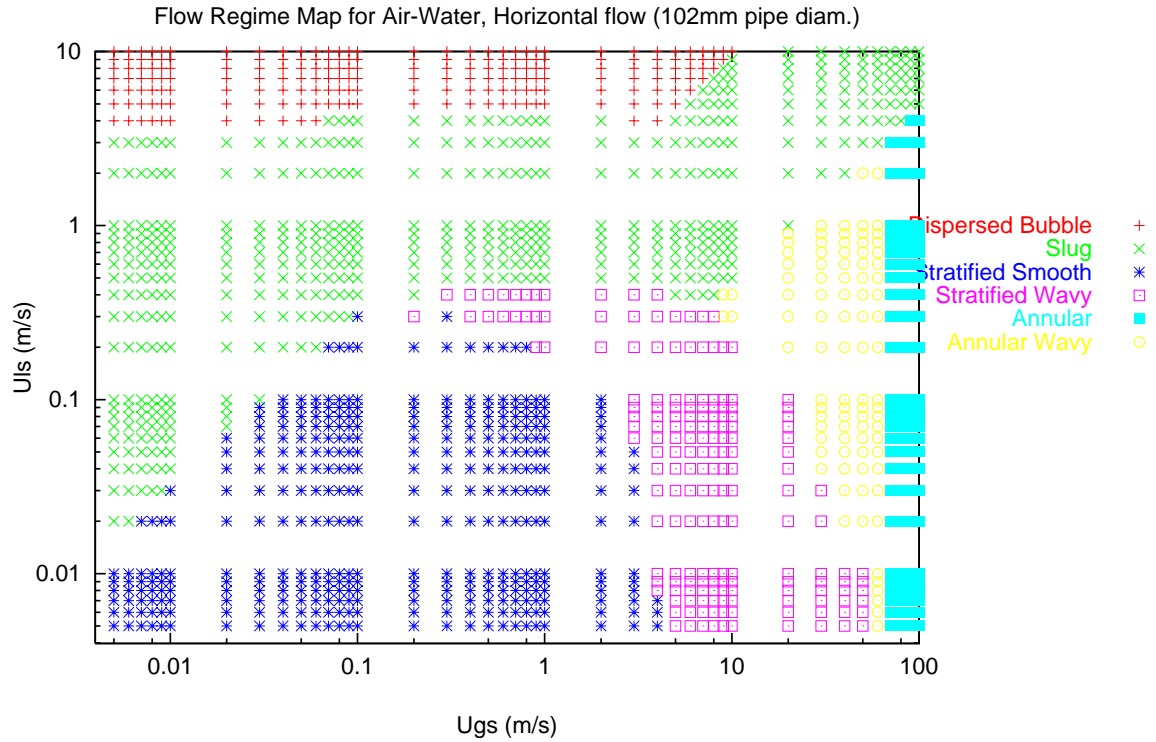


Figure 4.8: Flow regime map created using the *D. Barnea* unified model [2], for the 102 mm 'test rig' pipe diameter.

## 2-Phase Air-Water

There were 38 experimental points obtained on the flow regime map for this set of experiments. They are shown superimposed on the above flow regime map in Figure 4.9.

<sup>1</sup>Determines the flow regime in a flow given the gas and liquid velocities, pipe diameter and fluid properties. Software was provided by Christian Omgba-Essama from Cranfield University.

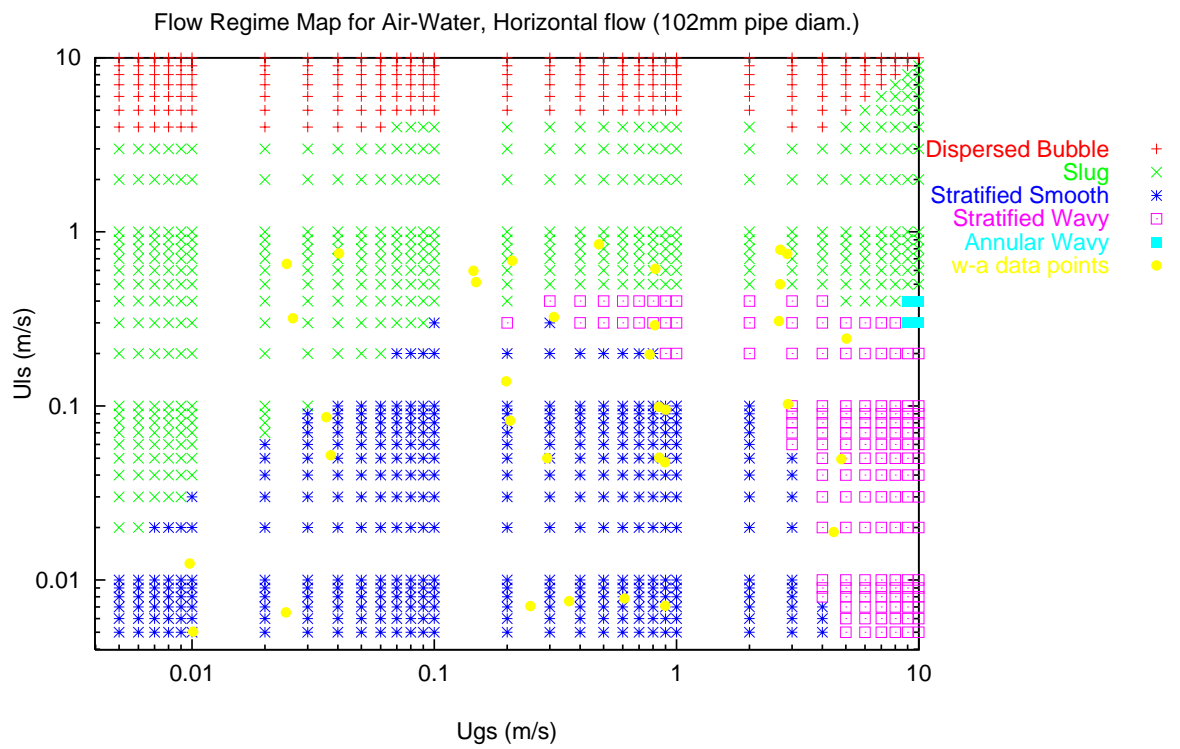


Figure 4.9: Experimental data points for the 4 inch horizontal pipe.

Experimental flow case	1	2	3	4	5	6	7	8	9	10
Flow regime class	StS	StS	StS	StS	StS	StS	StS	StS	StS	StS
Experimental flow case	12	13	14	15	17	18	19	20	21	22
Flow regime class	StS	StS	StS	StS	StS	StS	T(SSW)	StS	SW	T(BSW)
Experimental flow case	23	24	25	26	27	28	29	30	31	32
Flow regime class	SW	SW	B	T(BSW)	SW	SW	B	T(SW)	B	B
Experimental flow case	33	34	35	36	37	38				
Flow regime class	S	B	T(BS)	S	S	S				

Table 4.2: Table showing a summary of all the flow cases for which data was collected and the flow regimes they were classified with from visual observations.

#### 4.2.4 Data Analysis

The flow regime present in each of the flow cases was determined from visual analysis of video recordings and the time series of the collected data itself. The results of the analysis are summarised in Table 4.2

where

StS	=	Stratified Smooth
SW	=	Stratified Wavy
B	=	Bubble
S	=	Slug
T(SSW)	=	Transition between Stratified Smooth and Stratified Wavy
T(BSW)	=	Transition between Bubble, Slug and Stratified Wavy
T(SW)	=	Transition between Slug and Stratified Wavy
T(BS)	=	Transition between Bubble and Slug

A flow regime map that was drawn from the observations and Table 4.2 is shown in Figure 4.10

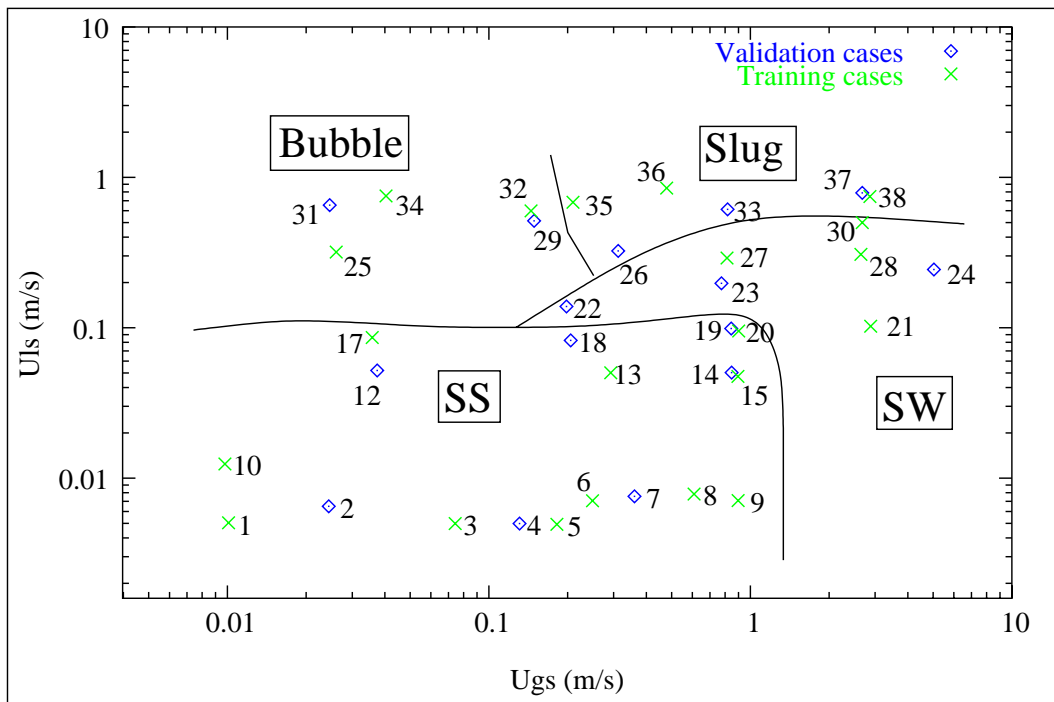


Figure 4.10: Flow regime of the Horizontal system, drawn from visual observations.

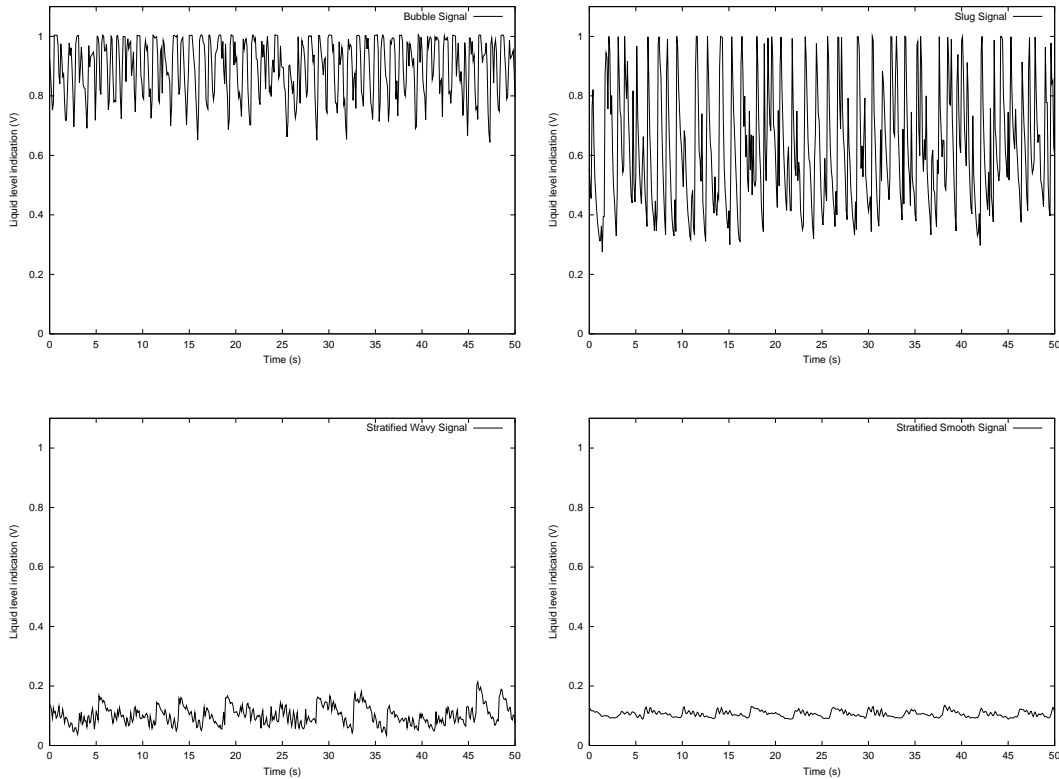


Figure 4.11: Examples of data from the four flow regimes (clockwise from top left): Bubble, Slug, Stratified Smooth and Stratified Wavy, collected from the Horizontal system.

As it can be seen from Figure 4.10 the data that was used belonged to the following four flow regimes

1. Bubble
2. Slug
3. Stratified Smooth and
4. Stratified Wavy

Example signals from all of the four flow patterns are shown in Figure 4.11.

From observing the stratified smooth signal one wonders why there are waves in this flow pattern. The explanation that can be given is the waves are present due to the pipeline geometry. More specifically at the inlet of the horizontal test section there was a small riser (see Figure 4.12), 60 cm



Figure 4.12: The small riser found at the inlet of the test section. This could be the cause for the small waves seen during stratified smooth flows.

in height and 70 in length, which could have caused at occasions, for the air to be blocked before the inlet of the riser, by the water inside it. Hence the blocked air would build up pressure until it is sufficiently high to push a small volume of water and reach the inlet of the small riser where it can push its way through the water. This displacement of the small volume of water causes the small ripples seen in the signal as the water is pushed in the horizontal section. A similar effect could be caused by the bigger riser found at the far end of the test section were the pipeline enters the inlet of the separator (see Figure 4.13). This riser was 167 cm in height. Due to its bigger size, this riser could explain the occasional sightings of the slightly bigger waves that can be seen in the time series of the stratified smooth signals.

This phenomenon was also presented by Takenaka [32] in his review of some problems found present in gas-liquid flows. He states that although



Figure 4.13: The slightly larger riser found at the end of the test section, where the pipeline enters the separator.

trapped air always absorbs surges of pressure, Kitagawa [17] has revealed in his 1975 paper (in Japanese) that under certain conditions, the pressure surge was enhanced by such an air chamber or trapped air. It is believed that such a condition is the one specified above. In more detail the trapped air at the bottom of the larger riser preceding the separator, builds up pressure. When this pressure becomes high enough it pushes the water in the riser causing a pressure drop in the pipe line. This pressure drop is followed by a sudden water level rise which is portrayed by the larger of the waves in time series of the Stratified flows shown in Figure 4.11. In turn the movement of the water reduces the pressure in the smaller riser on the other side of the test rig and allows the trapped air on that side to enter the riser and push a small amount of water into the horizontal section causing the smaller waves that follow the larger first one.



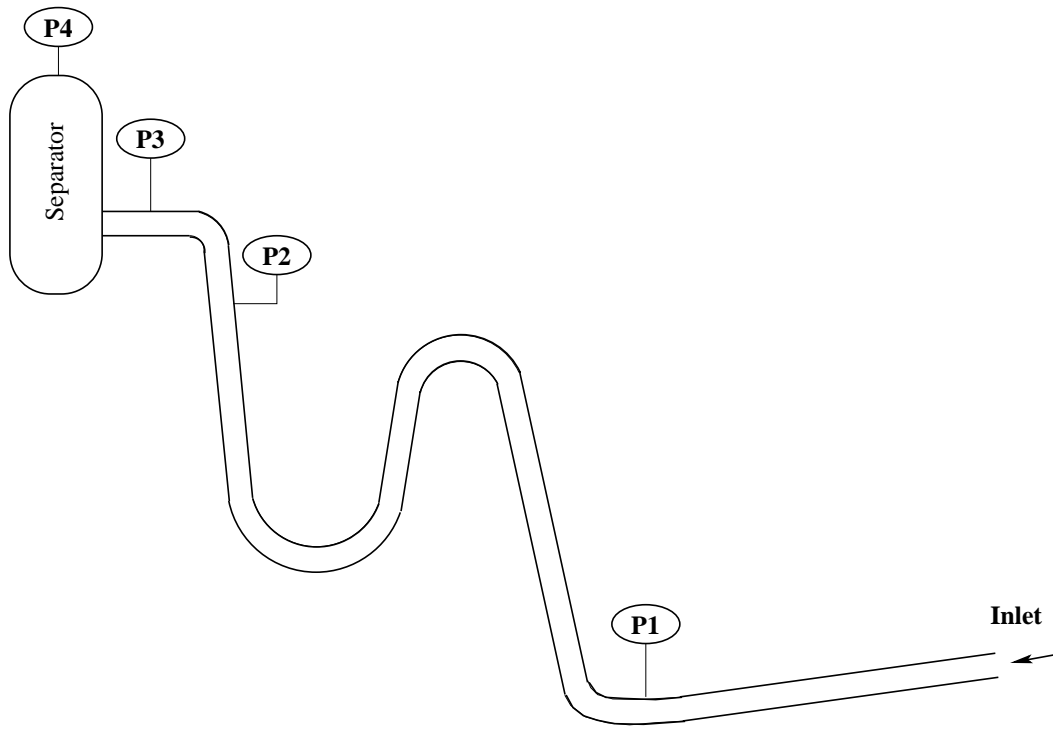


Figure 4.14: Simplified diagram of the S-shape riser rig used to collect the third set of data.

### 4.3 S-shape Riser System

These sets of data were collected by Montgomery and a more detail description of the rig and the data collected is given in his thesis [24]. For convenience a brief description is given here and a simplified diagram is shown in Figure 4.14. The S-shape riser system consisted of a 50 mm (2 inch) carbon steel flanged sections. The inlet section was inclined at  $-2^\circ$  to the horizontal and had a total length of 57.4 m. The riser was a Lazy-S configuration and had a total height of 10 m and length of 21 m. The flow from the top of the riser progresses around a  $90^\circ$  bend and exits the test section into a 0.5 m diameter separator. From the separator the fluids were metered and recombined to be returned to the base facilities.

There was pressure and liquid hold up monitored at different positions on the riser. From these, for the flow regime identification purposes of this work, the pressure signals were chosen to be used since pressure is a parameter which reflects the a state of a multiphase system in a more global manner than the liquid hold which only shows the condition of the system at the

point of measurement. This global representation of the system is important for online monitoring of flow regimes since identification of any changes are desirable well before the change in condition reaches the processing facilities. Also this is of much greater importance in S-shape risers and risers in general than horizontal pipes, because cycles are much longer there and the flow regime varies at different sections of the riser. From the total number of pressure signals that were available, P1, P2, P3 and P4 were chosen to be investigated for their fitness to our purposes and their positions are shown in Figure 4.14. The reasons behind these choices were the following. P1 gives an indication of what is happening in all the riser above it, which is the area of interest since its geometry is what causes any undesirable flow regimes to be formed. Still P1 is located at a position which in real life systems could be at the bottom of the ocean, hence difficult to reach and expensive for any instruments to be installed. Hence the other three pressure signals were also chosen for their convenience in locality and out of interest to see if there was any significant difference between them. As it is mentioned in more detail in the analysis of the data in Section 4.3.1 the difference between pressure signals P1 and P4 was chosen to be used for this work due to its best distribution and separation that it showed for each flow case signal. However the differences in shape between all of the raw signals were quite small and there is a strong possibility that the P2, P3 or P4 signals could have sufficed on their own.

All the flow cases that were used are shown on a flow regime map in Figure 4.15

As it can be seen from Figure 4.15 the data that was used belonged to the following four flow regimes

1. Bubble
2. Oscillation
3. Slug and
4. Severe Slugging 1

Example signals from all of the four flow patterns are shown in Figure 4.16.

### 4.3.1 Data Analysis

For this system, although each experimental set of data was all ready analyzed and classified into a flow regime, there was a number of pressure signals

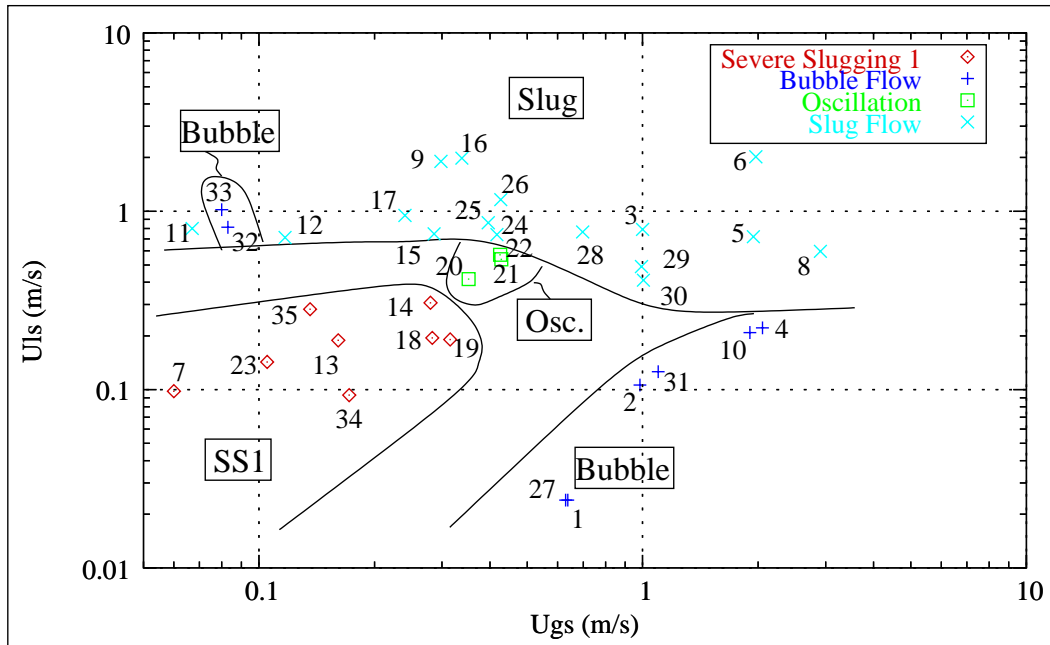


Figure 4.15: Experimental data points for the S-shape riser rig.

available to be used with the neural network methodology presented in this thesis. In order to choose which one would be best to use, it was highly desirable to try and visualize them.

It is always helpful to obtain a visual observation of data which will be attempted to be clustered, whether ANN are to be involved or not. A visual observation is usually obtained with a plot. This means that the data vectors can not have more than three dimensions. Some graphics applications can go a step further and plot up to four dimensional vectors by using as a fourth dimension on the plot, colour. Since for this set of data there were no visual observations from the experiments to help with their classification into the appropriate flow regimes or with the validation of their classifications, it was desirable to try and plot the data. In the case of the current methodology, the information used with the neural networks is formed from much higher dimensional sets. They go as high as 200 dimensions, which makes it impossible to obtain a visual image of it with the usual methods. For this reason the Sammon Mapping method (see section B in the Appendices) was used in order to map the high dimensional data into 2D and obtain an indication of the clusters they are separated into.

For the observations given below, plots of shuffled input data were used. This is because, to use all the data with the *Sammon* map software caused

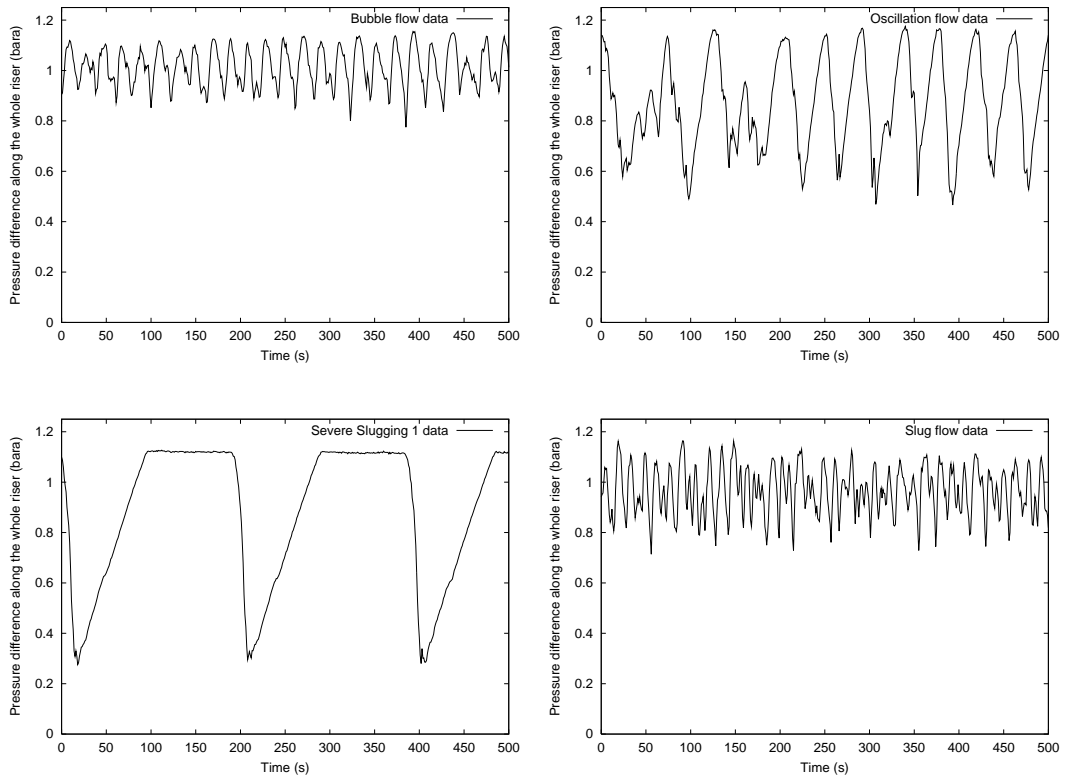


Figure 4.16: Examples of data from the four flow regimes (clockwise from top left): Bubble, Oscillation, Slug and Severe Slugging 1, collected from the S-shaped Riser.

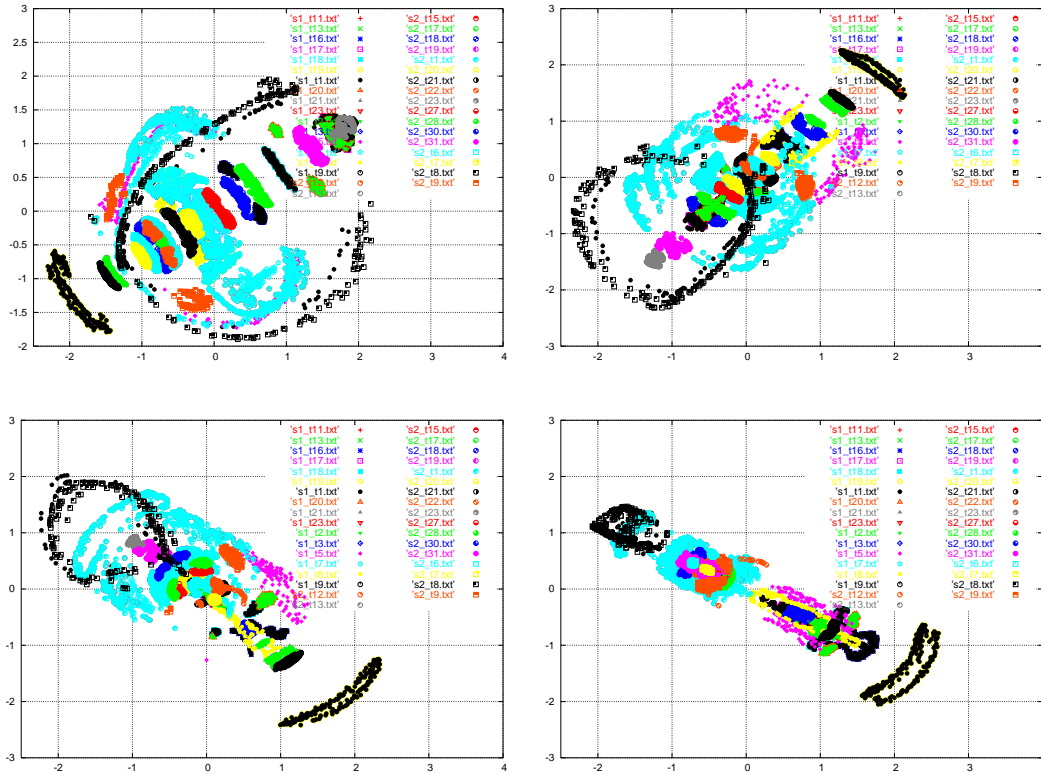


Figure 4.17: Sammon maps drawn for pressure signals collected from four different positions of the S-shape riser. The four positions, clockwise were P1-P4, P1, P3, P2.

the computer to run out of memory and stop the process without completing it. As it is mentioned in the appendices, this is a limitation of the software and it is caused due to the large amounts of computations that it carries out. Hence a smaller amount of less data was taken from each flow case file that was processed for SNNS. In order to get a good representation of the full signal from each flow case, the small number of 200 rows from each file were taken randomly, hence the shuffled input data. It should be mentioned just for comparison that 13 out of the 31 SNNS processed files, had 1400 rows. The rest were a mixture between 500 and 900 rows. Also the use of less data made the 2-D maps less cluttered, which helped in their observation. Referring to Figure 4.14, Figure 4.17 shows the Sammon maps for neural network input data sets generated from signals of the following pressures: P1, P2, P3 and P1-P4.

In order to help with their analysis, the more general Sammon maps shown in Figure 4.17 were further simplified by creating separate maps for

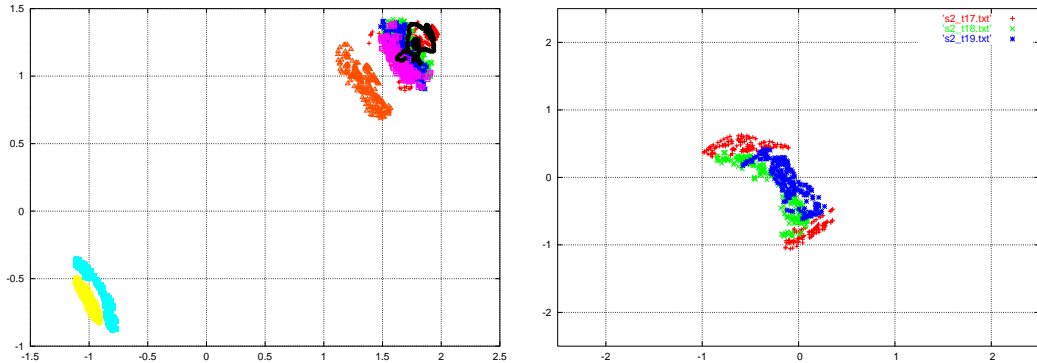


Figure 4.18: Sammon Map of the Bubble (left) and Oscillation (right) cases for the P1-P4 data.

each flow regime. Such maps are shown in the following paragraphs between Figures 4.18 and 4.23 for the P1-P4 data. Also magnifications of regions of the more general Sammon maps were created to help with the task. An example of such magnifications is shown for the P2 data in Figure 4.24 at the end of this chapter. These graphs are given with and without the SS1 cases, because as it will be shown below, the SS1 points in the Sammon maps, overlap with many of the data points of the other flow regimes.

The conclusion from the analysis was that the P1-P4 data showed less overlap between the different flow regime clusters than the P1, P2 and P3 data. By overlapping it is meant that parts of the signals from one flow regime show enough similarities with parts of the signals from other flow regimes for their vectors to fall on the same position of a two dimensional space. Such a characteristic of the data is undesirable if a neural network is to be trained to distinguish between them. In the following paragraph the detailed analysis is given for the P1-P4 data as an example of the method that was used to analyze them. For the flow case numbers refer to Figure C.1 in the appendices which follows the same labelling system as the labels in the Sammon maps.

### P1-P4 Sammon Map 2-D data analysis

- The Bubble and Oscillation data show no overlap at all (see Figure 4.18).
- Between the Bubble and Slug clusters (see Figure 4.19), there is only partial overlapping from some of the Slug case 11 data with some of the data from almost all but three of the Bubble cases. From examining the time series part of case 11 does look like bubble and it is also close

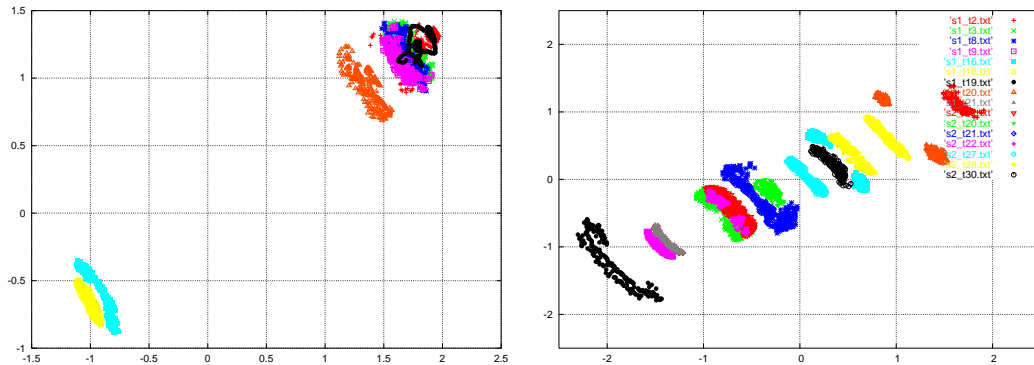


Figure 4.19: Sammon Map of the Bubble (left) and Slug (right) cases for the P1-P4 data.

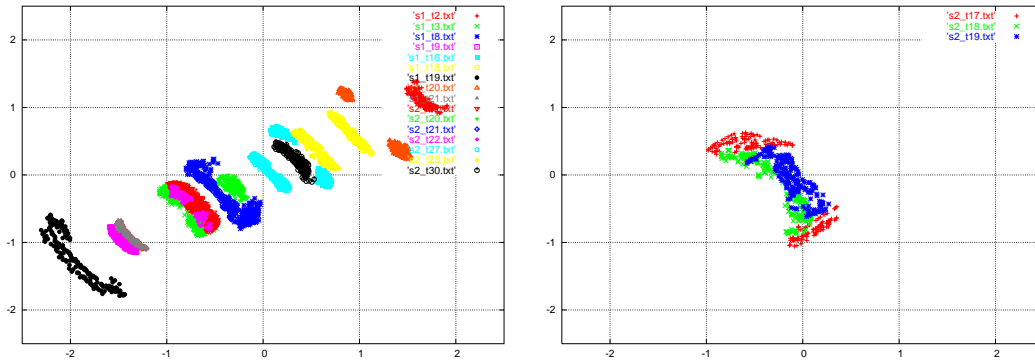


Figure 4.20: Sammon Map of the Slug (left) and Oscillation (right) cases for the P1-P4 data.

to the 32 and 33 bubble cases (see flow regime map in Figure 4.15). Hence it can be considered transitional.

- Between Slug and Oscillation cases (see Figure 4.20), there is only part of the Slug case 15 that overlaps with some of the Oscillation case 21 and Oscillation case 22 data. Still case 15 is close enough to the borders of the two flow regimes to be considered transitional. Also, case 15 was originally classified as Oscillation flow by Montgomery in his thesis. But a closer comparison of its time series with other Oscillation and the Slug flows available it was decided that it was more appropriate to classify it as Slug.
- Between the Bubble and SS1(see Figure 4.21): the Bubble cases 31, 32 and 33 are completely clear from any other flow regime data. The

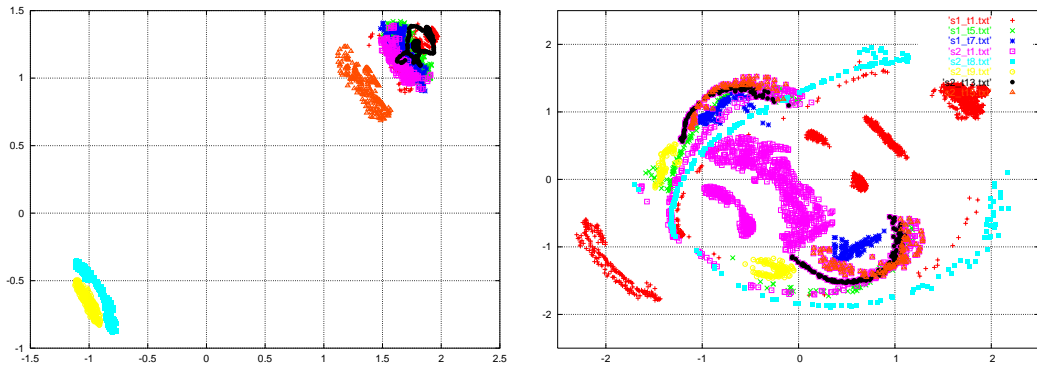


Figure 4.21: Sammon Map of the Bubble (left) and Severe Slugging 1 (right) cases for the P1-P4 data.

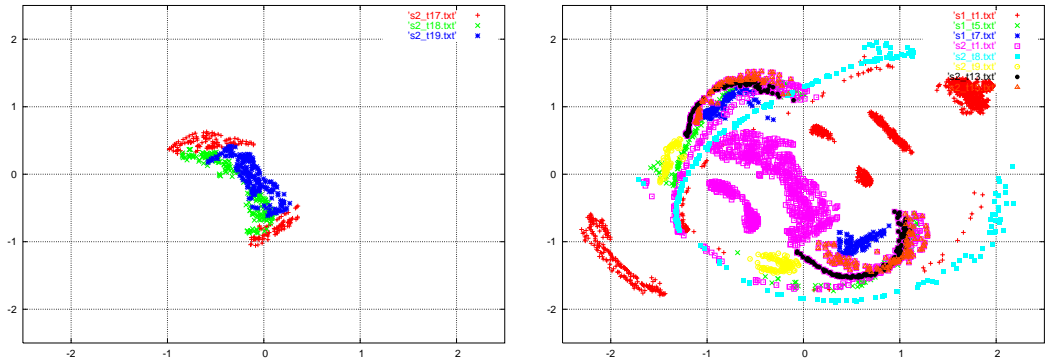


Figure 4.22: Sammon Map of the Oscillation (left) and Severe Slugging 1 (right) cases for the P1-P4 data.

rest of the Bubble cases which are on top of each other in one cluster overlap with some of the SS1 case 7 data.

- Between the Oscillation and the SS1 cases (see Figure 4.22), all the Oscillation data overlap with the SS1 case 23 data.
- Between the Slug and the SS1 cases (see Figure 4.23), there are the following data overlaps:
  - some of the SS1 case 7 data overlap with some of Slug case 11 data.
  - all of the Slug case 3 and 5 data overlap with some of the SS1 case 7 data.



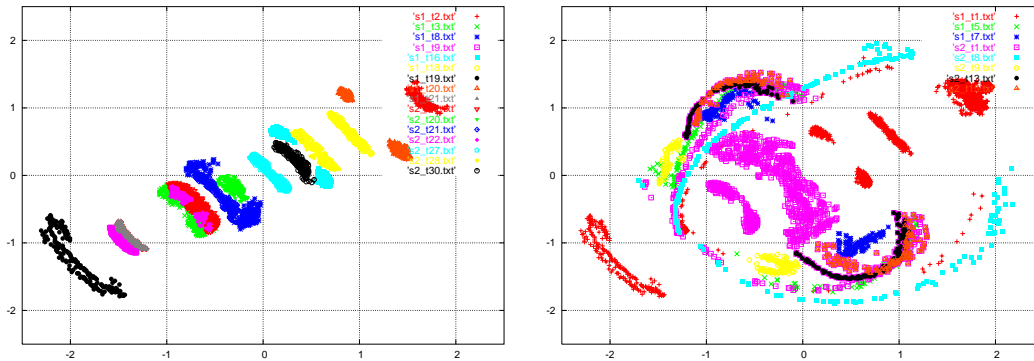
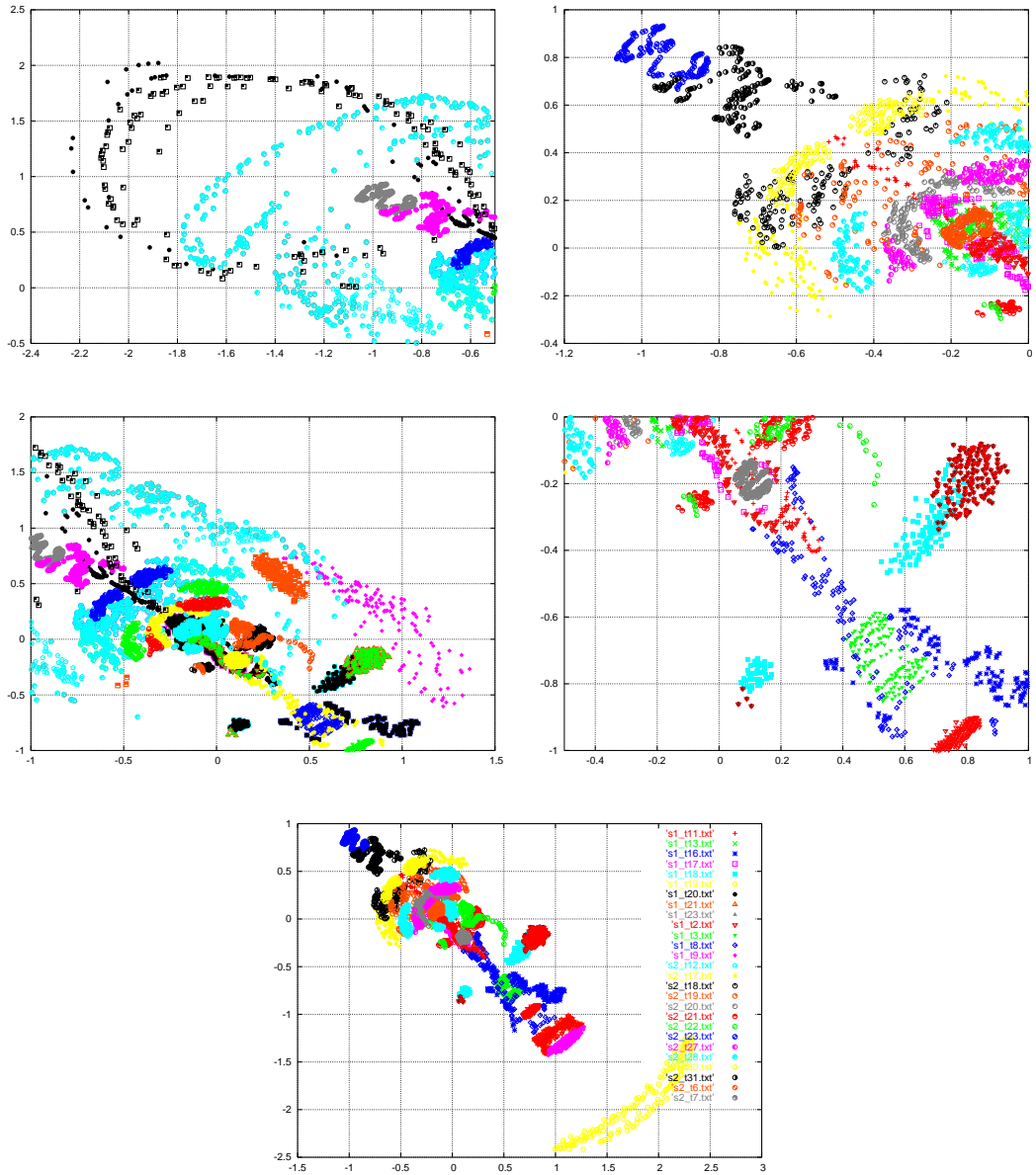


Figure 4.23: Sammon Map of the Slug (left) and Severe Slugging 1 (right) cases for the P1-P4 data.

- all of the Slug case 17 data overlap with some of the SS1 case 23 data.
- all of the Slug case 6 data overlap with some of the SS1 case 7 data.
- of course there is also the same overlap between the SS1 and the Slug cases, as it is mentioned above between the oscillation and the slug data, since all the oscillation cases overlapped with the SS1 case 7 data.



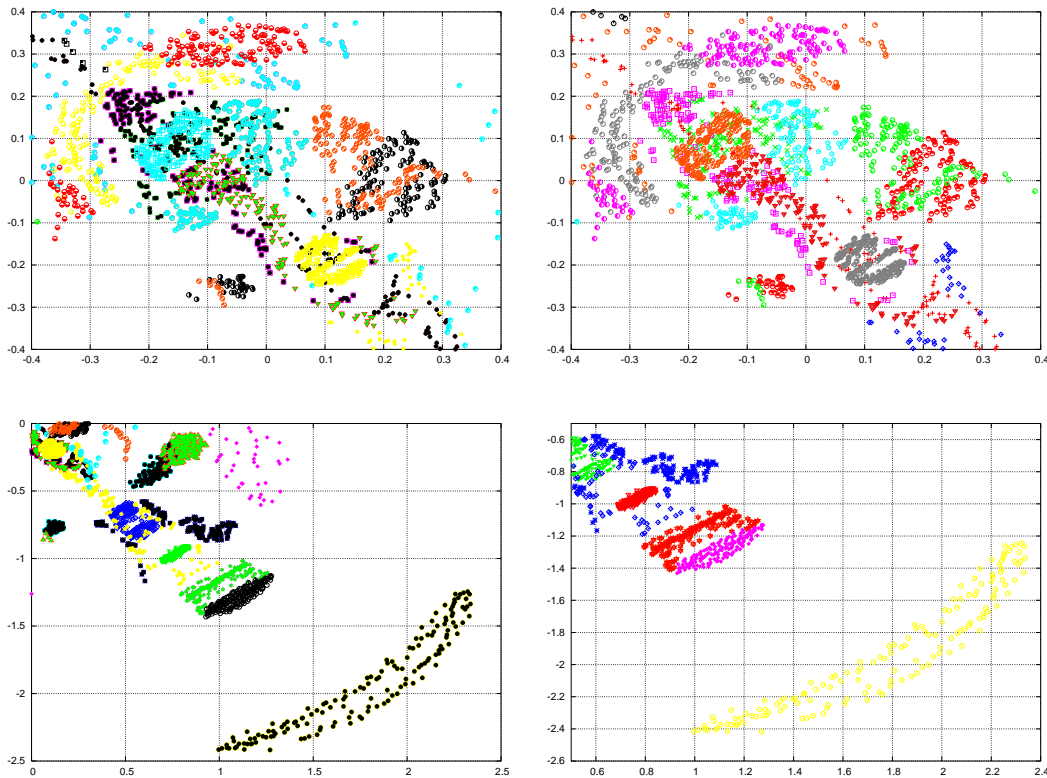


Figure 4.24: Sammon maps of the top left corner, the middle area, all the Sammon map without the SS1 cases (single graph), a magnification of the centre of the middle area and finally the bottom right corner of the complete map, which is shown in Figure 4.17 for the P2 pressure signal. Each row shows the specified map with and without the SS1 cases. The graphs on the left are with the SS1 cases, the ones on the right are without.



# Chapter 5

## New Methodology Tests and Results

According to the new methodology, described in Section 3, in order for a two-phase flow regime identification model to be build there is the requirement for the following two parts to be available:

1. A data signal which describes the characteristic condition in the pipe. For the systems that were used in this work this condition was; for the Horizontal system the liquid level at a cross section of the pipe; for the S-shape riser the pressure difference between the base and the top of the riser.
2. A Time Lagged Feedforward artificial neural network (TLFN).

In this chapter, flow regime identification models are build and described for input data signals obtained from the three different types of systems that were described in Chapter 4:

- An imaginary system with synthetic data
- A horizontal multiphase flow system and
- A S-shaped riser.

The performance of the resulting models is evaluated according to their ability to identify the type of signal that a given input belongs to. The main concepts of the data processing and neural network topology construction procedure are also described. These are common for all the neural network experiments that were carried out, therefore they are presented separately in the following sections.

## 5.1 Data Preprocessing

All the different cases of data for each experiment were split into:

- Training and
- Validation data.

The training data were used to train a new neural network for the specific task of identifying the flow regime the input data belong to. The Validation data were used to test the trained network with data from new cases that were not used during training. The training data were further split into:

- Training and
- Testing data

The training data were used to adapt the weights until the network produced the desired response. The test data were taken from the same cases as the training data however the actual input examples were not also present in the former, they were new. This set of data was used to assess the performance of the network during training. The results of this testing were used to decide when the network was sufficiently accurate or would not improve in performance anymore. This procedure was employed because it is of interest to obtain a network that performs well on a wide range of cases and not only on the ones present in the training data set. So it is important for the network to be able to generalize. Hence by testing the trained network on data it has not seen before, the network with the best generalization can be decided upon.

Furthermore the time series that were collected experimentally or generated synthetically, were sampled with a specific to each methodology–application *delay window* (see Section 3.1). It was found that the size of this window is dependent on the data obtained for each case of application, so it is identified and described separately in the following sections below, where the methodology applications are described.

For each two files (the training and the testing file) that were to be used during the training process were created for each of the experimental cases described in the following sections, according to Equations 5.1 and 5.2. These equations were used to determine how many data from each data file were to be used for the training data file and how many for the testing data file. The general rule was that a quarter of each data file (*test fraction*) was to be used for the testing data file and the rest three quarters (*training fraction*) for the training data file.

$$\text{test fraction} = \frac{(\text{data points in the file}) - (\text{size of delay window})}{4} \quad (5.1)$$

$$\text{training fraction} = 3(\text{testing fraction}) \quad (5.2)$$

Each row in these files is made of the input data together with their corresponding output data, with the inputs preceding the outputs. These rows of data made to be used with the neural network is called a pattern and every such file is called a pattern file. An example of a neural network pattern file is given in Section D.1. This is a specific pattern file to the SNNS (Stuttgart Neural Network Simulator) software that was used for all the neural network simulations.

### 5.1.1 Data normalisation

All the neural network input data before they were used with the neural networks they were normalised between the values of -2 and 2 according to Equation 5.3.

$$N = r \left( \frac{x - x_{min}}{x_{max} - x_{min}} \right) - s \quad (5.3)$$

where

- $x$  = Amplitude value from the time series that will be used as an input to the neural network.
- $r$  = Magnitude of the range within which the normalized data should lie in.
- $s$  = The shift coefficient that sets the start position of the data range specified by  $r$ .
- $x_{min}$  = The smallest amplitude value present, in all the timeseries used for the training and testing data sets.
- $x_{max}$  = The largest amplitude value present, in all the timeseries used for the training and testing data sets.

The normalization of the input to the neural network data was necessary because of the activation function that is used with all the hidden and output nodes of the neural network. This function is called the *Logistic Sigmoidal* function and its general form is described by Equation 5.4. In this equation  $\theta$  specifies the gradient of the curve. The larger the value of  $\theta$  the steeper the curve and the closer to the step function it reaches. For the experiments

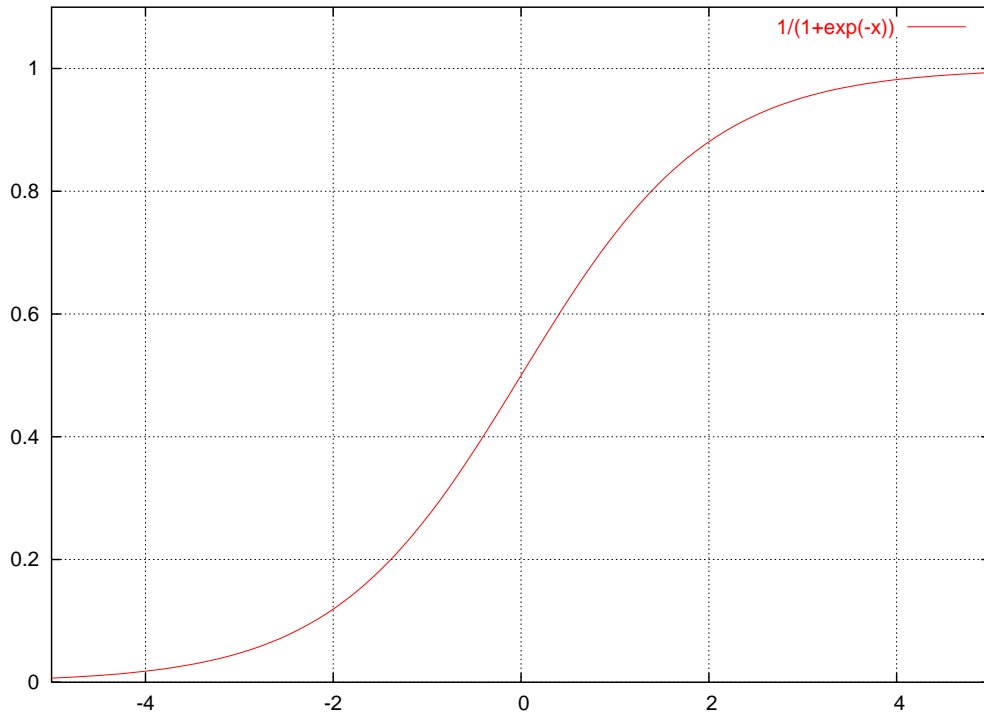


Figure 5.1: Plot of the activation function that was used for the input and hidden units in the neural networks.

presented here  $\theta$  was equal to one and a plot of the specific sigmoidal function is shown in Figure 5.1. The presence of the activation function in the neural network is justified in Section A.1.

$$y = \frac{1}{1 + e^{-\theta x}} \quad (5.4)$$

From the plot it can be seen that for any  $-5 < x < 5$  the output of the function  $y$  is constant. As the inputs that are used with the neural network are collected from real life systems, they could contain values much larger than 5 or much smaller than -5. This means that when these values are put through the nodes of the neural network and their activation function, they will cause the nodes to always output zero or one. This is not desirable as it will cause the neural network to output the wrong results. Hence the data were normalized between -2 and 2 in order to avoid as much as possible the regions of the Sigmoidal functions where it starts to become constant whilst at the same time utilizing as much as possible of its linear region.



## 5.2 Neural Network topology building concept

The neural network architecture that was considered for the creation of the flow regime identification model was the Multilayer Perceptron (MLP) with only one hidden layer (see Chapter 2). As with every neural network application there is the issue of deciding on the number of nodes to be used in each of the layers.

For the input layer a suitable *delay window* had to be determined. This would specify the number of the input units. An examination of the signals obtained for each specific system was carried out focusing mainly on the lengths of any obvious cycles in the data. Such lengths were usually obtained from distances between peaks, if these were present. From these observations and a few tests it was decided to use:

- 4 s for the synthetic data. This means there will be 16 inputs as the data were generated with a frequency 4 Hz.
- 20 s for the horizontal flow data, i.e. there will be 200 inputs as their sampling frequency was 10 Hz.
- 100 s for the S-riser data, i.e. there will be 100 inputs since their sampling frequency was 1 Hz.

The outputs of the neural network were the same as the number of classes that the data were obtained from. As there were four classes for all the experiments the output units for all the neural network models were four.

The number of hidden units was determined following the heuristic mentioned by Tarassenko [33] which states that the number of training examples ( $N$ ) (i.e. the number of input vectors in the training set) that should be used, at most, should be equal to ten times the number of weights ( $W$ ) in the network. This suggests that the network size is all ready known and the number of data to be used is the requirement. In our methodology we have taken the same idea in the reverse and more practical direction, where the size of the hidden layer is the unknown and there is all ready a set of data available which should be as large as it is reasonable, given some external restrictions.

Since  $W = IH + HO = H(I + O)$  and

$N = 10W$  then

$$N = 10H(I + O) \Rightarrow$$

$$H = \frac{N}{10(I + O)} \quad (5.5)$$

where

- $I$  = number of input units
- $H$  = number of hidden units
- $O$  = number of output units

This rule uses the number of training examples ( $N$ ) available as well as the all ready known sizes of the input and output layers. Since the size of the other two layers is fixed from the problem at hand, the size of the hidden layer is mainly dependent on the available data base. Hence by applying Equation 5.5 for the three sets of experiments, the number of hidden units that were used for each of the neural networks were:

- 7 for the conceptual system.
- 14 for the horizontal system.
- 10 for the S-shape riser system.

These estimations for the right number of hidden units may be slightly different in the following sections where the results are being presented. This is because these values were used as indications of the hidden units number that may be suitable. Extra tests were carried out in order to find the optimum number of hidden units for which the best results were obtained.

### 5.2.1 Mathematical Model

Every Neural Network model that has been created and described in the following sections, according to Figure 5.2 mathematically is represented with Equation 5.6.

$$y = \frac{1}{1 + e^{-k}} \quad (5.6)$$

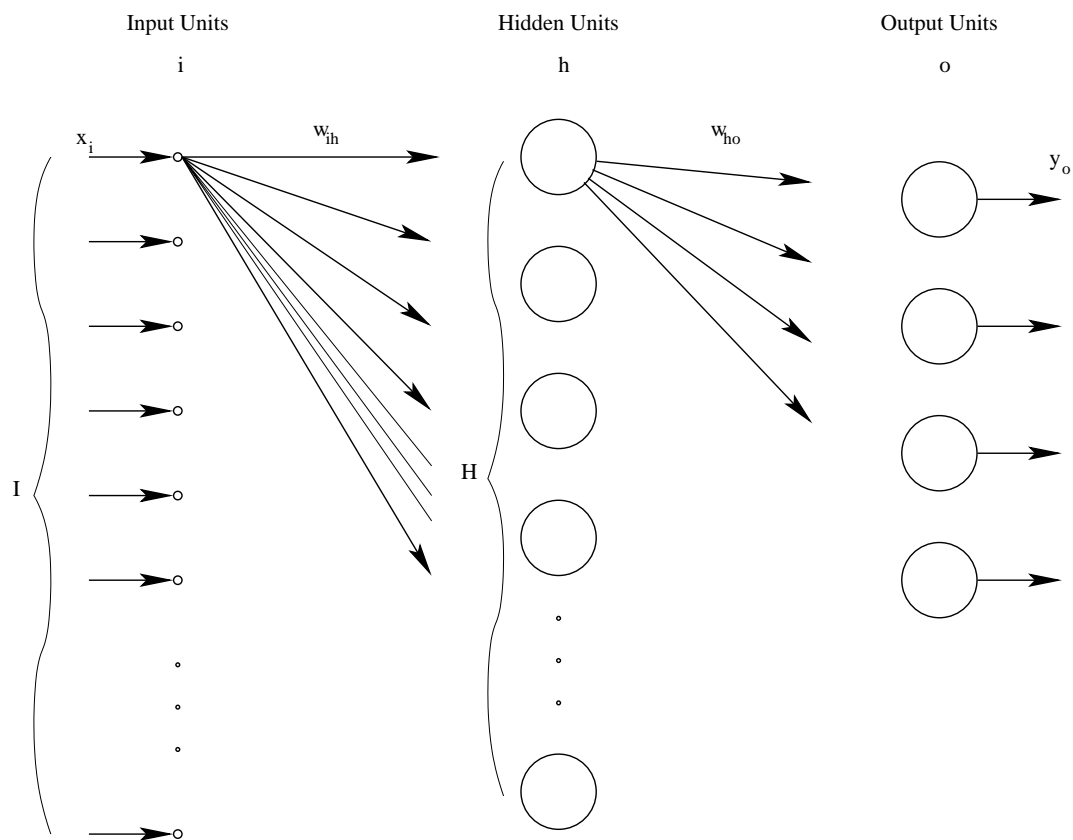


Figure 5.2: Example of an MLP neural network.

$$k = \sum_{h=1}^H (w_{ho} \frac{1}{1 + e^{-l}})$$

$$l = \sum_{i=1}^I (w_{ih} x_{ih})$$

where

- $x$  = inputs
- $i$  = input units index
- $h$  = hidden units index
- $o$  = output units index
- $w$  = weight values between the units specified by the indices

The only difference between each of the models is the number of input ( $I$ ) and hidden ( $H$ ) units and the number and values for their weights ( $w$ ). Hence in order for such a model to be used the above parameters are needed to be known. With neural network applications all this is stored in the network file. For the models mentioned later these network files are given in Appendix D.

The fraction  $\frac{1}{1+e^{-x}}$  is the activation function that was used for each of the hidden and output units (see above Section 5.1.1 and in the Appendix section A). The Equation 5.6 does not necessarily represent other models that were build with a MLP or a TLFN neural network. This is because this equation is dependent on the activation function that was chosen to be used and the connections between the units in the networks (see Section A.1). The networks that were used here were fully connected (all the units of the previous layer are connected with all the units of the next layer) but this is not always the case. Also the activation function that was used here was the *Logistic Sigmoidal* (see Section 5.1.1) but it could also be some other differentiable function.

### 5.2.2 The Training process

The neural networks were trained until they reached a state at which the difference between two consecutive training errors would not exceed the value of 0.001 for 100 consecutive training epochs. By epoch it is meant the cycle during which the weights of the network are adjusted for all the patterns in the training data set. The measure that was used to check the training state of the network was the Sum of Squared Errors (SSE) shown by Equation A.3.

All this process of training a network until the error of its outputs does not change anymore is called a *run* and there were 20 such runs carried out during the development of all the models presented later in this chapter. The difference between each run was in the *seed* that was used for the random initialization of the weights in the network. This seed had to be different every time and to achieve this the system time was used. This time had all its non numeric characters removed and was used as an integer made by the hours, minutes and seconds. The weight initialization was carried out once at the beginning of each run to ensure that each training attempt started with a network of a different set of weights. Otherwise each training run would lead each time to the same trained network. The idea behind starting each training run with a different set of weights is to try and find that set of weights for which the network will produce the smallest error possible (global minimum). This can not be guaranteed from only one run as the training process through the gradient descent method for reducing the error can lead to a number of local minima in the multidimensional surface of the error against the weights set. Hence a number of such runs have to be initiated by making sure that each time the network starts with the different set of weight values.

There were two different data files that were used during training. One of them (the training data file) was used to train the network, in other words to adjust the weights of the network. The second file (the test data file) was used only to test the trained network after each training epoch. The best trained network was chosen to be the one which gave the smallest SSE error for the test data.

The training phase involved the following steps:

- Step 1 Present all the examples from the training data (one epoch).
- Step 2 Adjust the weights.
- Step 3 Test the network that is being trained with the test data.
- Step 4 Check estimated outputs from the test data against the target outputs.
- Step 5 Repeat from Step 1.

By testing the network during the training phase and using the results from the test to evaluate the so far trained network's performance helps on monitoring if the network is over-training or not. This is achieved by plotting the error curves for both the training data and the test data. If the test error curve follows the training error curve then the network is over-training. This means that the network has reached a level where it is starting

to memorize (over-fitting) the training data and does not perform very well for any data outside the training set. In such a case it is said that the network can not generalize very well any more. If instead there is a point at which the test error curve takes an upward trajectory whereas the training error curve continues the downward motion, then the network is being trained properly. Examples of these two cases that occur during training are shown in Figure 5.3. The best trained network is chosen when the two error curves do diverge and the error of the test data is at its lowest. In the event where the network consistently shows over-training characteristics among all the training runs, either the test data set is too similar to the training data set or the training data are too few for the chosen network size and they are over-fitted. A work around this problem would be to either enlarge the training data set or reduce the size of the network by removing some of the hidden units. If this does not change the performance of the network then it must be a case of the training and test data sets are too similar. There is also the possibility for the network to show hi error values for both the training and the test data sets. This usually happens when the network is too small and does not have enough weights in order to map the inputs to the outputs. Hence the addition of hidden units should improve the performance. If this does not happen then either the problem is too complex for the neural network technology that has been chosen or the parameters of the system that are used as inputs to the neural network are not suitable.

### 5.3 Results

In this section the new methodology described in Chapter 3 is applied to three different systems. The requirement is to train an ANN on the task of identifying which class the input data belong to. The three systems were: a conceptual system whose data were synthetically generated, a horizontal multiphase flow pipe and a S-shape riser.

The performance of each trained network was assessed by determining the number of correct, incorrect and unclassified results given by each separate network on all the three data sets. The training, the test and the validation data sets. This assessment was carried out by analyzing the neural network results files with a function which uses two threshold values, a *lower* and an *upper* one, to determine whether the response of the network to an output is: correct, wrong or unclassified. For the analysis of the results given in the following sections the lower threshold was set to 0.49 and the upper threshold to 0.51. For example if the expected outputs from the output units in the network are 0 and 1, and the lower and upper thresholds are 0.49 and 0.51

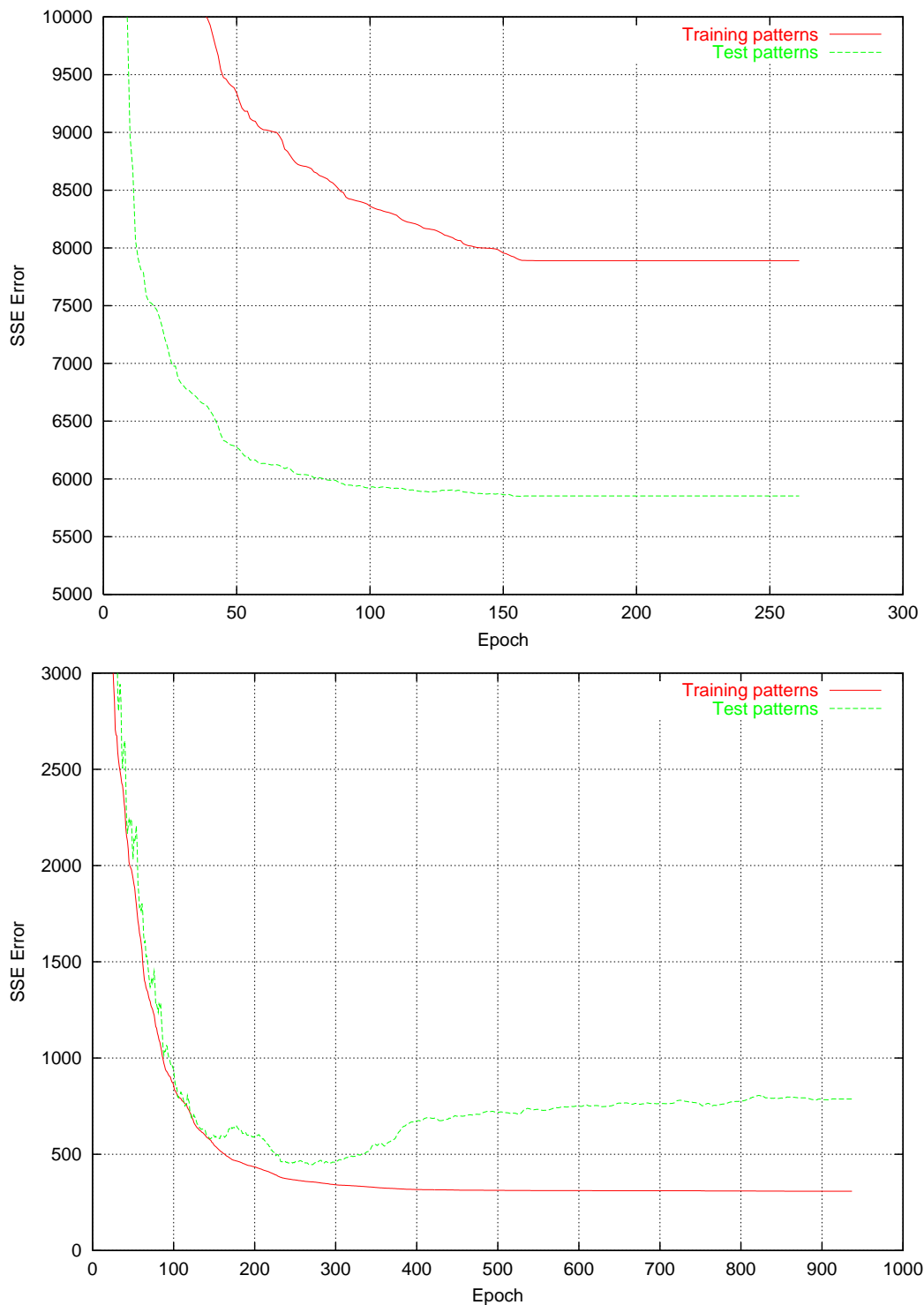


Figure 5.3: Examples of SSE error curves plotted for the training and test patterns. The plot on the top shows an example of how the curves look if the network is over-fitting the data, the curve for the test patterns does not reach a point where it starts to increase. The second plot shows the same curves for a more properly trained network, where it possible to establish when the network stops to generalize and begins to over-fit the data.

	Output-Unit Output			
Target Output	0	0	0	1
Correct	$y_1 < 0.49$	$y_2 < 0.49$	$y_3 < 0.49$	$y_4 > 0.51$
Incorrect	$y_1$ or $y_2$ or $y_3 > 0.51$			$y_4 < 0.49$
Unclassified	more than one output give $> 0.51$			
	non gives $> 0.51$			
	one or more give $0.49 < y < 0.51$			

Table 5.1: Criteria used by the 402040 function for determining the correct, incorrect and unclassified outputs, assuming that its lower and upper thresholds of the function are 0.49 and 0.51 respectively and the network has 4 output units.

respectively, then a neural network output is classified as correct, incorrect or unclassified according to the criteria specified in Table 5.1.

### 5.3.1 Synthetic signal identification model

The data used here were synthetically generated from combinations of sine waves. These were described in more detail in Chapter 4, Section 4.1. In practise they could be thought of belonging to a more general hypothetical system. For convenience the resulted data of the “noisy” versions of the signals is shown again in this chapter in Figure 5.4.

An ANN was trained, with part of the above data, to identify each of the signals from sections of these time series which the network had not seen before. For this the same number of data examples from all the four signals were presented to the neural network in the form of *time delays*. This means that not only was the current value used at each given neural network training step but also a number of previous values (data points). The number of these past data points is specified by the size of the *delay window*.

For the above mentioned time series data, a delay value of 16 data points was used. This delay represents the period, in data points, of signal 3 (see Figure 4.1), the largest found among the periodic signals.

This delay value was chosen because from previous experiments it was concluded that:

- the less inputs to the neural network the better
  - smaller network
  - less coefficients (weights) to adjust in order to improve results.
  - less data required to train it



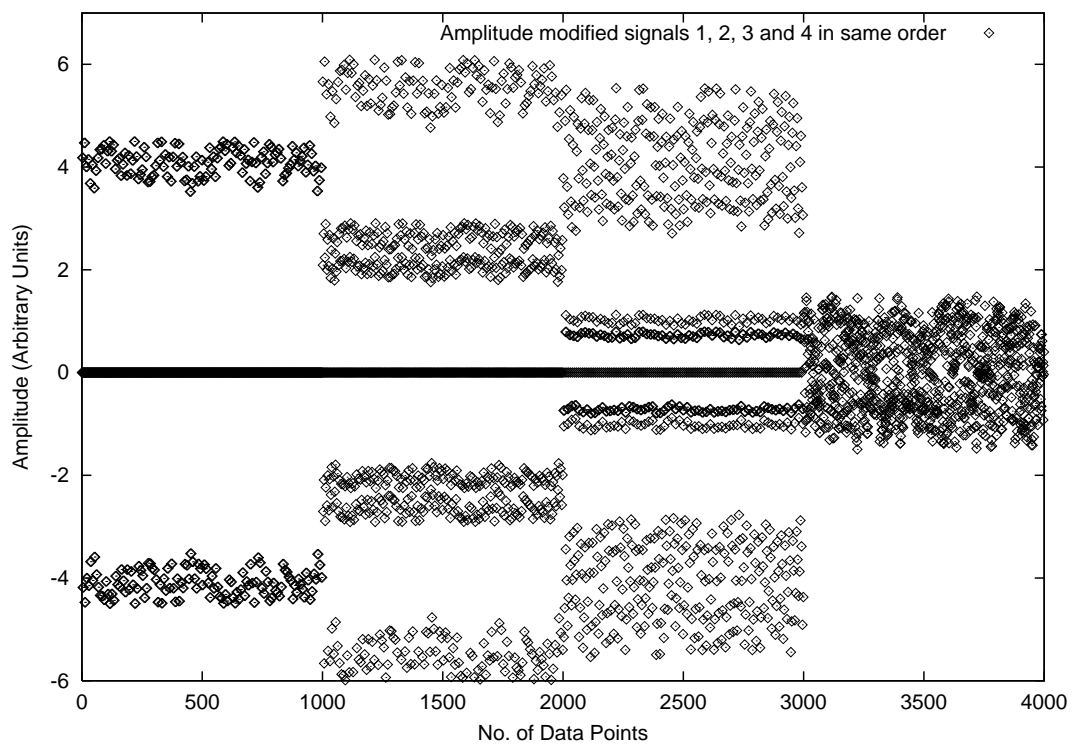


Figure 5.4: The “noisy” versions of the four synthetically generated time series. Their order is signal 1, 2, 3 and 4 from left to right.

- a more confident way to describe a periodic signal is to use at least enough data points to represent one cycle.

The neural network was asked to learn to identify which signal, each currently presented example belongs to. Since there were four signals, the network had four outputs. Each output was dedicated to only one of the signals, for examples of which it was expected to give the value of 1, and 0 for anything else. These two values 0 and 1 are called the *target output* values and are the ones the network is trained to give from each of its output units.

**The Neural Network** The “delayed” data was used to train a Time Lagged Feedforward Neural Network (TLFN) (see Section A.3) and also to validate it after it was trained.

The network contained three layers:

- the input layer (16 units)
- a hidden layer (7 units) and
- the output layer (4 units)

A justification for the number of units used in the input and output layers is mentioned in Section 5.2 and are related to the *delay* term and the number of signals used to build the training data.

The 7 units of the hidden layer were decided by following the heuristic also mentioned in Section 5.2 and a number of tests to find the optimum number. The heuristic which basically says that  $n$  training examples are sufficient to train a Neural Network that contains around  $n/10$  weights, indicated that 20 units would be a good number to start with. Since the training examples were 4000 (1000 from each signal see next paragraph) and the network has all ready been decided to have 16 inputs and 4 outputs, according to the problem at hand, the hidden layer should have around 20 units ( $16 \times 20 + 20 \times 4 = 400$  or  $4000/10$ ). However a network with this many hidden units for the set of data that was used to train it, showed that it was over-training and memorizing the data. This was established from observing the error curves for the training and the test data sets, recorded during the training process. They seemed to follow each other faithfully and at the end the test error curve would not take an upward trajectory while the train error curve carried out dropping. Hence further training attempts were carried out with networks of smaller hidden layers during which the optimum was found to be a 7 hidden layered network. The large difference between the estimated

number of hidden units and the optimum suggest that the data used for training and testing were not very different from each other, something that is also suggested by the results below. This is probably true as there were only four different signals used to build the whole data set. Still this is not so important at this stage of the research as the objectives for this set of experiments, as stated in Section 4.1 were to identify the major areas of importance in working with time series and ANN for classification. These were:

- How many inputs to be used in the ANN.
- Which ANN architecture would be suitable.
- Familiarisation with relevant software packages.
- Develop any extra software necessary.
- Develop the methodology and
- Test it on simple, clear cut cases and build the confidence that it can work.

These objectives were met. The network that managed to classify all the data correctly is shown in Figure 5.5 and the weights associated with it are given in Section D.2 of the Appendix.

**Model Performance** The training and testing data were created according to Equations 5.1 and 5.2, by using a delay window value of 16 and number of classes 4. The training data file contained 4000 training patterns and was made up of 1000 patterns from each of the signals. The test data file contained 2000 patterns made up from 500 patterns from each of the signals and the validation data file contained 1940 patterns. Patterns used in one of the data files were not used in the rest.

Finally the classification model was tested with all the three data sets, the training, the test and the validation data set. From the results it was concluded that all the examples of all the signals were classified 100% correctly and the methodology developed and presented in this thesis could work for real systems.

More detailed results with number of patterns for each data case and actual test errors from the neural network are shown in Appendix E.

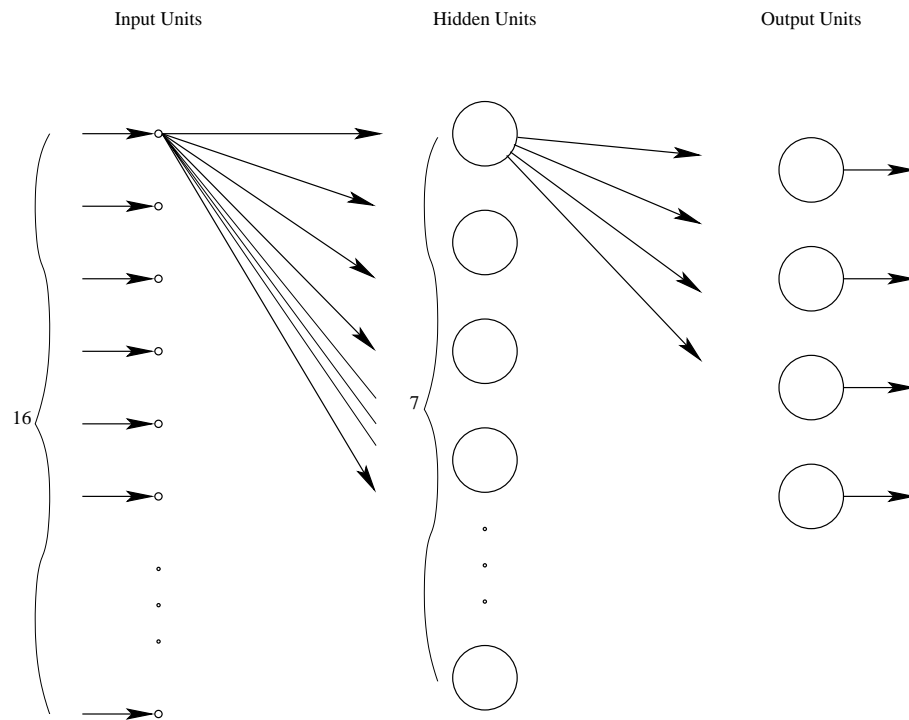


Figure 5.5: Neural Network that gave the best results for the Synthetic data.

### 5.3.2 Flow regime identification model for a horizontal pipe

A two-phase flow regime identification model was built in this part of the work for a 4 inch (102.3 mm) internal diameter horizontal pipe. The specific experimental rig is described in Section 4.2. The fluid used, was an air and water mixture.

The measured data from the pipe were of the liquid level indicating type, obtained from a capacitance measurement system (see Section 4.2). An example of a signal obtained from the instrument for a slug flow case, is shown in Figure 5.6.

The instrument was calibrated to output 1 Volt for water full pipe and zero for gas full pipe. Hence as it can be seen in the figure, the instrument showed 1 V or full pipe when a slug was passing through the section of the instrument and then eventually tailing off as the slug would get distanced.

Data were obtained only for four flow regimes due to limitations of the multiphase facilities available and the relatively large pipe diameter. These were:

1. Stratified Smooth (SS)

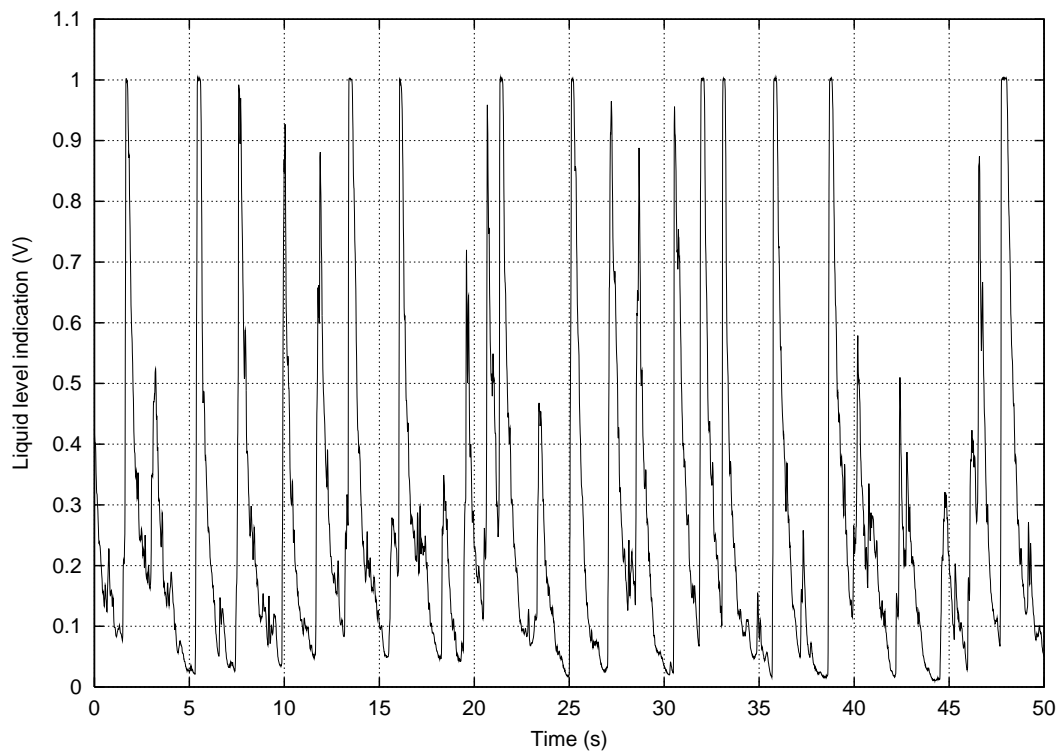


Figure 5.6: Signal example from the capacitance measuring instrument.

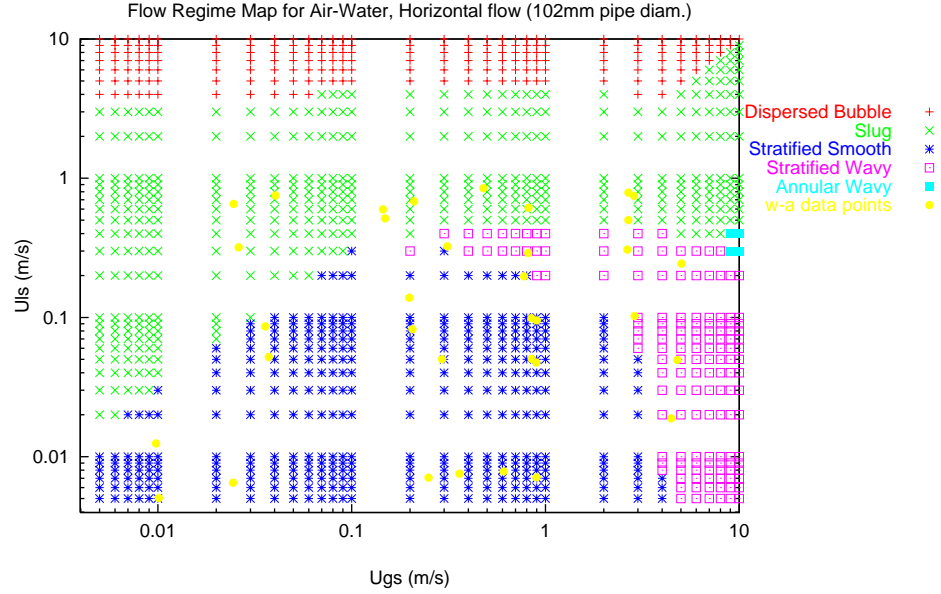


Figure 5.7: Experimental data points for the 4 inch horizontal pipe.

2. Stratified Wavy (SW)
3. Bubble (B) and
4. Slug (S).

The flow cases for which data were collected, are shown on a flow regime map in Figure 5.7.

**The Neural Network** A neural network was trained to identify the flow regime that a liquid indicating signal from each of the above cases belonged to. Again the signals were presented to the neural network through a time delay window. The size of this window was chosen to be 20 s (200 data points sampled at 10 Hz).

Hence the neural network for this model had

- 200 input units
- 14 hidden units and
- 4 output units.

The number of the hidden units were determined by using the Equation 5.5 in Section 5.2 with  $N = 30000$ . This network is shown in Figure 5.8 and the weights associated with it are given in Section D.3 of the Appendix.

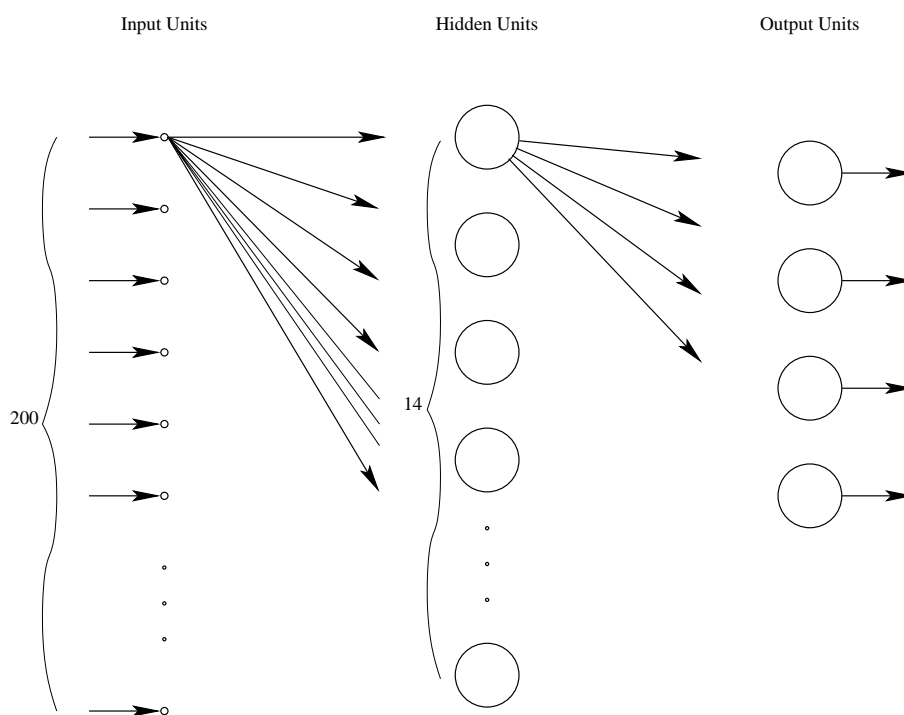


Figure 5.8: Neural Network that gave the best results for the Horizontal system.

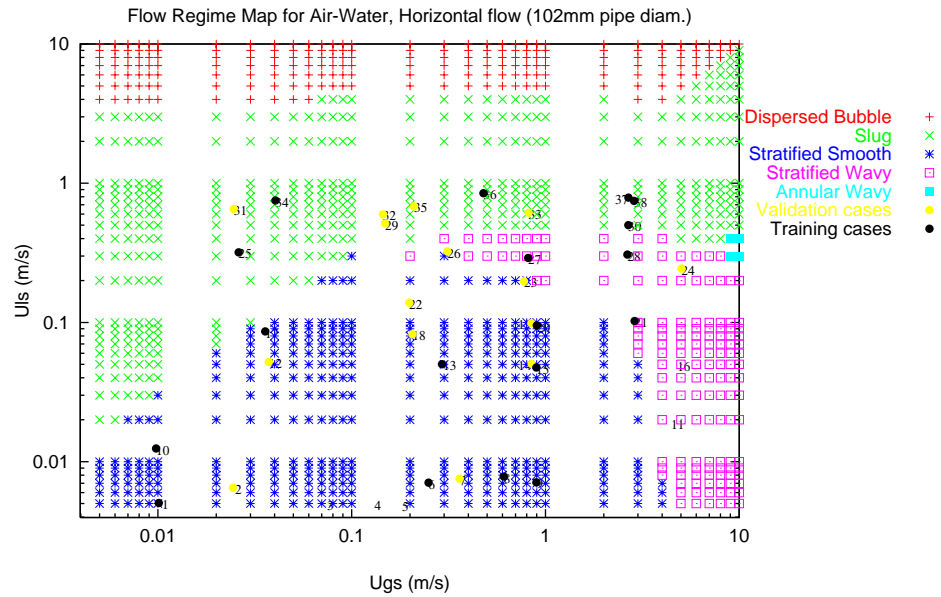


Figure 5.9: The training and model validation flow cases used.

**Model Performance** There were 38 cases of two-phase flow. From these 2 cases were excluded completely from the experiments as the liquid levels that were measured were very low, almost zero. These were cases 11 and 16. From the remaining 36 cases, 20 were used for training and 12 for Validating the finalized trained network. Their distribution into the two types of training patterns was done by making sure that examples from all the flow cases were present in both the groups and also an effort was made to include examples form all corners and mid areas of each flow regime in both groups. The remaining 4 cases were originally identified as transitional (T) and of no specific flow regime with respect to the classes that the rest of the data were grouped into. Hence these four cases were left outside from the model development process, of training, testing and validation. Still they were used to test the final model's performance on transitional flows. These cases were number 18, 22, 26 and 30.

The 20 training cases, which produced 50020 training patterns were split into, 30000 training and 20020 testing patterns. These two sets of data were generated by separating each flow case signal into two parts with no overlapping between the two of them, to make sure that there were shared data points. Ideally one would want to have different flow cases for each data set but there were simply too few cases for this to be practical. The 12 validation cases gave 47603 testing patterns. The training and validation cases are shown on the flow regime map in Figure 5.9



Data Type	Correctly Identified Inputs (%)	Incorrectly Identified Inputs (%)	Unidentified Inputs (%)
Training	96.35	3.24	0.41
Testing	91.19	7.30	1.51
Validation	91.04	6.92	2.04

Table 5.2: Total results for all the training, all the testing and all the validation data, obtained from the best trained neural network for the Horizontal flow system.

By using the training and validation cases mentioned above and processing the data as it was also mentioned above and in detail in Section 3.3, a model was created for the specific horizontal system. Its performance was tested by determining how many examples for each of the experimental cases shown in Figure 5.7 had their flow regime identified correctly. This was done for both the training and for the validation data and the results are summarized in Table 5.2. Results for the individual flow cases are shown in Table 5.3.

The above results are an improvement on the results published by Goudinakis [9]. The main source of the improvement came from normalizing the data between -2 and 2, whereas previous results were obtained from normalizing the data between 0.15 and 0.85 which was common practice. More detailed results with number of patterns for each data case and actual test errors from the neural network are shown in Appendix E.2.

Flow Case	Flow Regime	Correctly Identified Inputs (%)	Incorrectly Identified Inputs (%)	Unidentified Inputs (%)	Used During
1	SS	100	0.00	0.00	Training
2	SS	100	0.00	0.00	Validation
3	SS	98.93	1.00	0.07	Training
4	SS	99.54	0.39	0.07	Validation
5	SS	99.18	0.79	0.04	Training
6	SS	99.07	0.79	0.14	Training
7	SS	99.64	0.32	0.04	Validation
8	SS	99.86	0.11	0.04	Training
9	SS	97.07	2.64	0.29	Training
10	SS	100	0.00	0.00	Training
12	SS	100	0.00	0.00	Validation
13	SS	95.43	4.21	0.36	Training
14	SS	97.54	2.14	0.32	Validation
15	SS	93.65	5.86	0.50	Training
17	SS	100	0.00	0.00	Training
18	T	29.46	51.73	18.80	Test
19	SS	91.68	7.96	0.36	Validation
20	SS	93.86	5.86	0.29	Training
21	SW	59.46	39.61	0.93	Training
22	T	1.31	92.36	6.33	Test
23	SW	46.29	47.64	6.07	Validation
24	SW	74.93	24.71	0.36	Validation
25	B	100	0.00	0.00	Training
26	T	91.46	1.92	6.62	Test
27	SW	80.61	12.04	7.36	Training
28	SW	78.40	21.33	0.27	Training
29	B	99.99	0.00	0.01	Validation
30	T	65.00	27.07	7.93	Test
31	B	100	0.00	0.00	Validation
32	B	99.66	0.00	0.34	Training
33	S	87.93	3.32	8.75	Validation
34	B	100	0.00	0.00	Training
35	S	99.42	0.00	0.58	Training
36	S	98.34	0.05	1.60	Training
37	S	70.94	18.12	10.94	Validation
38	S	84.11	9.32	6.57	Training

Table 5.3: Results obtained from the best trained neural network for the horizontal flow data. Each flow case is shown on a flow regime map in Figure 5.9

### 5.3.3 Flow regime identification model for a S-shaped Riser

Data for these experiments were obtained from 2-phase flow experimental work done on a S-shape riser (see Section 4.3). These multiphase flow experiments were carried out by Montgomery [24].

Although a number of different parameters were measured from the riser and for a number of flow regimes, it was the pressure difference along the whole riser that was used for the current experiments (see Section 4.3.1). The flow regimes that was chosen to work with, were:

- Severe Slugging 1 (SS1)
- Bubble (B)
- Slug (S) and
- Oscillation (O)

The reason behind these choices was that these were the only ones from the 12 flow regimes in total, which contained a significant number of data examples. These flow cases are shown on a flow regime map in Figure 5.10

Following the methodology from the previous experiments with the synthetic data, i.e. use at least a whole cycle for each of the flow regime cases and from this cycle use as little data as possible to minimize the size of the neural network, the raw data were sampled down. The sampling frequency was decided to be 1Hz, as a result of plotting the data and estimating a sampling frequency as low as possible without modifying the shape of the time series data. Examples of the sampled signals are shown in Figure 5.11.

Again the data was presented to the neural network in the form of time delays. For this system the delay term was chosen to be 100 s (100 data points sampled at 1 Hz). This value was decided again after plotting the data and measuring the length of their cycles. Although some of the SS1 flow regime data had a cycle length of more than 200 data points, the delay of 100 was chosen to satisfy the previously mentioned methodology and because the shape of the SS1 signals is very distinctive with respect to the other flow regimes.

**The Neural Network** The sampled and delayed data were used to train and test once more a TLFN network of three layers:

- The input layer had 100 units.

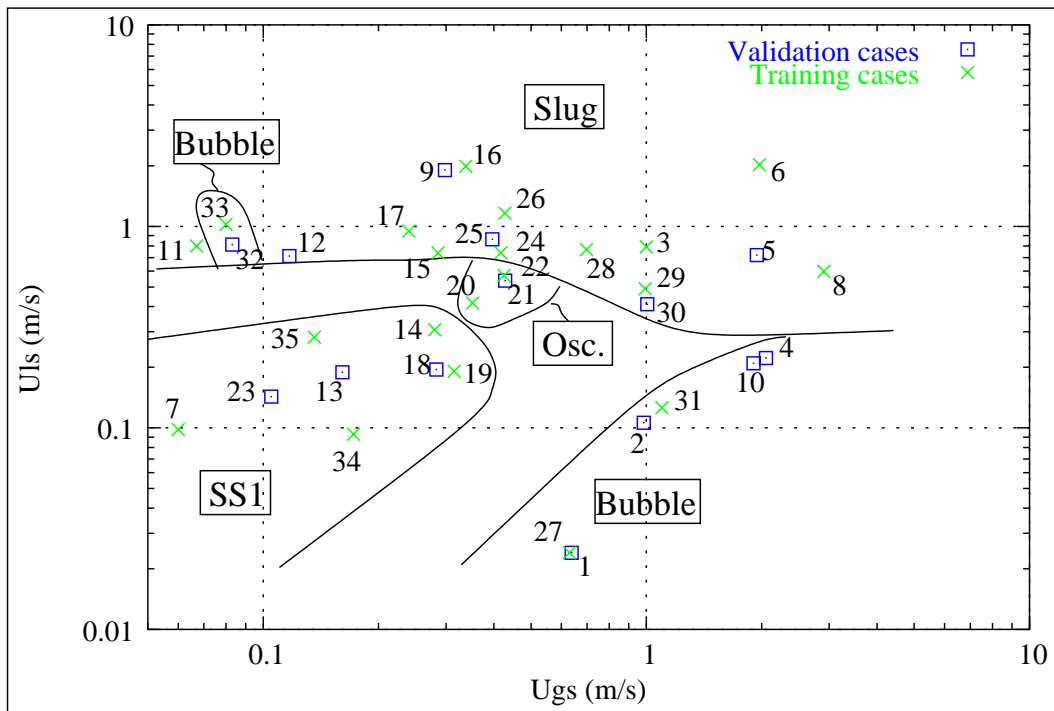


Figure 5.10: Flow regime map for the S-shaped Riser system. It shows all the flow cases that were used and which flow regime they belong to. Also it shows which cases were used to train the neural network and which to test it during the model validation stage.

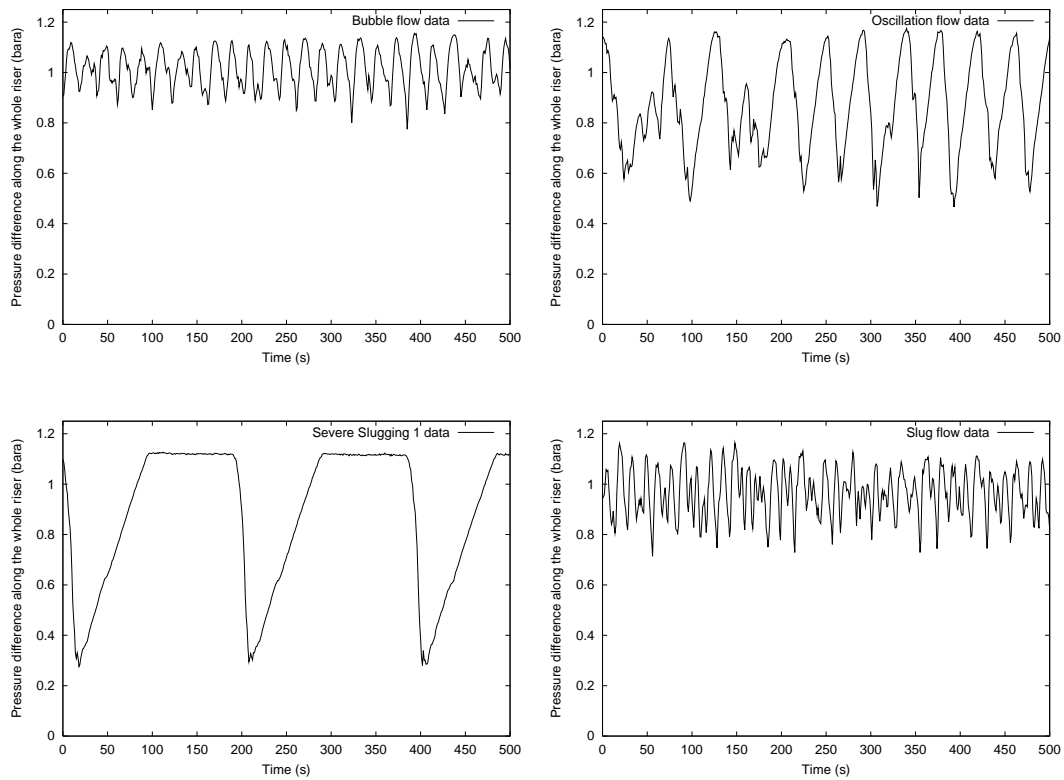


Figure 5.11: Some flow regime data examples of (clockwise from top left) the Bubble, the Oscillation, the Slug and the Severe Slugging 1 flow patterns, collected from the S-shaped Riser.

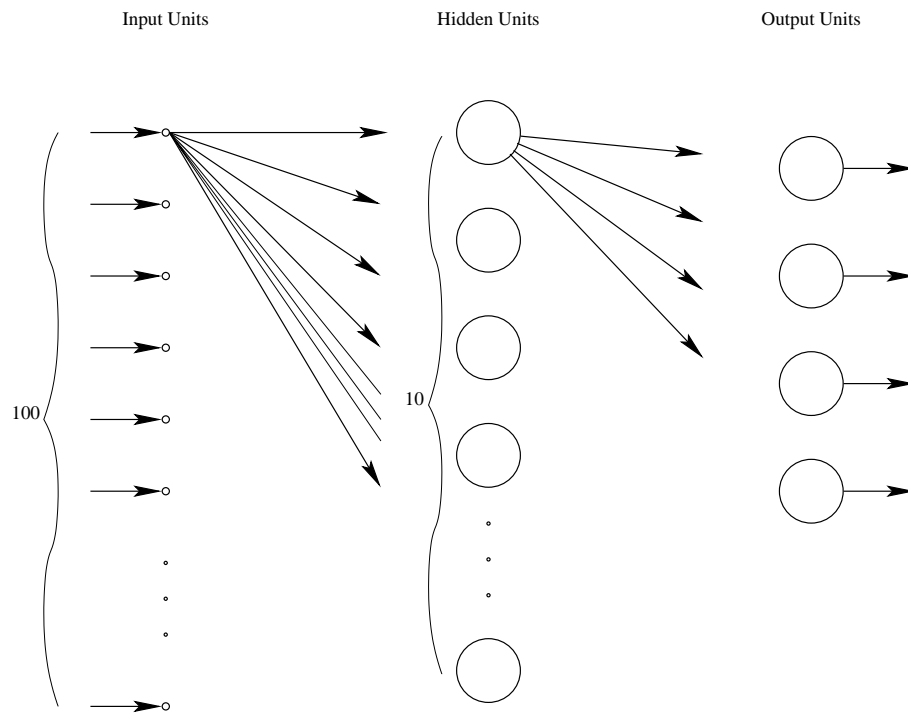


Figure 5.12: Neural Network that gave the best results for the S-shaped Riser system.

- The hidden layer had 10 units.
- The output layer had 4 units.

Again the 100 units of the input layer were due to the delay term of 100 data points (seconds) and the 4 units of the output layer due to the four flow regime classes chosen. The 10 units of the hidden layer were chosen again by using Equation 5.5 and carrying out a number of tests to optimize this number. Since the training patterns that were used were 6300, Equation 5.5 gave as a reasonable number for the hidden units to be 6. The network for this system is shown in Figure 5.12 and the weights associated with it are given in Section D.4 of the Appendix.

**Model Performance** There were 35 cases used for this system. From these 21 were used for training the network and the remaining 14, which generated 15233 patterns were used to validate the final model. Each of the signals from the 21 training cases were separated again as in the previous systems into two parts, the training and the test part. However for these files, because they were not of the same size, the segmentation was carried

Data Type	Correctly Identified Inputs (%)	Incorrectly Identified Inputs (%)	Unidentified Inputs (%)
Training	95.24	0.00	4.76
Testing	96.52	0.77	2.71
Validation	81.53	11.52	6.95

Table 5.4: Total results for all the training, all the testing and all the validation data, obtained from the best trained neural network for the S-shaped Riser system.

out in a slightly different way than in the previous two experiments. Instead of using the 3-to-1 ratio for all the files, where 3 parts of each signal went for training and the last part for testing, this time the smallest file would be found, then the 3-to-1 ratio would be applied on this file only. Then the size of this smallest signal that was calculated to be used for training according to the 3-to-1 ratio would also be used to separate the training parts from the rest of flow cases and the rest of the signals would be used for testing. This was done because it is very important to use the same amount of data from all the signals in the training set, to avoid training the network more for one case and less for the rest, which could affect its performance. Because of this alteration to the separation process of the signals into training and test parts the test patterns (8567) are much more than the training ones (6300) although, according to the 3-to-1 segmentation ratio, a bigger portion of the signals was supposed to be used for training.

The performance of the model that was created for the specific S-shaped Riser system was tested by determining how many examples for each of the experimental cases shown in Figure 5.7 had their flow regime identified correctly. This was done for both the training and for the validation data and the results are summarized in Table 5.4. Results for the individual flow cases are shown in Table 5.5.

More detailed results with number of patterns for each data case and actual test SSE errors from the neural network are shown in Appendix E.3.

Flow Case	Flow Regime	Correctly Identified Inputs (%)	Incorrectly Identified Inputs (%)	Unidentified Inputs (%)	Used During
1	B	100	0.00	0.00	Validation
2	B	100	0.00	0.00	Validation
3	S	98.93	1.00	0.07	Training
4	B	99.54	0.39	0.07	Validation
5	S	99.18	0.79	0.04	Validation
6	S	99.07	0.79	0.14	Training
7	SS1	99.64	0.32	0.04	Training
8	S	99.86	0.11	0.04	Training
9	S	97.07	2.64	0.29	Training
10	B	100	0.00	0.00	Validation
11	S	100	0.00	0.00	Validation
12	S	100	0.00	0.00	Validation
13	SS1	95.43	4.21	0.36	Validation
14	SS1	97.54	2.14	0.32	Training
15	S	93.65	5.86	0.50	Training
16	S	93.65	5.86	0.50	Training
17	S	100	0.00	0.00	Training
18	SS1	29.46	51.73	18.80	Validation
19	SS1	91.68	7.96	0.36	Training
20	O	93.86	5.86	0.29	Training
21	O	59.46	39.61	0.93	Validation
22	O	1.31	92.36	6.33	Training
23	SS1	46.29	47.64	6.07	Validation
24	S	74.93	24.71	0.36	Training
25	S	100	0.00	0.00	Validation
26	S	91.46	1.92	6.62	Training
27	B	80.61	12.04	7.36	Training
28	S	78.40	21.33	0.27	Training
29	S	99.99	0.00	0.01	Validation
30	S	65.00	27.07	7.93	Training
31	B	100	0.00	0.00	Training
32	B	99.66	0.00	0.34	Validation
33	B	87.93	3.32	8.75	Training
34	SS1	100	0.00	0.00	Training
35	SS1	99.42	0.00	0.58	Training

Table 5.5: Results obtained from the best trained neural network for the S-shaped Riser training data. Each flow case is shown on a flow regime map in Figure 5.10



## 5.4 Conclusions

The results obtained from the conceptual system gave the vote of confidence for the new methodology described in Chapter 3. Although the data that were generated were only for four different signals and it could be argued that these are not enough to train and test a network properly, they were enough to show that it is possible to train a network to identify signals which contained differences in frequency and amplitude, from inputs that were formed by only a section of the signal. The network that was trained had 16 input, 7 hidden and 4 output units and managed to identify all of the input data correctly, according to the 402040 analyzing function described in Table 5.1. This showed that the methodology under investigation is realistic and feasible which were the underlying objectives of this set of experiments.

Further tests were carried out with experimental data from real systems. One of these was the more simple horizontal pipe, multiphase flow system and the other one was the more complex and more close to real life systems the S-shape riser multiphase flow system. The results for both of these systems were very good. The horizontal system flow regime identification model gave more than 91% of correct identifications for more than 97 000 patterns (see Table 5.2). These includes the training and the validation data. The S-shape riser flow regime identification model gave more than 95% correct identifications for the training data (14867 patterns in total) and more than 81% correct identifications (see Table 5.4) for the validation data (15233 patterns). However these results have been influenced by subjectivity which was present at the original classification of the data and against which the neural network models' results have been compared. This is the case especially for the S-shape riser data where there were no visual observations of the flow and the data were analyzed from observing a number of measured signals.

A conclusion that was made from the numerous tests that were carried out through out the experiments mentioned in this Chapter, was of the importance that the size of the *delay window* has. This determines how much of the signal the neural network can see at a time and it is dependent on the system that the network was trained on.

Each of the models that were developed for the separate systems can be put in application by using Equation 5.6 and substituting each model's respective weights which are given in Appendix D and are also provided on a CD-ROM.

More details on the analysis of the results and a discussion on the actual abilities and inabilities of the new methodology is given in the following Chapter.



# Chapter 6

## Discussion

In this thesis a new methodology on the use of Artificial Neural Networks for the identification of flow regimes in pipes has been presented. The main characteristic of this methodology is the format in which, data from a pipe are presented to the neural network. This format is the raw, unprocessed nature of the data, presented in groups of consecutive data points. The size of the group is important and is specific to the system the data is collected from. The use of raw time series with ANN has been used for prediction purposes [7], [10], [40], [39], but it has not been used for classification tasks like the identification of flow regimes is. So far methodologies where ANNs were involved required for the data to be transformed into some other form of representation by extracting features in order to reduce the dimensionality and in turn also reduce the training time for the neural network. There is only one piece of work where a similar methodology to the one presented here was used. This is the work done by Selegim *et al.* [28]. Still they only tested the methodology on horizontal flows and presented it as another method that works. They did not identify the advantages of such a method and its extreme suitability to a specific real life application. This thesis shows that the methodology is suitable on a wide range of pipe configurations and identifies its major and significant advantage on its application to the control of multiphase flow, production pipelines.

In this Chapter the results that were obtained and are presented in Chapter 5 are discussed. Since the methodology was tested on three different types of systems, the results from each one of them are discussed separately in the respective Sections that follow. The flow regime identification models that were developed for each of the systems can be further utilized from anyone that wishes to, by using Equation 5.6 and substituting each model's respective weights which are given in Appendix D and are also provided on a CD-ROM. Finally there is a general discussion where the suitability of the

method on a number of applications is suggested and supported.

## 6.1 Synthetic data results

For these tests an MLP was trained with synthetically generated sine wave data on the task of identifying which type of signal a four second long section from each of them belonged to. These experiments are described in detail in Section 5.3.1.

In order to fulfill the objectives stated in the above section, this experiment was designed to test the new methodology on the task of identifying a number of time series which belonged to well defined classes in order to eliminate the possibility of any subjectivity being present and simplify the problem. This requirement was important at this stage of the development of the new methodology, because the presence of any subjectivity among the classes of the data, would lead training the neural network incorrectly and placing question marks on the results. The reason for this is the fact that a supervised training procedure was used to train the neural network, in which case the class of each given training input to the neural network is specified. If this class is not definite then the network could be trained to produce the wrong identification. The presence of subjectivity on the original classification of the training data obtained from real systems is always an issue when a neural network is to be used. The new methodology that has been presented and tested in this thesis has the potential of eliminating the possibility of incorrect classifications in the training data. This is discussed in more depth in Section 6.2 of this Chapter.

Hence for this experiment it was important that given a section of any of the signals it should be easy for a person to determine its class. Also, in order to make the experiment more realistic with respect to further tests that the new methodology would be placed under, these classes was determined to differ from one another in three areas: shape, frequency of oscillations in the signals and amplitude variations. These specifications were deduced from observations of pressure signals obtained from real multiphase flows in pipes that were published in the literature. Such a publication is the work carried out by Weisman et al. [41]. In work number of experiments of two phase flow were carried out in horizontal pipes, in order to investigate the effects of fluid properties on the flow patterns. The properties they considered were liquid viscosity, liquid density, interfacial tension and gas density. In order to determine the flow pattern for each of their experimental cases they used pressure difference along the pipe signals. From the study of these signals they developed relatively simple criteria in order to classify

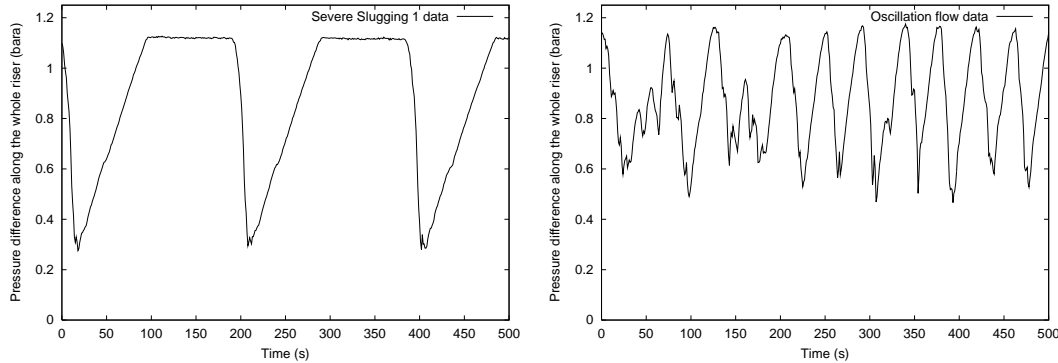


Figure 6.1: Examples of time series that differ in shape.

each case into the horizontal flow regimes. These criteria involved *amplitude* and *frequency* variations and were compared to visual observations with very good agreement.

As it can be seen from the model performance paragraph of Section 5.3.1, all the examples from the “noisy” signals were identified correctly. This means that any part of the signals which has a length of 4 seconds, sampled at 4 Hz (16 consecutive data points), the resultant neural network can identify its class. The classification model can be put to practice by using Equation 5.6 (see Section 5.2.1) with the weight values ( $w$ ) given in Appendix D.2.

One of the main points that were concluded when working with raw time series is that for a signal to be represented well, a section big enough will have to be used so that its main features are included. The choice of this length of time series section is used as an input to the neural network and in the previous Chapters it was referred as the *delay window* or just *delay*. These features are mainly related to the shape of the time series and their amplitude variations. A clear example of two time series which differ in their shapes and in their amplitude variations are shown in Figures 6.1 and 6.2 respectively. As it will be shown in Sections 6.2 and 6.3 below, these signals belong to flow regimes observed in Horizontal pipes and S-shape risers, and if enough of these features can be included in the delay window then their identification with a neural network and a section of the signal equal to the size of the delay window, is possible.

Over all, these tests were successful in every one of their objectives which were:

- familiarization with neural network application software
- familiarization on working with raw time series signals

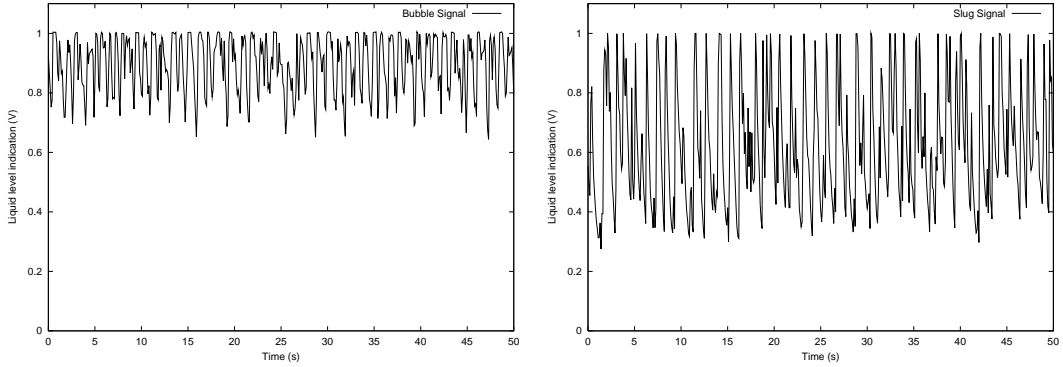


Figure 6.2: Examples of time series that differ in amplitude variations.

- test of the new methodology on a relatively simple problem, and validation of its applicability for more realistic problems, like the ones described in the following Sections.

## 6.2 Horizontal Flow data results

As it was shown in Section 5.3.2 the methodology was also applied on a horizontal multiphase flow system. The collection of the experimental data was described in Section 4.2 where a diagram of the experimental rig is also presented and the results are shown in Tables 5.2 and 5.3. From observing these two Tables the majority of the errors for the training and test patterns, as these were created from the same signals, in Table 5.2 are due mainly to the signals of cases 21 and 28. Case 21 was identified to be 40% Stratified Smooth (SS) and case 28 as 21% SS (see Appendix E.2), when they were originally classified as Stratified Wavy (SW). However from comparing the time series of case 21 with SS training cases such as 20, 13 and 17 (see Figure 6.3), one can clearly see the similarities. This suggests that, especially case 20 and also case 15 which is very similar to case 20, are transitional and their wavy patterns in their time series which were classified as the SS flow regime influenced the performance of the neural network on SW cases such as case 21 and also case 28 whose main difference from case 20 was the larger amount of slug patterns that it contained.

Another example of such is Validation case 23 which is responsible for 40% of the incorrect classifications of all the Validation patterns. This case was classified as 46% SS flow and 1% Slug flow. As it can be seen from Figure 6.4 this signal exhibits a few Slug patterns, with an average of about 1 Slug peak every 200 data points, 17 in total in the 3000 data point time

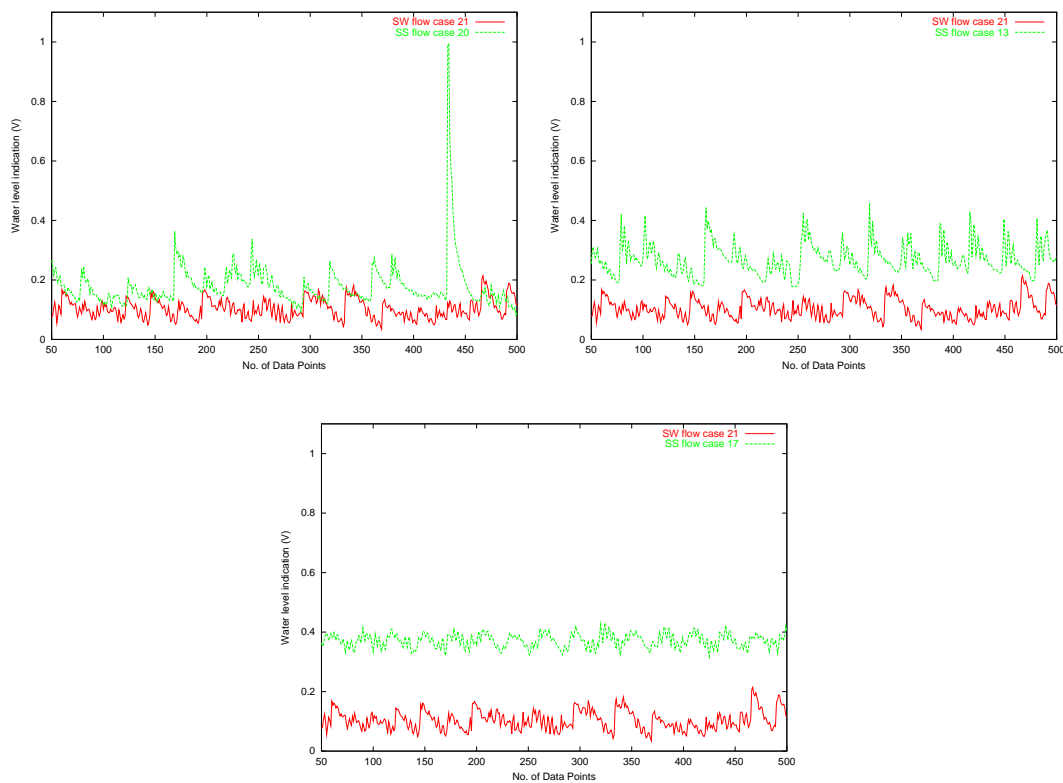


Figure 6.3: Time series sections for comparison between originally classified SS and SW cases 21, 20, 13 and 17.

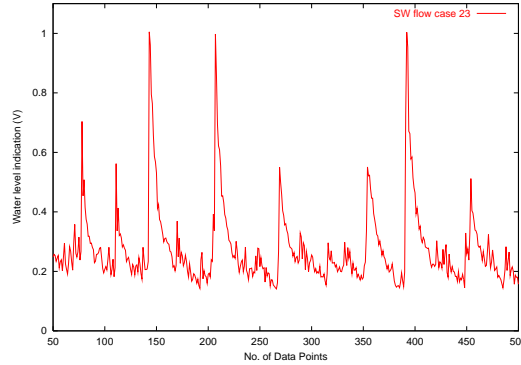


Figure 6.4: Time series section for originally classified SW flow case 23.

series.

The high percentage SS classification is probably due to Training case 20 which as it can be seen from the peak in the top left plot in Figure 6.3 it also contained Slug patterns, seven in total in the 3000 data point signal. Such Slug patterns are present in only one SW Training case, case 27 at twice the frequency. The domination of the SS flow cases over the SW flow cases is due to the fact that both groups of data as they were originally clustered, exhibit a number of similarities but the SS cases are more in number hence had a stronger influence on the training of the neural network. Hence an important conclusion that is drawn from this observation is that not only the same amount of data should be used for training from each signal but also the same number of cases should be used from each flow regime.

Other cases that caused significant errors in the Training, Test and Validation patterns were Training cases 27 and 38 and Validation case 37. SW flow case 27 was classified as 6% SS flow and 6% Slug flow, Slug flow case 37 was classified as 17% SW flow and 1% SS flow, and Slug flow case 38 was classified as 8% SW flow and 1% SS flow.

To all the above errors there is the addition of a much smaller number of patterns which were identified as more than one type of flow or were not identified at all. Such conclusions are established when more than one output units give a value above 0.51, or non of the output units give values above 0.49 for a given pattern. See Table 5.1 for explanations on the analyzing function that was used.

As a general conclusion from the above observations it can be said that a large number of the incorrect errors that have been specified are due to the global classification that is given to a signal. Because one signal is classified as belonging to a Stratified Smooth flow does not mean that there are no Slug patterns in the particular flow. If in the above presented results and



more generally in the ones shown in Tables 5.2 and 5.3, the flow regime identification model that has been developed for the Horizontal system, was shown to be identified incorrectly, for example Slug patterns in the SW flow cases, is not because there were not any such patterns but because these patterns were originally classified in the model development stage, incorrectly as SW flow patterns. A more objective test on the capabilities of the new methodology that is presented in this thesis would be to use training, test and validation flow cases which are carefully processed to incorporate patterns of a single flow regime only.

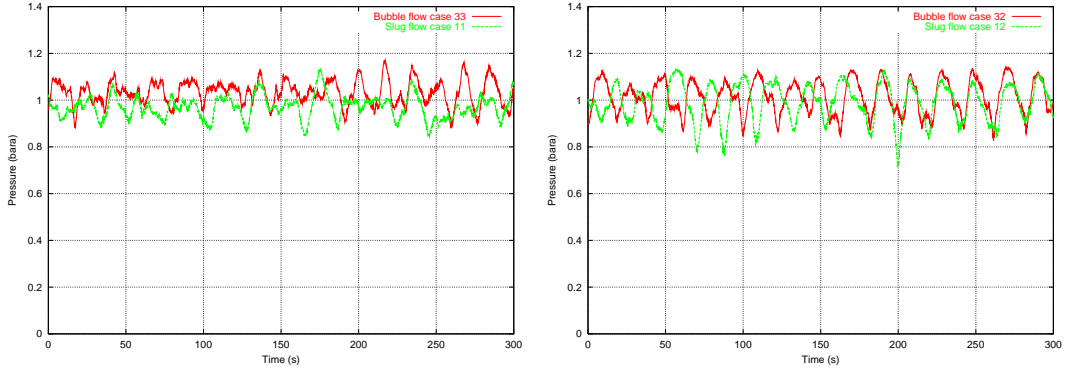


Figure 6.5: S-shape riser originally classified Slug flow cases 11 and 12 and originally classified Bubble flow cases 32 and 33.

### 6.3 S-shaped Riser data results

The same type of experiment as with the previous two systems discussed in this Chapter, was also carried out for the S-shape riser. Again a neural network was trained on the task of identifying the flow regime that a portion of a time series representing the pressure difference between the base and the top of the S-shaped riser, belonged to. The data that were collected were described in Section 4.3, the application of the new methodology on this system was presented in Section 5.3.3 and the results are shown in Tables 5.4 and 5.5.

A quick observation of the results shows that the major contributions to the total errors from the Training, Test and Validation patterns originate from Training case 33 and the Validation cases 32 and 21. Cases 32 and 33 were originally classified as Bubble flow, however the model identified case 33 as 2% SS1 flow and did not identify the rest 98% as any of the four given classes (see the results analysis in Appendix E.3.3). Since this case was used during training the above result suggests that the patterns of this case had no impact on the model's development. This also suggests that this case is different from all the others and there were very few examples present in order to influence the training process. As a consequence flow case 32 which is of the same type as case 33 (see flow regime map in Figure 5.10) and not used during training was identified as 99% Slug flow instead of Bubble. From observing the time series for cases 32 and 33 and comparing them with their neighboring originally classified Slug cases 11 and 12 (see Figure 6.5) it can be concluded that these four flow cases belong to the same group.

On further comparison to other neighboring Slug cases like, 15, 17, 25 and 26 (see Figure 6.6) it is realized that cases 32, 33, 11 and 12 are less

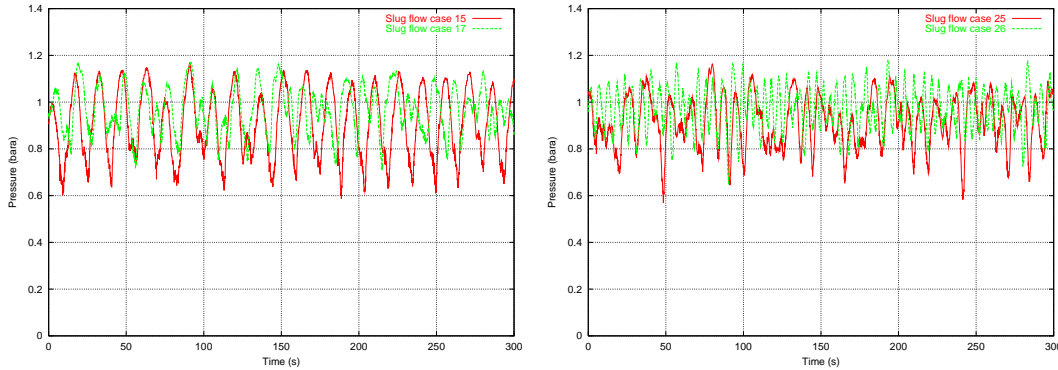


Figure 6.6: S-shape riser originally classified Slug flow cases 15, 17, 25 and 26.

similar to Slug flows and may be they should all be classified as Bubble flow with cases 15 and 17 being closer to transitional between the two.

The errors in identifying Oscillation flow case 21 was the consequence of the same reasons as for cases 32 and 33. This case also belongs to a small flow regime group, for which there were data from only three cases available. Although the two cases that were used for training seemed to be enough to influence the training of the neural network, since 87% of case 20 and 95% of case 22 was identified correctly. However they were not enough to make sure the network generalizes well enough to give better results for case 21, the validation case of the group. The outcome was for the model to identify case 21 as 33% Slug flow and 24% SS1 flow. A positive observation from these incorrect results, even though the data that were available for this flow regime was relatively small, the Validation case for the Oscillation flow regime was identified only as the flow regimes that are on either side of its region. This is quite impressive as the Oscillation flow is a transition from the Severe Slugging 1 (SS1) flow to the Slug flow. Hence if it was assumed that there was no data used to train the network for the Oscillation cases, which in effect is what has happened anyway, and the unknown case 21 was presented to the classification model for identification, the output would be that this case belongs to the transition region between the SS1 and the Slug flow, and closer to the Slug flow. This example shows the true potential of the new methodology that has been presented and tested in this thesis.

Other major contributions to errors were due to the SS1 flow cases 13 and 23 and the Slug flow case 25. These cases had significant sections of their time series confused with the opposite flow regime. SS1 flow case 23 was classified as 22% Slug flow and 16% as both Slug and SS1. SS1 flow case 13 was classified as 15% Slug flow and Slug flow case 25 was classified as 21%

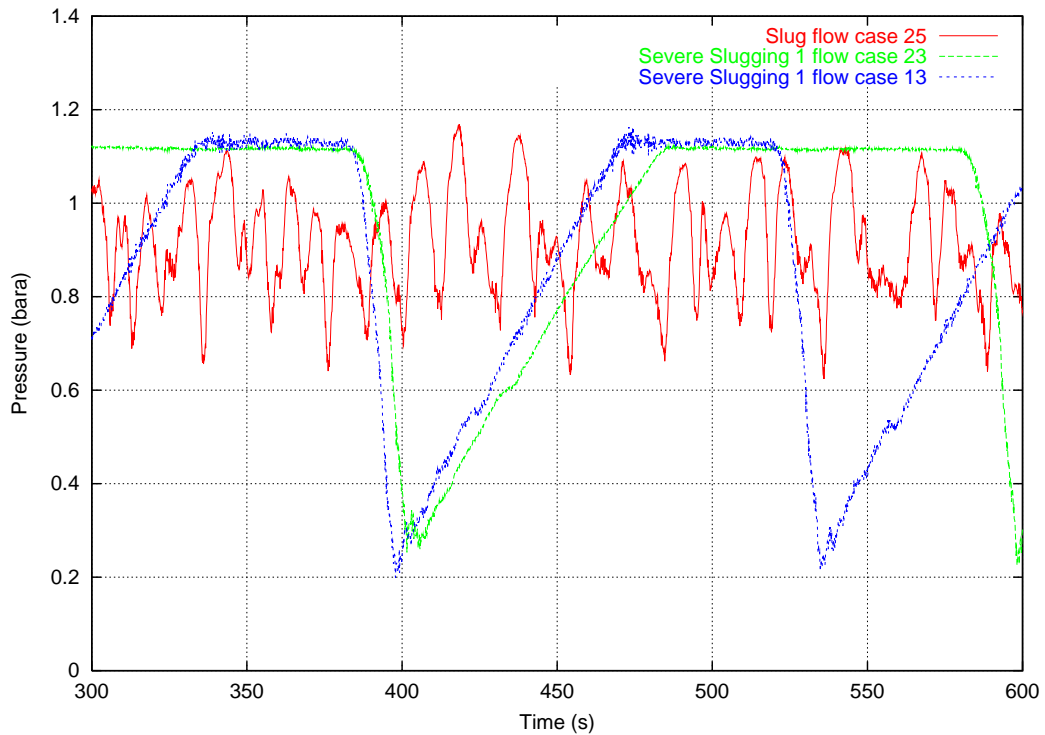


Figure 6.7: S-shape riser originally classified Slug flow cases 15, 17, 25 and 26.

SS1 flow and 12% unknown.

This confusion between SS1 flow cases and any other flow regime cases was unexpected, due to the very distinctive and consistent pattern that these signals have (see Figure 6.7).

By carrying out a more in depth analysis of the results, the patterns which were identified incorrectly were isolated and are plotted in Figure 6.8. From this figure it is obvious that specific patterns in the highly periodic, regular signals of the SS1 flow cases are the ones that are misclassified. The shapes of these patterns for the two cases are shown in Figures 6.9 and 6.10. As it can be seen from these figures these shapes are exactly the same for each cycle and they all involve all of the top relatively flat section of the signals.

A further investigation into the data that was used during the training process for the SS1 flow regime showed that only flow cases 14, 19 and 35 had a significant number of cycles present in the data set (see Figure 6.11). This is because only 300 data points (see *Model Performance* paragraph in Section 5.3.3) was chosen to be used for all the Training flow cases and the signals for cases 7 and 34 had too large cycles to fit into the 300 data points

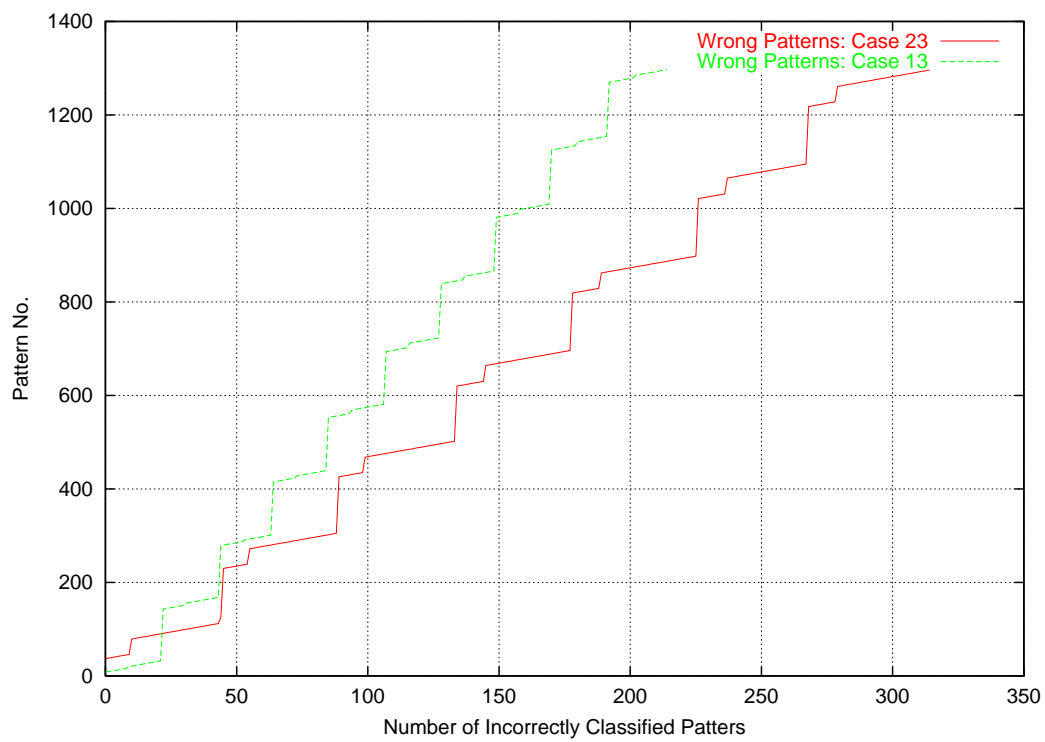


Figure 6.8: All the incorrectly identified patterns for SS1 flow cases 13 and 23.

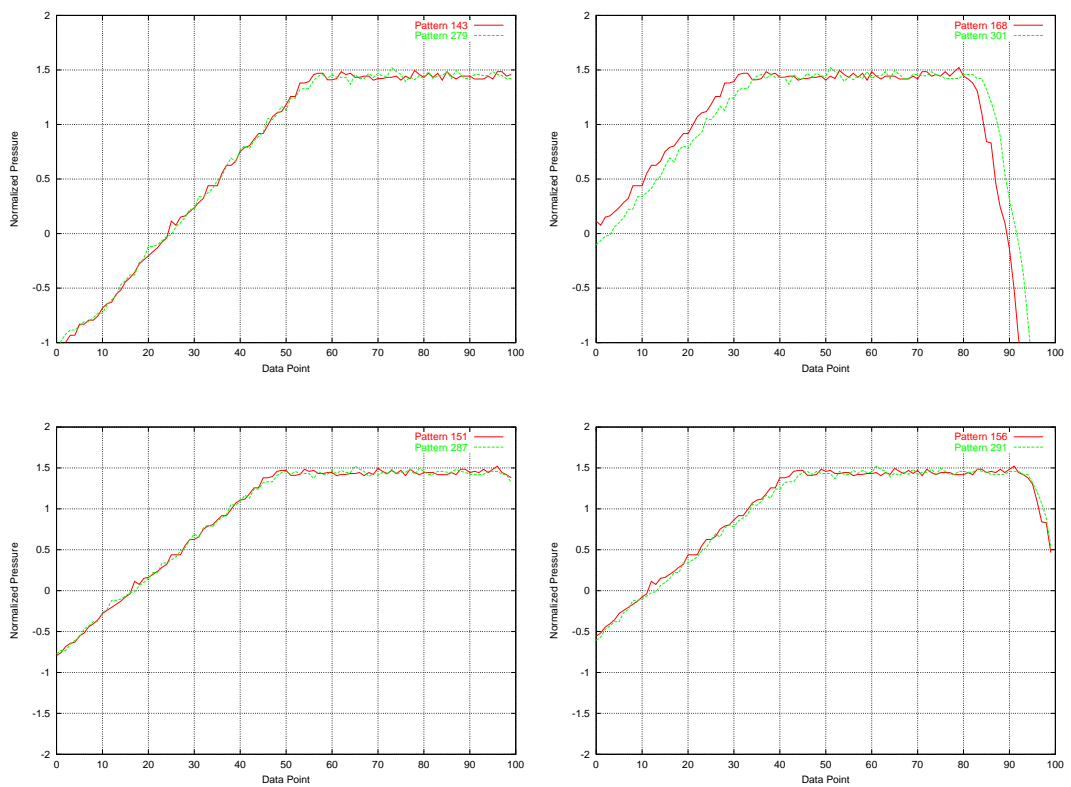


Figure 6.9: The shapes of the incorrectly classified patterns for the SS1 flow case 13.

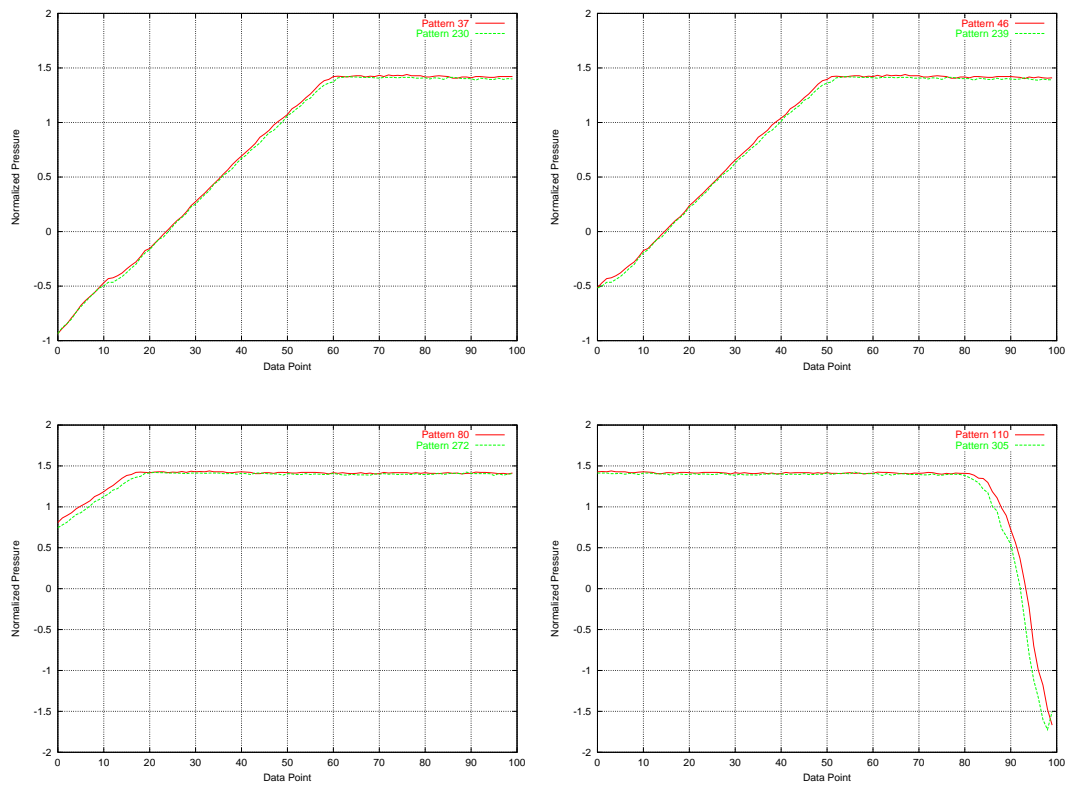


Figure 6.10: The shapes of the incorrectly classified patterns for the SS1 flow case 23.

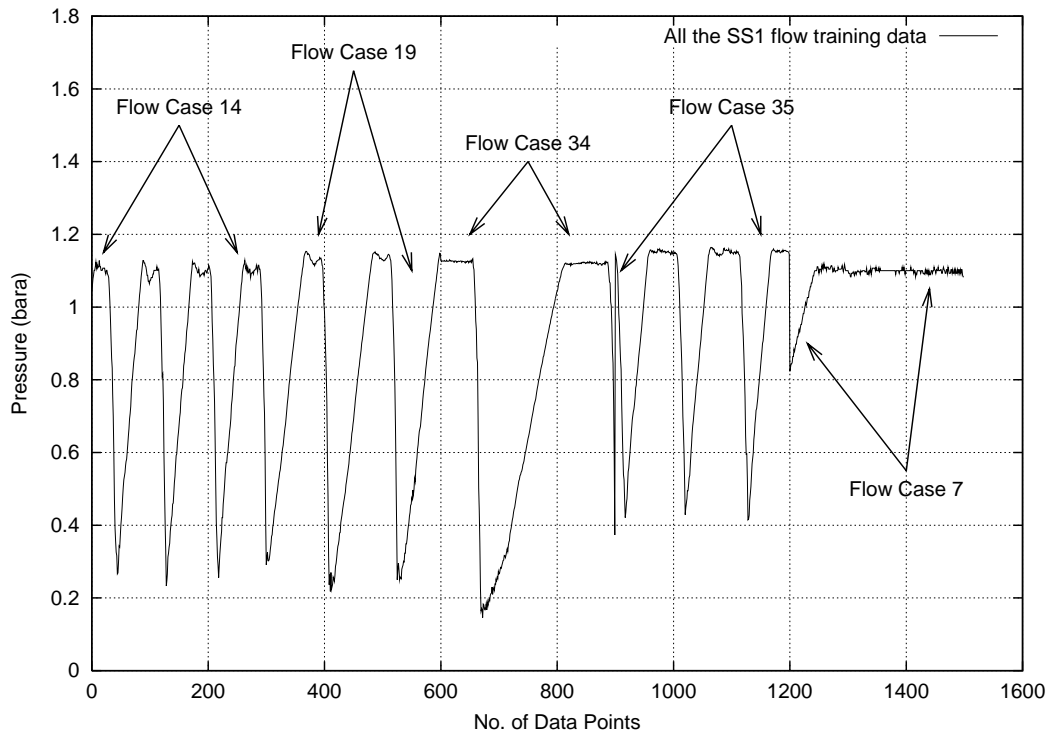


Figure 6.11: All the data that were used to create the Training patterns for SS1 flow regime.

selection window. Hence Validation flow cases 13 and 18 which are closer to cases 14, 19 and 35 in cycle length and general signal shape, were classified much better than Validation flow case 23 which has a larger cycle length (see Figures 6.13)

#### 6.12

As a conclusion it can be said that the errors that were reported for the S-shape riser system were widely due to original misclassifications of training cases, like for example flow case 11, and due to lack of data, as was the case for the Oscillation and some of the Bubble cases (cases 32 and 33). Moreover the lack of data for some of the cases had another negative impact on the results. This lack of data refers to the lengths of time series that were available for individual cases and not to number of flow cases for a given flow regime. The reason why this had a significant impact to the data of all the flow cases that were used for training is because the choice of the number of data points that were used for training for each Training case was determined by finding the file with the smallest number of data, then deciding how much of this file will be used for the Training data set and how much for the Test



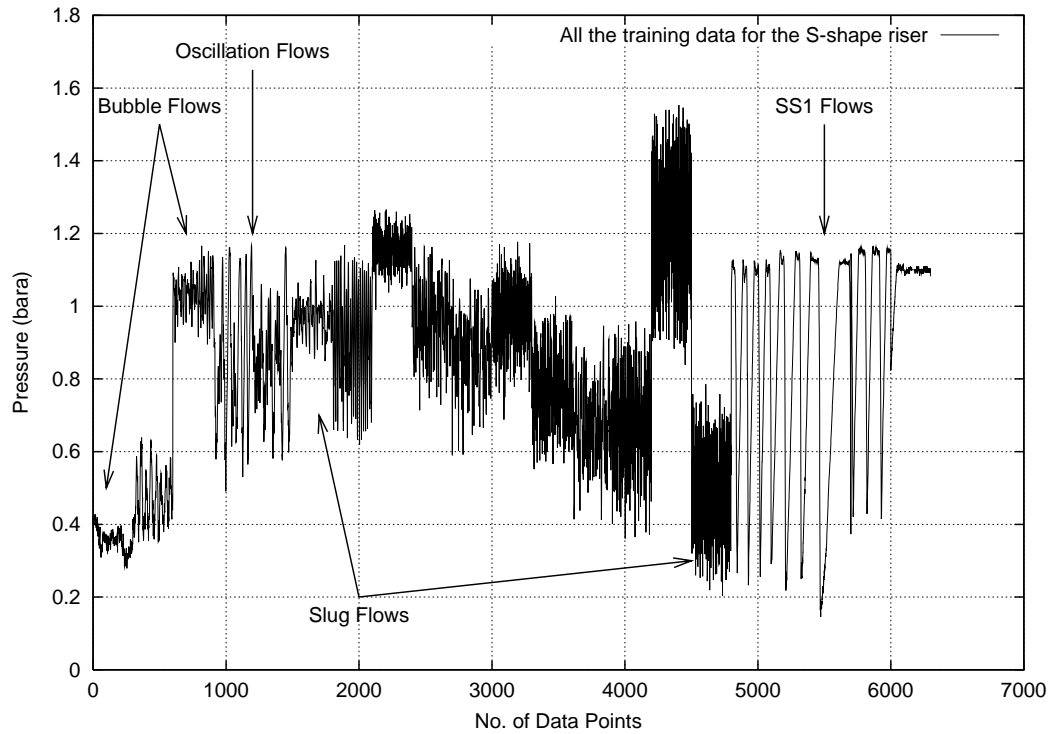


Figure 6.12: The data that were used to generate all the Training patterns for the S-shape riser.

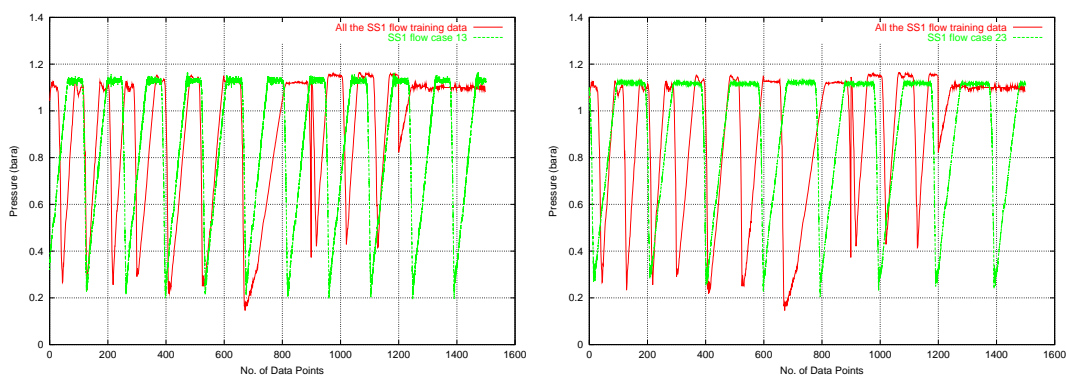


Figure 6.13: Comparisons between the Training SS1 flow data and the time series of the Validation SS1 flow cases 13 (left) and 23 (right).

data set. The size of this training section of the smallest file with in all the Training data cases was used to separate the training section from all the training cases. This was in accordance to the reasons specified in the *Model Performance* paragraph in Section 5.3.3. Hence because of this, flow cases with long cycles in their time series, larger than this training section selection window, were not represented well in the training process. This lead to the unexpected errors of the SS1 Validation cases.

## 6.4 Model creation process

For the experiments of the two laboratory systems mentioned in the previous sections of the Chapter, the Horizontal pipe and the S-shape riser, the following procedure was used to train a Time Lagged Feedforward Neural Network in order to develop a flow regime identification model.

The model creation procedure had two stages:

1. the *Training* stage and
2. the *Test* stage, in this thesis referred to as model *Validation* stage or just *Validation* stage.

During the *Training* stage two data files were used. The first file was used to adjust the weights of the network and it is called the *Training* data file and the second one was used to test the network under training at different stages. This second file is called the *Test* data file. During the *Validation* stage there is only one data file used, and was called the *Validation* data file. This file was used to test the final trained network with new data cases which were not used in the Training data file, and validate its fitness for purpose.

For the above mentioned experiments the three types of data files (Training, Test and Validation) that were used during the model creation process were generated from data obtained from a number of flow cases. These flow cases were split into:

- Training and
- model Validation cases, or simply Validation cases

The Training cases were used during the network training process and the Validation cases were used during the model validation process. Hence the Training and the Test data files that are used during the training process, were generated from the same set of flow cases, the training flow cases, while

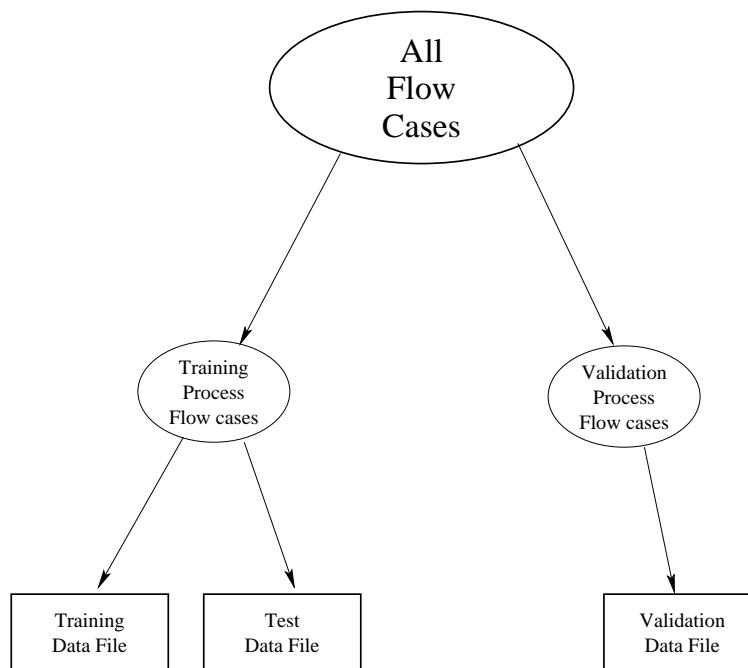


Figure 6.14: Diagram illustrating the process that was used to generate the Training, Test and Validation data files.

the Validation data file was generated from a separate number of flow cases, the validation cases. The data file creation is illustrated in Figures 6.14 and 6.15.

In more detail the training and test data files are generated by grouping all the cases of each flow regime into separate files and then randomly picking three fourths of them to be used as training data and the rest as test data.

It is reasonable for someone to suggest that by using the same flow cases for the training and test data files, it is possible that the two types of data may be highly correlated. Also because they are both used during the network training process, it becomes risky that the network is trained to overfit the data. Also as the training and test data are quite similar the training and test error curves that one monitors during the network training process follow very similar trajectories, almost identical and they do not reach the point of divergence which indicates that any further training will cause the network to over train.

This suggests that it would be necessary for the data in the two files to be less correlated. One way for this to be achieved is to create the two files from different flow cases instead of the same ones. Another way would be to change the way data for the two files are chosen. Instead of picking these

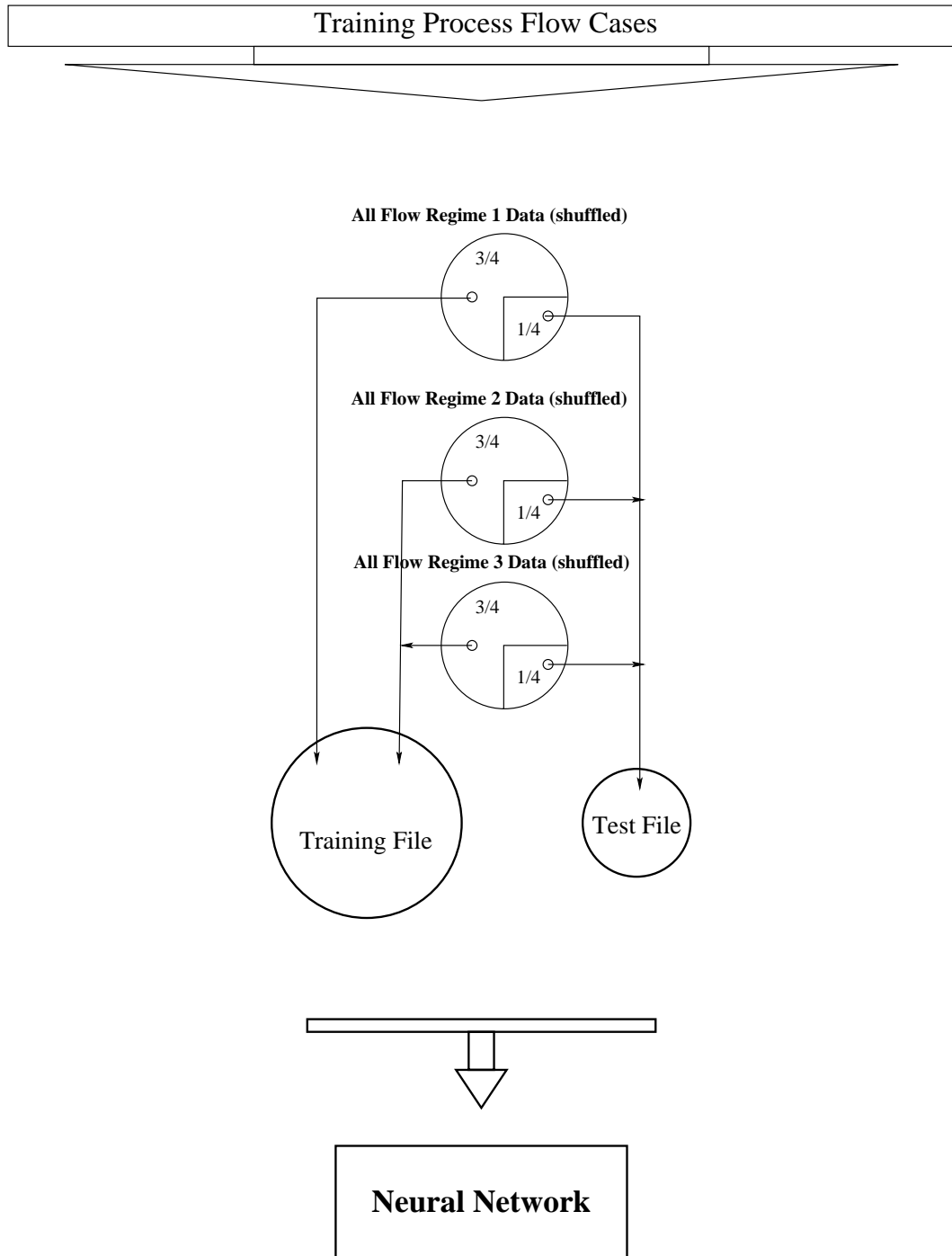


Figure 6.15: Processing flow cases data for training.

randomly the signal could be split into regions to be used for training data and regions to be used for test data. This way no single data point of the signal will be in both files. Due to the lack of data cases the last of the above procedures was used for the experiments of the Conceptual, the Horizontal and the S-shape riser systems.

## 6.5 Faster than Feature Extraction methods

As was mentioned in the literature review (Chapter 2) a common calculation that needs to be carried out for the determination of a number of features in Feature extraction methods is that of the mean of a signal. So far in this thesis it was stated that this calculation inherently causes significant delays to classification model, on identifying important changes in the signal. In this section it is shown why this is the case by considering examples of flow regimes which appear in a S-shape riser.

The graph in Figure 6.16 shows the different number of data points that it is required for a certain level of accurate calculation of the mean for a pressure signal obtained from a Severe Slugging flow. After 10,000 seconds (2 hours and 46 minutes) of monitoring the signal the most accurate calculation of the mean is by a value which contains a spread of  $\pm 0.25$  bara and even after the total length of the signal that was available, which is 14,000 s or 2 hours and 53 minutes, the mean does not converge to a more accurate value than one with a spread of  $\pm 0.02$  bara. However there are cases where the mean values for two signals representing completely different flow regimes can differ by a value of 0.004 bara. Such an example is shown in Figure 6.17 where the mean values are plotted for the S-shape riser flow cases 17 and 35 (see Figure 5.10) which are of the Slug and Severe Slugging flow types. This clearly forces the requirement of using very large time series in order to be able to separate the two. For the specific example of the flow cases 17 and 35, a signal length of almost 3 hours is not enough. Hence if a feature extraction methodology was used for flow regime identification and there was the scenario where flow case 17 was followed by flow case 35 due to some adjustments in the operation of the pipeline, then the classifier would require more than 3 hours of monitoring after the severe slugging flow had occurred before the incident was identified. The new methodology that has been presented in this thesis was shown to accomplish the task with in the time duration of 100 s (0.027 hours), which is the time series length of a single neural network input, at most. This is 140 times faster. Still it is possible that the neural network can identify the change even within the length of one input, although this has not been tested.

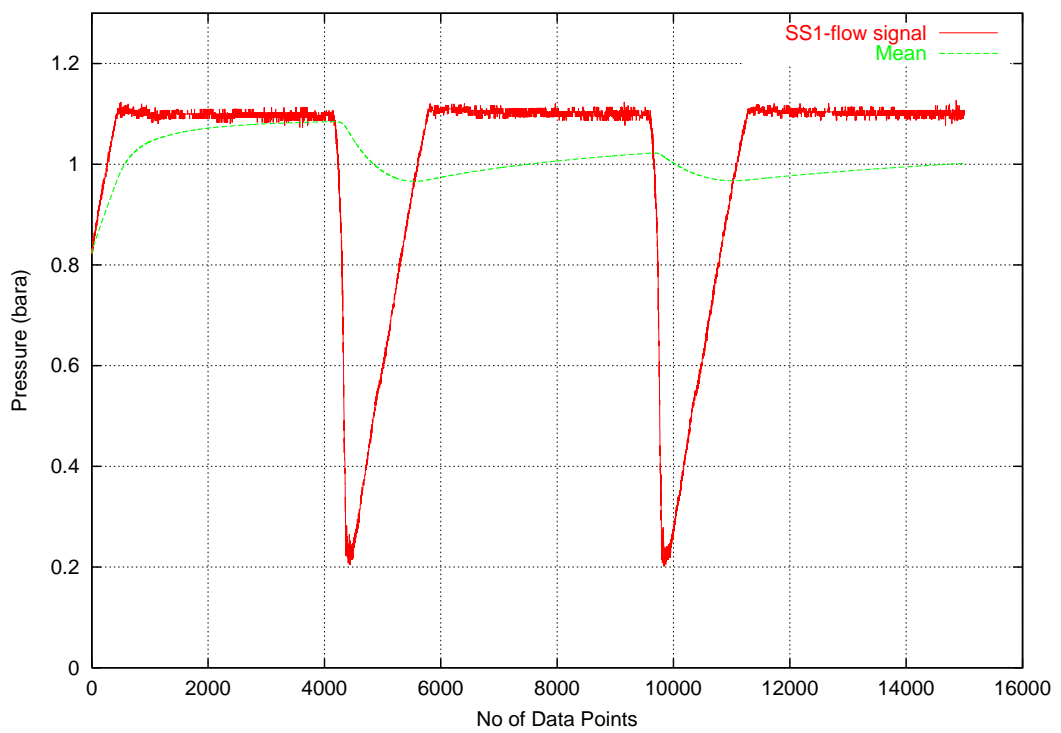


Figure 6.16: Example of a Severe Slugging 1 flow, pressure signal, together with its mean, calculated for a different number of data points.

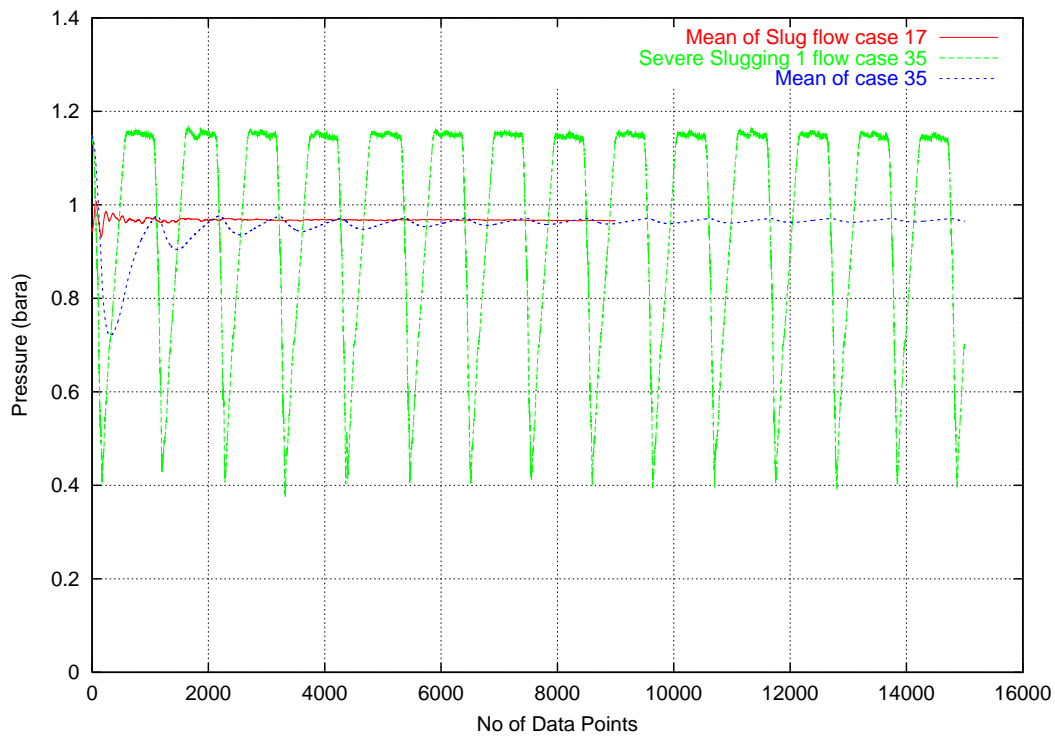


Figure 6.17: Mean signals calculated for a number of data points for the Slug flow case 17 and the SS1 flow case 35. The closeness of their mean values suggests that an accuracy of more than 0.004 bara is required if pressure signals from different flow regimes are to be identified correctly.

## 6.6 General Discussion and Summary

There were a number of significant results that were presented in Chapter 5 and were discussed in the sections above. These results showed that each of the flow regimes that could be present in a time series which represents the characteristic condition of a system will be identified with a high confidence factor. It can be argued that the results for the Horizontal flow system were all correct and the few errors that were found were due to original misclassifications of the data. This was caused by subjectivity in the decisions and the labelling of transitional cases with a single flow regime, which cases however contained patterns of more than one flow regimes. Due to these facts it can be concluded that a network should be trained on data cases for which there is no question of the flow regime they belong to.

In other words, when the methodology that is presented in this thesis is used, the training cases should not contain any major irregularities in their shape. This is because these irregularities will be identified correctly during training but will not agree with the general flow regime class of the specific flow case. The result will be a contribution to the total error of the network. As this error is the measure that is used to determine how well the network is trained, this will lead to incorrect training because the network will be forced to learn to classify the inputs incorrectly. For example consider a Slug flow case, whose signal includes regions where the picks do not reach above 0.5 or 0.6 i.e. show that the pipe is only 50 or 60% full, which can be true for cases close to the Wavy transition region. Such a signal is shown in Figure 6.18. If such a case is used during training, the wavy regions will be labelled as slug as each flow case is labelled according to its general flow type. Still because the signal is presented to the network in small parts, these “Slug” labelled wavy patterns will be used during training to teach falsely the network that such wavy patterns also belong to slug flows. In the long run such irregularities in the training patterns will cause confusion in determining wavy flows, with consequence of some regions of such signals to be identified as Slug.

Due to the nature of the methodology that was developed and used for the work in this thesis, to use only clear cut cases during training is possible and will not affect the performance of the classification model for cases close and within the transition regions. This is because such cases are formed by combinations of the time series patterns that are found in clear cut cases which are away from the transition boundaries. This fact surfaces the potential of using the flow regime classification methodology of this thesis for developing more realistic flow regime maps. In such maps transition boundaries will be represented with regions of transition, as it is in reality and not with thin lines.



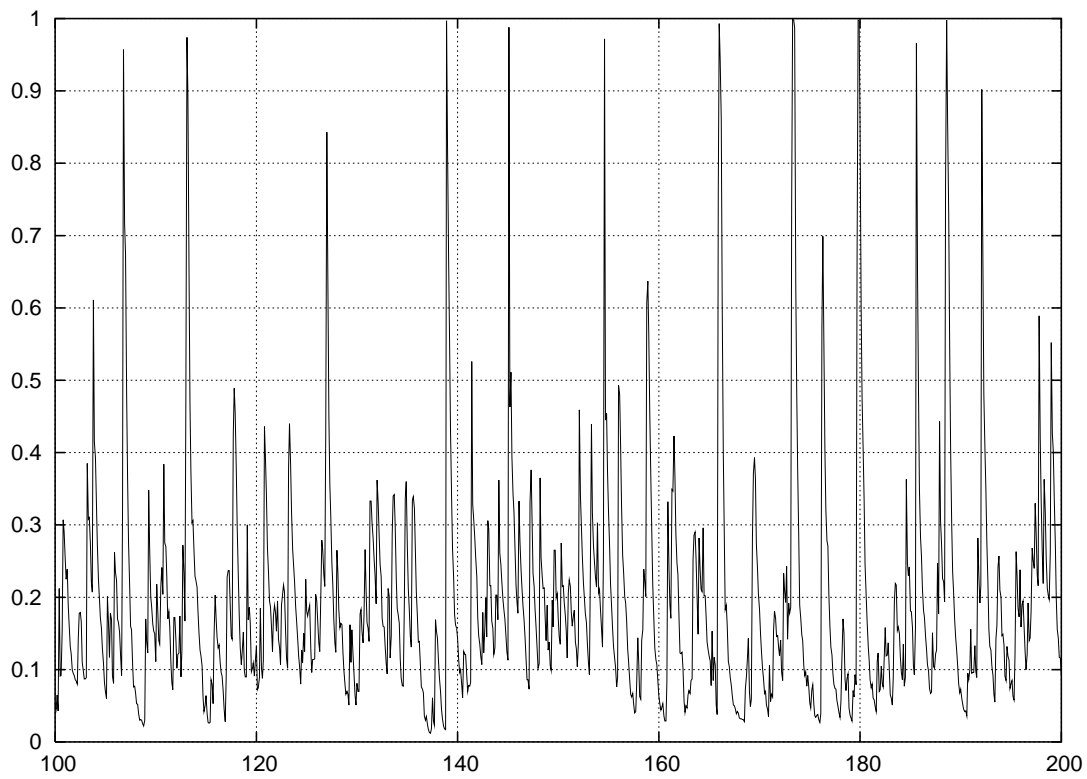


Figure 6.18: Example of a Slug flow case close to the Slug - Stratified Wavy boundary.

The errors that were observed in the results for the S-shape riser, apart from the reasons that were mentioned above for the Horizontal flow system, were due to insufficient time series lengths, in comparison to some of the very large cycle lengths that are found in the flows of such systems.

Another issue that had surfaced during the research work that was presented in this thesis was related to the grouping of the data in order to be used for training, testing and validating the classification model. Ideally different flow cases should be used for the data sets used for each of the three stages during the development of models with ANNs. However this requires a significant amount of data cases to be available for all the flow cases present for a given system. This amount of data was not available during the work described in this thesis. Hence it was reasonable to cluster the different flow cases into two groups only, the Training and the Validation groups, and use the same cases for the training and test activities during the training stage, by making sure that there will not be any shared data points between the two data sets.

Considering the data and the time that were available during the work that was carried out for this thesis it can be concluded that the new flow regime classification methodology that was the main subject of this work was very successful. Apart from its success in application, as it will be concluded in the next Chapter, it also presents a number of very important advantages and potentials, with respect to other methods, on the task of online monitoring of dynamic systems.

# Chapter 7

## Conclusions and Future Work

The new methodology that has been used for this research work involves the use of Artificial Neural Networks (ANNs) on the task of identifying the flow regime in a two phase flow inside a pipeline of various diameters and configurations.

The novelty of this methodology is in the way measured time series data from a system, are presented to the neural network. Earlier work has been carried out by extracting features from time series of one or more relevant measured quantities from a system where the neural network model was to be applied. Then these features were used as inputs to the neural network. Feature extraction though, as it was shown in Section 6.5, requires relatively large lengths of time series for accurate calculations of the features and the single values obtained for each time series hide a lot of the signal information from the processing model. This long duration that is required for a feature extraction method to identify a change in the condition of a system may not always be ignored and passed by as acceptable. Such examples are on-line monitoring of nuclear reactors or hydrocarbon transportation pipelines. In this work we omit the feature extraction process all together and analyze the data as it is in its raw, time series form.

The main advantage of this idea is that any changes in the behavior of a system which are also present in the monitoring system, will be available for consideration by the processing model. This fact, as it has been shown, has lead to the development of a model which is more powerful than it was originally aimed for.

The aim of this research work was to develop a model which would be able to determine the flow regime for an air-water flow inside a pipe which could have the shape of various geometries. What has been actually developed is a model that can not only do this but can also give an indication of where transitional boundaries lie together with an estimation of where the flow is

50/50 (50% of the flow regime of the one side of the boundary and 50% of the flow regime of on the other side of the boundary) or 60/40 or even where there are three patterns at once.

In more detail a separate flow regime identification model has been obtained for a horizontal 102mm internal diameter pipe and an S-shape riser of 50mm internal diameter by training a MLP artificial neural network. The flow regimes that were considered for each of the systems were:

- Horizontal system
  - Stratified Smooth
  - Stratified Wavy
  - Bubble
  - Slug
- S-shaped riser system
  - Bubble
  - Slug
  - Oscillation
  - Severe Slugging 1

The model managed to identify thousands of patterns for each flow regime and classified cases which were suspected to be transitional, as such, by identifying patterns for flow regime on each side of the boundary.

The measured quantities that were used to train the neural networks and develop the models, for each of the systems were:

- Horizontal system – liquid level in a pipe’s cross section.
- S-shaped riser system – pressure difference between the bottom and the top of the riser.

The time series of the appropriate system-variable was split into pieces of a suitable length (time delay). These time delays were given as inputs to the network while their respective classification identity was presented as an output for comparison during the training process. The amount of data (inputs) that was required for identifying the flow regime in the two systems was:

- horizontal system – 20 seconds of data sampled at 10Hz, ie 200 inputs

- S-shaped riser system – 100 seconds sampled at 1Hz, ie 100 inputs.

On the neural networks side of the methodology one Multilayer Perceptron was used with the logistic sigmoidal as an activation function for its hidden and output units. It was trained with the Scaled Conjugate Gradient error reduction method, which is an improvement on the standard Back Propagation method.

A requirement for such a methodology is the determination of a suitable time delay with which the system-monitoring-signal will be presented to the model. This has to be long enough for significant parts of the signal's cycle to be present but not too long as the larger the neural network the more data will be required to obtain the model. This in its turn leads to larger networks, longer training periods and longer calculation times from the final model.

By comparing the two systems that were mentioned above it was identified that:

- the S-shaped system by nature accommodates flows with long cycles, like for example the Severe Slugging flow regime which were taking as long as 230 sec.
- in the horizontal system on the other hand one would not see cycles take more than 10 seconds.

So the determination of the time delay is dependent on the system the classifier will be used on.

This leads us to the applicability of the classifier. As it stands the model of flow regime identification can be used only for the system it was trained on. This is because the pipeline configuration affects the flow regimes that will be present. For example, effectively there will be no stratified smooth regime in a pipeline with significantly sloped sections, and as it was mentioned above this will affect the number of inputs to the network, hence its overall topology.

A more general model though, suitable to a wider pipeline configurations could be achieved by training a neural network with data from a number of systems and determining an appropriate delay according to the flow regime with the largest cycle. As this will basically mean that a very large amount of information will be required from one neural network to be learned, which most certainly will lead to very large networks and long training times, a more optimistic approach would be to split the task into modules. This way, one network will perform classification only for one of the systems from which data have been obtained, leading to much smaller networks and training can be carried out in parallel and saving a lot of time.

Although the idea of using raw time series as inputs to a neural network was found to have been previously used by Seleglim *et al.* [28]. In that work separate ANNs were used to identify each flow regime (six in total) and a further winner-take-all (SOM) network was used at the end to resolve multiple identities for the same input. Also the classifier was only tested on a horizontal 60 mm pipe and they didn't attempt to distinguish between the "Bubble/Plug" and "Slug" flow regimes but considered them both as one, the "Intermittent" regime.

Also as an input system-parameter they used the outputs from an electrical impedance instrument of 16 electrodes. The time delay they used to split the time series was 20 seconds as well but their total ANN inputs was much bigger (320) as they took 20 seconds of inputs from each of the 16 electrodes in the instrument. So their model is very specific to the measuring instrument they have used and is restricted to the use of that one only. This may not be always available and it can be costly and difficult to install, especially in pipelines installed in considerable depths in the ocean.

Commenting on the results that were presented in Chapter 5 and the discussion that was made about them and the methodology in general it can be concluded that more realistic boundary region representation is possible with the new methodology. This is due to the fact that a signal is analyzed in its raw form, hence patterns from all the flow regimes which are present in the signal are considered and as it has been shown they are also correctly identified.

Any errors from the Horizontal system were due to original misclassifications of training cases. This misclassifications were mainly due to the fact that the cases belonged to transitional regions and their time series did not contain patterns of one flow regime only.

The large errors from the few Validation cases of the S-shape riser system were due to original misclassifications but also due to lack of data from the flow cases of some of the flow regimes. The short lengths of signals that were available for these flow regimes led to use, during the training process, time series lengths for a number of flow cases, of less than a cycle. This made the training incomplete for these flow cases with a consequence on the errors.

The tests that were carried out in this thesis validate the suitability and ability of the new methodology that was presented in Chapter 3. The methodology is suitable to be used on the identification of flow regimes for multiphase flows in pipelines and it is able to carry this task for a variety of pipeline geometries. It also provides a number of advantages and also highlights a number of potentials. The advantages are:

1. Faster identification of changes to the condition of the system. This

makes it highly suitable for real life applications.

2. Inexpensive. There are no requirements for highly specialized and expensive instruments. Any instrument that can provide a measure of the characteristic condition of the system is adequate.
3. Suitable for a variety of pipeline geometries.
4. Better performance. It gives a more realistic flow regime identification for cases close and well within transitional regions.

Its potential is that it provides the means to remove subjectivity from all of its classifications as it could be trained only from clear cut cases and still perform well for transitional cases.

## 7.1 Future Work

Although extensive tests were carried out during the course of this research, for the development and test of the new methodology, there are a number of areas, which at least from an academic point of view, demand further work.

Such an area is the detailed comparison between competing flow regime identification methods, especially between the FE and the current RD methods which utilize the neural network technology. This will give a more clear picture of the benefits that are presented by the RD method which was described in detail in the previous chapters.

Another area of future work is to take the synthetic data experiments presented in this thesis a step further and investigate the effect that various levels of noise in the data may have on the performance of the flow regime identification models. This is of significant importance if the methodology is to be used in real life applications.

In the preceding pages it was mentioned a number of times how important the size of the delay window is. This the window with which the time series are presented to the neural network. Although a number of tests had been performed for a number of delay sizes, a rigorous optimisation was not carried out, mainly because the results that were eventually obtained were all ready very good and the analysis did not give any indications that the obtained errors could have been improved by changing the delay size. Still due to the importance of this parameter a system is necessary to be devised with which a suitable value for the delay window can be determined satisfactorily. Also unlike the time consuming and tedious visual observations of the signals that was carried out during this work in order to determine this parameter, an

automatic determination could be attempted, suitable for different systems where the method could be applied on.

On page 77 it was mentioned that an improvement on the results was achieved by extending the normalization range that the input data was normalized with from the  $[0.15, 0.85]$  interval to the  $[-2, 2]$  interval. This suggests that the choice of the normalization range is important and further optimization may prove to be advantageous.

Furthermore it would be interesting and beneficial to the industry if the following areas were also investigated.

Speed of responding to change within one input. It has been shown that between two neural network input sets, a change in flow regime is identified. This makes the method as fast as the length of the delay window (size of the input section). However every input set that was used in this work was of the same flow regime. Would it be possible to identify a flow regime change within the same input set and how many inputs will have to be changed into the new flow regime before it is identified? Such a test will show if the methodology can become even faster.

A part of this work that could be considered incomplete is the fact that, due to experimental facility limitations, two major flow regimes were not considered for the Horizontal flow system. These were the Annular and Dispersed (Bubbly) flows. Hence the investigation if they can also be identified by the new methodology is important. Weisman et al. [41] showed that amplitude variations observed visually from liquid level indicating signals of horizontal flows are enough to distinguish between Annular flows and their neighboring Wavy, Slug and Bubbly flows, and also between the Intermittent Bubble and Slug flows. Hence this should be also possible with the use of neural networks and the methodology presented and tested in this thesis.

Another area of future work would be to utilize the better performance of the new methodology for the transitional cases and develop more realistic flow regime maps. In this task the use of only clear cut flow cases during training can also be applied to reduce the subjectivity in the results. This way the transition boundaries will be more objectively determined and will represent regions of transition where the flow regime on the one side of the boundary will show reduction in its presence in the flow, gradually as the flow moves towards the flow regime on the other side of the boundary. The boundary will be placed at the flow case positions where the two flow regimes are equally present in the signal of the specific flow case.

Finally it would be exciting to develop a working system for flow regime identification and incorporate it in a control system of a hydrocarbon transportation pipeline. Further more it would be interesting to investigate the application of the new methodology to other dynamic systems where moni-



toring of a time series, in real time, is important. In these new applications the inputs to the ANN can be data from one or more time series that represent the characteristic condition of the dynamic system.



# Bibliography

- [1] S. Ashforth-Frost, V. N. Fontama, K. Jambunathan, and S. L. Hartle. The role of neural networks in fluid mechanics and heat transfer. In *Conference on instrumentation and measurement technology*, pages 6–9, New York, NY, USA, 1995. IEEE.
- [2] D. Barnea. A unified model for predicting flow-pattern transitions for the whole range of pipe inclinations. *International Journal of Multiphase Flow*, 13(1):1–12, 1987.
- [3] C. M. Bishop and G. D. James. Analysis of multiphase flows using dual-energy gamma densitometry and neural networks. *Nuclear instruments & methods in physics research*, a327(2-3):580–593, 1993.
- [4] S. Cai, H. Toral, J. Qiu, and J. S. Archer. Neural network based objective flow regime identification in air-water two phase flow. *Canadian journal of chemical engineering*, 72:440–445, June 1994.
- [5] R. Callan. *The essence of neural networks*. Prentice Hall Europe, 1999.
- [6] C. Chatfield. *The analysis of time series: an introduction*. Chapman and Hall, 4th edition, 1989.
- [7] J. T. Connor, R. Douglas Martin, and L. E. Atlas. Recurrent neural networks and robust time series prediction. *IEEE Transactions on Neural Networks*, 5(2):240–254, March 1994.
- [8] J. Drahoš and J. Cermák. Diagnostics of gas-liquid flow patterns in chemical engineering systems. *Chemical engineering and processing*, 26:147–164, 1989.
- [9] G. Goudinakis, L. Hanich, C. Thompson, H. Yeung, and S. Dickson. An inexpensive ann methodology for fast identification of flow regimes in a variety of pipeline configurations. In *Proceedings of the Mutliphase'03 conference*, pages 87–102, San Remo, Italy, June 11-13 2003. BHR Group.

- [10] S. Haykin. *Neural networks: a comprehensive foundation*. Prentice Hall, 2nd edition, 1999.
- [11] E. Hervieu. Identification of gas-liquid flow regimes from a space-frequency representation by use of neural networks. In *4th International Conference on Multiphase Flow, ICMF'2001*, pages CD-ROM Proceedings paper 430, New Orleans, Louisiana, USA, May 27 - June 1 2001.
- [12] E. Hervieu and P. Seleglim Jr. An objective indicator for two-phase flow pattern transition. *Nuclear engineering and design*, 184:421–435, 1998.
- [13] G. Hetsroni. *Handbook of multiphase systems*. McGraw-Hill, 1982.
- [14] T. J. Hill. Gas-liquid flow challenges in oil and gas production. In *ASME Fluids Engineering Division Summer Meeting*, pages FEDSM97–3553. ASME, June 22-26 1997.
- [15] D. E. Rumelhart J. L. McClelland and the PDP Research Group. *Parallel Distributed Processing: Explorations in the Microstructure of Cognition, volume 2*. MIT Press, Cambridge, 1986.
- [16] O. C. Jones Jr. and N. Zuber. The interrelation between void fraction fluctuations and flow patterns in two-phase flow. *International Journal of Multiphase Flow*, 2:273–306, 1975.
- [17] A. Kitagawa, E. Urata, and T. Takenaka. *J. Jpn. Hydraulics & Pneumatics Soc.*, 6(2):78, 1975. (in Japanese).
- [18] T. Kohonen, J. Hynninen, J. Kangas, and J. Laaksonen. Som\_pak: The self-organizing map program package. Technical Report A31, Helsinki University of Technology, January 1996. <http://www.cis.hut.fi/research/software.shtml>; last accessed March 18, 2003.
- [19] G. Matsui. Identification of flow regimes in vertical gas-liquid two-phase flow using differential pressure fluctuations. *International Journal of Multiphase Flow*, 10(6):711–720, 1984.
- [20] W. S. McCulloch and W. H. Pitts. A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics*, (5):115–133, 1943.

- [21] Y. Mi, M. Ishii, and L. H. Tsoukalas. Vertical two-phase flow identification using advanced instrumentation and neural networks. *Nuclear engineering and design*, 184(2-3):409–420, 1998.
- [22] Y. Mi, M. Ishii, and L. H. Tsoukalas. Flow regime identification methodology with neural networks and two-phase flow models. *Nuclear engineering and design*, 204:87–100, 2001.
- [23] Y. Mi, M. Ishii, and L. H. Tsoukalas. Horizontal flow regimes identification using neural computing. In *4th International Conference on Multiphase Flow, ICMF'2001*, pages CD-ROM Proceedings paper 942, New Orleans, Louisiana, May 27 - June 1 2001.
- [24] J. A. Montgomery. *Severe slugging and unstable flows in a S-shaped riser*. Phd thesis, Cranfield University, School of Engineering, 2002.
- [25] E. A. Osman. Artificial neural network models for identifying flow regimes and predicting liquid holdup in horizontal multiphase flow. In *2001 SPE Middle East Oil show*, pages 1–8, Bahrain, 17-20 March 2001. Society of Petroleum Engineers.
- [26] N. Petalas and K. Aziz. A mechanistic model for multiphase flow in pipes. *Journal of Canadian Petroleum Technology*, 39(6):43–55, 2000.
- [27] J. W. Sammon Jr. A nonlinear mapping for data structure analysis. *IEEE Transactions on Computers*, c18(5):401–409, May 1969.
- [28] P. Seleglim Jr., K. C. O. Crivelaro, and E. Hervieu. Identification of horizontal two-phase flow regimes through a neural network models. In *4th International Conference on Multiphase Flow, ICMF'2001*, pages CD-ROM Proceedings paper 362, New Orleans, Louisiana, USA, May 27 - June 1 2001.
- [29] T. Smith, M. Ishii, Y. Mi, and Y. Aldorwish. Flow regime identification using impedance meters and self-organizing neural networks for vertical pipe sizes: 1/2", 2", 4", 6". In *4th International Conference on Multiphase Flow, ICMF'2001*, pages CD-ROM Proceedings paper 767, New Orleans, Louisiana, May 27 - June 1 2001.
- [30] Stuttgart University, <http://www.informatik.uni-stuttgart.de/ipvr/bv/projekte/snns/>. *SNNS user manual*, v4.2 edition.

- [31] Y. Taitel and A. E. Dukler. A model for predicting flow regime transitions in horizontal and near horizontal gas-liquid flow. *AICHE*, 22(1):47–55, January 1976.
- [32] T. Takenaka. Some problems on fluid transient phenomena. *JSME International Journal*, 30(266):1200–1206, 1987.
- [33] L. Tarassenko. *A guide to neural computing applications*. Arnold, London, 1998.
- [34] J. Ternyik, H. I. Bilgesu, and S. Mohaghegh. Virtual measurement in pipes: Part 2—liquid holdup and flow pattern correlations. In *SPE Eastern regional conference & exhibition*, pages 21–25, Morgantown, WV, USA, 17-21 September 1995. Society of Petroleum Engineers.
- [35] V. Tin. Severe slugging in flexible risers. In *Proceedings of the 5th international Conference on Multiphase Production*, pages 507–525. BHRg, 1991.
- [36] L. H. Tsoukalas, M. Ishii, and Y. Mi. A neurofuzzy methodology for impedance-based multiphase flow identification. *Engng Applic. Artif. Intell.*, 10(6):545–555, 1997.
- [37] N. K. Tutu. Pressure fluctuations and flow pattern recognition in vertical two phase gas-liquid flows. *International Journal of Multiphase Flow*, 8(4):443–447, 1982.
- [38] A. Tzes and J. Borowiec. Applications of fuzzy logic and neural networks to identification and control problems in fluid mechanics. In *Proceedings of the ASME fluids engineering division*, pages 29–34. ASME, FED-242 1996.
- [39] A. S. Weigend and N. A. Gershenfeld. Results of the time series prediction competition at the santa fe institute. In *IEEE International Conference on Neural Networks*, pages 1786–1793. IEEE, 3 1993.
- [40] A. S. Weigend, B. A. Huberman, and D. E. Rumelhart. Predicting the future: A connectionist approach. *International journal of Neural Systems*, 1(3):193–209, 1990.
- [41] J. Weisman, D. Duncan, J. Gibson, and T. Crawford. Effects of fluid properties and pipe diameter on two phase flow patterns in horizontal lines. *International Journal of Multiphase Flow*, 5:437–462, 1979.

- [42] H. Wu, F. Zhou, and Y. Wu. Intelligent identification system of flow regime of oil-gas-water multiphase flow. *International journal of multiphase flow*, 27:459–475, 2001.





# Appendix A

## Artificial Neural Networks: Theory

There are a number of good text books where one can find all the information necessary on Artificial Neural Network theory. Still the following sections are included here for completeness.

### A.1 The Multilayer Perceptron

An example of a Multilayer Perceptron (MLP) is shown in Figure A.1.

At each node in an MLP the inputs are summed after they have been multiplied by their respective weight ( $w$ ) (see Figure A.2) and then put through the activation function ( $g()$ ). Hence the output ( $y$ ) from each processing node is

$$y = g\left(\sum_{i=0}^3 w_i x_i\right) \quad (\text{A.1})$$

where

$$\begin{aligned} w_0 &= \theta \text{ the threshold or bias and} \\ x_0 &= \text{unity.} \end{aligned}$$

More specifically from Equation A.1 the output from each hidden unit is

$$y_h = g\left(\sum_{i=0}^I w_{ih} x_i\right)$$

and the output from each output unit is

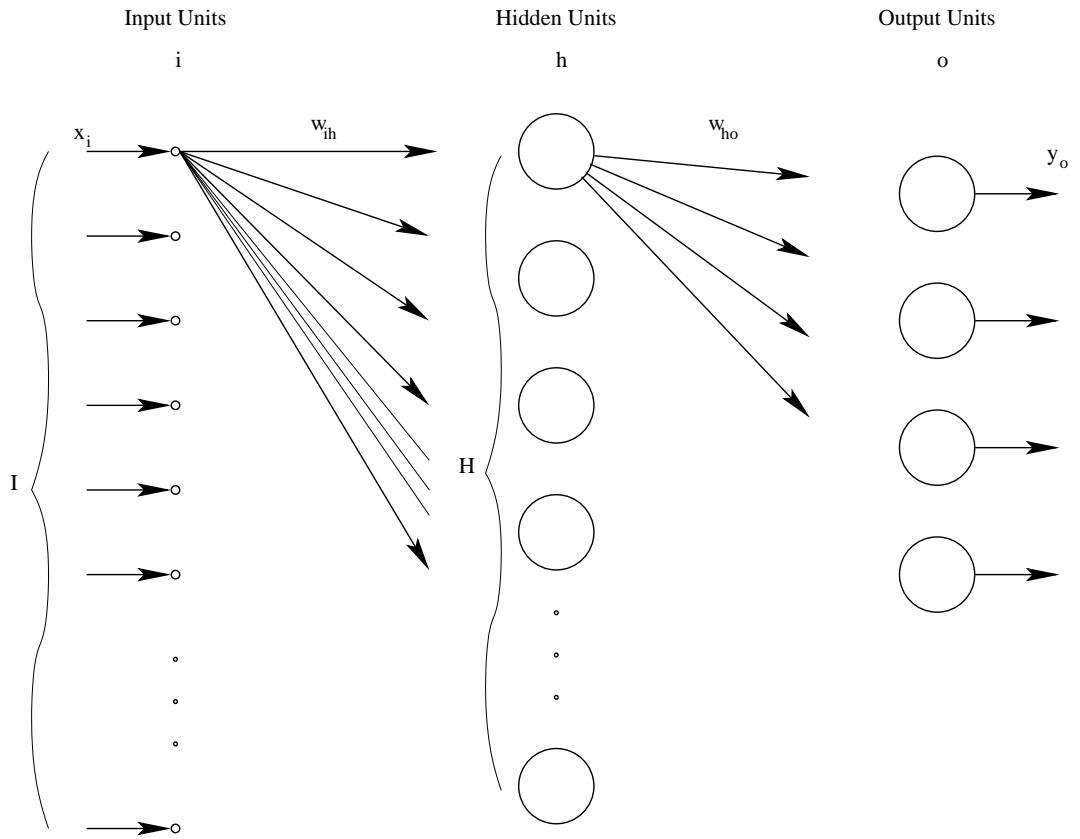


Figure A.1: Example of an MLP neural network.

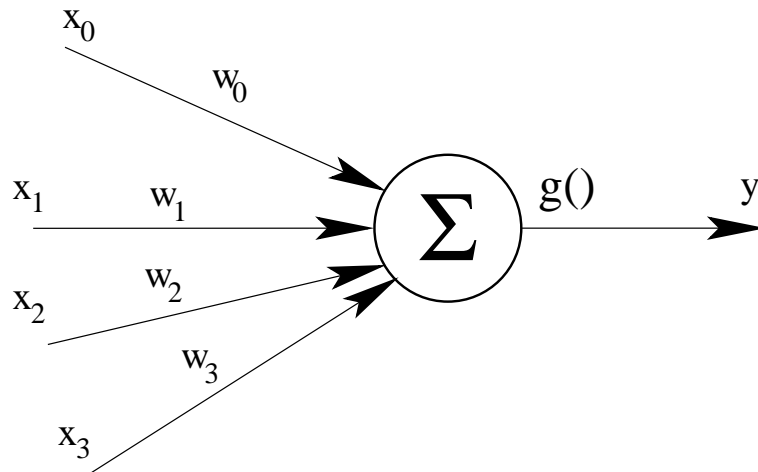


Figure A.2: Close up on a MLP processing node, the artificial neuron.

$$y_o = g\left(\sum_{h=0}^H w_{ho}y_h\right) = g\left(\sum_{h=0}^H w_{ho}g\left(\sum_{i=0}^I w_{ih}x_i\right)\right) \quad (\text{A.2})$$

## A.2 The Backpropagation Learning Algorithm

The only reason why artificial neural networks are of any use is because they can extract relationships between some inputs and outputs of the system under investigation. This is achieved through a learning process where examples ( $p$ ) of inputs and *target outputs* ( $t$ ) are feed to the neural network until, for a given input the network gives an *estimated output* ( $y$ ) close enough to the respective target output. In order to achieve this an error function is chosen which will have to be minimised using gradient descent. Such a function is the Sum of Squares Error (SSE) function given by Equation A.3

$$E = \frac{1}{2} \sum_{p=1}^N (y_o^p - t_o^p)^2 \quad (\text{A.3})$$

The minimisation is achieved by adjusting the weights in the network according to Equation A.4

$$\delta w = -\eta \frac{\partial E}{\partial w} \quad (\text{A.4})$$

From Equations A.3 and A.4 it can be shown [33] that the weights between the input and the hidden layers ( $w_{ih}$ ) and the weights between the hidden and output layers ( $w_{ho}$ ) are adjusted during each training epoch ( $t$ ) according to the following formulae

$$w_{ho}(t+1) = w_{ho}(t) - \eta \delta_o y_h \quad (\text{A.5})$$

where

$$\delta_o = (y_o - t_o)y_o(1 - y_o)$$

$$w_{ih}(t+1) = w_{ih}(t) - \eta \delta_h y_i \quad (\text{A.6})$$

where

$$\delta_h = \sum_k (\delta_o w_{ho}) y_h (1 - y_h)$$

The learning process includes the following steps

- Step 1 Initialise the weights randomly between a minimum and a maximum, usually -1 to 1.
- Step 2 Calculate the network outputs for all the training patterns using Equation A.2.
- Step 3 Adjust the weight values according to Equations A.5 and A.6.
- Step 4 Repeat the process from Step 2 until the SSE error is small enough according to some criteria.

### A.2.1 Conjugate Gradient method

They are general-purpose second order techniques that help minimise goal functions (like the error function concerned with the NNs) of several variables with sound theoretical foundations [30]. Second order means that these methods make use of the second derivatives of the goal function, while first-order techniques like standard backpropagation only use the first derivatives. A second order technique generally finds a better way to a local minimum than a first order technique, but at a higher computational cost.

Like standard backpropagation CGMs iteratively try to get closer to the minimum. But while standard backpropagation always proceeds down the gradient of the error function, the conjugate gradient method will proceed in a direction, which is conjugate to the directions of the previous descending steps. Thus the minimisation performed in one step is not partially undone by the next, as it is the case with standard backpropagation and other gradient descent methods.

One example of the CGMs is the Scaled Conjugate gradient method. As it is a CGM this is also slower due to additional computations. In one iteration it requires the computation of two gradients (second-order technique) and one call to the error function in contrast to one of each for the standard backpropagation. Using Miller's metric [30] one iteration of SCG is as complex as around 10-16 iterations of standard backpropagation.

But although this method is slow on computations it is faster on reaching final results and can, give better results than the standard back propagation, as it was experienced during the course of this project. Also the SCG does not incorporate learning parameters such as the step width of the gradient descent ( $\eta$ ) which are used in other BP methods, are important to the success of the training and need to be fine tuned to achieve optimum performance of the network. Its parameters are non critical and only influence the speed

of convergence and not the final result. Hence they can be given a constant value and ignored for the rest of the training process duration. Example values for these parameters are given in manual of the SNNS software [30] that was used in this work.

### A.3 Time-Lagged Feedforward Network (TLFN)

This type of neural network is the same as the simple feedforward Multilayer Perceptron (MLP) described above. The only difference is in that, for the time-lagged networks the parameters that were chosen to be used as inputs are not presented one value at a time, but a number of sequential values together (see Figure A.3). This implies that all the values for each of the input parameters must be part of a time series (signal). This sequence of values from the same signal that are presented to the network together form the time representation for the TLFNs.

Such a characteristic is important and useful in time series analysis where any features of the series such as periodical oscillations and their frequency, can only be observed by a number of values together (sample).

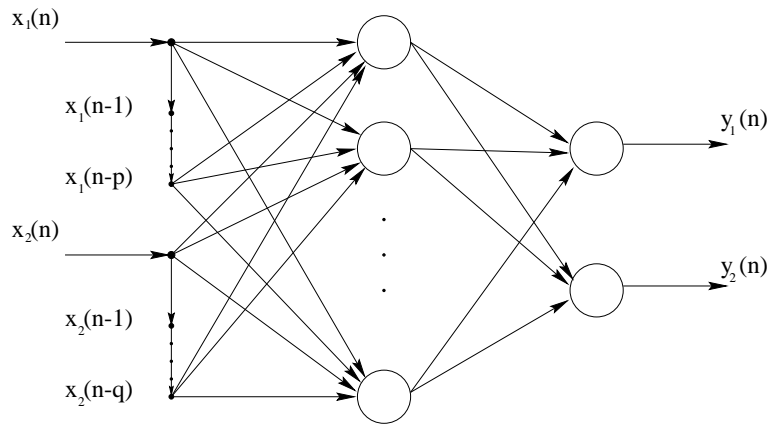


Figure A.3: An example of a Time-lagged feedforward network

The output (activation)  $y_j$  of each processing neuron, according to Figure A.3 becomes ([10], p. 649)

$$y_j(n) = f\left(\sum_{l=0}^p w_{1j}(l)x_1(n-l) + \sum_{l=0}^q w_{2j}(l)x_2(n-l)\right)$$

where  $n$  denotes the current value of the series and  $p$  and  $q$  are the order of the sample taken from each of the two input signals  $x_1$  and  $x_2$ .

In these neural networks where parts of the inputs are actual sections of the same signal, the simplified, for only the  $(x_1)$  input signal, above summation term

$$\sum_{l=0}^p w_{1j}(l)x_1(n-l)$$

which is part of the processing that is carried out by each of the neurons in the network, becomes a linear asymmetric filter that involves present and past values [6]. This would be more clear if we make the  $w_{ij}$  term constant ( $w_1$  and  $w_2$ ) for each of the signals. Then with  $w = \frac{1}{p+1}$  the last summation term becomes

$$\frac{1}{p+1} \sum_{l=0}^p x_1(n-l)$$

This gives the average of the  $x_1(n), x_1(n-1), \dots, x_1(n-p)$  values and for a number of such averaging steps it will smoothen (filter) out any fluctuations that fit within the  $n, n-1, \dots, n-p$  window.

Hence each of the processing units in the network is a linear filter. This is very useful as it shows the connection of the neural networks with a more traditional method of signal analysis, the statistical method.

## A.4 Time-Delay Neural Network (TDNN)

The time-delay neural networks (TDNNs) are similar to the time-lagged feed-forward networks, in that:

- they are also feedforward architectures
- they are based on the MLP
- each of the input variables (features) are presented to the network with a number of values (total delay) at the same time, hence
- each processing unit is a linear filter.

The two models are different in that:

- layers in the TDNNs are not represented by columns of units but by matrices of units and

- all of the hidden units are not connected to all of the input or output units.

Apart from the total delay there is a second delay length for the inputs, which specifies how many of the values from each of the feature units will be connected to each of the hidden units [30]. An example of a TDNN is shown in Figure A.4.

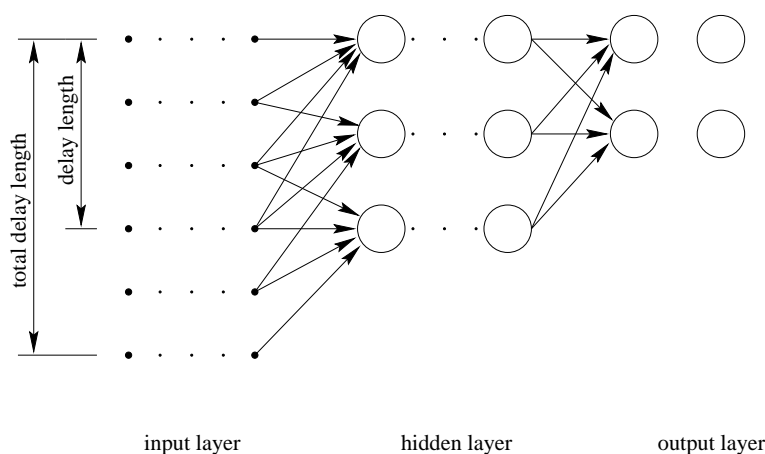


Figure A.4: Example of a TDNN

This characteristic of the TDNNs allow for the inputs between the different training steps of the neural network to be related together, as it splits the number of inputs from each feature into smaller groups. For example if a neuron in a TLFN, which acts as a linear filter (as mentioned above), produces an averaged value for the input values of the same input signal, a neuron from a TDNN will produce a number of averaged values (i.e. a smoothness curve). This number of the averaged values depends on the number of hidden units in the columns of the hidden layer. Hence each neuron does not only give an indication of amplitude but also an indication of gradient, which relates the values of one training step to the values of the next. Recurrent networks contain a characteristic feature in their architecture which could perform this relation between consecutive steps of inputs, as is mentioned below, without the need to present so many input values at the same time.

## A.5 Recurrent Network

The two models that were described above had a fixed number of input values (delay length), for each of the input signal. For a time series analysis the length of the delay for each of the input signals is determined by the length

of a fluctuation's cycle. The problem exists where such fluctuations can vary in length and it becomes difficult to decide how many inputs or what delay length should be used for each of the input signals [5]. A way around this problem is to use a recurrent network.

Recurrent networks are also based on the multilayer perceptron (MLP) but are distinguished from the feedforward architectures by the freedom of their neurons to feed their activations back to themselves (local feedback) or to other neurons of the same layer or previous layers (global feedback) in the network (see Figure A.5). This feeding back action of past activations as inputs to neurons during the next processing step of new inputs is how recurrent networks represent time. By disregarding the feedback connections, recurrent networks operate in the same way as the MLP, hence it is said that for every recurrent network there is a feedforward network with identical behaviour ([5], page 101).

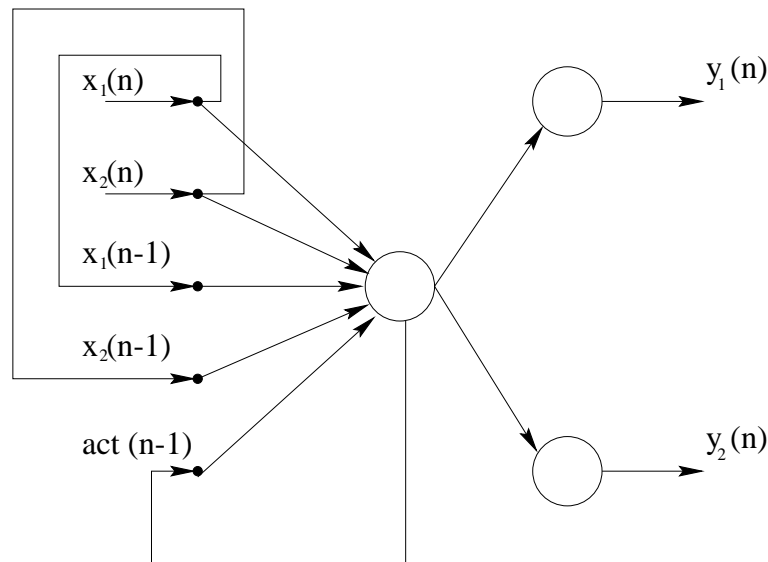


Figure A.5: Example of a recurrent network

An example of a simple recurrent network is the Elman model which has its hidden activations feed back as inputs for the processing of the next input values of a sequential input signal. These feed back inputs, are called *context* and can be seen as representing an internal reduced representation of the previous in the sequence input data. This internal representation can be understood by considering the filtering action of the processing neurons that was mentioned above in the TDNN model, which removes some of the fluctuations from part of the signal and reveals a reduced smoothed representation of it. Also the simultaneous presentation of present and past



processed values enhances the relation between previous and current inputs as the first are not observed without the consideration of the second. This is better illustrated by the Jordan model which has some of its input units feeding their past values back to themselves. This explains why recurrent networks are a solution to the problem stated at the beginning of this section, where fluctuations in a signal may vary and make the number of inputs that was initially chosen, inappropriate.



# Appendix B

## The Sammon Map

The Sammon Map was named after John W. Sammon Jr, who published a paper with the description of the nonlinear mapping (NM) algorithm in 1969 [27]. The algorithm was intended to be used for the analysis of multivariate data. With analysis it is meant to detect and identify "structure" which may be present in a list of  $N$   $L$ -dimensional vectors. Structure refers to geometric relationships among subsets of the data vectors in the  $L$ -space.

The algorithm maps the multi-dimensional data onto 2 or 3 dimensions by calculating the Euclidean distance (although the choice of this distance is not a requirement of the algorithm and other distance measures can be used) between the original vectors and creating the same number of the lower dimension vectors which approximately maintain the same Euclidean distances between each other. The creation of the new 2 or 3 dimensional vectors are created iteratively by comparing the two distances and aiming to reduce their difference as much as possible. So there is an error  $E$  that is attempted to be reduced. The error function that is used to do that is the following

$$E = \frac{1}{\sum_{1 < j} [d_{ij}^*]} \sum_{i < j} \frac{[d_{ij}^* - d_{ij}]^2}{d_{ij}^*}$$

- $d_{ij}^*$  is the distance between the high dimension vectors  $i$  and  $j$
- $d_{ij}$  is the distance between the 2 or 3 dimensions vectors  $i$  and  $j$
- $N$  is the total number of vectors in both dimensions.

Searching for the minimum of the error was done by using a steepest descent procedure.

The author of the paper identifies two limitations to the algorithm. The first one has to do with the reliability of the scatter diagram when displaying extremely complex high dimensional structures. With such structures it

could be that the minimum mapping error that is achieved during the error minimization is not small enough ( $E \gg 0.1$ ), hence the scatter plot will fail to portray the true structure of the original data. Still they feel that for data structures composed of superpositions of hyperspherical and hyperellipsoidal clusters the NM map will, in general, display adequate representations of the true data structure. The second limitation has to do with the number of vectors that can be handled as the algorithm needs to compute  $N(N - 1)/2$  elements. This limitation was experienced during the analysis of the S-shape riser data used for the research work described in this thesis. Any attempts to analyze all the data in once would cause the computer to run out of memory and crush the process. A work around this problem was achieved by selecting a smaller amount of the data to be visualized in random from the total cluster. In this way a realistic indication of the smaller clusters is still obtained, without having to consider all of the cases. Another disadvantage of the algorithm due to the large amounts of computations that it needs to carry out is that it makes it extremely slow.

For the work presented in this thesis, the Sammon algorithm was implemented with the SOM\_PAK [18] software package. SOM\_PAK was developed at Helsinki University of Technology by the SOM Programming team which includes among others Teuvo Kohonen, the creator of the *Kohonen* self organizing map. The software is an implementation of Self Organizing Maps (SOMs) and also includes a few tools for visualizing data sets and the output layer of trained SOMs.

# Appendix C

## Sammon Maps for the S-shape Riser data

For the labels shown in the legends of the Sammon maps found in this section refer to the flow regime map in Figure C.1.

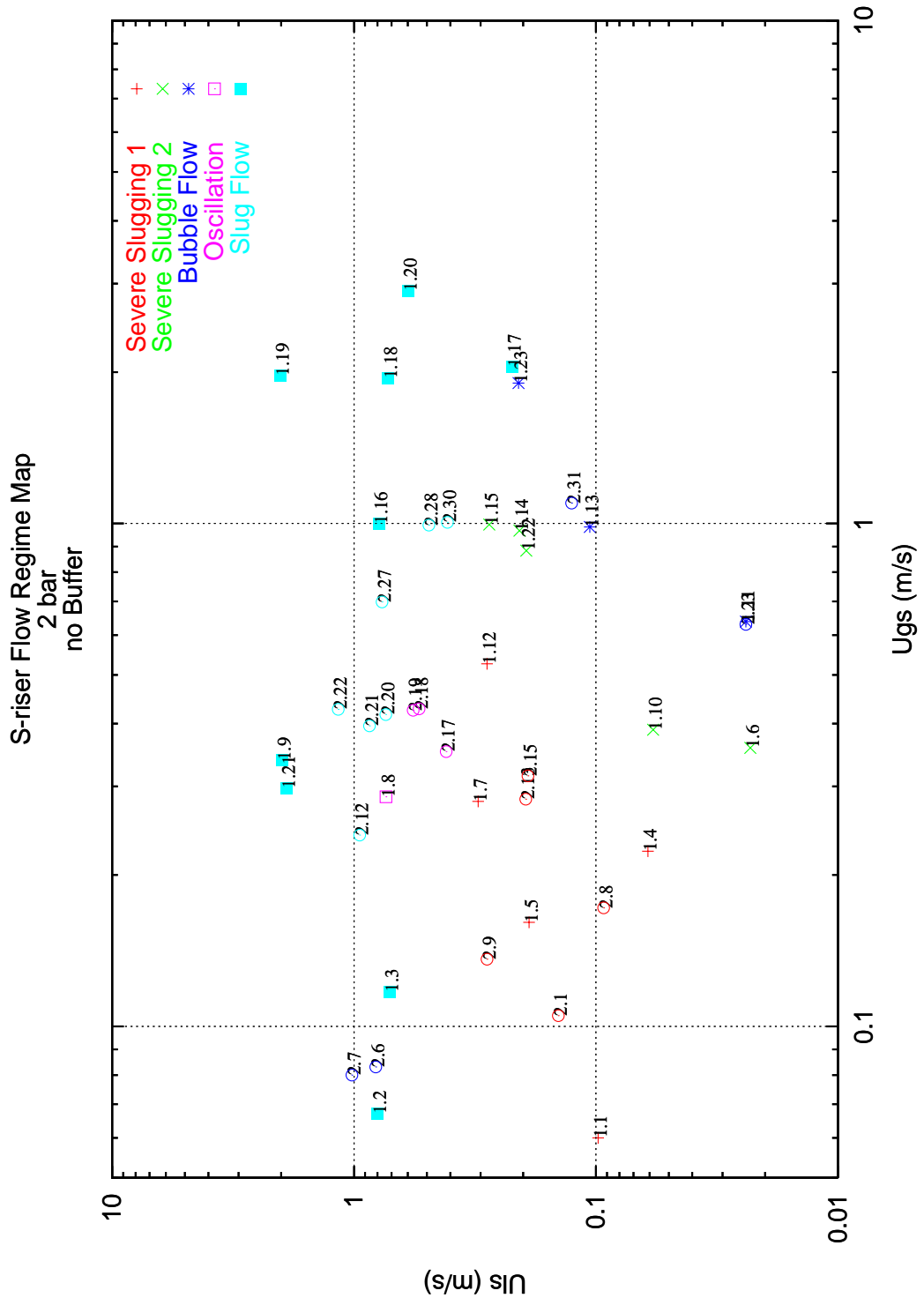


Figure C.1: Experimental data points for the S-shape riser rig, labelled following an older system.

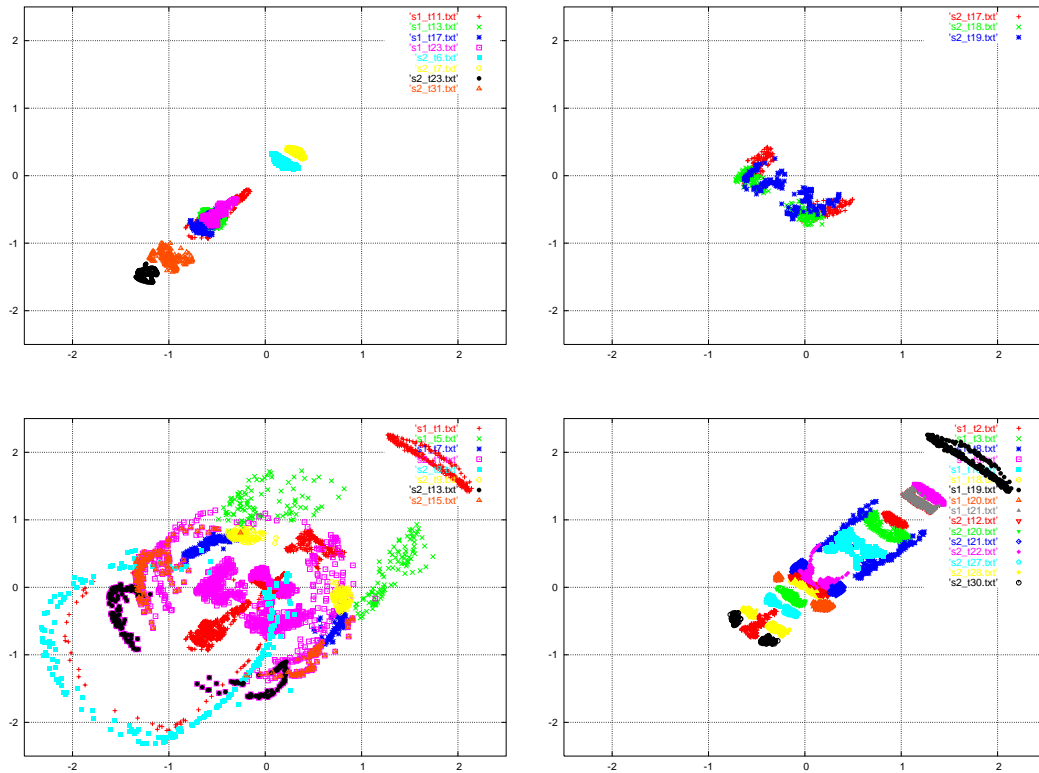


Figure C.2: Sammon maps for (clockwise from top left) the Bubble, Oscillation, Slug and Severe Slugging 1 cases for the P1 data.

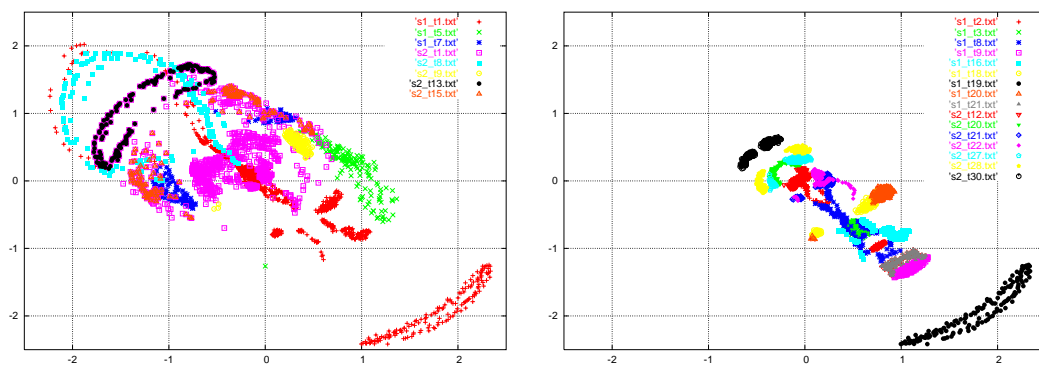


Figure C.3: Sammon maps for (clockwise from top left) the Bubble, Oscillation, Slug and Severe Slugging 1 cases for the P2 data.

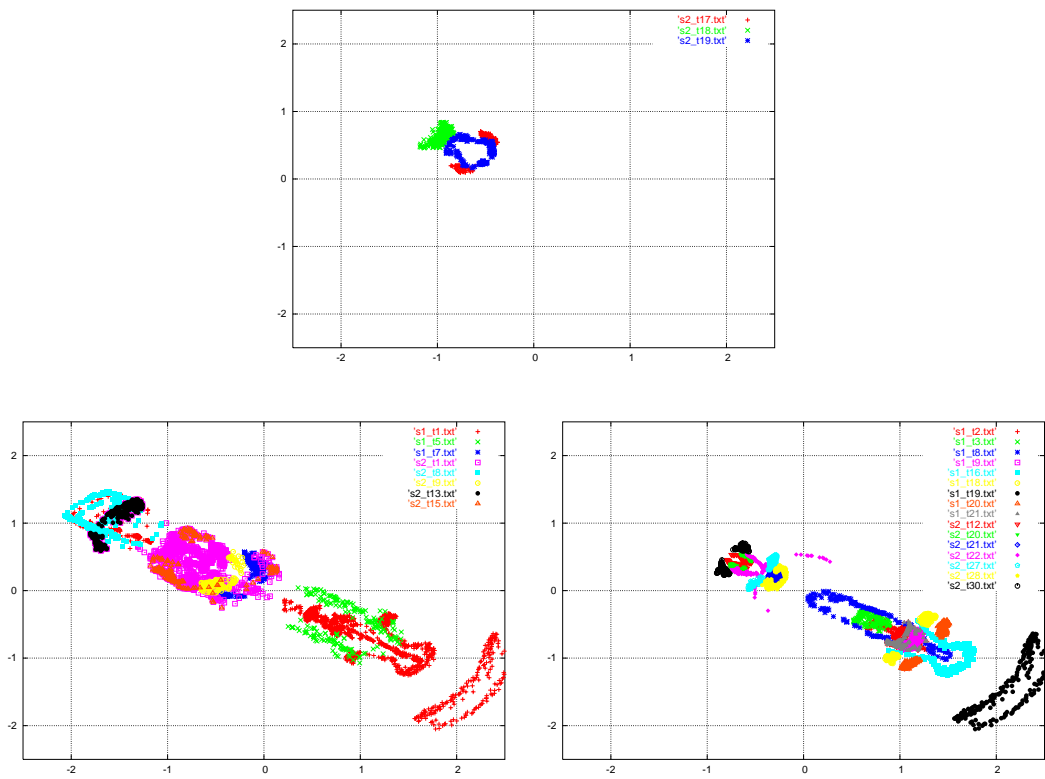


Figure C.4: Sammon maps for (clockwise from top left) the Bubble, Oscillation, Slug and Severe Slugging 1 cases for the P3 data.



# Appendix D

## Neural Network Files

In this section of the appendix two types of files are presented which were generated for use with the SNNS neural network software [30]. The first type is an example of a pattern file according to which data that are to be used with the SNNS software should be arranged. The second type of files are neural network definition files which represent flow regime identification models for the three systems that were used during the work of this thesis. These files can be loaded directly into the SNNS software as network files and used accordingly. Hence apart from the hard copies provided in the following pages they are also supplied in electronic format on the accompanying CD-ROM. In each of these files there are four sections:

1. General information, at the top
2. Default information for each of the units in the network
3. Unit definition section
4. Connection definition section

Attention should be given to sections two and four. The important parts of the second section are column six, titled *st* which gives the layer each unit in the network belongs to. The numbers for each of the units are given on column one. The other important part of this section is column five, titled *bias* which shows the bias values associated with each unit weight values that have index zero. All of section four is of great importance as it provides the remaining weight values which form each of the models. In this section the weights between the input and the hidden and the weights between the hidden and the output units are given in the same order, starting with the hidden units as targets in column one and the their source, input, units in

column three. These are followed by the output units as targets in column one and their source, hidden, units in column three.

## D.1 Example of a SNNS Pattern file

SNNS pattern definition file V1.4  
generated at Fri Oct 31 10:07:17 2003

No. of patterns : 10  
No. of input units : 10  
No. of output units : 4

#1

0.276075 0.274194 0.283132 0.289718 0.294422 0.301478 0.301949  
0.312298 0.303831 0.304301 0.000000 0.000000 0.000000 1.000000

#2

0.317473 0.328293 0.347110 0.351344 0.357460 0.359341 0.358871  
0.326411 0.331586 0.327823 0.000000 0.000000 0.000000 1.000000

#3

0.329704 0.325941 0.323589 0.313710 0.309476 0.299597 0.276546  
0.247379 0.247849 0.260551 0.000000 0.000000 0.000000 1.000000

#4

0.246909 0.258199 0.275134 0.269489 0.264785 0.248790 0.257728  
0.278898 0.293481 0.297245 0.000000 0.000000 1.000000 0.000000

#5

0.310417 0.323589 0.312298 0.309946 0.302890 0.299597 0.317473  
0.323118 0.335820 0.334879 0.000000 0.000000 1.000000 0.000000

#6

0.318414 0.328763 0.314180 0.295363 0.307124 0.301949 0.306183  
0.298185 0.291599 0.285484 0.000000 0.000000 1.000000 0.000000

#7

0.274664 0.269489 0.272782 0.273723 0.272312 0.270901 0.281720  
0.269960 0.259610 0.262433 0.000000 1.000000 0.000000 0.000000

#8

0.269960 0.270430 0.273723 0.296304 0.288306 0.286425 0.285954  
0.285013 0.304301 0.312298 0.000000 1.000000 0.000000 0.000000

#9

0.313710 0.317944 0.329704 0.340995 0.339583 0.346169 0.321237  
0.316532 0.324530 0.324059 0.000000 1.000000 0.000000 0.000000

#10

0.329704 0.339113 0.326411 0.303360 0.299597 0.299126 0.290659  
0.280309 0.266196 0.292070 1.000000 0.000000 0.000000 0.000000

## D.2 Weight values for the Conceptual System

SNNS network definition file V1.4-3D  
generated at Sun Nov 9 12:54:35 2003

network name : SNNS\_FF\_NET  
source files :  
no. of units : 27  
no. of connections : 140  
no. of unit types : 0  
no. of site types : 0

learning function : SCG  
update function : Topological\_Order

unit default section :

act	bias	st	subnet	layer	act func	out func
0.00000	0.00000	h	0	1	Act_Logistic	Out_Identity

unit definition section :

no.	typeName	unitName	act	bias	st	position	act func	out func	sites
1		unit	0.26985	0.97581	i	2, 2,-26102			
2		unit	0.50000	-0.66415	i	2, 3,-26102			
3		unit	0.73015	-0.29095	i	2, 4,-26102			
4		unit	0.50000	0.50152	i	2, 5,-26102			
5		unit	0.26985	-0.05656	i	2, 6,-26102			
6		unit	0.50000	-0.49835	i	2, 7,-26102			
7		unit	0.74939	-0.38826	i	2, 8,-26102			
8		unit	0.50000	-0.63945	i	2, 9,-26102			
9		unit	0.25061	0.97562	i	2,10,-26102			
10		unit	0.50000	-0.59343	i	2,11,-26102			
11		unit	0.74939	-0.62756	i	2,12,-26102			
12		unit	0.50000	0.46157	i	2,13,-26102			
13		unit	0.25061	0.54304	i	2,14,-26102			
14		unit	0.50000	-0.27641	i	2,15,-26102			
15		unit	0.73068	0.42075	i	2,16,-26102			
16		unit	0.50000	0.27955	i	2,17,-26102			
17		unit	0.15217	-1.67453	h	5, 2,-26102			
18		unit	0.98009	-0.30684	h	5, 3,-26102			
19		unit	0.01741	-1.32340	h	5, 4,-26102			
20		unit	0.99661	-0.64620	h	5, 5,-26102			
21		unit	0.79369	-3.14084	h	5, 6,-26102			
22		unit	1.00000	1.44850	h	5, 7,-26102			
23		unit	0.99783	1.94609	h	5, 8,-26102			
24		unit	0.00335	-1.64353	o	8, 2,-26102			
25		unit	0.00002	6.05283	o	8, 3,-26102			
26		unit	0.00011	-8.91071	o	8, 4,-26102			
27		unit	0.99725	-25.26987	o	8, 5,-26102			

connection definition section :

target	site	source:weight
17		1:-17.77803, 2:-16.90094, 3:-25.39218, 4:-20.66088, 5:-20.16482, 6:-11.48761, 7: 8.00996, 8:19.27583, 9:19.10409, 10:25.21169, 11:28.72409, 12:25.29601, 13:17.56765, 14: 3.38235, 15:-11.95089, 16:-22.61700
18		1:-6.34427, 2: 2.73206, 3: 3.96684, 4:-4.15715, 5:-3.82071, 6: 3.47854, 7: 2.58208, 8:-6.58403, 9:-5.92001, 10: 2.56879, 11: 4.63149, 12:-2.05232, 13:-3.34851, 14: 4.84806, 15: 3.95446, 16:-4.67928
19		1:-6.33288, 2:-2.52603, 3: 3.27681, 4: 8.92439, 5:10.59701, 6: 6.26855, 7:-3.61069, 8:-11.33393, 9:-11.43137, 10:-6.98392, 11: 0.51221, 12: 6.77272, 13: 8.23693, 14: 3.98042, 15:-2.87766, 16:-7.15810
20		1:-3.86021, 2: 0.81396, 3: 0.85018, 4:-8.01138, 5:-7.32820, 6: 6.57925, 7: 9.64112, 8:-0.20049, 9:-5.18932, 10: 1.10083, 11:-0.33507, 12:-8.43507, 13:-7.92662, 14: 5.25704, 15: 8.69542, 16: 0.27373
21		1:-15.66791, 2:-15.69746, 3:-24.33647, 4:-18.10777, 5:-17.52876, 6:-8.41858, 7: 8.48098, 8:17.39152, 9:17.44447, 10:21.98042, 11:28.93421, 12:25.69523, 13:18.80127, 14: 5.17513, 15:-11.44376, 16:-23.10811
22		1:-5.00684, 2: 5.55506, 3: 4.13507, 4:-5.83351, 5:-2.95151, 6: 8.78057, 7: 5.84568, 8:-6.94348, 9:-4.43556, 10: 5.96413, 11: 4.39041, 12:-6.13100, 13:-2.94667, 14: 8.39725, 15: 5.77634, 16:-6.27422
23		1:-12.52463, 2:-6.00979, 3: 6.33281, 4:11.52684, 5: 9.81939, 6: 3.57285, 7:-4.93569, 8:-10.30935, 9:-11.92389, 10:-3.60353, 11: 7.65062, 12:13.88461, 13:11.53185, 14: 3.08473, 15:-3.42596, 16:-10.42988
24		17:36.63534, 18: 5.95416, 19:-13.09620, 20:17.29565, 21:-37.52725, 22:-22.54038, 23:19.89780
25		17: 1.82612, 18:13.89910, 19:23.33184, 20:-5.07166, 21: 2.74663, 22:-7.68617, 23:-20.70656
26		17:-2.76665, 18:-13.60212, 19:-2.94219, 20:-5.54582, 21:-0.12993, 22:17.97838, 23: 1.25277

27		17:-37.15420, 18: 8.21103, 19:-18.33247, 20: 5.69230, 21:36.83509, 22:-14.08716, 23: 8.28391

## D.3 Weight values for the Horizontal System

SNNS network definition file V1.4-3D  
generated at Wed Apr 23 02:45:56 2003

network name : SNNS\_FF\_NET  
source files :  
no. of units : 218  
no. of connections : 2856  
no. of unit types : 0  
no. of site types : 0

learning function : SCG  
update function : Topological\_Order

unit default section :

act	bias	st	subnet	layer	act func	out func
0.00000	0.00000	h	0	1	Act_Logistic	Out_Identity

unit definition section :

no.	typeName	unitName	act	bias	st	position	act func	out func	sites
1		unit	-1.82329	0.21362	i	2, 2,-26102			
2		unit	-1.83534	0.41938	i	2, 3,-26102			
3		unit	-1.69478	0.41282	i	2, 4,-26102			
4		unit	-1.63454	0.99284	i	2, 5,-26102			
5		unit	-1.65462	0.57267	i	2, 6,-26102			
6		unit	-1.71084	0.40535	i	2, 7,-26102			
7		unit	-1.31325	-0.26904	i	2, 8,-26102			
8		unit	-1.38554	0.84933	i	2, 9,-26102			
9		unit	-1.48996	-0.96587	i	2, 10,-26102			
10		unit	-1.43374	0.76767	i	2, 11,-26102			
11		unit	-1.54619	-0.24958	i	2, 12,-26102			
12		unit	-1.71084	-0.79889	i	2, 13,-26102			
13		unit	-1.78313	-0.55979	i	2, 14,-26102			
14		unit	-1.87149	0.63159	i	2, 15,-26102			
15		unit	-1.85944	-0.91442	i	2, 16,-26102			
16		unit	-1.81124	-0.25724	i	2, 17,-26102			
17		unit	-1.91165	-0.43722	i	2, 18,-26102			
18		unit	-1.97590	0.69757	i	2, 19,-26102			
19		unit	-1.97992	-0.85635	i	2, 20,-26102			
20		unit	-1.97590	0.09179	i	2, 21,-26102			
21		unit	-1.96787	-0.92406	i	2, 22,-26102			
22		unit	-1.44177	0.96671	i	2, 23,-26102			
23		unit	-1.58233	-0.30679	i	2, 24,-26102			
24		unit	-1.66667	-0.26543	i	2, 25,-26102			
25		unit	-1.41366	-0.84342	i	2, 26,-26102			
26		unit	-1.46988	-0.97510	i	2, 27,-26102			
27		unit	-1.64659	0.81689	i	2, 28,-26102			
28		unit	-1.75100	-0.25426	i	2, 29,-26102			
29		unit	-1.71084	0.44167	i	2, 30,-26102			
30		unit	-1.73494	0.18128	i	2, 31,-26102			
31		unit	-1.84337	0.99660	i	2, 32,-26102			
32		unit	-1.93574	0.27998	i	2, 33,-26102			
33		unit	-1.89157	-0.19373	i	2, 34,-26102			
34		unit	-1.82731	-0.84410	i	2, 35,-26102			
35		unit	-1.94378	0.06342	i	2, 36,-26102			
36		unit	-1.93976	-0.72297	i	2, 37,-26102			
37		unit	-1.92771	-0.10586	i	2, 38,-26102			
38		unit	-1.98394	0.45306	i	2, 39,-26102			
39		unit	-1.75100	-0.78941	i	2, 40,-26102			
40		unit	-1.82731	0.44958	i	2, 41,-26102			
41		unit	-1.84739	-0.56802	i	2, 42,-26102			
42		unit	-1.90361	-0.24144	i	2, 43,-26102			
43		unit	-1.49799	-0.65185	i	2, 44,-26102			
44		unit	-1.67871	0.70209	i	2, 45,-26102			
45		unit	-1.67470	0.82739	i	2, 46,-26102			
46		unit	-1.77108	0.34563	i	2, 47,-26102			
47		unit	-1.82731	-0.50356	i	2, 48,-26102			
48		unit	-1.76707	-0.35984	i	2, 49,-26102			
49		unit	-1.85542	0.47419	i	2, 50,-26102			
50		unit	-1.25301	0.72074	i	2, 51,-26102			
51		unit	-1.46185	0.49014	i	2, 52,-26102			
52		unit	-1.60643	-0.02566	i	2, 53,-26102			
53		unit	-1.59036	0.49472	i	2, 54,-26102			
54		unit	-1.55020	-0.29102	i	2, 55,-26102			

55		unit		-1.63052		-0.59141		i		2,	56,-26102	
56		unit		-1.76305		0.32131		i		2,	57,-26102	
57		unit		-1.81526		-0.39153		i		2,	58,-26102	
58		unit		-1.83133		0.46193		i		2,	59,-26102	
59		unit		-1.85944		-0.63359		i		2,	60,-26102	
60		unit		-1.87952		-0.70449		i		2,	61,-26102	
61		unit		-1.64659		-0.45564		i		2,	62,-26102	
62		unit		-1.83534		-0.97107		i		2,	63,-26102	
63		unit		-1.84337		0.69067		i		2,	64,-26102	
64		unit		-1.83133		0.72497		i		2,	65,-26102	
65		unit		-1.82731		0.37105		i		2,	66,-26102	
66		unit		-1.91968		-0.80540		i		2,	67,-26102	
67		unit		-1.96386		0.27116		i		2,	68,-26102	
68		unit		-1.95984		-0.60880		i		2,	69,-26102	
69		unit		-1.90763		-0.39392		i		2,	70,-26102	
70		unit		-1.88755		-0.74996		i		2,	71,-26102	
71		unit		-1.42570		0.78486		i		2,	72,-26102	
72		unit		-1.57028		-0.31999		i		2,	73,-26102	
73		unit		-1.72289		-0.37086		i		2,	74,-26102	
74		unit		-1.57831		0.69827		i		2,	75,-26102	
75		unit		-1.60241		0.44593		i		2,	76,-26102	
76		unit		-1.63855		-0.04843		i		2,	77,-26102	
77		unit		-1.73896		0.25614		i		2,	78,-26102	
78		unit		-1.79116		0.03260		i		2,	79,-26102	
79		unit		-1.75502		-0.60699		i		2,	80,-26102	
80		unit		-1.74297		0.02632		i		2,	81,-26102	
81		unit		-1.84337		-0.83628		i		2,	82,-26102	
82		unit		-1.31727		0.57337		i		2,	83,-26102	
83		unit		-1.44980		-0.63571		i		2,	84,-26102	
84		unit		-1.54217		0.88969		i		2,	85,-26102	
85		unit		-1.48193		0.86547		i		2,	86,-26102	
86		unit		-1.55020		0.77701		i		2,	87,-26102	
87		unit		-1.62651		-0.90967		i		2,	88,-26102	
88		unit		-1.64257		-0.78707		i		2,	89,-26102	
89		unit		-1.71084		-0.84592		i		2,	90,-26102	
90		unit		-1.74297		-0.21591		i		2,	91,-26102	
91		unit		-1.77510		0.11065		i		2,	92,-26102	
92		unit		-1.86345		0.45834		i		2,	93,-26102	
93		unit		-1.89157		-0.79851		i		2,	94,-26102	
94		unit		-1.39759		-0.44047		i		2,	95,-26102	
95		unit		-1.55422		0.34176		i		2,	96,-26102	
96		unit		-1.57831		-0.20805		i		2,	97,-26102	
97		unit		-1.66265		-0.93769		i		2,	98,-26102	
98		unit		-1.75100		0.57825		i		2,	99,-26102	
99		unit		-1.83936		-0.36396		i		2,100,-26102		
100		unit		-1.85141		0.59247		i		2,101,-26102		
101		unit		-1.69879		-0.79336		i		2,102,-26102		
102		unit		-1.79518		0.37156		i		2,103,-26102		
103		unit		-1.87952		0.30858		i		2,104,-26102		
104		unit		-1.12450		0.56503		i		2,105,-26102		
105		unit		-1.02008		-0.68759		i		2,106,-26102		
106		unit		-1.00803		-0.41033		i		2,107,-26102		
107		unit		-1.12048		0.80460		i		2,108,-26102		
108		unit		-1.21285		-0.89194		i		2,109,-26102		
109		unit		-1.26908		-0.88321		i		2,110,-26102		
110		unit		-1.23293		0.73982		i		2,111,-26102		
111		unit		-1.40562		-0.44283		i		2,112,-26102		
112		unit		-1.48193		-0.87827		i		2,113,-26102		
113		unit		-1.57028		0.24281		i		2,114,-26102		
114		unit		-1.65462		0.08209		i		2,115,-26102		
115		unit		-1.69879		-0.03698		i		2,116,-26102		
116		unit		-1.77510		0.58940		i		2,117,-26102		
117		unit		-1.83936		0.01054		i		2,118,-26102		
118		unit		-1.92369		-0.07176		i		2,119,-26102		
119		unit		-1.95984		-0.80598		i		2,120,-26102		
120		unit		-1.97189		0.42874		i		2,121,-26102		
121		unit		-1.68273		-0.91754		i		2,122,-26102		
122		unit		-1.78313		-0.11383		i		2,123,-26102		
123		unit		-1.01606		-0.72927		i		2,124,-26102		
124		unit		-1.07229		0.93538		i		2,125,-26102		
125		unit		-1.22490		-0.00419		i		2,126,-26102		
126		unit		-1.40964		0.48259		i		2,127,-26102		
127		unit		-1.46185		-0.94924		i		2,128,-26102		
128		unit		-1.49799		-0.01344		i		2,129,-26102		
129		unit		-1.59839		-0.84043		i		2,130,-26102		
130		unit		-1.66265		-0.39017		i		2,131,-26102		
131		unit		-1.70281		-0.77766		i		2,132,-26102		
132		unit		-1.77510		0.61168		i		2,133,-26102		
133		unit		-1.88755		0.54244		i		2,134,-26102		
134		unit		-1.93574		0.87723		i		2,135,-26102		
135		unit		-1.95582		-0.66999		i		2,136,-26102		
136		unit		-1.87149		-0.13486		i		2,137,-26102		
137		unit		-1.87550		0.19880		i		2,138,-26102		

138		unit		-1.95984		-0.83068		i		2,139,-26102	
139		unit		-1.32530		-0.32563		i		2,140,-26102	
140		unit		-1.27711		0.66927		i		2,141,-26102	
141		unit		-1.27309		0.96019		i		2,142,-26102	
142		unit		-1.35341		0.45849		i		2,143,-26102	
143		unit		-1.50201		-0.40252		i		2,144,-26102	
144		unit		-1.57430		-0.33773		i		2,145,-26102	
145		unit		-1.66265		0.39638		i		2,146,-26102	
146		unit		-1.73896		-0.40727		i		2,147,-26102	
147		unit		-1.79518		-0.74302		i		2,148,-26102	
148		unit		-1.87550		-0.45909		i		2,149,-26102	
149		unit		-1.95181		0.69905		i		2,150,-26102	
150		unit		-1.97590		-0.24720		i		2,151,-26102	
151		unit		-1.97590		0.16786		i		2,152,-26102	
152		unit		-1.98394		0.09861		i		2,153,-26102	
153		unit		-1.98795		-0.01560		i		2,154,-26102	
154		unit		-1.98394		-0.61090		i		2,155,-26102	
155		unit		-1.77912		-0.69299		i		2,156,-26102	
156		unit		-1.80321		-0.48402		i		2,157,-26102	
157		unit		-1.89960		-0.98602		i		2,158,-26102	
158		unit		-1.93976		-0.48234		i		2,159,-26102	
159		unit		-1.83936		-0.21830		i		2,160,-26102	
160		unit		-1.93976		0.57055		i		2,161,-26102	
161		unit		-1.97590		0.20435		i		2,162,-26102	
162		unit		-1.97590		0.55607		i		2,163,-26102	
163		unit		-1.98394		-0.59790		i		2,164,-26102	
164		unit		-1.98795		-0.37985		i		2,165,-26102	
165		unit		-1.56225		-0.41098		i		2,166,-26102	
166		unit		-1.59036		0.66198		i		2,167,-26102	
167		unit		-1.72289		0.00752		i		2,168,-26102	
168		unit		-1.73494		-0.47289		i		2,169,-26102	
169		unit		-1.64659		-0.99361		i		2,170,-26102	
170		unit		-1.69076		0.51536		i		2,171,-26102	
171		unit		-1.81928		-0.79340		i		2,172,-26102	
172		unit		-1.81124		0.39001		i		2,173,-26102	
173		unit		-1.44980		-0.04408		i		2,174,-26102	
174		unit		-1.44980		0.34778		i		2,175,-26102	
175		unit		-1.59036		-0.97205		i		2,176,-26102	
176		unit		-1.71888		0.01927		i		2,177,-26102	
177		unit		-1.75904		-0.62485		i		2,178,-26102	
178		unit		-1.77510		0.92001		i		2,179,-26102	
179		unit		-1.86747		-0.34181		i		2,180,-26102	
180		unit		-1.91566		-0.26586		i		2,181,-26102	
181		unit		-1.92771		-0.02979		i		2,182,-26102	
182		unit		-1.93173		-0.79186		i		2,183,-26102	
183		unit		-1.97992		-0.61894		i		2,184,-26102	
184		unit		-1.90361		0.19049		i		2,185,-26102	
185		unit		-1.69478		-0.04614		i		2,186,-26102	
186		unit		-1.61044		0.36886		i		2,187,-26102	
187		unit		-1.71084		-0.46994		i		2,188,-26102	
188		unit		-1.77912		-0.28956		i		2,189,-26102	
189		unit		-1.73896		0.22266		i		2,190,-26102	
190		unit		-1.75100		0.67698		i		2,191,-26102	
191		unit		-1.88353		-0.17272		i		2,192,-26102	
192		unit		-1.97189		-0.16585		i		2,193,-26102	
193		unit		-1.97590		0.59804		i		2,194,-26102	
194		unit		-1.95984		-0.40675		i		2,195,-26102	
195		unit		-1.93976		-0.90302		i		2,196,-26102	
196		unit		-1.56225		-0.37393		i		2,197,-26102	
197		unit		-1.69478		0.06725		i		2,198,-26102	
198		unit		-1.74297		-0.07569		i		2,199,-26102	
199		unit		-1.40562		0.79975		i		2,200,-26102	
200		unit		-0.83132		-0.56125		i		2,201,-26102	
201		unit		0.00004		-28.71648		h		5, 2,-26102	
202		unit		1.00000		3.07337		h		5, 3,-26102	
203		unit		1.00000		-1.59320		h		5, 4,-26102	
204		unit		0.00000		-13.03296		h		5, 5,-26102	
205		unit		0.99537		13.85686		h		5, 6,-26102	
206		unit		0.00000		-4.37778		h		5, 7,-26102	
207		unit		0.00000		-2.49093		h		5, 8,-26102	
208		unit		0.81168		25.64724		h		5, 9,-26102	
209		unit		0.00000		2.09435		h		5, 10,-26102	
210		unit		1.00000		15.24584		h		5, 11,-26102	
211		unit		1.00000		-0.83087		h		5, 12,-26102	
212		unit		1.00000		6.01576		h		5, 13,-26102	
213		unit		0.00000		-4.15981		h		5, 14,-26102	
214		unit		0.00002		-0.06663		h		5, 15,-26102	
215		unit		0.11717		-11.76184		o		8, 2,-26102	
216		unit		0.90244		-3.20578		o		8, 3,-26102	
217		unit		0.00068		-8.46868		o		8, 4,-26102	
218		unit		0.00000		-1.36493		o		8, 5,-26102	



### D.3. WEIGHT VALUES FOR THE HORIZONTAL SYSTEM

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connection definition section :

target	site	source:weight		
201		1:-0.72921, 2:-0.30019, 3: 1.25269, 4:-0.29776, 5:-1.62397, 6: 0.30551, 7: 0.45578, 8:-0.10563,		
		9:-0.25527, 10: 0.19840, 11: 0.17527, 12:-0.71295, 13:-0.00235, 14:-1.33185, 15: 0.42795, 16:-0.22889,		
		17: 0.62373, 18: 0.78590, 19:-1.24712, 20: 0.32164, 21:-0.59038, 22: 0.69802, 23: 0.63832, 24: 0.80974,		
		25:-1.61800, 26:-0.04593, 27:-0.11117, 28:-0.23267, 29: 0.65018, 30: 0.04892, 31:-1.00626, 32:-0.09591,		
		33: 0.36838, 34: 0.50346, 35: 0.17763, 36:-0.37029, 37: 0.47407, 38:-0.25809, 39: 0.26792, 40:-0.88204,		
		41: 0.29788, 42:-1.27933, 43: 0.05575, 44:-0.77857, 45: 2.24235, 46:-0.41125, 47:-0.98735, 48: 0.28880,		
		49: 0.29861, 50:-0.00734, 51: 0.47506, 52:-0.23216, 53:-1.63819, 54:-0.25460, 55: 1.47016, 56:-2.21340,		
		57: 0.50658, 58: 1.22957, 59: 0.65734, 60: 0.38051, 61:-0.06250, 62: 0.27471, 63: 0.01227, 64:-0.49488,		
		65: 0.41879, 66: 1.15324, 67: 0.46866, 68: 0.56144, 69:-1.11247, 70: 0.44011, 71: 1.17428, 72:-0.98311,		
		73:-0.00116, 74:-0.19078, 75: 0.04739, 76:-0.18771, 77:-0.73327, 78: 1.90824, 79:-0.66917, 80: 0.80265,		
		81: 0.76446, 82:-1.05682, 83:-2.02826, 84:-1.38523, 85:-0.04324, 86:-1.07862, 87:-1.82142, 88: 0.06016,		
		89:-0.80416, 90: 0.77590, 91: 0.75363, 92: 0.00124, 93: 3.11771, 94: 4.03985, 95: 7.82760, 96: 7.22647,		
		97:11.27903, 98: 6.51887, 99: 6.16512, 100:-2.19139, 101:-7.94321, 102:-11.30757, 103:-13.18167, 104:-10.83249,		
		105:-3.66582, 106:-2.67941, 107:-0.06195, 108:-0.43755, 109: 0.20106, 110:-0.44447, 111: 0.21492, 112: 1.31917,		
		113: 0.22972, 114:-0.40568, 115: 0.12989, 116:-1.92130, 117: 0.43259, 118: 2.04789, 119: 0.09083, 120:-1.30938,		
		121: 0.88873, 122:-0.51372, 123:-0.05856, 124:-0.48542, 125: 0.25567, 126: 0.17043, 127: 0.04668, 128: 0.35973,		
		129: 1.07232, 130:-0.88719, 131: 0.96630, 132: 0.31857, 133:-1.57945, 134: 0.53570, 135: 0.37495, 136:-0.89772,		
		137: 0.52826, 138: 1.17291, 139:-0.96528, 140: 1.12915, 141:-0.65807, 142: 0.45099, 143:-0.43995, 144: 0.56753,		
		145:-0.08461, 146: 0.49578, 147: 0.44059, 148:-1.97773, 149:-1.00912, 150:-0.30246, 151: 0.31812, 152: 0.55495,		
		153: 0.43060, 154:-0.48329, 155:-0.57147, 156: 0.24090, 157:-0.71087, 158: 0.45934, 159: 0.51230, 160: 0.51705,		
		161: 1.38837, 162:-0.65291, 163:-1.55070, 164:-0.09877, 165:-1.13116, 166: 0.67466, 167: 1.46826, 168:-0.69811,		
		169: 0.34722, 170:-2.03200, 171:-0.56899, 172: 0.27174, 173: 0.26584, 174: 1.25567, 175:-1.31671, 176: 1.28065,		
		177:-1.35935, 178:-0.96313, 179:-0.19243, 180: 2.14361, 181:-0.96202, 182: 0.71610, 183:-1.04948, 184: 0.27187,		
		185:-1.23302, 186:-0.01991, 187:-0.51906, 188: 0.72036, 189: 0.25788, 190: 1.48435, 191:-0.44445, 192: 1.04629,		
		193:-0.42414, 194:-0.97085, 195: 0.66765, 196: 0.30490, 197:-0.65184, 198:-1.16690, 199:-1.09403, 200: 0.03345,		
		202		1:-0.80324, 2: 0.43941, 3:-0.59553, 4: 0.24103, 5: 0.84282, 6:-0.15643, 7:-0.68882, 8: 0.00435,
				9: 0.09830, 10: 0.71819, 11:-0.73365, 12: 0.74791, 13:-0.72061, 14: 0.16351, 15:-0.34438, 16:-0.01041,
				17: 0.09729, 18: 0.35248, 19:-0.42250, 20:-1.24157, 21: 0.27193, 22:-0.00451, 23:-0.02509, 24: 1.11223,
				25:-0.14387, 26: 0.53326, 27: 0.17990, 28:-0.30330, 29:-0.08594, 30:-0.27746, 31:-0.22777, 32:-0.86171,
				33: 0.19432, 34:-0.58286, 35:-0.03825, 36: 0.38101, 37: 0.36638, 38:-0.43125, 39: 0.15905, 40:-0.37336,
				41:-0.26873, 42:-0.38557, 43: 0.44231, 44: 0.65860, 45:-0.00148, 46:-0.05799, 47: 0.56512, 48:-0.97953,
				49: 0.63984, 50: 0.00638, 51: 0.21191, 52:-1.15588, 53:-0.65227, 54:-0.72354, 55: 0.90349, 56: 1.24253,
				57:-0.22889, 58: 0.29150, 59:-0.05862, 60:-0.23106, 61: 0.66879, 62:-0.64447, 63:-0.21998, 64:-0.96658,
				65: 0.61562, 66:-0.86444, 67:-0.02256, 68: 0.99224, 69: 0.59483, 70:-0.91031, 71:-0.85034, 72: 0.25631,
				73: 0.34058, 74: 0.15472, 75:-0.03716, 76: 0.11542, 77:-0.42114, 78:-0.10392, 79:-0.66151, 80: 0.09204,
				81: 0.34285, 82: 0.29624, 83:-0.51782, 84:-0.53787, 85: 0.25036, 86:-0.52632, 87:-0.06120, 88:-0.59412,
				89:-0.04010, 90:-0.12065, 91:-0.07543, 92:-0.39884, 93: 0.77736, 94:-0.37574, 95: 0.01270, 96:-0.45011,
				97:-0.41034, 98:-0.19049, 99:-0.28635, 100: 0.27657, 101: 0.65386, 102:-0.62132, 103: 0.31306, 104:-0.78395,
				105:-0.18659, 106:-0.45801, 107: 0.83786, 108: 0.88387, 109:-0.61774, 110: 0.55490, 111:-0.49347, 112: 0.06540,
				113:-0.87097, 114: 0.67213, 115: 0.41804, 116:-0.11839, 117:-0.93961, 118:-0.54171, 119: 0.65917, 120: 0.14534,
				121:-0.23917, 122:-0.22168, 123: 0.64972, 124: 0.14276, 125: 0.05417, 126: 0.57387, 127:-0.39111, 128:-0.03094,
				129:-0.69732, 130:-0.09713, 131: 0.49050, 132:-0.72699, 133:-0.27745, 134:-0.70138, 135:-0.30043, 136: 0.32152,
				137:-0.12955, 138: 0.18189, 139:-0.35252, 140: 0.67887, 141:-0.28138, 142:-1.00933, 143: 0.02109, 144:-0.73148,
				145:-0.44128, 146: 1.01731, 147:-0.63942, 148:-0.46136, 149: 0.16033, 150: 0.66593, 151:-0.02009, 152:-0.62116,
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	65: -0.46197,	66: 0.64682,	67: 0.37289,	68: 1.27040,	69: 0.35587,	70: 0.03726,	71: 0.52884,
	73: -0.67961,	74: -0.02055,	75: 1.33610,	76: 0.57996,	77: -0.94404,	78: -0.88639,	79: -0.08064,
	81: 0.55828,	82: 0.45179,	83: 0.39085,	84: 1.24486,	85: 0.20994,	86: -0.91381,	87: 0.94247,

D.3. WEIGHT VALUES FOR THE HORIZONTAL SYSTEM

Table with 20 columns of numerical values. Rows are grouped by labels 208, 209, and 210. Each row contains 20 values ranging from approximately -1.45 to 1.45.

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49:-0.17986, 50:-0.53011, 51:-0.04980, 52:-0.54304, 53:-0.24886, 54: 0.45102, 55: 0.78693, 56: 0.82400,  
57:-0.17044, 58:-0.99314, 59:-0.50586, 60: 0.68927, 61:-0.53026, 62:-0.74848, 63: 0.55967, 64: 0.64002,  
65:-1.08028, 66:-0.00560, 67: 0.38758, 68: 0.40064, 69:-0.47028, 70:-0.87782, 71: 0.16744, 72:-0.05706,  
73:-0.69947, 74: 0.09302, 75:-1.01882, 76:-0.87707, 77: 0.77581, 78:-0.85293, 79:-0.98882, 80:-0.07649,  
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212 | | 1: 0.66953, 2:-1.58030, 3:-0.75971, 4: 1.03255, 5: 1.28288, 6: 0.49486, 7: 0.57655, 8:-0.18892,  
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105: 0.11428, 106: 1.27170, 107: 0.86686, 108:-0.19434, 109: 1.84542, 110: 2.30161, 111: 1.82843, 112: 1.66294,  
113: 1.03236, 114: 0.03873, 115:-1.22138, 116:-0.93629, 117:-1.03266, 118: 0.79281, 119:-0.76474, 120: 0.60387,  
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137: 0.42648, 138:-0.83428, 139:-0.55165, 140:-0.48735, 141:-0.19260, 142: 1.56969, 143:-0.22253, 144:-0.61554,  
145:-0.39582, 146:-1.04314, 147: 0.11312, 148:-0.74134, 149:-2.50217, 150:-0.52326, 151:-1.99477, 152: 0.10551,  
153: 0.51100, 154: 2.85859, 155: 0.04044, 156: 2.11238, 157: 3.63230, 158: 1.63278, 159: 0.64733, 160:-0.77235,  
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177:-0.52945, 178:-0.71597, 179:-0.01369, 180: 0.69406, 181:-1.20325, 182: 0.33436, 183:-0.94238, 184:-1.53302,  
185: 0.14845, 186:-0.12429, 187: 0.37638, 188:-0.88481, 189:-1.80715, 190:-0.73290, 191: 0.53796, 192: 1.06688,  
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213 | | 1:-0.79711, 2: 0.27657, 3:-0.10204, 4: 0.01494, 5:-0.13159, 6:-0.32786, 7: 1.63034, 8: 1.26285,  
9: 1.19406, 10: 1.11148, 11: 1.30407, 12:-0.19239, 13:-1.86226, 14:-0.54136, 15: 0.07457, 16:-0.60202,  
17:-1.36077, 18: 0.68131, 19:-0.11173, 20:-0.04077, 21:-0.74094, 22: 1.80955, 23: 0.74810, 24:-0.24308,  
25: 0.51647, 26: 1.25819, 27: 0.26613, 28:-0.60256, 29: 0.11758, 30: 1.95289, 31: 0.92641, 32: 0.12474,  
33:-1.74342, 34:-2.14079, 35:-0.56603, 36: 0.32976, 37:-0.48350, 38:-1.77095, 39: 0.28599, 40: 0.54123,  
41: 0.12224, 42: 0.82594, 43: 0.63840, 44:-0.16486, 45: 0.70581, 46: 0.06157, 47: 0.37696, 48: 1.82036,  
49:-0.18467, 50: 2.02712, 51: 1.54604, 52:-1.44304, 53:-0.79783, 54:-0.01107, 55:-2.03427, 56:-1.57764,  
57:-2.57223, 58:-0.28621, 59: 1.23942, 60:-0.69847, 61:-0.03639, 62: 0.14771, 63: 0.55638, 64: 0.23661,  
65: 1.27099, 66:-0.03110, 67: 1.06340, 68:-0.54859, 69:-0.85367, 70:-0.72684, 71: 0.12655, 72: 0.24458,  
73: 0.90629, 74: 0.41520, 75:-0.18220, 76: 0.35027, 77:-0.65796, 78: 1.25715, 79: 0.23984, 80:-0.13897,  
81:-1.29945, 82: 0.07428, 83:-0.13678, 84:-1.01821, 85: 0.65169, 86: 0.74336, 87: 0.43633, 88: 0.31637,  
89: 1.14808, 90: 0.81435, 91: 0.91956, 92: 1.34655, 93: 2.02177, 94: 1.85544, 95: 0.84668, 96:-0.58129,  
97:-3.53610, 98:-3.19243, 99:-3.57040, 100:-3.21360, 101:-2.15748, 102:-2.04587, 103: 0.27636, 104: 1.36160,  
105: 0.47405, 106:-0.74703, 107: 0.09993, 108: 0.85267, 109: 2.13882, 110: 0.65499, 111:-0.93903, 112: 0.38473,  
113: 1.79153, 114: 0.21101, 115:-0.55116, 116:-0.66919, 117: 1.80453, 118:-0.47166, 119:-1.33940, 120:-0.49274,  
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129:-0.22925, 130:-0.07665, 131: 1.08058, 132: 1.31275, 133: 1.57924, 134: 0.21585, 135: 0.00706, 136:-0.67994,  
137:-0.85615, 138:-1.29524, 139: 0.51375, 140: 1.30184, 141: 0.96606, 142: 0.31655, 143:-1.53785, 144:-0.47617,  
145: 0.07312, 146: 1.52799, 147: 0.85587, 148: 0.90557, 149:-1.36120, 150:-0.93315, 151: 0.29805, 152: 0.40515,  
153: 0.12113, 154: 1.07995, 155:-0.44278, 156:-0.60912, 157: 1.62602, 158: 0.63846, 159: 1.19480, 160:-0.33560,  
161:-0.75178, 162:-0.11217, 163: 0.50153, 164:-0.72953, 165: 0.31140, 166:-0.18289, 167:-0.21761, 168: 0.11041,  
169:-0.04668, 170: 0.36172, 171: 0.36761, 172: 1.34259, 173: 0.49486, 174:-0.13533, 175: 1.70816, 176: 1.33221,  
177:-1.29753, 178:-2.63290, 179:-0.89365, 180: 0.46726, 181: 0.16340, 182: 0.44728, 183:-0.42326, 184:-0.53637,  
185: 0.26894, 186: 1.33569, 187: 1.50171, 188:-0.20906, 189: 0.59642, 190:-0.08225, 191:-0.06088, 192:-0.79794,  
193:-0.29986, 194: 0.12630, 195: 0.27436, 196:-0.72836, 197:-1.37827, 198: 0.04358, 199: 1.20091, 200: 1.84751

214 | | 1: 0.19527, 2: 1.20182, 3:-0.57909, 4: 1.67566, 5: 1.98699, 6: 2.35494, 7: 0.51805, 8: 1.22790,  
9:-1.60093, 10:-0.33307, 11:-1.17773, 12:-1.21900, 13: 0.26994, 14:-1.48947, 15:-2.09821, 16:-0.48975,



## D.4 Weight values for the S-shape riser

SNNS network definition file V1.4-3D  
generated at Sun Apr 27 21:09:02 2003

network name : SNNS\_FF\_NET  
source files :  
no. of units : 114  
no. of connections : 1040  
no. of unit types : 0  
no. of site types : 0

learning function : SCG  
update function : Topological\_Order

unit default section :

act	bias	st	subnet	layer	act func	out func
0.00000	0.00000	h	0	1	Act_Logistic	Out_Identity

unit definition section :

no.	typeName	unitName	act	bias	st	position	act func	out func	sites
1		unit	0.55645	0.44707	i	2, 2,-26102			
2		unit	0.58333	0.84326	i	2, 3,-26102			
3		unit	0.53763	0.27893	i	2, 4,-26102			
4		unit	0.53763	-0.39849	i	2, 5,-26102			
5		unit	0.55645	-0.16069	i	2, 6,-26102			
6		unit	0.55645	0.65146	i	2, 7,-26102			
7		unit	0.58333	-0.87491	i	2, 8,-26102			
8		unit	0.55645	-0.06872	i	2, 9,-26102			
9		unit	0.52957	0.30775	i	2, 10,-26102			
10		unit	0.58333	-0.71031	i	2, 11,-26102			
11		unit	0.58333	-0.63788	i	2, 12,-26102			
12		unit	0.55645	-0.70350	i	2, 13,-26102			
13		unit	0.58333	-0.10640	i	2, 14,-26102			
14		unit	0.58333	0.42145	i	2, 15,-26102			
15		unit	0.58333	-0.11809	i	2, 16,-26102			
16		unit	0.56452	-0.15178	i	2, 17,-26102			
17		unit	0.58333	-0.09337	i	2, 18,-26102			
18		unit	0.56452	-0.67762	i	2, 19,-26102			
19		unit	0.56452	0.61289	i	2, 20,-26102			
20		unit	0.55645	0.06899	i	2, 21,-26102			
21		unit	0.55645	-0.94499	i	2, 22,-26102			
22		unit	0.56452	-0.75660	i	2, 23,-26102			
23		unit	0.55645	-0.90265	i	2, 24,-26102			
24		unit	0.55645	0.17669	i	2, 25,-26102			
25		unit	0.55645	-0.53132	i	2, 26,-26102			
26		unit	0.58333	-0.71437	i	2, 27,-26102			
27		unit	0.58333	-0.65647	i	2, 28,-26102			
28		unit	0.55645	-0.61986	i	2, 29,-26102			
29		unit	0.58333	-0.40483	i	2, 30,-26102			
30		unit	0.58333	0.33286	i	2, 31,-26102			
31		unit	0.58333	0.95096	i	2, 32,-26102			
32		unit	0.53763	0.23510	i	2, 33,-26102			
33		unit	0.53763	0.68168	i	2, 34,-26102			
34		unit	0.56452	-0.01379	i	2, 35,-26102			
35		unit	0.53763	-0.50907	i	2, 36,-26102			
36		unit	0.58333	0.79168	i	2, 37,-26102			
37		unit	0.55645	-0.97460	i	2, 38,-26102			
38		unit	0.58333	0.88775	i	2, 39,-26102			
39		unit	0.55645	0.59076	i	2, 40,-26102			
40		unit	0.58333	-0.14728	i	2, 41,-26102			
41		unit	0.55645	0.27315	i	2, 42,-26102			
42		unit	0.55645	0.02098	i	2, 43,-26102			
43		unit	0.56452	-0.74954	i	2, 44,-26102			
44		unit	0.58333	0.74132	i	2, 45,-26102			
45		unit	0.53763	0.52029	i	2, 46,-26102			
46		unit	0.53763	0.22329	i	2, 47,-26102			
47		unit	0.58333	0.33867	i	2, 48,-26102			
48		unit	0.56452	-0.51318	i	2, 49,-26102			
49		unit	0.56452	-0.11739	i	2, 50,-26102			
50		unit	0.58333	-0.60875	i	2, 51,-26102			
51		unit	0.58333	-0.21011	i	2, 52,-26102			
52		unit	0.58333	-0.51634	i	2, 53,-26102			
53		unit	0.58333	-0.47908	i	2, 54,-26102			
54		unit	0.55645	0.82877	i	2, 55,-26102			

55		unit		0.58333		0.16859		i		2,	56,-26102	
56		unit		0.55645		-0.62456		i		2,	57,-26102	
57		unit		0.55645		0.05747		i		2,	58,-26102	
58		unit		0.55645		-0.52926		i		2,	59,-26102	
59		unit		0.56452		-0.51572		i		2,	60,-26102	
60		unit		0.55645		0.30776		i		2,	61,-26102	
61		unit		0.55645		0.05175		i		2,	62,-26102	
62		unit		0.53763		0.87326		i		2,	63,-26102	
63		unit		0.53763		-0.46634		i		2,	64,-26102	
64		unit		0.58333		-0.36676		i		2,	65,-26102	
65		unit		0.58333		0.15991		i		2,	66,-26102	
66		unit		0.55645		-0.07675		i		2,	67,-26102	
67		unit		0.58333		0.80658		i		2,	68,-26102	
68		unit		0.55645		-0.28111		i		2,	69,-26102	
69		unit		0.58333		0.08856		i		2,	70,-26102	
70		unit		0.58333		0.18479		i		2,	71,-26102	
71		unit		0.55645		-0.09317		i		2,	72,-26102	
72		unit		0.58333		-0.50768		i		2,	73,-26102	
73		unit		0.58333		-0.88155		i		2,	74,-26102	
74		unit		0.58333		-0.86706		i		2,	75,-26102	
75		unit		0.55645		0.38900		i		2,	76,-26102	
76		unit		0.55645		0.78554		i		2,	77,-26102	
77		unit		0.58333		-0.69546		i		2,	78,-26102	
78		unit		0.55645		-0.33645		i		2,	79,-26102	
79		unit		0.56452		-0.62668		i		2,	80,-26102	
80		unit		0.53763		0.12256		i		2,	81,-26102	
81		unit		0.53763		0.29200		i		2,	82,-26102	
82		unit		0.55645		0.11448		i		2,	83,-26102	
83		unit		0.55645		0.83891		i		2,	84,-26102	
84		unit		0.55645		0.30400		i		2,	85,-26102	
85		unit		0.58333		0.69980		i		2,	86,-26102	
86		unit		0.55645		0.46250		i		2,	87,-26102	
87		unit		0.58333		0.27543		i		2,	88,-26102	
88		unit		0.61022		-0.36402		i		2,	89,-26102	
89		unit		0.55645		-0.76440		i		2,	90,-26102	
90		unit		0.58333		0.71207		i		2,	91,-26102	
91		unit		0.56452		-0.35102		i		2,	92,-26102	
92		unit		0.56452		-0.17860		i		2,	93,-26102	
93		unit		0.61022		-0.01557		i		2,	94,-26102	
94		unit		0.53763		0.07949		i		2,	95,-26102	
95		unit		0.53763		0.26026		i		2,	96,-26102	
96		unit		0.58333		0.98694		i		2,	97,-26102	
97		unit		0.53763		-0.13379		i		2,	98,-26102	
98		unit		0.58333		-0.82435		i		2,	99,-26102	
99		unit		0.53763		-0.01590		i		2,100,-26102		
100		unit		0.58333		0.88439		i		2,101,-26102		
101		unit		0.96800		-2.99604		h		5,	2,-26102	
102		unit		0.99350		5.53834		h		5,	3,-26102	
103		unit		0.10138		-20.31278		h		5,	4,-26102	
104		unit		0.98703		-2.86665		h		5,	5,-26102	
105		unit		0.45767		4.95476		h		5,	6,-26102	
106		unit		0.00000		1.17697		h		5,	7,-26102	
107		unit		0.97428		-2.63886		h		5,	8,-26102	
108		unit		0.92642		-4.27375		h		5,	9,-26102	
109		unit		1.00000		8.13581		h		5,	10,-26102	
110		unit		0.00000		-9.28413		h		5,	11,-26102	
111		unit		0.97143		5.57508		o		8,	2,-26102	
112		unit		0.00002		-2.32903		o		8,	3,-26102	
113		unit		0.00903		-21.28129		o		8,	4,-26102	
114		unit		0.00000		-2.47878		o		8,	5,-26102	

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		97: 0.96962,	98: 1.03282,	99: 0.33034,	100: 0.08351				
111		101: 8.42425,	102: -11.47898,	103: -14.29568,	104: 5.98906,	105: -10.00127,	106: -0.55234,	107: 4.56877,	108: 8.12682,
		109: -10.66402,	110: 11.79521						
112		101: -9.47752,	102: 11.95402,	103: 21.32338,	104: -8.86108,	105: 5.40298,	106: -11.69273,	107: -7.19213,	108: -8.44941,
		109: 7.50695,	110: -7.21627						
113		101: 3.08403,	102: -5.92675,	103: -2.47414,	104: 3.83274,	105: -3.20055,	106: 15.51036,	107: 3.15440,	108: 3.45649,
		109: 11.14351,	110: -13.82436						
114		101: -1.77414,	102: -1.59320,	103: -4.31537,	104: -3.65101,	105: 0.48013,	106: -0.59155,	107: -5.18612,	108: -4.52440,
		109: -9.03734,	110: 8.88850						



# Appendix E

## Detailed Results

### E.1 Conceptual System

#### E.1.1 Total Results

#Training Patterns

```
STATISTICS ( 4000 patterns )
wrong      : 0.00 % ( 0 pattern(s) )
right     : 100.00 % ( 4000 pattern(s) )
unknown   : 0.00 % ( 0 pattern(s) )
error     : 0.081128
```

#Test Patterns

```
STATISTICS ( 2000 patterns )
wrong      : 0.00 % ( 0 pattern(s) )
right     : 100.00 % ( 2000 pattern(s) )
unknown   : 0.00 % ( 0 pattern(s) )
error     : 0.029920
```

#Validation Patterns

```
STATISTICS ( 1940 patterns )
wrong      : 0.00 % ( 0 pattern(s) )
right     : 100.00 % ( 1940 pattern(s) )
unknown   : 0.00 % ( 0 pattern(s) )
```

error : 0.033813

#Analysis Function Parameters  
-e 402040 -l 0.490 -h 0.510

## E.1.2 Individual Flow Case Results

#Signal 1

STATISTICS ( 1985 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 100.00 % ( 1985 pattern(s) )  
unknown : 0.00 % ( 0 pattern(s) )  
error : 0.053549

#Signal 2

STATISTICS ( 1985 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 100.00 % ( 1985 pattern(s) )  
unknown : 0.00 % ( 0 pattern(s) )  
error : 0.015783

#Signal 3

STATISTICS ( 1985 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 100.00 % ( 1985 pattern(s) )  
unknown : 0.00 % ( 0 pattern(s) )  
error : 0.025360

#Signal 4

STATISTICS ( 1985 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 100.00 % ( 1985 pattern(s) )  
unknown : 0.00 % ( 0 pattern(s) )  
error : 0.051390

```
#Analysis Function Parameters  
-e 402040 -l 0.490 -h 0.510
```

## E.2 Horizontal Multiphase System

### E.2.1 Total Results

#### #Training Patterns

```
STATISTICS ( 30000 patterns )
wrong      :  3.24 % ( 973 pattern(s) )
right     : 96.35 % ( 28905 pattern(s) )
unknown   :  0.41 % ( 122 pattern(s) )
error     : 1951.768188
```

#### #Test Patterns

```
STATISTICS ( 20020 patterns )
wrong      :  7.30 % ( 1462 pattern(s) )
right     : 91.19 % ( 18256 pattern(s) )
unknown   :  1.51 % ( 302 pattern(s) )
error     : 2766.916504
```

#### #Validation Patterns

```
STATISTICS ( 47603 patterns )
wrong      :  6.92 % ( 3292 pattern(s) )
right     : 91.04 % ( 43338 pattern(s) )
unknown   :  2.04 % ( 973 pattern(s) )
error     : 6549.362305
```

#### #Analysis Function Parameters

```
-e 402040 -l 0.490 -h 0.510
```

### E.2.2 Individual Flow Case Results

#### #Flow case 1

```
STATISTICS ( 2801 patterns )
wrong      :  0.00 % ( 0 pattern(s) )
right     : 100.00 % ( 2801 pattern(s) )
```

unknown : 0.00 % ( 0 pattern(s) )  
error : 8.149170

#Flow case 2

STATISTICS ( 5801 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 100.00 % ( 5801 pattern(s) )  
unknown : 0.00 % ( 0 pattern(s) )  
error : 17.099339

#Flow case 3

STATISTICS ( 2801 patterns )  
wrong : 1.00 % ( 28 pattern(s) )  
right : 98.93 % ( 2771 pattern(s) )  
unknown : 0.07 % ( 2 pattern(s) )  
error : 64.318222

#Flow case 4

STATISTICS ( 2801 patterns )  
wrong : 0.39 % ( 11 pattern(s) )  
right : 99.54 % ( 2788 pattern(s) )  
unknown : 0.07 % ( 2 pattern(s) )  
error : 30.434122

#Flow case 5

STATISTICS ( 2801 patterns )  
wrong : 0.79 % ( 22 pattern(s) )  
right : 99.18 % ( 2778 pattern(s) )  
unknown : 0.04 % ( 1 pattern(s) )  
error : 51.734482

#Flow case 6

STATISTICS ( 2801 patterns )  
wrong : 0.79 % ( 22 pattern(s) )  
right : 99.07 % ( 2775 pattern(s) )  
unknown : 0.14 % ( 4 pattern(s) )

error : 53.844448

#Flow case 7

STATISTICS ( 2801 patterns )  
wrong : 0.32 % ( 9 pattern(s) )  
right : 99.64 % ( 2791 pattern(s) )  
unknown : 0.04 % ( 1 pattern(s) )  
error : 23.204681

#Flow case 8

STATISTICS ( 2801 patterns )  
wrong : 0.11 % ( 3 pattern(s) )  
right : 99.86 % ( 2797 pattern(s) )  
unknown : 0.04 % ( 1 pattern(s) )  
error : 15.097422

#Flow case 9

STATISTICS ( 2801 patterns )  
wrong : 2.64 % ( 74 pattern(s) )  
right : 97.07 % ( 2719 pattern(s) )  
unknown : 0.29 % ( 8 pattern(s) )  
error : 167.305237

#Flow case 10

STATISTICS ( 3190 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 100.00 % ( 3190 pattern(s) )  
unknown : 0.00 % ( 0 pattern(s) )  
error : 5.039117

#Flow case 12

STATISTICS ( 2800 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 100.00 % ( 2800 pattern(s) )  
unknown : 0.00 % ( 0 pattern(s) )  
error : 3.826895



#Flow case 13

```
STATISTICS ( 2800 patterns )
wrong      : 4.21 % ( 118 pattern(s) )
right     : 95.43 % ( 2672 pattern(s) )
unknown   : 0.36 % ( 10 pattern(s) )
error     : 222.467819
```

#Flow case 14

```
STATISTICS ( 2800 patterns )
wrong      : 2.14 % ( 60 pattern(s) )
right     : 97.54 % ( 2731 pattern(s) )
unknown   : 0.32 % ( 9 pattern(s) )
error     : 106.733963
```

#Flow case 15

```
STATISTICS ( 2801 patterns )
wrong      : 5.86 % ( 164 pattern(s) )
right     : 93.65 % ( 2623 pattern(s) )
unknown   : 0.50 % ( 14 pattern(s) )
error     : 281.048492
```

#Flow case 17

```
STATISTICS ( 2800 patterns )
wrong      : 0.00 % ( 0 pattern(s) )
right     : 100.00 % ( 2800 pattern(s) )
unknown   : 0.00 % ( 0 pattern(s) )
error     : 7.679321
```

#Flow case 18

```
STATISTICS ( 11801 patterns )
wrong      : 51.73 % ( 6105 pattern(s) )
right     : 29.46 % ( 3477 pattern(s) )
unknown   : 18.80 % ( 2219 pattern(s) )
error     : 13286.876953
```

## #Flow case 19

```
STATISTICS ( 2800 patterns )
wrong      :  7.96 % ( 223 pattern(s) )
right     : 91.68 % ( 2567 pattern(s) )
unknown   :  0.36 % ( 10 pattern(s) )
error     : 377.278687
```

## #Flow case 20

```
STATISTICS ( 2801 patterns )
wrong      :  5.86 % ( 164 pattern(s) )
right     : 93.86 % ( 2629 pattern(s) )
unknown   :  0.29 % (  8 pattern(s) )
error     : 292.512329
```

## #Flow case 21

```
STATISTICS ( 2800 patterns )
wrong      : 39.61 % ( 1109 pattern(s) )
right     : 59.46 % ( 1665 pattern(s) )
unknown   :  0.93 % ( 26 pattern(s) )
error     : 1873.426392
```

## #Flow case 22

```
STATISTICS ( 11800 patterns )
wrong      : 92.36 % ( 10898 pattern(s) )
right     :  1.31 % ( 155 pattern(s) )
unknown   :  6.33 % ( 747 pattern(s) )
error     : 22216.748047
```

## #Flow case 23

```
STATISTICS ( 2800 patterns )
wrong      : 47.64 % ( 1334 pattern(s) )
right     : 46.29 % ( 1296 pattern(s) )
unknown   :  6.07 % ( 170 pattern(s) )
error     : 2468.751709
```

## #Flow case 24

```
STATISTICS ( 2800 patterns )
wrong   : 24.71 % ( 692 pattern(s) )
right   : 74.93 % ( 2098 pattern(s) )
unknown : 0.36 % ( 10 pattern(s) )
error   : 1186.005127
```

#Flow case 25

```
STATISTICS ( 2800 patterns )
wrong   : 0.00 % ( 0 pattern(s) )
right   : 100.00 % ( 2800 pattern(s) )
unknown : 0.00 % ( 0 pattern(s) )
error   : 0.309424
```

#Flow case 26

```
STATISTICS ( 4800 patterns )
wrong   : 1.92 % ( 92 pattern(s) )
right   : 91.46 % ( 4390 pattern(s) )
unknown : 6.62 % ( 318 pattern(s) )
error   : 440.638428
```

#Flow case 27

```
STATISTICS ( 2800 patterns )
wrong   : 12.04 % ( 337 pattern(s) )
right   : 80.61 % ( 2257 pattern(s) )
unknown : 7.36 % ( 206 pattern(s) )
error   : 793.602539
```

#Flow case 28

```
STATISTICS ( 4500 patterns )
wrong   : 21.33 % ( 960 pattern(s) )
right   : 78.40 % ( 3528 pattern(s) )
unknown : 0.27 % ( 12 pattern(s) )
error   : 1721.651978
```

#Flow case 29

```
STATISTICS ( 11800 patterns )
wrong   : 0.00 % ( 0 pattern(s) )
right  : 99.99 % ( 11799 pattern(s) )
unknown: 0.01 % ( 1 pattern(s) )
error   : 1.449908
```

#Flow case 30

```
STATISTICS ( 5800 patterns )
wrong   : 27.07 % ( 1570 pattern(s) )
right  : 65.00 % ( 3770 pattern(s) )
unknown: 7.93 % ( 460 pattern(s) )
error   : 3218.660645
```

#Flow case 31

```
STATISTICS ( 2800 patterns )
wrong   : 0.00 % ( 0 pattern(s) )
right  : 100.00 % ( 2800 pattern(s) )
unknown: 0.00 % ( 0 pattern(s) )
error   : 0.339914
```

#Flow case 32

```
STATISTICS ( 5800 patterns )
wrong   : 0.00 % ( 0 pattern(s) )
right  : 99.66 % ( 5780 pattern(s) )
unknown: 0.34 % ( 20 pattern(s) )
error   : 15.831513
```

#Flow case 33

```
STATISTICS ( 2800 patterns )
wrong   : 3.32 % ( 93 pattern(s) )
right  : 87.93 % ( 2462 pattern(s) )
unknown: 8.75 % ( 245 pattern(s) )
error   : 366.238098
```

#Flow case 34

```
STATISTICS ( 5800 patterns )
```

```
wrong   : 0.00 % ( 0 pattern(s) )
right   : 100.00 % ( 5800 pattern(s) )
unknown : 0.00 % ( 0 pattern(s) )
error   : 0.626762
```

#Flow case 35

```
STATISTICS ( 5850 patterns )
wrong   : 0.00 % ( 0 pattern(s) )
right   : 99.42 % ( 5816 pattern(s) )
unknown : 0.58 % ( 34 pattern(s) )
error   : 27.847963
```

#Flow case 36

```
STATISTICS ( 5800 patterns )
wrong   : 0.05 % ( 3 pattern(s) )
right   : 98.34 % ( 5704 pattern(s) )
unknown : 1.60 % ( 93 pattern(s) )
error   : 86.130341
```

#Flow case 37

```
STATISTICS ( 4800 patterns )
wrong   : 18.12 % ( 870 pattern(s) )
right   : 70.94 % ( 3405 pattern(s) )
unknown : 10.94 % ( 525 pattern(s) )
error   : 1967.843872
```

#Flow case 38

```
STATISTICS ( 2800 patterns )
wrong   : 9.32 % ( 261 pattern(s) )
right   : 84.11 % ( 2355 pattern(s) )
unknown : 6.57 % ( 184 pattern(s) )
error   : 622.427856
```

-e 402040 -l 0.490 -h 0.510

### E.2.3 Results Analysis

#### Incorrectly Classified Patterns

2801 patterns #Flow case 1

SW: 0

SS: 0

Slug: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong, 'r' = right).

5801 patterns #Flow case 2

SW: 0

SS: 0

Slug: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong, 'r' = right).

2801 patterns #Flow case 3

SW: 28

SS: 0

Slug: 0

Bubble: 0

There are 28 'w' outputs ('w' = wrong, 'r' = right).

2801 patterns #Flow case 4

SW: 11

SS: 0

Slug: 0

Bubble: 0

There are 11 'w' outputs ('w' = wrong, 'r' = right).

2801 patterns #Flow case 5

SW: 22  
SS: 0  
Slug: 0  
Bubble: 0  
There are 22 'w' outputs ('w' = wrong, 'r' = right).

2801 patterns #Flow case 6

SW: 22  
SS: 0  
Slug: 0  
Bubble: 0  
There are 22 'w' outputs ('w' = wrong, 'r' = right).

2801 patterns #Flow case 7

SW: 9  
SS: 0  
Slug: 0  
Bubble: 0  
There are 9 'w' outputs ('w' = wrong, 'r' = right).

2801 patterns #Flow case 8

SW: 3  
SS: 0  
Slug: 0  
Bubble: 0  
There are 3 'w' outputs ('w' = wrong, 'r' = right).

2801 patterns #Flow case 9

SW: 74  
SS: 0  
Slug: 0  
Bubble: 0

There are 74 'w' outputs ('w' = wrong, 'r' = right).

3190 patterns #Flow case 10

SW: 0

SS: 0

Slug: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 12

SW: 0

SS: 0

Slug: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 13

SW: 118

SS: 0

Slug: 0

Bubble: 0

There are 118 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 14

SW: 60

SS: 0

Slug: 0

Bubble: 0

There are 60 'w' outputs ('w' = wrong, 'r' = right).

2801 patterns #Flow case 15



SW: 164  
SS: 0  
Slug: 0  
Bubble: 0  
There are 164 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 17

SW: 0  
SS: 0  
Slug: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong, 'r' = right).

11801 patterns #Flow case 18

SW: 0  
SS: 825  
Slug: 5280  
Bubble: 0  
There are 6105 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 19

SW: 223  
SS: 0  
Slug: 0  
Bubble: 0  
There are 223 'w' outputs ('w' = wrong, 'r' = right).

2801 patterns #Flow case 20

SW: 164  
SS: 0  
Slug: 0  
Bubble: 0  
There are 164 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 21

SW: 0

SS: 1109

Slug: 0

Bubble: 0

There are 1109 'w' outputs ('w' = wrong, 'r' = right).

11800 patterns #Flow case 22

SW: 0

SS: 8

Slug: 10890

Bubble: 0

There are 10898 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 23

SW: 0

SS: 1304

Slug: 30

Bubble: 0

There are 1334 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 24

SW: 0

SS: 692

Slug: 0

Bubble: 0

There are 692 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 25

SW: 0

SS: 0  
Slug: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong, 'r' = right).

4800 patterns #Flow case 26

SW: 84  
SS: 8  
Slug: 0  
Bubble: 0  
There are 92 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 27

SW: 0  
SS: 170  
Slug: 167  
Bubble: 0  
There are 337 'w' outputs ('w' = wrong, 'r' = right).

4500 patterns #Flow case 28

SW: 0  
SS: 960  
Slug: 0  
Bubble: 0  
There are 960 'w' outputs ('w' = wrong, 'r' = right).

11800 patterns #Flow case 29

SW: 0  
SS: 0  
Slug: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong, 'r' = right).

5800 patterns #Flow case 30

SW: 0

SS: 775

Slug: 795

Bubble: 0

There are 1570 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 31

SW: 0

SS: 0

Slug: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong, 'r' = right).

5800 patterns #Flow case 32

SW: 0

SS: 0

Slug: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 33

SW: 91

SS: 2

Slug: 0

Bubble: 0

There are 93 'w' outputs ('w' = wrong, 'r' = right).

5800 patterns #Flow case 34

SW: 0

SS: 0

Slug: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong, 'r' = right).

5850 patterns #Flow case 35

SW: 0  
SS: 0  
Slug: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong, 'r' = right).

5800 patterns #Flow case 36

SW: 3  
SS: 0  
Slug: 0  
Bubble: 0  
There are 3 'w' outputs ('w' = wrong, 'r' = right).

4800 patterns #Flow case 37

SW: 801  
SS: 69  
Slug: 0  
Bubble: 0  
There are 870 'w' outputs ('w' = wrong, 'r' = right).

2800 patterns #Flow case 38

SW: 239  
SS: 22  
Slug: 0  
Bubble: 0  
There are 261 'w' outputs ('w' = wrong, 'r' = right).

**Unclassified Patterns**

2801 patterns #Flow case 1

SW: 0

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 0 unclassified inputs in total

5801 patterns #Flow case 2

SW: 0

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 0 unclassified inputs in total

2801 patterns #Flow case 3

SW: 0

SS: 0  
Slug: 0  
Bubble: 0  
SW + SS: 0  
SW + Slug: 0  
SW + Bubble: 0  
SS + Slug: 0  
SS + Bubble: 0  
Slug + Bubble: 0  
There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )  
There are 2 unclassified results where all outputs are  $< 0.51$   
There are 2 unclassified inputs in total

2801 patterns #Flow case 4

SW: 0  
SS: 1  
Slug: 0  
Bubble: 0  
SW + SS: 0  
SW + Slug: 0  
SW + Bubble: 0  
SS + Slug: 0  
SS + Bubble: 0  
Slug + Bubble: 0  
There are 1 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )  
There are 1 unclassified results where all outputs are  $< 0.51$   
There are 2 unclassified inputs in total

2801 patterns #Flow case 5

SW: 0  
SS: 0  
Slug: 0  
Bubble: 0  
SW + SS: 0  
SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 1 unclassified results where all outputs are  $< 0.51$

There are 1 unclassified inputs in total

2801 patterns #Flow case 6

SW: 0

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 4 unclassified results where all outputs are  $< 0.51$

There are 4 unclassified inputs in total

2801 patterns #Flow case 7

SW: 1

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 1 unclassified results where there is one output above 0.51 and



one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 1 unclassified inputs in total

2801 patterns #Flow case 8

SW: 0

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 1 unclassified results where all outputs are  $< 0.51$

There are 1 unclassified inputs in total

2801 patterns #Flow case 9

SW: 0

SS: 2

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 2 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 6 unclassified results where all outputs are  $< 0.51$

There are 8 unclassified inputs in total

3190 patterns #Flow case 10

SW: 0

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 0 unclassified inputs in total

2800 patterns #Flow case 12

SW: 0

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 0 unclassified inputs in total

2800 patterns #Flow case 13

SW: 0

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 10 unclassified results where all outputs are  $< 0.51$

There are 10 unclassified inputs in total

2800 patterns #Flow case 14

SW: 0

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 9 unclassified results where all outputs are  $< 0.51$

There are 9 unclassified inputs in total

2801 patterns #Flow case 15

SW: 2

SS: 1

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 3 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 11 unclassified results where all outputs are  $< 0.51$

There are 14 unclassified inputs in total

2800 patterns #Flow case 17

SW: 0

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 0 unclassified inputs in total

11801 patterns #Flow case 18

SW: 662

SS: 32

Slug: 670

Bubble: 0

SW + SS: 0

SW + Slug: 631

SW + Bubble: 0

SS + Slug: 30

SS + Bubble: 0

Slug + Bubble: 0

There are 703 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 855 unclassified results where all outputs are  $< 0.51$

There are 2219 unclassified inputs in total

2800 patterns #Flow case 19

SW: 0

SS: 1

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 1 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 9 unclassified results where all outputs are  $< 0.51$

There are 10 unclassified inputs in total

2801 patterns #Flow case 20

SW: 1

SS: 1

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 2 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 6 unclassified results where all outputs are  $< 0.51$

There are 8 unclassified inputs in total

2800 patterns #Flow case 21

SW: 3  
SS: 6  
Slug: 0  
Bubble: 0  
SW + SS: 0  
SW + Slug: 0  
SW + Bubble: 0  
SS + Slug: 0  
SS + Bubble: 0  
Slug + Bubble: 0

There are 9 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 17 unclassified results where all outputs are  $< 0.51$

There are 26 unclassified inputs in total

11800 patterns #Flow case 22

SW: 614  
SS: 16  
Slug: 635  
Bubble: 0  
SW + SS: 0  
SW + Slug: 607  
SW + Bubble: 0  
SS + Slug: 15  
SS + Bubble: 0  
Slug + Bubble: 0

There are 19 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 106 unclassified results where all outputs are  $< 0.51$

There are 747 unclassified inputs in total

2800 patterns #Flow case 23

SW: 5  
SS: 0  
Slug: 5  
Bubble: 0  
SW + SS: 0

SW + Slug: 4

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 6 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 160 unclassified results where all outputs are  $< 0.51$

There are 170 unclassified inputs in total

2800 patterns #Flow case 24

SW: 2

SS: 4

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 6 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 4 unclassified results where all outputs are  $< 0.51$

There are 10 unclassified inputs in total

2800 patterns #Flow case 25

SW: 0

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 0 unclassified inputs in total

4800 patterns #Flow case 26

SW: 273

SS: 12

Slug: 285

Bubble: 0

SW + SS: 0

SW + Slug: 270

SW + Bubble: 0

SS + Slug: 11

SS + Bubble: 0

Slug + Bubble: 0

There are 6 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 31 unclassified results where all outputs are  $< 0.51$

There are 318 unclassified inputs in total

2800 patterns #Flow case 27

SW: 23

SS: 0

Slug: 22

Bubble: 0

SW + SS: 0

SW + Slug: 21

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 24 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 161 unclassified results where all outputs are  $< 0.51$

There are 206 unclassified inputs in total



4500 patterns #Flow case 28

SW: 0

SS: 1

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 1 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 11 unclassified results where all outputs are  $< 0.51$

There are 12 unclassified inputs in total

11800 patterns #Flow case 29

SW: 1

SS: 0

Slug: 0

Bubble: 1

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 1 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 1 unclassified inputs in total

5800 patterns #Flow case 30

SW: 101

SS: 10

Slug: 110

Bubble: 0

SW + SS: 0

SW + Slug: 97

SW + Bubble: 0

SS + Slug: 9

SS + Bubble: 0

Slug + Bubble: 0

There are 115 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 239 unclassified results where all outputs are  $< 0.51$

There are 460 unclassified inputs in total

2800 patterns #Flow case 31

SW: 0

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 0 unclassified inputs in total

5800 patterns #Flow case 32

SW: 16

SS: 0

Slug: 4

Bubble: 20

SW + SS: 0

SW + Slug: 0

SW + Bubble: 15

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 3

There are 2 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 20 unclassified inputs in total

2800 patterns #Flow case 33

SW: 202

SS: 3

Slug: 209

Bubble: 0

SW + SS: 0

SW + Slug: 200

SW + Bubble: 0

SS + Slug: 2

SS + Bubble: 0

Slug + Bubble: 0

There are 8 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 35 unclassified results where all outputs are  $< 0.51$

There are 245 unclassified inputs in total

5800 patterns #Flow case 34

SW: 0

SS: 0

Slug: 0

Bubble: 0

SW + SS: 0

SW + Slug: 0

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$   
There are 0 unclassified inputs in total

5850 patterns #Flow case 35

SW: 26

SS: 0

Slug: 28

Bubble: 0

SW + SS: 0

SW + Slug: 25

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 3 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 6 unclassified results where all outputs are  $< 0.51$

There are 34 unclassified inputs in total

5800 patterns #Flow case 36

SW: 86

SS: 1

Slug: 89

Bubble: 0

SW + SS: 0

SW + Slug: 85

SW + Bubble: 0

SS + Slug: 0

SS + Bubble: 0

Slug + Bubble: 0

There are 4 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 4 unclassified results where all outputs are  $< 0.51$

There are 93 unclassified inputs in total

4800 patterns #Flow case 37

SW: 388

SS: 16

Slug: 415

Bubble: 0

SW + SS: 0

SW + Slug: 377

SW + Bubble: 0

SS + Slug: 15

SS + Bubble: 0

Slug + Bubble: 0

There are 33 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 100 unclassified results where all outputs are  $< 0.51$

There are 525 unclassified inputs in total

2800 patterns #Flow case 38

SW: 118

SS: 9

Slug: 130

Bubble: 0

SW + SS: 0

SW + Slug: 116

SW + Bubble: 0

SS + Slug: 7

SS + Bubble: 0

Slug + Bubble: 0

There are 9 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 52 unclassified results where all outputs are  $< 0.51$

There are 184 unclassified inputs in total

## E.3 S-shape Riser Multiphase System

### E.3.1 Total Results

#### #Training Patterns

```
STATISTICS ( 6300 patterns )
wrong      : 0.00 % ( 0 pattern(s) )
right     : 95.24 % ( 6000 pattern(s) )
unknown   : 4.76 % ( 300 pattern(s) )
error     : 307.321564
```

#### #Test Patterns

```
STATISTICS ( 8567 patterns )
wrong      : 0.77 % ( 66 pattern(s) )
right     : 96.52 % ( 8269 pattern(s) )
unknown   : 2.71 % ( 232 pattern(s) )
error     : 313.583618
```

#### #Validation Patterns

```
STATISTICS ( 15233 patterns )
wrong      : 11.52 % ( 1755 pattern(s) )
right     : 81.53 % ( 12420 pattern(s) )
unknown   : 6.95 % ( 1058 pattern(s) )
error     : 4163.135254
```

#### #Analysis Function Parameters

```
-e 402040 -l 0.490 -h 0.510
```

### E.3.2 Individual Flow Case Results

#### #Flow case 1

```
STATISTICS ( 1400 patterns )
wrong      : 0.00 % ( 0 pattern(s) )
right     : 93.29 % ( 1306 pattern(s) )
```

unknown : 6.71 % ( 94 pattern(s) )  
error : 86.790283

#Flow case 2

STATISTICS ( 905 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 93.26 % ( 844 pattern(s) )  
unknown : 6.74 % ( 61 pattern(s) )  
error : 51.898067

#Flow case 3

STATISTICS ( 800 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 100.00 % ( 800 pattern(s) )  
unknown : 0.00 % ( 0 pattern(s) )  
error : 0.103090

#Flow case 4

STATISTICS ( 1400 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 97.64 % ( 1367 pattern(s) )  
unknown : 2.36 % ( 33 pattern(s) )  
error : 28.219751

#Flow case 5

STATISTICS ( 1400 patterns )  
wrong : 5.07 % ( 71 pattern(s) )  
right : 93.21 % ( 1305 pattern(s) )  
unknown : 1.71 % ( 24 pattern(s) )  
error : 116.853195

#Flow case 6

STATISTICS ( 817 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 100.00 % ( 817 pattern(s) )  
unknown : 0.00 % ( 0 pattern(s) )

error : 0.419808

#Flow case 7

STATISTICS ( 1400 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 99.71 % ( 1396 pattern(s) )  
unknown : 0.29 % ( 4 pattern(s) )  
error : 4.038830

#Flow case 8

STATISTICS ( 622 patterns )  
wrong : 0.32 % ( 2 pattern(s) )  
right : 99.68 % ( 620 pattern(s) )  
unknown : 0.00 % ( 0 pattern(s) )  
error : 3.029054

#Flow case 9

STATISTICS ( 1400 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 99.86 % ( 1398 pattern(s) )  
unknown : 0.14 % ( 2 pattern(s) )  
error : 5.052010

#Flow case 10

STATISTICS ( 1400 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 96.43 % ( 1350 pattern(s) )  
unknown : 3.57 % ( 50 pattern(s) )  
error : 48.545624

#Flow case 11

STATISTICS ( 800 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 98.75 % ( 790 pattern(s) )  
unknown : 1.25 % ( 10 pattern(s) )  
error : 7.894430



#Flow case 12

STATISTICS ( 807 patterns )  
wrong : 8.30 % ( 67 pattern(s) )  
right : 88.97 % ( 718 pattern(s) )  
unknown : 2.73 % ( 22 pattern(s) )  
error : 139.956253

#Flow case 13

STATISTICS ( 1400 patterns )  
wrong : 15.36 % ( 215 pattern(s) )  
right : 78.64 % ( 1101 pattern(s) )  
unknown : 6.00 % ( 84 pattern(s) )  
error : 463.463531

#Flow case 14

STATISTICS ( 650 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 100.00 % ( 650 pattern(s) )  
unknown : 0.00 % ( 0 pattern(s) )  
error : 0.860633

#Flow case 15

STATISTICS ( 1400 patterns )  
wrong : 2.71 % ( 38 pattern(s) )  
right : 93.93 % ( 1315 pattern(s) )  
unknown : 3.36 % ( 47 pattern(s) )  
error : 97.012177

#Flow case 16

STATISTICS ( 810 patterns )  
wrong : 0.00 % ( 0 pattern(s) )  
right : 100.00 % ( 810 pattern(s) )  
unknown : 0.00 % ( 0 pattern(s) )  
error : 0.498109

## #Flow case 17

```
STATISTICS ( 800 patterns )
wrong   : 0.00 % ( 0 pattern(s) )
right  : 99.88 % ( 799 pattern(s) )
unknown : 0.12 % ( 1 pattern(s) )
error   : 1.246582
```

## #Flow case 18

```
STATISTICS ( 1400 patterns )
wrong   : 0.00 % ( 0 pattern(s) )
right  : 100.00 % ( 1400 pattern(s) )
unknown : 0.00 % ( 0 pattern(s) )
error   : 1.592925
```

## #Flow case 19

```
STATISTICS ( 1400 patterns )
wrong   : 0.00 % ( 0 pattern(s) )
right  : 100.00 % ( 1400 pattern(s) )
unknown : 0.00 % ( 0 pattern(s) )
error   : 1.113598
```

## #Flow case 20

```
STATISTICS ( 507 patterns )
wrong   : 8.68 % ( 44 pattern(s) )
right  : 87.18 % ( 442 pattern(s) )
unknown : 4.14 % ( 21 pattern(s) )
error   : 93.828728
```

## #Flow case 21

```
STATISTICS ( 797 patterns )
wrong   : 57.47 % ( 458 pattern(s) )
right  : 0.00 % ( 0 pattern(s) )
unknown : 42.53 % ( 339 pattern(s) )
error   : 1166.470093
```

## #Flow case 22

```
STATISTICS ( 542 patterns )  
wrong   : 3.87 % ( 21 pattern(s) )  
right   : 95.39 % ( 517 pattern(s) )  
unknown : 0.74 % ( 4 pattern(s) )  
error   : 37.525764
```

#Flow case 23

```
STATISTICS ( 1400 patterns )  
wrong   : 22.50 % ( 315 pattern(s) )  
right   : 60.64 % ( 849 pattern(s) )  
unknown : 16.86 % ( 236 pattern(s) )  
error   : 751.943848
```

#Flow case 24

```
STATISTICS ( 500 patterns )  
wrong   : 3.00 % ( 15 pattern(s) )  
right   : 92.00 % ( 460 pattern(s) )  
unknown : 5.00 % ( 25 pattern(s) )  
error   : 40.588840
```

#Flow case 25

```
STATISTICS ( 512 patterns )  
wrong   : 21.48 % ( 110 pattern(s) )  
right   : 64.45 % ( 330 pattern(s) )  
unknown : 14.06 % ( 72 pattern(s) )  
error   : 255.485550
```

#Flow case 26

```
STATISTICS ( 500 patterns )  
wrong   : 0.00 % ( 0 pattern(s) )  
right   : 99.80 % ( 499 pattern(s) )  
unknown : 0.20 % ( 1 pattern(s) )  
error   : 0.618865
```

#Flow case 27

```
STATISTICS ( 500 patterns )
wrong   : 0.00 % ( 0 pattern(s) )
right   : 100.00 % ( 500 pattern(s) )
unknown : 0.00 % ( 0 pattern(s) )
error   : 0.426723
```

#Flow case 28

```
STATISTICS ( 535 patterns )
wrong   : 0.00 % ( 0 pattern(s) )
right   : 98.88 % ( 529 pattern(s) )
unknown : 1.12 % ( 6 pattern(s) )
error   : 4.213898
```

#Flow case 29

```
STATISTICS ( 500 patterns )
wrong   : 0.00 % ( 0 pattern(s) )
right   : 99.60 % ( 498 pattern(s) )
unknown : 0.40 % ( 2 pattern(s) )
error   : 1.378908
```

#Flow case 30

```
STATISTICS ( 510 patterns )
wrong   : 3.73 % ( 19 pattern(s) )
right   : 88.63 % ( 452 pattern(s) )
unknown : 7.65 % ( 39 pattern(s) )
error   : 66.629425
```

#Flow case 31

```
STATISTICS ( 562 patterns )
wrong   : 0.00 % ( 0 pattern(s) )
right   : 94.84 % ( 533 pattern(s) )
unknown : 5.16 % ( 29 pattern(s) )
error   : 26.527973
```

#Flow case 32

```
STATISTICS ( 502 patterns )
```

```
wrong   : 99.60 % ( 500 pattern(s) )
right   :  0.00 % (  0 pattern(s) )
unknown :  0.40 % (  2 pattern(s) )
error   : 980.261353
```

#Flow case 33

```
STATISTICS ( 522 patterns )
wrong   :  2.11 % ( 11 pattern(s) )
right   :  0.00 % (  0 pattern(s) )
unknown : 97.89 % ( 511 pattern(s) )
error   : 529.876648
```

#Flow case 34

```
STATISTICS ( 1400 patterns )
wrong   :  0.00 % (  0 pattern(s) )
right   : 99.93 % ( 1399 pattern(s) )
unknown :  0.07 % (  1 pattern(s) )
error   :  2.491639
```

#Flow case 35

```
STATISTICS ( 1400 patterns )
wrong   :  0.00 % (  0 pattern(s) )
right   : 100.00 % ( 1400 pattern(s) )
unknown :  0.00 % (  0 pattern(s) )
error   :  1.386668
```

-e 402040 -l 0.490 -h 0.510

### E.3.3 Results Analysis

#### Incorrectly Classified Patterns

1400 patterns #Flow case 1

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong).

905 patterns #Flow case 2

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong).

800 patterns #Flow case 3

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong).

1400 patterns #Flow case 4

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong).

1400 patterns #Flow case 5

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 71  
There are 71 'w' outputs ('w' = wrong).

817 patterns #Flow case 6

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong).

1400 patterns #Flow case 7

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong).

622 patterns #Flow case 8

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 2  
There are 2 'w' outputs ('w' = wrong).

1400 patterns #Flow case 9

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0

There are 0 'w' outputs ('w' = wrong).

1400 patterns #Flow case 10

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong).

800 patterns #Flow case 11

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong).

807 patterns #Flow case 12

SS1: 67

Slug: 0

Oscillation: 0

Bubble: 0

There are 67 'w' outputs ('w' = wrong).

1400 patterns #Flow case 13

SS1: 0

Slug: 215

Oscillation: 0

Bubble: 0

There are 215 'w' outputs ('w' = wrong).

650 patterns #Flow case 14



SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong).

1400 patterns #Flow case 15

SS1: 0  
Slug: 0  
Oscillation: 38  
Bubble: 0  
There are 38 'w' outputs ('w' = wrong).

810 patterns #Flow case 16

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong).

800 patterns #Flow case 17

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong).

1400 patterns #Flow case 18

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong).

1400 patterns #Flow case 19

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong).

507 patterns #Flow case 20

SS1: 3  
Slug: 41  
Oscillation: 0  
Bubble: 0  
There are 44 'w' outputs ('w' = wrong).

797 patterns #Flow case 21

SS1: 193  
Slug: 265  
Oscillation: 0  
Bubble: 0  
There are 458 'w' outputs ('w' = wrong).

542 patterns #Flow case 22

SS1: 0  
Slug: 21  
Oscillation: 0  
Bubble: 0  
There are 21 'w' outputs ('w' = wrong).

1400 patterns #Flow case 23

SS1: 0

Slug: 315  
Oscillation: 0  
Bubble: 0  
There are 315 'w' outputs ('w' = wrong).

500 patterns #Flow case 24

SS1: 0  
Slug: 0  
Oscillation: 15  
Bubble: 0  
There are 15 'w' outputs ('w' = wrong).

512 patterns #Flow case 25

SS1: 110  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 110 'w' outputs ('w' = wrong).

500 patterns #Flow case 26

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong).

500 patterns #Flow case 27

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong).

535 patterns #Flow case 28

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong).

500 patterns #Flow case 29

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong).

510 patterns #Flow case 30

SS1: 0

Slug: 0

Oscillation: 19

Bubble: 0

There are 19 'w' outputs ('w' = wrong).

562 patterns #Flow case 31

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

There are 0 'w' outputs ('w' = wrong).

502 patterns #Flow case 32

SS1: 4

Slug: 496

Oscillation: 0  
Bubble: 0  
There are 500 'w' outputs ('w' = wrong).

522 patterns #Flow case 33

SS1: 11  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 11 'w' outputs ('w' = wrong).

1400 patterns #Flow case 34

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong).

1400 patterns #Flow case 35

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
There are 0 'w' outputs ('w' = wrong).

**Unclassified Patterns**

1400 patterns #Flow case 1

SS1: 94

Slug: 0

Oscillation: 0

Bubble: 94

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 94

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 94 unclassified inputs in total

905 patterns #Flow case 2

SS1: 61

Slug: 0

Oscillation: 0

Bubble: 61

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 61

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 61 unclassified inputs in total

800 patterns #Flow case 3

SS1: 0

Slug: 0  
Oscillation: 0  
Bubble: 0  
SS1 + Slug: 0  
SS1 + Oscillation: 0  
SS1 + Bubble: 0  
Slug + Oscillation: 0  
Slug + Bubble: 0  
Oscillation + Bubble: 0  
There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )  
There are 0 unclassified results where all outputs are  $< 0.51$   
There are 0 unclassified inputs in total

1400 patterns #Flow case 4

SS1: 33  
Slug: 0  
Oscillation: 0  
Bubble: 33  
SS1 + Slug: 0  
SS1 + Oscillation: 0  
SS1 + Bubble: 33  
Slug + Oscillation: 0  
Slug + Bubble: 0  
Oscillation + Bubble: 0  
There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )  
There are 0 unclassified results where all outputs are  $< 0.51$   
There are 33 unclassified inputs in total

1400 patterns #Flow case 5

SS1: 1  
Slug: 0  
Oscillation: 0  
Bubble: 2  
SS1 + Slug: 0  
SS1 + Oscillation: 0

SS1 + Bubble: 0  
Slug + Oscillation: 0  
Slug + Bubble: 0  
Oscillation + Bubble: 0  
There are 3 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )  
There are 21 unclassified results where all outputs are  $< 0.51$   
There are 24 unclassified inputs in total

817 patterns #Flow case 6

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
SS1 + Slug: 0  
SS1 + Oscillation: 0  
SS1 + Bubble: 0  
Slug + Oscillation: 0  
Slug + Bubble: 0  
Oscillation + Bubble: 0  
There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )  
There are 0 unclassified results where all outputs are  $< 0.51$   
There are 0 unclassified inputs in total

1400 patterns #Flow case 7

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
SS1 + Slug: 0  
SS1 + Oscillation: 0  
SS1 + Bubble: 0  
Slug + Oscillation: 0  
Slug + Bubble: 0  
Oscillation + Bubble: 0  
There are 0 unclassified results where there is one output above 0.51 and



one neutral ( $0.49 < ? < 0.51$ )

There are 4 unclassified results where all outputs are  $< 0.51$

There are 4 unclassified inputs in total

622 patterns #Flow case 8

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 0 unclassified inputs in total

1400 patterns #Flow case 9

SS1: 1

Slug: 2

Oscillation: 0

Bubble: 0

SS1 + Slug: 1

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 1 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 2 unclassified inputs in total

1400 patterns #Flow case 10

SS1: 50

Slug: 0

Oscillation: 0

Bubble: 50

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 50

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 50 unclassified inputs in total

800 patterns #Flow case 11

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 10 unclassified results where all outputs are  $< 0.51$

There are 10 unclassified inputs in total

807 patterns #Flow case 12

SS1: 17

Slug: 13

Oscillation: 2

Bubble: 0

SS1 + Slug: 11

SS1 + Oscillation: 2

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 6 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 3 unclassified results where all outputs are  $< 0.51$

There are 22 unclassified inputs in total

1400 patterns #Flow case 13

SS1: 71

Slug: 71

Oscillation: 0

Bubble: 0

SS1 + Slug: 70

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 2 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 12 unclassified results where all outputs are  $< 0.51$

There are 84 unclassified inputs in total

650 patterns #Flow case 14

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0  
Oscillation + Bubble: 0  
There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )  
There are 0 unclassified results where all outputs are  $< 0.51$   
There are 0 unclassified inputs in total

1400 patterns #Flow case 15

SS1: 0  
Slug: 23  
Oscillation: 19  
Bubble: 0  
SS1 + Slug: 0  
SS1 + Oscillation: 0  
SS1 + Bubble: 0  
Slug + Oscillation: 16  
Slug + Bubble: 0  
Oscillation + Bubble: 0  
There are 26 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )  
There are 5 unclassified results where all outputs are  $< 0.51$   
There are 47 unclassified inputs in total

810 patterns #Flow case 16

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
SS1 + Slug: 0  
SS1 + Oscillation: 0  
SS1 + Bubble: 0  
Slug + Oscillation: 0  
Slug + Bubble: 0  
Oscillation + Bubble: 0  
There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )  
There are 0 unclassified results where all outputs are  $< 0.51$

There are 0 unclassified inputs in total

800 patterns #Flow case 17

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 1 unclassified results where all outputs are  $< 0.51$

There are 1 unclassified inputs in total

1400 patterns #Flow case 18

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 0 unclassified inputs in total

1400 patterns #Flow case 19

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
SS1 + Slug: 0  
SS1 + Oscillation: 0  
SS1 + Bubble: 0  
Slug + Oscillation: 0  
Slug + Bubble: 0  
Oscillation + Bubble: 0  
There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )  
There are 0 unclassified results where all outputs are  $< 0.51$   
There are 0 unclassified inputs in total

507 patterns #Flow case 20

SS1: 0  
Slug: 6  
Oscillation: 5  
Bubble: 0  
SS1 + Slug: 0  
SS1 + Oscillation: 0  
SS1 + Bubble: 0  
Slug + Oscillation: 4  
Slug + Bubble: 0  
Oscillation + Bubble: 0  
There are 7 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )  
There are 10 unclassified results where all outputs are  $< 0.51$   
There are 21 unclassified inputs in total

797 patterns #Flow case 21

SS1: 0  
Slug: 0  
Oscillation: 0  
Bubble: 0  
SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 339 unclassified results where all outputs are  $< 0.51$

There are 339 unclassified inputs in total

542 patterns #Flow case 22

SS1: 1

Slug: 0

Oscillation: 1

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 2 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 2 unclassified results where all outputs are  $< 0.51$

There are 4 unclassified inputs in total

1400 patterns #Flow case 23

SS1: 226

Slug: 226

Oscillation: 0

Bubble: 0

SS1 + Slug: 225

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 2 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 9 unclassified results where all outputs are  $< 0.51$

There are 236 unclassified inputs in total

500 patterns #Flow case 24

SS1: 0

Slug: 15

Oscillation: 13

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 13

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 2 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 10 unclassified results where all outputs are  $< 0.51$

There are 25 unclassified inputs in total

512 patterns #Flow case 25

SS1: 4

Slug: 4

Oscillation: 0

Bubble: 0

SS1 + Slug: 3

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 5 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 64 unclassified results where all outputs are  $< 0.51$

There are 72 unclassified inputs in total



500 patterns #Flow case 26

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 1 unclassified results where all outputs are  $< 0.51$

There are 1 unclassified inputs in total

500 patterns #Flow case 27

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 0 unclassified inputs in total

535 patterns #Flow case 28

SS1: 0

Slug: 1

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 1 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 5 unclassified results where all outputs are  $< 0.51$

There are 6 unclassified inputs in total

500 patterns #Flow case 29

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 2 unclassified results where all outputs are  $< 0.51$

There are 2 unclassified inputs in total

510 patterns #Flow case 30

SS1: 0

Slug: 20

Oscillation: 21

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 20

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 1 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 18 unclassified results where all outputs are  $< 0.51$

There are 39 unclassified inputs in total

562 patterns #Flow case 31

SS1: 29

Slug: 0

Oscillation: 0

Bubble: 29

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 29

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 29 unclassified inputs in total

502 patterns #Flow case 32

SS1: 1

Slug: 1

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 2 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$   
There are 2 unclassified inputs in total

522 patterns #Flow case 33

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 511 unclassified results where all outputs are  $< 0.51$

There are 511 unclassified inputs in total

1400 patterns #Flow case 34

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 1 unclassified results where all outputs are  $< 0.51$

There are 1 unclassified inputs in total

1400 patterns #Flow case 35

SS1: 0

Slug: 0

Oscillation: 0

Bubble: 0

SS1 + Slug: 0

SS1 + Oscillation: 0

SS1 + Bubble: 0

Slug + Oscillation: 0

Slug + Bubble: 0

Oscillation + Bubble: 0

There are 0 unclassified results where there is one output above 0.51 and one neutral ( $0.49 < ? < 0.51$ )

There are 0 unclassified results where all outputs are  $< 0.51$

There are 0 unclassified inputs in total