DEVELOPMENT OF INFERENTIAL MEASUREMENT FOR AIR DENSITY USING NEURAL NETWORK

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DEVELOPMENT OF INFERENTIAL MEASUREMENT FOR AIR DENSITY USING NEURAL NETWORK

SHANKAR RAMAKISHAN

A report submitted in fulfilment of the
requirements for the award of the degree of
Bachelor of Chemical Engineering

Faculty of Chemical & Natural Resources Engineering
Universiti Malaysia Pahang

MAY 2008

I declare that this thesis entitled "*Development of Inferential Measurement for Air Density using Neural Network*" is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature	:	………………………………………..
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To my beloved father and mother

for their love and support

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ABSTRACT

In many industrial processes, the most desirable variables to control are measured infrequently off-line in a quality control laboratory. In these situations, use of advanced control or optimization techniques requires use of inferred measurements generated from correlations. For well-understood processes, the structure of the correlation as well as the choice of inputs may be known a priori. However, many industrial processes are too complex and the appropriate form of the correlation and choice of input measurements are not obvious. Here, process knowledge, operating experience, and statistical methods play an important role in development of correlations. This paper describes a systematic approach to the development of nonlinear correlations for inferential measurements using neural networks. A three-step procedure is proposed. The first step consists of data collection and preprocessing. Next, the process variables are subjected to simple statistical analyses to identify a subset of measurements to be used in the inferential scheme. The third step involves generation of the inferential scheme.

ABSTRAK

Dalam kebanyakan proses yang dijalankan di industri, pembolehubah-pembolehubah yang penting untuk dikawal adalah diukur secara “off-line” dalam makmal kawalan kualiti. Dalam situasi sebegini, pengunaan kaedah kawalan yang canggih atau teknik pengoptimuman memerlukan ukuran yang diperolehi melalui korelasi. Untuk proses yang difahami sepenuhnya, struktur korelasi dan pilihan input diketahui selepas kajian dijalankan. Sungguhpun begitu, kebanyakan proses yang dijalankan di industri adalah terlalu kompleks dan gaya sesuai korelasi dan pilihan ukuran input adalah kurang jelas. Dengan ini diketahui bahawa pengetahuan mengenai sesuatu proses, pengalaman mengoperasi dan kaedah statistik memainkan peranan penting dalam penghasilan satu sistem korelasi. Kertas kerja ini mengkaji satu pendekatan sistematik untuk menghasilkan sistem korelasi berdasarkan ukuran-ukuran inferens menggunakan Neural Network. Tiga langkah bertatacara telah dicadangkan untuk melaksanakan kajian ini. Langkah pertama adalah pengumpulan data dan pemprosesan data. Selepas itu, pembolehubah-pembolehubah proses dianalisis untuk mengenalpasti satu subset ukuran yang sesuai untuk digunakan dalam kaedah pengukuran inferens. Langkah ketiga melibatkan penghasilan kaedah pengukuran inferens.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
BL	Boltzmann learning
BP	backpropagation
CL	competitive learning
DCS	distributed control system
ECL	error-correlation learning
ELM	Elman network
FF	feedforward network
FPM	first principle model
LM	Levenberg-Marquardt
MAPE	mean absolute percentage error
MSE	mean square error
PI	proportional integral
PID	proportional integral derivative
PLS	partial least squares
RMSE	root mean square error
SSE	sum square error

LIST OF SYMBOLS

b	internal bias
f	transfer function
N	total number of data
N_{hdn}	number of hidden nodes
N_{inp}	number of input nodes
N_{out}	number of output nodes
N_{trn}	number of training data
N_{wgh}	total number of weights
v_i	variables
v_i^{max}	maximum value of variables
v_i^{min}	minimum value of variables
v_i^{norm}	normalize variables
w_{i}	weight factor
x_{i}	neuron input
y	neuron output
λ_1	minimum value of interval
λ_2	maximum value of interval

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CHAPTER 1

INTRODUCTION

1.1 Background of Study

Over the years, the application of Artificial Neural Network (ANN) in process industries has been growing in acceptance. This is because ANN is capable of capturing process information in a black box manner. Given sufficient input output data, ANN is able to approximate any continuous function to arbitrary accuracy. This has been proven in various fields such as pattern recognition, system identification, prediction, signal processing, fault detection and others (Demuth and Beale, 1992).

In general, the development of a good ANN model depends on several factors. The first factor is related to the data being used. This is consistent with other black box models where model qualities are strongly influenced by the quality of data used. The second factor is network architecture or model structure. Different network architecture results in different estimation performance. Commonly, multilayer perceptron and its variances are widely used in process estimation. The third factor is the model size and complexity. What is required is a parsimonious model. This is because a small network may not able to represent the real situation due to its limited capability, while a large network may overfit noise in the training data and fail to provide good generalization ability. Finally, the quality of a process model is also strongly dependent on network training. This stage is essentially an identification of model parameters that fits the given data; and is perhaps the most important factor among all (Sexton *et al*., 2002).

In this research, the ANN model is used for inferential estimation of air density in a Gas Flow Pressure Temperature Control Training System. The aim is to address the difficulty in measuring air quality in process plants. Most quality variables in process industries require some kinds of analysis to be carried out. The use of online analyzer for product quality variables has been limited due to large measurement delay, the need for frequent maintenance as well as high capital and operating costs.

In order to adapt to market conditions while maximizing profit, the demand for accurate inferential estimators for controlling the product quality variable becomes paramount. For this reason, this study introduces ANN as means of improving inferential measurement.

1.2 Problem Statement

Due to the complexity of process plants, the amount of information required to measure the variables is dependant both on the physics and the level of precision of analysis tools. Although physical experimentation provides accurate environmental measurements without the need for modeling assumptions, a comprehensive analysis would not only require expensive equipment, but would also require large amounts of time. Numerical modeling techniques as ANN can offer an effective method of measuring the air density under various design conditions within a virtual environment. Thus the amount of physical experimentation can be reduced considerably, although, as of yet, not eliminated.

1.3 Objective

The objective of this work was to develop an inferential measurement system for air density using Neural Network which is incorporated with Matlab.

1.4 Scope of the Research

To fulfill the objective, the following scope of research was carried out:

i. Data Collection using AFPT plant available in FKKSA lab
ii. Development of ANN based inferential estimator for air density using other secondary measurements using MATLAB
iii. Evaluation of modelling using experimental results of particular AFPT plant

1.5 Contribution of the Research

As over many years chemical plant systems have become tailored for specialized production, the need to maintain control over the primary output so that the requirements of the production system can be continuously met has become even more important. So, it is important to understand the interaction of all variables, alongside their contribution to the product quality. For this reason, this work has proposed an enhancement to inferential measurement. The ANN model was implemented in inferential estimation and control scheme for air density.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The birth of Artificial Neural Network (ANN) was believed to be founded by the fact that brain is far superior compared to conventional computation techniques. Although conventional computation techniques may perform better in task requiring high degree of numerical computation and repeatable steps, our powerful brain is fault tolerant and is able to perform parallel computation. The brain is also adaptive to new environment and is capable of interpreting imprecise information. Due to this reason, scientists have been trying to apply the knowledge gained in neural biology in the effort to improve the performance of conventional computing (Bhartiya *et al.*, 2000).

Over the past few decades, ANN has generated considerable interest among researchers and various different courses of ANN research have been explored. These included network architecture and training algorithm. As a result, different types of ANN model were developed. These models were implemented in diverse field including computer science, medicine, mathematics, physics, and engineering. The amount of research activities are expected to grow to improve the performance of ANN in various applications. This would be facilitated by the advancement in computing technology that enables complex network to be implemented. It is not a surprise that the ultimate ANN model would be a powerful, robust and reliable tool to be implemented in various areas (Demuth and Beale, 1992).

2.2 Overview of Artificial Neural Network

Artificial Neural Network (ANN) is collections of mathematical models that emulate the real neural structure of the brain. In general, ANN is made up of individual interconnected simple processing elements called neurons, arranged in a layered structure to form a network that capable of performing massively parallel computation. Architecture of a general ANN is illustrated in Figure 2.1.

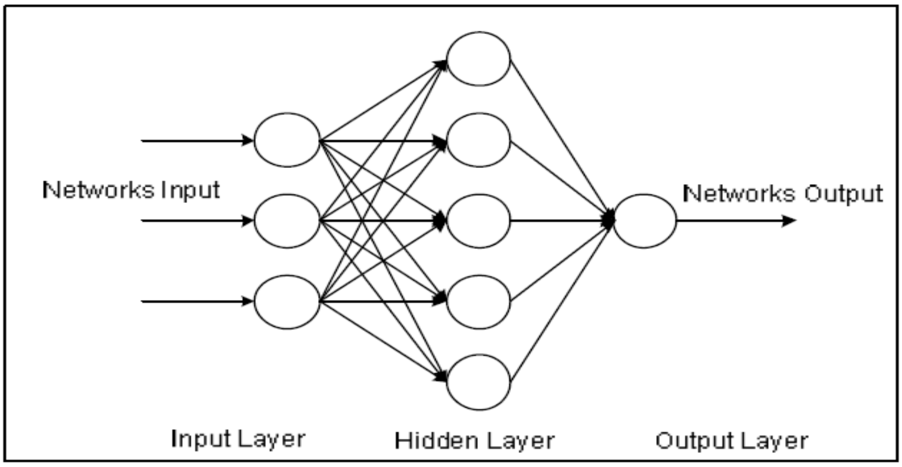

Figure 2.1: Architecture of Artificial Neural Network (Basheer & Hajmeer, 2000)

ANN can perform a human-like reasoning, learns and stores the relationship of the processes on the basis of the available representative data set. By mimicking the network of real neuron in the human brain, ANN performs mapping from an input space to an output space. Generally, the ANN does not need much of a detailed description or formulation of the underlying process. Depending on the structure of the network, a series of connecting neuron which weights are adjusted in order to fit a series of inputs to another series of known outputs. Since the connecting weights are not related to physical identities, the approach is considered as a black-box model. Such methods provide an analytical alternative to conventional techniques which are often limited by strict assumptions of normality, linearity, variable independence and so on (Hassoun, 1995).

2.2.1 Basic Element of ANN

A multilayer ANN is made up of at least three layers of neurons that are connected to each other. Input layer and output layer serve to receive the information from external resources and send the results out to external receptor. That also means most of the computing process is carried out in the hidden layer. In most networks, the output layer also performs similar transformation carried out by the hidden layer (Hassoun, 1995).

An example of artificial neuron is illustrated in Figure 2.2. The neuron input, x_i, is multiplied by the corresponding weight factor, w_i, before being sent to the neuron. This is followed by performing summation of all input in the neuron body. An internal bias, b is also introduced to enhance performance of the network. The result is passed through a nonlinear activation transfer function to obtain the output y:

$$y = f\left(\sum_i^n w_i x_i + b\right) \tag{2.1}$$

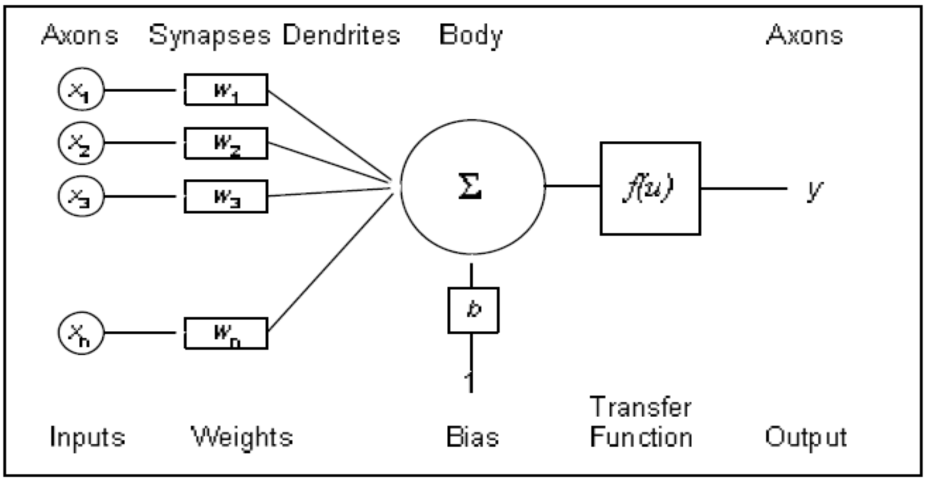

Figure 2.2: An example of artificial neuron (Hassoun, 1995)

Typical activation functions include sigmoidal function, hyperbolic tangent function, sine or cosine function. Some of these are shown in Figure 2.3. So far, there are no rules for the selection of transfer function but the sigmoidal function is the most popular choice. Besides, it is also not conclusively understood that the use of different types of transfer function will have major effect on the network performance (Demuth and Beale, 1992).

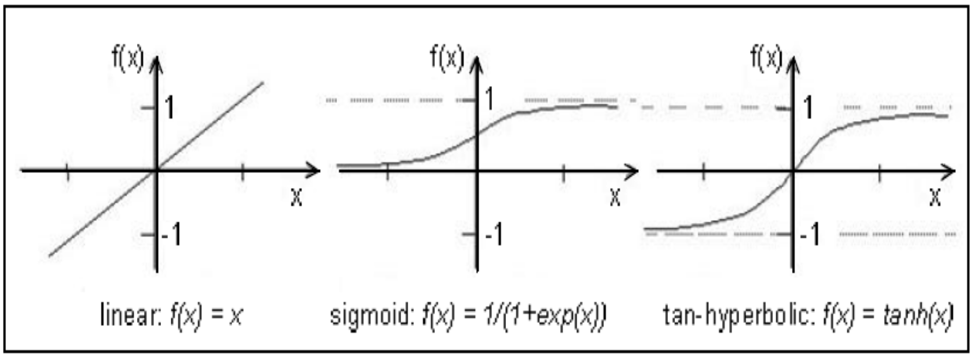

Figure 2.3: Different types of transfer function (Demuth & Beale, 1992)

2.2.2 Network Topology

Topology of an ANN refers to how the inner structure is or how the neurons are interconnected. Generally, each neuron's output from previous layer feeds into all neurons in the subsequent layer. In the ANN model development, the topology has to be pre-specified but leave the numerical values of weight and bias up to the training phase. The inner connection is therefore particularly important for obtaining a good result.

The various structure of an ANN can be classified into three groups by the arrangement of neurons and the connection patterns of the layers. These are the feedforward network (e.g. multilayer feedforward, radial basis), recurrent network (e.g. Elman, Hopfield) and self-organizing network (e.g. Kohonen). Different types of networks may be used for different purposes. In chemical engineering application, the most influential and mostly adopted by researchers is multilayer feedforward network. Recently, the trend of using recurrent network (Elman) is also increasing. The topology for these two types network is shown in Figure 2.4 (Demuth and Beale, 1992).

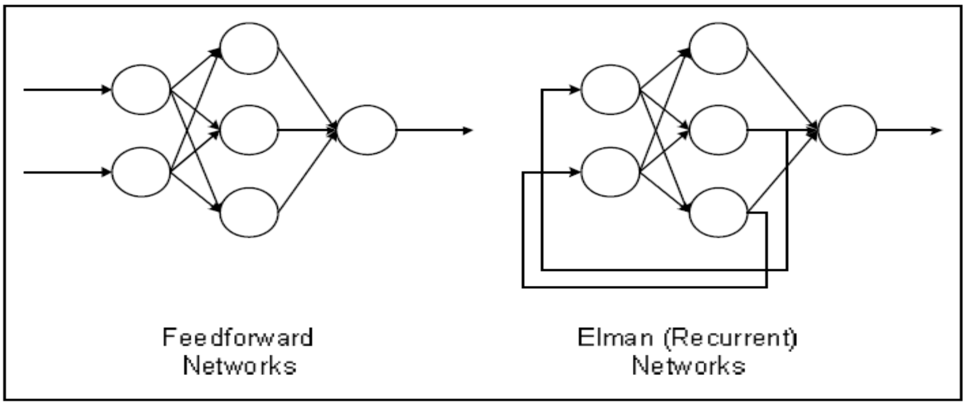

Figure 2.4: Topology of feedforward and Elman network (Demuth and Beale, 1992)

The feedforward network is named as such because the input data is transferred from input layer through hidden layers to output layers in a single direction. For Elman network, the connections are mainly feedforward but also include a set of carefully chosen feedback connections that let the network remember recent past values. The input layer is divided into two parts, i.e., the true input units and the context units that hold a copy of the activations of the hidden units from the previous time step. From the performance point of view, a feedforward network is much easier to construct and train compared to Elman network. However, since recurrent network is dynamic network that has the ability to store memory and produce output dependent of previous state of the network, it would be advantageous for the use in chemical processes since the process data are often auto correlated (Demuth and Beale, 1992).

Another important issue in ANN model development is topology selection which is referred to selection of the optimum number of hidden layers and hidden neurons. It was stated in the literature that one hidden layer is sufficient to approximate any continuous function to any desired accuracy (Irie and Miyake, 1988; Cybenko, 1989). However, some researcher used two hidden layers by considering that one hidden layer may require too many hidden neurons and this will worsen the network generalization ability and increase training time (Barron, 1994). Some researcher found that network with two hidden layers may benefit in certain specific problems. For example, Masters (1994) reported that two hidden layers may suitable for learning functions with discontinuities.

Compared to the number of hidden layers, the determination of required number hidden neurons is more complicated. Until today, the systematic way of selecting this parameter is still not well established. However, a number of rules of thumb had been proposed. In general, the optimum number of hidden neurons (N_{hdn}) is related to number of training data (N_{trn}), number of input neurons (N_{inp}), number of output neurons (N_{out}) and total number of weights (N_{wgh}). These examples are summarized in the Table 2.1. It is regretted that none of these rules can be applied perfectly to all problems.

Table 2.1: Optimum number of hidden neurons suggested

Study	**Optimum N_{hdn} Suggested**
Hecht-Nielsen (1990)	$N_{nhn} \leq N_{inp} + 1$
Jadid and Fairbairn (1996)	$N_{nhn} = \dfrac{N_{trn}}{R + N_{inp} + N_{out}}$; R= 5-10
Lachtermacher and Fuller (1995)	$\dfrac{0.11 N_{trn}}{N_{inp} + 1} \leq N_{nhn} \leq \dfrac{0.30 N_{trn}}{N_{inp} + 1}$
Masters (1994)	$N_{nhn} \approx \left(N_{inp} \cdot N_{out}\right)^{1/2}$
Upadhaya and Eryureka (1992)	$N_{wgh} = N_{trn} \log_2 \left(N_{trn}\right)$; N_{wgh} relate to N_{nhn}

The most practically and widely used method for optimum topology selection is trial and error search method. Basically, this was done by increasing the number of neurons from small to considerable large number of hidden neurons to be trained and then cross-validated. An increase in the number of hidden neurons used will decrease the cross-validation error. However, if too many hidden neurons are been used the network will tend to overfit the trend. Nevertheless, the final number of neuron is determined based on the smallest cross-validation error. In addition, rules of thumb may also apply as a starting point for try and error searching. Another more sophisticated method for network topology optimization is the growing and pruning methods (Sietsma and Dow, 1988).

2.2.3 Network Training and Validation

To develop an accurate process model using ANN, the learning process or training and validation are among the important steps. In the training process, a set of input-output patterns is repeated to the ANN. From that, weights of all the interconnections between neurons are adjusted until the specified input yields the desired output. Through these activities, the ANN learns the correct input-output response behaviour. For validation, the ANN is subjected to input patterns unseen during training, and introduces adjustment to make the system more reliable and robust. It is also used to determine the stopping point before overfitting occurs. A typical fitting criterion may be introduced to emphasis the model validity. Such criterion may be mean square error (MSE), sum square error (SSE) which is calculated between the target and the network output.

There are many different approaches to train the ANN. Basically, a successful learning process involves three main aspects, i.e., learning paradigm, learning rule and learning theory. Learning paradigm concerns about what information is fed to ANN. There are two types of learning paradigm, namely, supervised and unsupervised learning. In supervised learning, network is trained with the correct answer for every input data while correct answer is not provided in the unsupervised learning. Typically, most of the networks are using supervised learning except ANN model implemented in clustering or categorization.

Learning rule defines how network weight should be adjusted in the learning procedures. There are four basic types of learning rule: error-correlation learning (ECL), Boltzmann learning (BL), Hebbian learning (HL) and competitive learning (CL). Due to space limitation, the detail descriptions of these learning rules are referred to the work of Jain *et al*. (1996). Among all the training algorithms, backpropagation (BP) which follows error-correlation learning rule is the most popular choice. The famous BP is essentially a gradient steepest descent method, searching at error surface. Basically, BP involved two steps in each iteration: forward calculation to produce a solution and based on the error, backward propagation to adjust weights. However, the standard BP however is reported to suffer from several weaknesses such as slow convergence, lack of robustness and inefficiency (Rumelhart *et al*., 1986). A number of modifications have been proposed for the BP algorithm such as adaptive method and second order method to achieve better training process. Among them, Levenberg-Marquardt (LM) method which is hybrid of the Gauss-Newton nonlinear regression method and gradient steepest descent method is recommended in most optimization packages such as MATLAB.

The learning theory addresses the training data which is including issue related to data quality, data quantity and computation time. The selection data for training is important since it can affect the adaptability, reliability and robustness of an ANN. Normally, data that covers a wide range with sufficient excitation but free from outliers is preferred. Sometimes, the random noise may be injected to the training data to enhance the ANN robustness against measurement error. There is no defined rule to determine the amount of training data for ANN modelling. Generally, the data quantity is related to network structure, training method and complexity of the problem. Since ANN is needed to generalize unseen data, normally sufficient large quantity of data is needed to cover the possible unknown variable in the problem domain. The larger training data can increase the accuracy of network generalization. However, this also will increase the computation time for the learning process. Hence, there should be trade-off between these two criteria (Branke, 1995).

Another important issue regarding learning process is data normalization. The scaling of training data is needed to prevent data with larger magnitude from overriding the smaller and impede the premature learning process. Again, in this case there is no any standard approach to perform the data normalization. The simplest way is scale the variables (v_i) in the defined interval [λ_1,λ_2] using the maximum ($v_i^{\max}$) and minimum value ($v_i^{\min}$) of v_i in the database:

$$v_{norm} = \left(\frac{v_i - v_i^{min}}{v_i^{max} - v_i^{min}}\right)(\lambda_2 - \lambda_1) + \lambda_1 \qquad (2.2)$$

where v_i^{norm} is the normalize value of v_i

Training of an ANN is an optimization problem where convergence to global minimum is desired. Similar to other optimization tasks, the choice of algorithm will influence the end results. Gradient-based methods such as backpropagation provide fast convergence but are susceptible to sub-optimal solutions. On the contrary, random methods offer better probability for convergence at global minimum but can be relatively time consuming. When computing time is within acceptable level, global minimum convergence should be given consideration in this trade-off (Branke, 1995)

2.2.4 Application of ANN in Chemical Engineering

ANN is attractive due to its information processing characteristic such as nonlinearity, high parallelism, fault tolerance as well as capability to generalize and handle imprecise information (Basheer and Hajmeer, 2000). These characteristics have made ANN suitable for solving a variety of problems. The application of ANN in chemical engineering began in the late 1980’s. One of the pioneering works was reported by Hoskins and Himmelblau (1988). In subsequent years, the number of research publications on ANN in chemical engineering was steadily increased. Most of these publications cover five major areas: process control, dynamic modelling, forecasting fault diagnosis, and optimization.

In the area of process control, ANN was applied through adaptive control or model-based control. By monitoring the on-line process data, ANN could be used to adjust controller parameter for optimal performance. Dynamic modelling using ANN was also well practising in process industries. By exploiting the relationship among the process variables, ANN model was developed as estimator and to be implemented in advance control techniques. Similar to dynamic modelling, forecasting can also contribute in process industries by using prediction based on the history data. This enabled behaviour of important process variable to be forecasted in the next sampling time, thus preventive action could be taken. ANN was also useful in fault diagnosis since it has the ability to store knowledge about the process and learn from the quantitative historical fault information. ANN could be trained based on the normal operating condition and then compared to current operational data to determine faults that might happen (Hoskins and Himmelblau, 1988). Lastly, ANN was implemented in plant optimization for optimal parameter searching to ensure process plant is always safe and productive.

2.2.5 Process Estimation and Control using ANN

In recent years, ANN had been extensively studied in academia as process models and controllers (Hunt *et al.*, 1992; Ungar *et al.*, 1996; Hussain, 1999; Bhartiya and Whiteley, 2001; Ahmad *et al.*, 2001). Bhat and McAvoy (1990) applied ANN to dynamic modelling for a pH-controlled CSTR. The predicted pH values when compared to two other approaches demonstrated that ANN could predict more accurately than conventional method. Willis *et al.* (1992) discussed the application of ANN as both inferential estimator and predictive controller. Their results demonstrated that ANN could accurately predict the process output and significantly improved the control scheme. Pollard *et al*., (1992) utilized backpropagation trained ANN for process identification. They concluded that ANN was particularly useful when the input-output mapping was unknown since ANN was able to accurately represent nonlinear behaviour in a black box manner. All the successful implementations of ANN in process estimation and control had proved the suitability of ANN in solving chemical engineering problems.

2.2.6 Limitation of ANN

Undeniable, ANN has been well known for its effectiveness in representing nonlinear process system. However, ANN is not a solution that can solve all problems in the real world. Among the limitation of ANN, the followings should be given added emphasis:

i. Network architecture

There is a lack of fixed rule or systematic guideline for optimal ANN architecture design. Since there is no a prior knowledge about the problem complexity, the network architecture was typically set arbitrarily. The network topology was often determined by trial and error. This subjected the network to performance uncertainties since the size of network influence the network performance: too small a network cannot learn well, but too large may lead to overfitting. Thus, algorithms that can find appropriate network architecture are needed. This includes the determination of optimum number of neuron in each layer as well as number of hidden layer needed. Many networks were developed on the assumption of being fully connected. This can be implemented on a small network but it may not be feasible for more complicated network (Hintz and Spofford, 1990).

ii. Training algorithm

The best training algorithm still cannot be singled out for general neural network. Although BP algorithm has been widely used, it does not guarantee the global optimal solution. The training may result in ANN model that is only accurate in the same operating zones as in the training data set but inaccurate in others. Besides, the selection of some parameters in BP training also lacks of systematic guideline.

iii. Training data

The quality and quantity of training data is an important issue for ANN modelling. Usually, the success of ANN relies heavily on a large amount of data, but this demand more computing time for training. In order to reduce the amount of data whilst maintaining the model quality, the data used must be carefully selected to ensure that they are sufficiently ‘rich’. This demands project understanding on the process involved. Additionally, to eliminate noise and outliers, process data may require pre-processing prior to application in neural network model development.

iv. Process relationship

Being black-box method for modelling, ANN is criticized for unable to explain and analysis the relationship between inputs and outputs. This may cause difficulties in interpreting results from the network.

2.3 Process Estimation and Control

The increase of global competitiveness has pushed chemical plant operations into highly nonlinear regions near process constraints in order to meet the ever increasing product capacity and quality. For such operating condition, process control becomes more challenging. In general, two main issues aroused with respect to process control needs. First, operating in nonlinear regions, particularly near the constraints required advanced controllers. Secondly, the limitations due to measurement difficulties must be overcome. This work concentrates on the second issue. Measurement difficulties prevail due to a variety of reasons, including: lack of appropriate on-line instrumentation and reliability of on-line instruments. Process operation has to depend on laboratory assays, which means that results can be infrequent and irregular, in addition to long analysis delays. Depending on how the laboratory analyses are carried out, the reliability of the results are being questioned too. On-line sensors may be available but they may suffer from long measurement delays (e.g. gas chromatographs) or may be subjected to factors that affect the reliability of the sensor (e.g. drifts and fouling), despite the high capital and maintenance costs. As an alternative, inferential estimation has been designed for tackling this issue.

The inferential estimator, which is designed on the basis of the model, should provide an accurate and reliable estimation even when un-measurable disturbances are present. Among the estimation approaches, ANN model show its potential to deal with nonlinear process problems. Thus, this work proposed an estimator employing ANN model to be used for this research work.

2.3.1 Inferential Estimation

An inferential control model employs measurements of secondary variables to infer the effect of un-measurable disturbances on primary process outputs such as product quality. Due to the nature of chemical and process engineering systems, the states of many variables reflect the states of other variables. By exploiting these relationships, a particular variable of interest can be represented by others in a form of correlations or models. The variable of interest termed as the primary variable which is difficult to measure can therefore be estimated using values of easy to measure secondary variables. If the model is accurate, the estimation can then serve as the replacement to actual measurement for control purposes (Doyle, 1998; Parrish and Brosilow, 1988).

Inferential estimation in chemical processes has been studied extensively since mid-1970s (Jo and Bankoff, 1976; Joseph and Brosilow, 1978). It was found that this technique is very useful and important as it can be applied to process control, process monitoring, plant fault detection and data reconciliation (Soroush 1998). Joseph (1999) investigated the application inferential estimation in a distillation column and the use of intermediate tray temperature as secondary variables in a Shell challenge case study problem. Willis *et al.* (1991) had discussed an estimation procedure for feedback control of product composition from an industrial distillation column using overhead temperature. Amirthalingam *et al.* (2000) used several tray temperatures when applying their two step identification approach to a distillation column to estimate composition in distillate.

Apart from using temperature as secondary measurement, some researchers also used flow measurements together with temperature measurement to act as inputs to estimation model. Joseph and Brosilow (1978) concluded that temperature and flow measurement can adequately estimate the compostion of debutanizer column. Similiary, Tham *et al*. (1991) used “fast” measurement of column overhead vapour temperature together with reflux flow rate to provide estimations of product concentration from a high purity distillation column.

To enhance the performance in process estimation, what is the most concern is how to design a good inferential control system. This classical problem can be divided into two categories, the selection of inferential model and the selection of a control configuration. Many types of modelling techniques have been proposed in the literature such as first principle model (FPM), partial least squares (PLS), Kalman filter, ANN and hybrid model which refers to combination of more modelling techniques. Even though these modelling techniques offered adequately good estimation in inferential control task, they still lack of adaptability to cope with dynamic environment. For this reason, ANN model has been selected as modelling technique in this work.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Stages in Methodology

The objective of this work was to develop inferential measurement system for air density using NN. To achieve this target, the research methodologies were divided into several main phases. Those were data preparation, ANN model development, and finally process estimation. The steps of these phases are summarized in the flowchart as shown in Figure 3.1.

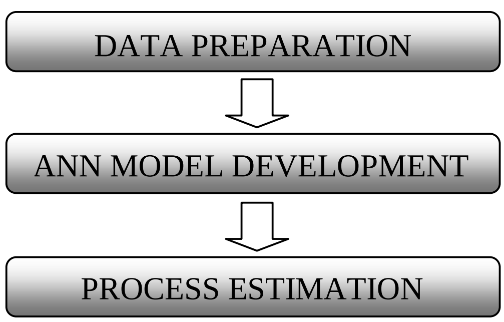

Figure 3.1: Methodology flowchart

3.2 Research Tools

Several tools have been used throughout this work. Among them, the most important software was Neural Network which is incorporated with Matlab and Model AFPT921 Gas Flow Pressure Temperature Control Training System. The training system provided the platform for all kinds of data analysis while MATLAB was used for the ANN model development. Both tools were incorporated to perform inferential measurement for air density.

3.2.1 Matlab

MATLAB is a mathematic analysis package produced by Mathworks. This program enables immediate access to high numerical computing and extended with interactive graphical capability. The entire modelling task was performed using MATLAB Version R2007A. This software provides Neural Network Toolbox for ANN model development with different types of network such as feedforward, Elman, Hopfield, Radial Basis as well as others.

3.3 Case Study – AFPT Plant

The research is carried out in local training plant, Model AFPT921 Gas Flow Pressure Temperature Control Training System which is situated in the chemical lab of Universiti Malaysia Pahang, Kuantan. The Model AFPT921 plant is a scale-down of real industrial process plant built on 5 ft x 10 ft steel platform, complete with its own dedicated control panel. The process equipment and process instrumentation are real industrial process type. The plant is constructed in accordance to industrial process plant standard and practices with fail-safe system. For example, the air heater cannot be turned on unless there is enough air flow in the pipeline. The process flowrates are at commercial production flowrates, using pipeline and not tubings.

3.3.1 Data Preparation

The research work began with the Model AFPT921 Gas Flow Pressure Temperature Control Training System for data collection. Before running the plant, the typical procedures involved were to manipulate the variables such as temperature and pressure, to define the control system and finally to start integration. Data may easily be obtained from the plant DCS (Distributed Control System) database. Data in DCS is recorded for every second as it shows the dynamic response for variables involved. The step test experiments were conducted by randomly changing selected inputs according to step size. Here three selected input variables (TIC91A, PIC91A, FIC91A) were integrated to generate sequences of random value of air density with varying temperatures and different pressure. During this process, data for all variables involved is recorded through DCS. In this work, the variables were chosen and corresponding dynamic responses in Model AFPT921 were studied. These variables are tabulated in Table 3.1.

Table 3.1: Variables in Model AFPT921

Variables	
DT	Density Transmitter
PT	Pressure Transmitter
FT	Flowrate Transmitter
TIC91A	Temperature PID Controller
TIC92A	Temperature PID Controller
TIC911A	Temperature PID Controller
FI91A	Flowrate Indicator
FIC91A	Flowrate PID Controller
PI911A	Pressure Indicator
PIC91A	Pressure PID Controller
PIC92A	Pressure PID Controller

Meanwhile the data collected is arranged and tabulated as in the format shown in table 3.2. The step change that should be manipulated is also stated in the appendix.

Table 3.2 : Tabulating the Data

Settings	**Time (min)**	**DT**	**PT**	**FT**	**Others Variables**
Pressure = 15 psig Flowrate = 20% Temperature = 40^{o}C	1 2 ..				
Pressure = 15 psig Flowrate = 20% Temperature = 60^{o}C	1 2 ..				

3.3.2 Data Conditioning

Since the performances of the resulting inferential measurement models are influenced significantly by the quality of the data used to generate them, the data collected from the process undergoes data conditioning. As the Figure 3.2 shows, the first and most important thing to do is to get rid of spurious points or outliers in the data. These can have significant impact on the model structure selection and estimator testing stages of the development cycle. Next, noise in the data should be attenuated as much as possible. On very noisy systems, this loss of predictive capabilities can be very pronounced.

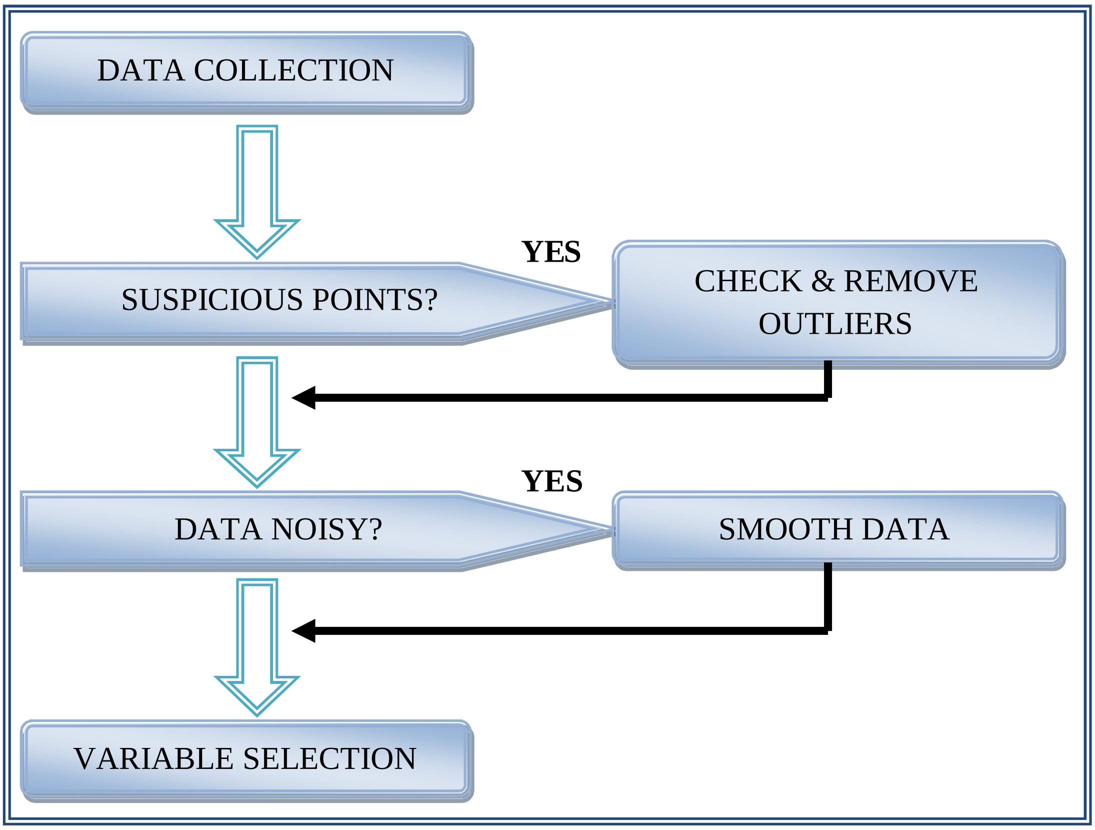

Figure 3.2 : Data Conditioning Flowchart

3.3.3 Secondary Variable Selection

It is important that we choose the appropriate secondary outputs and inputs to use in developing the inferential measurement model. The number of these 'explanatory' variables employed will influence the size and complexity of the final model. This impact on the size of the data set that has to be used in model development.

The objective here, and indeed for all process modelling activity is to make use of the least number of variables to develop a model of sufficient accuracy. In many situations, there will be a number of variables that will show relationships with the primary output. The task then is to choose those with the strongest relationships and to weed out those that are redundant. Here, knowledge of the process is a distinct advantage. Once a set of potential secondary variables is selected, the inferential model can be developed and tested. For this case study, four main variables have been chosen. Those are TIC91A, FIC91A and PIC91A which are chosen as input variables. Meanwhile DT is chosen as output variable.

3.4 Development of Artificial Neural Network

Process development of estimator model is the most crucial part in this work. A better understanding of the model development procedure can help in handling the research easily and faster. In this section, estimator models involved and model development procedure was discussed. The basic steps of developing ANN model are summarized in the flowchart as shown in Figure 3.3.

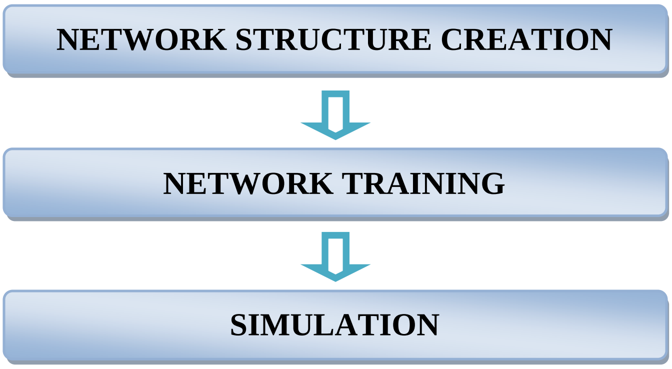

Figure 3.3 : Steps of Developing ANN

Basically, the development of successful ANN model involved several phases in a cyclic procedure. The development process started with data preparation. This included input variables selection and data generation as discussed in the previous section. Data generated from the training plant is not normally used directly in process modelling of ANN. This is due to the difference in magnitude of the process variables. The data was scaled to a fixed range to prevent unnecessary domination of certain variables. The choice of range depends largely on transfer function of the output nodes in ANN. Typically, [0,1] for sigmoidal function and [-1,1] for hyperbolic tangent function. Before the data can be fed to ANN model, the proper network design must be set up and the modeller must decide the type of network and method of training. In this study **feedforward (FF) network** were considered. The network trainings were accomplished using the **Levenberg-Marquardt (LM)** algorithm. This was followed by the optimal parameter selection phase. There were several parameters to be selected including number of hidden neuron, number of hidden layer, learning rates and acceptable error. However, this phase was carried out simultaneously with the network training phase. This was due to the fact that the parameters were selected based on the performance during training and validation.

In the training phase, connection weights were always updated until they reached the defined iteration number or acceptable error. Although the generalization ability of NN model had been tested in network validation, it was recommended that the network underwent model verification phase. This was done using different set of unseen data. Hence, the capability of ANN model to respond accurately was assured. If the model failed to perform the defined accuracy as expected, the development process was brought back to its starting phase.

The system implementation phase was a final test where the model developed was applied to real world problems. Here, ANN model was evaluated using real plant data.

3.5 Performance Evaluation

3.5.1 Error Criterion

There are several ways to evaluate the performance of estimator developed. The most important and easiest way perhaps is by measuring the estimation accuracy. The estimation accuracy can be defined as the difference between the actual and estimated values. The ultimate objective is to provide accurate and repeatable estimations. There are a number of approaches presenting the accuracy measures in the literature such as SSE (sum square error), RMSE (root mean square error), MAPE (mean absolute percentage error) and others. As mentioned by Zhang *et. al*. (1998) in their work, the most frequently used is the MSE (mean square error), defined as follow:

$$\mathrm{MSE} = \frac{1}{N}\sum_{n=1}^{N}\left(y_n - \hat{y}_n\right)^2 \qquad (3.1)$$

where y is actual target value, $\hat{y}$ is its estimated target value, and N is the total number of data.

3.5.2 Performance Test for Process Estimator

In this study, the performances evaluation of estimator developed was carried out in several stages. Firstly, ANN model developed were tested on their performance in network training and validation. These were done based on the systematically designed data which cover a wide range of process operation. Theoretically, a well-trained network could capture the relationship within range of training data due to its experience. However, ANN model may be poor in extrapolation of unseen data. Thus, the next stage of the performance evaluation would be estimation using several sets of data. These data sets were designed to be varied in the degree of fluctuation, thus covering different range of operating space.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Data for Modelling

A total of 454 set of data were generated using Model AFPT921 Gas Flow Pressure Temperature Control Training System for modeling purposes. Data for all variables are recorded and tabulated in MS Excel 2007. As a summary, a total of 11 variables were involved in this case study. It consists of six input variables and five output variables. These variables were tabulated in Table 4.1. In this work, three input variables were chosen and responses in air density were studied.

Table 4.1 : Input and output variables

Input Variables	Output Variables
TIC91A	DT
TIC92A	PT
TIC911A	FT
FIC91A	FI91A
PIC91A	PI911A
PIC92A	

4.2 Training and Validation Results

Data generated were used as model inputs for modelling purposes. These data were equally divided into training and validation set. The network was obtained after undergoing a series of training using **Levenberg-Marquardt (LM)** algorithms. In order to improve network generalization ability, early stopping technique was applied to LM training. In this technique, validation error was monitored during the training process. When the validation error increases for a specified number of iterations, the training was stopped to prevent overfitting. The performance of these estimators in tracking the actual process data during the training and validation testing stages are illustrated in Figure 4.1 and Figure 4.2.

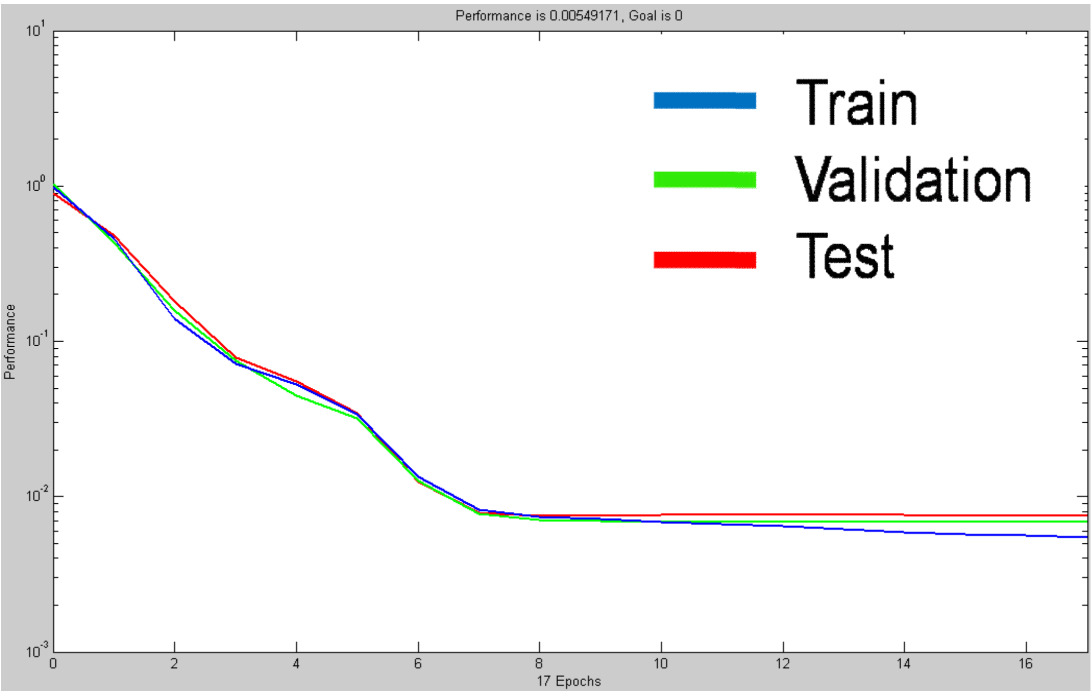

Figure 4.1: Performance of Estimator

This training stopped after 17 iterations because at that point the validation error increased. Training is accompanied by a plot of the training, validation, and test errors, shown in the following figure. For this system, the mean square error of the ANN model was found to be 0.00549171. The result here is reasonable, because the final mean square error is small, the test set error and the validation set error has similar characteristics, and it doesn't appear that any significant overfitting has occurred.

The next step was to perform some analysis of the network response. The entire data sets are put through the network (training, validation, and test sets) and a simulation between the network inputs and output is performed. The capability of neural networks in providing inferential measurement of the air density in the Model AFPT921 Gas Flow Pressure Temperature Control Training System is illustrated in the Figure 4.2. The red line denotes the actual value of the air density while blue line indicates the prediction value of air density.

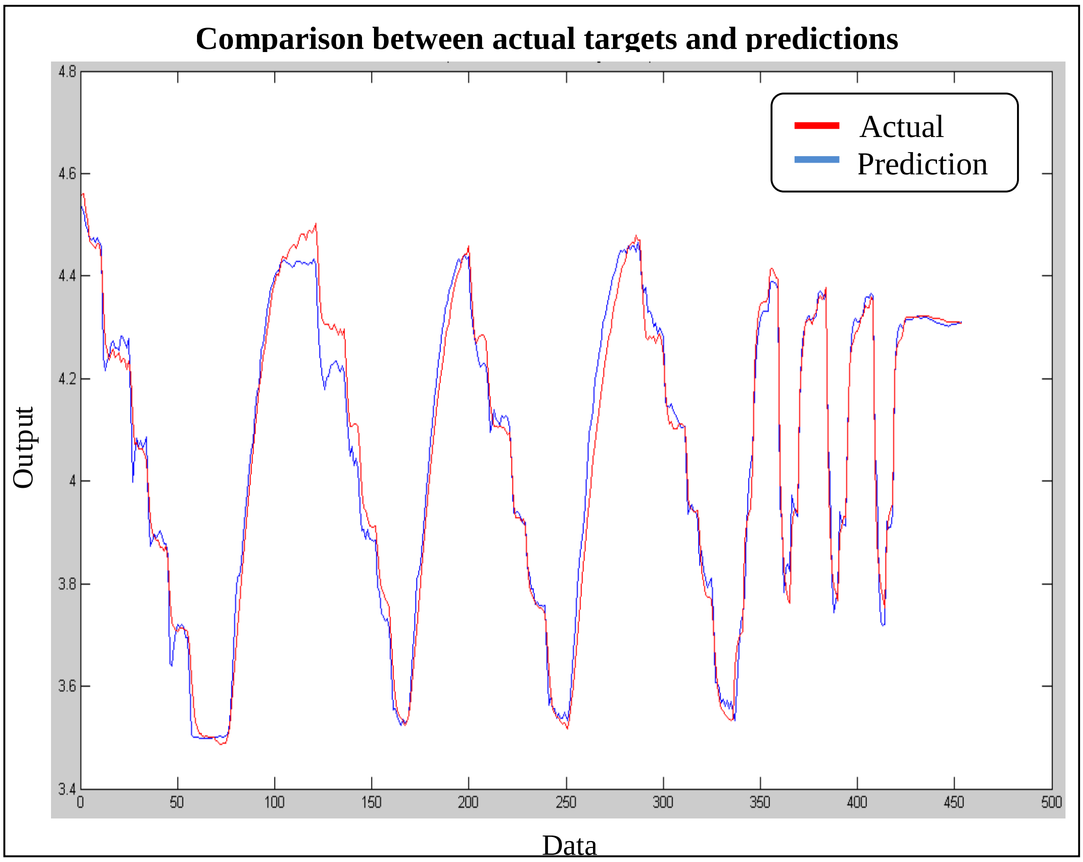

Figure 4.2 : Comparison between actual targets and predictions

To judge our network performance we can also use regression analysis. After post-processing the predicted values, a linear regression is performed between the network outputs, after they have been mapped back to the original target range, and the corresponding targets. The output tracks the targets very well, and the R-value is 0.98903 which is over 0.9. The linear regression is shown in Figure 4.3.

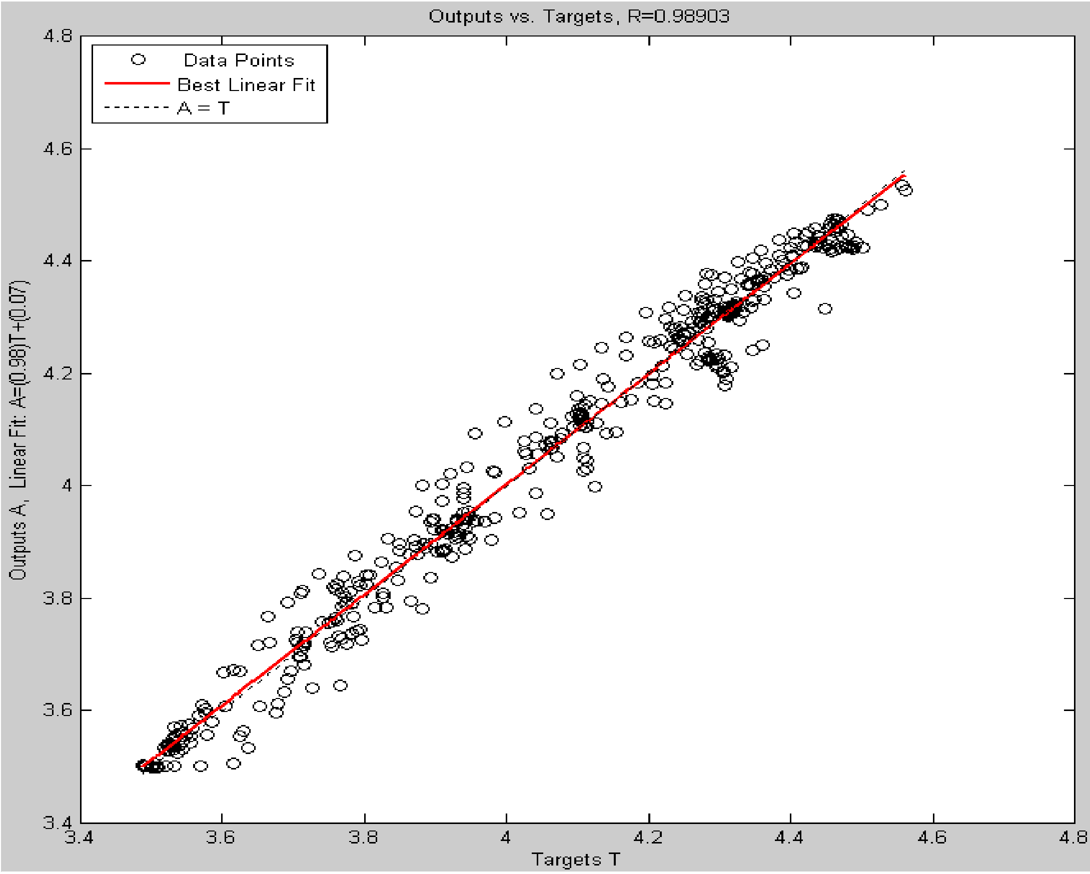

Figure 4.3: Linear Regression

If even more accurate results were required, these steps could be done:-

i. Reset the initial network weights and biases to new values with init and train again

ii. Increase the number of hidden neurons

iii. Increase the number of training vectors

iv. Increase the number of input values, if more relevant information is available

v. Try a different training algorithm

4.3 Estimator Testing Results

A total of 150 random data sets were taken from Model AFPT921 Gas Flow Pressure Temperature Control Training System for testing the network created using Matlab. These data is stimulated through the network which was developed to estimate the density of air in the training plant. The testing results were shown in appendix.

The testing results are then evaluated through comparison and regression analysis in Figure 4.4 and Figure 4.5 respectively. As clearly displayed, the ANN model is capable of estimating the air density accurately and a satisfactory performance was obtained.

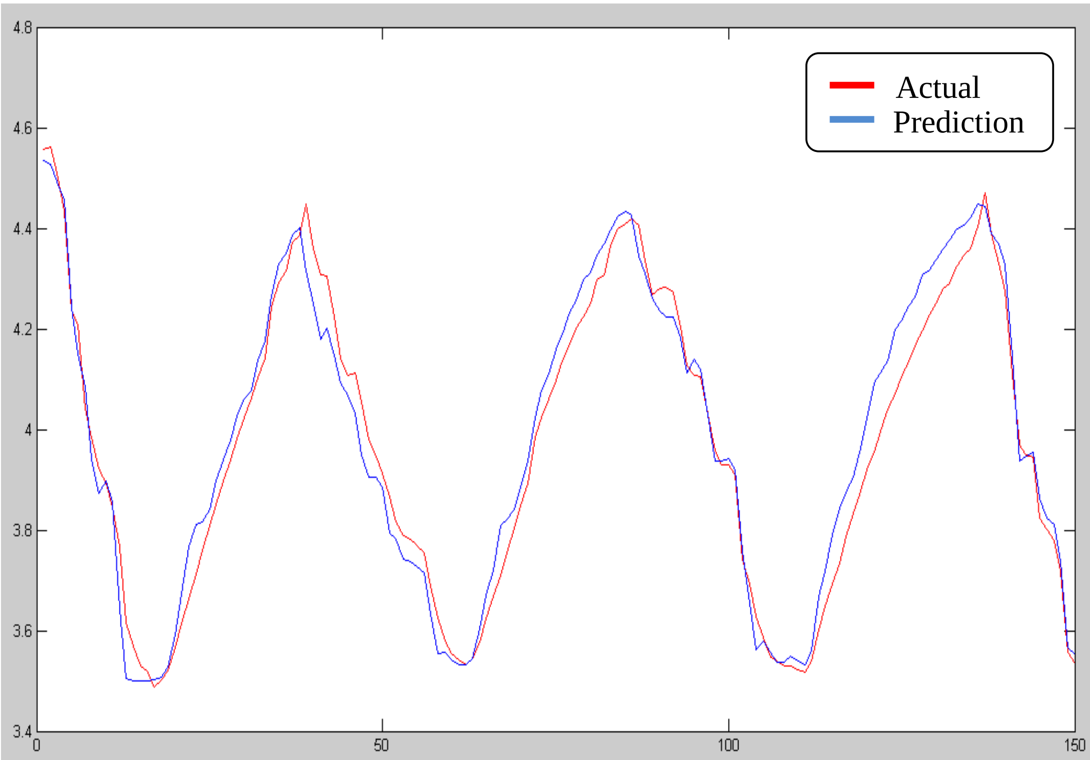

Figure 4.4: Comparison between actual targets and estimations for Testing Results

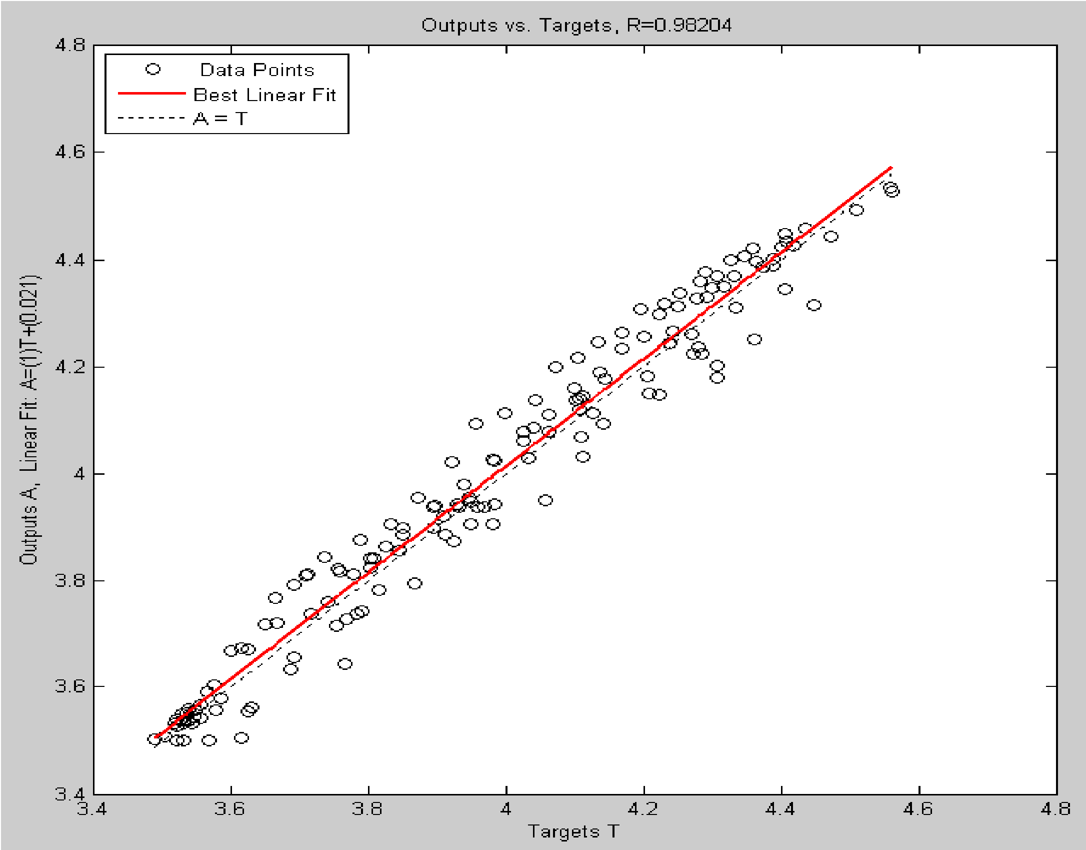

Figure 4.5: Linear Regression for Testing Results

The use of inferential estimators constructed using ANN has provided efficient estimation of the air density. In overall, estimator models display good performance in the validation set indicating that the models developed are able to represent the behaviour of the process in different operating condition.

4.4 Issues on Neural Network

Throughout the research, there were a number of issues encountered which if the project were to be repeated it would have made the development of ANN model significantly easier. The main issues that were encountered are described as below.

4.4.1 Data Issues

The availability of sufficient good quality data was a major recurring issue throughout the initiative. The problem was so acute that the success of the some ANN applications was limited as a result. Overall, the research has served to illustrate that how at least half of the effort expended in the development of ANN applications can and probably should, be spent on the data pre-processing stage. Some of the major data issues encountered are summarised below:

i. Data collection from the plant should be carefully planned to collect the required data with the minimum amount of process interruption
ii. Data sets should outlier and error free and should span the required operating space of the ANN model
iii. All variables that influence the process should be measured and provided explicitly as inputs to the ANN model

Process knowledge has been seen to be invaluable in the data pre-processing stage. This is particularly important for identifying the pertinent process variables and their inter-relationships, suggesting appropriate transformations or combinations of process variables and identifying anomalies in the data set.

4.4.2 Neural Network Issues

There were a number of important lessons learned regarding the configurations of ANN models. It was seen that the precise network topology was rarely critical and that, in general, time was better spent in improving data pre-processing than finely tuning the network topology.

Although the major thrust of this research is to develop ANN model, comparisons were made with more traditional linear techniques. In general, it was found that although ANN often provides more accurate models, the improvement in accuracy was of the order of 10-20%. ANN model however has a quite number of disadvantages, the model itself is not particularly transparent, stability are still the subject of much research and it is unreliable when extrapolating. However the overall suitability of using ANN must be considered on a problem specific basis through cost benefit studies.

A further issue encountered through this research related to people's perception of ANN. At the onset of the research, ANN was seen by many as suitable solutions for any difficult process engineering problem. The ANN application demonstrated however that it can be only used to model systems where correct input and output variables are available.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

ANN has been well recognized for its approximation capability provided the input-output data are available. Nevertheless, the conventional training algorithm utilized in the model development is always encounter difficulties to converge at global solution. The research objective was to establish inferential measurement system for air density using ANN. Hence, an inferential estimator was developed to provide the estimated value for air density using others secondary measurements. The task was completed using MATLAB as modelling tool. The modelling task was started with data preparation. In this study, network named feedforward was trained using training algorithms which is LM.

Nevertheless, when the models were applied beyond the range of training data during on- line estimation, some discrepancies were observed. This was due to the inherent nature of ANN models where they were unable to perform desirable extrapolations. Using retraining strategy, FF-LM displayed significant improvement in data set deviated from training data domain. Encouraging result was obtained proved that the ANN model can be successfully implemented in process estimation.

Based on the results obtained in this study, the main conclusions of this project are as follows:

i. ANN is an efficient and effective empirical modelling tool for estimating the chemical process variable by using other easily available process measurements.
ii. The conventional LM method is widely used in ANN model training due to its fast convergence. Although it is a second order gradient method, it is still susceptible to suboptimal convergence.
iii. The estimation and control performance of ANN model within its training data range was excellent. The dependence of estimators to training data has posed limitation when the operating range falls beyond the training data domain. Some discrepancies were observed indicated that ANN is poor in extrapolation.
iv. Promising results was achieved using inferential measurement system developed for air density in Model AFPT921 Gas Flow Pressure Temperature Control Training.

5.2 Recommendations for Future Work

Despite the encouraging finding was obtained, there are still several further works to be considered in order to implement ANN model in process estimation in a real plant. These include:

i. Evolution of network architecture

The inclusion of using different algorithms feature to improve model robustness can be extended to evolution of network architecture, which is typically number of hidden nodes. The evolution of network architecture requires new set of connection weights. Thus, the evolution of both aspects shall be carried out simultaneously.

ii. Evaluation on real plant data

The application of inferential control scheme using evolving ANN model can further evaluated on real plant data. Real plant data with process noise will provide a more practical environment for investigation. However, some form of appropriate filters may be needed to remove or to smooth out process signals before they can be used.

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LIST OF APPENDICES

A **Data from Model AFPT921**

A1 Step Change in Model AFPT921

A2 Data from Model AFPT921 with Selected Variables

B **MATLAB source code of ANN model development**

C **Data gained from Simulation (Testing Result)**

D **Photographic View of Model AFPT921**

APPENDIX A

DATA FROM MODEL AFPT921

A1 Step Change in MODEL AFPT921

Step change is conducted on Model AFPT921 by randomly changing the selected input variables. The three inputs are **TIC91A**, **PIC91A** and **FIC91A**. These variables can be manipulated randomly by based on these step sizes.

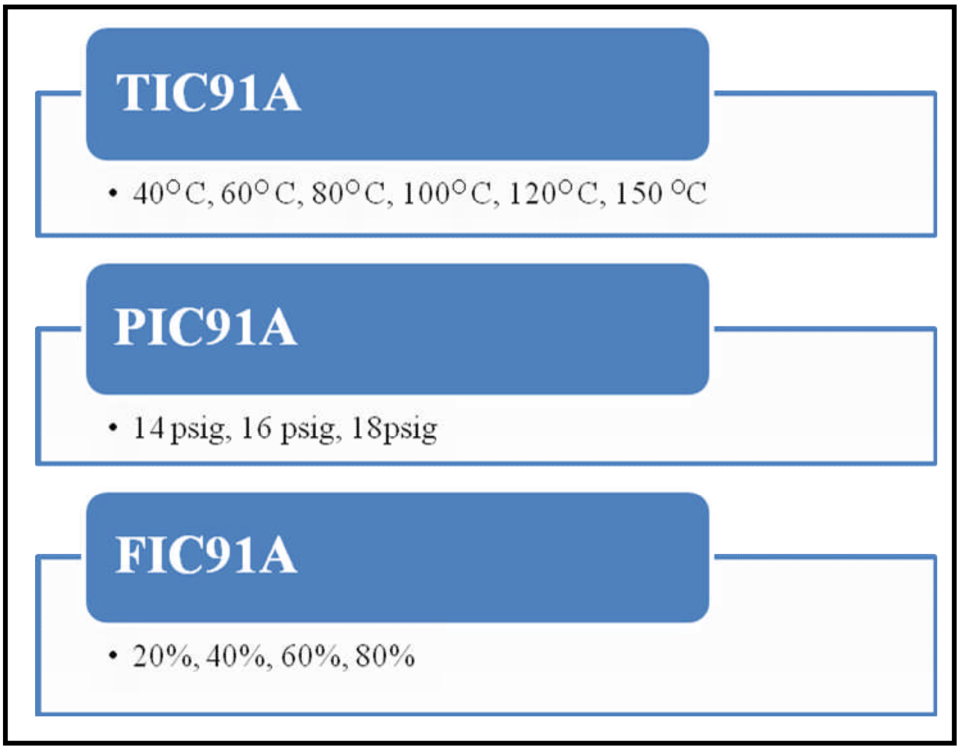

Figure A-1: Step Sizes for Model AFPT921

For example, the PIC91A is set at 14 psig, TIC91A is set at 40°C while the FIC91A is set at 20%. Data is recorded until the production value of the variables reach the set point. Next, change the set point of TIC91A to 60^{o}C while the PIC91A and FIC91A is maintained at 14 psig and 20% respectively. Then, the plant is run with TIC91A of 80^{o}C, 100^{o}C, 120^{o}C and 150^{o}C. After that, the system is run again with TIC91A set at 40^{o}C and PIC91A set at 14 psig but this time FIC91A is changed to 40%. The experiment is conducted till the last set of variable (**TIC91A ; 150^{o}C**, **PIC91A ; 18 psig**, **FIC91A ; 80%**)

A2 Data from Model AFPT921 with Selected Variables

TIME	DENSITY	TIC91A (oC)		FIC91A (kg/m3)		PIC91A (psig)	
(min)	kg/m3	OUTPUT	SETPOINT	OUTPUT	SETPOINT	OUTPUT	SETPOINT
1	4.557841	26.26173	40	42.82637	20	14.9666	15
2	4.561074	29.75223	40	42.27448	20	14.96779	15
3	4.528002	35.68895	40	41.68998	20	14.97315	15
4	4.509188	38.72644	40	41.29437	20	14.94633	15
5	4.467297	40.01869	40	41.23318	20	14.98448	15
6	4.463916	40.02346	40	41.31736	20	14.98508	15
7	4.459066	39.95193	40	41.17505	20	14.9815	15
8	4.454949	40.02346	40	41.25842	20	15.00177	15
9	4.463475	40.02346	40	41.32299	20	14.97435	15
10	4.461418	40.01869	40	41.12239	20	15.00296	15
1	4.434225	43.62364	60	40.70663	20	14.9505	15
2	4.345738	63.43176	60	39.70616	20	14.97375	15
3	4.26857	66.84596	60	39.69863	20	14.96064	15
4	4.254312	65.01488	60	39.85825	20	14.96362	15
5	4.236526	61.90585	60	39.96618	20	15.00057	15
6	4.249314	59.95079	60	40.30182	20	14.98925	15
7	4.257252	59.77436	60	40.33342	20	14.98746	15
8	4.24123	59.90788	60	40.18422	20	15.00773	15
9	4.245934	59.84588	60	40.24723	20	15.01011	15
10	4.250344	59.98894	60	40.03474	20	15.01726	15
11	4.231823	60.13676	60	40.00959	20	14.96779	15
12	4.238731	59.98894	60	39.99775	20	14.97196	15
13	4.23682	59.91742	60	40.1182	20	14.98925	15
14	4.217712	59.99371	60	40.01411	20	15.00892	15
15	4.234616	59.99371	60	40.13596	20	14.97613	15
1	4.207717	69.68318	80	39.41638	20	15.01667	15
2	4.123641	85.57641	80	38.39364	20	15.02024	15
3	4.071754	85.66224	80	38.75593	20	14.97494	15
4	4.074841	81.95239	80	39.10547	20	14.99521	15
5	4.063082	80.04978	80	38.94501	20	15.01845	15
6	4.0622	79.83521	80	38.99221	20	14.99998	15
7	4.062494	79.89243	80	38.90104	20	15.02024	15
8	4.05485	79.88766	80	38.92731	20	15.00296	15
1	4.040004	79.89243	100	39.07108	20	14.9958	15
2	3.983268	92.48589	100	38.24168	20	14.96004	15
3	3.923297	105.8518	100	37.8336	20	14.98686	15
4	3.901983	104.3355	100	37.98298	20	14.99521	15
5	3.892576	101.4076	100	38.1926	20	14.9815	15
6	3.885374	100.082	100	38.22112	20	15.02442	15
7	3.884198	100.1154	100	38.25811	20	15.00594	15
8	3.870087	99.77683	100	38.26969	20	14.97673	15
9	3.870969	99.92943	100	38.21415	20	15.01249	15

TIME	DENSITY	TIC91A (oC)		FIC91A (kg/m3)		PIC91A (psig)	
(min)	kg/m3	OUTPUT	SETPOINT	OUTPUT	SETPOINT	OUTPUT	SETPOINT
10	3.86362	99.92943	100	38.07275	20	14.98865	15
11	3.873762	100.001	100	38.06724	20	14.98865	15
1	3.845393	108.0835	120	37.63457	20	14.97911	15
2	3.765873	124.5251	120	36.88191	20	14.99461	15
3	3.725452	124.9113	120	36.82758	20	15.00951	15
4	3.715604	122.0264	120	37.0878	20	14.97911	15
5	3.708989	120.4337	120	37.22604	20	14.98925	15
6	3.706343	120.0475	120	37.32799	20	14.96958	15
7	3.713693	119.7566	120	37.27714	20	15.00415	15
8	3.71384	120.0475	120	37.32091	20	14.98806	15
9	3.712076	119.9044	120	37.26528	20	14.97673	15
10	3.709724	120.0904	120	37.0978	20	15.0113	15
11	3.706931	119.8997	120	37.07619	20	15.00355	15
1	3.676652	127.2478	150	36.71611	20	14.9809	15
2	3.615946	145.0008	150	36.02091	20	14.96779	15
3	3.568175	153.3694	150	35.73657	20	14.97613	15
4	3.530841	155.4103	150	35.7318	20	14.98627	15
5	3.519964	152.4586	150	35.88574	20	15.01726	15
6	3.507616	150.5608	150	36.14609	20	14.98388	15
7	3.507028	150.0267	150	36.06292	20	15.00475	15
8	3.502178	149.9552	150	36.114	20	14.99044	15
9	3.501737	150.0267	150	36.19294	20	14.97435	15
10	3.502031	150.0267	150	36.11648	20	15.01011	15
11	3.500561	150.0267	150	36.13585	20	14.99938	15
12	3.501002	150.0267	150	36.07587	20	14.9654	15
13	3.499973	149.9504	150	36.01378	20	14.97673	15
14	3.500414	150.0267	150	35.8658	20	15.01369	15
15	3.493359	150.0982	150	35.77777	20	14.9815	15
16	3.491007	150.0172	150	35.78466	20	14.96779	15
17	3.48792	149.9456	150	35.75276	20	15.0119	15
18	3.487626	149.9552	150	35.81565	20	14.98806	15
19	3.488067	149.9409	150	35.76572	20	14.98329	15
1	3.488361	150.0935	40	35.72933	20	15.00177	15
2	3.50306	145.7685	40	35.88757	40	15.01249	15
3	3.519964	137.4571	40	36.23481	40	14.98806	15
4	3.565971	129.0455	40	36.59222	40	14.97494	15
5	3.614623	120.8534	40	36.85483	40	15.01845	15
6	3.663129	113.0522	40	37.07906	40	14.97375	15
7	3.712223	105.8328	40	37.19501	40	15.01726	15
8	3.75823	99.07587	40	37.40994	40	14.96123	15
9	3.807912	92.90074	40	37.45563	40	14.99998	15
10	3.849656	87.00217	40	37.48388	40	14.99759	15

TIME (min)	DENSITY kg/m3	TIC91A (oC)		FIC91A (kg/m3)		PIC91A (psig)	
		OUTPUT	SETPOINT	OUTPUT	SETPOINT	OUTPUT	SETPOINT
11	3.896839	81.69012	40	37.61581	40	14.97554	15
12	3.939465	76.91215	40	37.69121	40	14.9654	15
13	3.981063	72.5061	40	37.77786	40	14.95408	15
14	4.023836	68.47677	40	37.94044	40	14.9809	15
15	4.062494	64.90997	40	37.98204	40	15.02382	15
16	4.10218	61.72465	40	38.14109	40	14.98984	15
17	4.142014	58.7253	40	38.09967	40	14.98627	15
18	4.183905	55.98821	40	38.11552	40	15.03455	15
19	4.207129	53.66599	40	38.24039	40	14.97136	15
20	4.242112	51.3962	40	38.25813	40	15.00773	15
21	4.260339	49.49359	40	38.2599	40	15.00594	15
22	4.292529	47.52422	40	38.21662	40	14.98806	15
23	4.315312	45.7742	40	38.29779	40	14.99759	15
24	4.347355	44.32936	40	38.19772	40	14.97971	15
25	4.372343	43.03712	40	38.22548	40	14.99938	15
26	4.387188	41.84501	40	38.14185	40	15.00236	15
27	4.403063	40.98192	40	38.14605	40	15.01011	15
28	4.400858	40.6672	40	38.09105	40	15.02084	15
29	4.42276	40.52892	40	38.06364	40	14.98627	15
30	4.43687	40.44785	40	38.02946	40	14.98984	15
31	4.434959	40.2285	40	38.02035	40	14.99223	15
32	4.433342	40.15221	40	38.06475	40	14.997	15
33	4.446424	40.07114	40	38.08293	40	15.00534	15
34	4.454068	40.15221	40	38.1192	40	15.00773	15
35	4.458478	40.07114	40	38.15316	40	15.01905	15
36	4.462006	39.99962	40	38.16864	40	15.0113	15
37	4.453333	39.99008	40	38.07191	40	14.99938	15
38	4.465386	39.99008	40	38.18517	40	14.98984	15
39	4.478615	39.99008	40	38.16307	40	14.98806	15
40	4.480967	40.07114	40	38.15345	40	14.9964	15
41	4.48082	40.033	40	38.13202	40	14.9964	15
42	4.471265	40.06638	40	38.06848	40	15.00653	15
43	4.487434	40.07114	40	38.1244	40	15.00653	15
44	4.489639	40.07114	40	38.07883	40	15.00296	15
45	4.485082	39.99008	40	38.15904	40	15.00236	15
46	4.491843	39.99485	40	38.23445	40	14.97375	15
1	4.501986	40.06638	60	38.14401	40	14.99759	15
2	4.447453	54.49092	60	37.3349	40	14.97196	15
3	4.359849	67.11299	60	36.68472	40	15.01786	15
4	4.317223	67.80442	60	36.83244	40	14.98627	15
5	4.309433	65.66815	60	37.06196	40	14.99223	15
6	4.306345	63.00736	60	37.30668	40	14.99879	15

TIME (min)	DENSITY kg/m3	TIC91A (oC)		FIC91A (kg/m3)		PIC91A (psig)	
		OUTPUT	SETPOINT	OUTPUT	SETPOINT	OUTPUT	SETPOINT
7	4.305317	60.56115	60	37.39999	40	14.99521	15
8	4.305905	60.04139	60	37.3638	40	15.02203	15
9	4.295909	59.88881	60	37.29052	40	15.01011	15
10	4.297673	59.89834	60	37.28918	40	15.00832	15
11	4.306052	59.9651	60	37.29632	40	14.98984	15
12	4.29635	59.9651	60	37.27675	40	14.99163	15
13	4.285326	59.9651	60	37.29368	40	15.01428	15
14	4.297085	60.04139	60	37.342	40	15.00951	15
15	4.285914	59.9651	60	37.39308	40	14.96421	15
1	4.295615	60.35134	80	37.42495	40	14.97375	15
2	4.22271	77.64648	80	36.45797	40	14.97554	15
3	4.141426	87.31689	80	35.9968	40	14.98746	15
4	4.107619	86.01511	80	36.31818	40	14.98806	15
5	4.107766	82.29572	80	36.50821	40	15.02143	15
6	4.111881	79.49187	80	36.84586	40	14.97494	15
7	4.111587	79.5634	80	36.77208	40	15.01547	15
1	4.107619	79.86858	100	36.85294	40	14.98984	15
2	4.05632	95.9144	100	36.00977	40	14.98508	15
3	3.979299	106.6672	100	35.61497	40	15.00773	15
4	3.94799	104.8457	100	35.79155	40	14.99461	15
5	3.941964	100.9642	100	36.14637	40	14.99938	15
6	3.926677	99.79591	100	36.0526	40	15.03157	15
7	3.913449	99.82929	100	36.1824	40	14.98984	15
8	3.910215	99.97234	100	36.20383	40	14.98448	15
9	3.910068	99.91512	100	36.22026	40	15.00177	15
1	3.911979	100.0534	120	36.19021	40	15.03455	15
2	3.865678	113.92	120	35.60887	40	14.96958	15
3	3.815114	126.5517	120	35.06372	40	15.03514	15
4	3.789538	124.2056	120	35.34955	40	14.98806	15
5	3.782042	121.1633	120	35.52553	40	15.03455	15
6	3.768666	119.8711	120	35.64587	40	14.97435	15
7	3.763815	119.9855	120	35.61539	40	14.99461	15
1	3.753673	122.9896	150	35.59288	40	15.00594	15
2	3.687529	140.1274	150	34.61987	40	15.01607	15
3	3.624912	150.3128	150	34.38966	40	14.97911	15
4	3.578905	155.6105	150	34.29615	40	15.02203	15
5	3.554358	153.7175	150	34.50052	40	15.0119	15
6	3.542894	151.133	150	34.73412	40	14.997	15
7	3.537014	150.1459	150	34.86565	40	14.96719	15
8	3.532164	149.917	150	34.79782	40	15.02442	15
9	3.524668	149.9981	150	34.85744	60	14.99282	15
1	3.531135	147.4947	40	34.95697	60	15.00594	15

TIME (min)	DENSITY kg/m3	TIC91A (oC)		FIC91A (kg/m3)		PIC91A (psig)	
		OUTPUT	SETPOINT	OUTPUT	SETPOINT	OUTPUT	SETPOINT
2	3.54451	140.0654	40	35.37075	60	14.97494	15
3	3.575966	131.7254	40	35.7203	60	14.99879	15
4	3.624324	123.5857	40	35.92454	60	15.01845	15
5	3.666657	115.8036	40	36.2067	60	15.00832	15
6	3.709136	108.5555	40	36.47701	60	15.00296	15
7	3.75529	101.7987	40	36.70041	60	14.98806	15
8	3.802767	95.49477	40	36.75672	60	14.99223	15
9	3.849215	89.72018	40	36.98685	60	14.99461	15
10	3.893311	84.22694	40	37.11204	60	14.98806	15
11	3.939612	79.40604	40	37.1152	60	14.98329	15
12	3.983708	74.85218	40	37.17973	60	15.02859	15
13	4.023836	70.82761	40	37.20872	60	15.00296	15
14	4.061318	67.02239	40	37.33559	60	15.00594	15
15	4.097771	63.75601	40	37.39289	60	14.9821	15
16	4.136135	60.64699	40	37.39954	60	15.02084	15
17	4.168912	57.76684	40	37.482	60	14.99223	15
18	4.200515	55.25387	40	37.57222	60	14.9958	15
19	4.223151	53.00317	40	37.54561	60	14.98925	15
20	4.25005	51.00042	40	37.66353	60	14.98806	15
21	4.27489	49.02151	40	37.69728	60	14.9964	15
22	4.298114	47.43362	40	37.76532	60	15.00892	15
23	4.306493	45.91249	40	37.75277	60	15.00713	15
24	4.342505	44.54871	40	37.86881	60	15.00355	15
25	4.363965	43.09911	40	37.8888	60	15.00832	15
26	4.383514	42.04051	40	37.92872	60	15.00355	15
27	4.399095	41.20604	40	37.94775	60	14.98925	15
28	4.407473	40.59568	40	37.88852	60	14.99104	15
29	4.41835	40.51938	40	37.93473	60	15.00534	15
30	4.437311	40.21897	40	37.93113	60	14.9958	15
31	4.442456	40.14744	40	37.77614	60	14.99998	15
32	4.441868	40.14744	40	37.8773	60	15.01249	15
1	4.457889	40.21897	60	38.01199	60	14.97375	15
2	4.404974	56.84176	60	36.97168	60	14.9809	15
3	4.333538	67.70905	60	36.37783	60	15.03157	15
4	4.281799	67.79012	60	36.5488	60	14.98388	15
5	4.269011	65.65385	60	36.77028	60	14.98686	15
6	4.280035	63.07412	60	37.00047	60	15.01726	15
7	4.282975	60.79481	60	37.21825	60	15.01726	15
8	4.285179	60.03662	60	37.32807	60	14.98329	15
9	4.283563	59.78866	60	37.34196	60	14.9809	15
1	4.272098	62.51144	80	37.09193	60	15.01965	15
2	4.204777	81.63767	80	36.04168	60	15.00534	15

TIME (min)	DENSITY kg/m3	TIC91A (oC)		FIC91A (kg/m3)		PIC91A (psig)	
		OUTPUT	SETPOINT	OUTPUT	SETPOINT	OUTPUT	SETPOINT
3	4.153773	87.98447	80	35.92906	60	15.00832	15
4	4.125992	85.69562	80	36.05735	60	15.01011	15
5	4.106884	81.68059	80	36.21547	60	14.97554	15
6	4.105855	79.63016	80	36.44704	60	15.02561	15
7	4.10365	79.62539	80	36.46034	60	14.99402	15
8	4.107766	79.72076	80	36.47604	60	14.97733	15
9	4.104826	80.01163	80	36.3921	60	15.02203	15
10	4.10365	79.85905	80	36.42195	60	15.00713	15
11	4.098652	79.86382	80	36.39972	60	15.00415	15
12	4.091156	79.93057	80	36.41144	60	15.01786	15
1	4.094684	80.07839	100	36.48287	60	15.0274	15
2	4.030891	93.12486	100	35.75861	60	14.9809	15
3	3.957545	106.5814	100	35.17537	60	14.98567	15
4	3.929911	105.5991	100	35.33611	60	15.00832	15
5	3.929323	101.3361	100	35.70988	60	14.96898	15
6	3.928882	99.88651	100	35.8493	60	14.97435	15
7	3.921974	99.74345	100	35.93587	60	14.98567	15
8	3.925354	99.82452	100	35.97339	60	15.03097	15
1	3.909774	103.4914	120	35.75798	60	14.99819	15
2	3.845981	121.1633	120	34.98519	60	14.98806	15
3	3.794095	126.2274	120	34.87674	60	14.99461	15
4	3.780719	122.7417	120	35.15574	60	14.9964	15
5	3.772635	120.4719	120	35.22424	60	14.99461	15
6	3.762052	120.0141	120	35.42186	60	14.99282	15
7	3.757789	120.0141	120	35.38106	60	14.97554	15
8	3.753085	119.9331	120	35.44287	60	15.01607	15
9	3.753526	120.0094	120	35.43901	60	15.01845	15
10	3.74897	119.9331	120	35.45545	60	14.99998	15
1	3.74118	121.9358	150	35.35021	60	14.97792	15
2	3.692379	137.9864	150	34.65412	60	14.98567	15
3	3.629469	149.7406	150	34.32391	60	14.9815	15
4	3.585667	155.5152	150	34.04711	60	15.01905	15
5	3.554799	154.4661	150	34.26646	60	14.9815	15
6	3.548038	151.6527	150	34.40666	60	15.03097	15
7	3.539366	150.2127	150	34.61428	60	14.95885	15
8	3.538043	149.979	150	34.55899	60	15.01011	15
9	3.529959	149.979	150	34.67345	60	14.98269	15
10	3.525108	149.9027	150	34.67263	60	14.98984	15
11	3.529077	149.979	150	34.5441	60	15.01845	15
12	3.522021	149.979	150	34.69997	60	15.01428	15
1	3.517906	149.3019	40	34.76893	80	14.97375	15
2	3.538631	142.9551	40	34.95248	80	15.00177	15

TIME (min)	DENSITY kg/m3	TIC91A (oC)		FIC91A (kg/m3)		PIC91A (psig)	
		OUTPUT	SETPOINT	OUTPUT	SETPOINT	OUTPUT	SETPOINT
3	3.570233	134.8917	40	35.29579	80	14.9815	15
4	3.600513	126.7567	40	35.64973	80	14.97852	15
5	3.649312	118.946	40	35.82772	80	15.04349	15
6	3.691351	111.5883	40	36.0589	80	15.01726	15
7	3.735741	104.7503	40	36.35839	80	14.97673	15
8	3.787627	98.26524	40	36.31868	80	15.04587	15
9	3.8329	92.38575	40	36.53451	80	15.03634	15
10	3.871263	86.90204	40	36.73775	80	14.98388	15
11	3.920357	81.82841	40	36.74152	80	15.00415	15
12	3.955487	77.27455	40	36.69385	80	15.03157	15
13	3.996937	72.94957	40	36.88812	80	15.00534	15
14	4.04118	69.22064	40	37.03918	80	15.00057	15
15	4.071166	65.73014	40	37.01921	80	14.99402	15
16	4.104385	62.5639	40	37.17851	80	14.98806	15
17	4.134518	59.73144	40	37.20105	80	15.01428	15
18	4.167443	57.15172	40	37.32401	80	15.00415	15
19	4.195811	54.79133	40	37.3257	80	14.9815	15
20	4.228736	52.59307	40	37.43103	80	14.99879	15
21	4.251666	50.60941	40	37.48639	80	14.99938	15
22	4.280329	48.81647	40	37.53207	80	14.997	15
23	4.289295	47.2858	40	37.50372	80	15.01667	15
24	4.325307	45.82666	40	37.54934	80	14.99163	15
25	4.346767	44.5201	40	37.60156	80	15.00236	15
26	4.358673	43.32322	40	37.60017	80	15.00594	15
27	4.382485	42.1931	40	37.76695	80	14.94693	15
28	4.404239	41.28233	40	37.72187	80	14.95229	15
29	4.420114	40.58614	40	37.69002	80	14.99223	15
30	4.425111	40.43832	40	37.54182	80	15.03216	15
31	4.438928	40.18082	40	37.78339	80	14.99521	15
32	4.455537	40.13314	40	37.64334	80	14.98567	15
33	4.461711	40.06638	40	37.69645	80	14.9958	15
34	4.466709	39.90425	40	37.54828	80	15.02442	15
35	4.463916	39.97578	40	37.62537	80	14.99104	15
36	4.480232	40.02346	40	37.71622	80	15.00475	15
37	4.471413	39.90902	40	37.53646	80	14.99342	15
1	4.470971	45.21153	60	37.18858	80	15.0119	15
2	4.388511	64.28531	60	36.22665	80	14.97435	15
3	4.330158	68.07622	60	36.0427	80	15.02084	15
4	4.281064	66.8698	60	36.126	80	14.97375	15
5	4.275478	64.51419	60	36.51228	80	15.00713	15
6	4.282681	61.85817	60	36.6834	80	14.99461	15
7	4.278712	60.18444	60	36.79218	80	15.01488	15

TIME (min)	DENSITY kg/m3	TIC91A (oC)		FIC91A (kg/m3)		PIC91A (psig)	
		OUTPUT	SETPOINT	OUTPUT	SETPOINT	OUTPUT	SETPOINT
8	4.282975	60.02232	60	36.92344	80	15.0119	15
9	4.269598	60.02232	60	36.89387	80	15.00653	15
10	4.278565	59.95556	60	37.02429	80	14.98806	15
11	4.286502	60.10338	60	36.96793	80	14.9809	15
12	4.272979	59.92218	60	37.01108	80	14.9815	15
1	4.244023	70.14572	80	36.35206	80	15.02382	15
2	4.174057	86.44427	80	35.74993	80	14.98806	15
3	4.134518	87.05939	80	35.74455	80	15.03872	15
4	4.111146	83.86931	80	36.04215	80	14.98806	15
5	4.116291	80.22621	80	36.27409	80	14.98329	15
6	4.10218	79.32021	80	36.39109	80	14.99104	15
7	4.102768	79.62062	80	36.40298	80	15.01786	15
8	4.102915	79.9258	80	36.40908	80	14.97315	15
9	4.112617	79.85905	80	36.46274	80	15.02442	15
10	4.111734	80.00687	80	36.48248	80	15.00653	15
11	4.110411	80.06886	80	36.47638	80	14.98925	15
1	4.103503	81.28481	100	36.38754	80	14.99282	15
2	4.040004	99.34291	100	35.40578	80	15.00594	15
3	3.968716	106.4908	100	35.21115	80	14.99163	15
4	3.949313	103.8396	100	35.45558	80	14.99521	15
5	3.945492	100.5732	100	35.65449	80	14.98806	15
6	3.939318	99.88651	100	35.80092	80	14.99223	15
7	3.941229	99.88174	100	35.8044	80	15.00594	15
1	3.942552	100.0868	120	35.91895	80	15.02143	15
2	3.892429	114.7927	120	35.13832	80	15.0113	15
3	3.824227	126.1511	120	34.7074	80	14.99938	15
4	3.801885	124.3963	120	34.93649	80	14.98806	15
5	3.778514	120.9821	120	35.09294	80	14.99879	15
6	3.773811	120.0046	120	35.22161	80	15.00057	15
7	3.773517	119.9283	120	35.16574	80	15.00534	15
1	3.768225	120.696	150	35.10106	80	15.0119	15
2	3.716192	135.3971	150	34.51258	80	14.99342	15
3	3.651517	148.6868	150	33.97923	80	14.9964	15
4	3.602571	154.8285	150	33.6909	80	14.9815	15
5	3.574937	154.9048	150	33.90518	80	15.03395	15
6	3.556564	151.8769	150	34.18091	80	14.98806	15
7	3.552154	150.3557	150	34.22515	80	15.01369	15
8	3.543776	150.0553	150	34.3036	80	14.96958	15
9	3.540395	149.9409	150	34.30885	80	15.03693	15
10	3.534515	149.9027	150	34.36761	80	14.96838	15
11	3.532605	149.9742	150	34.34792	80	15.03932	15
1	3.534809	100.0296	100	44.70287	20	11.85102	14

TIME (min)	DENSITY kg/m3	TIC91A (oC)		FIC91A (kg/m3)		PIC91A (psig)	
		OUTPUT	SETPOINT	OUTPUT	SETPOINT	OUTPUT	SETPOINT
2	3.636524	100.0248	100	42.99644	20	12.99067	14
3	3.675182	99.9485	100	42.11825	20	13.55156	14
4	3.695467	99.94373	100	41.59844	20	13.78164	14
5	3.702375	99.88174	100	41.30268	20	13.89906	14
6	3.706491	100.1011	100	41.14145	20	13.93363	14
1	3.881846	100.0248	100	37.338	20	15.59186	16
2	3.916241	100.1059	100	36.42312	20	15.79213	16
3	3.93873	100.1011	100	35.94786	20	15.88333	16
4	3.94461	99.87698	100	35.51168	20	15.94711	16
1	4.028099	100.02	100	31.65227	20	17.12193	18
2	4.223298	100.02	100	27.89626	20	17.37883	18
3	4.283268	100.0963	100	26.32494	20	17.55407	18
4	4.3281	100.1154	100	25.46798	20	17.70249	18
5	4.344562	100.1726	100	24.96816	20	17.80501	18
6	4.346914	100.1678	100	24.55476	20	17.88488	18
7	4.349266	100.0916	100	24.28591	20	17.91946	18
8	4.349266	100.0916	100	24.11549	20	17.94151	18
9	4.361907	100.0916	100	23.89116	20	17.95105	18
1	4.413352	99.93896	100	22.90834	20	18.78552	20
2	4.415116	100.0153	100	22.60483	20	18.94944	20
3	4.408061	100.0963	100	22.41566	20	19.0013	20
4	4.396154	100.0916	100	22.34834	20	19.02097	20
1	4.394391	99.93896	100	22.29628	40	19.02574	14
2	4.016781	100.0868	100	32.74966	40	15.25866	14
3	3.909921	99.71008	100	35.71129	40	14.60956	14
4	3.830842	99.71008	100	37.15902	40	14.31988	14
5	3.792037	99.87221	100	37.87525	40	14.17682	14
6	3.770871	100.0153	100	38.27485	40	14.10053	14
7	3.761464	99.86744	100	38.42475	40	14.0451	14
1	3.908892	99.9342	100	34.84948	40	15.69081	16
2	3.940347	100.0868	100	34.30047	40	15.87201	16
3	3.944463	99.86267	100	34.01239	40	15.94472	16
4	3.939024	100.0057	100	33.76212	40	15.98287	16
1	4.161563	99.9342	100	28.10538	40	17.23101	18
2	4.230794	100.2298	100	26.16019	40	17.46288	18
3	4.272538	100.0868	100	24.93119	40	17.65123	18
4	4.31002	99.9342	100	24.50903	40	17.78236	18
5	4.313842	100.082	100	24.18688	40	17.85687	18
6	4.318545	100.0582	100	24.01	40	17.87892	18
7	4.312519	99.8579	100	23.82787	40	17.89383	18
8	4.306787	100.0153	100	23.74111	40	17.898	18
9	4.32516	100.0772	100	23.5381	40	17.90217	18

TIME (min)	DENSITY kg/m3	TIC91A (oC)		FIC91A (kg/m3)		PIC91A (psig)	
		OUTPUT	SETPOINT	OUTPUT	SETPOINT	OUTPUT	SETPOINT
10	4.330158	100.0057	100	23.72387	40	17.94091	18
1	4.352352	99.92943	100	22.94966	40	18.56916	20
2	4.361613	100.0772	100	22.48052	40	18.81652	20
3	4.355733	100.001	100	22.33714	40	18.8791	20
4	4.362347	100.001	100	22.14374	40	18.90295	20
5	4.377047	100.0057	100	22.36018	40	18.9101	20
1	4.06367	100.3109	100	30.64344	60	15.53404	14
2	3.90948	99.8579	100	34.51565	60	14.81341	14
3	3.826579	99.691	100	36.20335	60	14.40273	14
4	3.794095	99.92466	100	37.16447	60	14.18219	14
5	3.783218	100.001	100	37.62835	60	14.08801	14
6	3.767784	99.72438	100	38.02711	60	14.02304	14
1	3.895957	100.0772	100	34.2667	60	15.71107	16
2	3.911097	100.001	100	33.74556	60	15.84637	16
3	3.931381	100.144	100	33.40049	60	15.93459	16
4	3.928588	100.0534	100	33.19296	60	15.96737	16
1	4.078516	100.001	100	29.17171	60	17.04802	18
2	4.219476	99.84837	100	26.29054	60	17.35439	18
3	4.262984	100.1488	100	25.16122	60	17.57434	18
4	4.274008	100.1488	100	24.3631	60	17.73706	18
5	4.290177	100.2298	100	23.94466	60	17.80621	18
6	4.291059	100.0677	100	23.83885	60	17.81932	18
7	4.300319	100.0772	100	23.53416	60	17.83958	18
8	4.320015	100.0725	100	23.57438	60	17.91767	18
9	4.322661	100.1488	100	23.38374	60	17.98979	18
1	4.343239	99.99142	100	22.5344	60	18.67585	20
2	4.338977	100.0248	100	22.37252	60	18.77539	20
3	4.338536	100.0677	100	22.2551	60	18.81175	20
4	4.359849	100.0677	100	22.3668	60	18.82963	20
5	4.352646	99.91989	100	22.41033	60	18.835	20
1	4.04221	100.144	100	31.13534	80	15.3582	14
2	3.881258	99.7673	100	34.54959	80	14.72519	14
3	3.826138	99.7673	100	36.1146	80	14.36279	14
4	3.79527	99.7673	100	36.91279	80	14.18517	14
5	3.774546	99.89605	100	37.23613	80	14.08205	14
6	3.752057	99.91512	100	37.3476	80	14.05225	14
1	3.897427	99.99142	100	33.93483	80	15.71822	16
2	3.931087	100.0629	100	33.23935	80	15.84876	16
3	3.944316	99.99619	100	32.8878	80	15.92863	16
1	3.953723	100.0677	100	32.74282	80	16.2803	18
2	4.205659	99.91989	100	26.57323	80	17.2781	18
3	4.257252	100.1011	100	25.11447	80	17.52546	18

TIME (min)	DENSITY kg/m3	TIC91A (oC)		FIC91A (kg/m3)		PIC91A (psig)	
		OUTPUT	SETPOINT	OUTPUT	SETPOINT	OUTPUT	SETPOINT
4	4.271069	100.0629	100	24.20161	80	17.70428	18
5	4.276801	100.1202	100	23.83711	80	17.76389	18
6	4.282827	99.99142	100	23.63689	80	17.77521	18
7	4.312372	99.91035	100	23.42425	80	17.89323	18
8	4.318692	99.99142	100	23.33513	80	17.94747	18
9	4.31884	99.99142	100	23.34258	80	17.95284	18
10	4.31884	99.98665	100	23.33111	80	17.9582	18
11	4.31884	99.99142	100	23.33231	80	17.96476	18
12	4.319133	100.0629	100	23.33276	80	17.97012	18
13	4.319869	100.0677	100	23.30964	80	17.97489	18
14	4.320603	100.0629	100	23.32457	80	17.98145	18
15	4.321191	99.99619	100	23.3107	80	17.988	18
16	4.321339	99.99142	100	23.27767	80	17.99456	18
17	4.321339	100.0582	100	23.24656	80	17.99813	18
18	4.321632	100.0629	100	23.22323	80	18.00231	18
19	4.321044	99.99142	100	23.18381	80	18.00588	18
20	4.320751	99.98665	100	23.15005	80	18.00886	18
21	4.320457	99.99142	100	23.11071	80	18.00886	18
22	4.318545	99.98665	100	23.07407	80	18.00529	18
23	4.317811	99.99142	100	23.04461	80	17.99992	18
24	4.317664	99.99142	100	23.02014	80	17.99217	18
25	4.316782	99.98665	100	23.00307	80	17.98323	18
26	4.31634	99.99142	100	23.01222	80	17.97429	18
27	4.31634	99.98665	100	22.99712	80	17.96595	18
28	4.312813	99.99142	100	22.99883	80	17.9582	18
29	4.311049	99.98665	100	23.0075	80	17.95045	18
30	4.310608	99.91989	100	23.05756	80	17.9427	18
31	4.310608	99.97711	100	23.09383	80	17.93495	18
32	4.310608	99.98665	100	23.13011	80	17.92899	18
33	4.310608	99.99142	100	23.15299	80	17.92184	18
34	4.310608	99.99142	100	23.17466	80	17.91826	18
35	4.310608	99.99142	100	23.20645	80	17.92005	18
36	4.308403	99.98665	100	23.22168	80	17.92542	18
37	4.306345	99.99142	100	23.22973	80	17.93495	18

APPENDIX B

MATLAB SOURCE CODE OF ANN MODEL DEVELOPMENT

B MATLAB source code of ANN model development

Data Scaling

```
>> [p2,ps] = mapminmax(p);
>> [t2,ts] = mapminmax(t);
```

Network Training

```
>> [trainV,val,test] = dividevec(p2,t2,0.20,0.20);
>> net = newff(minmax(p2),[20 1]);
>> net.trainParam.lr=0.3;       (learning rate)
>> net.trainParam.mc=0.6;     (momentum)
>> [net,tr]=train(net,trainV.P,trainV.T,[],[],val,test);
TRAINLM-calcjx, Epoch 0/100, MSE 0.982796/0, Gradient 2.31353/1e-010
TRAINLM-calcjx, Epoch 17/100, MSE 0.00549171/0, Gradient 0.00278861/1e-010
TRAINLM, Validation stop.
```

Data Descaling, Data Simulation & Plotting Graph

```
>> a2 = sim(net,p2);
>> a = mapminmax('reverse',a2,ts);
>> [m,b,r] = postreg(a,t);

>> plot(t,'r')
>> hold
Current plot held
>> plot(a)
>> title('Comparison between actual targets and predictions')
```

Data Scaling and Simulation for Testing Inputs

```
>> pnewn = mapminmax('apply',pnew,ps);
>> anewn = sim(net,pnewn);
```

Data Descaling & Plotting Graph for Testing Results

```
>> anew = mapminmax('reverse',anewn,ts);
>> plot(tnew,'r')
>> hold
Current plot held
>> plot(anew)
>> [m,b,r] = postreg(anew,tnew);

>> plot(tnew,'r')
>> hold
Current plot held
>> plot(anew)
>> title('Comparison between actual targets and predictions using random data')
```

APPENDIX C

DATA GAINED FROM SIMULATION

C Data gained from Simulation (Testing Result)

TIC91A (^oC)	FIC91A kg/hr	PIC91A psi	DENSITY(kg/m3)		ERROR(%)
			ACTUAL	ESTIMATE	
26.2617	42.8264	14.9666	4.5578	4.5357	0.484883058
29.7522	42.2745	14.9678	4.5611	4.5268	0.752011576
38.7264	41.2944	14.9463	4.5092	4.492	0.381442384
43.6236	40.7066	14.9505	4.4342	4.4583	0.543502774
61.9058	39.9662	15.0006	4.2365	4.2438	0.17231205
69.6832	39.4164	15.0167	4.2077	4.1503	1.364165696
79.8924	39.0711	14.9958	4.04	4.0853	1.121287129
92.4859	38.2417	14.96	3.9833	3.9425	1.024276354
105.8518	37.8336	14.9869	3.9233	3.8725	1.294828333
101.4076	38.1926	14.9815	3.8926	3.8964	0.097621127
108.0835	37.6346	14.9791	3.8454	3.8549	0.247048421
124.5251	36.8819	14.9946	3.7659	3.6444	3.226320401
145.0008	36.0209	14.9678	3.6159	3.5042	3.089134102
153.3694	35.7366	14.9761	3.5682	3.4996	1.922537974
155.4103	35.7318	14.9863	3.5308	3.4996	0.88365243
152.4586	35.8857	15.0173	3.52	3.4997	0.576704545
150.0935	35.7293	15.0018	3.4884	3.5023	0.398463479
145.7685	35.8876	15.0125	3.5031	3.5062	0.088493049
137.4571	36.2348	14.9881	3.52	3.5274	0.210227273
129.0455	36.5922	14.9749	3.566	3.5908	0.695457095
120.8534	36.8548	15.0184	3.6146	3.6722	1.593537321
113.0522	37.0791	14.9738	3.6631	3.7671	2.839125331
105.8328	37.195	15.0173	3.7122	3.8121	2.691126556
99.0759	37.4099	14.9612	3.7582	3.8157	1.52998776
92.9007	37.4556	15	3.8079	3.8419	0.89288059
87.0022	37.4839	14.9976	3.8497	3.8974	1.239057589
81.6901	37.6158	14.9755	3.8968	3.9396	1.098337097
76.9122	37.6912	14.9654	3.9395	3.9783	0.98489656
72.5061	37.7779	14.9541	3.9811	4.0265	1.140388335
68.4768	37.9404	14.9809	4.0238	4.06	0.8996471
64.91	37.982	15.0238	4.0625	4.0773	0.364307692
61.7246	38.1411	14.9898	4.1022	4.1381	0.875140169
58.7253	38.0997	14.9863	4.142	4.1765	0.832930951
51.3962	38.2581	15.0077	4.2421	4.2651	0.542184296
47.5242	38.2166	14.9881	4.2925	4.3306	0.887594642
45.7742	38.2978	14.9976	4.3153	4.3495	0.792528909
43.0371	38.2255	14.9994	4.3723	4.3854	0.299613476
41.845	38.1418	15.0024	4.3872	4.4015	0.325948213
54.4909	37.3349	14.972	4.4475	4.3146	2.988195616
67.113	36.6847	15.0179	4.3598	4.2502	2.513876783

TIC91A (^{o}C)	FIC91A kg/hr	PIC91A psi	DENSITY(kg/m3)		ERROR(%)
			ACTUAL	ESTIMATE	
87.3169	35.9968	14.9875	4.1414	4.0929	1.17110156
82.2957	36.5082	15.0214	4.1078	4.0677	0.976191635
79.4919	36.8459	14.9749	4.1119	4.0316	1.952868504
95.9144	36.0098	14.9851	4.0563	3.949	2.645267855
106.6672	35.615	15.0077	3.9793	3.9038	1.897318624
104.8457	35.7916	14.9946	3.948	3.9054	1.079027356
100.0534	36.1902	15.0346	3.912	3.8849	0.692740286
113.92	35.6089	14.9696	3.8657	3.7935	1.867708306
126.5517	35.0637	15.0351	3.8151	3.7823	0.859741553
124.2056	35.3496	14.9881	3.7895	3.7421	1.250824647
121.1633	35.5255	15.0346	3.782	3.7375	1.176626124
119.8711	35.6459	14.9744	3.7687	3.7277	1.087908297
122.9896	35.5929	15.0059	3.7537	3.7137	1.06561526
140.1274	34.6199	15.0161	3.6875	3.633	1.477966102
150.3128	34.3897	14.9791	3.6249	3.5542	1.950398632
155.6105	34.2962	15.022	3.5789	3.5572	0.606331554
153.7175	34.5005	15.0119	3.5544	3.5425	0.334796309
151.133	34.7341	14.997	3.5429	3.5316	0.318947755
147.4947	34.957	15.0059	3.5311	3.5318	0.019823851
140.0654	35.3708	14.9749	3.5445	3.5455	0.028212724
131.7254	35.7203	14.9988	3.576	3.6032	0.760626398
123.5857	35.9245	15.0184	3.6243	3.67	1.260933146
115.8036	36.2067	15.0083	3.6667	3.7206	1.469986636
108.5555	36.477	15.003	3.7091	3.8078	2.66102289
101.7987	36.7004	14.9881	3.7553	3.8209	1.746864432
95.4948	36.7567	14.9922	3.8028	3.8418	1.025560114
89.7202	36.9868	14.9946	3.8492	3.8842	0.90927985
84.2269	37.112	14.9881	3.8933	3.9363	1.104461511
74.8522	37.1797	15.0286	3.9837	4.0233	0.994050757
70.8276	37.2087	15.003	4.0238	4.0786	1.361896715
67.0224	37.3356	15.0059	4.0613	4.1108	1.21882156
63.756	37.3929	14.9821	4.0978	4.1597	1.510566646
60.647	37.3995	15.0208	4.1361	4.1894	1.288653563
57.7668	37.482	14.9922	4.1689	4.2325	1.525582288
55.2539	37.5722	14.9958	4.2005	4.2563	1.328413284
53.0032	37.5456	14.9892	4.2232	4.2976	1.761697291
51.0004	37.6635	14.9881	4.25	4.3132	1.487058824
47.4336	37.7653	15.0089	4.2981	4.3461	1.116772527
45.9125	37.7528	15.0071	4.3065	4.37	1.474515268
43.0991	37.8888	15.0083	4.364	4.3963	0.740146654
63.0074	37.3067	14.9988	4.3063	4.1792	2.951489678
60.5612	37.4	14.9952	4.3053	4.2016	2.408659095

TIC91A (^{o}C)	FIC91A kg/hr	PIC91A psi	DENSITY(kg/m3)		ERROR(%)
			ACTUAL	ESTIMATE	
77.6465	36.458	14.9755	4.2227	4.1468	1.797428186
56.8418	36.9717	14.9809	4.405	4.344	1.384790011
67.709	36.3778	15.0316	4.3335	4.3093	0.55844006
65.6538	36.7703	14.9869	4.269	4.2596	0.220192082
63.0741	37.0005	15.0173	4.28	4.2365	1.01635514
60.7948	37.2182	15.0173	4.283	4.2236	1.386878356
62.5114	37.0919	15.0196	4.2721	4.2236	1.135273051
81.6377	36.0417	15.0053	4.2048	4.1807	0.57315449
85.6956	36.0574	15.0101	4.126	4.1116	0.349006302
81.6806	36.2155	14.9755	4.1069	4.1399	0.803525774
79.6302	36.447	15.0256	4.1059	4.1201	0.345843786
93.1249	35.7586	14.9809	4.0309	4.0294	0.037212533
106.5814	35.1754	14.9857	3.9575	3.9379	0.49526216
105.5991	35.3361	15.0083	3.9299	3.9381	0.208656709
101.3361	35.7099	14.969	3.9293	3.9414	0.307942891
103.4914	35.758	14.9982	3.9098	3.9201	0.263440585
121.9358	35.3502	14.9779	3.7412	3.7581	0.451726719
137.9864	34.6541	14.9857	3.6924	3.6562	0.980392157
149.7406	34.3239	14.9815	3.6295	3.5623	1.851494696
155.5152	34.0471	15.019	3.5857	3.5783	0.206375324
151.6527	34.4067	15.031	3.548	3.5565	0.23957159
150.2127	34.6143	14.9588	3.5394	3.5366	0.079109454
149.979	34.6734	14.9827	3.53	3.5366	0.186968839
149.979	34.5441	15.0184	3.5291	3.55	0.592218979
149.979	34.7	15.0143	3.522	3.5388	0.477001704
149.3019	34.7689	14.9738	3.5179	3.5323	0.409335115
142.9551	34.9525	15.0018	3.5386	3.5581	0.551065393
126.7567	35.6497	14.9785	3.6005	3.6678	1.869184835
118.946	35.8277	15.0435	3.6493	3.7161	1.830488039
111.5883	36.0589	15.0173	3.6914	3.7925	2.738798288
104.7503	36.3584	14.9767	3.7357	3.8442	2.904408812
98.2652	36.3187	15.0459	3.7876	3.8764	2.344492555
92.3858	36.5345	15.0363	3.8329	3.9057	1.899345143
86.902	36.7378	14.9839	3.8713	3.9532	2.115568414
81.8284	36.7415	15.0042	3.9204	4.0222	2.596673809
77.2746	36.6938	15.0316	3.9555	4.0935	3.488813045
72.9496	36.8881	15.0053	3.9969	4.1134	2.914758938
69.2206	37.0392	15.0006	4.0412	4.1377	2.387904583
65.7301	37.0192	14.994	4.0712	4.1987	3.131754765
62.5639	37.1785	14.9881	4.1044	4.2154	2.704414774
59.7314	37.201	15.0143	4.1345	4.2447	2.665376708
57.1517	37.324	15.0042	4.1674	4.264	2.317992033

TIC91A (^oC)	FIC91A kg/hr	PIC91A psi	DENSITY(kg/m3)		ERROR(%)
			ACTUAL	ESTIMATE	
54.7913	37.3257	14.9815	4.1958	4.3082	2.678869346
52.5931	37.431	14.9988	4.2287	4.3169	2.085747393
50.6094	37.4864	14.9994	4.2517	4.3377	2.022720324
48.8165	37.5321	14.997	4.2803	4.3583	1.822302175
41.206	37.9478	14.9892	4.3991	4.4234	0.552385715
40.5957	37.8885	14.991	4.4075	4.4335	0.589903573
40.5194	37.9347	15.0053	4.4184	4.4266	0.185587543
47.2858	37.5037	15.0167	4.2893	4.3763	2.028302987
45.8267	37.5493	14.9916	4.3253	4.399	1.703928051
44.5201	37.6016	15.0024	4.3468	4.4064	1.371123585
43.3232	37.6002	15.0059	4.3587	4.4203	1.413265423
41.2823	37.7219	14.9523	4.4042	4.449	1.017210844
45.2115	37.1886	15.0119	4.471	4.4437	0.610601655
64.2853	36.2266	14.9744	4.3885	4.3898	0.029622878
68.0762	36.0427	15.0208	4.3302	4.3694	0.905269964
64.5142	36.5123	15.0071	4.2755	4.3284	1.237282189
83.8693	36.0422	14.9881	4.1111	4.1434	0.785677799
106.4908	35.2112	14.9916	3.9687	3.9367	0.806309371
103.8396	35.4556	14.9952	3.9493	3.9461	0.081027017
100.5732	35.6545	14.9881	3.9455	3.9534	0.200228108
126.1511	34.7074	14.9994	3.8242	3.863	1.014591287
124.3963	34.9365	14.9881	3.8019	3.8246	0.597069886
120.9821	35.0929	14.9988	3.7785	3.8107	0.852190022
135.3971	34.5126	14.9934	3.7162	3.7381	0.589311662
151.8769	34.1809	14.9881	3.5566	3.5668	0.286790755
100.0296	44.7029	11.851	3.5348	3.5526	0.503564558

APPENDIX D

PHOTOGRAPHIC VIEW OF MODEL AFPT921

D Photographic View of Model AFPT921

Figure D-1: Photographic View Of Model